PNW-SGDP-TPR-Vol.1-Rev.1.0
PNWD-4438, Volume 1

Pacific Northwest Smart Grid Demonstration Project Technology Performance Report Volume 1: Technology Performance

Battelle Memorial Institute
Pacific Northwest Division
Richland, Washington 99352

Prepared for
U.S. Department of Energy
National Energy Technology Laboratory
Project Management Center
Contract ID: DE-OE0000190

June 2015

LEGAL NOTICE

Pacific Northwest Smart Grid Demonstration Project Technology Performance Report

Volume 1: Technology Performance

PNW-SGDP-TPR-Vol.1-Rev.1.0

Approved By:

6/26/2015

Ron Melton, Battelle Project Director — Date

6/24/2015

Evan Jones, Battelle Project Review Board Chairman — Date

This material is based upon work supported by the U.S. Department of Energy under Award Number DE-OE0000190.

Executive Summary

The Pacific Northwest Smart Grid Demonstration (PNWSGD), a $179 million project that was co-funded by the U.S. Department of Energy (DOE) in late 2009, was one of the largest and most comprehensive demonstrations of electricity grid modernization ever completed. The project was one of 16 regional smart grid demonstrations funded by the American Recovery and Reinvestment Act. It was the only demonstration that included multiple states and cooperation from multiple electric utilities, including rural electric co-ops, investor-owned, municipal, and other public utilities. No fewer than 55 unique instantiations of distinct smart grid systems were demonstrated at the projects' sites. The local objectives for these systems included improved reliability, energy conservation, improved efficiency, and demand responsiveness.

The demonstration developed and deployed an innovative transactive system, unique in the world, that coordinated many of the project's distributed energy resources and demand-responsive components. With the transactive system, additional regional objectives were also addressed, including the mitigation of renewable energy intermittency and the flattening of system load. Using the transactive system, the project coordinated a regional response across the 11 utilities. This region-wide connection from the transmission system down to individual premises equipment was one of the major successes of the project. The project showed that this can be done and assets at the end points can respond dynamically on a wide scale. In principle, a transactive system of this type might eventually help coordinate electricity supply, transmission, distribution, and end uses by distributing mostly automated control responsibilities among the many distributed smart grid domain members and their smart devices.

PNWSGD: Assembling the Team and Initial Steps

The origins of the demonstration project and eventual deployment of the transactive system can be traced to a Request for Interest jointly issued by the Bonneville Power Administration (BPA) and Battelle Memorial Institute in 2009. Many prospective PNWSGD participants responded to the request, and from these, ten distribution utilities and the University of Washington campus were chosen as demonstration test sites. Because of the BPA's interest in this research, the demonstration's geographical extent naturally included much of the Pacific Northwest. The selection of the 11 participant sites extended the region to represent five Northwest states—Idaho, Montana, Oregon, Washington, and Wyoming. The PNWSGD worked with each of these site owners to understand and document how the smart grid assets to be tested at each site were distributed among and monitored within its distribution system. In short, the project was one of the first and largest efforts to experiment with how to actually implement a smart grid.

Five additional organizations that came to be called "project-level infrastructure providers" were selected to apply their systems expertise, which was critical to the development of the transactive system. 3TIER (now Vaisala) offered measurements and predictions for most of the wind generators. Alstom Grid helped calculate the transactive signals. International Business Machines Corp. (IBM) was the system's chief architect and simulated transactive system performance. QualityLogic, Inc., offered system testing and interoperability expertise. Netezza, which was purchased by IBM during the PNWSGD, offered its massively parallel database appliance. During the course of the project, Spirae, Inc., was added to the group with the task of supporting the utilities in their deployment and testing of their transactive system components. Battelle Memorial Institute's Pacific Northwest Division (operator of the Pacific Northwest National Laboratory) was asked to be the technical and organizational lead.

The PNWSGD was accomplished in four phases that were scheduled for the timely installation of smart grid hardware and software and the new transactive system. A kickoff meeting was held in December 2009 to share and align participants' expectations for the demonstration. The project followed an aggressive schedule to complete its designs and installations by mid-2012, which was planned to allow for a two-year data collection window before the end of August 2014. Closeout activities, including the drafting of this final technical report, continued into 2015.

Engaging Electricity Users and New Technologies

Although all of the PNWSGD partners played pivotal roles in the project, the demonstration test sites, and their interfaces with the customers who eventually will use and benefit from smart grid technologies, were particularly important elements of the project. One objective of a smart grid is to improve the reliability of electric power for its end users. Toward this, PNWSGD utilities automated their distribution systems to enable more rapid restoration of customers' power after outages, including the application of fault detection, isolation, and restoration. Several of the project's utilities took advantage of automated power-quality alerts that have become available from advanced premises metering to help them more quickly pinpoint and respond to outages, abnormal supply voltages, and other conditions. Still others installed batteries and automated distribution switching to define high-reliability zones, including some that may separate from the rest of the grid and operate as microgrids when they become threatened by power outages.

Another objective of a smart grid is to conserve energy and improve the system's overall efficiency. One of the simplest means to conserve energy is to replace existing equipment with more energy efficient alternatives, as Avista Utilities did when they replaced approximately 800 existing distribution transformers with more efficient smart transformers. Others changed and automated their management of their distribution systems. Examples include using reduced feeder voltages that reduce the power consumed by some end-use loads, correction of power factor that reduces power line losses, or coordinated volt and reactive power control that can both reduce power load and reduce system losses.

Information itself can motivate consumers to conserve energy. Several of the participating utilities informed their customers of their historical electricity consumption via web portals or in-home displays. The University of Washington campus greatly increased the metering of individual buildings on its campus, and it generated new methods to inform building managers and occupants of their historical energy practices, either monthly or in real time. A very interesting effort at the campus was to empower its students, giving them tools to manage energy in their dormitory rooms and engaging them still further via social media.

The participating utilities reported a variety of benefits from their participation in the project and the smart grid technologies they deployed. Anecdotal reports of their experience have been compiled as “A Compilation of Success Stories” by BPA.[1]

Bringing Transactive Concepts to Life

The technical centerpiece of the project—the glue that connected the test sites, technologies and electricity resources—was the transactive system, which was implemented to dynamically respond to emerging conditions in the region’s power grid. The transactive system was distributed, providing a means of coordinating behavior of demand-responsive components through a forward-looking incentive signal and forward estimates of load behavior. The transactive system produced incentive signals, constructed by blending energy costs and conditions of the region’s bulk generation and grid. The system’s incentive signals were dynamic in space as well as time, representing variability across 14 geographic zones within the BPA balancing area based on location of the region’s bulk generation resources. The system of incentive signals predicted the delivered costs of energy in the near term and several days into the future. Large demand-side resources engaged by the transactive system included distributed generation, campus chillers and heating, ventilation, and air conditioning, renewable energy generation, and stationary battery energy storage systems. Smaller demand-side resources, often installed at residential premises, included sets of communicating thermostats, water heater controllers, and smart appliances.

The region’s bulk generation and a simplified transmission structure were emulated for the project by Alstom Grid using their energy-management and market-management system tools. The condition of the region’s generation and transmission systems was informed by a combination of actual grid status and static, seasonal representations of diurnal patterns. The bulk delivered costs of electricity were also estimated from this process, much as is done today in regions where locational marginal pricing is practiced. It is the flexibility with which costs and incentives may be dynamically applied in this transactive system that may help mitigate challenges of wind intermittency, encourage economic efficiency, and flatten system load.

While the project’s transactive system did not engage demand-side assets as well as had been hoped, the project was understood from the beginning to not be large enough to by itself have an impact on the grid. A bold step had been taken by the demonstration to launch the transactive system so generally, across such a large region, and to include its predictive days-ahead planning horizon. In order for the system to have been fully proven, no fewer than eight subsystems would have necessarily been accurately and meaningfully deployed. A key result of the project is, however, that much of the transactive system worked as intended. Experience with the transactive system helps prepare the region to operate an increasingly distributed electric power system making maximum use of its growing renewable energy supply and demand-side solutions. The project leaves an updated technical specification for the transactive system that leverages the five years of development and deployment experience. The updated

[1] Bonneville Power Administration. 2015. Pacific Northwest Smart Grid Demonstration Project: A Compilation of Success Stories. Accessed at https://www.bpa.gov/Pages/home.aspx.

specification and a corresponding reference implementation provide an important platform for future research into transactive energy systems.

When the project looked at the transactive subsystems (as is done in Chapter 2), about half of the subsystems were found to have performed well. Among the successes, wind resources were accurately stated and predicted within the region by the demonstration. Unit costs and incentives were indeed generated to represent bulk resource costs and the demonstration's stated operational objectives. The incentive signals were meaningfully blended at, and communicated between, the system's multiple nodes. A library of functions was developed that automatically determined times of events to which responsive demand-side assets, such as water heaters, battery energy storage, and thermostats, were to respond.

There is a key observation about the performance of the transactive coordination system as compared to conventional demand response. Even when the responses to the transactive system were automated, utilities placed limits on the number of allowed responses. Customer agreements often specified a maximum number of allowed events in a month. Conventional demand-response programs, either direct load control or otherwise, are generally event-driven and are targeted toward managing few, short-lived incidents like critical peaks. Several well-placed asset responses may be adequate for conventional demand-response programs. Transactive systems, on the other hand, reveal a continuum of incentives to the utilities and asset systems and could engage assets much more dynamically according the each asset's capabilities and the flexibility of the asset's owner. This granularity of responses by many customers enables those customers who are both willing and able to respond (via automated systems) to participate according to their preferences rather than having their participation limited according to predetermined agreements.

In addition to the results gained from the deployment of the transactive system, IBM used a model of the regional system to assess the impact of a scaled up deployment of the transactive system. This simulation showed that the region's peak load might be reduced by about 8% if 30% of the region's loads were responding to the transactive system.

At the end of the project's data collection period, the transactive system was turned off. The regional incentive signals produced using the Alstom tools were not linked to operational needs of the BPA, the regional system operator. In the absence of such linkage, there was no basis for continuing to generate the signals once the research was completed. There are efforts underway to continue to use a small subset of the deployed transactive control system for further regional research. If BPA or other balancing area operators in the region define an incentive signal, the PNWSGD utilities could, in principle, resume the use of their transactive systems.

Exploring Data—and Associated Challenges

Now that the demonstration project has concluded, it leaves behind a rich database—almost 350 billion data records. Organization of the data is based on the 55 smart grid systems defined by the project. An extraordinary effort was needed to accurately specify the many data series that might be used to monitor those smart grid systems. The disparity of data sources, databases, intervals, and utility data practices that was encountered during the demonstration made the challenge even greater. The transactive system featured a predictive time dimension that exponentially increased the volume of data that was automatically collected from the transactive system.

The project's experience is an example of dealing with the vast amounts of new data that become available in a smart grid. In the demonstration, much of that data was found to be unusable. Data cannot be converted into actionable information if its quality is poor or if its units, location, or validity is uncertain. Investments should be made to improve the quality of meter data, databases, and smart grid data processes at all levels. As a part of these investments, there is a need for better tools to be developed for utilities to use in managing the devices and information found in a smart grid.

Moving Forward

Along with data challenges, this report addresses the technical performance of all the smart grid asset systems that were tested at the PNWSGD sites. It also critiques the performance of the transactive system that was featured by the demonstration. After an introductory chapter, the performance of the transactive system is discussed. In the three following chapters, the performances of reliability, conservation and efficiency, and demand-responsive systems are generalized, referring to the 55 smart grid systems that were demonstrated at the PNWSGD sites. The performance of each site owner's smart grid systems is presented in the final 11 chapters.

At its conclusion, the PNWSGD leaves a legacy of smart grid equipment installed with its site owners. Eighty-eight percent of the smart grid assets remain installed and functional after the demonstration. The remainder succumbed to the challenges of grid modernization in the early 21st century. Some of these systems could not be successfully integrated due to interoperability problems with other new and legacy systems with which they needed to interact. Some sets of residential devices were removed after having been installed, due to unexpected safety problems or at the request of residential customers. Some vendors failed to deliver their smart grid products or went out of business during the demonstration. Nine of the removed systems were wind turbines that were taken down at a renewable park due to safety concerns after a tower catastrophically failed and a turbine had thrown a blade. These are considered learning experiences. The demonstration project facilitated the maturation of the smart grid industry, and helped advance our collective thinking about the path forward. Please read further to understand why the participants in the PNWSGD remain optimistic about smart electric power grids of the future.

Acknowledgments

Author:	
D Hammerstrom	Battelle Memorial Institute
Coauthors:	
D Johnson	Avista Utilities
C Kirkeby	Avista Utilities
Y Agalgaonkar	Battelle Memorial Institute
S Elbert	Battelle Memorial Institute
O Kuchar	Battelle Memorial Institute
C Marinovici	Battelle Memorial Institute
R Melton	Battelle Memorial Institute
K Subbarao	Battelle Memorial Institute
Z Taylor	Battelle Memorial Institute
B Scherer	Benton PUD
S Rowbotham	City of Ellensburg
T Kain	City of Milton-Freewater
T Rayome-Kelly	Flathead Electric
R Schneider	Flathead Electric
R Ambrosio	IBM
J Hosking	IBM
S Ghosh	IBM
M Yao	IBM
R Knori	Lower Valley Energy
W Jones	Lower Valley Energy
J Pusich-Lester	NorthWestern Energy
M Simpson	Peninsula Light Company
R Grinberg	Peninsula Light Company
K Whitener	Portland General Electric
S Chandler	Portland General Electric
M Phan	Portland General Electric
L Beckett	Portland General Electric
C Mills	Portland General Electric
D Garcia	Portland General Electric
R Bass	Portland General Electric
W Sanders	Portland General Electric
M Osborn	Portland General Electric
W Lei	Portland General Electric

The following individuals and organizations are recognized for their valuable contributions:

<u>Vaisala (formerly 3Tier, Inc.)</u>
M Grundmeyer
J Lerner
P Storck
A Vandervoort

<u>Alstom Grid</u>
M Atkinson
M Chungyoun
J Corkey
H Jaffarbhoy
P Jap

Alstom Grid (Continued)
E Jensen
J Lelivelt
C Shaw
X Wang
G Wooster
M Yao

Avista Utilities
H Cummins
P Duncan
G Fischer
L Jue

Avista Utilities/Washington State University
A Bose
T Ryan

Battelle Memorial Institute
B Akyol
R Anderson
J Bernsen
P Boyd
T Carlon
K Carneau
D Chassin
P Christensen
L Connell
K Cook
A Cooke
J Dahl
G Dayley
T Edgar
M Engels
S Ennor
T Esram
A Faber
N Foster
V Genetti
B Gerber
P Gjefle
A Haas
R Hafen
D Hardman
J Hathaway
K Huston
C Imhoff
J Jao

Battelle Memorial Institute (Continued)
E Jones
R Jones
S Kanyid
D King
S Kowalski
T Ledbetter
O Love
D Manz
T McKenna
J Melland
V Mendon
M Newhouse
L O'Neil
P O'Toole
C Owen
M Parker
R Pratt
C Raymond
N Sargent
B Simanton
S Singh
D Sisk
B Slonecker
A Somani
V Srivastava
S Tackett
B Vyakaranam
M Wagner
F White
D Zimmerman
M Zimmerschied

Benton PUD
C Bartram
R Dunn
J Henderson
J Sanders

Bonneville Power Administration
T Brim
L Hall
T Oliver
K Pruder-Scruggs
S Reed
D Watkins
J Williamson

City of Ellensburg
T Barkley
L Dunbar
B Faubion
B Leader
G Nystedt
J Richmond
B Titus
W Weidert

City of Milton Freewater
B Chadek
M Charlo
City of Milton Freewater
L Hall
R Rambo

CVO Electrical Systems
B Leland
J Newland

Electsolve Technology Solutions & Services, Inc.
J Newland

Flathead Electric
M Johnson

IBM
K Bodell
M Cohen
D Gil
J Hosking
G Janssen
J Kidwell
J Kilbride
J Malczyk
D Melville
S Nathan
D Phan
J Reid
M Rosenfield
B Schloss
B Schmidt
G Soumyadip
S Srinivasan
M Steiner
H Wang

IBM (Continued)
K Warren
A Webb
J Xiong

Idaho Falls Power
V Ashton
J Flowers
M Reed
H Dory

Lower Valley Energy
W Jones
R Knori
J Webb

National Energy Technology Laboratory for the U.S. Office of ElectricityDelivery and Energy Reliability
M Sciulli

Netezza
B Walker

NorthWestern Energy
P Corcoran
G Horvath
J Pusich-Lester
B Thomas

Peninsula Light Company
S Anderson
B Draggoo
R Grinberg
J Pilling
M Simpson
D Walden
J White
J Wigle

Portland General Electric
J L Becket
J Dalzell
C Eustis
P Farrell
S Klotz
E Medina
C Mills

Portland General Electric (Continued)
M Mohammadpour
M Moir
J Poppe
J Ross
K Teague
K Whitener

QualityLogic, Inc.
G Cooper
B David
D Jollota
S Kang
C Kawasaki
J Mater
M Osborn
L Posson
E Prabhakaran
L Rankin
J Zuber

RAI, Inc.
S Hamilton
B Mantz

Spirae, Inc.
B Becker
M Fanning
J Harrell
S Oliver
O Pacific
A Russell

University of Washington
J Angelosante
J Carlson
J Chapman
C Kennedy
N Menter
J Park
G Sakagawa
J Seidel

U.S. Department of Energy, Pacific Northwest Site Office
J Erickson

U.S. Office of Electricity Delivery and Energy Reliability
M Smith

WISDM Corp.
B Burner
M Hansen

Acronyms and Abbreviations

3TIER	3TIER, Inc., now part of Vaisala
ACS	advisory control signal
AGRS	Avista-generated request signal
AGS	Avista-generated signal
aHLH	average heavy-load hour energy
AMI	advanced metering infrastructure
BPA	Bonneville Power Administration
CAIDI	Customer Average Interruption Duration Index
CPUC	California Public Utilities Commission
CVR	conservation voltage reduction
DA	distribution automation
DDC	direct digital control
DMS	distribution management system
DOE	U.S. Department of Energy
DR	demand response
DRU	demand-response unit
DSG	distributed standby generation
EIOC	Electricity Infrastructure Operations Center
FDIR	fault detection, isolation, and restoration
FEMS	facility energy management system
GE	General Electric
GFA	grid friendly appliances
HAN	home area network
HLH	heavy-load hour
HVAC	heating, ventilating, and air conditioning
IBM	International Business Machines Corp.
iCS	Internet-Scale Control System software
IEEE	Institute of Electrical and Electronics Engineers
IHD	in-home display
IM	impact metric
IST	interval start time
IT	Information Technology
IVVC	integrated volt/VAr control
LCM	load-control module
LLH	light-load hour

LTC	load tap changer
LV	prefix for Lower Valley, Wyoming, project tests
MAIFI	Momentary Average Interruption Frequency Index
MAN	metropolitan area network
MDM	meter data management
O&M	operations and maintenance
OMS	outage management system
OMT	Outage Management Tool
p.u.	per unit
PCT	programmable communicating thermostat
PHEV	plug-in hybrid electric vehicle
PLC	power line carrier
PNWSGD	Pacific Northwest Smart Grid Demonstration
PRB	Project Review Board
PUD	Public Utility District
PV	photovoltaic
RTU	remote terminal unit
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	supervisory control and data acquisition
SCL	Seattle City Light
SEL	Schweitzer Engineering Laboratories
SSPP	Salem Smart Power Project
ST	field site node (of the transactive coordination system topology)
STP	Smart Thermostat Pilot
SVC	static VAr compensator
T&D	transmission and distribution
TFS	transactive feedback signal
TIS	transactive incentive signal
TWACS	Two-Way Automatic Communication System
TZ	transmission zone
UC	unit commitment
UW	University of Washington
VVO	volt/VAr integration and optimization
WECC	Western Electricity Coordinating Council
WSU	Washington State University

Units

$/h	dollars per hour
°C	degree(s) Celsius
F	Fahrenheit
GW	gigawatts
GWh	gigawatt-hour(s)
kV	kilovolt(s)
kVAr	kilovolt-ampere(s) reactive
kW	kilowatt(s)
kWh	kilowatt-hour(s)
kWh/h	kilowatt-hour(s) per hour
m	meter(s)
mph	miles per hour
MW	megawatt(s)
MWh	megawatt-hour(s)
p.u.	per unit
s	second(s)
VAr	volt-amperes reactive
W	watt(s)
y	year

Contents

Figures

Tables

1.0 Introduction

This Technology Performance Report for the Pacific Northwest Smart Grid Demonstration (PNWSGD) project is a project deliverable to the U.S. Department of Energy (DOE). It is a major component of the project's final reporting. The purpose of this document is to present the results of all analysis conducted by the project. As a technology performance report, this document addresses the technologies that were installed and tested during the PNWSGD. The plan for this analysis was reported previously in the project's Metrics and Benefits Reporting Plan (PNWSGD 2013a).

Details regarding the design of the project's transactive control technology and other related project elements are provided in separate project deliverables, including the following:

- PNWSGD Project – Conceptual Design (PNWSGD 2014)
- PNWSGD Project – Interoperability and Cyber Security Plan (PNWSGD 2011).
- PNWSGD Project – Transactive Coordination Signals (PNWSGD 2013b).

Except where necessary to support the representation of analysis results, in this report we refer readers to the related documents to avoid duplicating the material.

This introduction provides a summary of the key points of the project and describes the organization and contents of the report.

1.1 The PNWSGD Project

The PNWSGD was one of 16 regional smart grid demonstration projects that were co-funded by the DOE under the American Recovery and Reinvestment Act of 2009 (DOE 2013). The DOE funding required a minimum of 50% cost-share by the project team.

Battelle Memorial Institute's Pacific Northwest Division; operator of the Pacific Northwest National Laboratory) was the prime recipient of the DOE funds and led the PNWSGD. Another five sub-recipients were infrastructure participants, including IBM (International Business Machines Corp., Thomas J. Watson Research Center), system architect of the transactive coordination system; QualityLogic, interoperability testing; 3TIER (now Vaisala), wind energy forecasting; Alstom Grid, transmission and generation system modeling; and Netezza (acquired by IBM during the project), large-scale data management. Bonneville Power Administration (BPA), a federal regional power marketing agency and transmission system operator, provided funds to support Battelle's activities, data representing the regional system, and actively participated in advising the project. Field demonstration sites in a five-state region of the northwestern United States were hosted by another 11 funding sub-recipient participants, including rural electric cooperatives, a public utility district (PUD), municipalities, investor-owned utilities, and a university campus.

This project implemented one of the world's first transactive coordination systems—a system in which both supply and demand communicate and negotiate the cost and quantity of electrical energy that will be supplied and consumed. Twenty-five of the project's 55 asset systems were made responsive to the transactive coordination system. Other asset systems were installed to improve grid reliability (11 asset systems) or to conserve energy (25 asset systems).

The PNWSGD was planned as a five-year project. The project exceeded that time; it started in December 2009 and concluded in June 2015.

1.1.1 Objectives

The primary objectives stated at the beginning of the PNWSGD project were to accomplish the following:

- Create the foundation for a sustainable regional smart grid that continues to grow after the completion of this demonstration project.
- Develop and validate an interoperable communication and control infrastructure using incentive signals to coordinate a broad range of customer and utility assets, including demand response, distributed generation and storage, and distribution automation; engage multiple types of assets across a broad, five-state region; and extend from generation through customer delivery.
- Measure and validate smart grid costs and benefits for customers, utilities, regulators, and the nation, thereby laying the foundation of business cases for future smart grid investments.
- Contribute to the development of standards and transactive control methodologies for a secure, scalable, interoperable smart grid for regulated and non-regulated utility environments across the nation.
- Apply smart grid capabilities to support the integration of a rapidly expanding portfolio of renewable resources in the region.

1.1.2 Regional Geographical Map

Figure 1.1 shows a regional geographical representation of the project. This map identifies the geographical locations of project sites in relation to political boundaries, energy balancing authority boundaries, major transmission, major regional hydro generation resources, major regional renewable energy resources, major regional load centers, and major conventional electrical generation. Of note is the geographic scope of the effort. The scope covers two time zones and five states. This project is, to the best of our knowledge, the first to deploy technology intended to coordinate the response of multiple utilities across a region to provide a benefit to the region. Note that Inland Power, shown in the figure, was an original member of the project team but withdrew from the project shortly after it started.

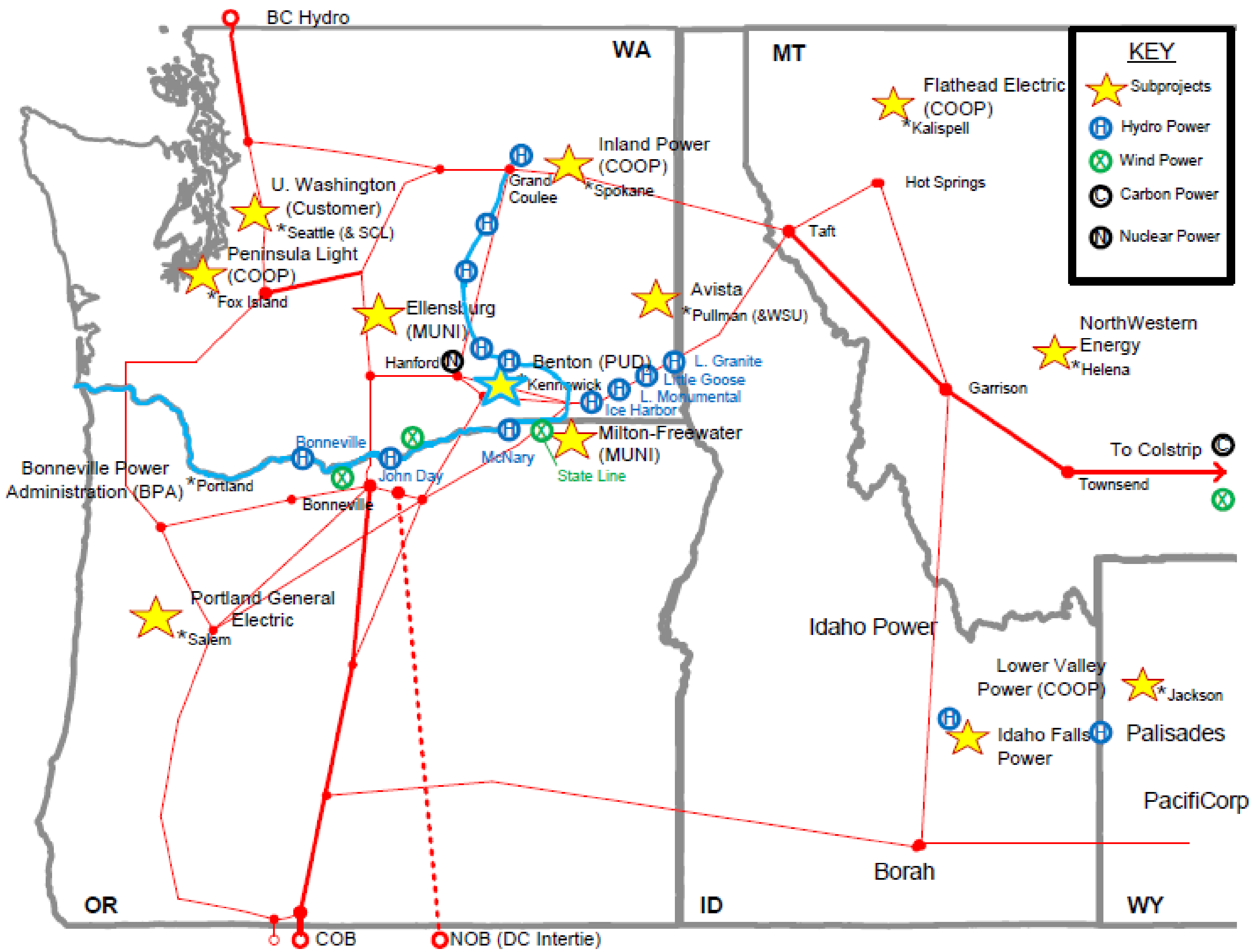


Figure 1.1. PNWSGD Geographical Region, Including Participants' Locations and Major Generation and Transmission Corridors

1.2 Technical Approach

The project organized its technical approach around the asset systems deployed by the participating utilities. The PNWSGD defines an *asset system* as "all the components that are needed to provide desired smart grid functionality." DOE provided guidance making a further distinction between the components based on whether they had been paid for with project funding (*project*) or not (*system*). This distinction was used during the reporting of quarterly build metrics to DOE, but these distinctions are not critical to the assessment of asset-system costs and benefits in the PNWSGD analysis approach. The project's quarterly build metrics are available at (DOE-OE 2015).

Regional utilities competed for the opportunity to participate in the PNWSGD by responding to a solicitation from BPA during the fall of 2009. Respondents were asked to identify which assets or systems they were willing to allow to respond to the planned time-varying incentive signal and to identify smart grid technologies they had already installed, planned to install, or proposed to install as a part of the project. From the responses, 12 utilities were selected for the proposal and subsequent project. As noted earlier, one utility, Inland Valley, withdrew from the project shortly after funding was awarded.

The project's tests were organized into three categories of smart grid functionality:

- Conservation and efficiency − asset systems that were installed to conserve energy or to improve efficiency. Targeted efficiencies may include either operational efficiencies or energy efficiencies.
- Demand-responsive (Transactive) − asset systems that have been installed responsive to demand-response signals from the project's transactive system
- Reliability − asset systems that have been installed to provide more reliable service to distribution customers.

An asset may have been used in more than one of the test categories.

1.3 The Demonstration Test Sites and Asset Systems

In this document, we summarize the performance of smart grid technologies that were installed and implemented at the project's 13 field sites. The owners of these field sites selected commercial smart grid technologies that they were interested in and selected vendors to install the technologies. The field site owners paid at least half of the technologies' costs, and the DOE paid the other half. Table 1.1 lists the field sites, field site owners, and technologies that were installed by the PNWSGD project.

Table 1.1. Site Owners, Sites, and Asset Systems of the PNWSGD

Site Owners	Field Sites	Asset Systems	Cat.[a]
Avista Utilities (Avista Corporation 2013)	Pullman, WA, including parts of the WSU campus	Voltage Optimization	1 & 3
		Configuration Control for Optimization	3
		Smart Transformers	3
		Residential Loads and Web Portals	1 & 3
		AMI and In-Home Displays	3
		Biotechnology Generator for Outage Prevention	2
		Configuration Control for Optimization (FDIR)	2
		WSU Controllable HVAC Load	1
		Controllable WSU Chiller Load	1
		Diesel Generator	1
		WSU Generator 1	1
		WSU Generator 2	1
Benton PUD (Benton PUD 2011)	Reata Substation, Kennewick, WA	DataCatcher™ and AMI	2
		Demand Shifter™ and DataCatcher	1
City of Ellensburg (Ellensburg 2013)	City of Ellensburg Renewables Park, Ellensburg, WA	Recloser Switch	2
		Polycrystalline Flat Panel 58 kW PV System	3
		Thin-Film Solar Panel 54 kW Array	3
		Honeywell WindTronics 1.5 kW Model WT6500	3
		Windspire® 1.2 kW Wind Turbine	3
		Home Energy Int. 2.25 kW Energy Ball® V200	3
		Southwest Windpower 2.4 kW Skystream 3.7®	3
		Bergey WindPower 10 kW Excel 10	3
		Tangarie Alternative Power 10 kW Gale® Wind Turbine	3
		Urban Green Energy 4 kW Wind Turbine	3
		Ventera Wind 10 kW Turbine	3
		Wing Power 1.4 kW Wind Turbine	3
Flathead Electric (Flathead Electric 2013)	Libby, MT	AMI for Outage Recovery − Libby	2
		In-Home Displays − Libby	1
		Demand-Response Units − Libby	1
		Smart Appliances − Libby	1
	Haskill Substation, MT	AMI for Outage Recovery − Haskill	2
		In-Home Displays − Haskill	1
		Demand-Response Units − Haskill	1
		Smart Appliances − Haskill	1

Table 1.1. (cont.)

Site Owners	Field Sites	Asset Systems	Cat.[a]
Idaho Falls Power (Idaho Falls Power 2013)	Idaho Falls, ID	Automated Voltage Reduction	1 & 3
		Automated Power Factor Control	2
		Distribution Automation	2
		Water Heater Control	1 & 3
		PHEV, Solar, and Battery Storage	1
		Thermostat Control	1 & 3
		In-Home Displays	3
Lower Valley Energy (Lower Valley Energy 2013)	Teton-Palisades Territory, WY	Existing AMI and In-Home Energy Displays	3
		Demand-Response Units	1
		Demand-Response Units/AMI	2
		Adaptive Voltage Regulation	3
		SVC for Power Factor Improvement	3
		Battery Storage System	1
		20 kW Solar Photovoltaic System	3
		Four 2.5 kW WindTronics Wind Turbines	3
City of Milton-Freewater (City of Milton-Freewater 2013)	Milton-Freewater, OR	Load Control with Demand-Response Units	1
		Conservation-Voltage-Regulation Peak Shaving	2
		Voltage-Responsive Grid-Friendly DRUs	1
		Conservation from CVR on Feeders 1-4	3
NorthWestern Energy (NorthWestern Energy 2013)	Helena, MT	Automated Volt/VAr Control − Helena	3
		Fault Detection, Isolation, and Recovery	2
		Demand-Response Units	1
	Philipsburg, MT	Automated Volt/VAr Control – Philipsburg/Georgetown	3
Peninsula Light Company (Peninsula Light Company 2013)	Fox Island, WA	Load Reduction with Load-Control Modules	1
		CVR with End-of-Line Monitoring	1 & 3
		Padmount & Overhead Automated Switching	2
Portland General Electric (Portland General Electric 2013)	Salem, OR	Residential Demand Response	1
		Commercial Demand Response	1
		Commercial Distributed Standby Generation	1
		Battery Storage in High-Reliability Zone	1
		Distribution Switching and Residential/Commercial Microgrid	2

Table 1.1. (cont.)

Site Owners	Field Sites	Asset Systems	Cat.[a]
University of Washington Facilities Services (University of Washington Facilities Services 2011)	University of Washington Campus, Seattle, WA	Steam Turbine	1
		Diesel Generators	1
		Solar Renewable Generation	3
		Direct Digital Controls	1 & 3
		FEMS Data for Campus Building Managers	3
		Impact of Energy Reports to Building Managers	3

Key to test-case categories: 1-transactive coordination, 2-reliability, and 3-conservation and efficiency.

AMI = advanced metering infrastructure
CVR = conservation voltage reduction
FDIR = fault detection, isolation and restoration
FEMS = Facility Energy Management System
HVAC = heating, ventilating, and air conditioning
PHEV = plug-in hybrid electric vehicle
PV = photovoltaic
SVC = static VAr compensator
VAr = volt-amperes reactive
WSU = Washington State University

Each individual utility chapter (Chapters 7 – 17) describes the mapping for the site owner's asset systems within its distribution system. The PNWSGD referred to these diagrams as *layout diagrams*. They proved very useful for referencing the relationships between distribution system data and the asset systems. They also point out the potential for confounding results at places where the asset systems overlap and may influence the results of each other.

1.4 Demonstration Data and Data Processes

Over the course of the project about 16 TB of data were collected. The project followed its cyber security risk management process in the design, implementation, and operation of the transactive control system and in the approach used to collect the technical and engineering data for the project. Please refer to the project's Interoperability and Cyber Security Plan for details (PNWSGD 2011).

The data collected by the project is of two major types: data having a prediction horizon and data having no prediction horizon. The transactive system consumes and creates predictions. Each transactive incentive signal, for example, includes predictions for a series of 56 future time intervals. The PNWSGD often referred to this predictive data simply as *transactive data*. Other project data does not include predicted intervals. These other data—meter readings, for example—were often collected in real time as series of time intervals.

Data statistics for the data collected by the project are summarized in Table 1.2. The project collected and organized an expansive data archive documenting the performance of the systems and various technologies involved. Battelle and DOE are working on the protocol for making the data available to researchers and students after the project has concluded.

Table 1.2. Data Statistics

Volume	Velocity	Data Type	Multiplicity
~16 TB of data stored on an IBM PureData System (Netezza)	Near real time	Configuration files and location information	For each transactive node and test case
	Daily – historical utility data uploads	Transactive signal data	Incentive signal, resource, and load predictions
		Measurement data	Feeder (substation and end-of-line), PV, Wind, AMI, etc.
	Manual – monthly, yearly or one-time submissions of data	Weather data	Actual data from MesoWest and typical meteorological year data
		Test and device events	Status reporting
		System management events	System logs

The project experienced significant problems with consistent reporting of data and data quality. As a result, we are concerned that many utilities are not prepared to manage the large volumes of data that can be generated by smart grid technology, in particular detecting and correcting equipment problems and faulty data. New tools are needed to enable utility operators to detect intelligent end-device or sensor problems and prevent bad data from entering smart grid systems.

1.5 Organization of this Report

This Technology Performance Report has two volumes. This volume contains information about the technologies deployed by the project and their performance. The second volume is the Interoperability and Cyber Security report. Due to the sensitivity of the information contained in that volume it has limited distribution.

This volume consists of summary chapters covering

- the transactive coordination system,
- conservation and efficiency test cases,
- transactive coordination test cases, and
- reliability test cases.

The transactive coordination system chapter (Chapter 2) presents background on the design and implementation of the transactive coordination system, assessment of performance of the system relative to BPA system events, and the results of modeling and simulation of the regional system and utility assets considering a scaled-up implementation.

Chapters 3, 4, and 5 summarize the findings for the 3 categories of tests across the 11 participating field sites. Conclusions are discussed in Chapter 6.

Chapters 7 through 17 address details from the analyses of all of the utilities' asset systems that they demonstrated during the PNWSGD. Each of the site chapters is intended to be self-contained. The following discussion provides background on the methods used in analyzing and reporting the tests for the utility projects. This should help in understanding the material presented in Chapters 7 through 17.

The analysis of data generated by the utility participants was an ambitious undertaking. The participants provided data from a variety of smart grid asset systems across the three categories of test cases: transactive coordination, reliability and conservation, and efficiency.

With the overall amount of time available for analysis there were inherent limits to the amount of time that could be spent on each individual test case. For many of the test cases there were multiple iterations with the corresponding utility to answer questions about the data, fill in missing data, correct time labels, provide metadata, and so on. Only when this data triage process was complete and the data were put into a standard format could the analysis proceed. In some cases it was not possible to complete this step and the test-case analysis could not be completed.

This was a field project and the challenges in working with the data are characteristic of such a project. The participating utilities are operational entities for which meeting the needs of their customers naturally comes first. The utilities were cooperative in working with the Battelle team to address questions about the data, but even so, there were limits to what they could do.

The PNWSGD was a *demonstration*. The Principal Investigator took this to mean that benefits were to be *verified* from the field data that the project collected. This is a higher bar than the creation of a business case for a technology. Early in the PNWSGD, project staff sat face-to-face with the utility staff to help define their asset systems, including the definition of testable objectives, the definition of metrics by which those objectives might be verified, data that would be needed, and the control of potentially confounding influences. The project encouraged the careful definition of baseline control groups, where appropriate, so that meaningful side-by-side comparisons might be possible between the performances of those who were affected by a test system and those who were not. The project next worked with the utilities to collect the data into the project's relational database. This was an iterative process, because the project had to work with a utility if their data were found deficient. A simplified *view* of the database was created for each utility to support the analysis of its assets. A data dictionary was created for each view, and this dictionary defines each named data series that is available to analysts. Finally, most of the analysis was completed and reported by Battelle staff. Some utilities chose to also conduct their own analysis, and where this occurred, the results of the utilities' analyses have been included. We encourage other researchers to work with the data, and where possible, perform more in-depth analysis and confirm or correct the project's analysis results.

The discussions in the following test chapters about the asset systems tested by each utility have these three subsections in common:

1. Introduction − The reader is introduced to the asset system and its components. This subsection includes a compilation of the system's annualized costs.
2. Available data and characteristics of the asset − Events, if relevant, are shown or listed. The relevant data series to be used by the analysis are shown at the level of aggregation available to analysts. Data problems and remedies, if any, are described. Assumptions are stated.
3. Analysis and analysis results − Analysis methods and results, if supported, are stated. The descriptions of methods are terse, so as not to repeat the details of methods that were used similarly for multiple asset systems. The monetary impacts that directly follow from the analysis are compiled.

Annualized costs. The project worked with each utility to capture the costs of its asset systems. The utilities were advised to state the costs that would be incurred for the *next* implementations of their systems, thus giving them permission to omit the research and organizational costs that were, perhaps, unique to the PNWSGD. In this cost model, the starting point is critical. For example, it must be made clear whether the costs of existing advanced metering infrastructure that are needed by an asset system were included or not. The set of components should include all devices and subsystems that must exist if the asset system's functionality is to be achieved. The project elected to annualize the costs. Subsystems having different lifetimes are thereby accommodated by presuming that each subsystem is replaced after its lifetime and maintained in perpetuity. Where a subsystem was used in more than one of a utility's asset systems, its costs were allocated proportionally among them. The present value and annualized equivalent costs were calculated by discounting the future lifecycle costs at a 7% discount rate.

Monetized benefits. The PNWSGD intended to evaluate all of the anticipated benefits and the monetized values of all of the benefits, from which cost-benefit analysis could be completed and reported. The PNWSGD fell short in this effort. The benefits, based on the project's analysis methods and available data, often fell short of those anticipated or were not, in fact, convincingly demonstrated at all. The monetization of energy benefits from the utilities' perspectives followed from the costs of wholesale electricity rates in the Pacific Northwest, which remain relatively low. The calculated values of deferred energy purchases and avoided demand charges were, therefore, often less than compelling. Softer outcomes, like changes in truck rolls and changes in operations costs, were not consistently available or captured across the multiple organizations. And even fewer of these indirect benefits are verifiable to the degree that they could be claimed as having been *demonstrated*. A parallel effort by BPA generated business cases for the classes of tested asset systems.

The analysis approach by test-case categories is summarized below.

Analysis of reliability asset systems. The goal of these asset systems was to improve distribution system reliability. From the perspective of a *demonstration*, metrics should verify that the circuits are more reliable after the installation of the asset system than before. This is challenging because the region's circuits are already very reliable, and the asset systems strive to further reduce what are infrequent events. Outages are as unpredictable as the weather. Regardless, the project attempted to use existing, accepted reliability indices to observe impacts and trends. A long history of circuits' performance was requested. Monthly assessments are important if useful trends are to be observed. There is a troubling encroachment of self-reported indices for the valuation of reliability asset systems. These are useful for the formulations of business cases, but they are backward-looking and do not seem to truly verify improved system performance going forward.

Conservation and efficiency assets. These asset systems were to conserve energy or achieve operational efficiencies. The project attempted to confirm that the circuits or premises that received the asset system used less energy after the asset system had been engaged than before. Where available, control groups were used to mitigate otherwise uncontrolled influences like load growth, affluence, etc. The treatment and control groups were often found to be dissimilar, which might be attributed to selection or self-selection biases. Knowing the precise date of the installation or precise timings of the applications was critical. Much historical data was needed from before the installation or application of the asset system. The comparison of historical and recent data was exacerbated by the fact that new meters themselves were sometimes components of the systems being tested.

Demand-responsive (transactive) asset systems. These systems were intended to modify (usually curtail) energy consumption during relatively short events. The project requested that these systems automatically respond to advice from the PNWSGD transactive system, but the coincidence between the utilities' reported events and the transactive system's events was found to be poor. The project therefore focuses on quantifying the impacts of the asset systems on power during the events, during the rebound hour immediately following events, and throughout days that events had occurred. This entailed creating baselines that emulated power at the pertinent feeders or premises as if the events had not occurred. Where a useful control group was established, the consumption of the control group could be normalized to be as similar as possible to the test group at times that events were idle. Alternatively, linear regression models of the test groups' power were created to represent their characteristic behaviors. The actual power consumption of the test group was then compared with the *modeled* or *controlled* baselines. If an impact had occurred, it should be evident as a difference between the test and baseline powers during the event periods. It is critical that the list of event periods is accurate so analysts know where to look for these differences. This analysis also relies heavily on the accuracy and precision of fine-interval metering. A 15-minute event may be difficult to detect with 1-hour meter intervals. The calculated impact will become diminished if the meters' intervals misalign with the asset-system events or if the meters' timestamps have not been calibrated to a precision such that their measurements of the short events will be aligned. Finally, the meter points themselves must, in fact, monitor the asset system's impacts and must be close enough to the impacts that the impact might be measureable among the meters' baseload and noise.

2.0 The Transactive System

Additional chapter coauthors:
OA Kuchar and C Marinovici − Battelle Memorial Institute

The Pacific Northwest Smart Grid Demonstration (PNWSGD) project featured an innovative transactive system. This chapter discusses the technical performance of that system. Its purpose was to coordinate the dispatch of electric energy with responsive electricity demand in a way that reduced system peaks, reduced costs, and mitigated the challenges from emerging intermittent energy resources like wind. The system partitioned the Pacific Northwest (PNW) power grid into 27 nodes, and these nodes communicated with their nearest neighbors every 5 minutes during the project (1) the delivered cost of electricity and (2) the predicted energy to be exchanged now and during a set of future intervals.

Section 2.1 presents context that the reader might need as system performance is discussed. The project generated many presentations and documents that describe the transactive system. This chapter will not repeat all of the details and concepts from the other presentations and documents.

First, understand that the candidate architectures, advantages, and limitations of transactive systems are under active discussion. The project's system is one example among several candidate system approaches. The Gridwise Architecture Council has become a forum for this technical discussion. So, some of the most general discussion about transactive systems may be found on the Council's Transactive Energy webpage (Gridwise Architecture Council 2015). An important product of its present activities is its Gridwise® Transactive Energy Framework.

For historical context from the Olympic Peninsula Project report that preceded and set the stage for the PNWSGD transactive system, read the GridWise Testbed Projects report by Hammerstrom et al. (2007). Some of the earliest conceptual groundwork specifically for the PNWSGD transactive system may be found in a presentation by Hammerstrom et al. (2009). For publicly available overview presentations about the project's transactive system, refer to Melton and Hammerstrom (2011, 2012, 2014), or Melton (2013).

Perhaps the most detailed discussion about the PNWSGD transactive system design may be found in the Transactive Coordination Signals project report (Battelle Memorial Institute 2013). That report includes much detail about the two classes of transactive signals; the way the project designed and implemented transmission-zone and site nodes; the timing approach used for system signals, including its predictive future intervals; and the functional interfaces between the system and its resources and loads.

A comprehensive list of the technical documents generated by the PNWSGD project is listed in Appendix A. The list includes reports, design specifications, test specifications, and a user guide.

2.1 Context Needed to Discuss Performance of the PNWSGD Transactive System

This subsection presents the context for discussion of the performance of the transactive system that was designed and deployed by the PNWSGD project.

Figure 2.1 is a greatly simplified functional block diagram of a node of the project's transactive system. The large, inclusive block titled "solver/optimizer" represents the algorithmic framework of the calculations that took place at a single system location, a *transactive node*, of the regional transactive system. The project established 14 such transactive nodes (*transmission zones*) to represent large sections of the PNW power grid's transmission and generation, and it defined 13 additional transactive nodes to represent the project's participating utility and university sites. The algorithmic framework at a transactive node was intended to be scalable and self-similar, regardless of the device or group of devices that is being represented by the transactive node.

The main block in Figure 2.1 titled "solver/optimizer" shares a functional responsibility to compute a blended unit cost of energy at this transactive node (marker "3a") and distribute the impact of the blended unit cost through the system. It shares a responsibility to plan for energy balance at the transactive node (marker "6a") and to communicate the impact of that action into the system. Finally, a fundamental responsibility of the block is to accurately balance its energy, including the energy it negotiates to be exchanged with (either imported from or exported to) its transactive neighbors (marker "7").

The transactive node's position within the power system defines its set of *transactive neighbors*. *Transactive neighbors* are the transactive nodes to which the transactive node is electrically connected. A *transactive neighbor* furthermore must be a member of the transactive system, meaning that it has agreed to exchange transactive signals with this transactive node and all of its other transactive neighbors. The blocks at the top of Figure 2.1 represent the transactive node's interface with its transactive neighbors. For the PNWSGD project, these blocks simply implemented an application programming interface. Using extensible markup language, the application programming interface defined the intervals and other contents of the transactive signals and several system management signals. Because the interface was specified the same for all transactive nodes in the project's transactive system, the individual implementations were amenable to conformance testing.

Transactive neighbors necessarily exchanged two paired signals—energy unit cost and energy quantity—with one another. These signals addressed the present and future exchange of energy between the two transactive nodes during a set of future time intervals. The unit-cost-like signal was called the *transactive incentive signal* (TIS, marker "3b") and the energy signal (actually defined as average interval power) was called the *transactive feedback signal* (TFS, marker "6b"). This exchange was bidirectional. Each transactive node was required to both send and receive both signal types to and from each of its transactive neighbors. The project transactive nodes used a common set of 57 sequential future time intervals that ranged in duration from 5 minutes to 1 day. The entire set of intervals predicted cost and quantity for from 3 to 5 days into the future.[1] The signals were exchanged every 5 minutes during the project. More than one signal was sent during some 5-minute intervals if the transactive node determined that its new state differed from the one that was last communicated by an amount that exceeded a defined relaxation criterion.

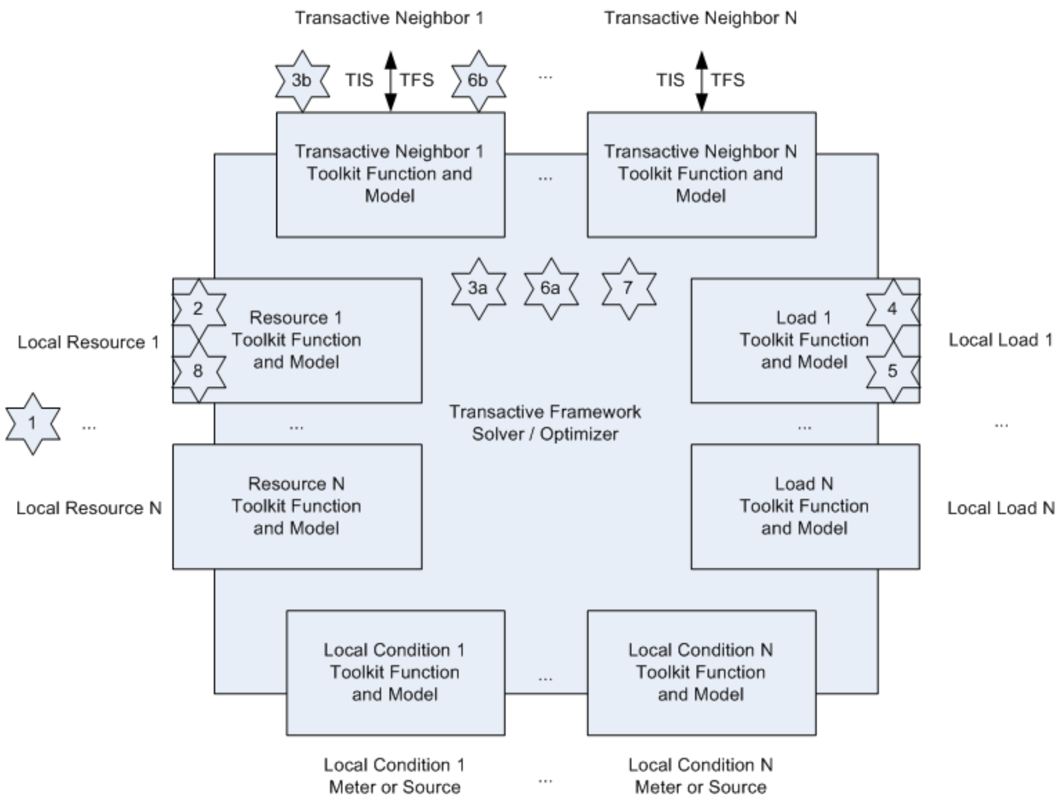


Figure 2.1. Simplified Functional Block Diagram of a Transactive Node. The numbered stars refer to functions that will be referenced as the performance of the transactive system is being discussed in this chapter.

Depending on its sign, the energy exchanged between transactive neighbors is either a resource that is available to, or a load that must be supplied by, the transactive node. A transactive node might also have local electricity resources and an obligation to supply local electric loads.

If a transactive node has its own resident generation resources, then its interface to each generator supply should be represented by a resource toolkit function. These functions are shown at the left side of Figure 2.1. The function represents to the transactive node the energy that is available during each interval and the cost of the available energy. The interface responds to external resources by notifying them if and when they should be dispatched.[2]

[1] The total duration described by the transactive signals varied because of the way the intervals were aligned with 15-minute, hourly, 6-hour, and Pacific Time day boundaries.

[2] The predictive dimension in a decentralized control system like this is perhaps similar to economic unit commitment in today's centralized grid control. The concept of firm future resource commitments may be ccommodated by a decentralized control system, but resources lose some of their value to the system once the commitment becomes finalized.

The theoretical responsibilities and capabilities of resource toolkit function interfaces were greatly simplified for the PNWSGD project. The scale of the demonstration did not allow for the operations of large Pacific Northwest generators to be altered by the project. Instead, the project created a set of informed simulation models that strived to accurately track and predict the dispatch of several of the most important resource types. If the given resource type exists at a transmission zone, a single function represented the aggregate energy from that resource and the calculated wholesale unit cost of that energy.

The following functions were created to model the bulk resources of each type within the transmission zones:

- Hydropower − The Bonneville Power Administration (BPA) helped the project track the dispatch of hydropower generation, and the Dow Jones Mid-Columbia price index was used to emulate the unit cost of the hydropower energy, which closely tracks the costs that are eventually revealed by the recent history of bilateral energy exchanges in the region.
- Wind power − 3TIER, Inc. and BPA helped the project predict and track generated wind power in each transmission zone. The project included the cost of wind power among infrastructure costs, which added a relatively constant offset to the incentive signal at each of the transmission nodes of the transactive system. Thus, the incentive signals, represented as unit costs of electrical energy, decreased when and near where wind power is being produced.
- Thermal power − Alstom Grid and BPA helped the project track the dispatch of thermal resources in the region. The wholesale unit costs were calculated using fuel costs and typical conversion heat rates.
- Transmission power exchanged at the boundaries of the transactive system − BPA helped the project estimate and predict the energy moving across the system's transmission boundaries and the unit costs of this energy. The system was connected to Canada, Montana, Wyoming, Nevada, and California transmissions that were not part of the project's transactive system.

Information about generation dispatch practices, history, and costs was found to be very business sensitive. Access to real-time generation information was sparse and incomplete. Access to accurate historical information from which useful trends might be gleaned was reluctantly made available. The project's knowledge of the region's wind generation was strong, but the project was required to aggregate the information so that accurate information about no single wind site could be gleaned.

The coordinated operations of these resource functions were much more centralized than was hoped for demonstrating a decentralized transactive system. Acting on the project's behalf, Alstom Grid set up and solved economic power flow and economic dispatch for the entire transactive system region. The approach was similar to that used for locational marginal pricing that calculates price differentials over both time and across geographical separation. The solution determined which resources would likely be dispatched in each transmission zone and at what price. The project referred to these aggregate resource functions as an *informed simulation* because they necessarily predicted and emulated the behaviors of the region's generators and system operators from incomplete, dated, and otherwise imperfect available information.

The above discussion addressed the formulation of wholesale energy and its costs. The impacts of incentives that were not directly proportional to energy supply were also represented by functions. The project implemented two such functions. First, because the project strived to represent the TIS as “the delivered cost of energy,” the project applied an infrastructure cost function at transmission zones to represent the remainder of wholesale costs beyond what was already represented by the costs of the generated energy alone. The granularity of the project’s transactive system was too coarse to represent each piece of infrastructure and its cost, but the aggregate impact was estimated from the differences between wholesale electricity prices paid by participating utilities (less than $0.05/kWh) and the aggregate blended cost of energy from the energy resources alone (often less than $0.02/kWh).

Several participating utilities that are supplied by BPA and the University of Washington campus designed and implemented incentive functions to predict and represent the impacts of BPA or Seattle City Light time-of-use price differentials and demand charges on their unit energy costs. These functions effected a price differential on the delivered cost of energy (i.e., the TIS) at the transitions between peak and off-peak hours. They furthermore predicted monthly peak hours and reflected the demand charges that would be incurred as new demand peaks were being encountered.

In summary, the toolkit functions—resource or incentive—have the responsibility to monetize resource costs and incentives (Figure 2.1, marker “2”), and should be responsive to the transactive node’s attempts to balance loads and resources, especially as the system’s loads respond to the TIS (marker “8”). The behaviors of the actual generation resources (marker “1”) must be accurately represented by the toolkit resource functions if the transactive system is to perform well.

Toolkit load functions are shown on the right-hand side of Figure 2.1 at interfaces between the transactive node and its locally served electric loads. Much of the system load is inelastic, unresponsive to any change in the TIS. The inelastic load must be represented and predicted anyway because of its impact on energy balance at the transactive node and throughout the transactive system. At transmission zone transactive nodes, the total forecasted BPA load, which is quite inelastic, was scaled and allocated among the 14 transmission zones. IBM worked with the owners of individual site transactive nodes (i.e., the utility sites) to create and train a function that would accurately predict the inelastic load magnitude at the point where the site electrically connected to the remainder of the transactive system. The only responsibility of an inelastic load function was to accurately predict the energy consumption (Figure 2.1, marker “5”).

More interesting are the elastic loads and their toolkit functions. These functions represented individual, or systems of, electric loads that might change their energy consumption when informed of changes to the TIS. The first responsibility of these toolkit functions is to determine the timing and degree of the elastic loads’ responses based on the TIS and available local conditions (marker “4”). The project found it helpful to categorize the responsive loads as having event-based, daily, or continuous-response capabilities. The differences between the various systems’ responses within each of these categories could often be tailored simply by modifying configuration parameters. The capabilities and limitations of the systems’ responses must be accurately configured if these responses are to also be accurate and meet their owners’ objectives.

Each toolkit load function is also responsible for maintaining a model of its performance from which the energy impact of an elastic response by the load may be estimated and predicted for the transactive system. For example, a toolkit function that represents a thermostatically controlled building might model changes in its consumed heating or cooling energy as a function of thermostat setting, outdoor temperature, building thermal storage, building occupancy, and so on. The modeled change in load must be accurate (marker “5”) if its impact is to be recognized and influence its transactive node and the larger transactive system. Asset models were created and implemented for systems of battery energy storage, distributed generators, portals and in-home displays (i.e., voluntary responses), voltage management, thermostatic space conditioning, and electric tank water heaters.

In the prior discussion, the words *resource* and *load* have been used to differentiate the purposes of toolkit resource and load functions. Some may prefer the terms *price-maker* and *price-taker* instead for resource and load functional interfaces, respectively. Indeed, the project modeled distributed generators and renewable generation resources using toolkit *load* functions. The distinction is perhaps that the actions of the systems being represented by toolkit resource functions have their energy production specified during the balance of the system energy, and they compete and influence the system by affecting blended costs in the system. The systems represented by toolkit load functions receive unit cost information and compete based on their flexibility and ability to modify the net electric load at the transactive node. With this understanding, the distinction of *source* (as generation) versus *load* (as energy consumption) becomes less important. It is entirely possible that a more complex asset system may be represented by either or both resource and load toolkit functions, as conditions dictate. The separation of price-maker and price-takers’ responsibilities may be an important construct for the architectures of distributed energy systems.

The last interfaces remaining to be introduced are the transactive node’s interfaces to local conditions, as shown at the bottom of Figure 2.1. The above-mentioned functional interfaces to loads and resources may be influenced by local conditions. For example, the prediction of inelastic load is usually dependent upon local ambient temperatures. The individual toolkit load or resource functions may individually procure access to such information, but the system may be simplified if frequently needed information, like local ambient temperature predictions, is available from a single interface between the transactive node and the sources of such information. Information sources may be simple meters, systems of meters (e.g., occupancy sensor systems), or accessible Web services, for example.

The following eight markers in Figure 2.1 point to specific functions that were necessarily well implemented and accurate for the transactive system to have achieved and demonstrated useful outcomes. These functions will be referenced as the performance of the project’s transactive system is reviewed in the remainder of this chapter:

1. The system must accurately represent the region’s strategies for the dispatch of its energy resources.
2. The system must meaningfully monetize resource costs and incentives.
3. Energy costs and incentives must be blended and distributed throughout the transactive system.
4. The responsive loads in the system must be able to allocate their responses and events, based on the incentive signal and local conditions.
5. Responsive loads must accurately predict the energy impacts of their responses.

6. The exchanges of power with the system must be predicted and communicated throughout the transactive system.
7. Plans to exchange energy with the transactive system must be accurate.
8. Supply resources must respond to planned energy exchanges to the degree that the exchanges dynamically affect system balance.

2.2 Step 1: The System Must Accurately Represent the Region's Strategies for the Dispatch of its Energy Resources

Additional section coauthors: SF Joseph and D Watkins − Bonneville Power Administration

The project investigated whether the transactive system accurately reproduced the mix of resources and other grid conditions that actually transpired in the Pacific Northwest region that was modeled by the transactive system. The results of that investigation are reported in this subsection. If grid conditions were accurately represented, then there is a chance that the incentives generated by the transactive system, which were driven by the resource mix and grid conditions (as to be described in Section 2.3), were meaningful and useful. Otherwise, the system diverged from and misrepresented actual power grid conditions. Incentive signals based on erroneous resource mixes and incorrect grid status would unlikely prove to be meaningful or useful.

The transactive system's data-collection layer kept track of its modeled energy resources in several broad categories—hydropower, wind power, thermal power, and power that is either imported into or exported from the region to locations outside the transactive system. A matrix manipulation was devised to also decompose the power being exchanged between the transactive nodes into these four listed categories. Therefore, the project can reproduce a precise accounting of the modeled energy resource mix at each system node. These findings will be reported in this section for a full project year term and by season. The region-level result may be compared against data from BPA, but the comparison is not perfect because the modeled transactive region differs from BPA's.

The project worked closely with BPA to analyze whether not only the static mix of resources, but also the dynamic dispatch of resources and events, matched what BPA reports to have actually happened in the grid. The project determined to conduct this evaluation by comparing the project's transactive system data with data from the BPA's transmission system during exemplary project days. The days were selected by BPA because they represented times when the power grid might have become stressed by extreme weather conditions, generation outages, wind incidents, or transmission incidents. Altogether, seven such scenarios were identified for this investigation,[1] as follows:

[1] The analysis in Section 2.2 was conducted collaboratively by SF Joseph, S Kerns and D Watkins (BPA) and DJ Hammerstrom (Battelle). Much of the text and most of the figures in this section were adapted from unpublished presentation materials that were prepared for and presented at a Project Review Board Meeting, BPA Headquarters, Portland, Oregon on June 5, 2014.

- winter and summer peaks[1]
  - peak winter load event on December 5, 2013
  - peak summer load event on August 5, 2013
- generator outage
  - outage at the Columbia Generating Station on February 5, 2014
- wind incidents
  - rapid wind ramp event on February 15, 2014
  - periods of wind undergeneration and overgeneration on March 5, 2014
- transmission incidents
  - transmission outage on April 1, 2014
  - overloaded flowgate event on April 11, 2014.

Historical BPA loads and resources are reported for hourly intervals by BPA (2015) using substantially the same four resource categories as used in the transactive system data collection. The project did not track any distinction between federal and non-federal hydropower resources, so the federal and non-federal hydropower magnitudes from BPA data were combined in the figures of this section.

The total electric loads will be consistently shown as negative quantities among the diagrams in this section. This practice facilitates visual confirmation that system power is balanced—that all resources and load are being shown. Wherever a visual comparison is being invited between BPA and project data sets, the scales of the figures' power axes were forced to be identical.

The PNWSGD total load was necessarily inferred. The project failed to capture in its data-collection system layer the total system load and allocated node site loads. Therefore, the total system load was necessarily calculated from the sum of all the modeled resources in the region, including the energy imported or exported through the modeled exchange boundaries to entities outside the transactive system.

Finally, the grid region of the PNWSGD transactive system is even larger than that covered by BPA. BPA operates impressive hydropower resource and manages much of the transmission system in the Pacific Northwest. But there are other balancing authorities with generation and transmission assets in the project region. Consequently, total project load should be somewhat greater than that in the BPA data, and the project's resources in the summed categories may be greater as well.

[1] The weeks leading up to winter and summer peak days were also selected for simulation studies (Section 2.10).

2.2.1 Generation Mixes Modeled by the Transactive System

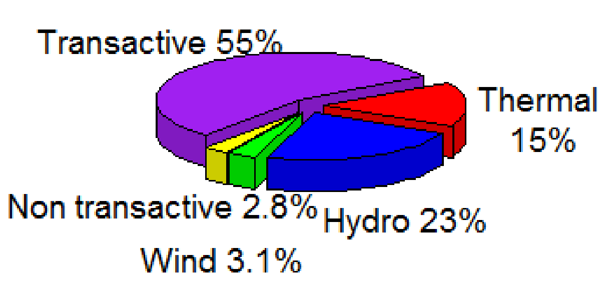
The data-collection layer of the PNWSGD transactive system allowed analysts to reconstruct the mix of energy resource types that were modeled to have been used in the region. The accounting of these resources was quite naturally accomplished in the transactive system because the incentive signal was formulated, in part, by the blended unit costs of these resources. The history of resource usage at each location would not normally be broadly shared between the owners of system nodes, but the information was centrally captured by the project for this research.

Five broad types of energy resources were tracked at each transmission-zone node of the system: hydropower, thermal, wind, imports from outside the transactive region, and the energy received from neighboring transactive nodes. Each of these resources contributed at each node to the node’s blended incentive signal in proportion to the magnitude of energy received from that resource. The sum generated and imported energies were then eligible to be consumed or exported at the blended unit cost.

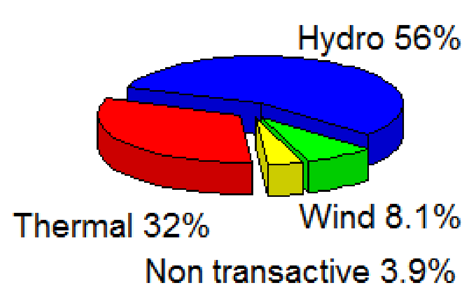
While the power imported from a node’s transactive neighbor is a useful magnitude in the distributed system, the component is not itself informative about the resource types that it includes. Fortunately, the project collected complete information of every transactive neighbor’s resources. Therefore, a matrix operation was developed to decompose the imported transactive energy components into the remaining four resources—hydropower, thermal, wind, and the imports from the boundaries of the transactive region.

The transactive system had no knowledge of the resources that compose the energies imported at the boundaries of the transactive region, so that component cannot be further decomposed. The project referred to these imports at the region’s exchange boundaries as “non-transitive” imported energies.

Figure 2.2 compares the average relative resource mixes of the transactive system before and after the matrix operation that decomposed imported energy from transactive neighbors into its component parts. The data from a complete project year (September 2013 through August 2014) were used. The right-hand figure is the project’s best representation of the resource mix that was modeled by the transactive system throughout the last year of the project.



(a) Before Reallocating Exchanged Resources



(b) After Reallocating Exchanged Resources

Figure 2.2. Composition of Modeled Resources of the Entire Transactive System in the Last Full Project Year (a) Before and (b) After the Energy that Was Exchanged between Transactive Nodes (the “Transactive” Component) was Reallocated

For comparison and using the same 1-year term, the averaged BPA resource mix (compiled from data on the BPA transmission webpage [2015]) included 67% hydropower, 23% thermal generation, and 9.7% wind. While direct comparison is not possible because the project region differs from that of BPA, the comparison is informative. The project's usage of hydropower is less than BPA's because the transactive region extended outside the Columbia River basin that is the source of the abundant hydropower in the Pacific Northwest. The difference is made up for by using additional thermal resources that become more prevalent toward the south and southeast boundaries of the transactive region. The wind resource percentages are comparable between the transactive and BPA data.

While the non-transactive component should be comparable to BPA's "exchange" component, the term is not accounted for similarly in BPA data and for the transactive system. BPA is almost always a net energy exporter. Project analysts did not have ready access to the individual BPA exchanges, some of which would at times *import* energy. The transactive system, on the other hand, counted imported exchange energy as a resource, even if the entire transactive region might have been a net energy exporter at the time.[1] For these reasons, the BPA data offered for comparisons in this section will not show an exchange resource component, but the transactive system will show a non-transactive exchange component.

The project reformulated the comparison by season in Figure 2.3. The relative resource mixes of the transactive system and BPA system are compared side by side for the four seasons of the last full year of the PNWSGD project (September 2013 through August 2014). All of the limitations of the comparison that were discussed in the prior paragraphs apply to these seasonal comparisons, too.

By season, relative hydropower and thermal energies rose and fell in the transactive system model much as in the BPA system. Every season, the BPA system used a relatively greater percentage of hydropower and relatively smaller percentage of thermal resource than the transactive system did.

[1] Similarly, little or no distinction is made by the transactive system between electric load and the exportation of electrical energy.

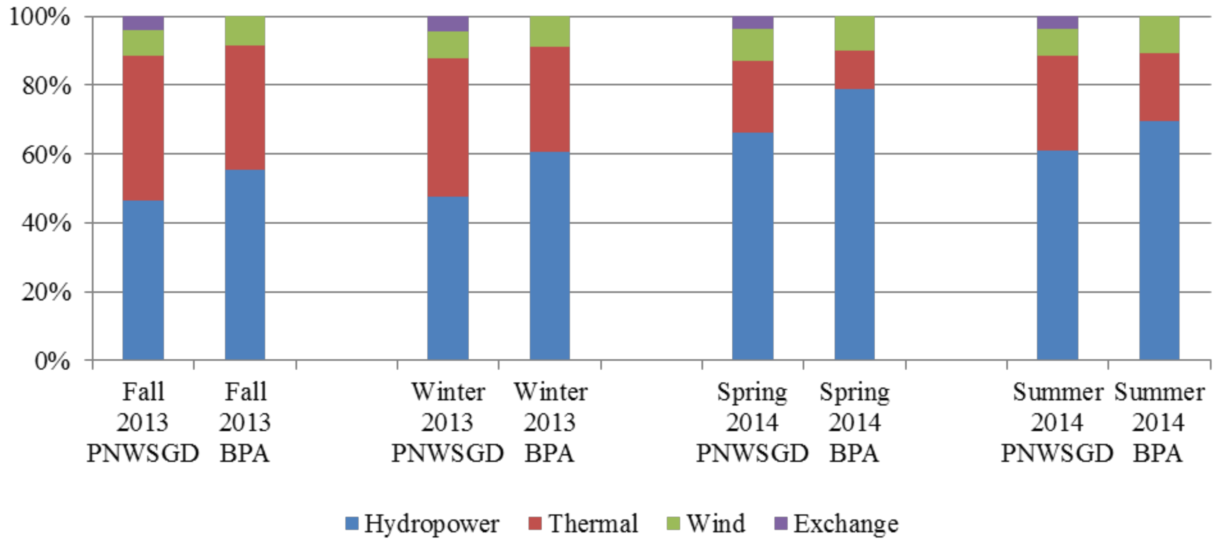
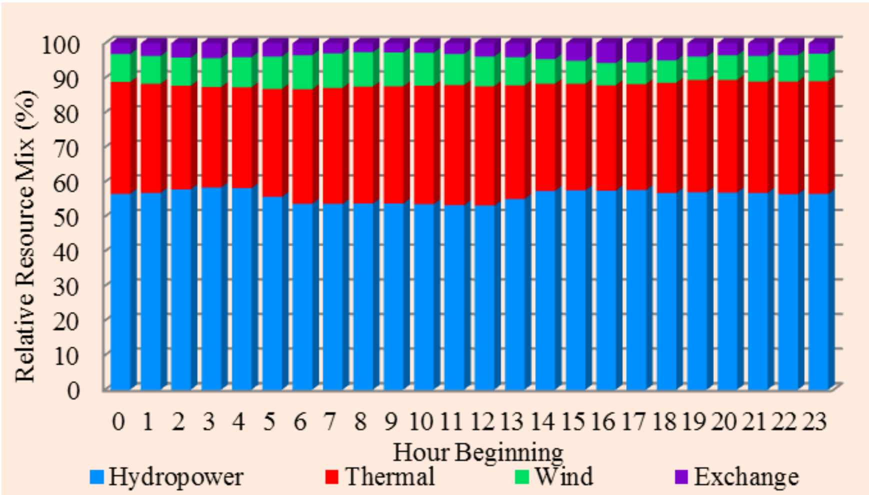


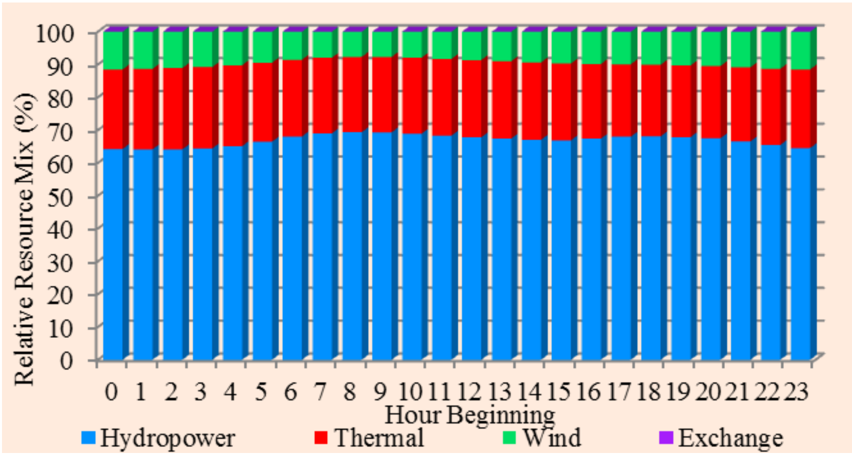
Figure 2.3. Comparison of Average Relative Resource Mix that Was Modeled by the Transactive System and the Mix from BPA Data for the Same Four Seasons

Figure 2.4 compares the modeled resource mix with that of BPA data by hour of day. These data sets both cover the time period from September 2014 through August 2014. As before, the imported exchange energy does not appear in the BPA data because the source for the data did not separate imported energy from exported. This omission will cause the small percentage of imported exchange resources to have been distributed among the other resources in the relative resource mix of the BPA data.

According to this figure, the transactive system relied primarily on thermal resources to balance diurnal load, while the BPA system relied primarily on hydropower resources to do so. This statement follows from the swell of one or another of the resource types especially in late morning when peak load often occurs.



(a) PNWSGD Transactive System



(b) BPA Data

Figure 2.4. Average Relative Resource Mixes (a) Modeled by the PNWSGD Transactive System and (b) According to BPA Data (BPA 2015) from September 2013 through August 2015

Figure 2.5 provides interesting insights into the variability in the transactive system's resource usage according to site locations. Pie charts have been displayed for each of the 14 transmission-zone nodes that were modeled by the project (Appendix B). Data were included from the entire final year of the PNWSGD from September 2013 through August 2014. The pie charts have been approximately positioned at their sites' relative geographical locations among the five Pacific Northwest states that had representation in the PNWSGD. The relative mix of especially hydropower, thermal generation, and wind power are shown to vary according to the local resources at each location. For example, the region's largest hydropower resources reside in the modeled Northcentral Washington zone, where a great fraction of hydropower resource is shown. The Northeast Oregon node includes impressive Columbia Gorge wind resources. The importation of non-transactive exchange energy is most evident in the northernmost and northeast zones that frequently import energy from Canada and eastern Montana.

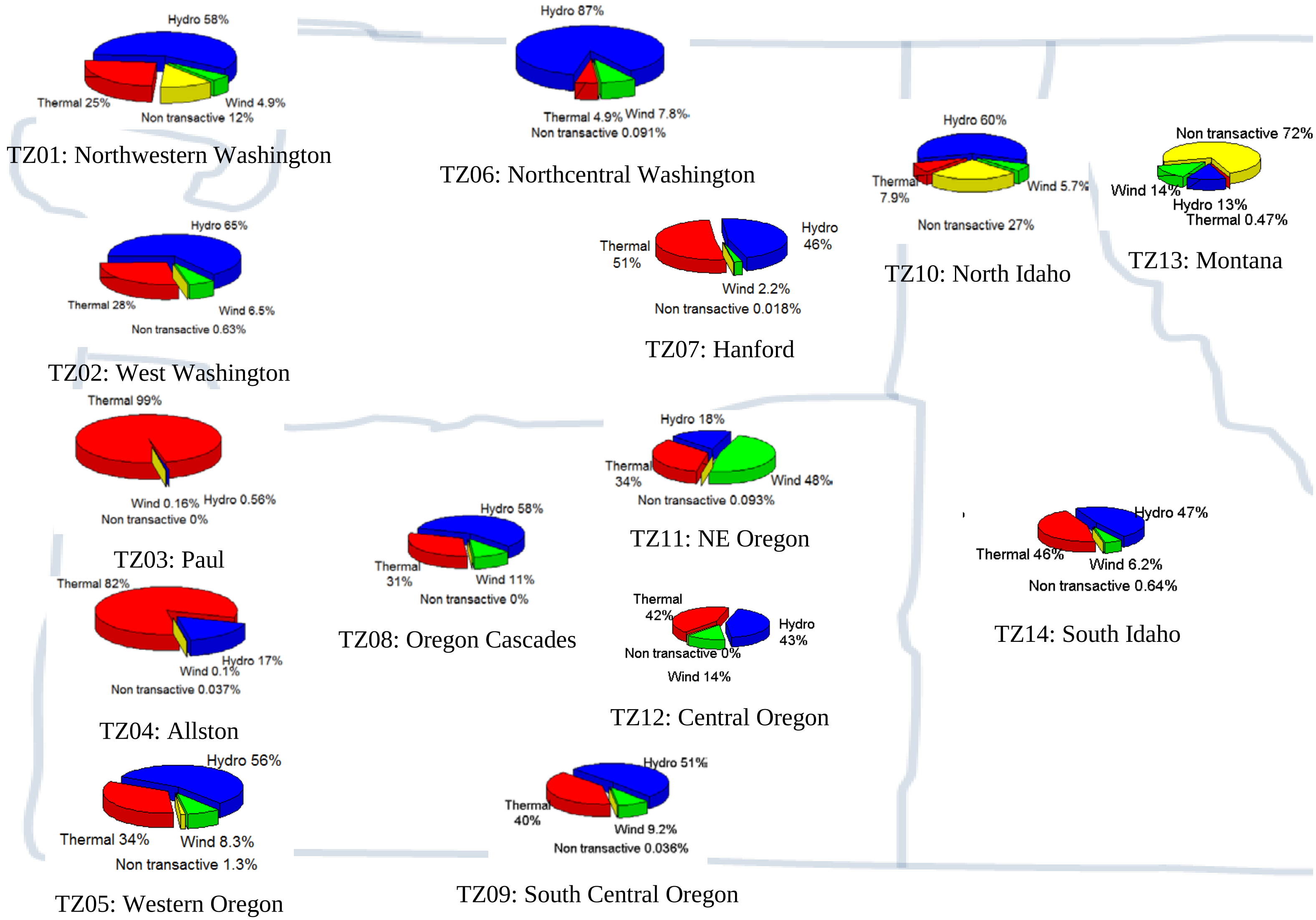


Figure 2.5. Average Relative Mix of Generation Resources Available at Each Transmission-Zone Node during the Last Full Year of the PNWSGD. Each node's pie chart has been placed near its approximate geographical location in the Pacific Northwest.

The sections that follow will investigate the dynamics of transactive systems.

2.2.2 Winter and Summer Peaks

The days of peak winter and summer demand in 2013 were selected by BPA for evaluation, based on the peak total load that it served. These scenarios might be expected to stress the power system as it strives to supply the year's greatest heating and cooling loads.

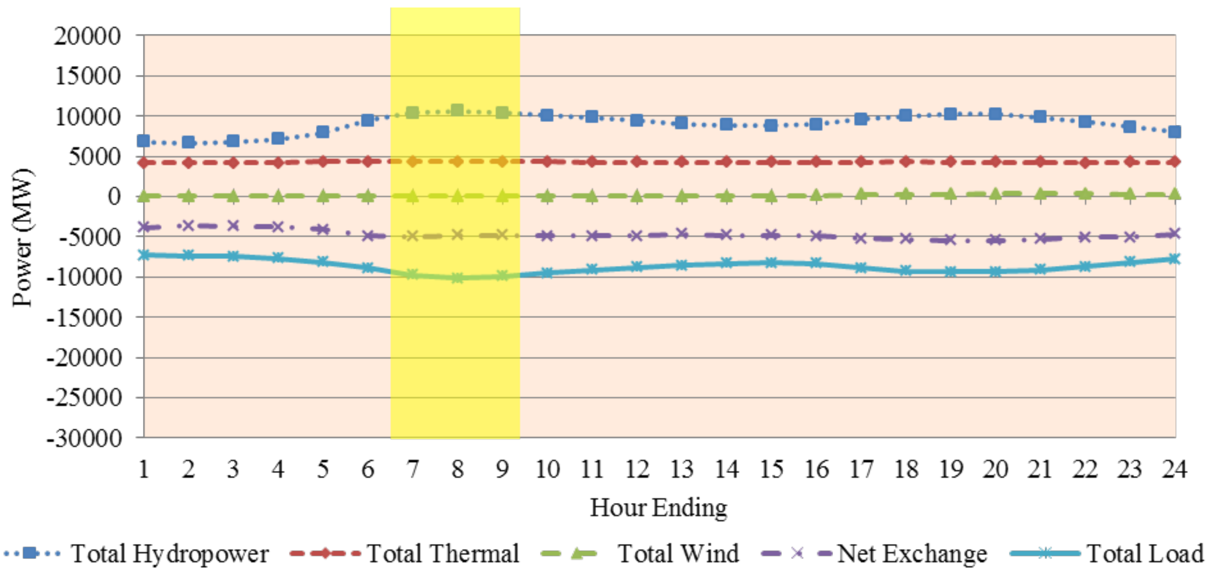
Peak Winter Load on December 5, 2013. A winter cold snap occurred in the region on December 4–10, 2013. On December 5, morning peak generation by the federal hydropower system that is managed by BPA reached almost 11.5 GW. Because of the cold weather that day, BPA needed to purchase 18 GWh and had little surplus energy to sell. BPA experienced its peak winter load during the hours ending 07:00−09:00.

The BPA and project total generation and load data are compared for this day in Figure 2.6. The components being compared include total hydropower, total thermal generation, total wind generation, and total net exchange power in the BPA and modeled transactive systems. Unlike Section 2.2.2, the total net exchange powers include the sums of all imported and exported exchange and are therefore fairly compared. Exported exchange power is shown as a negative value, as is total system load.

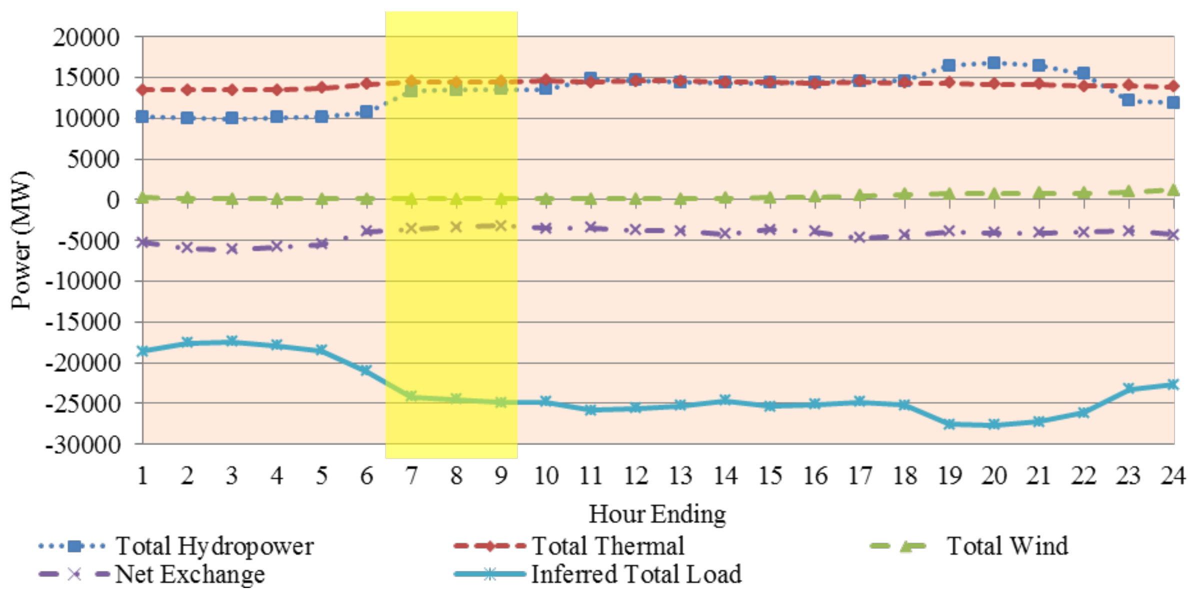
The transactive system modeled a considerably larger peak load than the BPA system on this day. The PNWSGD peak load occurred in the afternoon hours 17:00−19:00, not in the morning. Wind is minimal on this day in both the BPA and project system representations. The magnitudes of net exchange are also similar in the two representations, but there appears to be disagreement concerning the patterns of the increased and decreased exchange power during the day.[1]

Hydropower and other resources are managed differently in the BPA and project representations on this day. First, the transactive system relies more heavily than the BPA system on thermal resources during this cold snap. At midday, there is more than three times as much thermal generation modeled in the transactive system as in the BPA one. Some of the difference may be attributed to the transactive system's extension west beyond the Columbia River hydropower basin. Thermal resources were almost constant in the BPA system, mostly unaffected by BPA system load magnitude, but the transactive system changed its dispatch of its thermal resources during the day.

[1] Exchange power was made available to the project only as typical seasonal trends, leaving the designers of the transactive system model to infer the ways the exchange would be managed. The mismatch between actual and modeled exchange powers means that the strategy was not inferred well in this case.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

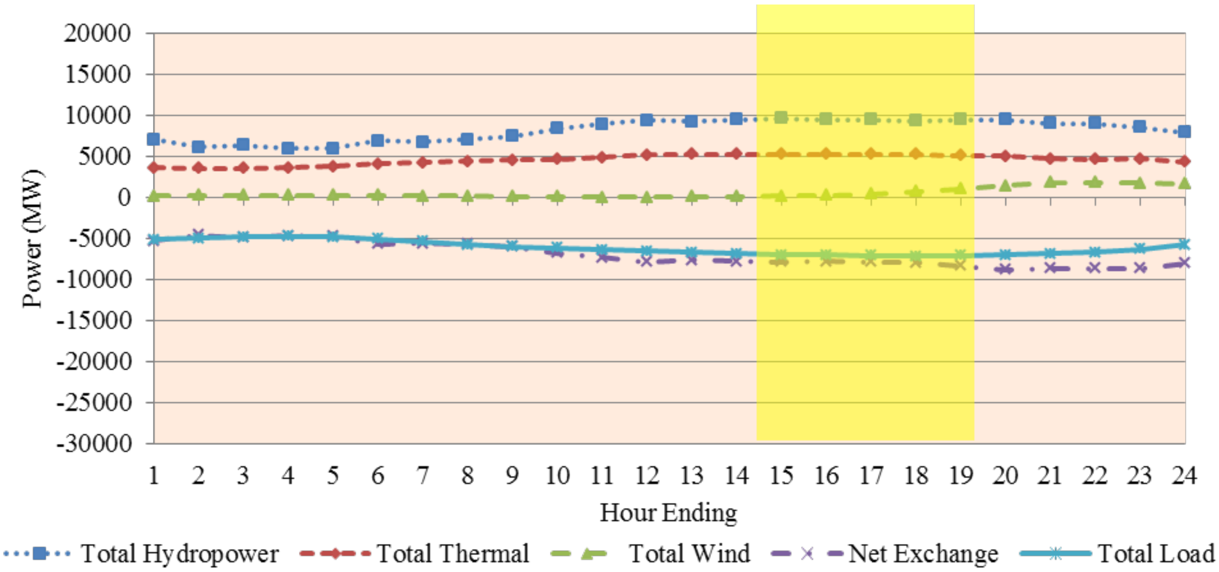
Figure 2.6. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System Model on December 5, 2013

A peak summer load event on August 5, 2013. The peak 2013 summer load occurred on the BPA system August 5, 2013, between hours ending 15–19.[1] The total BPA resources and load are compared against those of the project's transactive system on that day in Figure 2.7.

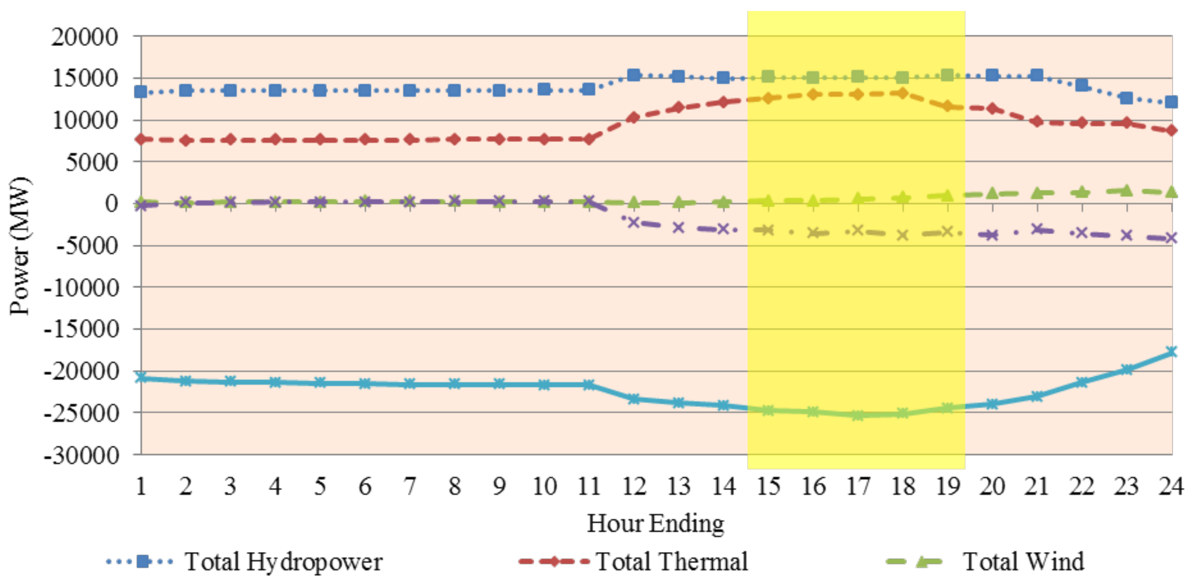
The transactive system data agreed with the BPA data that the peak total load occurred in the afternoon. However, the project modeled about 4 times as much total load as in the BPA data. The transactive system's total load was designed to be a scaled version of BPA system load. The patterns for the various resources were similar through the day for the compared systems. However, the transactive system required more of each resource type to balance the much greater system load.

The biggest difference between the transactive system and BPA data was in the strategies that were followed to dispatch thermal resources. The transactive system used thermal resources more than the BPA system to follow the diurnal load pattern. The transactive system more than doubled its thermal resources to supply the afternoon peak load.

[1] BPA uses "hours ending." Hours ending 15−19 covers the time period 14:00–19:00.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

Figure 2.7. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System Model on August 5, 2013

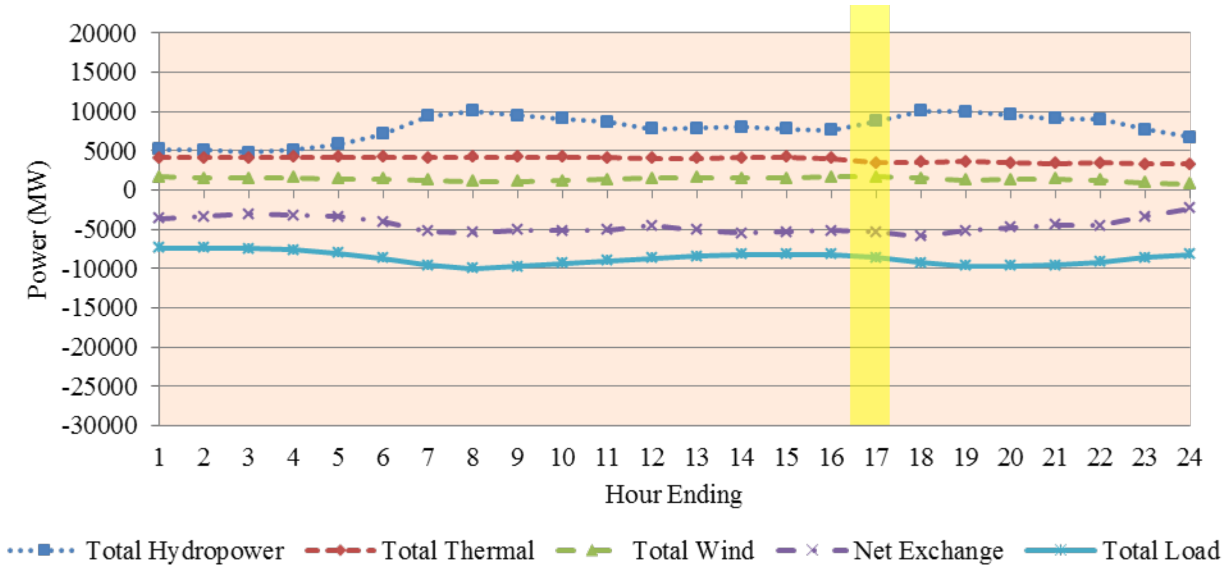
2.2.3 Generator Outage

The following event was selected to determine whether the PNWSGD transactive system accurately tracked a generator outage in the BPA system.

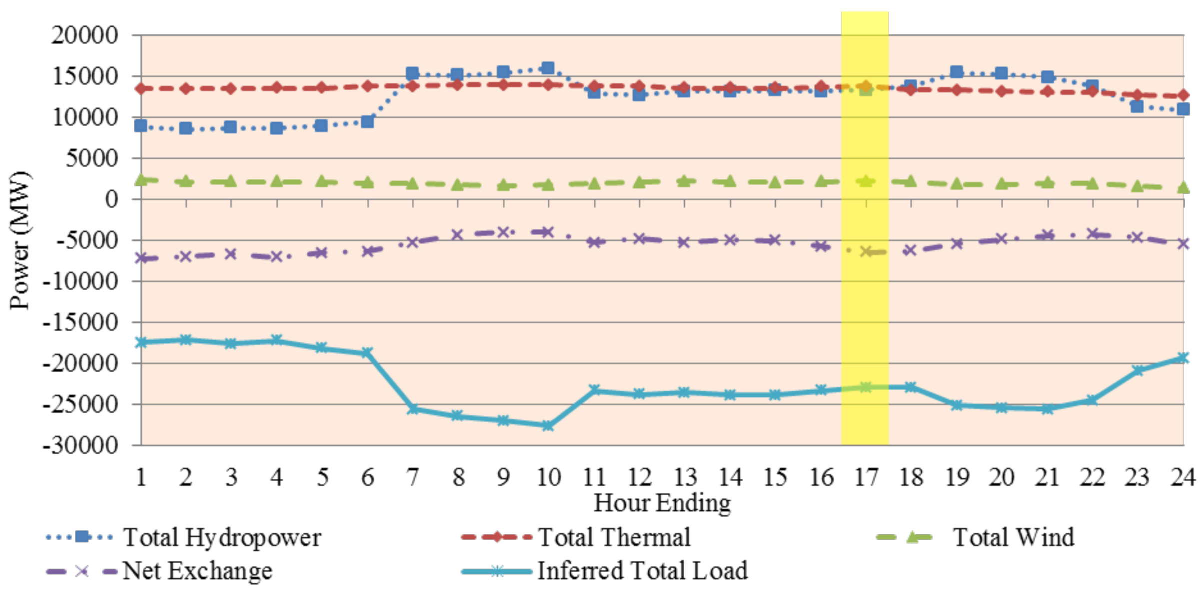
Outage at Columbia Generating Station on February 5, 2014. Columbia Generating Station is the Pacific Northwest region's only nuclear power generator. At hour ending 17 (16:00) on February 5, 2014, the Columbia Generating Station went into single-loop operation because of a recirculation pump trip that was traced to an electrical circuit breaker malfunction. Its normal average generation is 1,128 MW, but generation dropped during the outage to 477 MW, less than half of its normal generating capacity.

The BPA and transactive system data from this day are compared in Figure 2.8. Nuclear power generation was grouped with other thermal resources by the transactive system model. While the generator outage in the BPA system (i.e., a loss of ~0.5 GW) was substantial, the change was quite small at this figure's scale, even in among the BPA thermal generation data that was certain to have represented the outage.

The total modeled thermal resources in the transactive system were about 3 times as great as in the BPA data throughout this day.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

Figure 2.8. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System on February 5, 2014

Figure 2.9 focuses on only the thermal generation resources. BPA's thermal generation data in this figure is the same as what was shown in Figure 2.8. At this improved scale, the impact of the outage is evident hour ending 17. The thermal power generation remains reduced at this level for the remainder of the day. The figure also shows both the transactive system's total thermal power generation and the thermal generation in the Hanford transmission zone (TZ07), in which the Columbia Generating Station is located. About 0.6 GW of thermal generation was dropped that hour according to the transactive system model. However, the impact appears after a 1-hour delay in the transactive system data. The source of this delay was not determined.

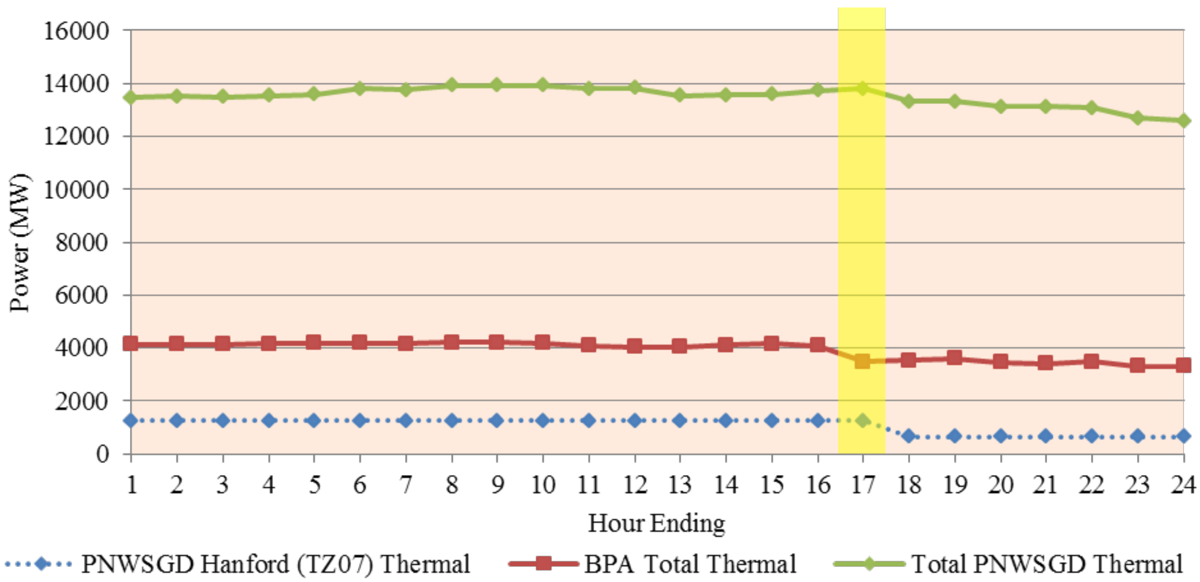


Figure 2.9. Comparison of BPA's and PNWSGD Transactive System's Thermal Generation Data on February 5, 2014, when a Significant Thermal Generator Outage Occurred

With the exception of exchange power, modeled resources in the PNWSGD transactive system are proportional to those in BPA data. The consistency of this proportionality through the day may be seen in Figure 2.10. Here, the resource and load data from Figure 2.9 has been expressed as the modeled transactive system data divided by the BPA data that represents the same resource or load. The transactive system did not curtail as much thermal load as in the BPA system upon the Hour-17 generator outage. Otherwise the dispatch strategies were similar.

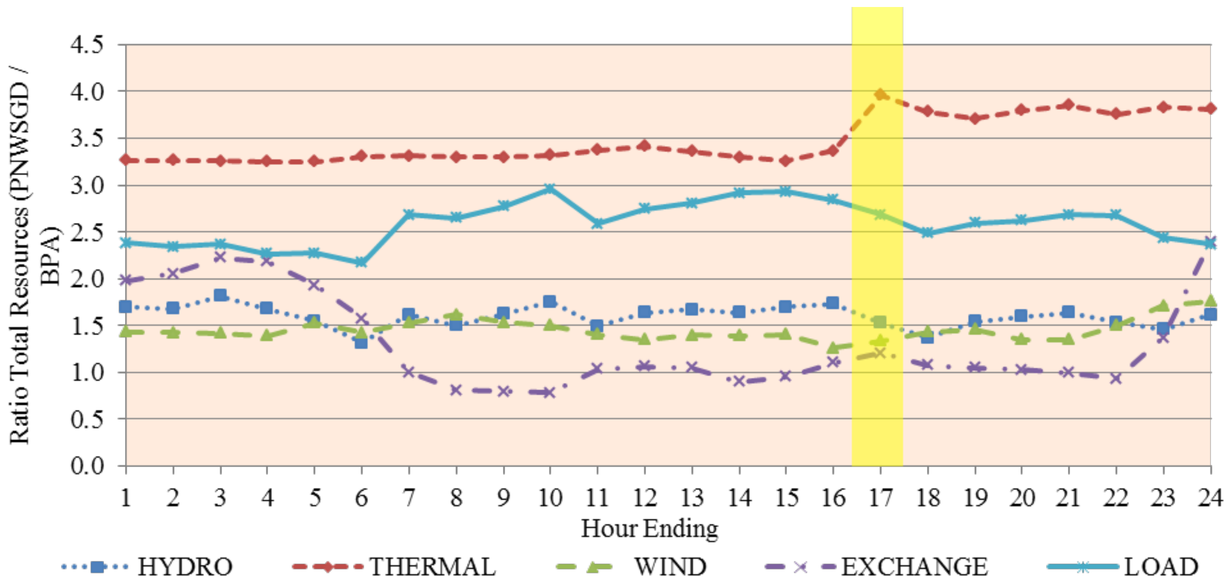


Figure 2.10. Ratio of Transactive System and BPA Total Resource and Load Powers on February 5, 2014. The Columbia Generating Station outage happened during hour ending 17.

BPA described its actions on this day as follows: BPA had forecasted a need for additional power because February 4, 2014, was the first day of what was anticipated to be a 3-day cold snap. BPA purchased over 31 GWh and sold over 3.2 GWh on this day. The purchases were to meet its balancing obligations. The generator outage did not trigger any significant change in its energy purchasing strategy that day.

Figure 2.11 presents the TISs for the entire project region and for select transmission zones at or near the Hanford TZ07 where the affected generator was modeled to reside. The incentive signal should have been affected hour ending 17 when the outage occurred. An increase in the TIS incentive is observed at the TZ07 Hanford zone and at two of the three zones that are attached to the Hanford zone. The change was about $0.01/kWh. The effect on the overall average regional incentive was quite small, but the changes to the nearby transmission zones' incentive were in a direction that would help mitigate the outage. That is, the neighbors that receive energy from the Hanford transmission zone incurred a cost increase that might have reduced load and helped mitigate the generator outage.

The response in the incentive signal is delayed an hour. The source of this delay was not determined.

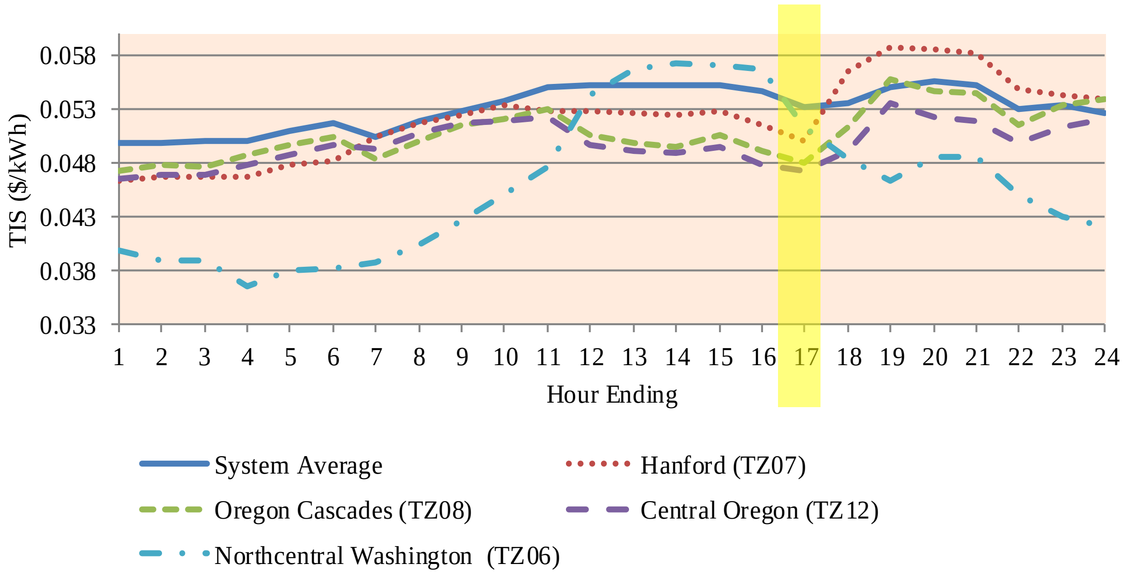


Figure 2.11. Average Transactive System TIS and for Selected TZ Nodes February 5, 2014, when a Significant Thermal Generator Outage Occurred

2.2.4 Wind Incidents

Pacific Northwest renewable wind resources have grown fast. The region is challenged to integrate the growing intermittent resource. This subsection evaluates how accurately the project's transactive system modeled its energy resources, including wind, during rapid ramping of wind energy and at times that BPA reported its wind resource predictions to have been inaccurate.

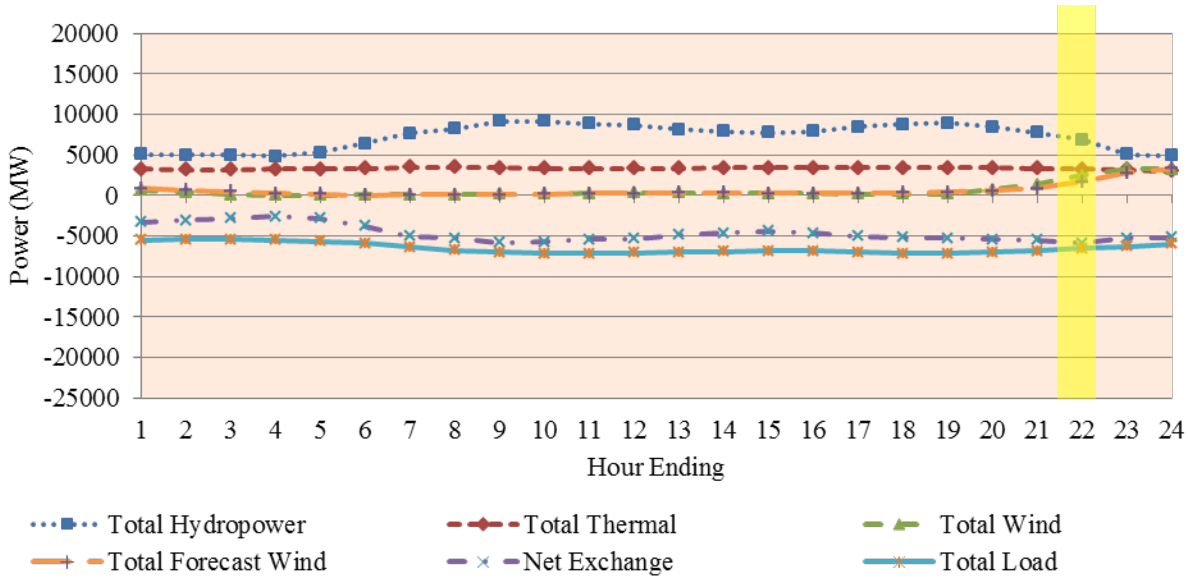
Rapid wind ramp event on February 15, 2014. Wind plant limitation orders were sent out by BPA between 20:10 and 20:15 Pacific Time on February 15, 2014, when wind generation peaked at 2,884 MW. This peak triggered a fleet level limit order (DSO216) to deploy balancing reserves once the peak pushed balancing reserve levels beyond −995 MW, or 90% of the available "dec" reserves. No further mitigation was needed to recover from the temporary oversupply.

Overall system generation was at a shortfall because the Columbia Generating Station was operating at only 25% capacity, because of scheduled maintenance. At first glance, it appears contradictory that a wind overgeneration incident can occur on a day that there is a generation shortfall.

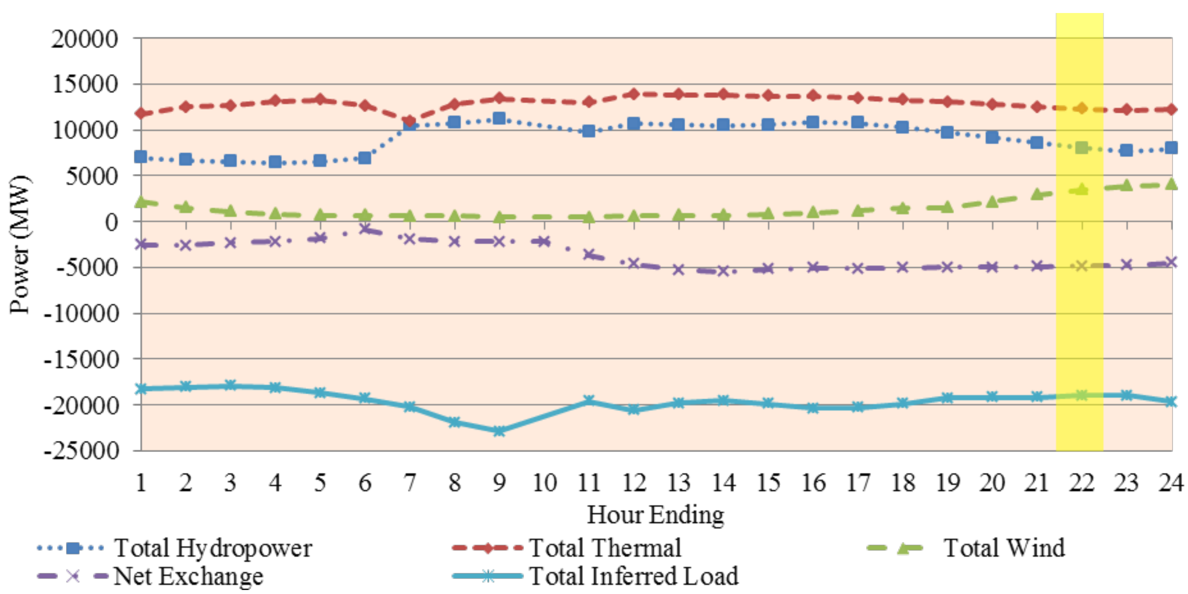
Refer to Figure 2.12, which compares BPA data and project data for this day. A new data series—total wind forecast—was added to the BPA data to help explain the seemingly contradictory conditions. During hour ending 22, the generated wind exceeded the forecast wind. Because more wind occurred than had been forecasted during these hours of rapidly increasing wind resource, BPA had to call on the types of reserves that can either reduce overall generation or increase system load.[1] As the reserves are

[1] These are referred to as "dec" resources.

dispatched, the pool of remaining reserves of this type decreases. As the available reserves diminish to certain threshold values, the balancing authority must take actions to maintain system balance and reestablish the depleted reserves. Emergency actions can include the curtailment of wind resources in the region.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

Figure 2.12. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System on February 15, 2014

Based on BPA data, hydropower resources were used heavily on this day to both follow system load and to respond to the increase in wind resource late in the day.

The wind resource in the transactive system data is very similar in magnitude and shape to the wind resource shown in the BPA data. This is not terribly surprising given the attention that the PNWSGD project paid to monitoring and predicting wind resources in the region. As for the BPA system, hydropower may be seen to track the impacts of changes in load and wind resource. However, the transactive system's modeled thermal loads were much more dynamically controlled and responsive than the thermal generation in the BPA data. Furthermore, there was more thermal generation resource than hydropower resource in the modeled transactive system, the opposite ordering observed in the BPA data.

The PNWSGD transactive system did not compare wind generation against forecast wind as was described to affect BPA this day. Generating units were not modeled to become committed (*scheduled*) in the project's transactive system implementation. The project predicted wind generation, but the predictions were used on the transactive system's planning horizon without resulting in commitments from the modeled wind farms.[1]

Figure 2.13 features the BPA and transactive system wind data that was shown in Figure 2.12. The source of the BPA data was the BPA transmission webpage (Wind Generation & Total Load in the BPA Balancing Authority, BPA 2015). The discrepancy between forecast and generated wind is easily seen as the wind ramped up. Transactive system data was unavailable for the hour ending 10 on this day. The project had broader visibility of and participation by wind resources than exist within the BPA system, so the magnitude of wind energy was typically greater for the transactive system. The transactive system modeled the rapid wind ramp well. The timing of the wind ramp was similar between the two systems.

[1] Had the impacts of scheduling accuracy and reserve margins been incorporated into the transactive system, the system might have responded to help mitigate over- and under-generation events. Nothing prevents a future transactive system from including the impacts of resource commitments, but committed resources are no longer available and responsive to help mitigate emergent situations thereafter.

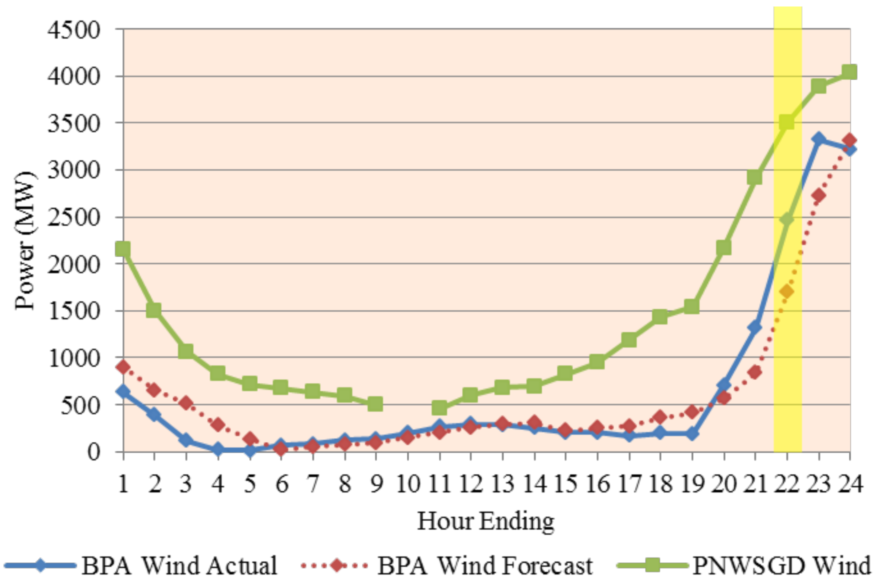


Figure 2.13. Comparison of Transactive System Wind Generation, BPA Wind, and BPA Forecast Wind Data from February 15, 2014

On this day, BPA purchased 1.4 GWh and sold over 25 GWh. Observe in Figure 2.14 that both the averaged transactive system incentive signal and that of the Oregon Cascades transmission zone, from which much of the region's wind emanates, decrease late in the day as wind power increases. Some of this regional impact is a natural diurnal pattern caused by load following, but the transactive system's wind resource functions were designed to make the TIS incentive signal inversely proportional to the magnitude of wind power that is being generated, thus creating a downward pressure on the incentive costs especially at the Oregon Cascades transmission zone.

No significant change occurred in the TIS the hour that BPA observed an overgeneration event. The TIS was not expected to be influenced by forecast errors or by the status of system reserves. These influences were not represented among the inputs to the transactive system. If the system had been responsive to scheduling errors, a wind resource function would have been designed to decrease the TIS in response to the imbalance near hour ending 22. The reduced incentive would encourage consumption and discourage generation until the imbalance was resolved.

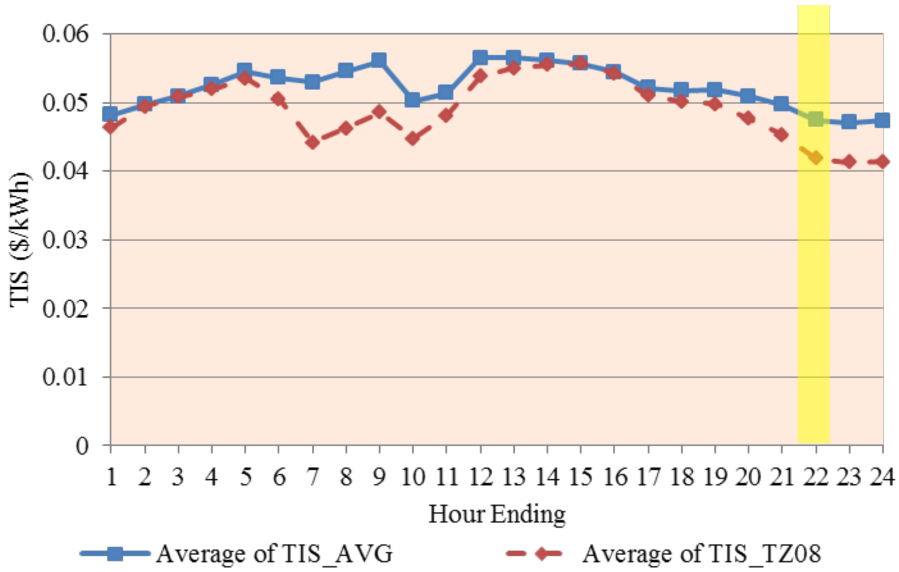


Figure 2.14. Transactive System Average TIS and TIS in the Oregon Cascades TZ08 on February 15, 2014

The inverse relationship between wind generation and the TIS may be seen in Figure 2.15. This figure plots the incentive signal of the Oregon Cascades transmission zone as a function of average hourly wind power generated in this transmission zone. The trend line seems to confirm the inverse relationship. Remember that many inputs, not wind magnitude alone, influence the incentive signal.

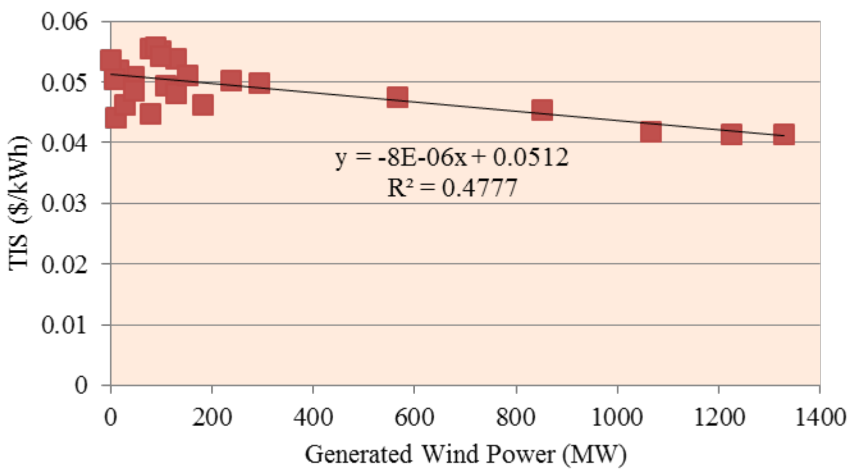
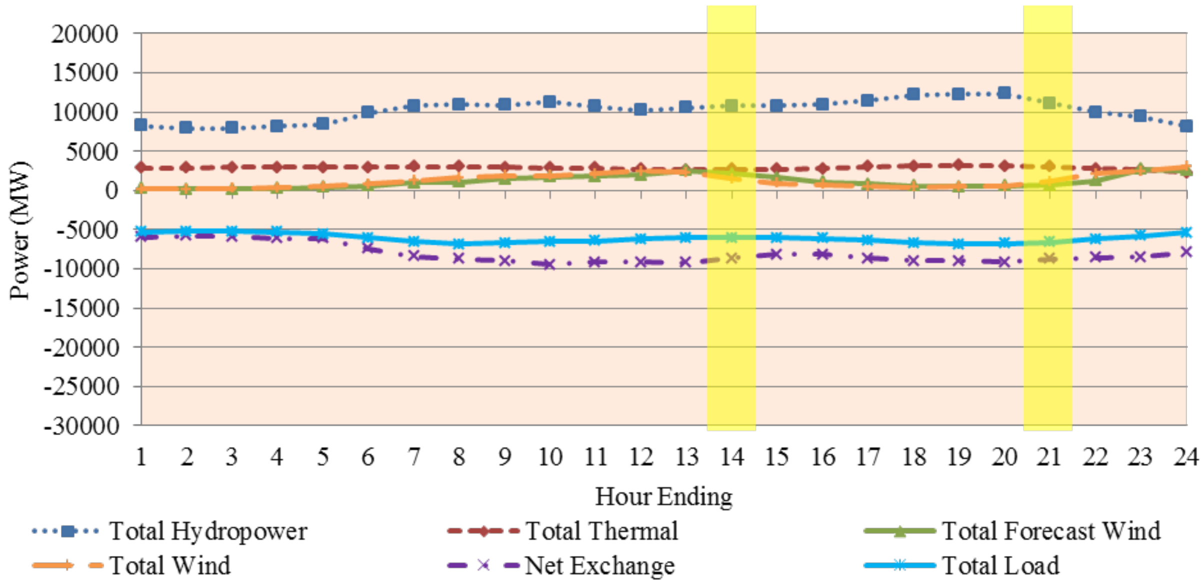


Figure 2.15. TIS as a Function of Wind Power in the Oregon Cascades TZ08 on February 15, 2014. The slope of the line is −$0.008/kWh per GW of generated wind power.

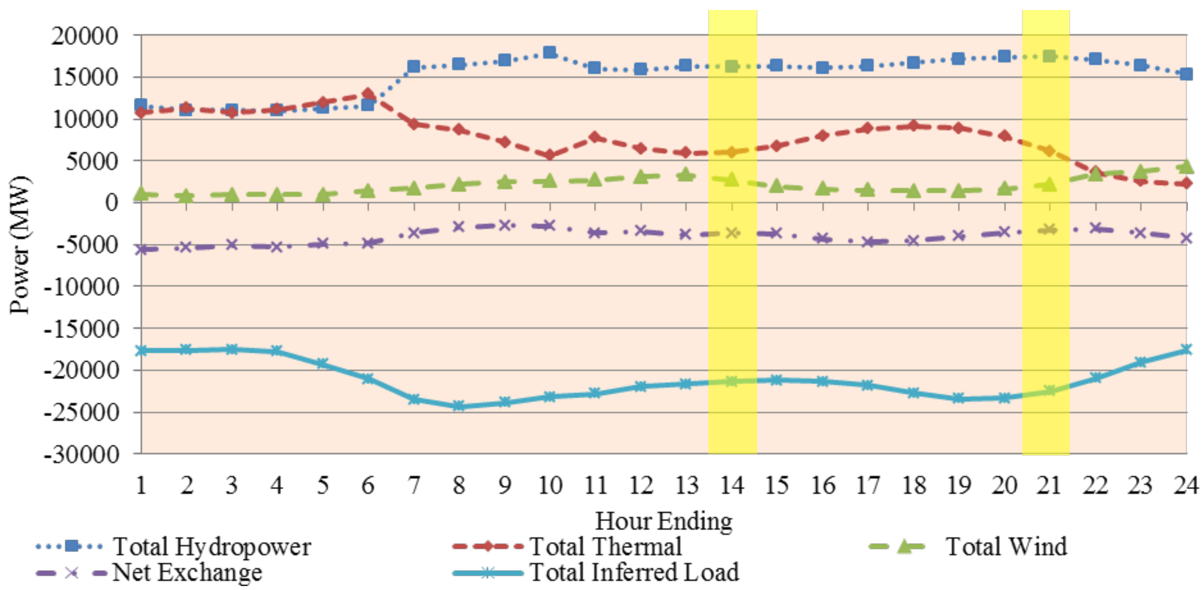
Periods of wind undergeneration and overgeneration on March 5, 2014. Another day of challenging wind conditions occurred on March 5, 2014, when both over- and undergeneration events occurred and were attributed to inaccurate wind forecasts. BPA experienced very heavy wind generation on this day. During Hour 14, wind generation fell short of scheduled wind generation by almost 1 GW. Up to 91% of the available “inc” resources—reserved generation resources—were exhausted to make up the shortfall. Wind states 1 and 2 were issued by BPA as an alert that its “inc” resources were nearing depletion.

The resource and load data from the modeled transactive system and BPA data are compared in Figure 2.16. The most striking observation may be that the transactive system modeled the dispatch of thermal resources to have assisted with load and wind following, whereas thermal resources remained unchanged in the BPA data. The transactive system did not reproduce the resource dispatch strategy in this case.

To make matters even more interesting, starting Hour 21, wind generation then exceeded scheduled wind generation by up to 1.2 GW. Over 90% of the available “dec” resources then became exhausted. Wind states −1 and −2 were issued.



(a) BPA Data (BPA 2015)



(b)PNWSGD Transactive System Data

Figure 2.16. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System on March 5, 2014

Figure 2.17 focuses in on the wind components that were shown in Figure 2.16. Wind generation in the PNWSGD transactive system closely paralleled that reported by BPA. However, the impacts of differences between scheduled and actual wind generation are not addressed by the transactive system. Wind power may contribute to the need for “inc” resources when the resource falls below the forecast, and “dec” resources when the resource exceeds the forecast.

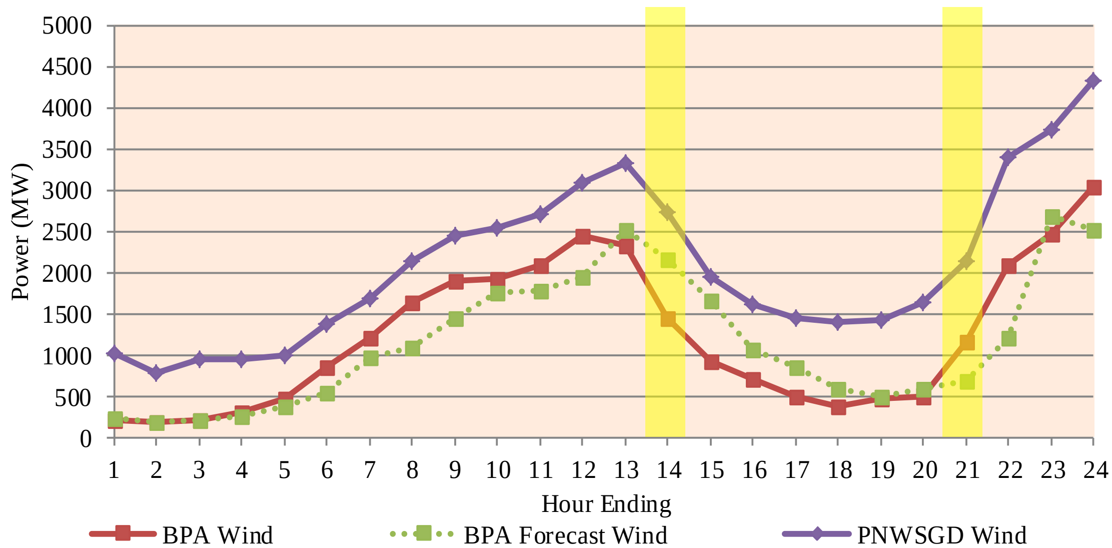


Figure 2.17. Comparison of BPA and PNWSGD Transactive System Wind Generation Data on March 5, 2014

Some influence may be seen in the TIS incentive signal at windy zones like TZ08 − Oregon Cascades (Figure 2.18). The effect is not obvious in the TIS averaged over the entire region. The incentive costs do not reflect the system imbalance, but overall costs were reduced near peak wind power generation near hours ending 12 and 24. The influence is not large because wind remains a relatively small fraction of the total system energy resources.

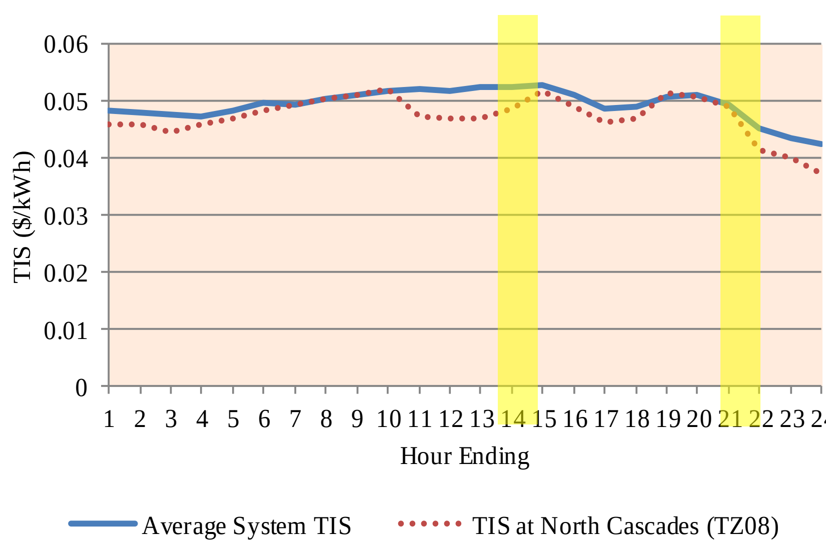


Figure 2.18. Average Transactive System TIS and the TIS at the Oregon Cascades TZ08 on March 5, 2014

Again, the trend is for a zone's TIS to decrease with increasing wind power, as was designed. This trend is demonstrated in Figure 2.19, which plots the incentive signal of the modeled Oregon Cascades TZ08 as a function of wind power that was generated there. The correlation is weak because many conditions influence the blended cost incentive signal.

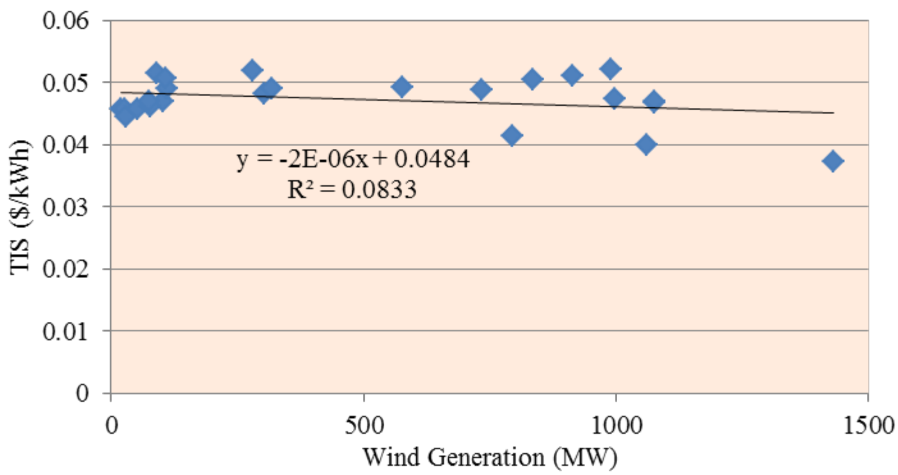


Figure 2.19. TIS as a Function of Generated Wind Power in the Oregon Cascades TZ08 of the Transactive System. The slope of the line is −$0.002/MW. The slope is $0.002/kW per GW of wind generation, but the correlation is poor this day.

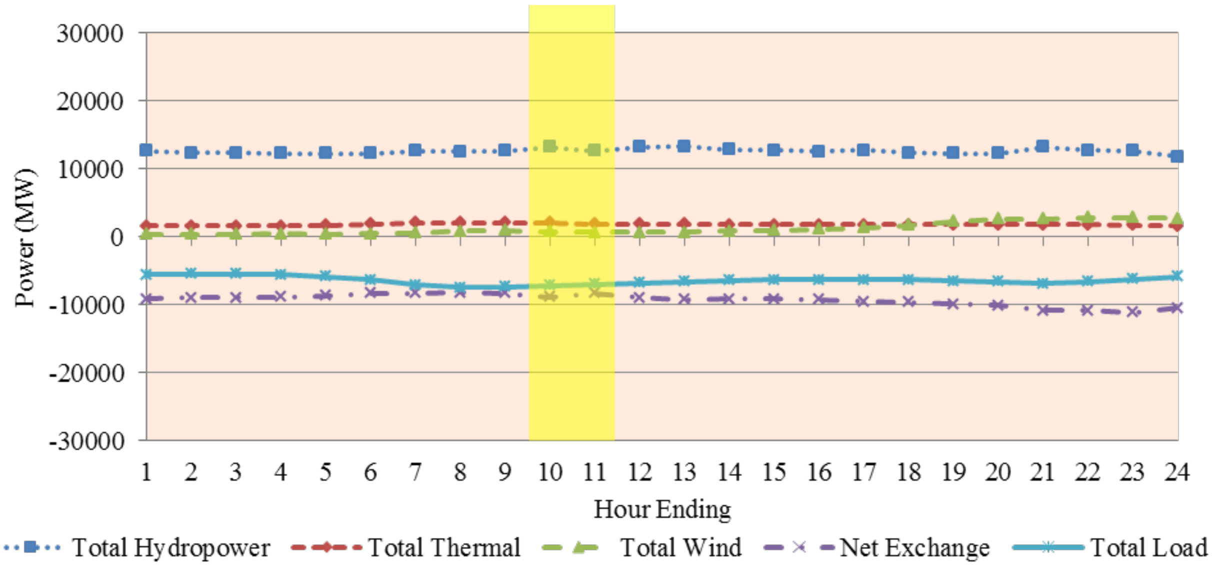
2.2.5 Transmission Incidents

This section compares BPA and PNWSGD transactive system data for two BPA transmission system events. At times, this section refers to flowgates, which are transmission lines, or groups of transmission lines, the loading of which are carefully tracked as potential locations of transmission congestion.

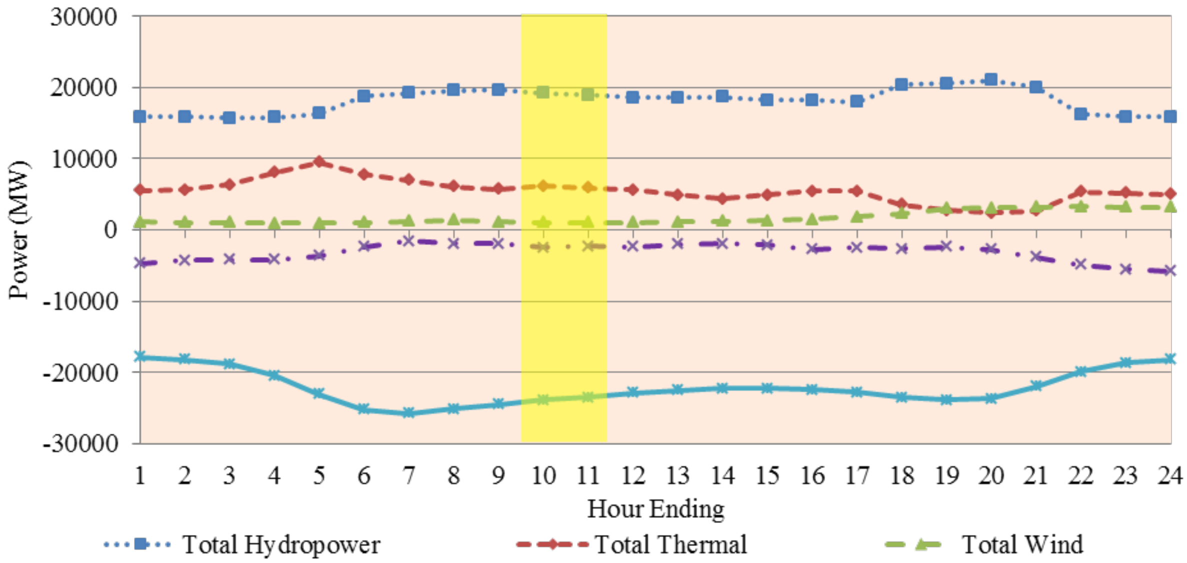
A transmission outage on April 1, 2014 (North of Monroe). On April 1, 2014, a transmission curtailment occurred hours ending 10 – 11 on the North-of-Echo-Lake flowgate after the flowgate came within 8 MW of its normal transfer capacity. A planned outage on a nearby transmission line had caused the operating limit to become reduced. BPA reported to the project that load on the flowgate peaked at 1,219 MW at 9:45 Pacific Time, within 7 MW of its maximum normal transfer capability. Between 10:00 and 10:15, the curtailment order decreased load on the line in excess of 90 MW and then an additional 100 MW between 10:15 and 11:00. The curtailment shifted balancing reserves deployed from drawing 260 MW at 09:50 to backfilling 231 MW by 10:20.

Despite the multiple changes made to manage the transmission capacity, BPA purchased no power and sold 24,448 MWh on this day. During the curtailment period, there were no adjustments from the plan for sales on the day-ahead market.

The impact is apparent at the system level in neither BPA nor PNWSGD transactive system data. See Figure 2.20.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

Figure 2.20. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System on April 1, 2014

Figure 2.21 more narrowly focuses on the reported power flow in the North of Monroe flowgate on this day and on the way this flowgate was modeled by the transactive system. This flowgate is modeled approximately by the modeled flow between TZ01 and TZ02. Precisely, the flow is therefore modeled by the TFS between these two nodes of the transactive system.

The modeled flow from TZ01 to TZ02 approaches the constraint level at about the time of the event. The flow is much less, however, off peak. The flows are not intended to be identical in the PNWSGD model, but they are found to have comparable magnitudes during the peak period of the day. The transactive system did not implement the construct of a normal transfer capacity during the PNWSGD. The project failed to design and implement a satisfactory function that would have monetized stresses on the transmission system using the incentive signal. The project would not have been able to usefully help BPA avoid this incidence of transmission congestion given the lack of accuracy with which the transactive system emulated the magnitude of power on this flowgate. The magnitudes of individual flowgate power could not be directly mapped to power flows in the project's simplified transmission model.

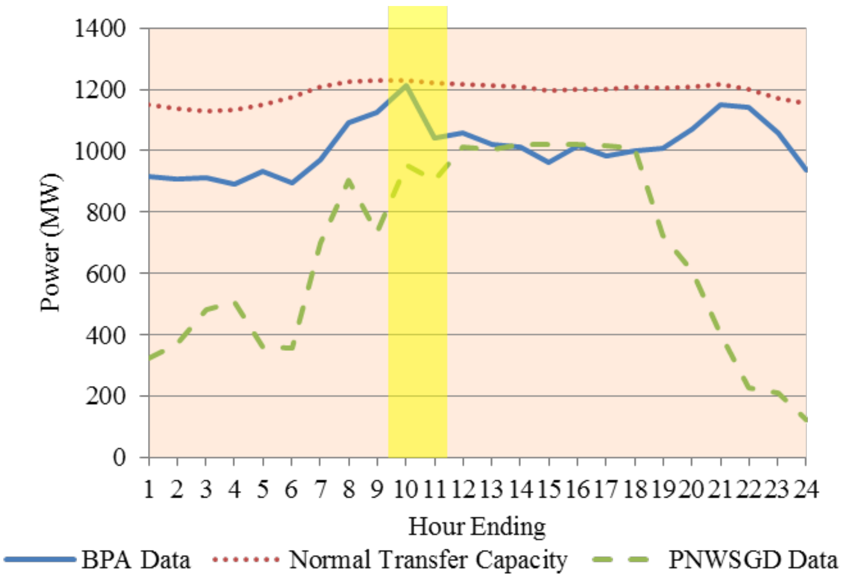


Figure 2.21. TFS Flow North of Monroe on April 1, 2014 According to BPA Data and PNWSGD Transactive System Data

During the event, the magnitudes of the TIS incentive signals at TZ01 and TZ02 do not have the correct relationship that would have helped mitigate the overloaded transmission, as is shown in Figure 2.22. If the transactive system were to help mitigate the overload condition, an incentive difference should appear across the flowgate to discourage consumption (or encourage generation) downstream from the overloaded lines. That is, an incentive would be introduced to make the TIS at TZ02 relatively larger than that at TZ01. The transactive system did not recognize or help mitigate this condition. The incentive signals are found to have the opposite relationship.

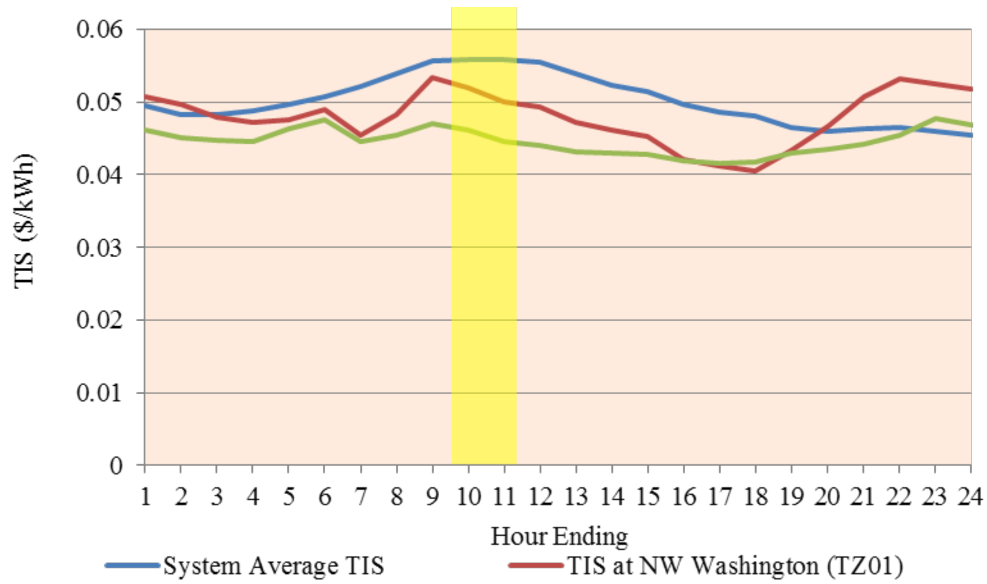
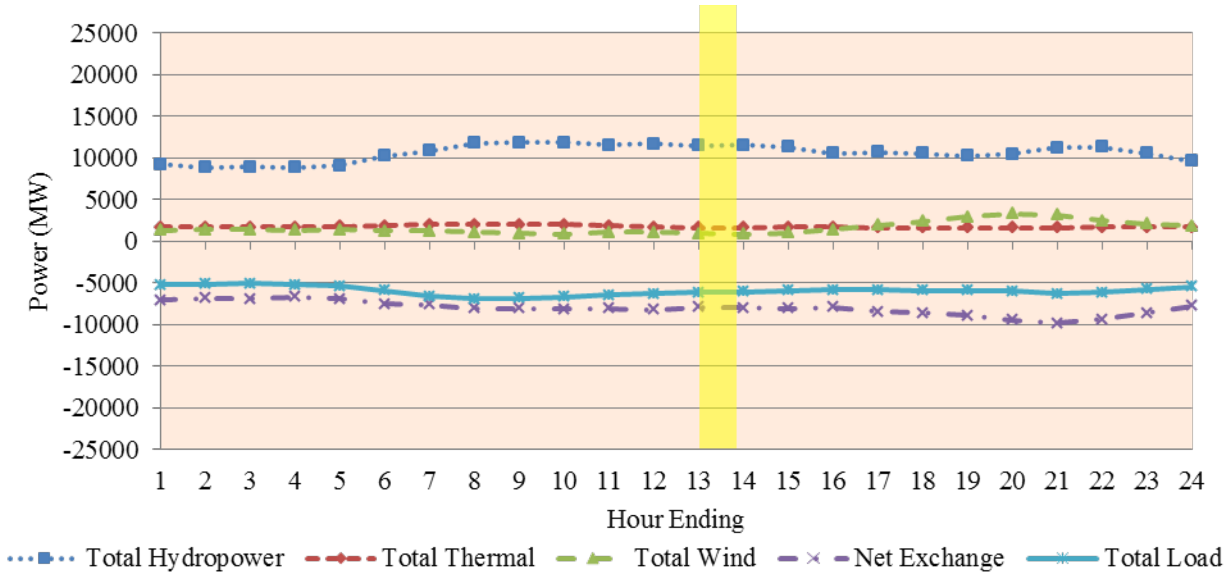


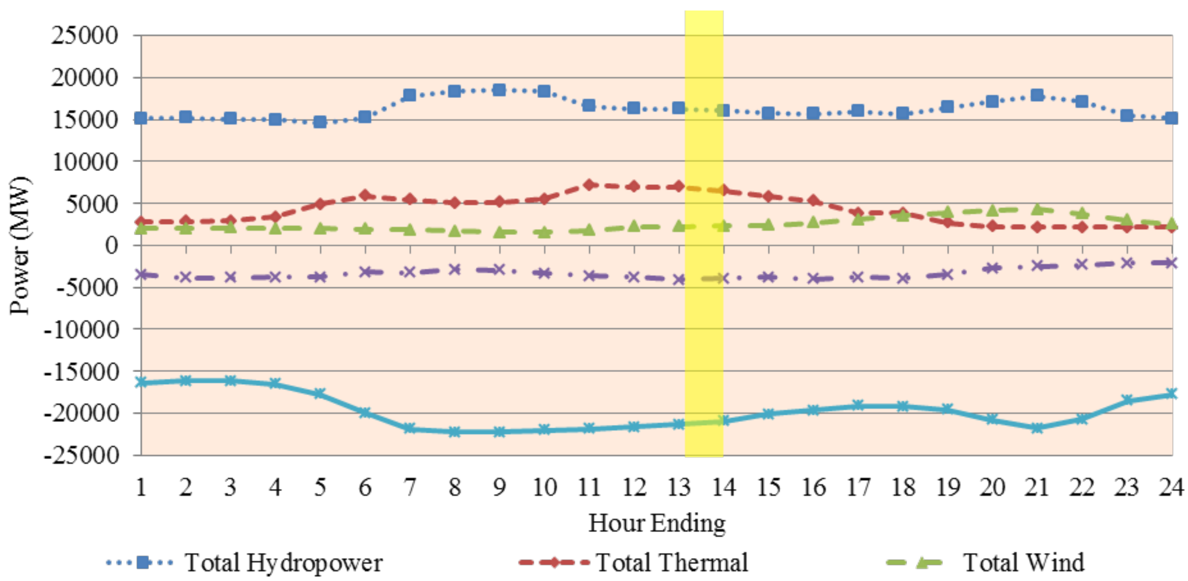
Figure 2.22. TIS Values on both Sides of the Transmission Outage and the Average TIS for the Entire Transactive System

An overloaded flow gate event on April 11, 2014. On April 11, 2014, the flowgate North-of-John-Day system operating limit became surpassed by 120 MW at around 13:30 hours. The system operating limit had been reduced due to a planned outage of two nearby 500 kV transmission lines.

Figure 2.23 compares the resources and loads that day as captured by BPA data and by the transactive system model. No impacts are evident in either the BPA or transactive system data at this level. The traces are similar, and the dynamics are mostly uneventful.



(a) BPA Data (BPA 2015)



(b) PNWSGD Transactive System Data

Figure 2.23. Comparison of Total Generation Resource and Load Data for BPA and the PNWSGD Transactive System on April 11, 2014

The PNWSGD models the sum of power flowing from TZ07 to TZ08 and TZ12 as being comparable to that of the North-of-John-Day flowgate. The sum of these two TFS flows from zone TZ07 (Hanford) to zones TZ08 (OR Cascades) and TZ12 (Central Oregon) is a pretty accurate representation of the actual flowgate loading on this day, as shown in Figure 2.24. The sum power flow that emulated the flowgate power flow exceeded the net transfer capability of the flowgate at times on this day.

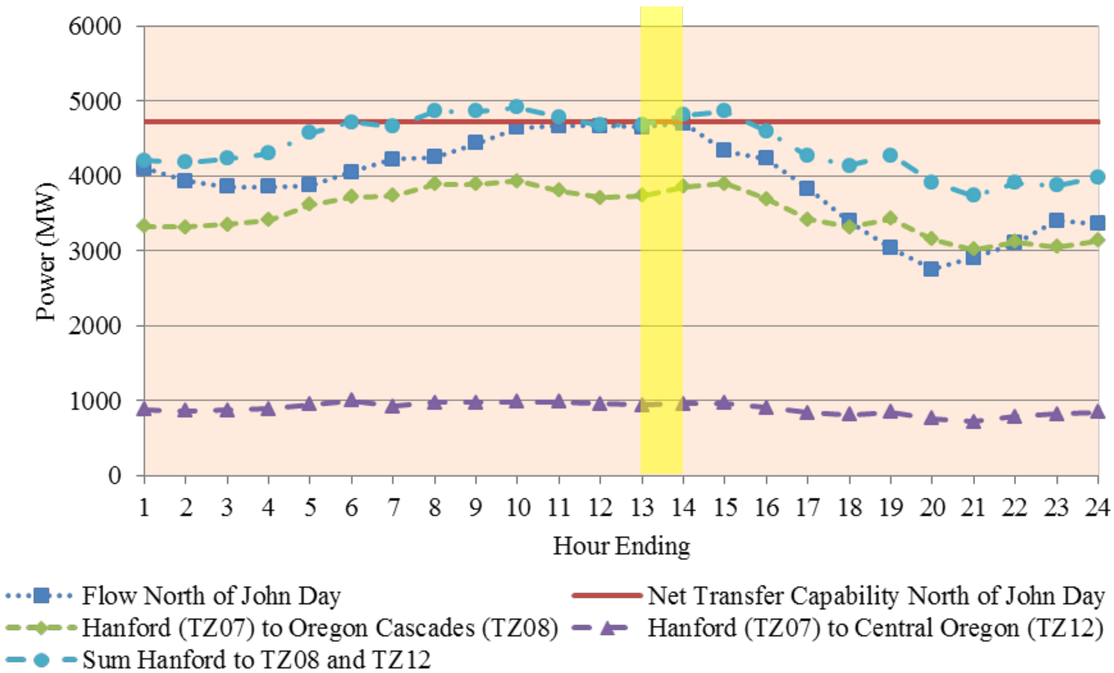


Figure 2.24. Comparison between the Actual Power Flow North of John Day and the Sum of Power Flows between the Transactive System's Hanford TZ07 and Neighboring Transmission Zones Oregon Cascades (TZ08) and Central Oregon (TZ12) on April 11, 2014

2.2.6 Relative Accuracy of Resource Predictions

The PNWSGD transactive system included a predicted future time horizon several days into the future. The predicted future dispatch of resources and incentives were therefore updated every 5 minutes. This proved to be a very challenging innovation for the project implementers. The intention of the future prediction horizon had been to facilitate day-ahead planning, much as is accomplished today by day-ahead and shorter-term markets, but with even greater resource flexibility.

As was discussed in Section 2.3, the value of the TIS follows directly from the unit costs of the energy resources that are being dispatched and perhaps other incentives that follow less directly from the dispatch plan and other grid conditions. If the present or future predicted dispatch and other grid conditions are incorrect, the incentives will also be incorrect and might induce undesired behaviors.

The future predictions would be critical in a truly distributed transactive control system where resources might be viewing both the balance of power and the incentive signal to determine when best to operate and not. The accuracy of the future intervals is especially critical for demand-side elastic loads that often have very few available event periods with which to participate.

Figure 2.25 demonstrates one symptom of an inaccurate resource prediction that badly plagued the transactive system implementation. The horizontal axis represents the difference between the time that predictions are made and the time interval for which conditions are being predicted. The far left position is the nearest-term prediction—the prediction that is being made for the next 5-minute interval. Toward the right, the predictions are being made further into the future until the far right where predictions are being made almost 4 days into the future.

The vertical axis of Figure 2.25 is the average of the summed resources that are being predicted the given time into the future. The window of these calculations progressed 5 minutes each 5-minute interval to include about one-half month from May 18 to June 4, 2013. "Total resources" means the sum of both the power that is modeled to have been generated within the given transmission zone and any power that was imported into the transmission zone from transactive neighbors or non-transactive exchange boundaries. Results are shown for all the transmission zones (see Appendix B).

If total resources are averaged over multiple hours and weeks, the average should represent an accurate average of the total resources; if predicted total resources are averaged over hours and weeks, the same average should be calculated. If not, a bias exists in the predictive calculations. In this case, all of the transmission zones undergo a significant change in average predicted total resource for the predictions that are being made about 3.5 or more hours into the future. Some increase, others decrease. Regardless, no such change should occur in the calculations.

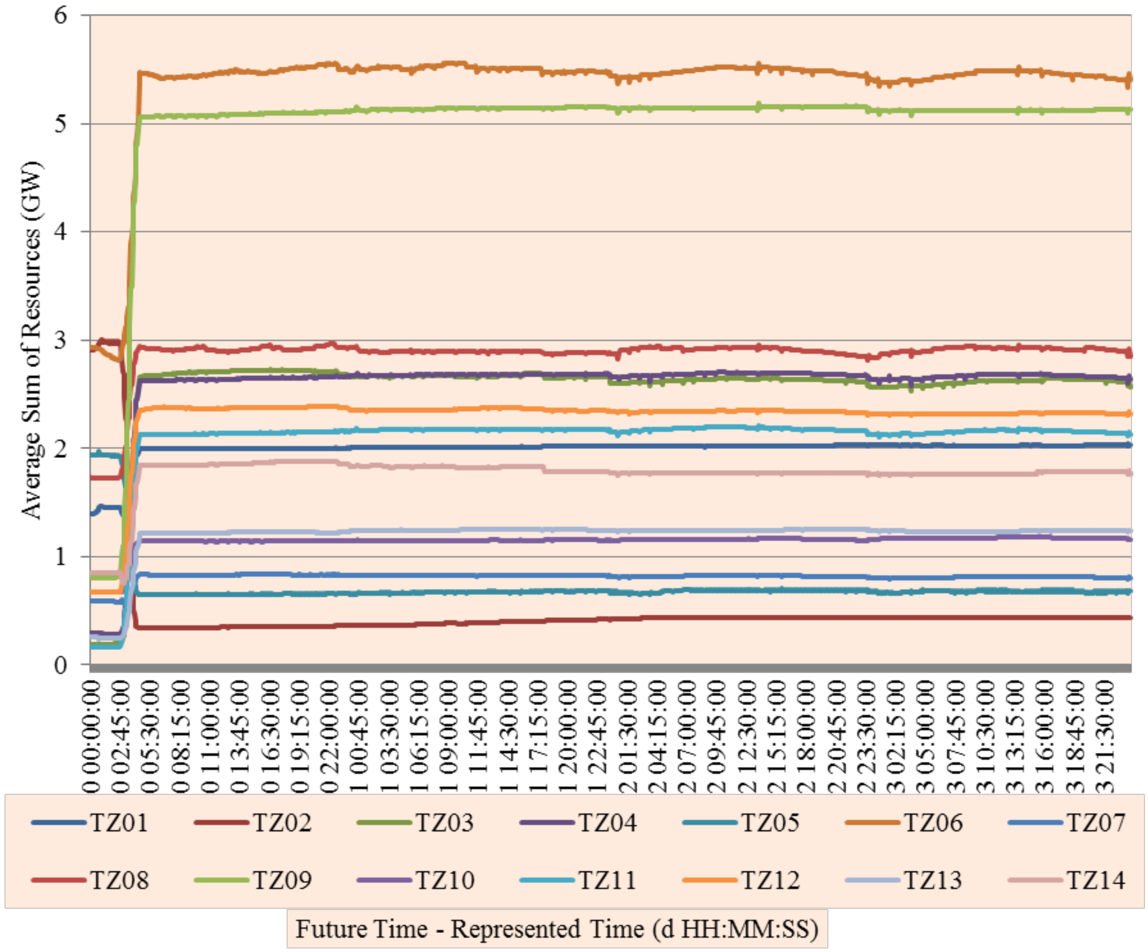


Figure 2.25. Average Total Resource Energies at TZs of the PNWSGD Transactive System Plotted against the Distance into the Future that the Predictions Were Made. This plot includes values from the transactive system production environment between May 18, 2013 and June 4, 2013 before the future predictions were improved.

The project hypothesizes that the change was caused by the use of different calculations in the Alstom Grid-informed simulation for intervals predicted less than and more than about 3.5 hours into the future. After much effort, Alstom Grid managed to decrease the magnitudes of the changes, as is shown in Figure 2.26. They were not able to completely eliminate the discontinuity.

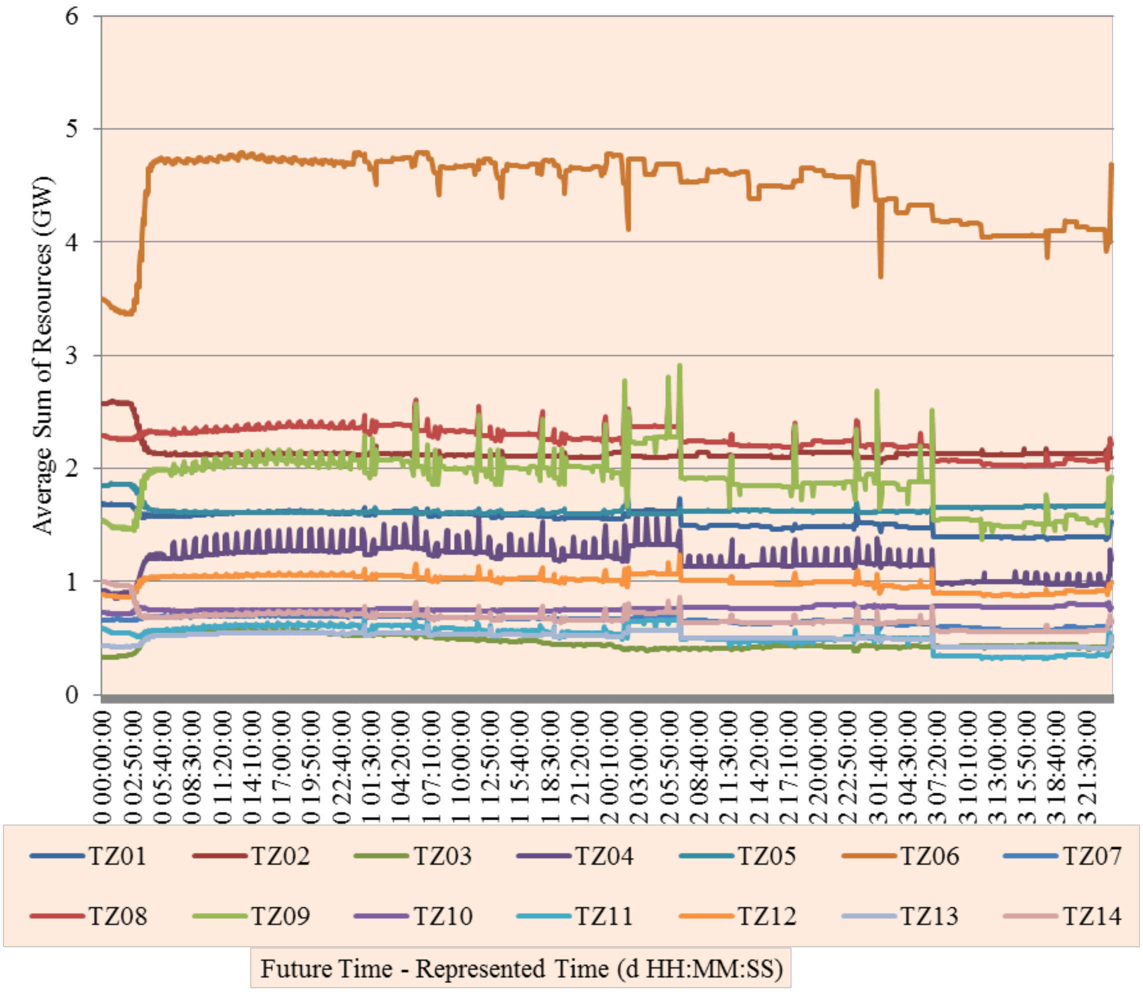


Figure 2.26. Average Total Resource Energies at TZs of the PNWSGD Transactive System Plotted against the Distance into the Future that the Predictions were Made. This plot includes values from the transactive system test environment between May 18, 2013 and June 4, 2013 after the future predictions had been improved.

2.2.7 Step 1 Evaluation Conclusions

In Step 1 of the analysis of the performance of the PNWSGD transactive system, the transactive system was confirmed to have represented the actual statuses of regional generation and transmission where such data was made available to it.

- The mix of generation resource types modeled by the transactive system paralleled those that had been reported by the BPA system. The system separately modeled thermal, hydropower, and wind power, plus the power that was imported into or exported from the region, of which the resource type was unknown. A direct comparison was impossible because the transactive system's region was larger than that of BPA, but the relative resource mixes were credible.
- The transactive system achieved superior visibility of actual and predicted wind power resources throughout the Pacific Northwest. The magnitude of wind resources closely paralleled BPA's wind

power data. The project could therefore anticipate and observe wind power magnitudes and rapid changes in wind power magnitudes—both up and down. However, the project was oblivious to the impact of wind power intermittency on BPA balancing reserves. The status of such reserves was not revealed to the transactive system.

- The transactive system appears to have recognized and represented an unexpected outage at a large power generator. However, the visibility of the outage in the transactive system may have been delayed for an hour. Because the transactive system's model of the Pacific Northwest transmission is coarse, the impact from losing even 1 GW of generation was relatively small at the incident's node.
- The transactive system did not accurately represent and respond to transmission events, including line outages and actions taken to keep loads under capacity limits. The transactive system's transmission model was not formally designed from the actual transmission system in a way that maintained correspondence between individual transmission loading and modeled ones. The status of the system was not explicitly available to the system, so it was expected that the transactive system would not represent such events. The project failed to implement a function that would incentivize transmission loading levels, the purpose of which would have been to assist constrained economic dispatch that is used today.

2.3 Step 2: The System Must Meaningfully Monetize and Predict Resource Costs and Incentives

In this evaluation step, we review the methods by which the transactive system monetized its energy resources and the system objectives to which incentives were applied. In the ideal—a fully distributed system of nodes, where each node independently selects its supply resources and its objectives to be incentivized based on transactive signals and local conditions—the functions might be unknowable and uncountable. What the PNWSGD project was able to implement was instead an "informed simulation" having a small number of defined resources and incentives that were designed by and fully monitored by the project. The project referred to the functions as "toolkit functions" to emphasize that once designed, the functions could be placed in a toolkit library of functions available to be adopted, revised, or reconfigured to suit the needs of future implementers.

The project possesses much unpublished documentation about the workings of the informed simulation that was used to monetize the transactive region's resources and incentives. Figure 2.27 supports an adequate review of how this subsystem worked.

Four dynamic data feeds are shown at the top. These four inputs drove the dynamics of the informed simulation:

- BPA hydropower schedule
- BPA load forecast
- 3TIER wind forecasts
- independent power producer generation schedules.

Other more static system data is also important, including the typical status of the Western Electric Coordinating Council region generators that are needed to emulate the exchange of energies at the transactive system's exchange boundaries, tables of fuel prices and infrastructure costs that especially affect the region's modeled thermal resources, the topology of the transactive system that states the connectivity between the system's nodes, and the mapping of the region's resources into the transactive system's nodal model.

At the bottom left, the region's circuit state was modeled from a limited number of representative historical condition sets ("NETMOM"). These models affected load flow calculations and at times modified the modeled generation and load profiles.

Alstom Grid used its unit-commitment and economic dispatch engines to facilitate the scheduling of modeled resources for the project. From the perspective of Alstom Grid and the informed simulation that is portrayed in Figure 2.27, its resource and incentive toolkit functions (bottom right) were the mappings of the resources' costs and dispatched powers allocated according to the model of the system, grid, and modeled generation resources.

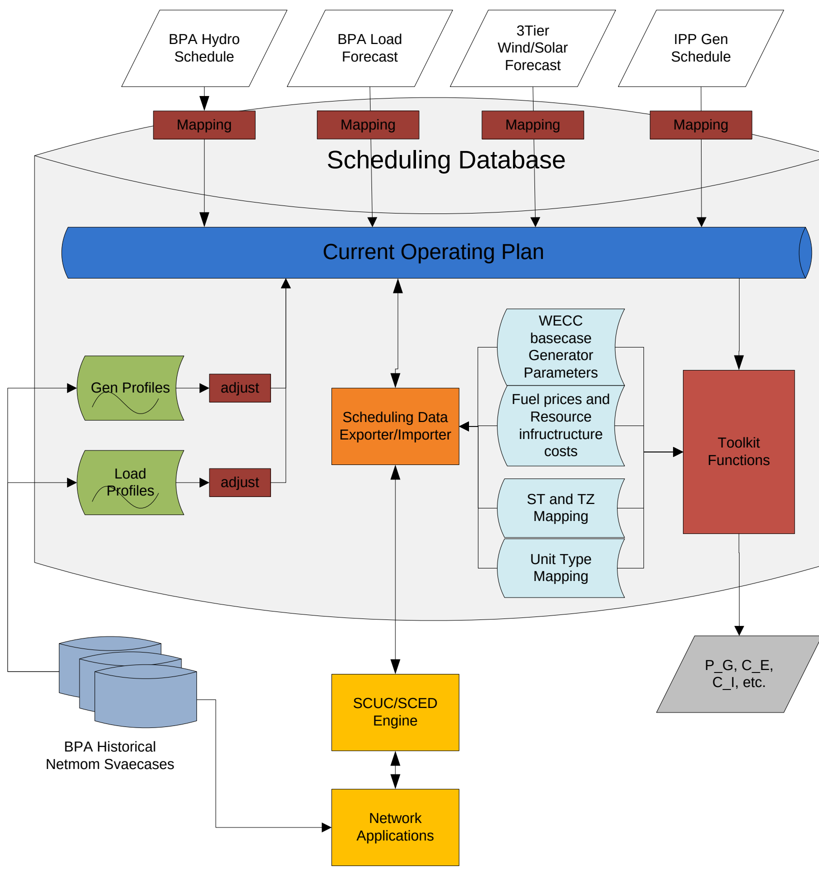


Figure 2.27. Alstom Grid Toolkit Functional Overview[1]

[1] From p. 1 of PNWSGD ALSTOM Toolkit Function Description, Version 0.3. Alstom Grid, 10865 Willows Road NE, Redmond, WA 98033, September 9, 2014, unpublished.

2.3.1 Toolkit Resource and Incentive Functions

Each resource or Incentive Toolkit Function was specified by the project as a black box having defined inputs and outputs. Many of the inputs were different from one function to the next, but the set of output coefficients were specified to facilitate calculations of the blended TISs, as discussed in Section 2.4.1. Only the limited set of coefficients could be assigned values. The limited set of allowed output coefficients fosters interoperability at this interface.

The purpose of each function's monetization is to influence the delivered cost of energy, but the dynamics with which the influence becomes applied over time is a free design variable that is available to the resource's owner (in this case, the project acted on behalf of resource owners) to further incentivize desired energy behaviors. This concept was challenging for the project's utility participants to grasp and accept. It is not the way electricity costs are charged today. Today's regulatory environment would need to be changed to allow this approach while still enforcing fairness.

The sum costs represented by the toolkit functions should sum, at least over long periods of time, to the actual cost of electrical energy at its location in the transactive system. With this understanding, the cost of infrastructure had to be modeled to represent any discrepancy between the transactive systems energy costs and the energy costs that are eventually borne by the region's distribution utilities. The TIS must be equivalent to the price of energy over time if, in the future, the transactive system is ever to be accepted as a basis for energy billing.

These following resources and incentives were monetized by the transactive system. The parenthetical numbers reference the project's numbering convention for its toolkit resource and incentive functions. The project generated as-built design documents for each (see Appendix A).

- Non-transactive imported energy (1.1) − This function emulated the impact from the exchange of power across the region's exchange boundaries. The energy that was imported through these boundaries was treated as a resource to the importing transactive node. The unit cost of the imported energy was based on recent trends in the Dow Jones Mid-Columbia price index.
- Transactive imported energy (1.2) − This is a trivial function, but it is included for completeness. No new calculations were required in the informed simulation. This function is accomplished by the correct blending of neighbor nodes' transactive signals such that the quantity and costs of energy imported from these transactive neighbors influences this node's TIS.
- Hydropower (2.1) − Scheduled hydropower generation was assigned costs according to the recent history and trends of the Mid-Columbia Dow Jones Price Index that was subscribed to and used by the project. Most of the modeled hydropower inflexibly followed schedules. Two large hydropower generators were modeled to be responsive to changes in system power balance.
- Wind power (2.3) − Total wind power in the region was reported and predicted by BPA and 3TIER. No cost was applied for the energy itself, but the infrastructure costs of wind farms were included among the general infrastructure costs (function TKRS 4.0). This approach might encourage consumption of wind power when and near where it is available. There was a downward pressure on the incentive signal magnitude as wind was blowing.

- Thermal generation (3.0) − Scheduled thermal generation was assigned costs according to heat rate curves and fuel costs for the corresponding generator types.
- General infrastructure costs (4.0) − At each transmission-zone node, a cost offset was assigned to represent the costs of infrastructure that had not been otherwise represented in the system. The target costs were based on typical wholesale prices paid by utilities near the given transmission zones. The coefficient slowly tracked that target price with a response time of about 1 month.
- Transmission congestion (5.1) − This function was implemented and used prior to May 2013, but it was turned off at all system locations after it was found to create undesirable, rapid changes in TIS values. The intention had been to disincentivize consumption downstream and incentivize production upstream from any congested flowgate.
- Demand-charges functions (7.x) − These incentive functions were implemented at utility sites, not at the transmission-zone nodes, so they were not part of the informed simulation. However, they fit into the present discussion because these functions modify the effective TIS at utility locations to reflect the impact of demand charges that are imposed by the energy supplier at the site. The University of Washington campus function also included time-of-use impacts that are part of the campus's contract with supplier Seattle City Light.

2.3.2 The Accuracy of TIS Predictions

The TIS represents the blended costs of resources and incentives. This section reviews the relative accuracy of TIS predictions as a surrogate for the aggregated resource and incentive influences. Every TIS included a series of predictions for 56 sequential time intervals. The nearest-term prediction was for the imminent 5-minute interval (interval start time IST0). Successive prediction intervals represented a series of 5-minute, 15-minute, 1-hour, 6-hour-long, and day-long future time intervals.

Figure 2.28 shows the relative prediction error at one of the transactive sites for the 8 months that the PNWSGD was operating in 2014. This refers to the Fox Island site (field site node ST01) in Washington, just one location in the transactive system. By the time the system is acting on the information from a specific
5-minute interval, the TIS of the interval has been predicted many, many times. The relative prediction error here is defined as the average difference between those predictions and the final, best calculation of the TIS that occurs just prior to the interval time, divided by the final calculated TIS value.

A positive result means that the predictions, on average, were greater than the final TIS calculation. Negative results, of course, then mean that the TIS tended to be under predicted. The results are averaged for each of the future 56 time intervals. The averages were further separated out by project month, as is indicated by the figure's legend.

Only the values that were calculated by the TIS are being compared. The true representation of the delivered cost of energy that the TIS emulated was nowhere dynamically available for comparison. Today, one would need to compare long-term averages of the TIS to average energy costs to complete a meaningful comparison against actual energy costs. And comparable costs are rarely available.

The principal observation from Figure 2.28 is that the predictions were mostly accurate before prediction interval 20, but the accuracy became worse further into the future. This boundary between prediction intervals corresponds roughly to the transition between 15-minute and 1-hour prediction intervals that occurs about 3 hours into the future.

The prediction accuracies became progressively worse through winter 2013 and spring 2014. A persistent negative bias is observed, meaning the transactive system tended to under predict the TIS at this site. The prediction bias was between 0 and −4.5%.

A surprise was that the day-long intervals used to predict multiple days into the future exhibited among the worst biases. While the challenge is increased by the distance into the future that the predictions are being made, these are also the coarsest averages of TIS intervals.

Future implementation should eliminate biases like these, tracking and correcting them over time.

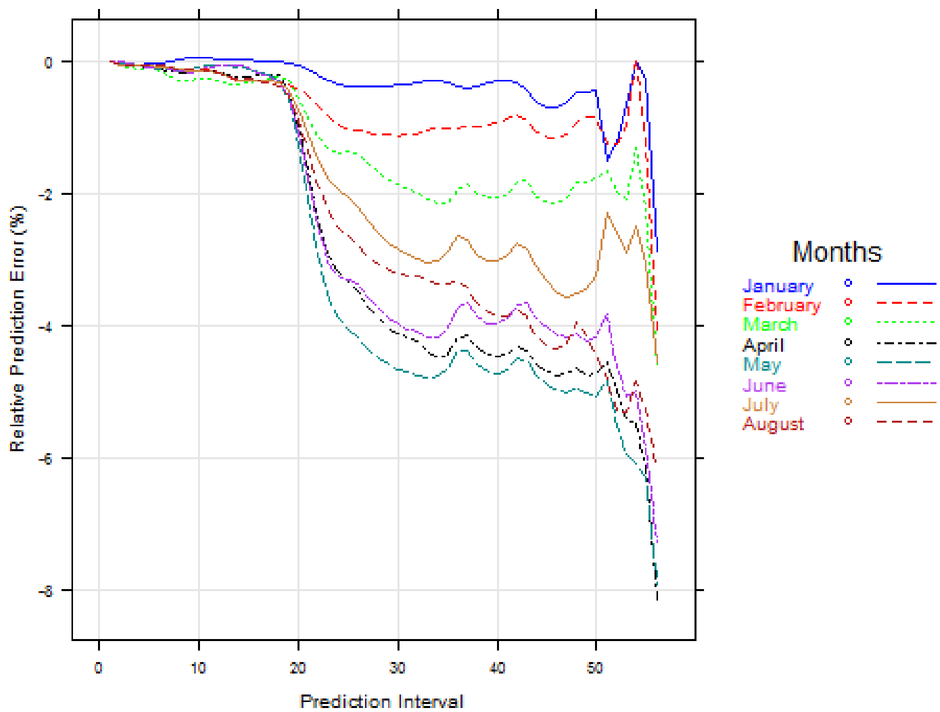


Figure 2.28. Average Monthly Relative Prediction Errors of the TIS Prediction Intervals throughout the Project Months of 2014 at the Fox Island Site (ST01)

Figure 2.29 exhibits standard deviations of the same relative errors that had been shown in Figure 2.28. As should be expected, the standard deviations of the relative errors increase with the predictions' distances into the future. The standard deviations ranged from 0 to about 8%, and the results were similar from month to month.

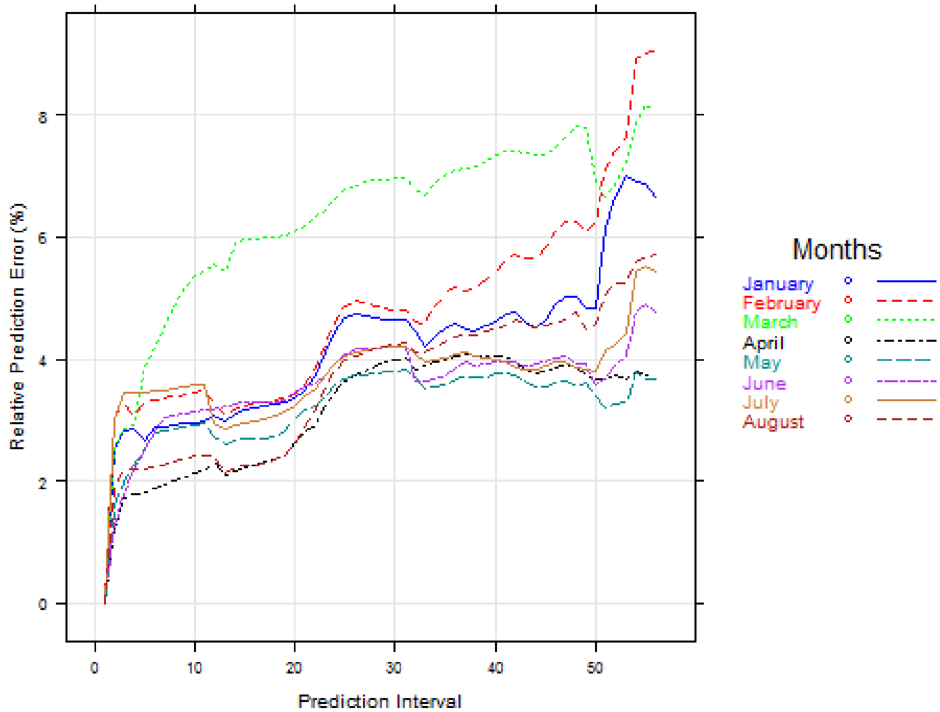
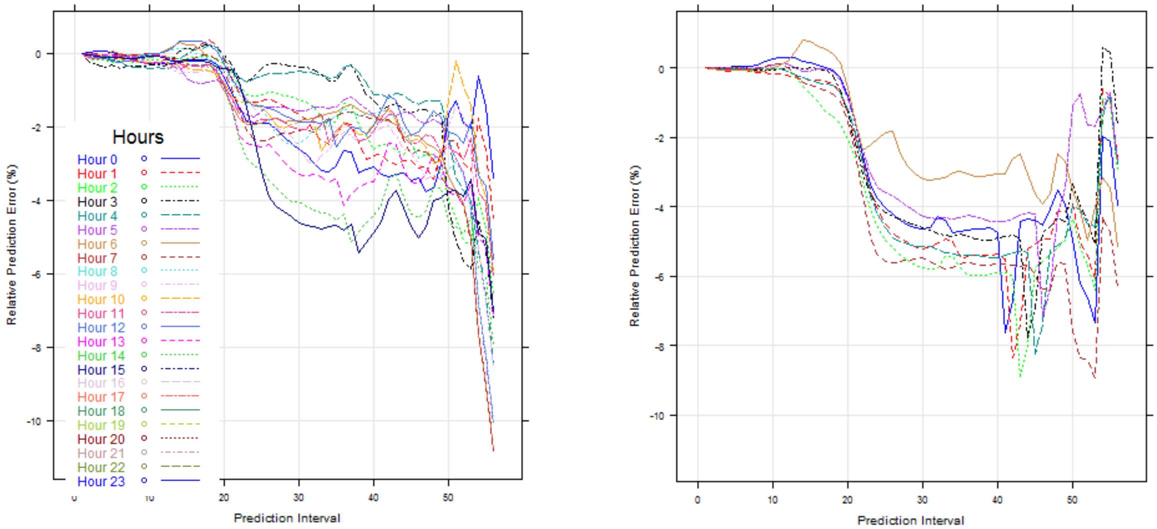


Figure 2.29. Standard Deviations of the Monthly Relative Prediction Errors Eight Months of 2014 at the Fox Island Site (ST01)

Figure 2.30 shows the calculated relative prediction errors again, but this time the results have been parsed by the local hour of day in which the predicted interval fell. Panel (a) graphs heavy load hours (HLHs), and panel (b) plots light load hours (LLHs). The HLHs were generally predicted with less bias than the LLHs. Some of the artifacts in the last intervals (e.g., 55, 56) were predicable. A coarse, day-long interval will tend to under predict the TIS during HLHs and over predict it during LLHs.

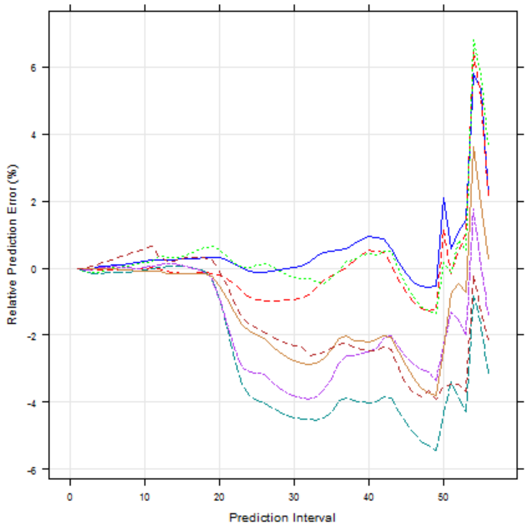


(a) Heavy Load Hours (b) Light Load Hours

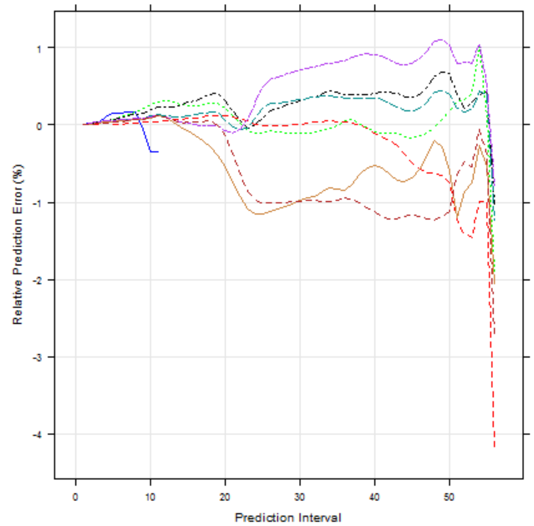
Figure 2.30. Average Relative Prediction Errors of (a) Heavy Load Hours and (b) Light Load Hours at the Fox Island Site (ST01) from January through August 2014

The comparison was also made by interval minute. There were 12 5-minute intervals each hour. The results were similar for all the sub-hourly intervals. As for the monthly and hourly assessments, the accuracy diminished rapidly near interval 20.

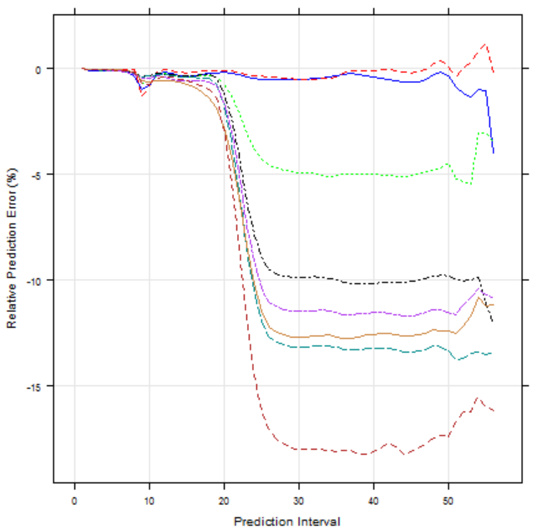
The relative prediction errors for another 10 of the other transactive system sites over the 8 project months of 2014 are shown in the panels of Figure 2.31. The prediction error biases were found to be pretty evenly split among those that over and under predicted the TIS. The relative prediction errors were generally small before interval 20, about 3 hours into the future. Predictions of TIS were probably most accurate in panel (b) for the Salem, Oregon site (ST03). Predictions at the Teton-Palisades Interconnect site (Lower Valley Energy ST12) were probably least accurate, approaching 30% error at least one of the months.



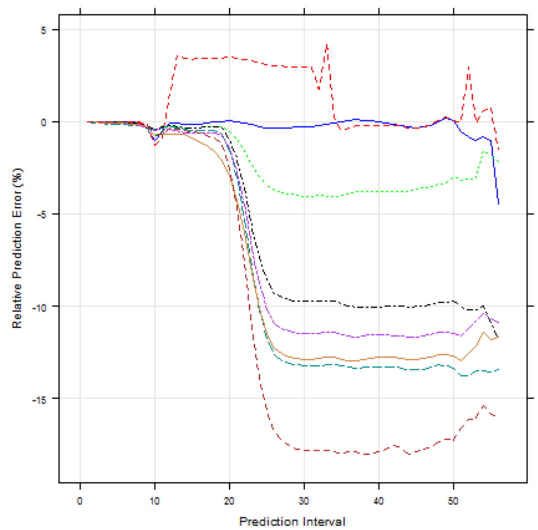
(a) U. Washington Campus Site (ST02)



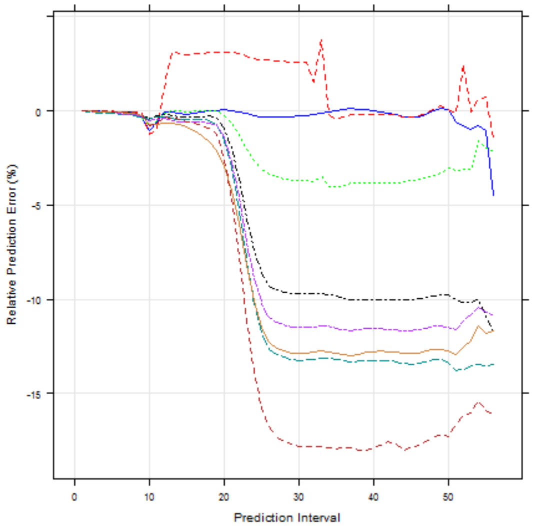
(b) Salem, Oregon Site (ST03)



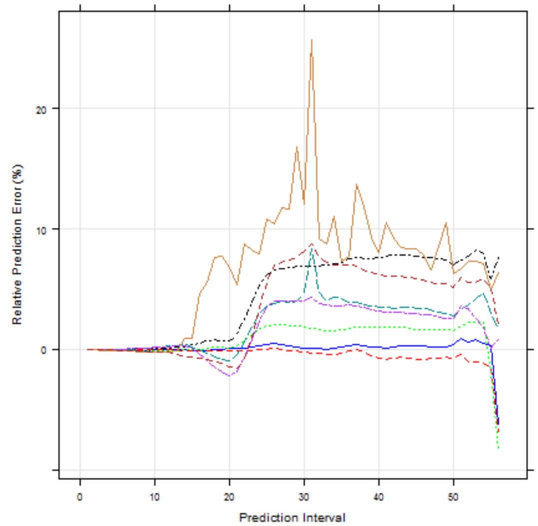
(c) Reata Site (ST06)



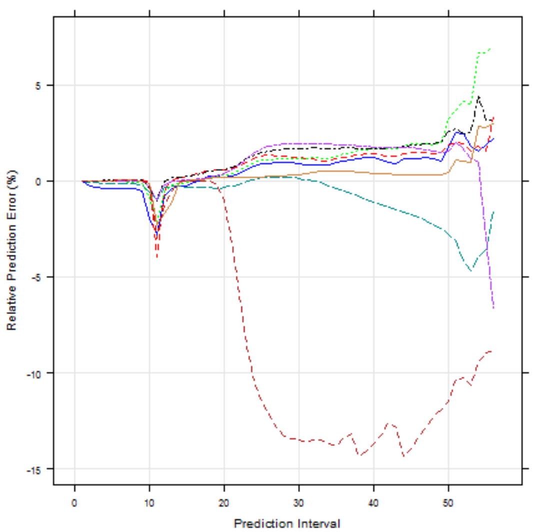
(d) Libby, Montana Site (ST07)



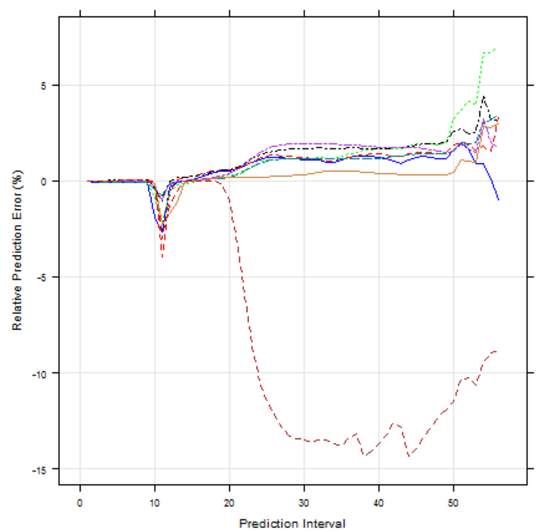
(e) Marion/Kila, Montana Site (ST08)



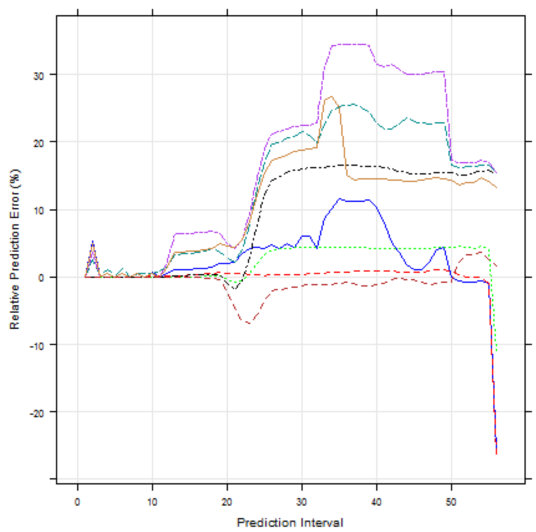
(f) Milton-Freewater Site (ST09)



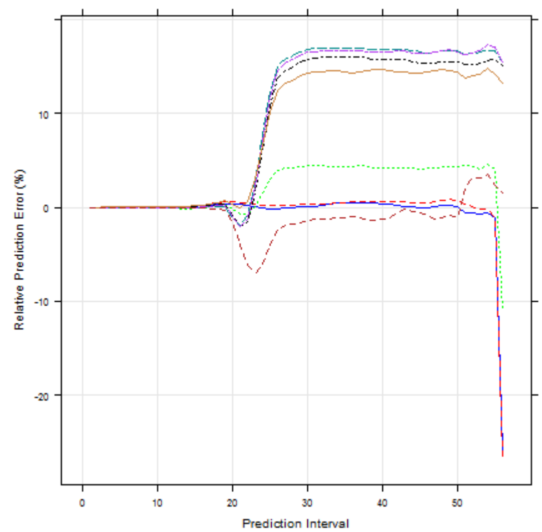
(g) Helena, Montana Site (ST10)



(h) Philipsburg, Montana Site (ST11)



(i) Teton-Palisades Interconnect Site (ST12)



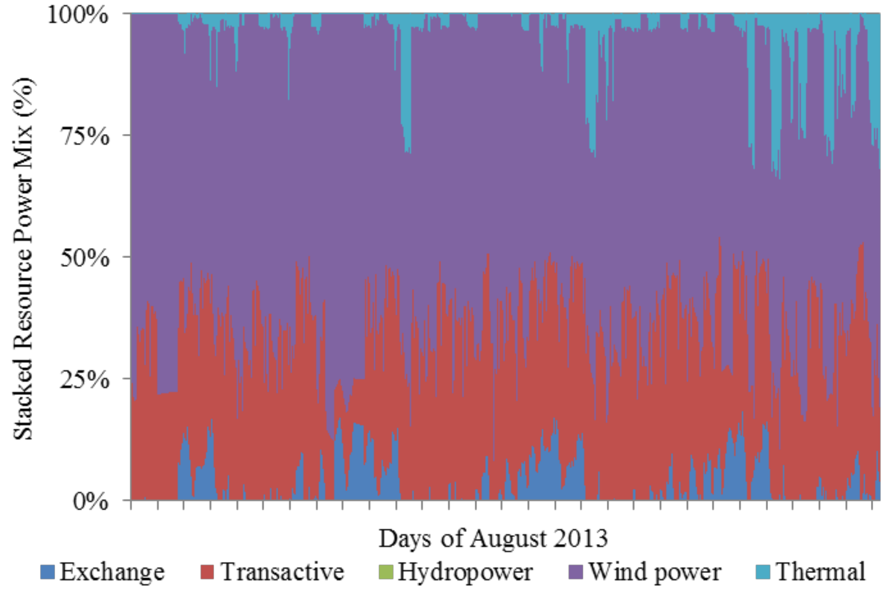
(j) Idaho Falls, Idaho Site (ST14)

Figure 2.31. Relative TIS Prediction Errors for the First Eight Months of 2014 at Ten Transactive System Sites. The month legend from panel (a) works for all the 10 panels.

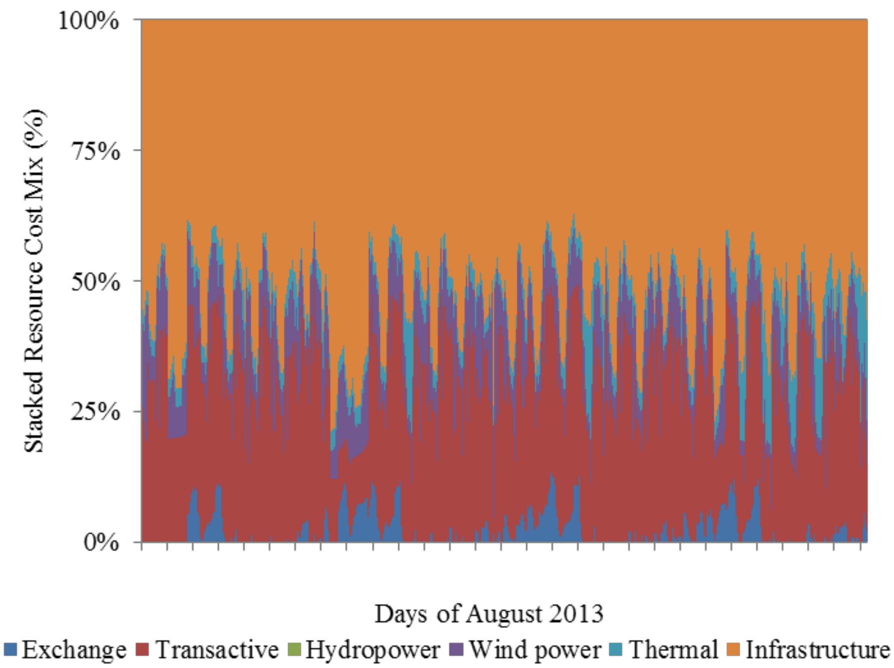
2.3.3 Changes in Monetized Incentive Mix over Time

Figure 2.32 compares relative resource power mix and relative resource cost mix at one of the transmission-zone nodes over time. This example happens to be for the North Idaho TZ10 during August 2013, but any other transmission zone or month might have supported the comparison equally well or better. The raw resources are shown, just as they are accounted for by this node as it calculates its TIS values. This node occasionally imports non-transactive power from Canada. It typically imports about one-third of its power from its transactive neighbors. Hydropower at this location is not a significant part of the raw resource mix, but there is much wind resource. Thermal resources at times make up one-quarter of the raw resource power mix.

Looking now at panel (b), nearly half the energy cost is allocated to infrastructure costs. Wind energy has been assigned only a small cost. The relative fractions of power and costs are similar for the power and cost panels because the neighbors' costs have already been blended at the neighbors' locations.



(a) Relative Resource Power Mix



(b) Relative Resource Cost Mix

Figure 2.32. Comparison of (a) Relative Resource Power Mix and (b) Relative Resource Cost Mix for the North Idaho TZ during August 2013

A general observation is that the dispatch of resources may be wild and discontinuous over time. Changes in the dispatch of bulk generation in the transactive system model necessarily created step changes in both the resource mix and the corresponding mix of costs. The next dispatched resource might be distant from the prior one, potentially even causing reversals of power flow in the meshed transmission system. Some of the wild behaviors in the transactive system were caused by the coarseness of the system's transmission model. Some may have been caused by oversimplification or incorrect understandings of the region's resource dispatch strategies. If the discontinuities are real and immutable, this may have adverse implications for the viability of automated distributed control systems like the transactive system.

2.3.4 Lessons Learned Concerning Monetization and Prediction of Resource Costs and Incentives

Need improved prediction tools. The informed simulation that emulated the dispatch of the transactive region's resources persistently predicted values that were either greater than or less than the final resolved value. Some of these biases may be attributed to having used different calculation methods for the long-term and nearer-term predictions. Regardless, the biased predictions of resources also produced biased cost predictions. This was found to be a serious issue. Elastic responsive assets reviewed the predicted incentives to plan their responses. The prediction biases caused these assets to either respond too soon or incorrectly defer their responses depending on whether predicted incentives were always greater than or less than the unbiased value. Much more work must be done to improve the accuracy of predictions.

Integrating wind. The project learned too late during the project term that the toolkit function chosen to monetize wind energy in the transactive system did not adequately address the project's stated objective to integrate wind energy resources. While the project's approach did indeed incentivize consumption of wind energy, it did not monitor and help correct the occasional depletion of balancing reserves that is attributed to wind intermittency. The state of BPA balancing reserves was unavailable to the transactive system.

Demand charges. The demand-charges functions were moderately successful, but fundamental challenges were revealed during the project. The main objective of imposing demand charges is to incentivize a flatter, more consistent electrical load. BPA and other energy suppliers design workable metrics that indicate the overall "peakiness" of the loads. Often only the worst hour of the month is monetarily penalized by the metric. Distribution utilities currently have few resources with which they can truly flatten their load shapes, so they carefully aim their few resources at the one or two worst monthly peaks. They sometimes miss. Regardless, the impact on the transactive system was that its demand-charges functions also behaved this way and applied the modeled monetary impacts (according to the actual incentives) at the peak hour. And the hour was not identified as accurately as we would have liked. The actual cost impacts, when applied to the few peak intervals, were overwhelming and created cost discontinuities in the TIS. In future implementations of demand-charges functions, implementers should do the following:

- Improve the accuracy of the predicted distribution system load.

- Smooth the function's disincentive over more time intervals, perhaps including statistical functions to apply the disincentives in line with the likelihood the peak will be occurring during a given hour.
- Employ enough responsive smart grid resources to truly flatten distribution system load.

In addition, BPA should consider revising its demand-charges metric to incorporate data from many hours, not just the peak hour each month.

Infrastructure cost impacts. A problem was encountered early in the project with the general infrastructure costs function. Its impacts were initially incorporated in a way that unintentionally disincentivized the flattening of system load. This issue is discussed more in Section 2.4.

2.3.5 Step 2 Evaluation Conclusions

- The PNWSGD used a centralized "informed simulation" to emulate the dispatch of generation resources and their impacts on the delivered costs of electricity.
- Toolkit functions, working in conjunction with the informed simulation, specified how much of each type of dispatched energy was to be modeled in the system and this resource's impact on the delivered costs of energy in the transactive system. The project was able to reproduce the power and costs introduced by each resource through its data-collection system. Consumers' energy behaviors may be influenced by the way that resource costs are monetized by the functions.
- Toolkit functions may have merit as a template for distributed calculations. A defined set of output coefficients from the functions served as an interoperability interface in the transactive system. The system must be tested using more distributed nodes to fully confirm the value of the construct.
- The project did not correctly understand and respond to BPA's objective for improved integration of wind power. Future implementations must track and disincentivize the depletion of balancing reserves, which turned out to be the real challenge of wind integration for BPA.
- Incentive functions were similar to resource functions. The project failed in its attempt to design and implement an incentive function for the mitigation of transmission congestion. The demand-response incentive functions were more successful, but further improvements are needed.
- The costs of infrastructure were included in the incentive signal. Unlike locational marginal pricing, the transactive system strived to represent all costs of the delivered energy, not just the marginal costs.
- The dispatch of the transactive system's modeled resources was discrete and at times created discontinuities in the incentive signals. The project hypothesizes that some smoothing might occur in richer transactive systems that have more, and more independently acting, nodes and resources.

2.4 Step 3: Costs and Incentives Must Be Meaningfully Blended and Distributed through the System

Having reviewed the way that the transactive system emulated the dispatch of energy resources and monetized the various resource components, the next analysis step evaluates how those influences were blended and distributed throughout the transactive system. There are certainly many ways that the signals and their conveyance through the system could have been designed and accomplished, and the best method remains debatable. This section will simply remind the reader of the system's specification and affirm that the project's design was adhered to.

2.4.1 The Transactive Incentive Signal Is a Blended Cost

Each nodal location "owned" a unique TIS time series that represented the blended costs of all of its available resources at each time interval. Its TIS represented the unit cost of the energy that was either consumed there or was exported from there to another transactive neighbor node or through an exchange boundary.

The TIS equation—Equation (2.1)—is from the Transactive Coordination Signals report (Battelle Memorial Institute 2013, p. 2.8). The TIS was calculated—blended—at each node by summing all energy-related costs at the nodal location and dividing that total cost by the total energy resources that were available to the node during the interval. The costs may include the costs of generated energies, cost impacts of power capacity during an interval (demand charges, for example), or pure monetary impacts (resource startup costs, for example). In addition, offset costs shown in Equation (2.1) proved useful to represent bulk infrastructure costs. Total energy resources refer to all of the generated and imported energy that is available to be consumed or exported from the nodal location. The resulting units of measure for the TIS are dollars per energy (e.g., $/kWh).

$$TIS = \frac{energy\ cost + capacity\ cost + other\ costs}{total\ energy\ resources} + offset\ costs \tag{2.1}$$

The project collected all component costs and energy quantities that had been used at each nodal location and for each 5-minute data interval, and the project affirms that its calculations adhered to Equation (2.1). A TIS can be recalculated to confirm its value at any system location and time.

2.4.2 Distribution of Paired Energy Quantity and Unit Price Confirmed

Equation (2.1) is recursive in that the costs of energy from transactive neighbor nodes were also necessarily represented in the calculation. Neighboring transactive nodes are required to share their TIS (i.e., a unit energy cost) with one another. The two neighbors must also negotiate and resolve, through iteration, the power that is to be exchanged between them—the TFS.

The TIS of the node that *receives* power from the other is affected by the transactive node that supplies the power. As the recipient node uses Equation (2.1) to calculate its TIS, the supplying neighbor's TIS is among the energy costs, and the quantity of supplied energy—the TFS—is included among the summed total resources.

Therefore, the influences of energy costs and incentives were distributed through the system in the direction of power flow and in proportion to the magnitudes of energy that will flow between the system's nodes. This distribution of influence is confirmed again by the fact that the project can accurately recalculate a TIS at any system location and time.

2.4.3 Lessons Learned Concerning the Blending and Distribution of Incentive Signals

The TIS of the node that *receives* power from the other is affected by the transactive node that supplies the power. The term worked as intended, evenly allocating a constant dollar cost at each transmission zone where the toolkit function had been implemented. The unintended consequence was that, when this term was divided through by total resource energy (see Equation [(2.1]), an undesirable inverse relationship was created for the TIS, which is expressed as a unit cost of energy. That is, the unit cost of energy became smaller when the node had large total resource energy and greater when it had little. This had the unintended consequence of disincentivizing energy consumption when less energy was being generated and consumed. The preferred impact would have disincentivized energy consumption during peak load, thus helping flatten the system load.

The undesirable inverse relationship was fixed by moving the constant cost to the cost offset term, which is unaffected by the magnitudes of resource energy (and load). This correction also demonstrated the flexibility of the transactive incentive calculation. The same infrastructure costs were represented before and after the correction, but the dynamics of the costs could be changed to incentivize preferred energy consumption.

Iterative solution required. As the transactive system was being formulated, there was much debate about whether the impacts of changes in the system would adequately permeate throughout the system. The system's electrical connectivity (Appendix B) defined a network of peer-to-peer communication pathways. Must the timing of communications then be ordered and controlled to ensure that the impacts extend beyond the nearest neighbors? In the end, simplicity won out, and the timing of most communication events became scheduled at 5-minute intervals. Simple logic was adopted to receive anticipated signals from neighboring nodes. The simple timing approach worked for now because the topology was small and shallow, and risks could be managed. In addition, influence within the system was found to fall off quite quickly with distance in the transactive system.

A compromise was the design of relaxation[1] logic that would instigate further rounds of signal exchanges if received signals were found to have modified output signals by more than a configurable threshold. This approach worked. Iterations were occasionally found to have happened, but they were infrequent. The system converged quickly because, in part, the balancing responsibilities of the nodes were deferred (as discussed in Section 2.9), and the incentives of the transmission zones were centrally calculated by the informed simulation, not calculated in a distributed fashion.

Consensus is growing among the project's system implementers that the exchange of signals in the transactive system should become more event-driven and less timed. Iterative calculations and exchanges of the transactive signals will be needed.

[1] The word *relaxation* is borrowed from a well-known simulation solution technique. The convergence of the system is beginning to resemble that of other problems that are set up to solve by relaxation methods. Relaxation methods often employ criteria that cause more iterations to occur where they are most needed.

2.4.4 Step 3 Evaluation Conclusions

- Equation (2.1) guided the blending and distribution of energy cost influences in the transactive system. The equation, while similarly implemented at each system location, provides a great deal of flexibility for implementers to represent the costs of energy resources while also incentivizing desirable dynamic energy behaviors.
- An undesirable inverse relationship was at first created by the way the costs of infrastructure were modeled in the system. The influence was corrected using an alternative representation of costs in Equation (2.1), but the correction did not break the system design.
- The demonstration topology was probably not rich enough to confirm the validity of the combination of time-based intervals and event-based iterative calculations. Future systems should probably become more event-driven, as was exemplified by the systems relaxation criterion. These issues might be resolved by simulation.

2.5 Step 4: Responsive Loads in the System Must Be Able to Allocate Appropriate Responses Using the Incentive Signal

Presuming that the incentive signal is meaningful and is a representation of the actual cost of energy at a location in the transactive system, is a responsive load system able to discern response event periods using the incentive signal and other locally available information? For example, can a system of responsive water heaters select the no more than five useful curtailment periods each month that the customers had been promised? This question refers specifically to the responses determined by toolkit load functions, a module of the transactive system at a transactive node. These toolkit functions are diverse, but the following categorizations proved useful:

- Event-driven − the challenge is to allocate a limited number of allowed events and limited event durations over a relatively long period like a month or year. The event-driven function therefore anticipates and responds to monthly peaks, for example, in the TIS.
- Daily − the challenge is to allocate a limited number of events and limited event duration each day. The daily function therefore anticipates and responds to daily peaks in the TIS. Often, these functions are configured to respond differently (or not at all) on weekends, weekdays, and holidays.
- Continuous − a continuum of allowed responses is possible based on the real-time assessment of the relative magnitude of the transactive system’s transactive signal. Battery energy storage was the only type of asset in the PNWSGD that responded this way. The continuous functions may be configured to constrain the responses of the asset for their given power and energy capacities and other of the owners’ operational preferences.

The output signal from the toolkit load functions was called an advisory control signal (ACS), a signed byte advising assets when to respond and by what relative magnitude. Most responsive asset systems responded in a binary way and had the capacity to either curtail their loads (ACS = 127), or not (ACS = 0). Battery systems, in principle, could be advised to discharge at full power (ACS = 127), charge at full power (ACS = −127), or respond at any charge or discharge power level between these two extremes.

The project preferred that the loads be made automatically responsive to the advisory control signals, but not all systems were amenable to automation. The connection between the functions' advice and assets' actual performance was often tenuous. This section reports the functions' output—the status of the advisory control signals—even though many of the asset systems were found to have, in fact, often ignored the advice from the transactive system.

2.5.1 Event-Driven Function Events

Event-driven functions were designed to anticipate and generate a given number of events over relatively long periods (e.g., a month). The allowed numbers of events, the minimum and maximum durations of an event, and the sum of all of the event durations in the longer period were configurable. The occurrences of events could be configured differently and allowed or disallowed by hour, weekday, and holiday. For example, many of the PNWSGD utilities were subject to demand charges during defined HLHs, and the functions at these locations should have therefore been configured to preferentially respond during these HLHs if that was the preference of the asset's owner.

The event-driven functions individually maintained histories of the local incentive signals' statistics; the statistics helped the functions learn which incentive signal values were high, low, or normal. Thresholds were managed by each event-driven function to help it detect the TIS magnitudes at which the function's asset should respond. As the allowed numbers of monthly responses were used up, the threshold was then readjusted to best use the remaining events within the remainder of the present month.

The allowed numbers of events and event durations were often defined according to agreements that utilities or aggregators had made with their customers. Through configuration of the functions, each utility could enforce that its customers not be inconvenienced more than they had been promised.

In the PNWSGD, event-driven functions were frequently combined with asset models that represented electric water heater curtailment, thermostat setback, distributed generator control, dynamic voltage management, or in-home and portal notifications. The role of the asset models in the transactive system was to predict the impact of the assets' responses on load if they indeed responded at the times that become determined by the event-driven toolkit function.

Altogether, the performances of 14 event-driven functions are combined in Figure 2.33. Persons familiar with electricity supply will recognize the similarity of this figure to price duration curves that show an ordering of unit price of energy from the most expensive hours (left side) to least costly (right). This similarity is intentional. In this case, all of the interval values of the TIS during 2014 have been ordered from highest unit cost (left) to least unit cost (right).

For each 5-minute data interval of 2014 and for each event-driven function, a response flag was paired with the local transactive site's TIS value. Because the definition of relatively high and low TIS values may differ from site to site, the TIS values were transformed at each site to numbers of standard deviations above or below the site's average TIS. The interval pairs were then combined from 14 event-driven functions and the pairs were ordered from greatest to smallest relative TIS. Finally, the events of the event-driven functions were summed from smallest relative TIS (right side) to greatest (left side) and were scaled to represent cumulative event hours for the event-driven functions across the entire transactive system.

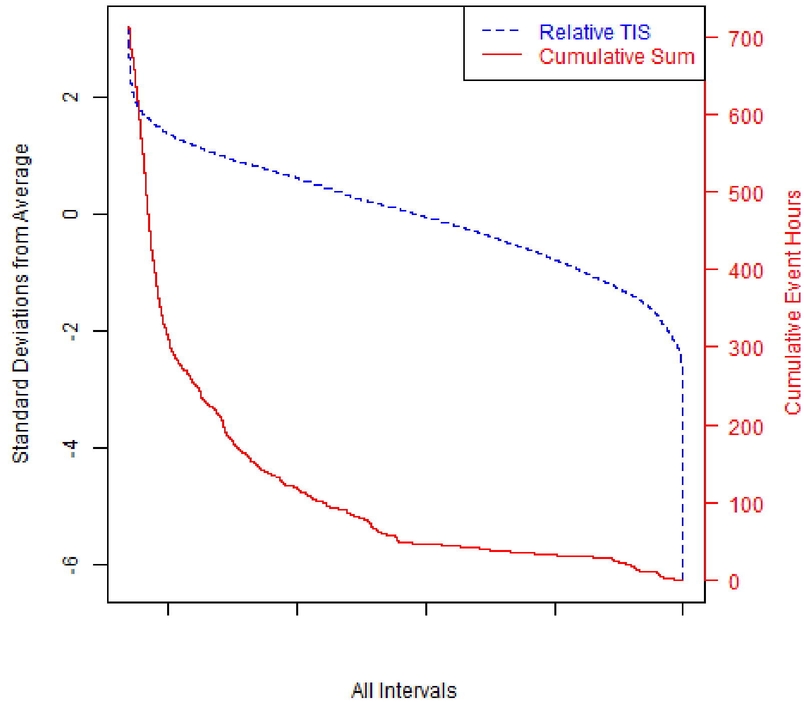


Figure 2.33. Ordered Relative TIS, Stated as Numbers of Standard Deviations from the Average TIS, Paired with the Cumulative Sum of Event Hours from all the Event-Driven Toolkit Functions during 2014

The relative TIS values were quite normally distributed. This figure excluded about 10 high TIS values that had occurred at certain sites. Such high values sometimes occurred at sites that had deployed demand-charges toolkit functions to help them anticipate and lessen their monthly demand charges. The demand-charges functions were found to apply very high costs (disincentives) as demand was peaking, but the additional costs were applied over only several 5-minute intervals, thus causing spikes in the local TIS.

The sites also observed several zero TIS values, which were not removed from the data for Figure 2.33. By 2014, the project had prohibited negative TIS values throughout the system. Earlier in the project, erroneous TIS values, including negative values, had plagued the system.[1] Naturally, the problematic TIS values had caused many of the assets to respond at nonsensical times. Therefore, the figures in this section include only January through August 2014 project data.

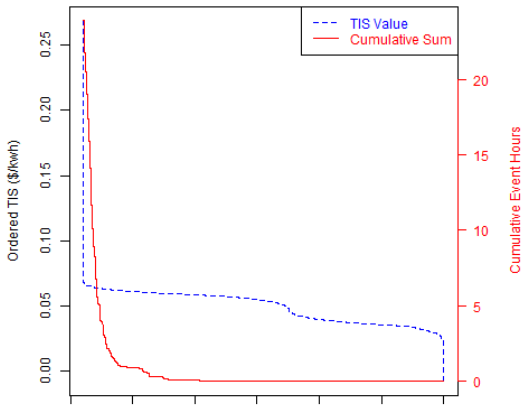
Now looking at the cumulative event hours in Figure 2.33, curtailment event periods occurred preferentially at high relative TIS values, as was intended. Overall, the 14 event-driven functions advised about 700 hours of asset responses in 2014. That cumulative duration accounts for about 6-1/4 active hours, on average, per asset per month. Had the events been randomly selected, the cumulative sum of event hours would have been nearly linear. The project did considerably better than that.

[1] Fundamentally, there is no reason to constrain the system from applying negative TIS values, but the project chose to constrain the system to encourage more stable behavior as the system was being designed and tested.

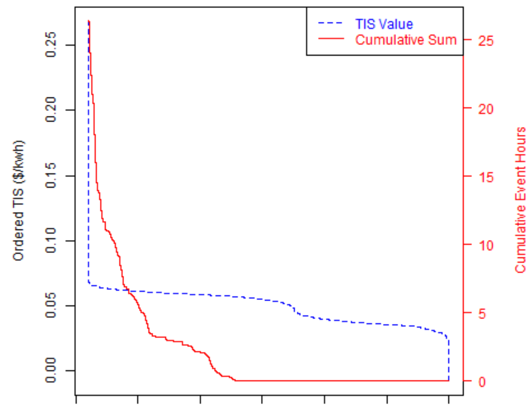
About 50 of the event hours occurred at TIS values that lie below the median relative TIS value. These event periods were undesirable and might have been avoided by better function design and better, more attentive configuration of these toolkit functions. For example, at least one event-driven function had been configured to allow practically unconstrained event durations, and the function therefore advised that events should continue almost indefinitely. On the plus side, about 85% of event periods were advised by event-driven functions while the relative TIS was in its highest quartile.

Panels of all of the individual event-driven functions' performances have been provided in Figure 2.34 to help demonstrate the range of individual performance by these functions. Because each asset was influenced by only one site's TIS, there was no need to normalize the TIS values at the individual sites. Observe that differences exist in both the TIS ranges and patterns of occurrences at the different transactive sites. As was discussed above, very large TIS values were discarded from the set of intervals at several of the sites, even though the values may have meaningfully resulted from a demand-charges function. All sites encountered intervals when the TIS value was zero.

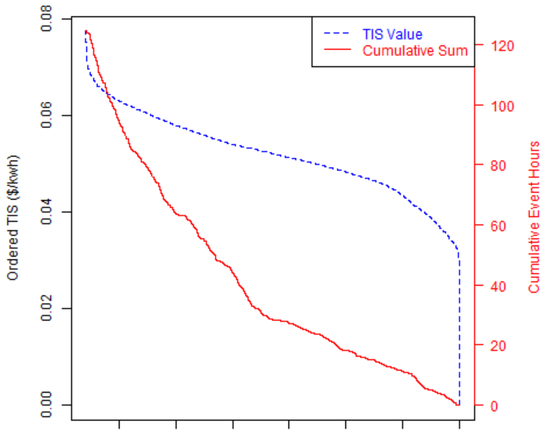
The cumulative response hours for each asset and site need not be individually discussed. Discussion preceding Figure 2.33 should have provided enough background for the interpretation of the panels of Figure 2.34. The best performing event-driven functions correctly identified the TIS intervals representing the greatest delivered unit costs of electrical energy. Ideally, all event-driven responses should have been advised while the TIS was at its very greatest values, far to the left side of these figures. Panel Figure 2.34c exemplifies decent performance; panel Figure 2.34e, not as good.



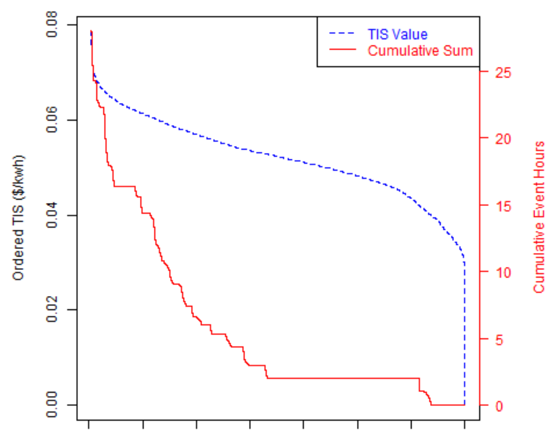
(a) University of Washington: Building HVAC



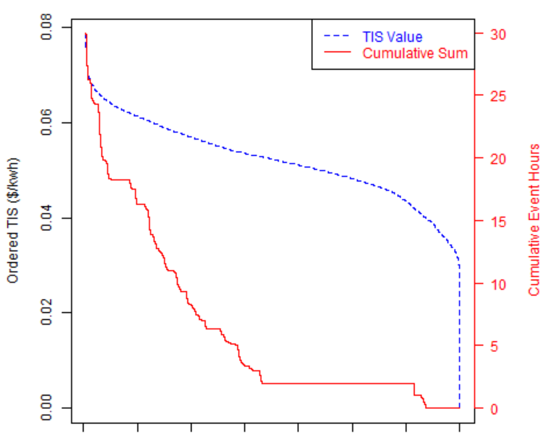
(b) University of Washington: Diesel Generators



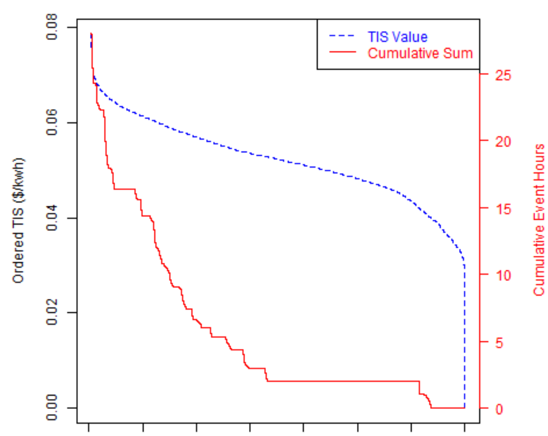
(c) Avista Utilities: Residential Demand Response



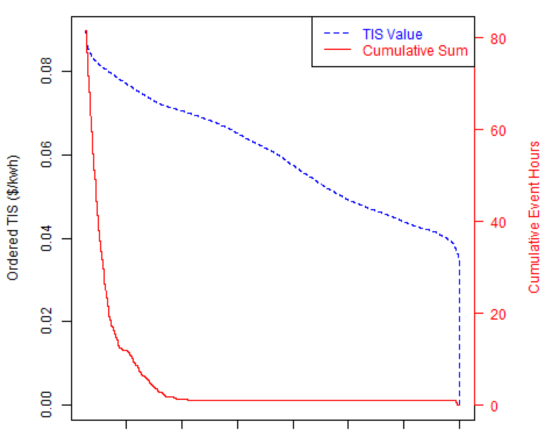
(d) Flathead Electric Coop.: Water Heaters



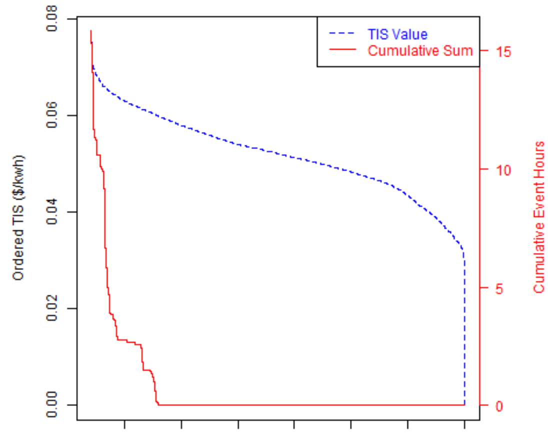
(e) Flathead Electric Coop.: Smart Appliances



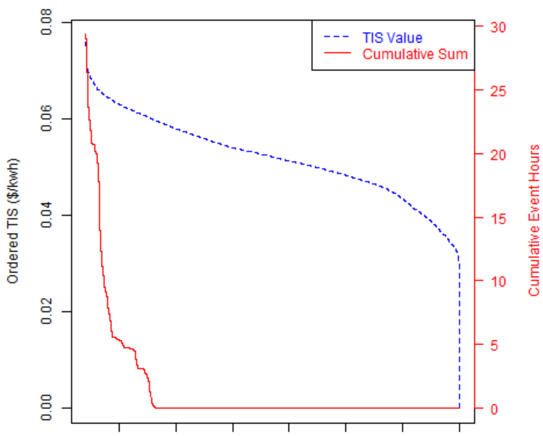
(f) Flathead Electric Coop.: In-Home Displays



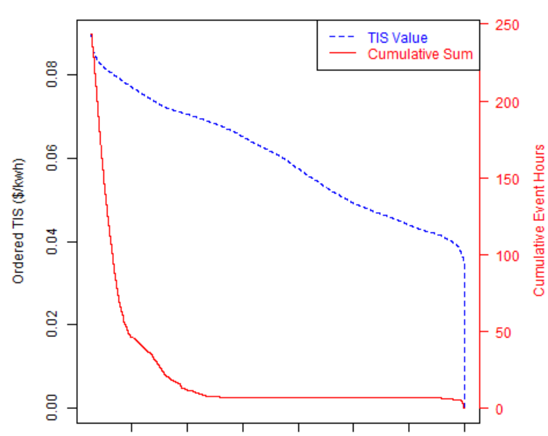
(g) Milton-Freewater: Demand-Response Units



(h) Avista Utilities: WSU Chiller Control



(i) Avista Utilities: WSU HVAC Control



(j) Milton-Freewater: Dynamic Voltage Management

Figure 2.34. Cumulative Responses of Individual Event-Driven Assets to the Transactive System's Incentive Signal. (HVAC = heating, ventilation, and air-conditioning; WSU = Washington State University)

2.5.2 Daily Function Events

The *daily* functions were designed to select one or more event periods in a day. The function reviewed the TIS values that had been predicted more than 24 hours into the future and selected the event period when the delivered costs of energy represented by the TIS would be maximal. Because all of the controllable assets that were selected by PNWSGD utilities targeted *curtailment* of electric load, every project implementation identified the maximum TIS values, when the consumption of the most expensive energy might be avoided. Similar principals would guide the development of functions that would take advantage of minima in the TIS to preferentially consume energy during those periods.

The project had originally called these functions "time-of-use," but that term did not adequately communicate the dynamic flexibility and economic elasticity that were possible and intended. Utility participants and implementers had preconceived interpretations of what "time-of-use" functions were and how they would behave based on the prior application of the term to demand-response programs. The alternative "daily" was recommended instead.

As for the event-driven functions described above, the daily-event functions could be configured to behave differently on different weekdays, to favor or allow responses certain hours, and to modify the allowed event durations. Some utilities, for example, configured the functions to allow daily events only during HLHs.

The daily-event functions were paired by the PNWSGD utility site owners with various asset systems and their models, including communicating thermostats, dynamic voltage management, networks of in-home displays or Web portals, distributed generators, and water heater control. The role of asset models was to model the impacts on system load when daily events were under way.

Figure 2.35 is a summary of all of the event periods that were designated by nine daily-event functions during 2014. This figure pairs ordered relative TIS interval values with the cumulative hours that the daily-event functions advised events during 2014. These intervals have been ordered from the most expensive intervals (left), when the TIS was at its greatest, to least expensive on the right. Additional details about the representation in Figure 2.35 were provided during the discussion of Figure 2.33 above and will not be repeated here.

The distribution of relative TIS values was quite normal during 2014 after a small number of very large TIS values were removed. The event hours were distributed through much of the range of the relative TIS, but the numbers of event hours increased with increasing relative TIS. About 2,500 total event hours are represented in this figure, which accounts for about 35 event hours per asset system per month, on average. The daily-event function typically designates more events and more active event hours than the event-driven functions. As expected, the cumulative sum of event durations is less steep and gradual than was the case for the event-driven functions (review Figure 2.33). That is expected because daily-event functions could correctly identify the lowest costs in a day, but the day's energy may have been relatively inexpensive compared to the rest of the month or year. About three-quarters of the event hours were advised while the relative TIS was greater than its median.

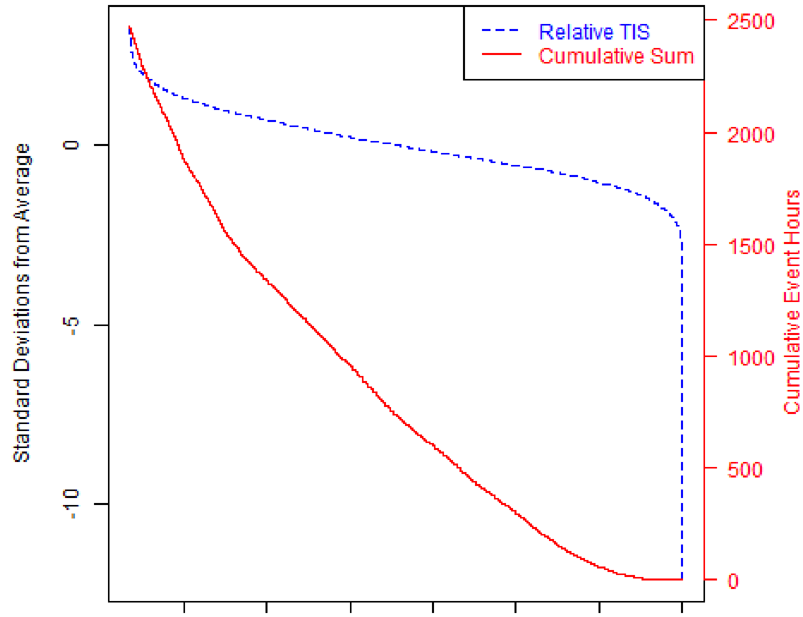
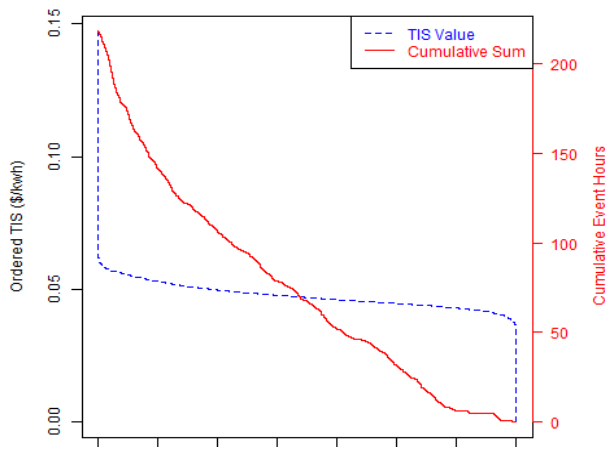


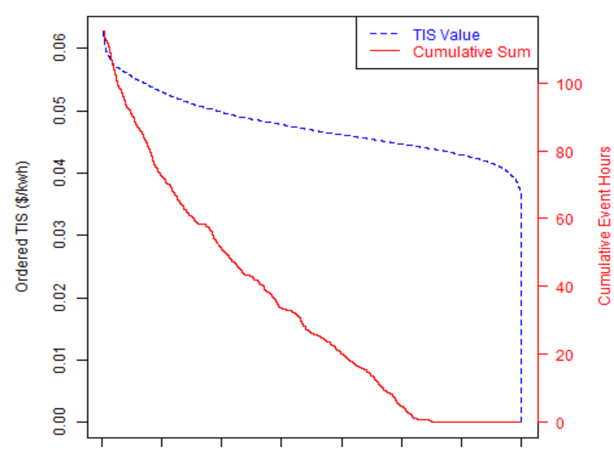
Figure 2.35. Ordered Relative TIS, Stated as Numbers of Standard Deviations from the Average TIS, Paired with the Cumulative Sum of Event Hours from All of the Daily-Event Toolkit Functions during 2014

The range of responses by the individual daily-event toolkit functions to their local TIS values is shown in Figure 2.36. The asset types have also been indicated for each. TIS values greater than about $0.25/kWh were removed from these representations because the several large values disallowed observation of the variability of the TIS values. The large TIS values had been generated at some sites by the demand-charges toolkit functions, which increased the local TIS values to deter consumption during monthly peak demand periods.

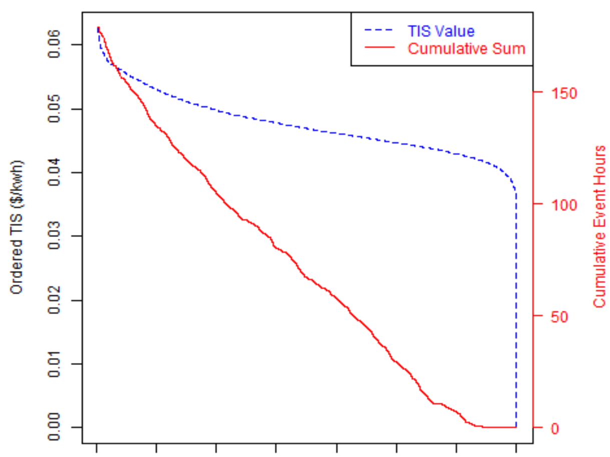
Had the daily events been determined randomly, the cumulative event hours would have exhibited a nearly linear relationship with the ordered TIS values. Again, the PNWSGD did considerably better than that. Generally speaking, the best performance of these functions is indicated by having the cumulative event hours pushed close to the left side of these figures.



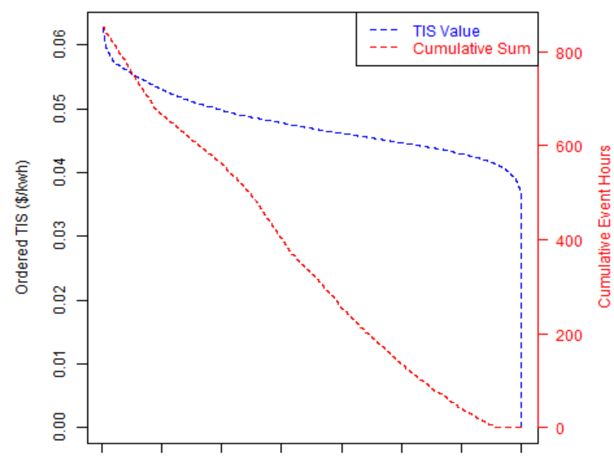
(a) Lower Valley Energy: Water Heaters



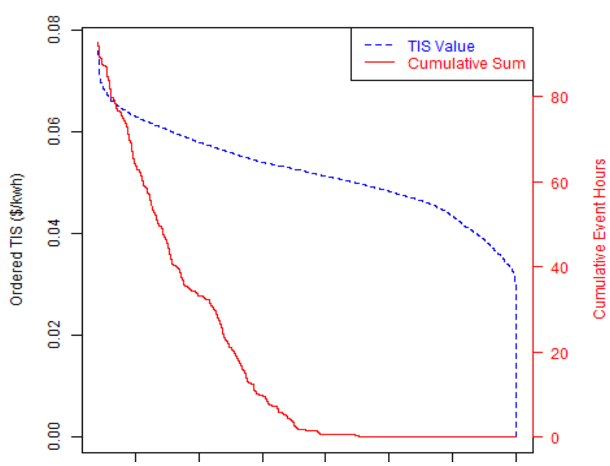
(b) Idaho Falls Power: Water Heaters



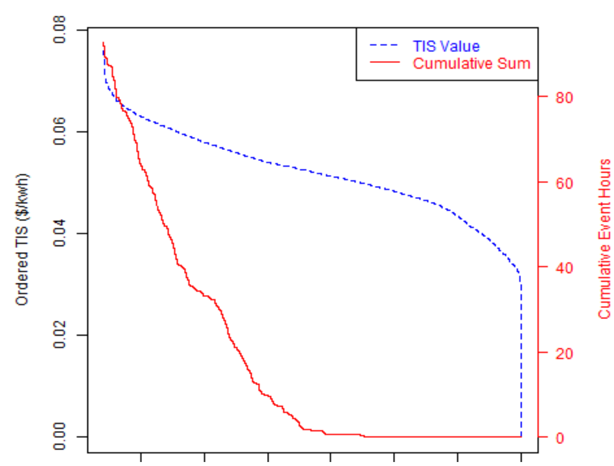
(c) Idaho Falls Power: Thermostats



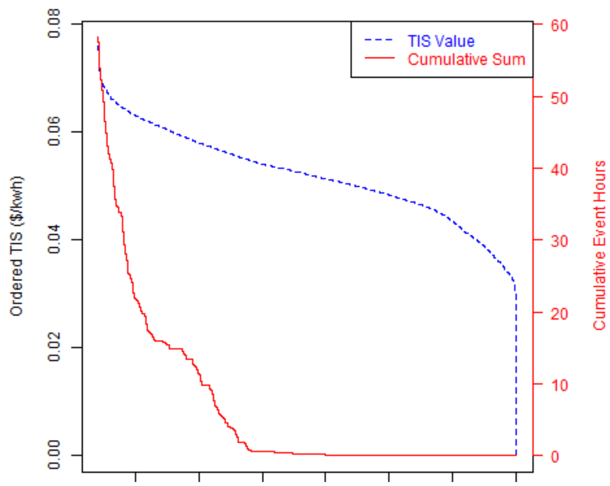
(d) Idaho Falls Power: Voltage Management



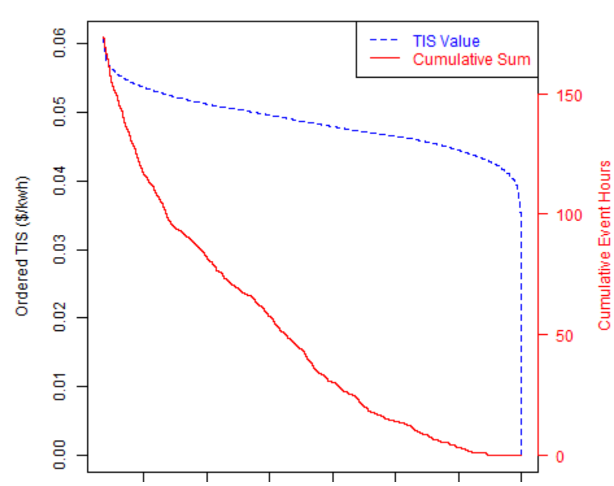
(e) Avista Utilities: WSU Gas Generator #1



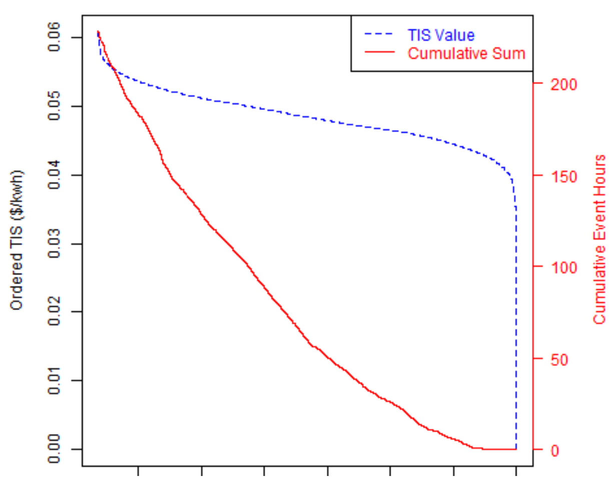
(f) Avista Utilities: WSU Gas Generator #2



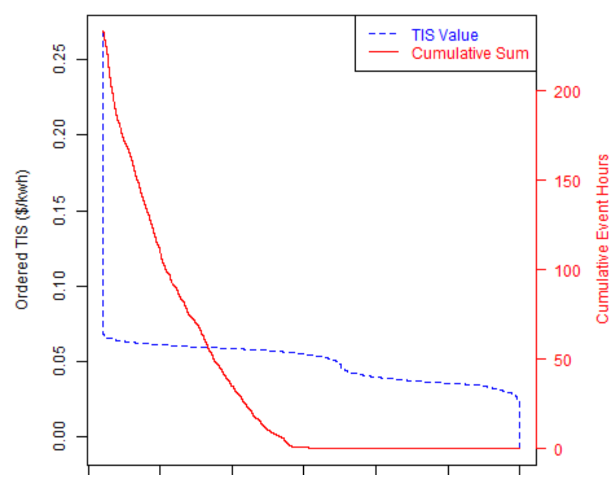
(g) Avista Utilities: WSU Diesel Generator



(h) Peninsula Light Company: Water Heaters



(i) Peninsula Light Co.: Voltage Management



(j) University of Washington: Steam Generator

Figure 2.36. Cumulative Responses of Individual Daily-Event Assets to the Ordered Transactive System's Incentive Signal at Each Transactive Site during 2014. The event hours are accumulated from right (lowest TIS) to left (highest TIS).

2.5.3 Continuous Function Events

Continuous functions were designed to generate a dynamic range of responses—more or less power consumption each interval—based on the predicted TIS values. In the PNWSGD, continuous functions were applied to only battery energy storage systems. The function managed the battery systems' states of charge while optimizing an arbitrage of energy value. The function strove to recharge batteries with the cheapest energy and discharge the most expensive energy, according to the delivered costs of energy represented by the time-dependent TIS. The system was constrained, through configuration, by the batteries' allowed states of charge and by the power ratings of the batteries' converters. The utilities and battery venders constrained the systems even more according to their preferences and concerns about affecting battery life.

An interesting feature of the function's formulation was a dissipation term that tempered the responsiveness of the system. Without the term, the function advised rapid changes between charge and discharge modes nearly every time interval. Because the function was based on an optimization, the system might be advised to switch from full charge mode to full discharge and back after each 5-minute interval in response to small changes in the TIS. Battery vendors typically advocate much more gentle treatment of their systems. The dissipation term, once introduced, moderated the numbers of times that the system alternated between charge and discharge modes. For example, the term could be tuned to advise no more than one charge and discharge event per day.

A classical optimization solver was used by the function that represented the Lower Valley Energy battery energy storage system. Its cumulative charge and discharge durations are shown along with the ordered TIS at this site during 2014 in Figure 2.37. The ordering of TIS magnitudes for figures like this has been discussed already in conjunction with Figure 2.35 and Figure 2.33. The cumulative charge and discharge durations have been shown separately here. Discharge events should correspond to high delivered costs of energy and were accumulated from lowest costs (right side) to highest (left side). The function advised discharge mode using positive advisory control signals.

Charging events were advised at lower costs using negative signals. The charging event durations were accumulated from lowest costs (left side) to highest (right side).

Because a continuum of responses between full discharge to full charge was allowed, the right-side axis has been stated as "cumulative capacity hours," defined as the product of the fraction of the converter's full capacity multiplied by the duration over which the response was advised. In practice, the optimization function often requested that whenever the system was active it should charge and discharge at the greatest allowed power.

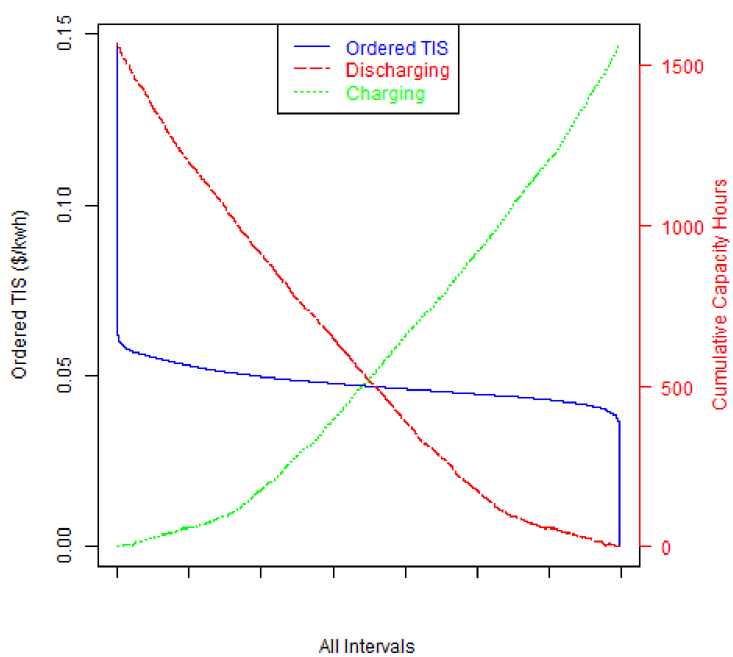


Figure 2.37. Discharging (Red) and Charging (Green) Capacity Hours Advised to the Lower Valley Energy Battery System during 2014

A continuous function was used with the Idaho Falls Power battery system, too, but that function was not updated after the system's vendor stopped supporting the battery system.

The continuous functions that represent battery energy storage necessarily monitor the system's actual state of charge. State of charge is one example of "other local conditions" that must be known by a toolkit function. If the state of charge is unknown to the toolkit function, the function's state will diverge from reality, and the function will incorrectly recommend charge and discharge events. When the function was misinformed about the actual system state, performance was even worse. For example, if the function was advised that the battery was fully charged when it was not, the function would never then advise the system to charge, even if that should have been the preferred control action.

2.5.4 Step 4 Analysis Conclusions

Three different classes of toolkit function were designed by the project and represented assets having event-driven, daily, and continuous event types. These three methods of determining events were found to be applicable to a wide variety of assets. Furthermore, the selections of events by these functions could be configured by the assets' owners to address the assets' specific capabilities and the asset owners' preferences.

The PNWSGD transactive system was, in fact, able to determine event periods based on the TIS and other local conditions. Toolkit functions—event-driven, daily, and continuous—were flexible and effective tools for accomplishing this objective. The functions must be well designed and configured if they are to perform well.

2.6 Step 5: Responsive Assets Must Accurately Predict the Impacts of Their Reponses

Presuming that event periods are being selected well by the toolkit functions and further presuming that the assets do indeed respond to the events, do the asset models accurately predict total load and the impact of the events on elastic load? This section evaluates the asset model algorithms and also tests the care with which the asset models were configured.

The discussion in this section has been divided into two components. At most of the project sites, the project collected data about the total site electric load that should be directly comparable to the transactive feedback signal, or TFS, that was intended to represent and predict that total load. Section 2.6.1 discusses how well the actual load was modeled by the TFS and whether the predictions were self-consistent. Section 2.6.2, discusses the accuracy of the individual models relative to whether the predicted changes in load were meaningful.

2.6.1 The Utility Sites' Demonstrated Abilities to Predict Their Total Load

Each of the project's 11 utility sites was asked to model and predict its total electric load. Total electric load, in this case, referred to either a defined subset of the site owner's distribution system that was participating in the project or the site owner's entire load.

The total electric load was predominantly inelastic—not affected by the price-like incentive signals of the transactive system. IBM worked with site owners to create and calibrate models of the bulk inelastic load at the project's sites. Using time of day, day of week, temperature, and a history of prior electric load at the site, IBM used regression to predict the sites' load curves, represented by a set of periodic smoothing-spline basis functions as described by Harvey and Coopman (1993). The predictions were updated every 5 minutes for each of the 56 time intervals of the project's transactive signals. This modeling approach was found to be computationally efficient.

Each elastic, demand-side asset system further modeled the *change* in load that would occur as it responded to changes in TIS. What is important here is that the responses from those assets changed the total predicted load at the site.

Based on an analysis of the TFS signals between the project's Fox Island, Washington site (Peninsula Light Company site ST01) and the West Washington TZ02 for 8 months of 2014, Figure 2.38 depicts, by month, the average relative error between TFS magnitudes as they were predicted for each of the 56 transactive future intervals and the final prediction of that interval (i.e., the first 5-minute interval at IST_0). The Fox Island site is used to support some general observations about the project's predictions by month, hour type, and minute. Then the available prediction errors at all the project's sites are shown.

The transactive prediction intervals shown in Figure 2.38 on the horizontal axis are displayed such that the prediction closest to the observation (e.g., the prediction 5-minutes preceding the observation) is displayed on the left-hand side of the plot, and the prediction with the greatest lead time (i.e., the estimate of this observation that was generated approximately 4 days prior) is displayed on the right-hand side of the plot. On the vertical axis, the relative prediction error from the observation value was calculated. Relative prediction error was calculated as shown in Equation (2.2).

$$\text{Average Relative Prediction Error for Interval } i = 100\% * \frac{1}{N}\sum_{n=1}^{N}\frac{x(n,i)-x(n,0)}{x(n,0)}, \qquad (2.2)$$

where N is the total number of predictions of this interval's value in the month (e.g., $N = 1$ for the other 5-minute intervals, but $N = 12$ for the hour-long intervals because the interval was predicted 12 times during those hours), n is one of the N intervals, i is one of the transactive signal's intervals from 0 to 56, and x is the predicted TFS value in kilowatts.

Graphing the relationship between the average prediction interval and the relative prediction error allows prediction quality to be assessed relative to the amount of time in advance that the prediction was made. If the prediction methods had been successful at eliminating all but random errors, the plot would be mostly flat. The plot shows data series for 8 months in 2014 (January–August) to compare prediction quality between these months.

The prediction error being addressed here references the nearest-term prediction that was produced just prior to an interval's final 5-minute prediction. That is why the relative prediction error of the first, far left prediction interval is always zero.

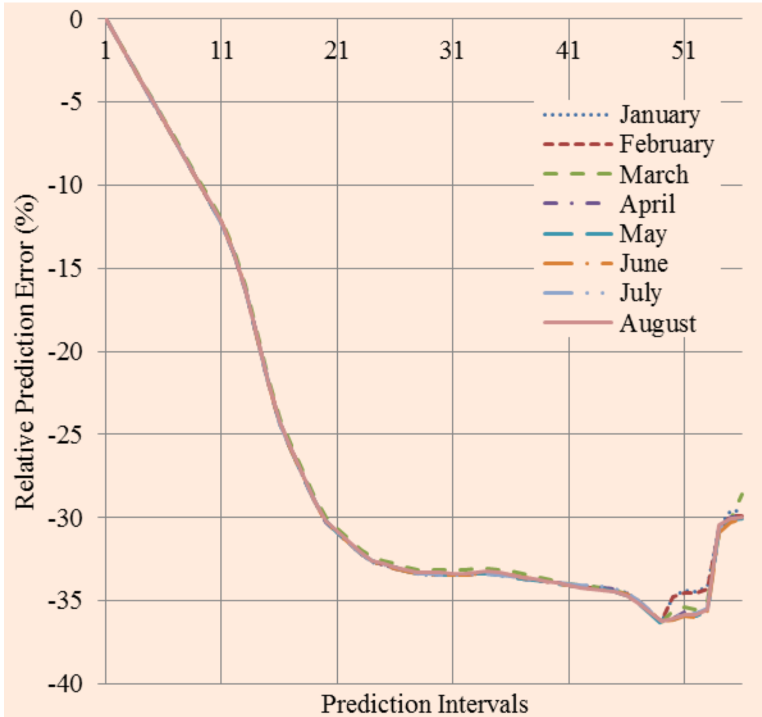


Figure 2.38. Average of the Transactive System's Relative Load Prediction Errors at the Fox Island Site (ST01) Site for the Eight Project Months of 2014

The magnitude of relative prediction errors increased the further into the future that the predictions were made, dropping to about a 35% underestimation of what would eventually become the final prediction. This is a bias in the prediction horizon. The load was found to be persistently under predicted. A prediction error greater than about 10% is probably harmful to resource planning. Only the prediction errors of the first nine intervals fall within 10% error or less, mapping to a successful look-ahead prediction horizon of about 45 minutes.

Every month, the relative prediction error between intervals 1 and 49 was the same. The transactive node stubbornly applied the same training set and methods each month, failing to learn from its prediction errors and adapt.

Figure 2.38 described an average relative prediction error over time, but the variability of the individual prediction errors over time must also be addressed. Figure 2.39 presents the standard deviation of those same relative prediction errors over the same 8 months of 2014.

The magnitudes of the standard deviations increased into the future. At the last prediction intervals, the standard deviation was about 25%. Magnitudes of the standard errors were almost as large as the average prediction error biases. The standard errors in March were a little greater than for other months. The standard errors the other 7 months were indistinguishable at most of the prediction intervals.

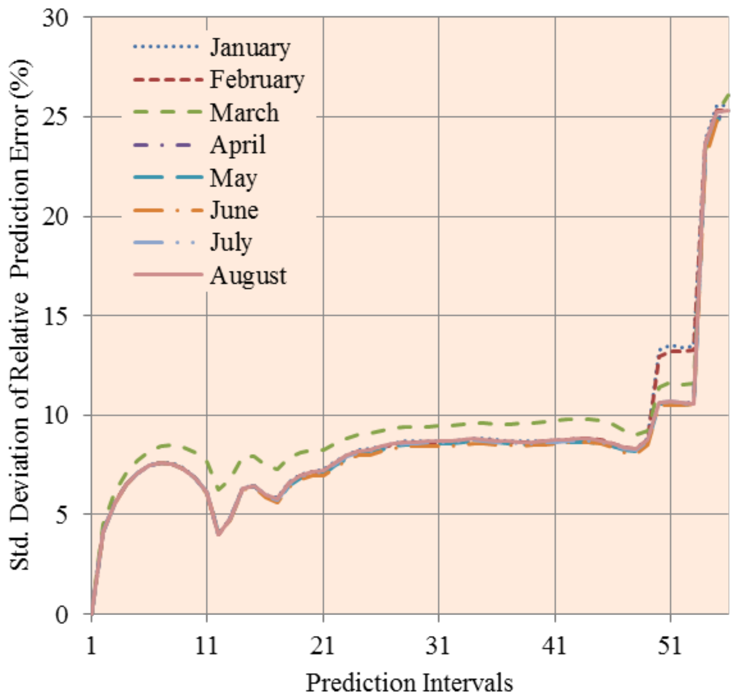


Figure 2.39. Standard Deviation of the Transactive System's Relative Load Prediction Errors at the Fox Island Site (ST01) for Eight Project Months of 2014

Figure 2.40 drives home the magnitudes of these standard deviations. The relative prediction error is shown for only March 2014. The error bars represent the standard deviations of the relative prediction errors during March 2014. It was shown that the monthly average errors and their standard deviations were similar for all months of 2014 at this, the Fox Island, Washington site.

The predictions at this site proved to be persistently under predicted, almost always lower than the final prediction. The ramification of this bias is that mistakes would be made while planning. This site underrepresented its future load. Had the transactive system and this region accepted and acted on the under predicted load, too few energy resources would have been scheduled and dispatched, possibly resulting in the purchase of more costly real-time resources than might have otherwise been procured.

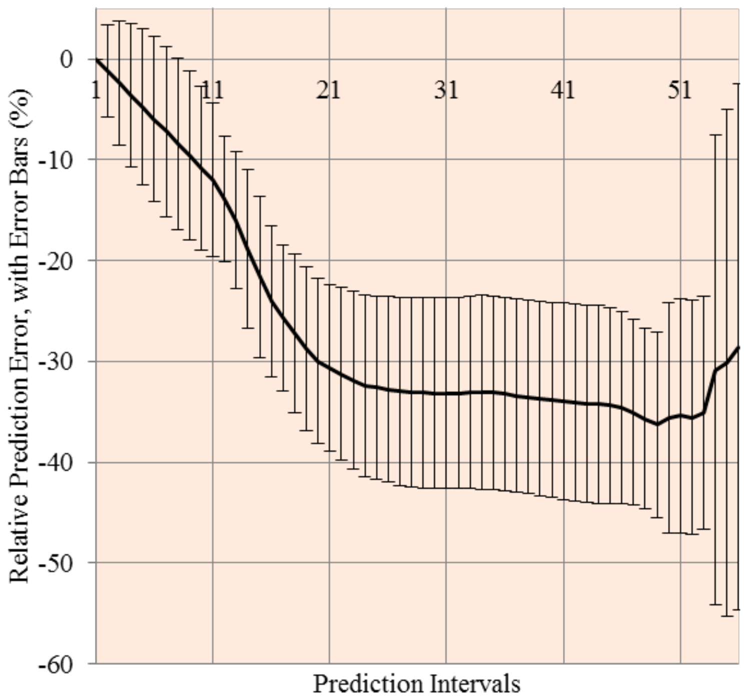


Figure 2.40. Average of the Transactive System's Relative Load Prediction Errors and Standard Deviations of the Average Prediction Errors (Error Bars) at the Peninsula Light Company Site for March 2014

Figure 2.41 depicts the same data as Figure 2.39, but the data is summarized by hour, removing day and month variability. For example, all data between 01:00 and 02:00 local time (i.e., 01:00, 01:05, 01:10, etc.) is denoted as Hour 1 in Figure 2.41. The data set included all 5-minute intervals from January 1 to September 1, 2014. The predictions during Hour 0 (midnight to 01:00) provide the best load prediction (an under prediction of 20% or better) and Hour 3 (03:00 to 04:00) the worst at the Fox Island site this year. Clearly, there is room for improvement.

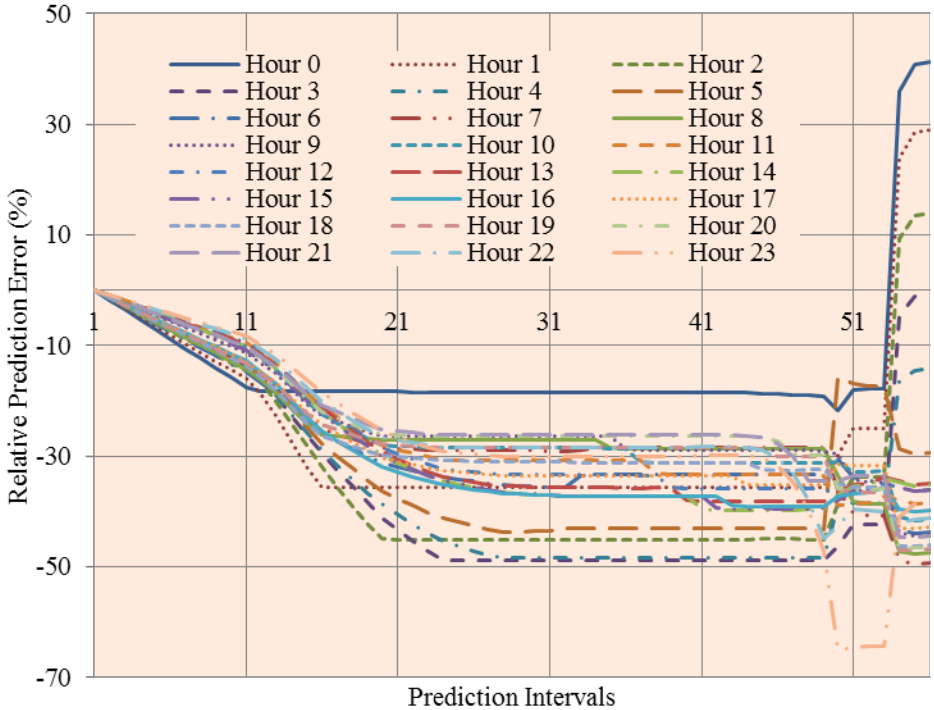


Figure 2.41. Average of the Transactive System's Relative Load Prediction Errors at the Fox Island Site (ST01) by Local Starting Hour. All the 5-minute intervals from 2014 were used.

Figure 2.42 depicts a further breakdown of the hourly summary for HLHs (left) and LLHs (right) at the Fox Island site in 2014. The axes are the same as those defined for Figure 2.41 above. BPA defines LLHs between 10:00 to 06:00 Pacific Time Monday through Saturday and all day Sunday; HLHs are the remainder of the hours. Consider HLHs at Interval 12 (future prediction of load ~1 hour prior to its occurrence). At this point, the prediction value has a percent difference of ~10% load underestimation. The relative load predictions for both hour types quickly become under predicted. The biggest difference between the predictions for the two hour types occurs in the last intervals that predict load multiple days into the future. As might be reasonably expected, the HLHs are under predicted by the day-long intervals and the long intervals over predict the LLH loads.

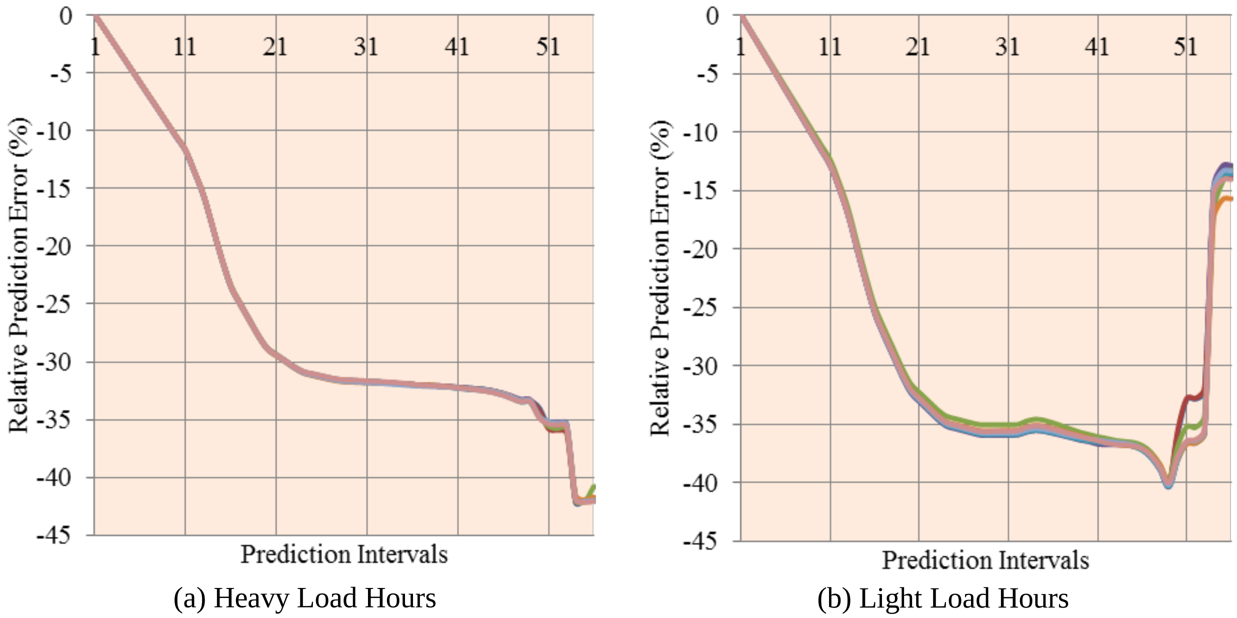


Figure 2.42. Average of the Transactive System's Relative Interval Prediction Errors during 2014 for the Fox Island, Washington Site (ST01) for (a) HLH Hours and (b) LLH Hours. Results from 8 months are shown. Small distinctions between the months' results are not critical to discussion.

Analysis of weekday versus weekend and holiday versus non-holiday periods did not reveal any particularly interesting distinctions in the relative prediction intervals' accuracy.

Figure 2.43 depicts the same data as Figure 2.39, but the data is summarized based on an interval's starting minute, removing hour, day, and month variability. For example, all data that start 5 minutes past an hour (i.e., 01:05, 02:05, 09:05, etc.) are denoted as Minute 5 in Figure 2.43. The data set used is all 5-minute intervals from January 1 to September 1, 2014.

Overall, data predicted for time intervals that begin on an hour or 5 minutes past an hour are predicted more accurately than others. The "waterfall" effect seen in the first 12 intervals is an interesting phenomenon and shows some weaknesses in the predictions' implementations. This effect is probably caused by the dynamic representation of 5-minute data in a system where transmission dynamics were being updated instead no more often than hourly.

Minute 55 was accurate throughout the first 10 intervals, almost an hour into the future. As the clock minutes decreased (with the exception of Minute 0 and Minute 5) the predictions more quickly diverged from the final predicted values. This finding was unexpected. Clearly, more work is needed on predictive algorithms.

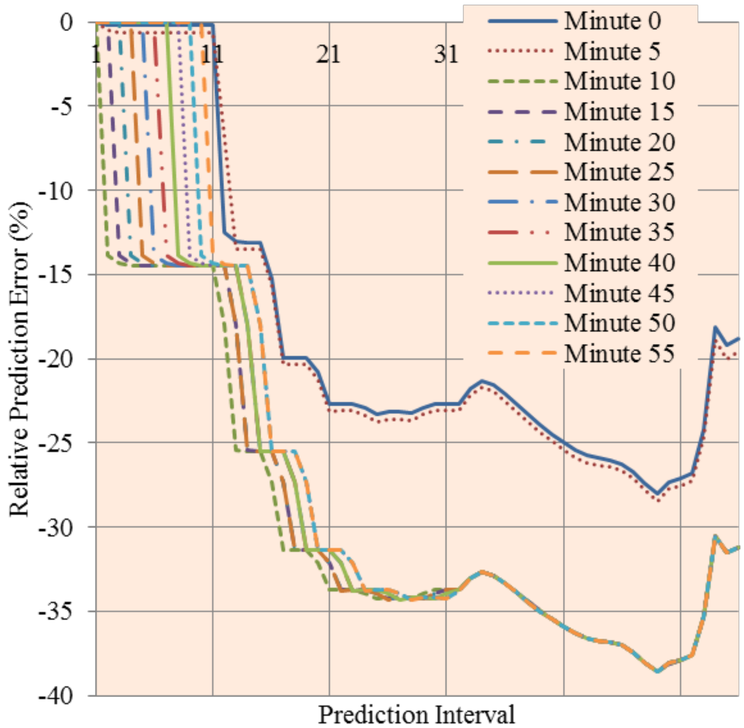
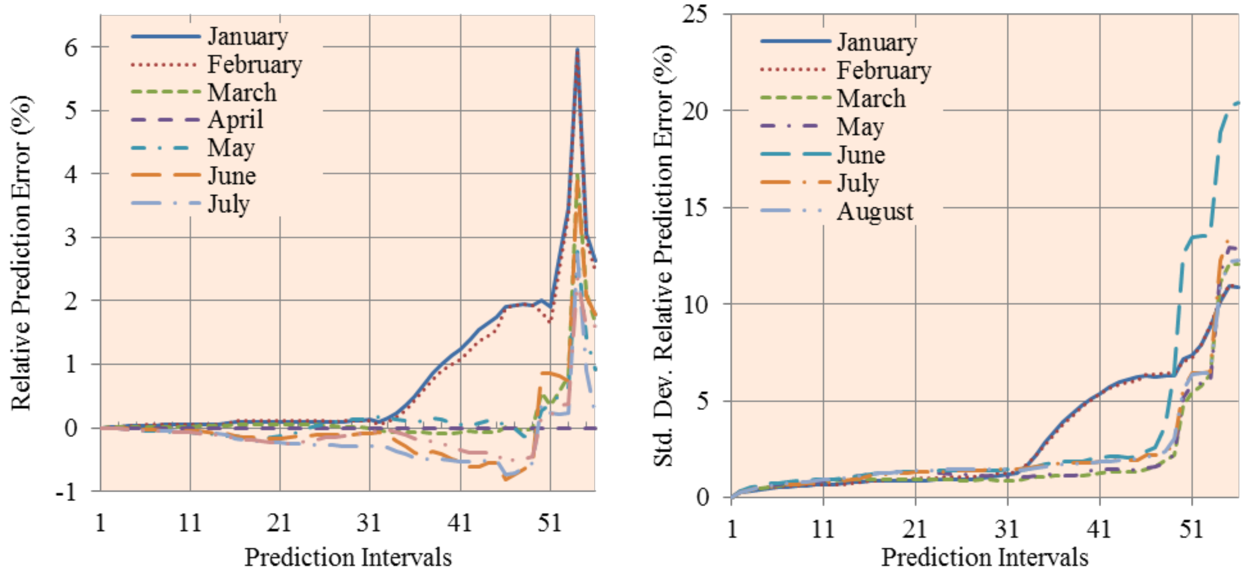


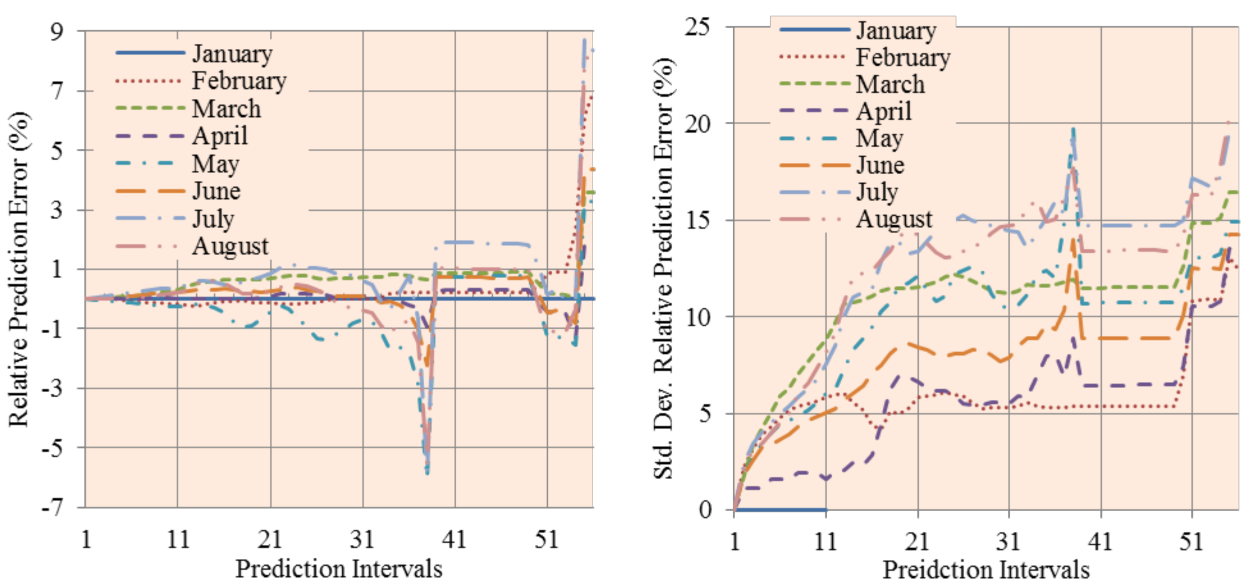
Figure 2.43. Average of the Transactive System's Relative Load Prediction Errors at the Peninsula Light Company Site by Starting Minute of the Hour. Data includes all the intervals of January through August 2014.

Having examined the relative accuracy of prediction errors at one project site according to the data interval's month, hour, and minute, we now sample the remaining sites to understand the variability of this relative prediction accuracy across the set of project sites of the transactive system. Figure 2.44 presents such a sampling across the sites for which transactive data became available to the project. Two utility sites therefore have been omitted—Ellensburg, Washington (ST04) and the Benton Public Utility District Reata Substation (ST05)—because these two did not become active transactive system sites during the PNWSGD.

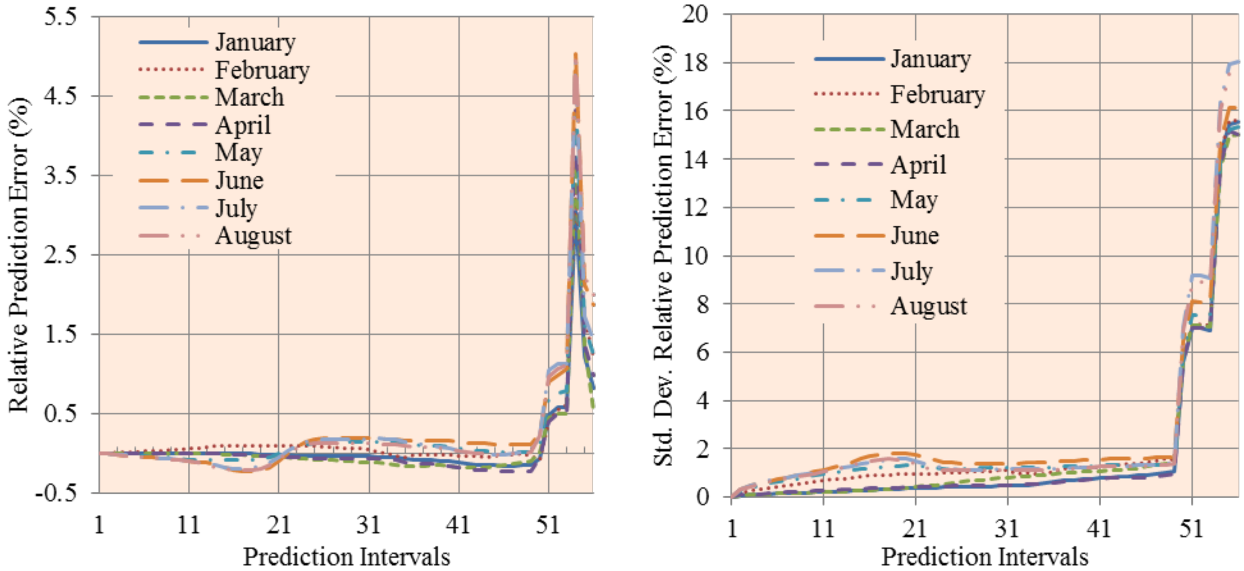
For each site, a pair of figures shows (left) the average relative prediction error and (right) the standard deviation of the relative prediction error. These two paired plots were introduced using the Fox Island site (ST01) in Figure 2.38 and Figure 2.39, respectively. The left-side plots show bias errors, where the transactive system tended to persistently under or over predict the final predicted value at times into the future. The standard deviations refer more to the dynamic variability with which those predictions were made.



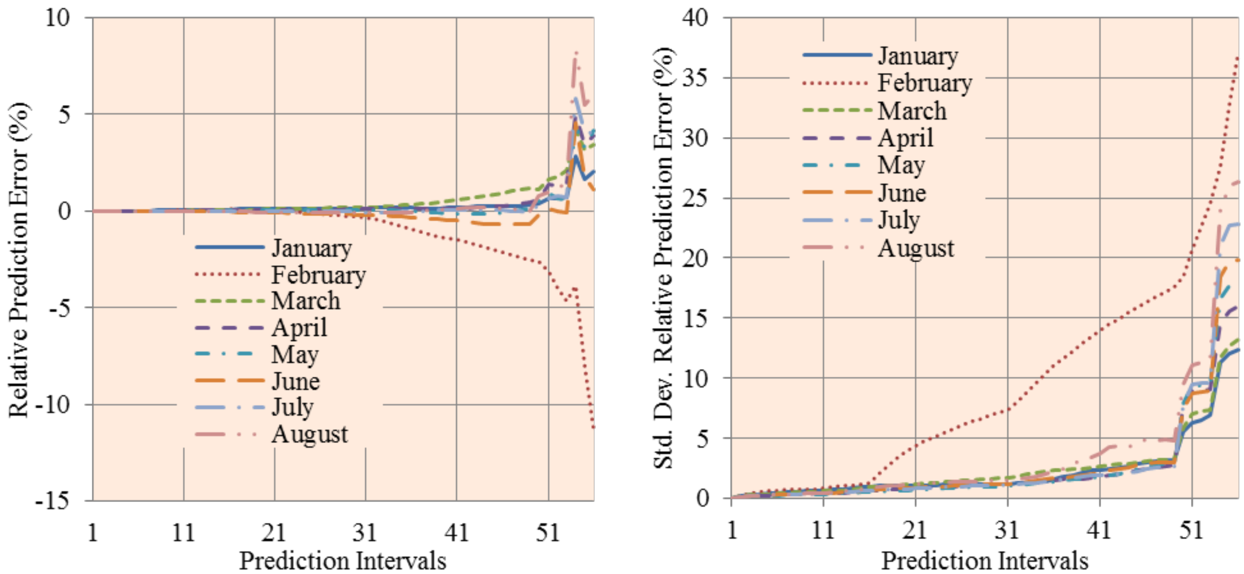
(a) University of Washington Campus Site (ST02). This system was down during April 2014.



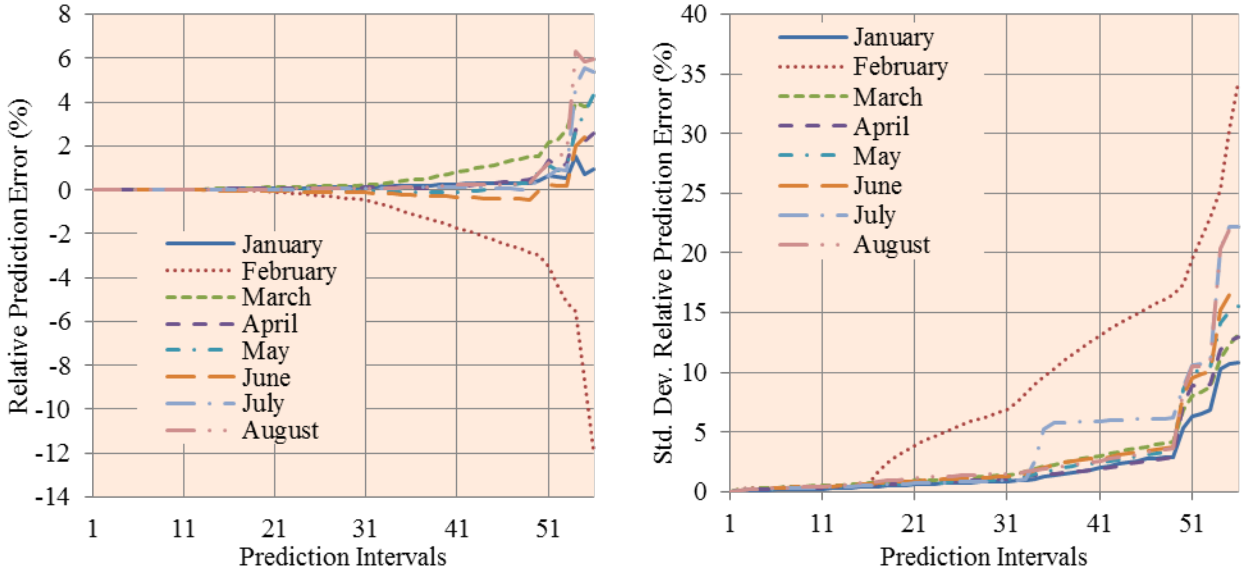
(b) Salem, Oregon Site (ST03)



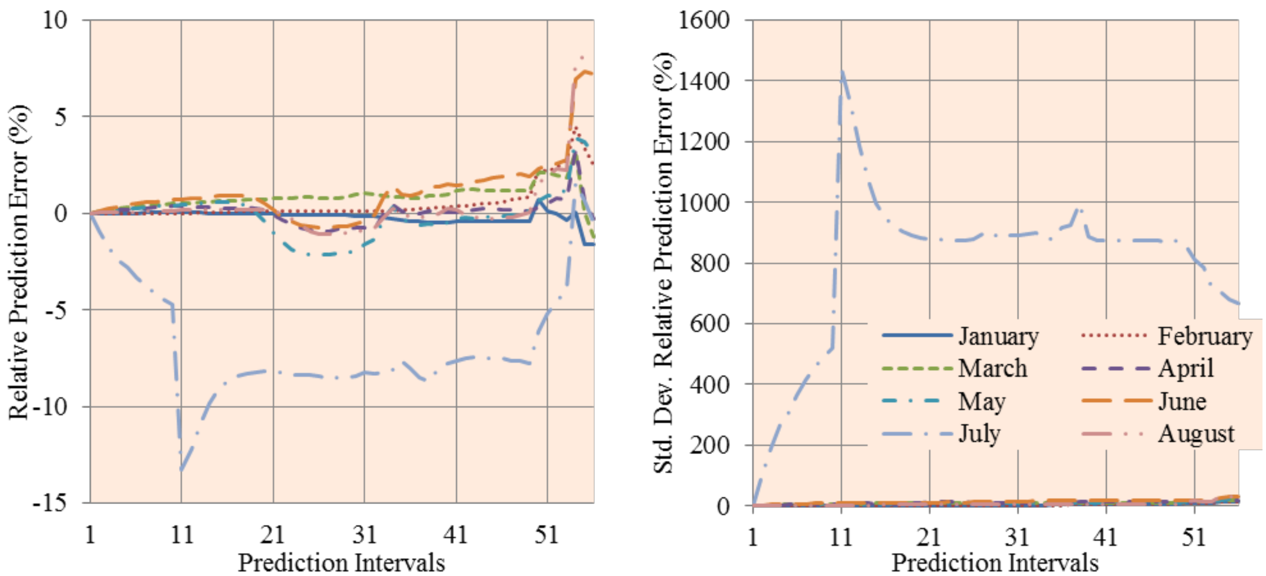
(c) Pullman, Washington Site (ST06)



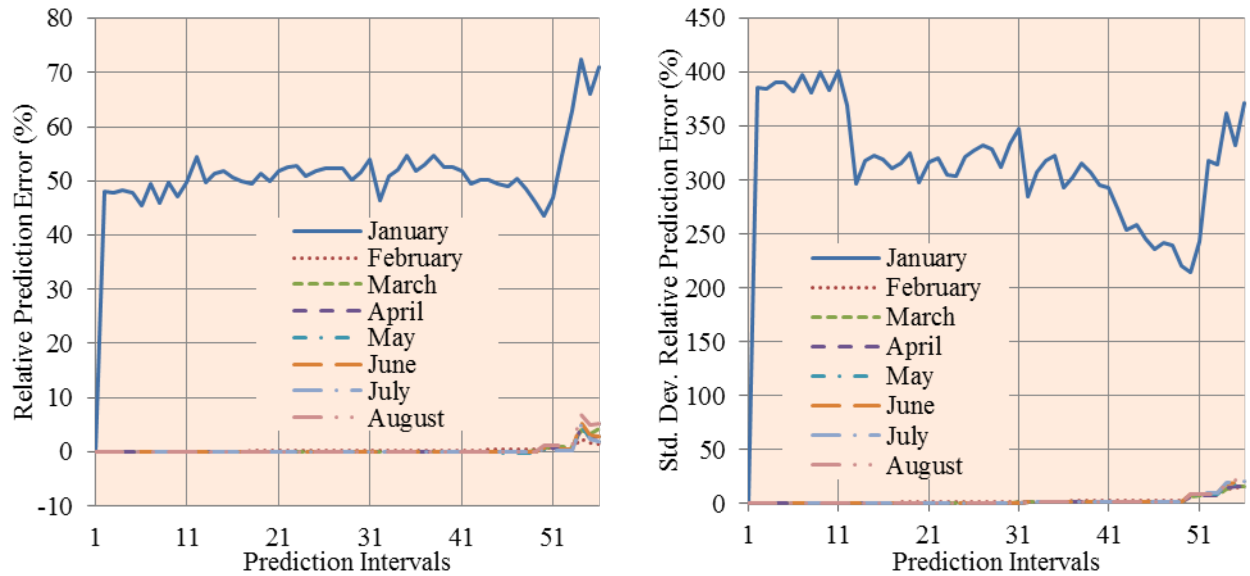
(d) Libby, Montana Site (ST07)



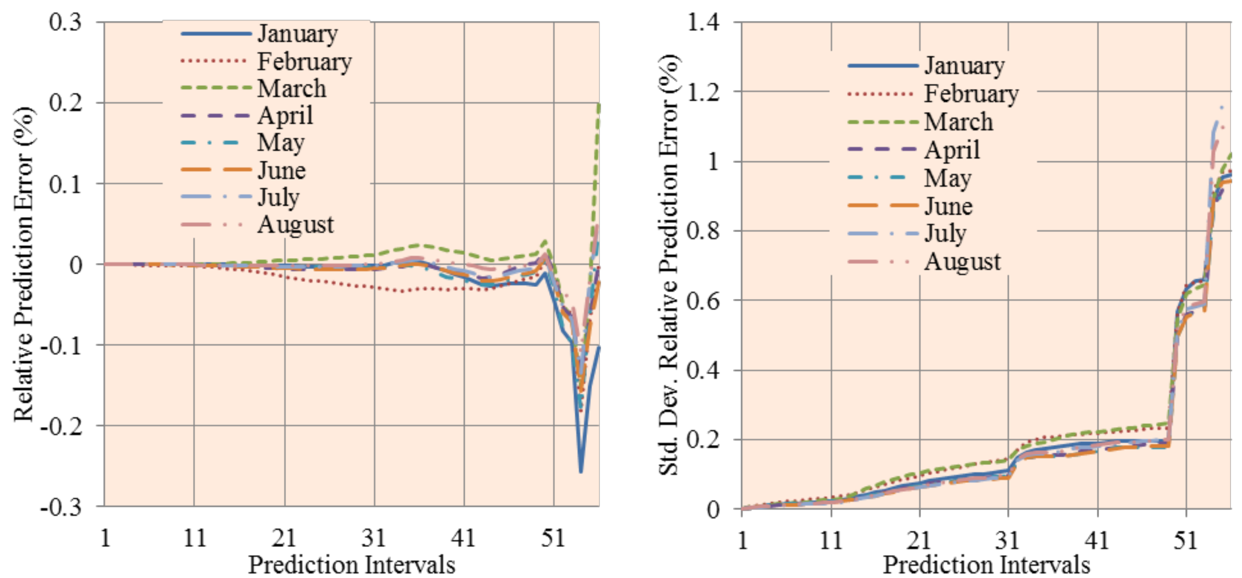
(e) Marion-Kila, Montana Site (ST08)



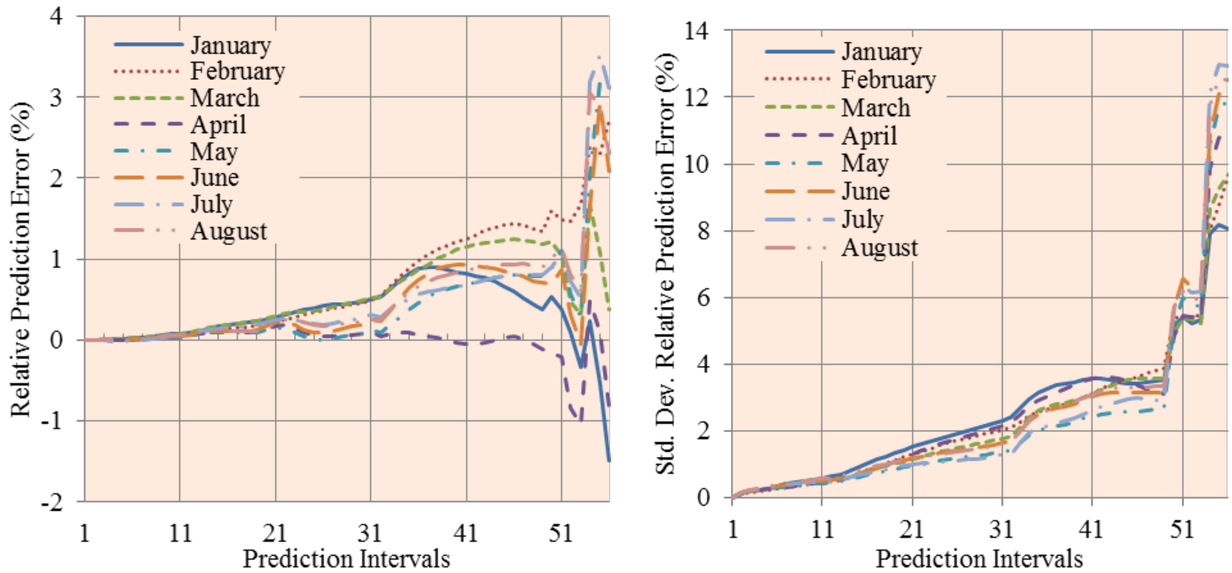
(f) Milton-Freewater, Oregon Site (ST09)



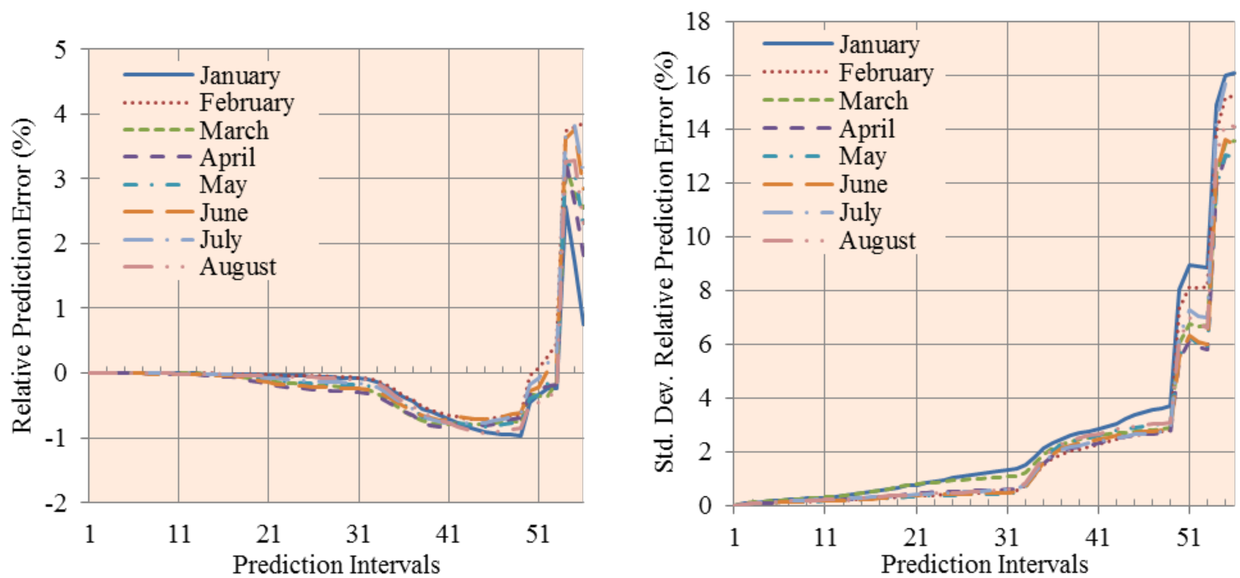
(g) Helena, Montana Site (ST10)



(h) Philipsburg, Montana Site (ST11)



(i) Teton-Palisades, Wyoming Site (ST12)



(j) Idaho Falls, Idaho Site (ST14)

Figure 2.44. Paired Average Relative Load Prediction Errors (Left) and Standard Deviations of those Errors at PNWSGD Utility Sites January–August 2014

2.6.2 Asset Models' Modeled Load

Presuming that each function that represents a transactive asset system at a utility site chose time periods when responses from the assets would be useful, each transactive site must then model the asset system to predict the change in load that would accompany the response during those periods. The resulting modeled change in load modifies the TFS, representing the elasticity of the site in light of the TIS to which the site functions are responding. If the response periods were selected during times that the TIS was maximal, the asset system should automatically act to either curtail load or generate more power. Either of these responses reduces the net load that must be supplied by relatively costly energy at this location. The asset model strives to accurately represent the magnitude by which net system load will be reduced by its response.

The functional asset models predicted these impacts during the project for both the impending interval (i.e., at IST0, the next 5 minutes) and for future intervals. The ranges of modeled magnitudes of these power changes are listed in Table 2.1. These are the magnitudes that were automatically calculated at utility sites and reported to project data collection. The table bins the responses rounded to the nearest 10, 100, or 1,000 kW.

The far left column states the site's owner. In a transactive system, the site owner would normally take responsibility for the responsive asset system, would represent the asset in the transactive system, and would benefit from the responses made by the asset. In the transactive system, the asset is operated from the perspective of the site owner. The responsibility might be contractually delegated, as happens today when an aggregator controls assets on behalf of a distribution utility. The degree to which the project's site owners owned this responsibility varied. Utilities today lean heavily on aggregators and other vendors to provide demand-response services for them.

The site, column 2 in Table 2.1, is the defined part of the transactive system topology (Appendix B) that would benefit from the response. A curtailment by a responsive asset system reduces the net load that must be supplied to the site.

Several types of systems have been listed in the column "Asset Description." Similar systems would normally be modeled similarly, but different system capabilities and site owner preferences may be accommodated by functions and their configurations. The functional asset models' details would normally not be shared or revealed between different site owners. The project has considered, however, libraries of functions from which site owners might select. Vendors could compete in this market to offer the most accurate, interoperable, and easily configured functions and asset models. No such libraries of examples existed prior to the project, so the project unilaterally developed examples for the utilities. Of the 11 participating utilities, only one—Portland General Electric—wrote its own functions and asset models from scratch. The others accepted the ones that the project offered them.

Table 2.1. Range of the Modeled Changes in Load by the Various Elastic Transactive Assets at the PNWSGD Project Sites

Site Owner	Site	Asset Description	Asset ID[a]	Load Function[a]	Modeled Change in Power (kW)[a,b]
Peninsula Light Company	Fox Island, WA	Water Heater Control	302	2.4	{−80, …, 0}
			382	3.4	{−350, −310, …, −40, 0}
		Dynamic Voltage Management	383	3.5	{0}
University of Washington	UW Campus, Seattle, WA	Building HVAC Management	303	2.4	{−10, 0, 10}
		Two Diesel Generators	304	2.5	{0, 1500}
		Steam Turbine	305	3.7	{−1500, 0, 10, 1500}
Portland General Electric	Oxford Rural Feeder, Salem, OR	Residential DR	NA	NA	NA
		Commercial DR	NA	NA	NA
		Distributed Generators	NA	NA	NA
City of Ellensburg	Renewable Energy Park, Ellensburg, WA	None	NA	NA	NA
Benton PUD	Reata Feeder, Kennewick, WA	Energy Storage Modules	316	4.1	{−40, …, 10}
Avista Utilities	Pullman, WA	Residential DR	321	2.4	{−10, 0, 10}
		Dynamic Voltage Control	322	3.5	{−430, …, −230, 0}
		WSU Tier 1 HVAC Control	320	2.4	{−7800, −1500, …, −300, 0, …, 800, …, 1200}[c]
			381	2.4	{0}
		WSU Tier 2 Chiller Control	378	2.4	{0}
		WSU Tier 3 Gas Generator Control	379	3.7	{−1000, 0, 1000}
		WSU Tier 4 Gas Generator control	377	3.7	{−1000, 0, 1000}
		WSU Tier 5 Diesel Generator Control	380	3.7	{−1400, 0, 1400}

Table 2.1. (contd)

Site Owner	Site	Asset Description	Asset ID[a]	Load Function[a]	Modeled Change in Power (kW)[a, b]
Flathead Electric Coop.	Libby, MT	Water Heater Control	326	2.4	{−80, …, 0}
		Smart Appliances	327	2.4	{−80, …, 0}
		In-Home Displays	328	2.4	{−190, …, 80, 100, 110, 120, 150, 160}
	Marion / Kila, MT	Water Heater Control	336	2.4	{−20, −10, 0}
		Smart Appliances	337	2.4	{−10, 0}
		In-Home Displays	338	2.4	{−40, …, 20}
City of Milton-Freewater	Milton-Freewater, OR	Water Heater (DRU) Control	344	2.4	{−700, −600, …, −100, 0}[c]
			375	2.4	{−14,000; −13,000; …; 9,000; 10,000}[c]
		Dynamic Voltage Control	345	3.5	{−30, …, 0}
			376	3.5	{−650, …, −240, 0}
			401	2.2	{−440, …, −220, 0}
Northwestern Energy	Helena, MT	Water Heater Control	NA	NA	NA
		Dynamic Voltage Control	NA	NA	NA
	Philipsburg, MT	Water Heater Control	NA	NA	NA
		Dynamic Voltage Control	NA	NA	NA
Lower Valley Energy	Teton-Palisades Interconnect, WY	Water Heater Control	349	3.4	{−410, −390, …, −40, 0}
		Battery Energy Storage	350	4.1	{−130, …, 130}
			402	4.1.1	{−130, …, 130}
Idaho Falls Power	Idaho Falls, ID	Building DR Management	358	2.4	{−5,800, −5,100, −1,100, …, −800, −300, −0, …, 300, …, 700, 3300, 3,700}[c]

Table 2.1. (contd)

Site Owner	Site	Asset Description	Asset ID[a]	Load Function[a]	Modeled Change in Power (kW)[a, b]
		Water Heater Control	359	3.4	{−170, 0}
		Thermostat Control	360	3.4	{−6,000, −5,000, …, 2,000, 4,000}[d]

(a) "NA" in this column means that the asset system was never fully connected to the transactive system or data was never provided for the asset system from the site's transactive system implementation.

(b) The ellipses in this column mean that the series continues incrementally by bins of 10 kW unless otherwise stated. Unless otherwise stated, the bin size is 10 kW.

(c) These modeled changes in load have been rounded to the nearest 100 kW. Ellipses mean that the series continues by bins of size 100 kW.

(d) These modeled changes in load have been rounded to the nearest 1,000 kW. Ellipses mean that the series continues by bins of size 1,000 kW.

DR = demand response

DRU = demand-response unit

PUD = Public Utility District

The column "Load Function" refers to an organization of the project's example functions. The digits shown are the last two digits of the classification of load functions (e.g., "TKLD_2.4"). The first digit indicates the type of response event that would be selected by the function. For example:

- "2.x": Event-driven responses. The asset responds infrequently and for relatively short durations.
- "3.x": Daily responses. Responses may occur each day. Weekends were often excluded.
- "4.x": Continuous. A continuum of responses is possible.

The second digit (e.g., "TKLD_2.4") refers to the asset model. The project was slow to recognize the opportunity to mix and match event determination (i.e., the first digit) and the functional model. That is, nearly any combination of event function and asset model is feasible. The functional responsibilities of the event function and asset model might be separable, resulting in more efficient coding and a more flexible "code library." Because the project was slow to recognize the power of asset modeling, some inconsistencies emerged in the numbering system. However, "x.1" models were for energy storage, "x.4" models were for water heater and thermostatic loads, "x.5" models were for voltage management, and "x.7" ones were for distributed generators.

Battery system model. An optimization was developed to manage a battery system. The battery model strives to optimize its net cost given the predicted unit cost of energy. The charging and discharging may be constrained within allowed states of charge and conversion power capabilities. A parameter was found to moderate the aggressiveness of the charge and discharge, effectively reducing the numbers of charge and discharge cycles. Surprisingly, the project's battery energy storage systems were found to have quite limited allowed numbers of charging cycles, effectively preventing the batteries from being cycled more than once per day.

Water heater model. Based on the principal investigator's prior work with water heaters, the diurnal pattern of water heater average power consumption was scaled to represent the number of controlled water heaters. Therefore, the number of controlled water heaters and an interpolated time of day could be used to estimate the amount of power that was likely being curtailed by the set of water heaters. Future improvements could model the impacts of event duration more accurately. A water heater dynamic model might be used.

Thermostat model. A first-order building model was created for the project. The model could be configured to calibrate it with the aggregate behaviors of a group of buildings. Once calibrated, an event represents a perturbation of the model's operation. Depending how the asset system is controlled, the thermostat set point might be modified, the heating and cooling might be fully curtailed, or the heating and cooling power might be cycled, giving the buildings a fraction of the heating and cooling energy they would otherwise need. Consequently, the modeled interior temperature falls or rises, and the buildings' thermal mass cools or heats. Snapback was modeled at the end of an event as the modeled building worked to recover from the perturbation. This is a rich research area where more accurate, higher order models of thermostatically controlled buildings might be adopted.

Voltage management model. A simple voltage management model was developed. The model was based on conservation voltage reduction (CVR) factor. A CVR factor states the relative reduction in load that should accompany a reduction in the feeder's voltage. The CVR factor is unique to the circuit and may be affected by season, time or day, and other variables. Regardless, a static CVR factor allowed for a relatively simple prediction of the change in feeder power.

Distributed generator model. The distributed generator model was perhaps the simplest of the project's asset models. The model was simply configured to output the full or a fractional nameplate capacity of the distributed generator while events were active. The output was presumed to be constant during the event.

2.6.3 Step 5 Analysis Conclusions

The future predictions of load by the transactive system sites were used as a metric for how well the assets were able to predict their electric load. These predictions were supplied by the project's inelastic load prediction functions. Analysis reviewed the relative prediction errors and the standard deviations of those errors. These errors were always referenced to the system's final prediction.

The relative prediction error analysis revealed multiple prediction biases, where the transactive system was found to have under or over predicted the final load prediction for the given data interval. Most of the sites predicted their loads well up to a day, or so, into the future, but some of the bias errors were significant even for near-term predictions. Had the region used these biased predictions to schedule generation resources, resources too might have been under or over scheduled.

The elastic, responsive assets also predicted how they would change the load when advised to do so by the transactive system. The ranges of these power differences were listed for each responsive transactive asset system. The predictions are affected by the quality of the asset models that represent them. The asset models are also configurable to scale and otherwise tailor the prediction to the unique assets. Some assets were found to have not been configured properly or to have accepted the default configurations without further modification, which would misrepresent the impacts of the asset systems in the transactive system.

2.7 Step 6: The Plans to Exchange Power with the System Must Be Calculated and Communicated throughout the System

The TFS was intended to predict and state the electrical power to be exchanged between nodes in the transactive system. The calculation of the TFS is, in principle, simpler than the blending of unit costs described in Section 2.4 for the other transactive signal—the TIS. In a branched power distribution system, the TFS is calculable from the balance of generated, consumed, and exported powers. The challenge is much greater in a network of transactive nodes, where one node might import power at times from more than one other transactive node.[1] This significant challenge was deferred by the project after it determined that the transmission region was to be represented by a centrally calculated, informed simulation that was run by Alstom Grid for the project.

Two separate methods emerged to calculate the TFS in the transactive system. The utility sites used transactive toolkit functions and asset models to emulate their electric loads. The relative prediction errors of those predictions were discussed in Section 2.6, and the absolute accuracy of the TFS calculations at the utility sites are addressed in Section 2.8. The biggest influence on these predictions was the prediction of inelastic load, which constitute the vast majority of the utility loads. The elastic assets' behaviors modified the total load according to the event-driven, daily, and continuous toolkit functions that determined the events and the asset models that predicted the impact the asset would have on net power.

One issue that emerged was that the inelastic load predictions by the transactive system became inaccurate where the functions had been inadequately trained and where the systems operated in open-loop mode, unaware of the actual power metering. Accurate modeling and prediction of distribution loads is an important, ongoing research area.

Another lesser issue emerged from the modeling of responsive loads. First, more work is needed to make models correspond to actual asset system behaviors. Even then, the functions that model the assets' effect on system load must be carefully configured. The asset owners must assume the responsibility for ensuring that accurate impacts are being predicted. And finally, the connections between the transactive system and the utilities' asset systems were tenuous. The fact that the transactive system had advised that an event should take place did not mean that the assets, in fact, responded to the event.[2]

The transmission-zone nodes within which the utility sites resided in the PNWSGD model possessed no independent means of correcting or negotiating the power needed by the utility sites, as was revealed by their TFSs. A simple fix was made to accommodate this limitation without breaking the system and its expectations that the transactive signal be exchanged. The transmission zones simply parroted back the TFS values stated by utility sites. There was no negotiation.

[1] The point is that while transmission power flows have been centrally calculated for many years, the methods for doing so with distributed calculations, where each node may observe only its own status, are still emerging.
[2] The issue is not so much whether the assets' owners heeded advice from the transactive system as it is that the status of the transactive system was allowed to diverge from reality.

The TFSs between the transmission zones were calculated centrally by the central informed simulation that was run by Alstom Grid. The responses of asset systems did not affect these calculations. This caused a feedback loop to be broken in the transactive system. The project determined that a simulation would be required to implement the feedback loop and test its performance. The resulting simulation activities are described in Section 2.10.

In Section 2.2, the connection between the power flowing between transmission zone nodes in the transactive system were said to be difficult to accurately pair with real-world power flows. Some similarities were observed in the modeled power-flow dynamics and those in the BPA data. Nothing prevents the flow from being more accurately measured as the granularity of the system model improves and as the transactive system becomes better informed about the status of the actual transmission system that it strives to emulate.

In summary, the system reliably exchanged its transactive signals, including the TFSs. The TFS values were calculated as planned at the utility nodes, although the accuracy of those TFS predictions may be further improved. The transmission-zone nodes relied on the Alstom Grid-informed simulation to calculate their TFS values for them, which broke a critical feedback loop in the transactive system. More research is needed to insert distributed power-flow calculations into transactive systems at this grand scale.

2.8 Step 7: The Modeled Exchange of Energy within the Transactive System Must Be Accurate

The TFSs were to have represented the near-term and predicted future power that was being exchanged between connected transactive nodes. This next step assesses whether the TFS at a node accurately represented the power being exchanged by the connected nodes. In the PNWSGD transactive system, the calculations of TFSs were accomplished differently between connected transmission-zone nodes and connections between transmission zones and the site nodes that they served. Therefore, the accuracies of the TFSs for these two connection types are addressed separately in this section.

2.8.1 Accuracy of the TFS between Transmission Zones

The power exchange between transmission zones of the PNWSGD transactive system was calculated within the *informed simulation* that Alstom Grid had designed to emulate the operations of bulk generation and transmission in the region. The region had been divided into 14 transmission zones. The boundaries between those transmission zones had been defined where the region's transmission could be defined by one transmission line, or by no more than a few transmission lines. Alstom Grid represented this nodal system by allocating the region's loads and resources among the transmission zones. A power flow was periodically performed to help ensure that the solutions were feasible, but the impacts of resource dispatch decisions were estimated between these calculations using influence factors.

Formulation of the simulation model for emulation of the regional grid behaviors proved very challenging. First, the reduced model was imperfect. Different resource names were used by different entities in the region. When they were available to the project, lists of resources did not always use the same or compatible and interoperable formats. And it was found to be surprisingly difficult to allocate resources to one side of a transmission-zone boundary or the other with the methods deployed by Alstom Grid. The allocation of generation and transmission resources might have proceeded more smoothly if the process were less time constrained and if Alstom Grid had created the reduced-order grid model from the start using rigorous model reduction methods.

Furthermore, access to real-time operational data was quite limited, so the emulated regional grid's behaviors diverged from the actions that were actually taken by grid operators. Today's regulatory environment dissuaded utilities from sharing much time-sensitive information that would have been useful for this exercise.

2.8.2 Accuracy of the Utility Sites' TFS

At the interface between the PNWSGD transactive system's utility site nodes and transmission-zone nodes, the TFS represents the power that is received by the utility site from the transmission zone in which the site resides. The site owners had worked with the project to define this interface, preferably at a well-metered location. At several of the utility sites, a direct comparison is therefore possible between the TFS and the total metered load that the signal was intended to emulate and predict.

At most sites, bulk load was modeled using algorithms that were developed and trained for the project by IBM. These were the main source of the TFS values that were generated at sites to emulate the sites' electric loads. The relative accuracies of the TFS predictions at site locations are addressed in Section 2.6.1. This section addresses only comparisons at the sites between the nearest-term predictions of the TFS[1] and the meter data.

Table 2.2 compares the TFS against the metered power at the Peninsula Light Fox Island site (ST01) during 2014. The monthly averages and standard deviations are shown for the eight project months of 2014. The last column shows the differences between the monthly averages stated as a fraction of the average metered power.

Stepping down the rows of this table by month, a clear trend emerges. Underestimation improved from January to March. From April through August, a trend toward increasing overestimation emerged. The greatest difference between the monthly averages, a relative error of 60.2%, occurred in June 2014. The model failed to track seasonal changes in load. Because March appears to be the month with the least error, and the errors increasingly diverge before and after March, the project suspects that the load predictor was trained using March data. This site did not make use of real-time feedback from the meters that might have improved prediction accuracy over time.

[1] The project refers to the near-term prediction interval as that corresponding to interval start time zero (IST0) that predicted behavior for the next 5 minutes.

Table 2.2. Comparison of Average Metered Power at the Fox Island Site (ST01) and Its Representation by the Transactive Feedback Signal for the Eight Project Months of 2014

	Average Metered Power[(a)] (MW)	Average TFS[(a,b)] (MW)	% Error[(c)]
January	22.0 ± 4.6	17.8 ± 4.4	−18.8
February	21.1 ± 4.7	17.9 ± 4.4	−15.2
March	18.2 ± 4.6	18.0 ± 4.4	−1.48
April	14.8 ± 3.7	17.9 ± 4.4	21.0
May	11.8 ± 2.6	17.9 ± 4.4	52.3
June	11.2 ± 2.1	17.9 ± 4.4	60.2
July	11.8 ± 2.6	17.9 ± 4.4	51.4
August	11.5 ± 2.4	17.9 ± 4.4	56.7

(a) Unless otherwise stated, both the TFS and metered power have been averaged over the period from January 1 to September 1, 2014. The variability is the standard deviation.

(b) For TFS power, only the “Operational” signals were included in the calculations. If relaxation occurred during a given 5-minute interval, the last result for that interval was the only one used in the calculation.

(c) This error is simply the difference between the average TFS and average metered power expressed as a percentage fraction of the metered power.

Table 2.3 shows a similar comparison, but this comparison was for the power received by the University of Washington campus site (ST02) from the West Washington TZ02. The transactive system consistently underestimated the amount of energy that would be, in fact, required by the utility. The site was offline during April 2014 and came back online the next month with some relatively inaccurate calculations in May. This outage of the site’s transactive node was attributed by the university to a server reconfiguration problem that coincided with a cyber security event at a vendor’s location. The University of Washington continued to have meter data-collection issues, which may be the result of the unusually high metered value in May 2014.

Table 2.3. Comparison of Average Metered Power at the University of Washington Site and Its Representation by the Transactive Feedback Signal for the Project Months of 2014

	Average Metered Power[(a)] (MW)	Average TFS[(a,b)] (MW)	% Error[(c)]
January	32.1 ± 4.8	27.9 ± 3.6	−13.1
February	32.8 ± 4.5	27.9 ± 3.6	−14.8
March	31.3 ± 4.0	27.0 ± 3.7	−13.6
April	28.2 ± 7.8	-	-
May[(d)]	61 ± 1070	28.8 ± 4.3	−52.8
June	33.6 ± 4.6	27.1 ± 4.7	−19.5
July	36.8 ± 5.5	30.4 ± 4.6	−17.4
August	37.4 ± 5.0	30.9 ± 4.2	−17.4

(a) Unless otherwise stated, both the TFS and metered power have been averaged over the period from January 1 to September 1, 2014. The variability is the standard deviation.

(b) For TFS power, only the “Operational” signals were included in the calculations. If relaxation occurred during a given 5-minute interval, the last result for that interval was the only one used in the calculation.

(c) This error is simply the difference between the average TFS and average metered power expressed as a percentage fraction of the metered power.

(d) The project believes the unusually high averaged meter power May 2014 was due to persistent data-collection challenges. The comparison is probably not valid this month.

The comparison was repeated for the Portland General Electric demonstration feeder site in Salem, Oregon (ST03). The results are shown in Table 2.4. The project was unable, working with Portland General Electric, to define a meaningful test region and site metering that might confirm the accuracy of the transactive system’s TFS calculations at the Salem, Oregon node. The comparison between these two quantities is not meaningful.

Table 2.4. Comparison of Average Metered Power at the Portland General Electric (Salem, Oregon) Site (ST03) and Its Representation by the Transactive Feedback Signal for the Project Months of 2014

	Average Metered Power (MW)	Average TFS[a,b] (MW)	% Error[c]
January	18,504	-	-
February	175,014	17.4	-
March	17,289	18.7	-
April	17,432	17.8	-
May	19,088	18.0	-
June	11,651	18.1	-
July	20,253	14.4	-
August	21,419	18.2	-

(a) Unless otherwise stated, both the TFS energy and metered energy have been averaged over the period from January 1, 2014 00:00:00 to September 1, 2014 00:00:00 local time.

(b) For TFS energy, only "Operational" signals were included in the calculations. In addition, if relaxation occurred during a given 5-minute interval, the "last" data point was the only one used in the calculation.

(c) The comparison is not valid at the Salem, Oregon site. The TFS clearly was not emulating this metered energy. The result of this calculation would be an extremely large negative percentage.

The comparison was repeated for the Avista Utilities Pullman, Washington site (ST06). The results are shown in Table 2.5. On average, the TFS overestimated the sites power by about 9%. The most inaccurate comparison occurred in June 2014 when the relative error was 62.4% overestimation of the metered value. However, this error appears to be attributable to a problem with the metered quantity, not the calculated TFS values.

Table 2.5. Comparison of Average Metered Power at the Pullman, Washington Site (ST06) and Its Representation by the Transactive Feedback Signal for the Eight Project Months of 2014

	Average Metered Power[a] (MW)	Average TFS[a,b] (MW)	% Error[c]
January	2,215 ± 529	NA	NA
February	2,170 ± 903	2,229 ± 256	2.71
March	2,009 ± 467	2,184 ± 285	8.68
April	2,018 ± 376	2,152 ± 276	6.67
May	2,138 ± 824	2,148 ± 303	0.45
June	1,348 ± 1180	2,190 ± 323	62.4
July	2,269 ± 899	2,124 ± 334	−6.36
August	2,399 ± 645	2,116 ± 328	−11.8

(a) Unless otherwise stated, both the TFS and metered power have been averaged over the period from January 1 to September 1, 2014. The variability is the standard deviation.

(b) For TFS power, only the “Operational” signals were included in the calculations. If relaxation occurred during a given 5-minute interval, the last result for that interval was the only one used in the calculation.

(c) This error is simply the difference between the average TFS and average metered power expressed as a percentage fraction of the metered power.

Table 2.6 compares the calculated TFS at the Philipsburg, Montana site (ST11) and the metered data that it was to represent. Both the average metered load and the averaged TFS representation were consistent from month to month. The differences between metered and TFS values are relatively small. The TFS was no longer being dynamically calculated during the last 3 months of the project. The same average value is reported with no standard deviation.

Table 2.6. Comparison of Average Metered Power at the Philipsburg, Montana Site (ST11) and Its Representation by the Transactive Feedback Signal for the Eight Project Months of 2014

	Metered Energy[a] (MW)	TFS[a,b] (MW)	% Error[c]
January	1,024.1 ± 11.0	1,023.4 ± 7.5	0.07
February	1,030.8 ± 13.5	10,37.4 ± 14.3	−0.64
March	1,022.2 ± 11.0	990.9 ± 14.8	3.15
April	1,018.0 ± 9.8	976.8 ± 9.9	4.22
May	1,011.9 ± 10.5	964.6 ± 11.6	4.90
June	1,008.5 ± 10.1	956.8 ± 0.0	5.40
July	1,004.8 ± 11.9	956.8 ± 0.0	5.01
August	1,005.1 ± 11.5	956.8 ± 0.0	5.04

(a) Unless otherwise stated, both the TFS energy and metered energy have been averaged over the period from January 1, 2014 00:00:00 to September 1, 2014 00:00:00 local time.

(b) For TFS energy, only “Operational” signals were included in the calculations. In addition, if relaxation occurred during a given 5-minute interval, the “last” data point was the only one used in the calculation.

(c) This error is simply the difference between the TFS and metered energy expressed as a percentage fraction of the metered energy.

The calculated TFS values at the Idaho Falls, Idaho site (ST14) were typically twice as great as the metered quantity the TFS was to emulate, or more, as shown in Table 2.7. Implementers must have misunderstood the connection between the TFS and the metered quantity that it was to predict.

Table 2.7. Comparison of Average Metered Power at the Idaho Falls, Idaho Site (ST14) and Its Representation by the Transactive Feedback Signal for the Eight Project Months of 2014

	Metered Energy[(a)] (MW)	TFS[(a,b)] (MW)	% Error[(c)]
January	38.4 ± 4.4	77.6 ± 11.3	102
February	36.3 ± 5.7	75.9 ± 11.2	109
March	31.4 ± 4.1	72.4 ± 9.3	131
April	28.2 ± 4.2	71.1 ± 9.0	152
May	26.2 ± 3.7	69.3 ± 8.6	165
June	25.9 ± 3.8	68.9 ± 8.8	166
July	29.0 ± 5.0	70.1 ± 9.9	142
August	25.2 ± 7.8	68.3 ± 9.0	171

(a) Unless otherwise stated, both the TFS energy and metered energy have been averaged over the period from January 1, 2014 00:00:00 to September 1, 2014 00:00:00 local time.

(b) For TFS energy, only "Operational" signals were included in the calculations. In addition, if relaxation occurred during a given 5-minute interval, the "last" data point was the only one used in the calculation. The stated variability in this case is the standard deviation of the interval values.

(c) This error is simply the difference between the TFS and metered energy expressed as a percentage fraction of the metered energy.

2.8.3 Step 7 Analysis Conclusions

The project's modeling of its electric load was probably not accurate enough for transactive systems of the design used by the PNWSGD. The relative errors between the TFS values at site nodes and the metered power that the TFS values should have modeled were found to be large. The accuracy varied wildly during the months of 2014. If a transactive system is to use feedback from its nodes to inform and plan the dispatch of its resources, the inaccuracy of such feedback (i.e., the TFS) must be small compared to magnitudes of resources being dispatched. Otherwise, the dispatch of resources will also be inaccurate, and the system will not properly plan the balance of resource to load.

Load forecasting is today done by balancing authorities. The project's utilities did not eagerly accept or own a new responsibility to predict their dynamic loads. If nodes are to accurately predict and report their loads, then automated systems must be developed to track and predict such loads. The load must be metered, and the metered data must be made available to the transactive prediction algorithm in real time.

The PNWSGD transactive system neither rewarded accurate predictions nor penalized inaccurate ones. In the future, incentives should be built into the system to reward accuracy and deter inaccuracy.

2.9 Step 8: Resources Must Respond to Dynamic System Load Predictions, Including the Plans from Flexible Loads

To conclude analysis of the complete control loop, this last analysis step should evaluate whether the predicted loads—both the predictions for inelastic and responsive elastic load in the transactive system—affected the actual dispatch of bulk load in the region. There is not much to discuss for this step. The PNWSGD transactive system was not permitted to directly influence bulk generation in the region. Its scale was considered too small to have a substantial influence, and as an experimental system it was not yet trusted to modify dispatch schedules.

It might be argued that the behaviors of responsive transactive loads did, in fact, change system balance and therefore affected the region's resources and resource mix. If so, this was a passive benefit. The dispatch and scheduling of the region's energy resources were accomplished entirely by existing mechanisms that the region's balancing authorities rely upon.

Having recognized early during the design of the PNWSGD that this step would not be successful in the field system, the project planned to simulate the system, including a more direct influence of the transactive system's actions on the dispatch and scheduling of the region's resources. This simulation is described in the next section.

2.10 Simulation Analysis of the Pacific Northwest Smart Grid Demonstration Transactive System

Additional section coauthors:
S Ghosh, M Yao, R Ambrosio, G Jensen, A Koc,
D Phan, H Wang, and K Warren −
IBM TJ Watson Research Center

IBM designed and built a simulation platform to closely mimic the operations of the PNW power grid. The PNWSGD project has designed transactive response assets to dynamically respond to extreme stresses in the system, and balance the cost of electricity over time. The aim of this simulation effort has been to study the behavior of the grid when the presence of distributed transactive response assets is high, consisting of up to 30% of all load being transactive in nature.

The simulation results show that the transactive control mechanisms designed by this PNWSGD project respond in the expected fashion to reduce the peak total system costs. In addition, certain types of responsive assets are effective in balancing the cost of electricity throughout a day, by consuming energy when system-wide costs are low and reducing load when the costs are high. The strength and the consistency of the response were estimated. The magnitude of the response depends on the number of transactive assets in the system, and can lead to up to about an 8% reduction in total peak costs in the PNWSGD region when the presence of load that is transactive in nature is high.

A second important goal of this simulation study is to analyze the interactions of the high transactive penetration system with the presence of renewable generation as a large part (up to 30%) of the total generation portfolio. Renewable generation has a complex interrelation with the transactive system.

Renewables are considered the cheapest per-unit source of power in the simulation. However, output from renewables is subject to various weather factors and is hard to schedule or predict. So the effect of renewables depends on the periods when high output is realized. If high renewables output coincides with the low-cost periods in the day, the cost-balancing assets that take advantage of lowest-cost electricity increase their interaction. On the other hand, high renewables in otherwise peak-cost periods have the effect of tamping the peak by themselves, thus not requiring further action from the peak-shaving parts of the transactive system. Overall, the summer data set shows wind to have a weakening effect on the transactive response, while in the winter and shoulder data sets, transactive response is strengthened by the presence of renewables.

2.10.1 Introduction to the Simulation and its Objectives

This simulation study seeks to understand the effect of the PNWSGD transactive system in its capability of withstanding extreme events and ensuring grid reliability for now and the future, as the transactive solutions are scaled up within the PNW power grid. The premise of introducing transactive assets into the grid is that they will help mitigate the effect of extreme events, as manifested in peak systemic costs, and the effect of uncertainty in predicting and scheduling renewable generation. Our study aims to find out if its promise is borne out by the design of the transactive control mechanisms introduced and studied in the PNWSGD. More importantly, the dynamic, interactive nature of transactive systems must be fully understood, evaluated and tested before the technology can be deployed at a large region-wide scale. Since the production environment cannot be risked for such a study, simulations are the only method that can be used to fully study and understand these systemic behaviors. In addition, simulations allow the controlled study of the effects of unpredictable, sudden, and fleeting stresses on the system.

Another important motivation for creating a simulation environment is to predict the effects of scaling the level of renewable power generation far higher than the current level of penetration. We study the complex interactions between being highly responsive and having a higher penetration of renewables in the electricity grid.

This IBM transactive system simulation is based on a combination of simplified grid network topology and a simplified model of some existing functionalities (like the ones implemented by Alstom Grid for the PNWSGD project) at regional transmission and bulk generation levels, while using real control toolkit functions (like the ones deployed by the project's participating utilities) at the distribution asset level. A scaled-down model that would allow for fast execution was envisioned. While being fast enough to allow for a large number of simulations to be carried out, this model must be detailed enough to allow for the thorough exploration of various inputs and alternative grid conditions. The inputs to the model should be controllable in order to simulate the effects of interesting scenarios (e.g., simulating extreme weather conditions) and the grid model should be configurable in order to study different network topologies and differing numbers of modeled resources.

2.10.2 The PNWSGD Transactive System

To facilitate the timely intervention of the transactive assets in ameliorating highly constrained situations that might arise in an electricity grid, this demonstration project suggests that certain pieces of information be exchanged in 5-minute intervals between all interconnected electricity assets. The information sent by any asset to its neighbors consists of two values:

- a value representing the average cost of the power required by each node to meet its local demand and export targets, measured in dollars per kilowatt-hour. The cost consists of components that measure the per-unit cost of generating power locally (cost of fuel, etc.), infrastructure costs that capture the amortized cost of installing any infrastructure in the node's local area of control, and the cost of importing power from its neighbors.
- a neighbor-specific value that represents the expected interchange of power (in kilowatts) between itself and the neighbor.

Predictions for these two values are published by each electrical asset in the transactive system over a forecast horizon of up to 5 days, with the information being broken down into fine intervals for the first day and coarser intervals for the rest. The published data allow each node to understand the impact of its local decisions on its own average cost as well as that of its neighbors, and is expected to help make decisions on transactive-load management that are to the benefit of the overall system.[1]

The transactive-load systems in the simulation respond to the forecast average cost of power in the node where they reside. Three types of transactive asset loads are defined by the demonstration project and modeled in the simulated system, distinguished by the nature of the control logic:

- daily-event – these loads typically activate up to once per day, trying to match their load reduction to the period with the highest predicted average cost of electricity within the day at its connecting node. The asset classes behind this control type can be residential appliances such as water-heaters, air-conditioning units, washer-dryers, etc.
- event-driven – these loads activate up to a set number of times within a given rolling or fixed time horizon, again trying to match their activation to the period with the highest predicted average cost of electricity within the time horizon at its connecting node. Unlike the daily-event assets, these could allow a time horizon of any length and could be activated multiple times in the time horizon. This simulation study models event-driven assets that act three or four times within a rolling period of a week. The asset classes that provide this response type are similar to the daily-event type.
- continuous-response – these loads continually try to identify an opportunity to use both low-cost and high-cost periods to strike a beneficial tradeoff between electricity usage and load reduction. A

[1] This design of transactive information has a key limitation that will affect the simulation results when high renewable penetration is being studied. Note that the infrastructure cost component of the average cost is applied to *all* power generated in or imported into the node. In particular, this makes renewable generators an unusually low-cost method of power generation under this scheme, in that its unit cost of production (fuel costs, etc.) is zero, and the cost of installing the infrastructure is applied uniformly to *all* power generation, i.e., not just the renewables but also thermal and hydro plants, and to imported energy. This limitation in the design, namely not being able to attribute structural costs to each source of power separately, will affect some of the effectiveness observed in integrating renewables in this simulation, but we fully expect the broad trends observed here to remain true even when the cost accounting for renewables is changed.

typical example is an electricity storage device such as a large battery installation. Unlike the first two control types that typically model assets that can only drop load when activated (e.g., usage of a residential appliance is postponed or rescheduled), the continuous-response assets can either charge from the grid (increase net load) or discharge to the grid (decrease net load).

2.10.3 Advantages of the Simulation Platform

This work leverages IBM Research's expertise and experience on platform integration, simulation and optimization to construct such a simulation system. The simulation addresses several challenges that are very difficult to resolve in the actual demonstration project, in order to study interesting PNWSGD behavior:

Feedback to bulk generation dispatch. In the field demonstration, Alstom Grid provided static, immutable inputs to the transactive nodes that then were used to calculate the node's average cost of electricity. The input information is calculated by Alstom from grid-level information it obtains from BPA (network load, conventional generation etc.) and 3TIER (renewables output). However, the demonstration project did not leave a pathway for the feedback obtained from the transactive system to be provided to Alstom Grid to modify its calculation. In other words, the predicted changes in system-wide loads due to the presence of transactive assets did not inform the calculations. In essence, this breaks a key feedback mechanism of the transactive system, and results in an open-loop system. This was a sensible choice that limited the real-world impacts that an experimental system such as the transactive system could have, but limited the effectiveness of the demonstrated transactive system. The simulation model closes this loop in order to be able to model various scenarios, such as modeling a system with a higher participation rate of renewable generation resources or to model increased loads. In order for fully closed loop feedback to be enabled, Alstom's proprietary management platform was replaced with an IBM-built unit-commitment and economic dispatch module.

Simulation speed (real-time simulation vs. speed-up simulation). Rapid simulation times are needed for tens of thousands of scenarios to be evaluated quickly to allow for a thorough evaluation of the different possible grid configurations with different generation and consumption patterns. This can only be accomplished by speeding up the simulations—by allowing simulated time to be accelerated more rapidly than real (wall clock) time.

Multiple scenario simulation for transactive system optimization. To design a good transactive system, a number of design parameters need to be optimized. A thorough evaluation of the solution space requires easy scenario specification. Such a flexible, parameterized configuration mechanism that could be used to specify the scenarios under consideration does not exist today. Subsequently, optimization techniques could possibly be used to select the best solution that would meet the objectives of the system under consideration.

2.10.4 Core Design Components of the Simulation Platform

The logic functional block diagram for the IBM simulation system is shown in Figure 2.45. It captures the key system components (light blue blocks), data flows (solid black arrow lines), and important configuration inputs required to run the simulation. In summary, the regional transactive system simulation is achieved through interaction between a collection of simulated transactive nodes (modified and based on field model of PNWSGD) and simulated regional balancing components (unit commitment [UC] and economic dispatch [ED]) that represent bulk generations and transmission. The setup enables simulation of distributed, end-to-end transactive feedback control loops within each modeled network zone and over whole simulated regions. The construct provides a simple mechanism to simulate and evaluate how regional generation resources are dispatched and used under the influence of the transactive system. The simulation itself was carried out in a distributed fashion over multiple compute nodes; the use of a distributed architecture for the original PNWSGD project allowed for an easy porting of the distributed nature of computation to the simulation. This greatly aided in being able to pursue a large, complex set of simulation scenarios for the analysis.

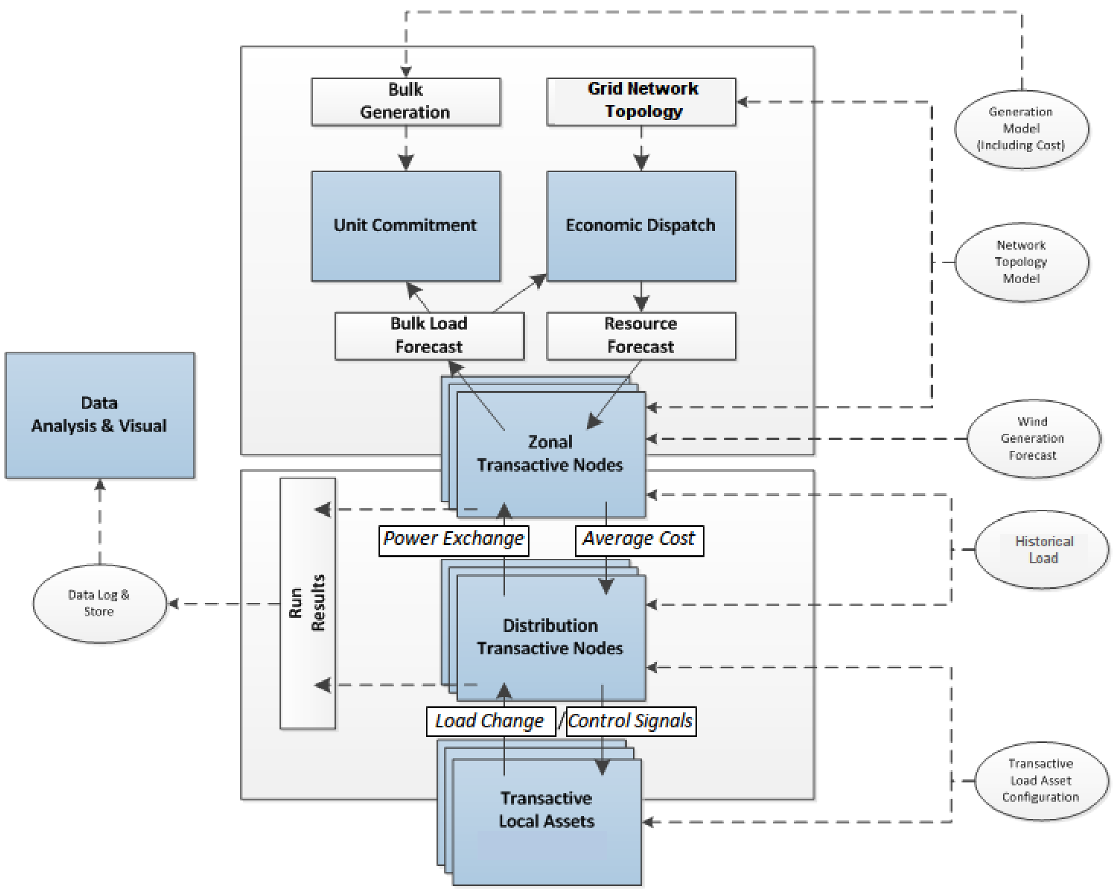


Figure 2.45. Schematic of the IBM Simulation Platform Built to Simulate the PNW Electricity Grid

The simulator is configured and controlled by seven key inputs described below.

Transmission network model. To reduce complexity and computation resource, Alstom Grid developed a reduced model for the bulk generation and transmission network. The reduced regional network model includes 14 transactive bus nodes, representing the transactive system of the region and 4 non-transactive bus nodes representing boundary energy exchange between the simulated transactive system and outside. The 18 node buses and links between them represent the simplified, reduced network model of the simulated regional grid. Figure 2.46 provides a diagram of the simplified network used in this simulation study.

Bulk generation. At each bus node, three types of bulk generation are modeled and provided by Alstom Grid: thermal, hydropower, and wind. The generation model includes generation characteristics, such as minimum and maximum capacities, minimum and maximum on and off times, and cost functions. Both UC and ED simulation components share the same configurational inputs from the bulk generation and transmission network model.

Unit commitment. A day-ahead hourly generation schedule is created by the UC block. This schedule (how much power should each generator generate each hour) is computed using information about load forecasts (how much is needed) and conventional generation characteristics (how much can the generator provide, how long does it take to start up, etc.), how much renewable energy is available, network topology, and cost models corresponding to the cost of generation.

Economic dispatch. The simulation uses the ED module to determine all three cost components of the average cost of electricity at each node. The hourly schedule produced by UC is fed into ED block, which will be run every 5 minutes (in simulated time) to generate actual generation schedules that contain dispatch values (how much power to generate) for the generators so that the overall system load will be met at the lowest cost. For each ED execution, power-flow simulations are also triggered to determine the power flowing through the grid, ensuring that the power flow is within the operating limits. The power-flow simulations are also used to determine power exchanges between different transactive nodes. Each ED execution event produces the output of multiple computations, each run based on bulk-load forecast periods in the power-interchange signal. Correspondingly, the output ED is a forecast, with same time series as the input, of all bus generation capacity (kW), cost ($/h), and power flows of the regional network. These outputs are passed to a transactive control node system for average-cost computation to influence the behavior of responsive local assets across the simulated region.

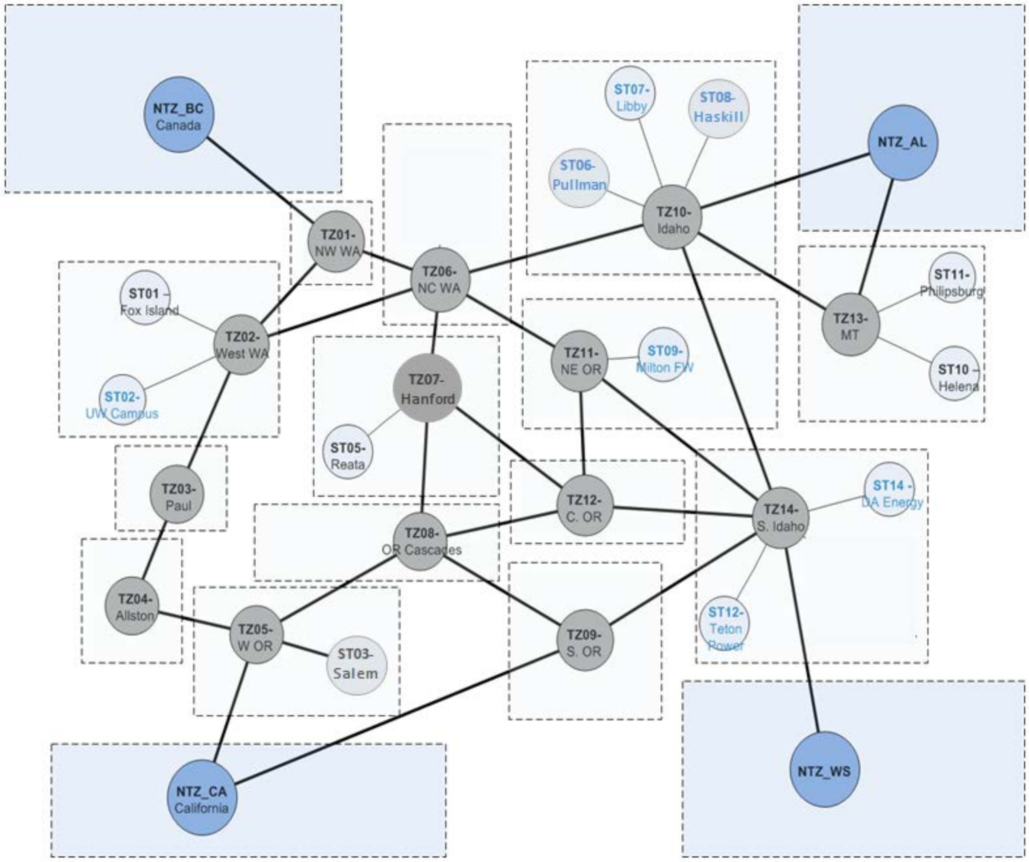


Figure 2.46. Simplified Model of the Pacific Northwest Electricity Grid

Bulk inelastic load. Based on BPA data, bulk inelastic load files for each transactive zone bus were provided for the three simulation seasons. These historical load files provide baseline inelastic load for each transactive node bus and are used to compute and calibrate transactive and renewable wind-penetration levels for the simulation. These are described further in the next section.

Renewable wind generation. For each simulated season, the historical wind power is provided as a renewable wind forecast. To simplify the simulation, the wind power resource was taken into account as negative load on the demand side instead of as dispatchable resource on the supply side. Combined with bulk inelastic load, wind power contributes as base-load for overall net-load forecast computation by a transactive node and is submitted to ED as load forecast. A wind power multiplier is implemented as a configuration parameter to scale the simulated wind-penetration level.

Transactive local assets configuration. All local responsive assets are created and configured by transactive local asset configuration files. These configuration files specify number, type, and characteristics of transactive responsive assets created for each simulation run. These configuration parameters in combination with other controllable input parameters determine the transactive penetration level of the simulation.

The results of simulators are collected as output files for data analysis and visualization. The key output files include the following:

- average-cost predictions – JavaScript Object Notation (Json)-based data collection, each published forecast recorded containing data for each forecast interval, and a breakdown of the cost factors for each type of generation resources and additional infrastructure costs.
- interchange-of-power predictions – Json-based data collection, each forecast published by each node for each of its neighbors containing data for each forecast interval. Also recorded were the local inputs of inelastic load forecast, elastic load change forecast due to transactive assets and control signals for each local responsive asset.
- inputs provided to the ED and UC module, including the net-load predictions for each node as submitted to ED/UC modules.

2.10.5 Simulation Scenarios and Experiment Run Setup

Simulation scenarios were defined and controlled by various configuration inputs and parameters:

Distinct seasons of the year (from 2013). This is configured and controlled by feeding the simulator with different base-load and wind power data corresponding to different seasons of the year. Three season periods, each lasting 1 week and ending in that season's observed peak load for 2013, are defined and targeted, as described in Table 2.8. The shoulder period was selected as a fall season week approximately halfway between the summer and winter peaks.

Table 2.8. Seasonal Data Sets Used in Simulation

Season Data Set	Start Time	End Time
Summer	2013-07-30 08:00:00 UTC	2013-08-06 08:00:00 UTC
Winter	2013-11-29 08:00:00 UTC	2013-12-06 08:00:00 UTC
Shoulder	2013-09-28 08:00:00 UTC	2013-10-05 08:00:00 UTC

UTC = Coordinated Universal Time.

Figure 2.47, Figure 2.50, and Figure 2.53 plot the total system-wide load under the three season data sets. The days in the summer data set have a single flat peak through the 09:00−17:00 (local) period, indicating a likely correlation with cooling load incurred because of the day time temperatures, while the other two data sets have pronounced morning and evening peaks, with the morning peak usually being higher than that in the evening.

Penetration Level of Wind Generation. Wind-penetration level is defined by wind peak power generation capacity divided by total peak base-load power in the region. A calibrated wind power multiplier is applied to the wind power generation forecast input data, consisting of recordings of forecasts for the present from each node in the network, to control wind-penetration level. Three different levels of wind penetration were planned and simulated, as listed in Table 2.9. Figure 2.48, Figure 2.51, and Figure 2.54 plot the total system-wide generation under the medium wind case for each data set. No clear pattern is discernible in the wind output, which serves to underlie its variability and dependence on local weather phenomena.

Table 2.9. Wind-Generation Cases

Wind Generation Penetration	Wind as Percentage of Peak Total Bulk Load
No Wind	0%
Medium Wind	10%
High Wind	30%

Penetration Level of Transactive Control. Three different levels of transactive penetration are planned and simulated, as described in Table 2.10 below.

Table 2.10. Transactive-Load Penetration Cases

Transactive Penetration	Peak Transactive Response as Percentage of Peak Bulk Load
No Transactive Load	0%
Medium Transactive Load	10%
High Transactive Load	30%

To achieve these levels of transactive load, the following steps were applied:

- The total number of transactive-load assets of the three types (event-driven, daily-event, and continuous-response capabilities) was scaled such that the sum of their total peak load reduction equaled the chosen percent of the peak total bulk load observed in the system, for each seasonal data set.
- The relative proportions of the three transactive asset types were always maintained at 20% continuous-response loads, 40% daily-event loads, and 40% event-driven loads.
- The control logic for the event-driven and daily-event type of assets respond to predicted peak average cost of electricity. Having a high number of assets of the same type throughout the network may lead to synchronous large changes in load due to transactive response. In order to simulate a scenario that more closely represents the likely future of uncoordinated asynchronous responsive assets, and also to prevent adverse effects from the simplification of the PNW transmission grid into a 14-node network, we apply a randomization factor to the number of assets that may respond at any given time. In the simulated system, the randomization factor is sampled afresh every 5 minutes uniformly from the range 50−100%, and represents the number of the event-driven and daily-event assets that may be active in that 5-minute period. So, an average of 75% assets of these types is expected to be reacting to incentives at any period.

In addition to the above control parameters, the following configuration parameters were controllable inputs:

- time acceleration factor (defaulted to 50)
- simulation start and end times (to match the start and end times of simulated scenario).

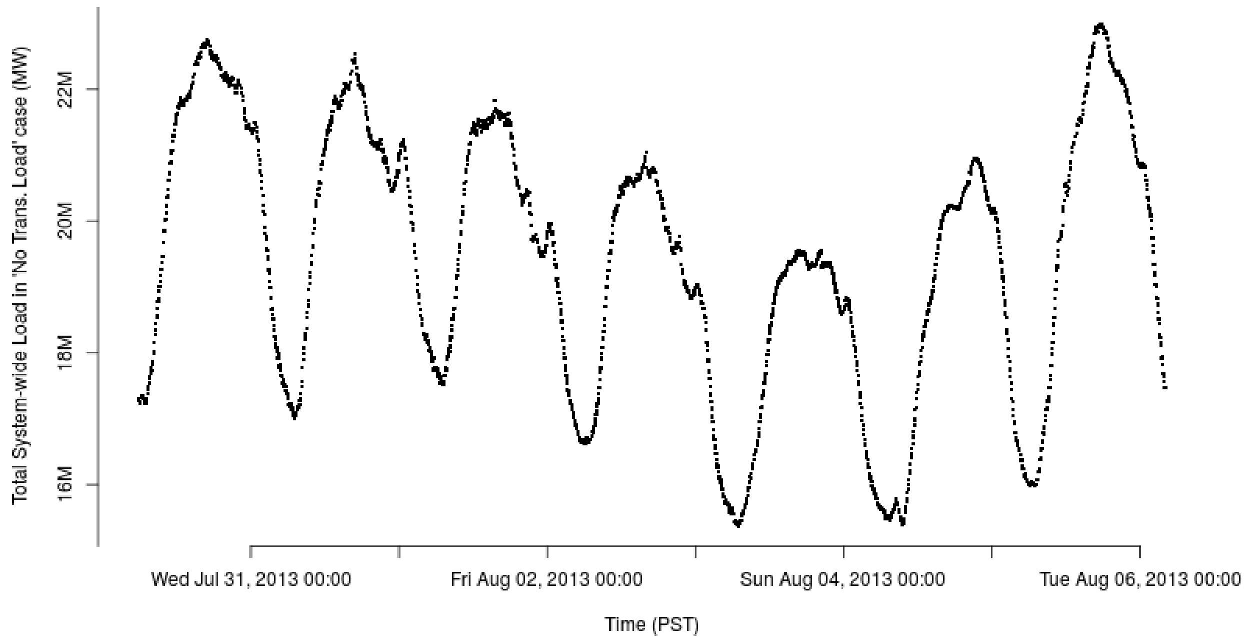


Figure 2.47. Total System-Wide Load in the Summer Data Set in the No-Transactive-Load Case

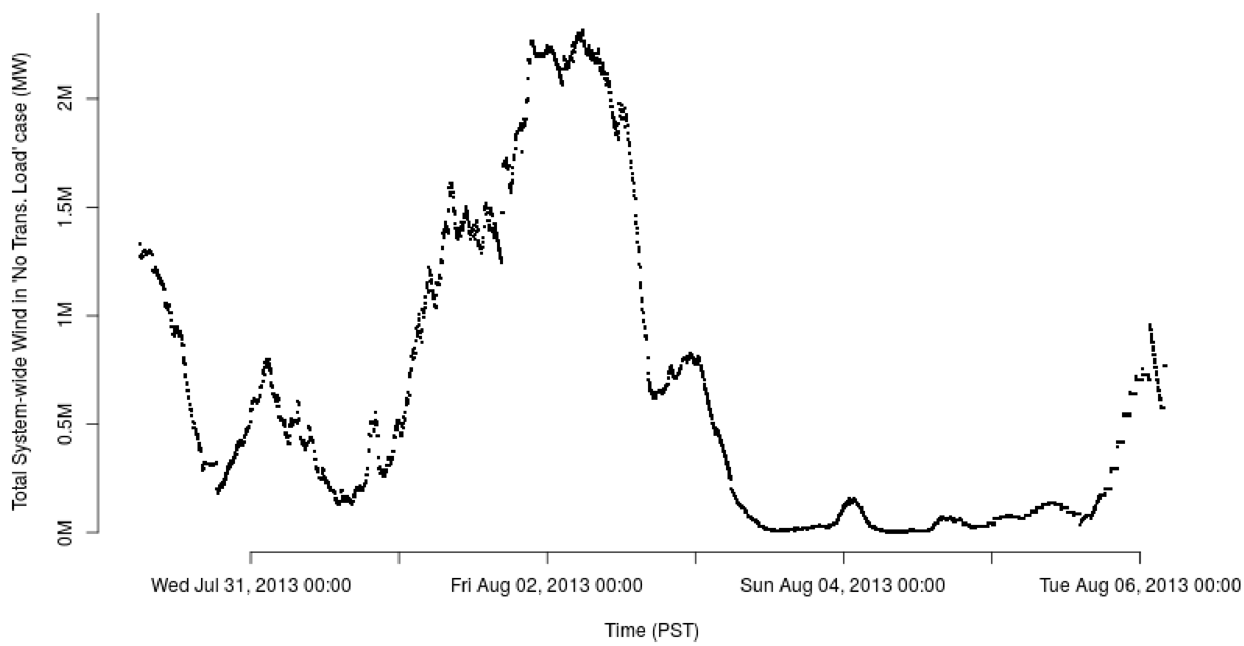


Figure 2.48. Total System-Wide Wind Generation in the Summer Data Set for the Medium Wind-Penetration Case

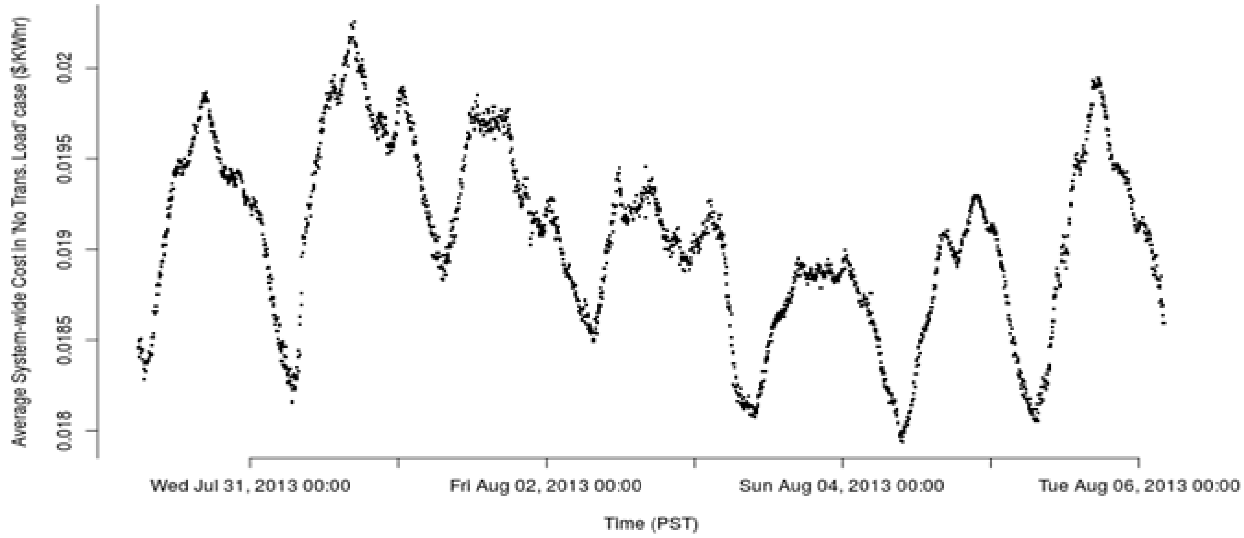


Figure 2.49. Average System-Wide Energy Cost of Electricity in the Summer Data Set under the No-Transactive-Load and No-Wind Cases

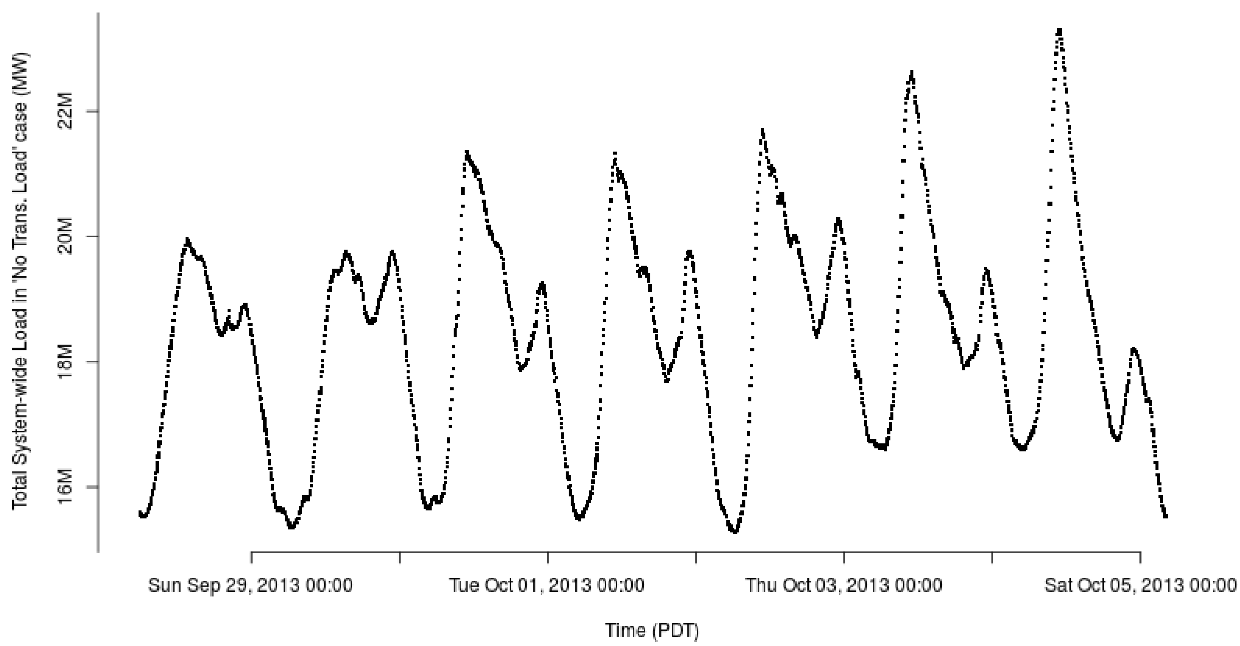


Figure 2.50. Total System-Wide Load in the Shoulder Data Set in the No-Transactive-Load Case

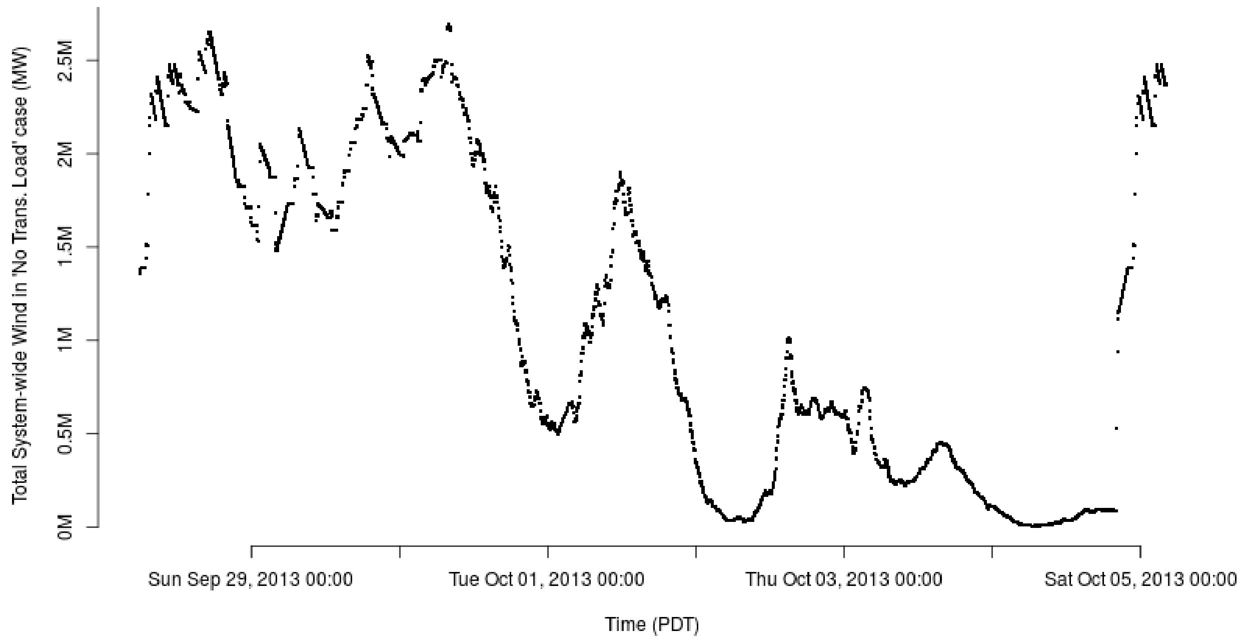


Figure 2.51. Total System-Wide Wind Generation in the Shoulder Data Set for the Medium Wind-Penetration Case

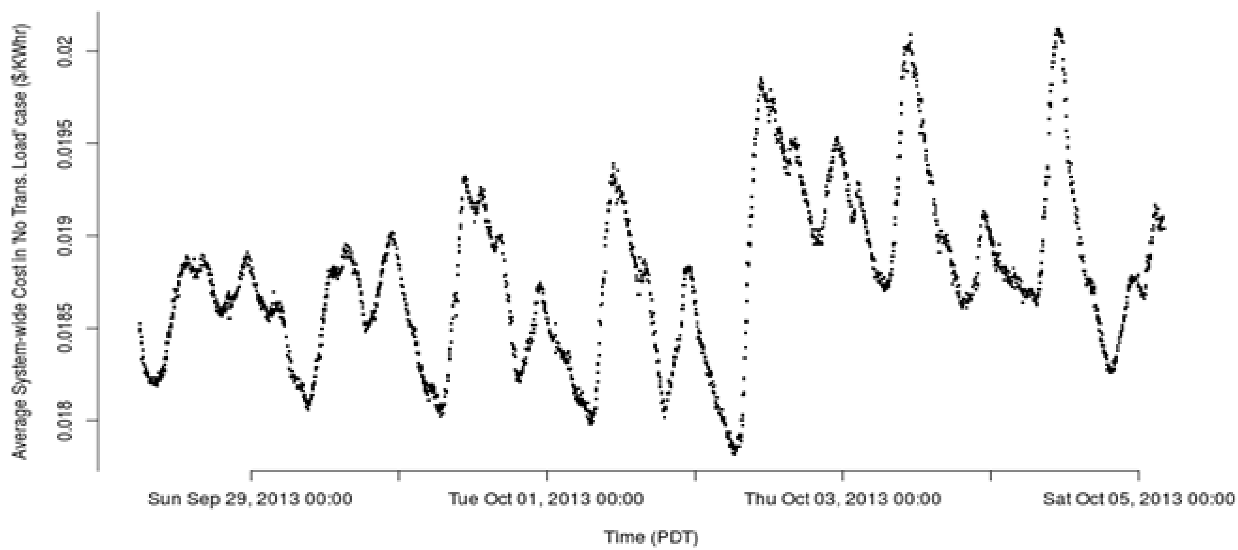


Figure 2.52. Average System-Wide Cost of Electric Energy in the Shoulder Data Set under the No-Transactive-Load and No-Wind Cases

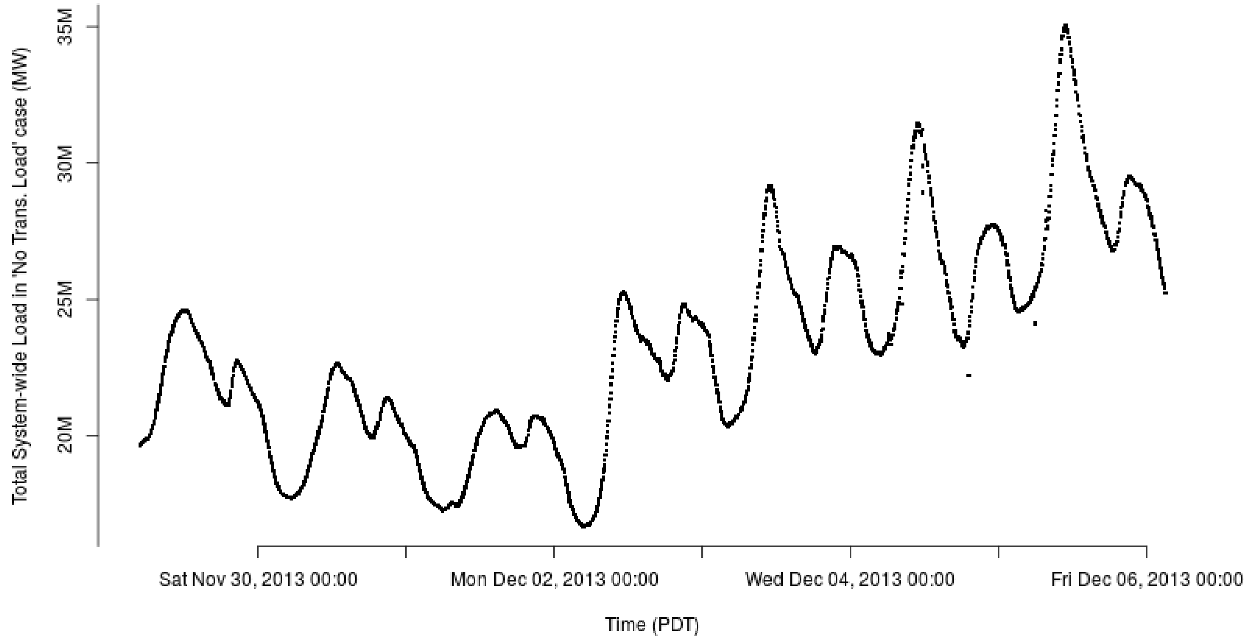


Figure 2.53. Total System-Wide Load in the Winter Data Set under the Case Having No Transactive Assets

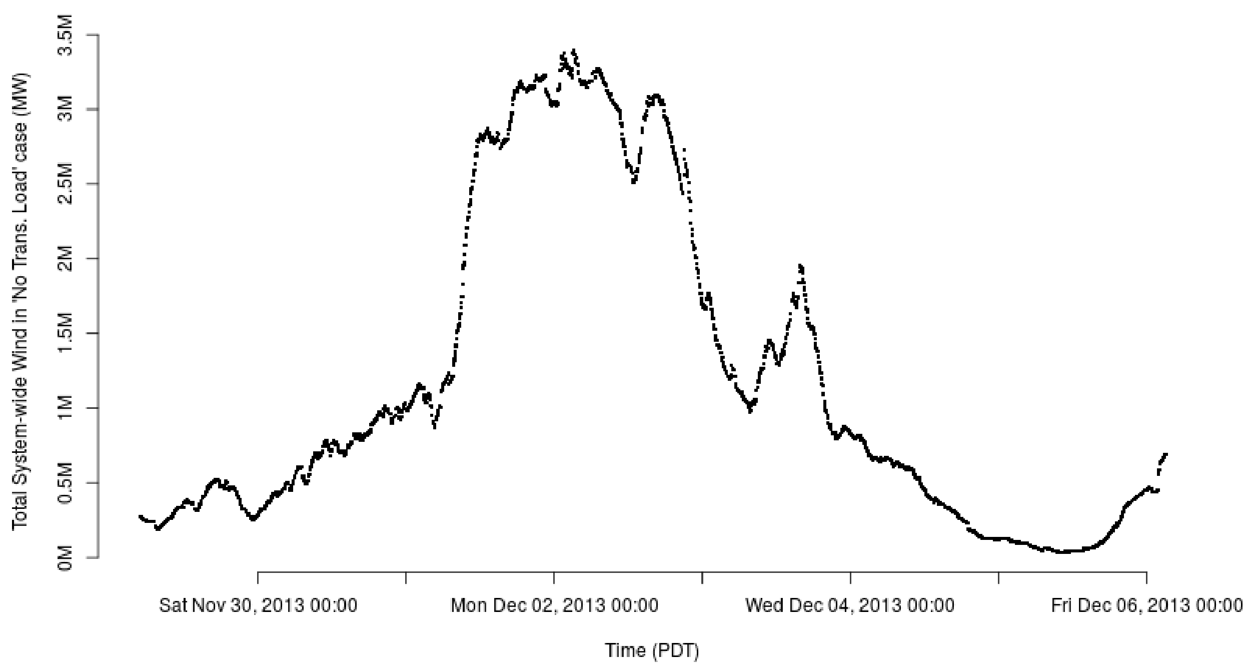


Figure 2.54. Total System-Wide Wind Generation in the Winter Data Set for the Medium Wind-Penetration Case

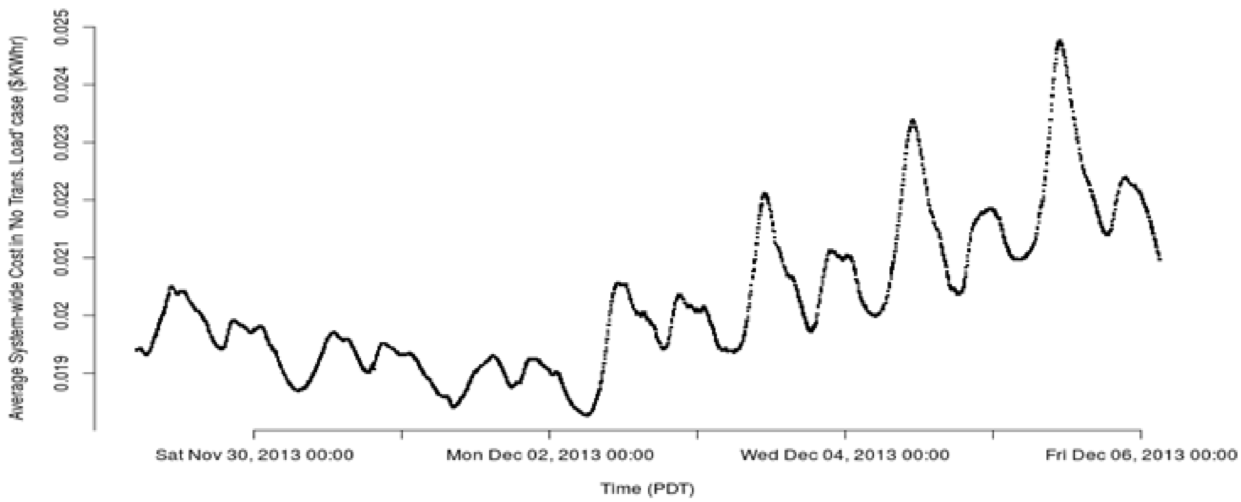


Figure 2.55. Average System-Wide Cost of Electric Energy in the Winter Data Set under the No-Transactive and No-Wind Cases

2.10.6 Output Analysis

This section will analyze the network-wide effects of the transactive system. Recall that all transactive asset control mechanisms are designed to respond to the average cost of electricity at their connecting nodes. Figure 2.49, Figure 2.52, and Figure 2.55 provided the system-wide average cost of electricity for the three data sets when no transactive load or wind is allowed to affect in the system. Overall, the average cost seems to follow the patterns observed in the total system-wide load. Both the winter and shoulder data sets show marked peaks in the day, which will be the times chosen by the event-driven and daily-event responsive assets. The summer data set exhibits flatter high system-wide average costs through the middle of the day, and in this instance the time chosen by the assets to respond will depend more on the average costs in each node.

Key metrics used to elucidate the performance of the transactive system are the total load (W) measured throughout the system at any time period, and the corresponding total hourly cost ($/h) borne by the system to meet this demand.

The first few analysis steps tease out the characteristics of the transactive system independent of the presence of wind in the system, and so use only the no-wind scenarios. The effect of wind over the transactive system is then analyzed.

The simulation scenario that models no transactive load and no wind will often serve as a benchmark for comparison between the other combinations of cases, and so will be referred to as the “base-case” scenario.

A note on the plots displayed in this section: The axes display three quantities with units, the time of day, total system-wide costs in units of dollars per hour ($/h), and the total load incurred in the system in watts (W). On occasion, the displayed units may scale up by a multiple of 10^3, 10^6 or 10^9 to k, M, or G units (e.g., k$/h or MW), as will be indicated. Three dimensionless quantities, scaled total cost and percent relative change in load or cost are also used, and will be introduced prior to first use.

2.10.7 Understanding Transactive Systems

It is instructive to start by taking a deeper look at how the transactive system responds to high-stress situations for the electricity grid in an attempt to alleviate the situation. Toward this goal, we take a closer look at two days from the data sets and the response under all three transactive scenarios, but with the modeled wind-penetration modeling no wind penetration.

The total system-wide costs for the fourth day of the summer data set are plotted in Figure 2.56. The no-transactive-load case has a relatively small, flat peak, in that the peak hours extend from 08:00 to 14:00. The control logic for all of the transactive assets are designed to respond to peak costs, and hence the high transactive load case is seen to significantly respond by reducing total cost. There is no sharp reduction in a single period, but response seems to be spread out in the 10:00 to 14:00 period. This is seen more clearly in Figure 2.57, which plots the change in total system-wide load through the day for the two transactive cases compared to the "No Trans. Load" case. Note the load-reduction response at peak periods being spread over the morning peak. The transactive loads respond to peaks in average costs at their connecting nodes, and these are given in Figure 2.58. The average costs at the nodes are seen to generally peak in the morning but each node's peak occurs during different periods spread over the 08:00 to 14:00 range. This leads to the spread-out response in the total-load views in Figure 2.56 and Figure 2.57.

Also of note in Figure 2.57 are the slight increases in total load during periods of low average or total costs. This is due to the continuous-response units, which constitute 20% of the total responsive load, consuming extra energy while costs are advantageous.

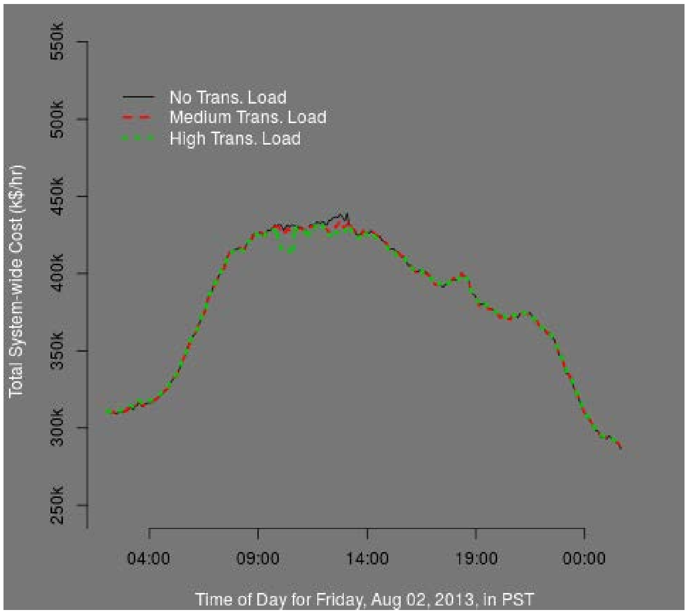


Figure 2.56. Total System-Wide Cost (day 4, summer)

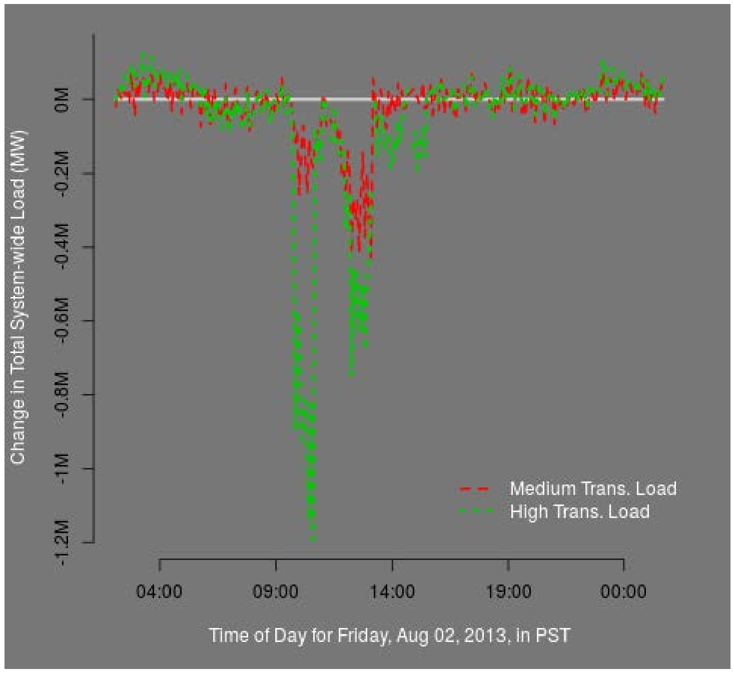


Figure 2.57. Difference in Total System-Wide Load (day 4, summer)

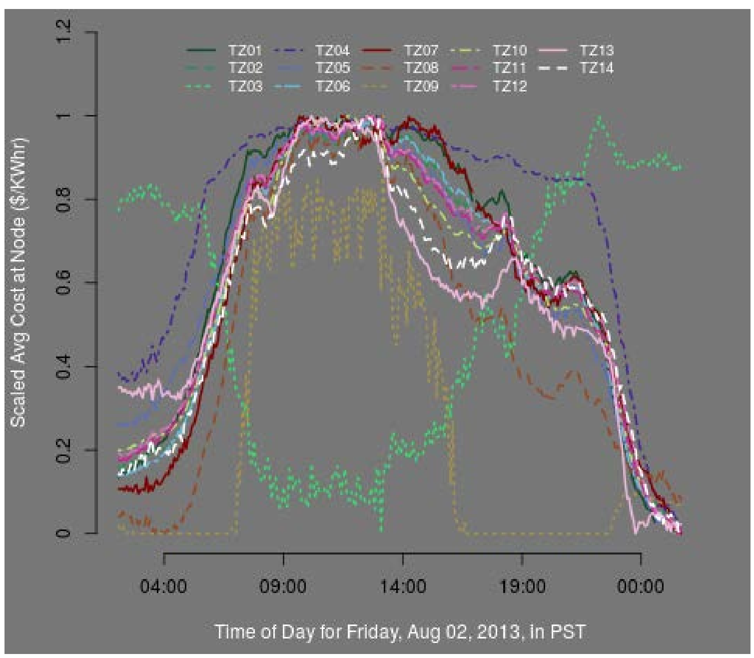


Figure 2.58. Average Cost of Electricity at Nodes (day 4, summer)

The average system-wide cost of electricity in winter (Figure 2.55) and shoulder (Figure 2.52) data sets display two peaks per day as opposed to the single flat peak in summer (Figure 2.49). Figure 2.59 shows the fourth day in the winter data set, which is the most interesting of the twin-peak days because the peak total system-wide cost values are similar for both intra-day peaks. The corresponding drop in total system-wide load in Figure 2.60 displays significant load reductions during both the two short, sharp morning and evening peaks. The individual responses of each asset depends on the average costs at each node (Figure 2.61), which show that each node experiences a slightly different individual morning or evening peak, leading to the responsive loads choosing the corresponding peak for load-reduction activation.

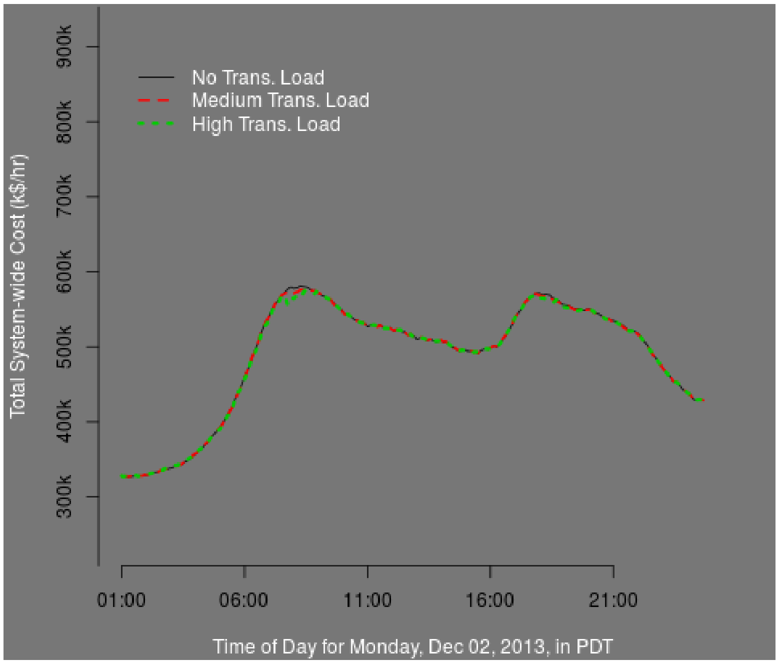


Figure 2.59. Total System-Wide Cost (day 4, winter)

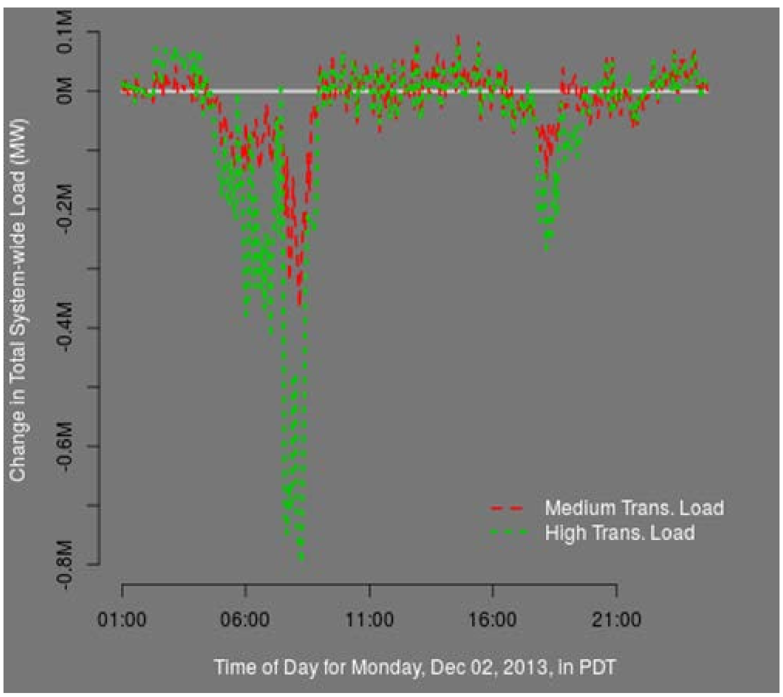


Figure 2.60. Difference in Total System-Wide Load (day 4, winter)

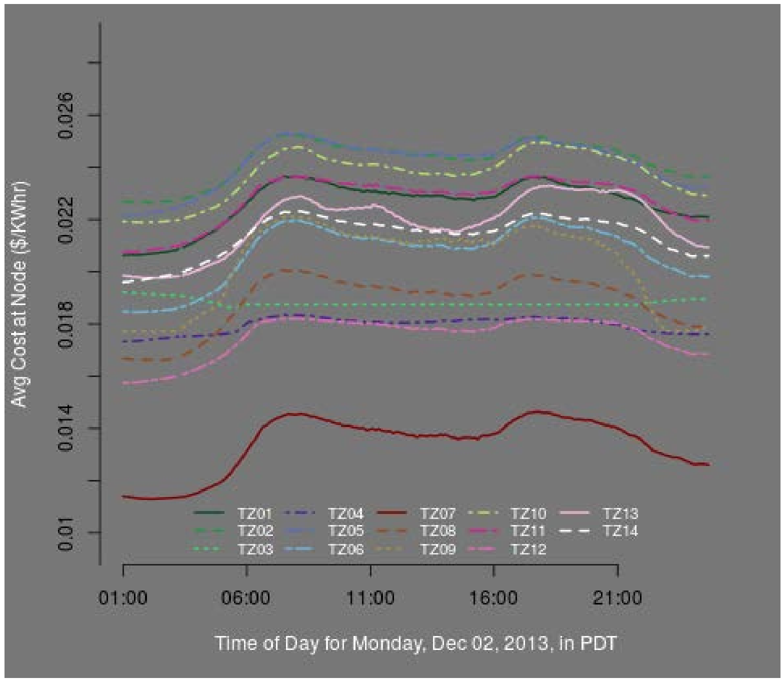


Figure 2.61. Average Cost of Electric Energy at Nodes (day 4, winter)

2.10.8 System-Wide Effects of Transactive Assets

Figure 2.62 graphs the total system-wide cost and total load in system for the base-case scenario. Each point represents a 5-minute interval in the 7-day simulation over the summer data set. Further, each day's data is represented by a different color and point-type. From Figure 2.47, the peak load is observed on the day of Monday August 5, 2013, and the corresponding total system-wide costs (in yellow squares) reach the top-rightmost part of the graph. A key observation is the almost linear relation between the total cost and total load, especially on a per-day basis. This is a result of the ED module, which is able to maintain an almost constant average cost of generation over the entire range of total load in system given the input models of the costs and ranges of thermal and hydro generation in the PNW power grid. The average unit costs vary slightly between days as shown in Figure 2.49. The cost variation for the same total load seems to be due to the slightly different breakdown of the same total load over the nodes of the network in different periods.

Figure 2.63 plots the same two quantities for the high transactive-load case. A general pattern emerges that matches the observations made earlier from the individual day plots. While most of each day's series remains the same as that under the no-transactive-load case, the top-right-most parts of each series are affected by the presence of transactive load. The points on those corners can be visually identified to have moved either to the left or the bottom (or both) of their original location on the left figure, indicating that the total cost and/or load have been reduced as desired.

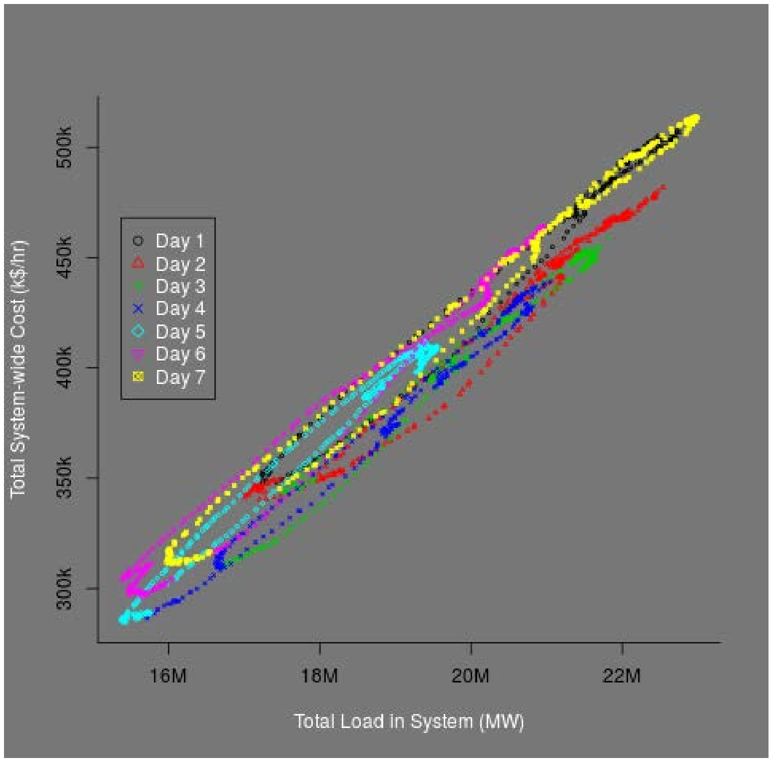


Figure 2.62. Total System-Wide Cost vs. Total Load for the Base-Case

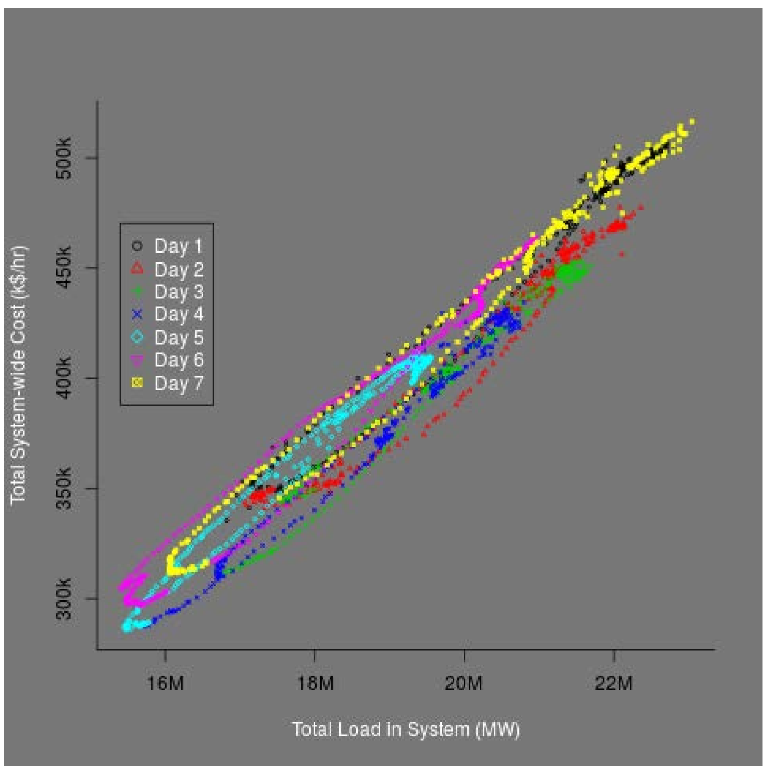


Figure 2.63. Total System-Wide Cost vs. Total Load for High Transactive-Load Case

The response is seen within each day's peak period, and in particular, a transactive response may be observed even in days with peaks that are lower than (to the lower left of) days with higher peaks. This is because of the presence of a significant percentage (40%) of daily-event responsive loads. Further, the event-driven responsive loads may choose to respond in the lower peaks if sufficient event activation budget is available. Moreover, continuous responsive loads may be able to realize a successful tradeoff between relative costs within a day. Indeed, these assets may respond to tradeoff costs in smaller intervals, which we will observe when the effect of wind is taken into account.

Table 2.11 provides the maximum observed changes in total system-wide load between the medium and high transactive-load cases and the base-case. Note that the drops in load generally happen during peak average-cost periods in the day when all responsive assets act by dropping some load, while increases in load occur during low average-cost periods when the continuous-response type assets charge up on cheaper energy. The maximum response in dropping load depends on the season, and can be as high as 7.8% during peak periods.

The next subsection studies the nature of the responsiveness of the transactive system in more detail.

Table 2.11. Maximum Observed Changes in Total System-Wide Load with Respect to the Base-Case Scenario

	Medium Transactive Load		High Transactive Load	
Season	Maximum Drop in Total Load (%)	Maximum Increase in Total Load	Maximum Drop in Total Load (%)	Maximum Increase in Total Load (%)
Summer	−4.34	0.61	−5.78%	1.51%
Shoulder	−7.79	0.65	−7.26%	8.94%
Winter	−4.26	7.86	−4.99%	7.77%

2.10.9 Responsiveness of the Transactive System

An analysis of the transactive responses first needs to adjust for local peaks and troughs in the time series of total system-wide costs. This is achieved in a straightforward manner by defining a new dimensionless quantity that is calculated by scaling the total system-wide cost or load by the corresponding peak and trough within the day. Figure 2.64 plots the result of this scaling, which produces values within the interval [0, 1] for the base-case scenario. While the inter-day variation in the peaks and troughs observed in Figure 2.49 are eliminated here, the intra-day variation in total cost is retained by this scaling.

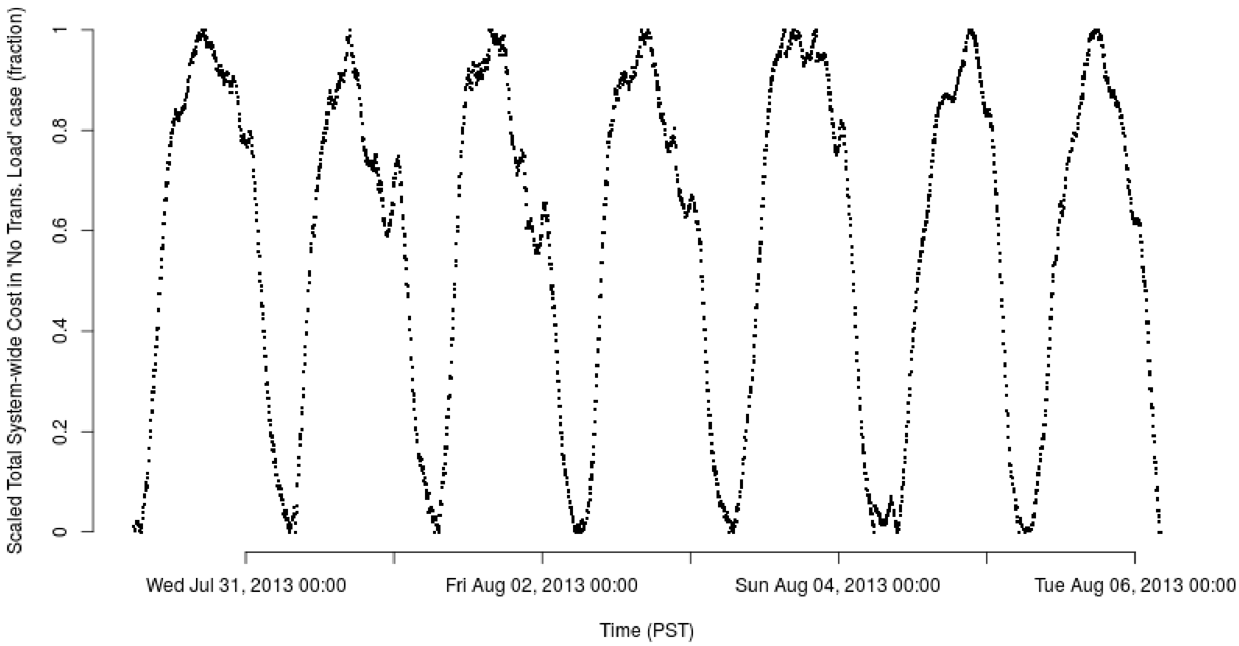
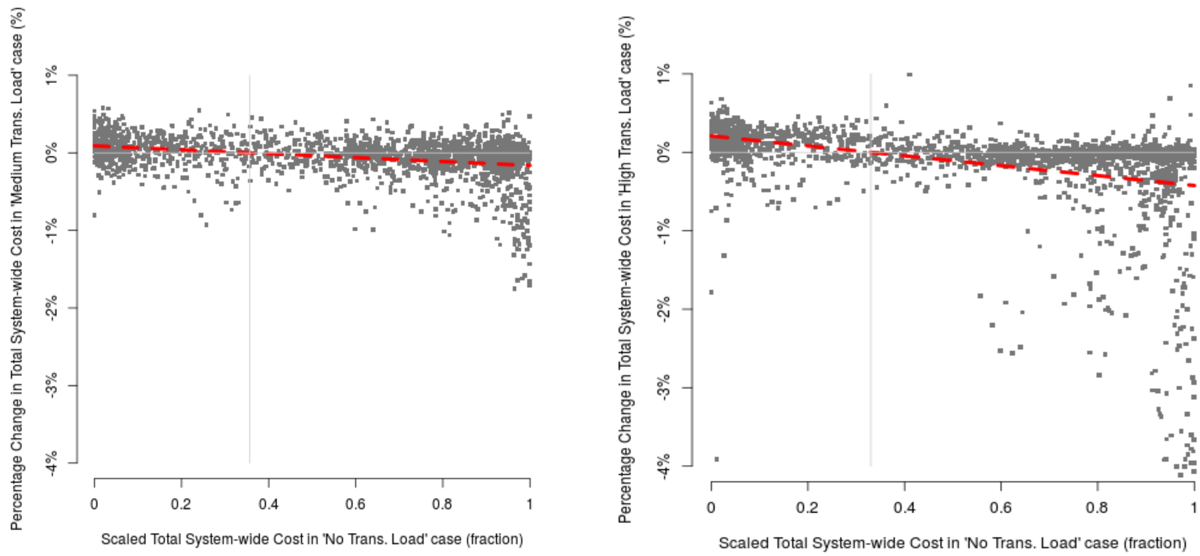


Figure 2.64. Total System-Wide Cost Expressed as a Scaled Dimensionless Quantity, for the Case that Had No Transactive Load in the Summer Dataset

Figure 2.65 provides scatter-plots of the percentage change in the total system-wide cost for each 5-minute interval in the medium and high transactive penetration cases, respectively, as a function of the scaled load value of the total system cost in the base-case. A striking observation is immediately evident: when the system-wide cost is at its highest within a day, the transactive assets generally have the effect of reducing the total cost by reducing their load. The more responsive high transactive penetration case is able to achieve larger relative drops. On the other hand, in the lowest cost periods within a day, a reverse behavior is observed, where the transactive assets might *increase* the total system cost by imposing additional load in the system. This is due to the continuous-response assets using the lower costs to charge up for a successful arbitrage during higher cost periods. The magnitude of the increase of relative total cost near zero-scaled-cost is more modest than the reduction near the high-cost end, which is a reflection of the smaller relative proportion of continuous-response assets (20% of total) against event-based assets (80% of total).

A vertical line on each plot in Figure 2.65 indicates the switch-over from dropping load to increasing load. In both cases, this seems to happen around when the scaled load represents the 35% percentile. The maximum responses observed in these plots are tabulated in Table 2.12.



(a) Medium Transactive-Load Penetration (b) High Transactive-Load Penetration

Figure 2.65. Scaled Total System-Wide Load vs. Percentage Change in Total Load under the (a) Medium and (b) High Transactive-Load Penetration Cases

Table 2.12. Maximum Observed Changes in Total System-Wide Load with Respect to a Base-Case Scenario that Had No Transactive Load

	Medium Transactive Load		High Transactive Load	
Season	Maximum Drop in Total Load (%)	Maximum Increase in Total Load (%)	Maximum Drop in Total Load (%)	Maximum Increase in Total Load (%)
Summer	−4.34	0.61	−5.78	1.51
Shoulder	−7.79	0.65	−7.26	8.94
Winter	−4.26	7.86	−4.99	7.77

Table 2.13 provides the results of a linear-regression model fit to the scatter-plots in Figure 2.65. The results for all seasonal data sets are provided. The slope of the modeled linear response is stronger under high transactive load for all data sets. Moreover, the intercept value at zero is always positive and at one is always negative, indicating an appropriate response from the continuous-response assets. The intercepts for the high transactive-load cases are about double those under the medium transactive-load case.

The linear-regression model indicates a direction of response due to the transactive load in the system. A good measure of the strength or determinacy of the response in this single-factor regression model is the correlation value between the percentage change in total load and the scaled load value in the no-transactive-load case. In the summer and winter data sets, we see a fairly high negative correlation value of around −0.30. This indicates that the decreasing relation between the two is significant. The correlation is weaker at −0.19 in the shoulder data set.

Table 2.13. Linear-Regression and Correlation Coefficients for No-Wind Cases for All Seasons and Medium and High Transactive Penetration Levels

Season	Transactive Penetration[a]	Slope (% Change/ Change in Scaled Cost)	Intercepts at 0 (% Change)	Intercepts at 1 (% Change)	Correlation
Summer	Medium	−0.25	0.09	−0.16	−0.32
	High	−0.63	0.21	−0.42	−0.34
Winter	Medium	−0.26	0.06	−0.20	−0.28
	High	−0.62	0.12	−0.49	−0.30
Shoulder	Medium	−0.22	0.04	−0.18	−0.19
	High	−0.65	0.16	−0.49	−0.18

(a) In this column, “medium” refers to the 10% transactive penetration case and “high” refers to the 30% transactive penetration case.

2.10.10 Direction of Transactive Response

This section delves deeper into the directions in which the transactive loads move the system-wide costs and loads simultaneously. To do this, Figure 2.66 divides the points in Figure 2.64 into three groups that we will call “terciles” using the two percentile values 33.3% and 66.7% of the scaled load data values. Each tercile is given a distinct point-type and color gradation.

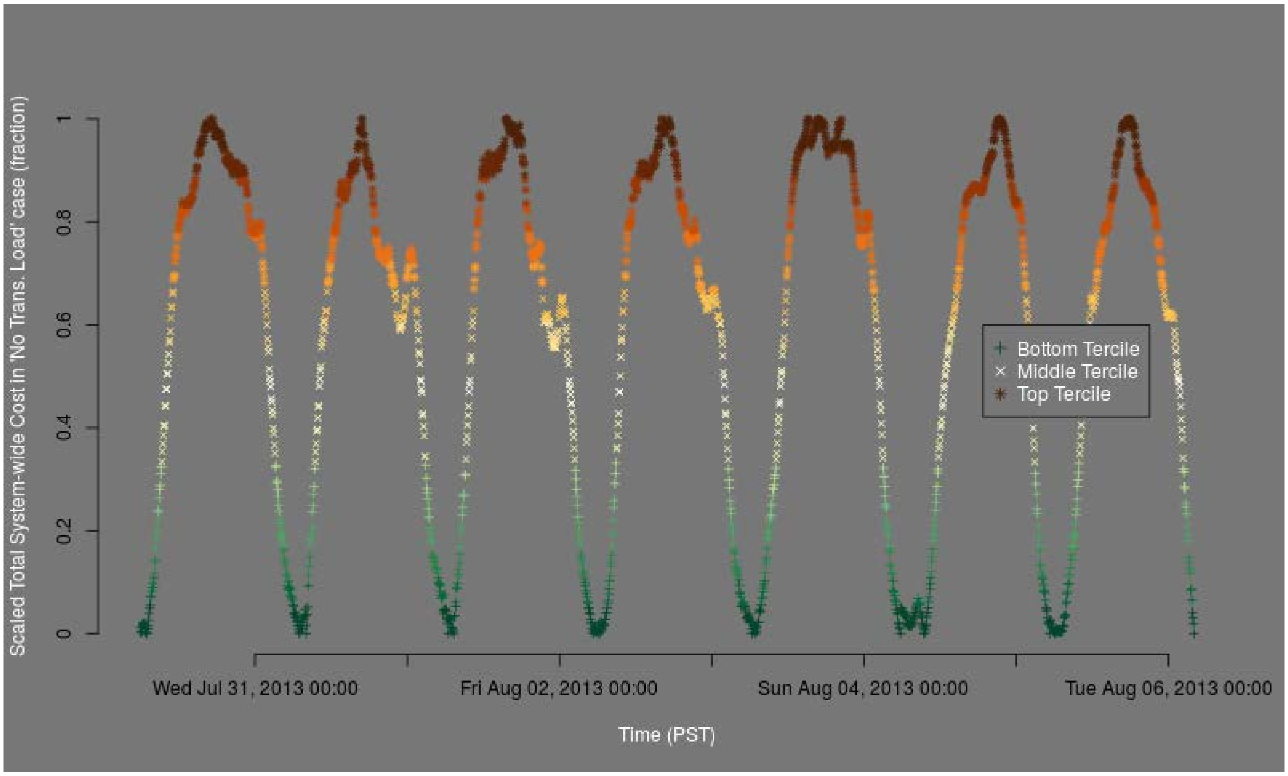
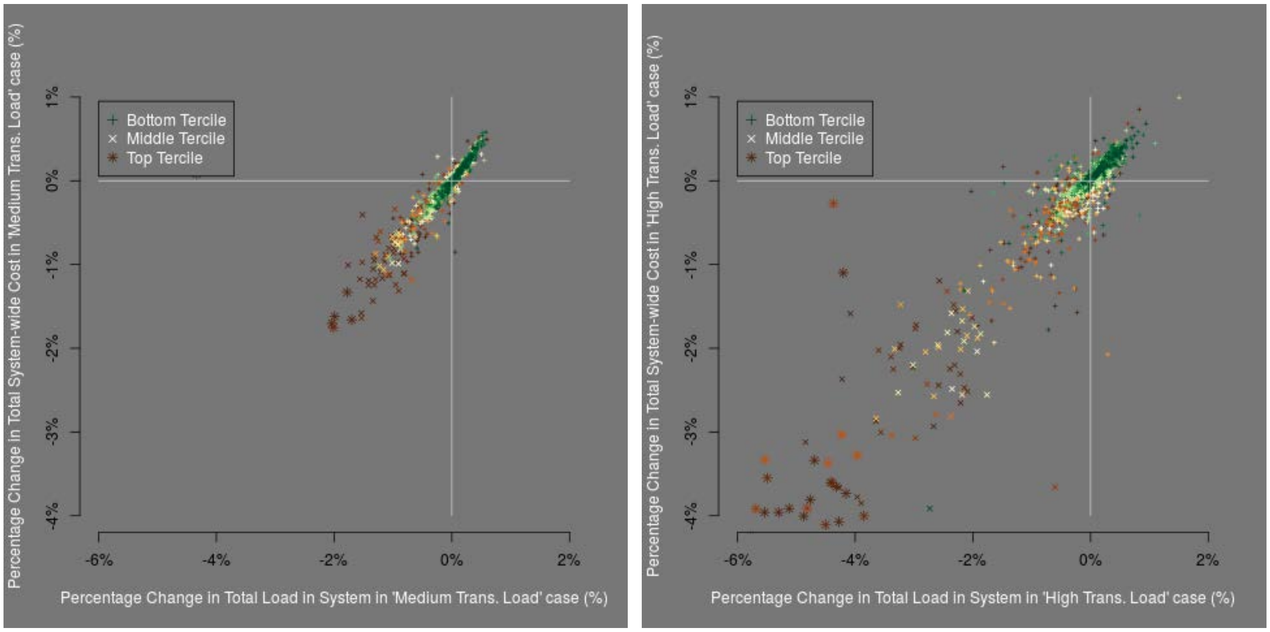


Figure 2.66. Total System-Wide Cost Expressed as a Scaled Dimensionless Quantity, for the No-Transactive-Load Case, using Distinct Colors and Point Types for Each Tercile of the Scaled Total Cost

Figure 2.67a and Figure 2.67b plot the relative change in total system-wide cost and load for each 5-minute simulation period using the colors and point types introduced in Figure 2.66. On the left, the relative change in the medium transactive-load case shows that most of the response has a positive, almost equal, relation between load and cost. In other words, a decrease (increase) in total load leads to the ED engine being able to calculate a corresponding decrease (increase) in total system-wide cost. Also, the larger decreases happen when system loads and costs are high, as was observed in Figure 2.65(a). The plot on the right shows the high transactive-load case. In addition to the observations on the left being strengthened on the right, the periods when load and cost increase concurrently are seen to be predominantly from the bottom tercile, when cost and load are both low. This confirms that most of these responses are due to the continuous-response assets leveraging cheaper energy to attenuate the higher cost periods.

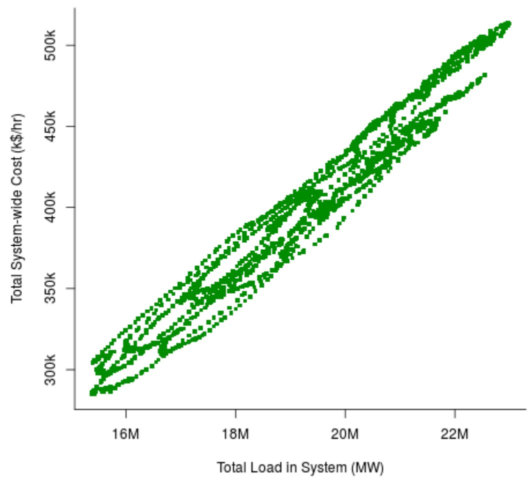


(a) Medium Transactive Load (b) High Transactive Load

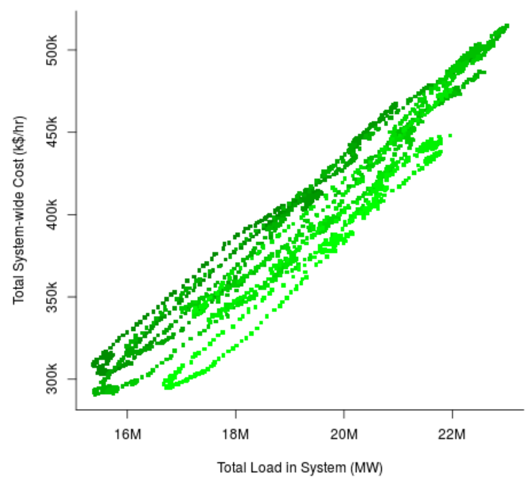
Figure 2.67. Percentage Change in Total Cost vs. Load for (a) Medium and (b) High Transactive-Load Cases

2.10.11 Effect of Wind on Total System-Wide Costs

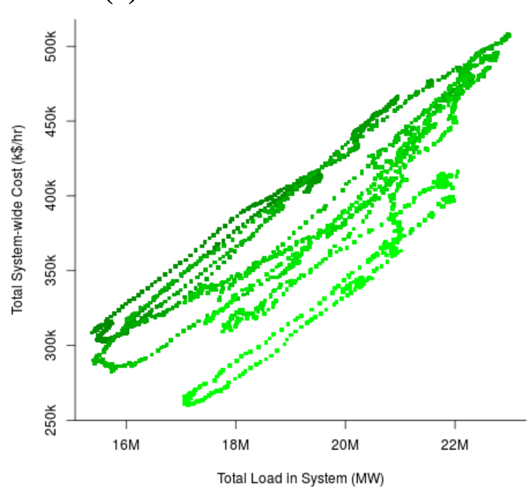
Figure 2.68 plots the variation in total system load vs cost for each 5-minute simulation period as the wind penetration in the portfolio is ramped up from no wind to medium wind and even high-wind cases, keeping the amount of transactive load at zero in all three cases. The points take a lighter shade of green if the total wind in the system is high at that 5-minute period. Wind, having been modeled as a zero-cost quantity, clearly has the effect of decreasing the cost of meeting the rest of the total system-wide load that is not served by the wind generation output.



(a) No Wind Penetration



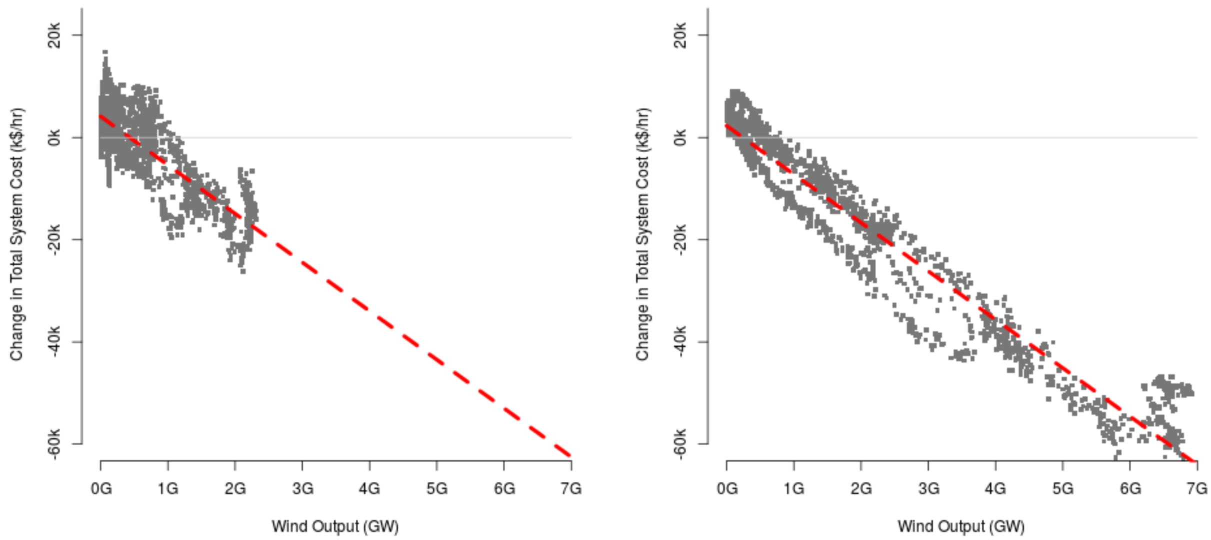
(b) Medium Wind Penetration



(c) High Wind Penetration

Figure 2.68. Total Load in System vs. Total System-Wide Cost for the No-Transactive-Load Case, with (a) No, (b) Medium, and (c) High Wind-Penetration Levels

A clear correlation is noticed between the reduction in system-wide total cost and the strength of the wind generation output. This correlation is more clearly observed in Figure 2.69, which plots the net change in total system-wide costs between the no-wind case and the medium- or high-wind cases against the corresponding wind generation output. Table 2.14 provides the coefficients of the linear-regression model fit over the data in Figure 2.69. The parameters from each seasonal data set and keeping the transactive load constant show a remarkable consistency in the direction and strength of the linear response. The direction of response (slopes of the linear model) is noticeably weaker in the winter data set. However, a weak positive relation is noticed in the slopes for this data set with the amount of transactive load in the system. This indicates that the two attributes, transactive load and wind-penetration level, may interact in a complex manner. This is the next subject of our analysis.



(a) Medium Wind-Penetration Case (b) High Wind-Penetration Case

Figure 2.69. Total Wind Output vs. Change in Total System-Wide Costs from the No-Wind Case, with No Transactive Load for (a) Medium and (b) High Wind-Penetration Cases

Table 2.14. Linear-Regression and Correlation Coefficients between Change in Total System-Wide Costs from the No-Wind Case and Medium and High Wind-Generation Outputs, for Various Transactive Load Penetration Levels

		Medium Wind			High Wind		
Season	Transactive Penetration	Slope (k$/GWh)	Intercept (k$/h)	Corr.	Slope (k$/(GWh)	Intercept (k$/h)	Corr.
Summer	None	−15.45	9.74	−0.95	−10.97	4.42	−0.97
	Medium	−15.44	9.51	−0.92	−10.97	4.29	−0.97
	High	−15.62	9.90	−0.78	−10.91	4.12	−0.97
Winter	None	−9.52	4.12	−0.82	−9.48	2.28	−0.97
	Medium	−9.65	4.26	−0.91	−9.51	2.37	−0.97
	High	−9.70	4.32	−0.70	−9.55	2.57	−0.96
Shoulder	None	−12.44	6.43	−0.95	−9.98	3.98	−0.97
	Medium	−12.63	6.64	−0.92	−9.99	4.01	−0.97
	High	−12.37	6.27	−0.93	−9.98	3.98	−0.97

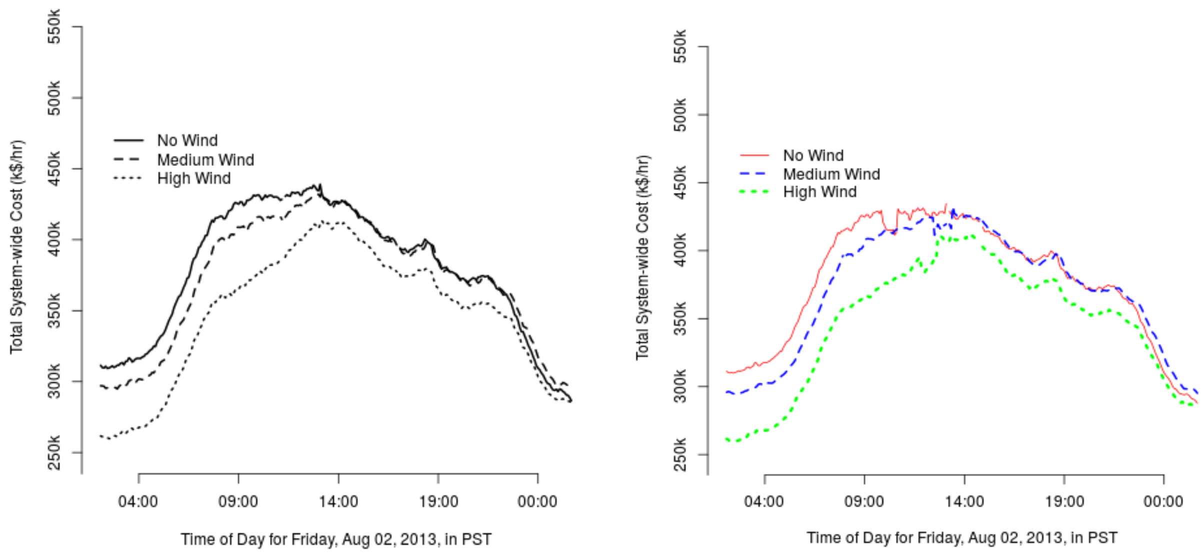
Recall that the transactive control algorithms are designed to target the most stressed periods in the day. Table 2.15 takes a look at the interaction between wind power availability and the peak periods in a day. Correlations are provided between the observed total system-wide load and cost (as depicted in Figure 2.66 using distinct colors and point types for each tercile of the scaled total cost) for the no wind and the wind output in the medium and high wind cases. In all scenarios, the transactive load is maintained at the zero transactive-load case. Also provided are the correlations between the wind output and the observed average system-wide cost of electricity. The correlations in the summer data set are the weakest across the board, with no clear strong inference possible. On the other hand, the winter data set exhibits strong negative correlations. In other words, the wind output in the winter data set often occurs when the grid tends to have tighter constraints and higher costs in the system. This is also true in a weaker sense in the shoulder data set. Note that the correlations under the medium and high wind-penetration data sets are identical because the correlation metric is insensitive to linear scaling, and each wind data set is derived by linearly scaling a currently observed wind generation to the desired level.

Table 2.15. Correlations between Medium and High Wind-Penetration Cases and Observed Values from the No-Wind Case

Season	Wind Penetration	Total System-Wide Load	Total System-Wide Cost	System-Wide Average Cost
Summer	Medium	0.03	−0.08	0.15
	High	0.03	−0.08	0.16
Winter	Medium	−0.45	−0.38	−0.52
	High	−0.45	−0.38	−0.52
Shoulder	Medium	−0.10	0.01	−0.24
	High	−0.10	0.01	−0.24

2.10.12 Interaction of Wind Output and Transactive Response

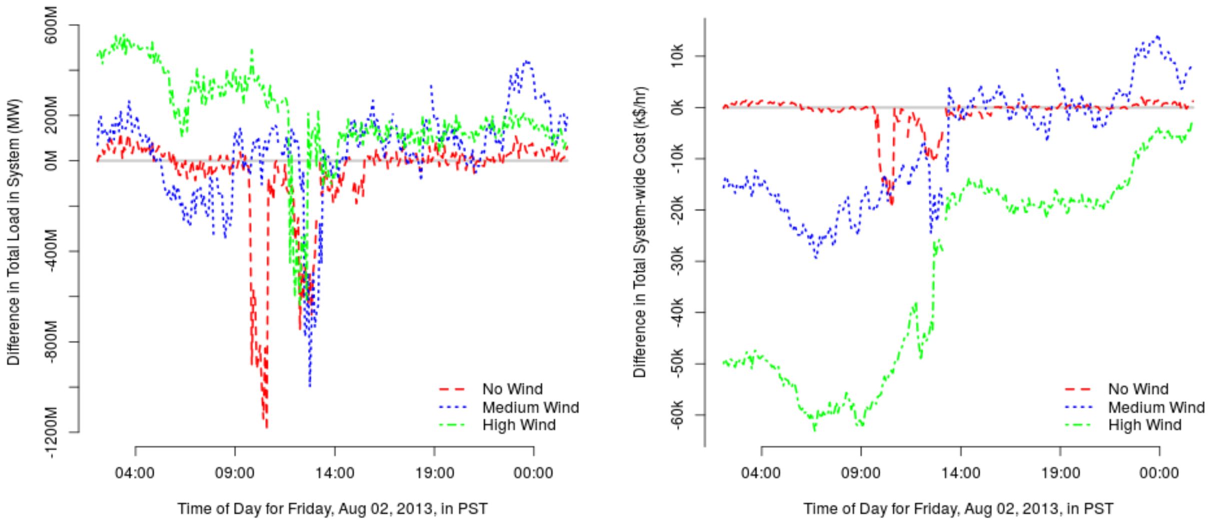
Transactive assets are most active at the time periods in the day when the total system-wide costs are at their highest. Wind generation depends solely on weather conditions. Thus, complex interactions may be observed in cases where the high wind period of the day also coincides with periods when the total system costs are traditionally higher. Figure 2.70 graphs such an interaction observed in a day of simulation using the summer data set. On the left is the total system-wide cost under different cases of wind output while no transactive load is imposed on the system. The peak wind period is seen to significantly affect costs, changing a flat peak from 08:00 to 13:00 in the no-wind scenario into a pronounced peak at 14:00 when the effect of high wind penetration is included. For these same wind outcomes, when the system additionally allows high transactive loads, the response from the transactive loads show a marked interaction with the wind outcomes. It is apparent that the peak period of response from these assets changes with respect to the amount of wind available, with a peak response in the no-wind case at about 10:00, which moves to 13:00 and 12:00 for the medium and high wind-penetration cases, respectively.



(a) No Transactive Load (b) 30% Transactive Load

Figure 2.70. Total System-Wide Cost for a Day in the Summer Data Set, with (a) No Transactive Load and (b) 30% Transactive Load Penetration

Figure 2.71 provides some very interesting data on the interactions between transactive load and wind generation. On the left is plotted the difference in total load in the system in a case that combines high transactive load with no, medium, and high wind penetration against a base total load measured in the no-transactive-load and no-wind cases. The plot on the right gives the corresponding differences in total system-wide costs. These plots show that when no zero-cost source such as wind is available, the appropriate response from the transactive loads is to reduce load at appropriate peaks as was observed in Figure 2.70, realizing concomitant reduction in total systemic costs. However, when wind is available, the nature of the local peak in average cost to the system changes significantly. This is most clearly observed in the high wind-penetration case. As observed earlier from Figure 2.70a, the wind generation is high on this particular day during the peak hours, and changes the flat long peak to a short sharp peak. In terms of the average cost of power, some of this formerly high-average period is actually converted to a low average valley in the high wind-penetration case. In Figure 2.71a, we also notice that in the high wind-penetration case, the amount of wind output is high enough for the transactive assets, principally the continuous-response assets, to take advantage of inexpensive wind power by actually increasing their load on the system. This increases the total load in the system during a period that was formerly part of the long flat peak in the absence of wind. However, this increase in load does not affect the overall cost in the system, which continues to be below the no-wind case, as observed on the right. So, wind output being high during peak systemic load can be very beneficial when a significant portion of the load can respond quickly in the transactive system.



(a) Effect on Total Load in System (b) Effect on Total System-Wide Cost

Figure 2.71. Effect of Interaction of the High Transactive-Load Penetration with Wind Output. Each trace shows a difference between high and no-transactive-load cases, with separate traces for scenarios having no, medium, or high wind penetration.

Table 2.16 provides the coefficients of linear-regression models fit to the percent change in total systemic costs observed in medium or high transactive-load cases compared to the no-transactive case costs as a function of the scaled total cost in the no-transactive case. These coefficients are similar to the values provided in Table 2.14 except that they treat the cases where wind is also present in the simulation, either at high or medium penetration levels.

The interaction of transactive assets and wind output shows a markedly different nature in the summer and winter and shoulder data sets. Presence of higher wind output seems to moderate the impact of having transactive load in the system for the summer results, as seen in the declining slope values of the linear-regression models. This may be attributed to the pattern of wind output being slightly in sync with periods when transactive loads typically act (i.e., high systemic cost periods), as discussed in the preceding example in Figure 2.71. On the other hand, wind output has the impact of strengthening the transactive response in the winter months, as evidenced by the similar or higher slope values in this case. This is possible when the pattern of wind output does not match or is antithetical to the high-cost periods, as observed in Table 2.15. However, in all cases, the quality or determinacy of the fit, as measured by the correlation value, decline compared to the no-wind case, indicating that the pattern of wind output and the peaks and troughs of total systemic costs are only very weakly related, as can be expected from the fact that wind output is driven only by weather phenomena.

Note that a majority of the transactive assets studied in this simulation can only intervene by dropping pre-existing residential loads during periods of high average cost of electricity, but are not designed to increase or shift consumption to periods of low average costs. Thus, the intersection of wind output and transactive response is mostly observed when high wind output reduces the peak average costs and obviates the need for a transactive response. A more sophisticated responsive asset that could also respond to high-wind presence facilitating drops in average costs is suited to extract more systemic benefit by providing mitigation to both high and low costs, as they are affected by renewable generation.

Table 2.16. Linear-Regression and Correlation Coefficients Modeling Percent Change in Total Cost in 10% or 30% Transactive-Load Cases as a Function of the Scaled Total Cost in the No-Transactive-Load Case for 10% and 30% Wind-Penetration Scenarios

		No Wind				Medium Wind				High Wind			
			Intercepts				Intercepts				Intercepts		
			at 0	at 1			at 0	at 1			at 0	at 1	
Season	Transactive Penetration[b]	Slope[a]	(% change)		Corr.	Slope[a]	(% change)		Corr.	Slope[a]	(% change)		Corr.
Summer	Medium	−0.25	0.09	−0.16	−0.32	−0.169	0.050	−0.119	−0.084	−0.049	−0.033	−0.082	−0.043
	High	−0.63	0.21	−0.42	−0.34	−0.266	0.000	−0.266	−0.103	−0.290	0.019	−0.271	−0.155
Winter	Medium	−0.26	0.06	−0.20	−0.28	−0.238	0.004	−0.234	−0.101	−0.256	0.030	−0.226	−0.170
	High	−0.62	0.12	−0.49	−0.30	−0.723	0.160	−0.563	−0.113	−0.587	0.063	−0.524	−0.189
Shoulder	Medium	−0.22	0.04	−0.18	−0.19	−0.32	0.09	−0.22	−0.11	−0.29	0.08	−0.21	−0.12
	High	−0.65	0.16	−0.49	−0.18	−0.54	0.09	−0.46	−0.22	−0.74	0.20	−0.54	−0.18

(a) The units for this column are % change/change in scaled cost

(b) In this column, “medium” refers to the 10% transactive penetration case and “high” refers to the 30% penetration case.

2.10.13 Conclusions

IBM's PNWSGD simulation platform demonstrated the complex interrelations that emerge from having a high penetration of transactive assets and renewables in the PNW power grid. Here are some key observations and conclusions derived from the simulation study:

- The transactive assets that use the event-driven or daily-event control logics designed in this project are effective in targeting load reduction to peak-cost periods in a day. The accuracy of the response depends on the sharpness of the peak of the average cost of electricity, as seen in Figure 2.56 through Figure 2.61.
- The cost and output characteristics of the bulk generation capacity in the PNW power grid lead the ED module to maintain a similar average system-wide cost throughout the range of total load (Figure 2.62 and Figure 2.63), but there is enough variation for the transactive assets to behave in the manner expected.
- Transactive assets that are continually responding to peaks and valleys in the average cost of electricity attempt to balance the overall energy usage by buying (charging) more power at low-cost periods (valleys) and selling (discharging) power at high-cost peak periods. This is observed in Figure 2.65 and is more clearly apparent in Figure 2.67.
- The transactive system responds to high average-cost of electricity by reducing the total system-wide load, and also increases the total-load in low average cost periods. As an example, a reduction in total cost of up to about 8% is observed in peak-cost periods when the presence of transactive assets in the system is high (Table 2.12).
- The change in total consumption when transactive assets are introduced in the system exhibits an inverse relationship with total system-wide costs, with a significant negative slope when modeled as a linear function (Figure 2.65).
- The presence of wind in the portfolio of generation has a strong impact in reducing overall system costs in meeting demand (Figure 2.68 and Figure 2.69). Table 2.14 shows that a reliably strong, negative relation exists between renewable production and total system cost. This impact is higher with higher presence of wind.
- The interaction of renewable generation and the transactive system can be complex. Presence of renewable generation can change the periods when transactive assets take action (Figure 2.69a). When high wind output suppresses costs in an otherwise peak-cost period, transactive assets designed only to shave peak load do not show any response. The cost suppression can the high-wind case also create periods of low enough average costs in former peak periods that the continuous response assets that seek the lowest costs of the day exhibit a strong activation (Figure 2.69b).
- The overall effect of wind on the strength and repeatability of the transactive response to the system costs depends on the pattern followed by the wind output.

- Table 2.16 shows that in the summer data set, the presence of wind weakens the transactive response, while in the winter data set its presence does not affect, or even slightly strengthens, the transactive response observed.

2.10.14 Summary and Need for Further Work

The PNWSGD transactive system created an informed simulation to represent much of the region's transmission and generation. It accurately represented wind, thermal, and hydropower resources when timely production data from these resources were explicitly available. The system accurately emulated the scheduling and dispatch order of various load-following resources when those resources had to instead be inferred. The mapping of actual resources, load, and transmission into the transactive system's topology proved to be challenging and the accuracy of the mapping was not convincing.

The TISs were constructed at distributed locations to represent the delivered unit cost of electricity at the nodal location and time. The transactive system's method of monetizing and blending resource energy and incentives was workable. Resistance was encountered to dynamically stating the incentives over time, and much work remains before we should anticipate acceptance of the method by regulators and as the basis for a real energy tariff. A set of parameters were recommended and used to represent dynamic cost components into the TIS formulation, and this approach may be a basis for interoperability in systems like this that must formulate distributed incentives. Caution must be used, however, because the selection of parameters from among this set can create undesirable consequences, as was the case when the project elected to represent infrastructure costs using a parameter with units dollar per hour, which had the undesired consequence of lowering costs during periods of highest energy demand.

The transactive system included predictions over a set of sequential time intervals that extended several days into the future. The TIS predictions and component resource predictions were found to suffer from prediction biases. A step difference was found about 3-1/2 hours into the predicted future that caused some of the transmission nodes to over predict future TIS values and others to under predict them. The project hypothesized that these biases occurred because different calculation methods were used before and after the time. These prediction errors may have serious adverse consequences for assets that rely on the predictions to schedule their operations.

Despite the challenges encountered in formulating the TIS values, the PNWSGD transactive system itself was robust and reliable at communicating its signals throughout the region. IBM created a reference implementation that was eventually adopted by nine of the utility participants. Four utilities attempted to create their own implementations from the project's specifications. Of these, one succeeded, another later accepted the IBM reference implementation, and two were unable to establish a compliant instantiation.

A suite of functions were developed by the project to help the participating utilities identify times that its assets should respond. Different functions were needed for infrequent events, daily events, and continuous responses. The approach proved workable, and the responses were shown to have occurred as they should during the corresponding high and low incentive values. The correlation was, however, strongly influenced by the care with which the functions had been configured. The functions that remained poorly configured or entirely unconfigured did not, of course, perform well.

The responsive asset systems—water heaters, thermostats, dynamic voltage control, etc.—also modeled and predicted their impacts on net load for times that the assets were advised by the transactive system to respond. Simple models were used by the PNWSGD, but these models could be made more accurate by future implementers. The project reported the ranges of the modeled power impacts, but the project lacked means to accurately calibrate or validate the impacts. Again, the approach proved workable, but the accuracy was strongly affected by the attention paid to calibration and configuration of the models.

The changes in load were summed at the utility nodes and were reflected in the predicted net load (TFS) between the utility sites and the respective transmission zones based upon which the sites were modeled to receive their energy supplies. At many sites, the corresponding TFS could be directly compared with the power meter data. The comparison was disappointing at many of the sites. Some sites failed to calibrate their load predictions. Others calibrated the power from only a couple months' data, and the corresponding models then failed to track seasonal variations. All of the sites would have benefited from stronger connections between the models and the real-time metered data that was to be tracked and predicted. The load predictions would need to be accurate (better than about ± 5%) if these predictions are to usefully inform the predictions of the balance between load and supply at the distributed transactive sites. Much future work is needed in this area.

Finally, the PWNSGD transactive field demonstration was not permitted to directly affect the scheduling and dispatch of the region's power resources. Analysis Step 8 (Resources Must Respond to Dynamic System Load Predictions, Including the Plans from Flexible Loads) could not be tested in the field. Instead, simulation was conducted by IBM to help the project scale up the modeled penetration of transactive assets and to close the control loop so that the connection between assets' responses and the dispatch of regional resources could be tested. Total load and total incentive costs were observed in the simulations to have decreased as the daily peak incentive costs were occurring. A smaller increase in load and incentive costs was observed as modeled battery systems reacted when minimum daily incentive costs were occurring. There was a complex interaction between dynamic wind power and these impacts within the transactive system because the wind power dynamically affected incentive values.

Here are some specific recommendations for issues and future work to be addressed in the development of future transactive systems:

- Many more responsive assets are needed. If a truly distributed system is to become viable, the changes in power offered by its responsive assets must be comparable in total magnitude to the changes in power available today from the supply side.
- More flexibility should be available from each asset. Today's demand-response programs and their assets allow for only several events each month for a few hours at a time. These programs might address peak demand, but they are otherwise limited in the services they can provide.
- Even battery systems, which were anticipated to offer great dynamic responsiveness, were found to be limited to no more than about one charge and discharge cycle per day.
- The project instigated the exchange of its transactive signals based mostly on timed 5-minute intervals. There is emerging consensus among project participants that future transactive system implementations should be more event-driven than timed. Communication of transactive signals

should only take place when there is evidence or likelihood that the system has appreciably changed or that predictions have become inaccurate since the time that the information was last communicated.

- In a loosely connected, distributed system, the validity and accuracy of the signals that are being received from neighbors might be in question. The project defined, but did not implement, a confidence attribute that could accompany transactive signals to state the sender's confidence in the calculated quantities. The confidence attribute might then temper the recipient's trust in the signal's values, which might further temper the actions that the recipient takes based on the signal's questionable values.
- Another incentive function had been planned that would have represented impacts of transmission congestion on energy costs, but this function was not successfully implemented by the project. Dispatch opportunities that would stress transmission capacities are outright disallowed today. The project's intention was that as transmission approached a stressful capacity, the cost of the transmission might be smoothly incremented to dissuade consumption of that power. A function having such smooth response was not found. The function's output rapidly changed the unit cost of energy faster than these changes could be responded to by the system. Furthermore, the responses from the transactive system were inadequate to mitigate the congestion and therefore could not stabilize the proposed function.

3.0 Conservation and Efficiency Test Cases

Additional chapter coauthor: ST Elbert − Battelle

An objective of a smart grid is to conserve energy and improve the grid's overall efficiencies. This section reports on asset systems that were deployed by the Pacific Northwest Smart Grid Demonstration (PNWSGD) project so that less electrical energy would be consumed to perform a given task (i.e., *efficiency*) or less energy would be consumed (i.e., *conservation*). Furthermore, the implementation of some of these asset systems was found to achieve *operational efficiencies* that reduce the costs of operating the system, but do not necessarily accomplish either conservation of energy or energy efficiency.

The project has chosen to employ four organizational headings in this chapter, as described below.

The power of information − portals, in-home displays, and customer education. Information itself can motivate consumers to conserve energy. Several participating utilities informed their energy consumers of their historical electricity consumption via Web portals or in-home displays. Energy customers may also become educated during their engagements with their electricity suppliers to make better decisions about their energy consumption. The education may be quite intentional, as occurred when the University of Washington campus created monthly energy reports to educate its campus building managers. On the other hand, energy customers may become better energy consumers after simply receiving smart grid devices and the utilities' accompanying informational fliers.

Replacing inefficient equipment and tuning existing equipment. One of the simplest means of conserving energy is to replace existing equipment with more energy efficient alternatives, as Avista Utilities did when it replaced approximately 800 existing distribution transformers with more efficient smart transformers.

Efficient distribution management. Still other utilities changed and automated the management of their distribution systems. Examples include the reduction of feeder voltages that reduces the power consumed by some end-use loads, correction of power factor that reduces power line losses, or coordinated volt and volt-ampere reactive control that can both reduce power load and reduce system losses.

Renewable energy. The project has also chosen to report renewable energy generation in this chapter. Numerous solar and wind generator systems were built and monitored during the PNWSGD. These new resources displaced supply energy that would otherwise have been purchased by customers' electricity suppliers. While much of the bulk electric supply in the Pacific Northwest is already environmentally green, the renewable generation may displace dirtier energy resources. The timing of the renewable energy generation also has implications for the generators' owners concerning the time-costs of the displaced energy supply and the renewable generation's potential effect on the customers' demand charges.

3.1 The Power of Information − Portals, In-Home Displays, and Customer Education

Advanced customer meters were critical components of many of the PNWSGD's smart grid systems. At many sites, especially those that had already invested in power line carrier communication networks, the meters were important, but not necessarily essential, links to responsive devices, including the switches that controlled water heaters and space conditioning. The project relied heavily on aggregated power data from the premises meters to analyze the performance of the many systems. Table 3.1 summarizes how many meters at each utility provided data for the project and the data intervals that were supported by the meters.

Table 3.1. Premises Meter Counts and Data Intervals by Utility

	Data Interval (h:m)	Premises Meter Count
Avista Utilities	0:05	14,334
Flathead Electric Cooperative	1:00	349
Idaho Falls Power	0:15 or 1:00[a]	17,303
Lower Valley Energy	1:00	548
Milton-Freewater	0:15	1,434
NorthWestern Energy	0:15	196
Portland General Electric	0:15	50
Peninsula Light Company	24:00	2,650

(a) Idaho Falls Power was found to have meters that reported at two different data intervals.

The focus of this section is the impact of the energy information that is available from the communicating meters. For example, the power consumption data from these meters may be displayed to the energy consumers via in-home displays or Web portals, and the informed persons may elect to change their energy consumption habits. Even the process of receiving a new meter or display, often accompanied by additional educational fliers from the utility, may change the recipients' energy consumption patterns. Five of the PNWSGD tests looked at this impact.

Avista Utilities finished installing advanced metering information (AMI) throughout Pullman, Washington, early in the project's term Section 7.5). By the project's assessment, the customers given access to an energy Web portal and their historical energy consumption reduced their electricity consumption by about 5 kWh per month, or by about 0.07% of their normal electricity consumption. (The uncertainty in this analysis was large.) By the utility's assessment, it will save $157,000 per year reading the meters remotely, $70,000 per year through reduced in-person customer service, and $8,000 per year upon reducing onsite serviceperson calls. The utility estimated a reduction of 220 truck rolls per month in the project months of 2014. Interestingly, the AMI data may now be compared against data from smart distribution transformers in Pullman to detect and reduce electricity theft.

Idaho Falls Power also tested the impact of AMI and in-home displays on its residents' electricity consumption (Section 11.7). The test was performed with the customers supplied by one of its substations. Those who received only AMI had their premises consumption reduced by 92 ± 56 kWh per month, but those who had received both AMI and in-home displays instead had their consumption increase by a small, insignificant amount. When surveyed at the conclusion of the test, 39% of the test residents reported that they had looked at their in-home displays daily.

Lower Valley Energy conducted a similar test of its cooperative members who had received only AMI and those who had received both AMI meters and in-home displays (Section 12.2). The project's analysis suggested that both sets of premises had experienced rather large reductions in their power consumption—270 +/- 70 W for those who had received only AMI, and 210 +/- 70 W for those who received both AMI and in-home displays. An even larger impact was calculated for those AMI members who had also received demand-response unit switches to control their water heaters. It seems the impact of the in-home displays was very small compared to the impact of receiving the AMI.

The University of Washington campus, while not using conventional premises AMI equipment, individually metered its buildings during the PNWSGD. The information from the meters was conveyed to its building managers in two ways. Section 17.6 describes a real-time Facilities Energy Management System, and Section 17.7 describes a program in which building managers were supplied a building energy report once each month.

3.2 Replacing Inefficient Equipment and Tuning Existing Equipment

The asset systems addressed here aim to improve energy efficiency by installing, tuning, or replacing existing infrastructure. The three asset systems specifically address replacement of distribution conductors, the tuning up of a university campus heating and cooling system, and replacement of existing distribution transformers with efficient smart transformers.

When Avista Utilities planned to automate circuit switching in Pullman, Washington, it found it would be constrained unless it upgraded conductors on two of its distribution lines (Section 7.2). The utility estimated that it will save about 24 MWh per year in reduced line losses by making these improvements. The value of this energy is only about $3,000 per year, but the new conductors greatly increased the utility's operational flexibility.

Avista Utilities also replaced about 800 inefficient distribution transformers with efficient, communicating transformers (Section 7.3). The new transformers monitor and report many measurements, including voltage, temperature, current, and power. These newly available measurements were found useful for detecting possible energy theft, verifying acceptable voltage delivery, and monitoring transformer health. By the utility's estimates, savings of 130 kW, or 1,120 MWh annually, were derived from the improved efficiency alone.

The University of Washington replaced many of its stand-alone control systems at campus buildings with direct digital building controls, which it expects will glean additional efficiencies from the improved operation of its commercial-scale buildings (Section 17.4).

3.3 Efficient Distribution Management

This subsection includes distribution-scale asset systems that strive to conserve distribution system energy by better managing circuit voltages, by reducing reactive power, or by simultaneously managing both system voltage and reactive power.

Voltage management or conservation voltage reduction was featured at Idaho Falls Power (Section 11.1), the City of Milton-Freewater (Section 13.5), Peninsula Light Company (Section 15.2), and at the two NorthWestern Energy sites (Section 14.1). The project calculated that the Idaho Fall, Idaho test feeder used about 137 kW less power while its voltage was actively reduced, thus potentially avoiding about $5,420 supply energy costs if the system were active throughout the year. Another estimated $6,770 might be avoided if the asset were consistently used to reduce the utility's demand charges.

In the City of Milton-Freewater, four feeders were estimated to reduce their consumption by about 26 kW, on average (about 0.8% of the average load), while the feeders' voltages were reduced by about 1.5%.

The project made no conclusion about the conservation voltage reduction impacts of tests conducted by Peninsula Light Company. The measured voltages were not found to have been altered at the times the utility said it had reduced the voltage, and the changes in system power, too, were insignificant.

The first NorthWestern site in Helena, Montana, consumed 16.6 ± 1.5 kW less when the IVVC system was "Engaged" than it did while it was "Not Engaged." That is about 0.9% of the average power on the circuit during 2014 and about 0.4% of the peak power during 2014. The second site, on the east side of Helena, produced inconclusive results.

Reactive power was managed at Idaho Falls (Section 11.2) and Lower Valley Energy (Section 12.6), where a static volt-ampere reactive compensator was installed. The power factors on two Idaho Falls test feeders were improved to better than 0.99, which suggests that feeder line losses were likely reduced by 7.5 and 22% at the two feeders. At Lower Valley Energy, line losses were likely reduced by between 7.5 and 33%.

A more complex integrated control of both voltage and reactive power was installed and tested by Avista Utilities. The system attempted to optimize both. Because of the tradeoffs in this optimization, one of the feeders was observed to have actually increased its voltage at the times the system was active. The installation was preceded by a careful correction of static power factors in the April 2013 time frame. Much effort was also expended to make the remote end-of-line voltage metering sufficiently accurate to safely support the system's automated distribution control. The project estimated that the system could conserve 2.1% of Pullman's energy consumption—similar to the utility's estimate of 1.85%. The power factors of the controlled feeders were noticeably improved while the system was active. Perhaps four of the feeders reduced their line losses by more than 1%, and the biggest feeder impact might have resulted in about a 4.6% reduction in its line losses. Avista Utilities estimated that the distribution automation will save about $500,000 per year in Pullman.

3.4 Renewable Energy

This subsection reports on solar photovoltaic and wind renewable energy generation assets at scales typically installed by customers or communities. At these scales, the monetary value of generated renewable energy lies primarily in the displacement of electrical energy, avoided power kWh purchases as well as mitigating system peaks (kW) and avoiding demand charges, that must otherwise be supplied to the electrical distribution system.

The total energy production of each renewable generator system was evaluated by season and by year. For utilities supplied by the Bonneville Power Administration, production may be evaluated separately for heavy-load and for light-load hours, during which a utility's energy supply charges may differ. The yearly energy production may be compared quite directly against the annualized cost of constructing and operating the renewable generator system.

The average rate of renewable energy generation—power—is evaluated for hourly or even shorter intervals. Once the typical hourly generation profile of a renewable resource is known by month and hour, the impact of the renewable generation on demand charges (where these exist) may be estimated.

Many of the project's renewable energy generators were at the Ellensburg Community Renewable Park in Ellensburg, Washington. Residents of Ellensburg could purchase shares in the energy production of the generators at this community park. The municipality installed, maintained, and completed distribution connectivity of these generators for the residents. It thereby consolidated renewable resources that might otherwise be installed piecemeal throughout the city. The experiment with wind turbines encountered a number of challenges, and when one of the turbine towers failed, the City of Ellensburg committed to quickly remove all of its towers.

Two subsections below address the two types of renewable energy being demonstrated—solar and wind renewable generator systems.

3.4.1 Solar Renewable Energy Systems

The PNWSGD included five solar energy generator installations. These installations are listed in Table 3.2 along with their nameplate power capacity, demonstrated seasonal energy production, and calculated seasonal capacity factors. A *capacity factor* is the system's average power production divided by the system's nameplate power rating. The table also lists the report sections where additional details about the project's analysis may be found in this report. Two of the four systems were installed at the City of Ellensburg Renewable Energy Park, one was installed at the Lower Valley Energy Hoback Substation in Bondurant, Wyoming, and two were installed on the University of Washington Campus in Seattle, Washington. The reporting of capacity factors and actual seasonal energy production for these arrays should help others in the Pacific Northwest decide whether to pursue similar installations.

The seasons here are defined as sequential 3-month groupings of months December through February (winter), March through May (spring), and so on.

Unlike the wind turbine systems reported in Section 3.4.2, energy production from solar generators was relatively reliable and predictable. For each system, in seasons having the greatest energy production, production was about 2 to 4 times as much as in the seasons having the worst energy production. Capacity factors ranged from about 9 to 40%.

Table 3.2. Seasonal Nameplate Capacity, Energy Production, and Capacity Factor for the Demonstrated Solar Generation Systems

Site/Technology	Nameplate Capacity (kW)	Report Section	Season[a]	Energy Production (MWh)	Capacity Factor (%)
City of Ellensburg – Polycrystalline	56	9.2	**Project**	**165**	**33.8**
			Summer 2012[b]	9.45	41.9
			Fall 2012	16.5	31.4
			Winter 2012	10.7	24.6
			Spring 2013	23.7	35.9
			Summer 2013	26.8	36.4
			Fall 2013	19.3	33.4
			Winter 2013	10.7	25.2
			Spring 2014	20.3	35.1
			Summer 2014	28.0	37.9
City of Ellensburg – Thin-Film	54	9.3	**Project**	**173**	**34.5**
			Summer 2012[b]	17.6	35.5
			Fall 2012	15.9	31.4
			Winter 2012	10.3	24.6
			Spring 2013	23.8	37.4
			Summer 2013	27.5	38.7
			Fall 2013	18.9	33.9
			Winter 2013	10.1	24.6
			Spring 2014	20.1	36.2
			Summer 2014	28.4	39.9
Lower Valley Energy	20	12.8	**Project**	**39.8**	**34.4**
			Fall 2012[b]	1.97	29.4
			Winter 2012	4.56	28.0
			Spring 2013	9.58	39.5
			Summer 2013	9.58	36.8
			Fall 2013	5.87	33.9
			Winter 2013	4.02	28.2
			Spring 2014	3.94	40.0
			Summer 2014[b]	.208	25.4

Table 3.2. (cont.)

Site/Technology	Nameplate Capacity (kW)	Report Section	Season(a)	Energy Production (MWh)	Capacity Factor (%)
University of Washington – Small − Mix of Thin-Film, Mono- and Polycrystalline Technologies	6.2	17.3	**Project**	**13.7**	**30.5**
			Summer 2012(b)	0.289	34.8
			Fall 2012	1.26	24.3
			Winter 2012	0.423	11.2
			Spring 2013	2.19	33.7
			Summer 2013	3.31	45.6
			Fall 2013	1.12	22.2
			Winter 2013	0.490	12.8
			Spring 2014	1.57	32.0
			Summer 2014	3.06	39.9
University of Washington − Large	67.2	17.3	**Project**	**76.8**	**19.4**
			Summer 2013(b)	18.6	25.9
			Fall 2013	11.6	14.5
			Winter 2013	6.38	9.13
			Spring 2014	14.2	20.8
			Summer 2014	26.1	24.5

(a) Seasons have been defined as winter (Dec. – Feb.), spring (Mar. – May), summer (Jun. – Aug.), and fall (Sep. – Nov.)
(b) Data was incomplete for this period.

For most of the demonstrated solar power generation installations, the project was able to further estimate the monthly energy production by light- and heavy-load hours. This then allowed the project to estimate the value of the supply energy that might be displaced by the solar power generation each calendar month. For the two utilities supplied energy by Bonneville Power Administration, the project also estimated the impact the generation would have on the demand charges that are incurred by the utilities.

3.4.2 Wind Renewable Energy Systems

The PNWSGD included 10 small- and medium-scale wind turbine installations. Nine of the 10 were installed at the City of Ellensburg Renewable Energy Park. The capacities and energy production from these nine systems are summarized in Table 3.3. The table further lists the report sections where more details about the project's analysis of these wind turbines may be found. Columns of the table also report the nameplate power generation capacities and installed tower hub heights of these installations. Total energy generation is listed for each project season for which data was available and is summed for the entire project. The last column states the capacity factor, which is the average power generation divided by the system's nameplate generation capacity.

The referenced report sections contain additional details about monthly generation from these systems during light- and heavy-load hours. For some of the systems, the project could estimate the value of the supply energy that might be displaced by the wind turbine generators each month. For many of the systems, the project was further able to estimate the likely impact they would have each calendar month on the demand charges that are incurred by the utility.

Table 3.3. Seasonal Nameplate Capacity, Energy Production, and Capacity Factor for City of Ellensburg Wind Turbine Systems

Make/Model	Report Section	Capacity (kW)	Height (ft)	Season	Energy Production (kWh)	Capacity Factor (%)
Honeywell WindTronics® WT6500[c]	9.4	1.5	37	**Project**	**10**	**0.24**
				Fall 2012[a]	0.155	0.03
				Winter 2012	8.60	0.27
				Spring 2013[a,b]	1.46	0.30
Windspire® v1.2[c]	9.5	1.2	35	**Project**	**38**	**0.68**
				Summer 2012[a]	17.9	2.46
				Fall 2012	9.93	0.38
				Winter 2012[a,b]	9.83	0.84
Home Energy International Energy Ball® V200	9.6	2.5	50	**Project**	**160**	**0.67**
				Fall 2012[a]	13.1	0.31
				Winter 2012	18.8	0.35
				Spring 2013	54.2	0.99
				Summer 2013	66.3	1.21
				Fall 2013[a,b]	7.12	0.21
Southwest Windpower Skystream® 3.7	9.7	2.4	51	**Project**	**1,782**	**7.11**
				Summer 2012[a]	30.7	1.72
				Fall 2012	49.9	0.97
				Winter 2012	243	4.68
				Spring 2013	612	11.7
				Summer 2013	726	13.9
				Fall 2013[a,b]	121	4.91
Bergey WindPower Excel 10	9.8	10	95	**Project**	**6,945**	**8.39**
				Fall 2012[a]	46.5	1.36
				Winter 2012	1,001	4.63
				Spring 2013	2,480	11.4
				Summer 2013	2,887	13.2
				Fall 2013[a,b]	531	3.78

Table 3.3. (cont.)

Make/Model	Report Section	Capacity (kW)	Height (ft)	Season	Energy Production (kWh)	Capacity Factor (%)
Tangarie Gale®[c]	9.9	10	97	**Project**	**431**	**3.05**
				Summer 2012[a,b]	431	3.05
Urban Green Energy[c]	9.10	4	115	**Project**	**664**	**2.87**
				Summer 2012[a]	389	6.55
				Fall 2012	194	2.63
				Winter 2012	71	0.82
				Spring 2013[a,b]	11	0.91
Ventera VT10	9.11	10	-	**Project**	**5,824**	**8.30**
				Winter 2012[b]	662	5.47
				Spring 2013	2,131	9.76
				Summer 2013	2,524	11.6
				Fall 2013[a,b]	506	3.51
Wing Power Energy[c]	9.12	2	-	**Project**	**338**	**1.63**
				Summer 2012[a]	69	4.67
				Fall 2012	75	1.77
				Winter 2012	28	0.64
				Spring 2013	73	1.27
				Summer 2013	81	1.86
				Fall 2013[a,b]	11	0.59

(a) Data is incomplete for this season.
(b) Asset was taken out of service during this season.
(c) These systems were not functioning by the time they were dismantled in fall 2013.

Five of the nine demonstrated City of Ellensburg wind turbine systems had failed by the time the city removed them in fall 2013. This accounts for the different numbers of seasons for which data were reported for the nine systems. After a turbine tower collapsed, the city resolved that wind systems should not operate so close to residential foot traffic in the Renewable Energy Park. The PNWSGD collected data as long as it remained available.

The tenth wind turbine system was installed by Lower Valley Energy at its Hoback substation—four 2.5 kW WindTronics Energy Solutions wind turbines. Power data from all four turbines was received from October 26, 2012 until September 1, 2014. A total of 16,046 hourly records were received in this period but 13,398 of the records were zero. Of the remaining records, 335 showed a total of 52.37 kWh being produced, mostly in 0.13 kWh increments (285 of them), and 313 showed 74.35 kWh as being *consumed*, again mostly in 0.13 kWh increments (310 of them). Project analysts could not determine whether the badly discretized production and consumption values were meaningful. The product's vendor closed on January 14, 2013. Some additional analysis details may be found in Section 12.9 of this report.

According to Table 3.3, the turbine systems' seasonal capacity factors were quite low, ranging from 0.3 to almost 14%. The systems having greater nameplate capacities typically achieved significantly better capacity factors than did the smaller, residential-scale turbine systems.

4.0 Transactive System Test Cases

Additional chapter coauthor: RB Melton – Battelle

The Pacific Northwest Smart Grid Demonstration (PNWSGD) transactive system described in Chapter 2 interacted with 30 asset systems at 10 of the 11 participating utilities. Chapter 2 described the functionality and general performance of the transactive system itself. This chapter summarizes the transactive system's requests for asset responses and the assets' actual responses. The project had requested that these assets be made responsive the PNWSGD transactive system, but the asset systems' responses were analyzed regardless whether they had been initiated by the transactive system or by alternative utility objectives and processes.

4.1 Asset System Summary

All of the utilities except the City of Ellensburg integrated one or more of their asset systems with the dynamic PNWSGD transactive system. Each utility established one or more transactive sites that received transactive incentive signals that had been calculated specifically for that site. The incentive signal was interpreted by one or more transactive toolkit functions at the utility site, and an asset control signal (ACS) output was provided from the site to the asset system's controller. The ACS was designed to request demand-response event periods from the asset system.

There are several important points to note about the interface between the transactive site and the asset system. First, just because the transactive site requested an event does not mean an event happened. In some cases the asset system had a human operator, and that person made the final decision whether to respond or not. A special case of this was output of requests to in-home-displays, in which case the energy customer made the final decision whether to respond or not.

Even when the responses were automated, utilities placed limits on the number of allowed responses. Customer agreements often specified a maximum number of allowed events in a month. Conventional demand-response programs, either direct load control or otherwise, are generally event-driven and are targeted toward managing few, short-lived incidents like critical peaks. Several well-placed asset responses may be adequate for conventional demand-response programs. Transactive systems, on the other hand, reveal a continuum of incentives to the utilities and asset system controllers and could engage assets much more dynamically according the each asset's capabilities and the flexibility of the asset's owner. This granularity of responses by many customers enables those customers who are both willing and able to respond (via automated systems) to participate according to their preferences rather than having their participation limited according to pre-determined agreements.

The responsive asset systems are summarized in Table 4.1. The primary assets were residential systems including water heaters with demand-response units, programmable thermostats, and smart appliances. In-home displays were also used by a small number of the utilities. Other assets included utility-scale battery storage, several types of distributed generators, building or commercial systems, and dynamic voltage control.

Table 4.1. Responsive Asset System Implementations at Transactive System Sites

	Residential	In-Home Displays	Battery Storage	Distributed Generation	Building / Commercial	Voltage Control
Avista Utilities	X	X		X	X	
Benton PUD			~~X~~[(a)]			
Flathead Electric Coop.	X	X				
Idaho Falls Power	X[(b)]		~~X~~[(a)]			X
Lower Valley Energy	X		X			
City of Milton-Freewater	X					X
NorthWestern Energy	X	X				
Peninsula Light Company	X					X
Portland General Electric	~~X~~[(b)]		X	X	X	
University of Washington				X	X	

(a) This asset system was eliminated due to the vendor going out of business.
(b) This residential water heater demand-response component was cancelled due to safety concerns.

4.2 Transactive System Costs

The project's transactive system may be coarsely divided into distributed and centralized infrastructure.[1] The costs of distributed infrastructure are allocated to the individual asset systems and their test cases in the project's model for tracking costs. The infrastructure required for a responsive asset system to participate in the transactive system might include

- system software
- computers, servers, or other computational infrastructure that can host system software
- network connectivity (almost exclusively internet for the PNWSGD participants)
- licenses, if required for access to needed software, hardware, or intellectual property
- backroom expenses (e.g., server and data management)
- security costs, including the costs to design and manage performance dashboards or otherwise monitor the system
- design labor
- installation labor expended for this infrastructure.

[1] The conceptual system model does not require centralized infrastructure. The objectives of transmission zones, which represent large bulk parts of transmission and generation in the Pacific Northwest, are represented centrally with Alstom Grid acting as surrogate owner of bulk generation resources and transmission. If the system were more distributed, as allowed in the conceptual model, one might instead discuss costs of participation in a transactive system at nodes that represent utilities, premises, or devices, but there would unlikely be a centralized part of the system to address.

Table 4.2 shows the annualized costs of transactive systems that were installed and implemented by the respective utilities at their sites.

- "Transactive Node": This column includes the equivalent annualized cost for installing, implementing, and testing the transactive nodes, and addressing cyber security at the respective utility sites. The annualized costs were calculated using the reported (and assumed when missing) lifetimes of the constituent system components. This column does not include the costs asset systems that were to be integrated with the transactive system.
- "Transactive Node and Equipment": This column includes both the equivalent annualized cost of transactive nodes, as listed in the column to the left, plus the annualized costs of asset system equipment, such as advanced metering infrastructure (AMI), responsive devices (e.g., water heater controllers), in-home displays, battery systems, voltage control devices, etc., that were procured by the utilities. The costs associated with the network infrastructure required for communications between the utility transactive site and the meters/devices are included in this column, too. Costs associated with licensing, customer participation incentives, etc., are also included. The costs of those components that were shared by more than one of a utility's asset systems were pro-rated across the asset systems. That is, the costs were allocated to the cost of the asset systems based on the reported proportional usage of that component by the various asset systems. For instance, if AMI was used by two asset systems, then 50% of the AMI's cost was likely allocated to the cost of each asset system.

Table 4.2. Transactive Asset System Costs Deployed by the Utilities

	Transactive Node (Annualized $K)	Transactive Node and Equipment (Annualized $K)	Affected Electricity Consumers (Thousands)	Number of Deployed Asset Systems
Avista Utilities	343	3,479	314	7
Benton PUD	26	84	39	1
City of Ellensburg	-	-	9	-
Flathead Electric Cooperative	377	788	48	6
Idaho Falls Power[(a)]	451	614	22	3
Lower Valley Energy[(b)]	8	209	29	2
City of Milton-Freewater	10	230	5	3
Northwestern Energy[(c)]	-	668	335	4
Peninsula Light Company	9	558	26	2
Portland General Electric[(d)]	109	2,485	714	4
University of Washington	156	1,100	355	3

(a) Includes PHEV (655K, 158K) and automated voltage regulation (557K, 117K) asset system costs that were not implemented
(b) Transactive node cost is only the cost of transactive signal integration. There may be other transactive node related costs that are not explicitly reported.
(c) Cost of transactive node system is not explicitly reported
(d) Includes cost of battery system

There is no obvious correlation between the service territory population and the costs of deploying the transactive asset systems. The project expected to observe a weak correlation between the costs of establishing a transactive site and the complexity of the sites, but the costs also do not show any discernible pattern with the number of asset systems. A deeper study is required to discern any relationship of deployment costs with the complexity/sophistication of the backend systems (energy management system, distribution management system, etc.), number of responsive assets, types of communications infrastructure, etc.

In the PNWSGD cost model, we must also sum the cost of the centralized infrastructure and fairly allocate these centralized expenses among the transactive asset systems. The following Table 4.3 shows the cost of centralized parts of the project's transactive system, i.e., the equipment needed to enable interaction of the utilities' transactive node sites with the project's central operations center.

Table 4.3. Costs of the Centralized Parts of the Project's Transactive System

Equipment Type	Description	Cost ($K)
Computer	Computer Servers	59
Data Storage	Data Servers	46
Appliance	Firewall Network Security Equipment	316
Switch	Network Switches	2
Total		**$423K**

The project elected to track costs primarily from a utility's perspective, and the above-listed costs of centralized infrastructure become calculated and allocated quite naturally to the utilities, which often assumed the role of an aggregator in the PNWSGD. The participating utilities worked closely with the project to state the costs of their asset systems. These costs are archived in sets of spreadsheets that the project refers to as "subproject workbooks" and are summarized in cost tables where the utilities' asset systems are discussed in Chapters 7–17.

A lesson learned was that vendors in the smart grid arena often prevent their utility customer from revealing specific cost information. This environment of secrecy sometimes forced the project to only report highly aggregated cost information, from which the costs of individual components could not be accurately inferred.

As a demonstration effort, the PNWSGD certainly incurred research and development costs that might not apply to the next system implementation. The project's cost model strives to estimate the costs of a second implementation of the project's transactive system. In summary, the centralized cost of the transactive system that must be allocated among all the transactive asset systems, including installation and design labor is about $850,000, which was estimated by doubling the equipment costs that were listed in Table 4.3.

Note that many of the centralized and the distributed asset system expenses of a transactive system would almost certainly have been expended similarly if one were to implement a more traditional demand-response program instead of a transactive system.

4.3 Addressing Impacts of Demand Charges

Explicit functions were applied at project sites Flathead Electric Cooperative, Lower Valley Energy, and the City of Milton-Freewater (see Table 4.4) to help them reduce their demand charges. These are among the project's utility participants that are Bonneville Power Administration (BPA) Preference customers and are therefore subject to BPA demand charges. The purpose of these functions was to predict and observe utility demand and to estimate the demand charges that are accruing as new monthly peak demands are becoming established. The calculated demand charges are then added to the sites' incentive signal and may thereby induce the sites' asset systems to respond. The resulting disincentive should encourage loads to curtail and generators to engage. The demand charges are real, and utilities are economically rewarded if they can avoid them.

Another demand-charge function was applied at the University of Washington campus. However, this location addressed both peak demand charges and daily time-of-use charges that the campus pays to Seattle City Light, its electricity supplier.

Even if a peak magnitude is accurately predicted, minor differences in the prediction of the new peak event may cause the demand-charges disincentive to be entirely misplaced in time. If this approach is used again in the future, implementers are advised to spread the impact over time to address the uncertainty with which the peak can be predicted in time.

Finally, load predictions must be informed by recent measurements of the load that is being tracked. Our site implementers did not provide and use such measurements. Consequently, load predictions were too inaccurately modeled, and the component influences from demand charges were not predicted and applied by the project as well as should be possible.

Table 4.4. Summary of Demand-Charge Results

Utility	Estimated Demand-Charge Impact
Flathead Electric Cooperative	Reduction of ~$3,500 per year for in-home displays. The in-home display impact was based on extrapolation from data observed during March 2014
	Reduction of ~ $1,163 ± 11 per year for demand-response units
	Reduction of ~$190 ± 10 per year for smart appliances
Lower Valley Energy	Reduction of ~$120 ± 40 per year for battery system
City of Milton-Freewater	Reduction of ~$4,400 ± 1,300 per year for water heater demand response estimated
	Reduction of ~$1,620 ± 260 per year for voltage responsive water heater demand response
	Reduction of ~$4,400 ± 1,500 per year using conservation voltage reduction on feeders 1–4
University of Washington	Insufficient data to estimate

The results are not especially compelling, but do show promise for use of demand response to avoid demand charges. Whether automated or manual, the challenge is for the utility to accurately predict the peak heavy load hour (HLH) every month. The project tested algorithms to automate this with limited success. Increasing the number of asset systems' allowed events and their durations would increase the probability of reducing load during the HLH and thus the impact of the program. Another challenge is the ability to accurately predict load in a distribution system, a key input into an automated demand-charge-management algorithm. Based on the PNWSGD experience, the project believes that such algorithms can be improved with further research.

4.4 Summary Asset Responses

The following steps were to occur as an asset system responded to the project's transactive system:

First, presuming that the site node hosts a functional interface (i.e., a *toolkit load function*) between the transactive system and one of its asset systems, the functional interface reviews local conditions and the incentive signal and determines if and when the asset system should respond. Many, but not all, the asset systems respond in a discrete way with discrete events in time (usually *curtailment* events).

One output from the functional interfaces to the physical asset system advises it when and how much it should respond.[1] Another output from the functional interface predicts the change in energy consumption if the asset system responds as it has been advised, based on a dynamic model of the asset system that resides at the functional interface.

The next two paragraphs address data collection practices that the PNWSGD established to record and confirm asset's responses:

When the asset system, in fact, becomes engaged, regardless of the reason, a confirmation is submitted to the project in the form of a *test-case event* indicator.[2] Accompanying the test-case event indicator is the new status. For example, if an asset system becomes curtailed, the asset system might send the project a test-case event indicator titled "curtailment status has changed" along with the asset's new status "curtailed." Another test-case event should be sent to the project at the time the asset system returns to its normal status.

While not a feature included within the transactive system, the project asked asset system implementers to supply meter instrumentation with which the magnitudes and timing of asset system responses can be verified. Therefore, the project received two independent assessments of the change in energy that accompanies an asset's responses—the measured response and the change in energy that has been predicted for the asset system by the functional interface (i.e., by the *toolkit load function* and its *asset model*). The predicted change in energy for the asset systems was discussed in Chapter 2 "The

[1] A clever, normalized, *advisory control signal* was developed by and specified by the project. This byte signal ranges over [−127, 127] to represent an asset's entire normalized capacity to consume or generate, based on fractions of nameplate ratings.

[2] The test-case event indicator was implemented as part of the PNWSGD data collection system. Future implementers should consider integrating this validation signal into the transactive system. It is different from most transactive system data in that it does not include predictions.

Transactive System." In this chapter the analysis of the measured responses is summarized. The details of the analysis are found in Chapters 7–17 for the corresponding utilities.

Table 4.5 summarizes the responses of all asset systems.

Table 4.5. Asset System Response Summaries

Site Owner	Site	Asset Description	Number of Events Observed	Number of Response Points	Average Observed Response
Peninsula Light Company	Fox Island, WA	Water Heater Control	217	500	NMI
		Dynamic Voltage Management	-	6 capacitor banks	NMI
University of Washington	UW Campus, Seattle, WA	Building HVAC Management	-	1	Insufficient data
		Two Diesel Generators	32	2	Insufficient dispatch and data
		Steam Turbine	136	1	+253 ± 29KW summer; +468 ± 91 kW winter
Portland General Electric	Oxford Rural Feeder, Salem, OR	Residential DR	-	20	No Data Received
		Commercial DR	-	8	NMI
		Distributed Generators	-	3	-
		Battery Storage	Indeterminate	1	No observable response relationship to incentive signal
City of Ellensburg	Renewable Energy Park, Ellensburg, WA	None	-	-	-
Benton PUD	Reata Feeder, Kennewick, WA	Energy Storage Modules	-	5	No useful data received
Avista Utilities	Pullman, WA	Residential DR	636	57	18 W reduction per premises
		Dynamic Voltage Control	-	13	Test Case Cancelled
		WSU Tier 1 HVAC Control	12	39	239 ± 41 kW reduction during events
		WSU Tier 2 Chiller Control	5	9	0.38 ± 0.07 MW reduction per event
		WSU Tier 3 Diesel Generator Control	2	1	Not dispatched
		WSU Tier 4 Gas Generator control	3	1	Not dispatched
		WSU Tier 5 Gas Generator Control	0	1	Not dispatched

Table 4.5. (cont.)

Site Owner	Site	Asset Description	Number of Events Observed	Number of Response Points	Average Observed Response
Flathead Electric Coop.	Libby, MT	Water Heater Control	19	85 to 92	239 ± 28 W reduction per premises
		Smart Appliances	19	67 to 101	140 ± 40W reduction per premises
		In-Home Displays	56	90	140 ± 80 W reduction per premises
	Marion/Kila, MT	Water Heater Control	20	15 to 21	142 ± 42 W reduction per premises
		Smart Appliances	19	12 to 17	215 ± 43W reduction per premises
		In-Home Displays	7	12	Insufficient data
City of Milton-Freewater	Milton-Freewater, OR	Water Heater (DRU) Control	200	800	100 ± 10W reduction per premises
		Voltage Responsive DRU	217	152	170 ± 40W reduction per premises
		Dynamic Voltage Control	217	5	100 ± 100 kW increase per event
Northwestern Energy	Helena, MT	Water Heater Control and Dynamic Voltage Control	397	0	- -
	Philipsburg, MT	Water Heater Control	-	-	-
		Dynamic Voltage Control	-	-	-
Lower Valley Energy	Teton-Palisades Interconnect, WY	Water Heater Control	306	104	370 ± 80 W reduction per premises
		Battery Energy Storage	3,236	1	$120 ± 40 per year reduction in demand charges
Idaho Falls Power	Idaho Falls, ID	Building DR Management	-	-	Test case cancelled
		Water Heater Control	288	213	Not observable
		Thermostat Control	410	42	0.052 ± 0.054 kW reduction per premises

"-" means that the asset system was never fully connected to the transactive system or data was never provided for the asset system from the site's transactive system implementation.

DR = demand response
DRU = demand-response unit
HVAC = heating, ventilation, and air conditioning
NMI = no measurable impact
WSU = Washington State University

The performance of transactive/demand responsive asset systems varied widely across the project participants. As shown in the table above, some utilities demonstrated very promising results—primarily through manual control of the asset systems rather than response to the project's transactive incentive signal.

In general, the signal-to-noise ratio was quite low. In some cases, the utilities were unable to report the necessarily time-aligned data to analyze the events. For example, voltage management assets permitted the project to independently confirm the event periods that were reported to the project, and the accuracy of the reported events was often found to be inadequate. In the case of Peninsula Light Company, only daily summaries were available at the premises level. Individual premises events were usually unobservable at the feeder level due to their small magnitude of the impacts compared to total feeder load.

The signal-to-noise ratio problem was further compounded by small numbers of response points relative to total feeder population. Several of the utilities were unable to achieve their target numbers of participants.

Overall, the results are encouraging enough that several of the utilities are continuing to use and even expand their demand-response systems. The detailed analysis for each of the utilities' asset systems is discussed in Chapters 7–17.

5.0 Reliability Test Cases

Additional chapter coauthor: YP Agalgaonkar − Battelle

One objective of a smart grid is to improve the reliability of electric power for its end users. Toward this end, Pacific Northwest Smart Grid Demonstration (PNWSGD) utilities automated their distribution systems, including the application of fault detection, isolation, and restoration (FDIR) to more rapidly get customers' power restored after outages. Several of the project's utilities took advantage of automated power-quality alerts that have become available from advanced metering infrastructure (AMI) and new distribution equipment to help them more quickly pinpoint and respond to outages, abnormal supply voltages, and other conditions. Still others installed batteries and automated distribution switching to define high-reliability zones that may separate from the rest of the grid and operate as microgrids when they become threatened by power outages.

Reliability is one of the PNWSGD's three major technology performance report categories. The reliability test case summary provided here is structured as follows. The standard reliability indices definitions are summarized first. Then the effectiveness of smart grid assets such as AMI and FDIR on reliability indices is discussed next. The important lessons learned and utility recommendations conclude this summary.

This next section briefly discusses the reliability indices used by project participants to evaluate the performance of their distribution systems.

5.1 Reliability Indices

Distribution utilities measure the performance of their feeders using standardized reliability indices. These indices measure the utilities' performance while responding to power outages. They provide information regarding the number of customers affected by the power outage, outage duration, etc. These indices enable fair comparison of the performance of different utilities' feeder circuits. A utility can also compare performance among its own feeders. And the PNWSGD further used the indices to validate the benefits that had been anticipated from certain novel smart grid systems and tools, and looked for improvements in theses indices after the new technologies were installed.

Several reliability indices are listed and described in Table 5.1. These indices are defined in accordance with the IEEE guide for electric power distribution reliability indices (IEEE 2004). Typically these indices monitor *sustained* outages, which are interruptions that last more than 5 minutes. Typical annual median values for sustained indices for the U.S. utilities are also listed.

Table 5.1. Distribution System Reliability Indices

Index	Index Definition	Mathematical Calculation	Typical Values (IEEE 2004)
CAIDI	Average duration of sustained customer interruptions	Total customer outage duration/total number of customer interruptions	1.26 hours per interruption
SAIDI	Average total duration that a customer was interrupted by sustained interruptions	Total customer interruption duration/total number of customers served	1.5 hours per customer
SAIFI	Average number of times that a customer was interrupted by sustained interruptions	Total number of customer interruptions/total number of customers served	1.1 interruptions per customer

CAIDI = Customer Average Interruption Duration Index
SAIDI = System Average Interruption Duration Index
SAIFI = System Average Interruption Frequency Index

5.2 Effect of Smart Grid Assets on Reliability

Each of the smart grid asset systems reported in this category has been implemented by participating utilities to improve distribution system reliability or power quality. The analyses relied heavily upon standard reliability indices that were reported to the project by the owners of the asset systems. While the analysis of reliability was found to be consistent throughout this report, the report discusses asset systems into two categories. These subcategories are based upon the minor differences in the types of data collected for reliability analysis. The categories are as follows:

- Effect of AMI on reliability: AMI provides information concerning outages and other performance indicators.
- Effect of distribution automation and distributed generation on reliability: Asset systems facilitate automation that should improve distribution system reliability.

5.2.1 Effect of AMI on Reliability

Two utilities—Flathead Electric Cooperative (Section 10.1), and Lower Valley Energy (Section 12.4)—upgraded their metering infrastructures during the PNWSGD and supplied the project reliability indices to evaluate the impacts of the new metering infrastructure on system reliability. Also, Benton Public Utility District (PUD) (Section 8.1) had installed smart meters at most of its customer locations by the beginning of the PNWSGD project and completed the installations by 2012. Benton PUD's AMI system featured an interesting set of outage and power-quality alerts. Benton PUD provided the historical reliability data from before the AMI was implemented for 2010-2011 period, and its 2014 values were its best system reliability values in recent years. For all years reported by Benton PUD, reliability values were better than the typical System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) values reported in Table 5.1. But the project cannot conclude from this limited data that system reliability improved for Benton PUD due to features of its AMI system.

Similarly for Flathead Electric Cooperative, the historical data prior to and after implementation of AMI infrastructure was not available. The reported SAIFI and SAIDI indices however were mostly worse than the typical values listed in Table 5.1. Lower Valley Energy provided the historic data prior to implementation of AMI, but there was a steady increase in SAIFI values. The project could find no clear trend in the SAIDI value decrement. Thus, for Lower Valley Energy, AMI infrastructure did not necessarily result in measurably better reliability indices. Hence, improved reliability was not clearly evident for any of the three studied utilities and could not be concluded from available reliability data.

Other utilities involved in this project opted for FDIR implementation rather than AMI. Their results are discussed next.

5.2.2 Effect of Advanced Distributed Automation Investment on Reliability

NorthWestern Energy (Section 14.2), Avista Utilities (Section 7.7), Idaho Falls Power (Section 11.3), and Peninsula Light Company (Section 15.3) upgraded their infrastructures using FDIR systems.

NorthWestern Energy installed FDIR on four circuits at one of their sites to automatically reconfigure circuits after an outage and restore service to as many customers as possible. They reported data on distribution restoration costs, CAIDI and SAIDI values from the beginning of 2010 till August 2014. The reported distribution restoration costs from 2010 to 2013 were not significantly different. There was no clear trend for the yearly CAIDI values. SAIDI values reported from 2011 to 2013 were better than 2010. SAIDI values for 2014 were very low, however no clear conclusion could be drawn as data collection only lasted until August. NorthWestern, however, reported anecdotally that the effectiveness of FDIR could not be conclusively established based on the reported data from several events that had occurred since they implemented FDIR.

Avista incorporated FDIR capability and fault circuit indicators within its distribution management system. Avista provided the project with detailed outage information and calculations of several reliability indices; however, the utility later said that its calculations had not excluded certain long outages that should have been omitted from the analysis. The project's comparison concluded that SAIFI values were trending slightly toward worse until the end of the project in 2014. SAIDI values for Avista in years 2013 and 2014 were perhaps slightly trending toward worse as well. The project's findings from the reliability indices were inconsistent with Avista's projections of their avoided outage durations. Avista reported that few outage had occurred during the PNWSGD of the type that would lock out their site's reclosers and engage the capabilities of FDIR.

Idaho Falls Power implemented remotely controlled switches, an AMI system, and fault indicators to quickly detect faults on the feeder. The system was expected to reduce outage durations due to quick identification of a fault's location. Due to limited availability of historical data, the project cannot report any strong conclusions regarding reliability at Idaho Falls. But, Idaho Falls Power reported no outages during the last nine months of the project, which is very promising, providing this trend endures. This promising performance in the last nine months, however, cannot be directly attributed to the utility's investment in smart grid infrastructure.

Peninsula Light Company used supervisory-control-and-data-acquisition connected distribution switches to monitor fault currents. The supervisory-control-and-data-acquisition maintained the real-time status of the connected network and calculated an optimal network configuration. Reliability indices were made available for the months from June 2012 through August 2014. The average SAIDI for all project months at this site was approximately 1 hour. Peninsula Light Company also recorded outage response times. The average of all of its monthly outage response times collected by the project was 2 hours 25 minutes per outage. From the available data, no clear trends in SAIDI values and outage response times were evident. The installation of the FDIR system occurred in September 2012; however, SAIDI values improved only since March 2014. Hence, correlation between the newly implemented FDIR system and improvement in reliability values cannot be fully established.

5.3 Observations and Lessons Learned

- In many cases utilities reported insufficient data to derive requisite conclusions concerning changes in reliability. Where sufficient data was available, smart grid infrastructure did not always yield desired results. In some cases reliability indices became worse.
- Utilities should consistently apply data collection and reliability analysis procedures to study and validate benefits from smart grid technologies. The data collection methods prescribed in the latest IEEE Guide for Collecting, Categorizing, and Utilizing Information Related to Electric Power Distribution Interruption Events (IEEE 2014) can help achieve this.
- This study contributed a novel analysis method to examine the impact of smart grid technologies. The populations of indices before and after the implementation of smart grid technologies are treated as independent sets. Then, Student’s t-test was applied to objectively compare the two populations. The process marches through the successive months and reports whether the indices in the following months have significantly reduced values when compared with those in the preceding months. The utilities should consider this as a practice to continuously observe whether changing distribution utility practices are improving or harming service reliability. Even after using this method, strong conclusions about changes in reliability were difficult to assess among the natural randomness of the infrequent outages.
- Economic impacts from changes in reliability index values before and after implementation of FDIR or AMI systems could not be assessed with project data. No improvement in reliability could be clearly verified in this particular study. Utilities should consistently use accepted data collection practices and calculation procedures. Indices and methods should be revised to better identify best and worst performing feeders, and best and worst performing technologies. Results must ultimately be verifiable.

6.0 Conclusions

The Pacific Northwest Smart Grid Demonstration (PNWSGD) was among the most expansive, inclusive smart grid demonstrations ever conducted. Nineteen organizations participated directly in the PNWSGD. Many other product and service vendors worked tirelessly to supply, install, and support the smart grid equipment that the PNWSGD installed at its various field sites. Many residential, commercial, and industrial electricity customers accepted and interacted with the project's smart meters, displays, and controllable premises-level equipment. Still more individuals trusted their utilities to install and demonstrate novel distribution tools, like distribution automation and distribution-scale battery systems.

This section concludes the reporting of PNWSGD technical performance. After stating some general conclusions, conclusions about the project's transactive system are stated. Given the project's massive data collection efforts, some comments are offered concerning the challenges encountered by the project concerning its data and data collection. Then, some conclusions about each of the three asset categories—demand-responsive (i.e., transactive), conservation, and reliability—are provided. At the end of each section, future research topics addressing the conclusions are listed.

6.1 General Conclusions

The PNWSGD was funded by the U.S. Department of Energy, in part, for economic stimulus. The utilities participating in the project spent about $80M on the region's smart grid infrastructure, and about 88% of that investment remains installed and useful. A project infrastructure highlight is the Salem, Oregon high-reliability zone and its 5 MW distribution battery energy storage system. The buildings on the University of Washington (UW) campus in Seattle, Washington, were largely unmetered prior to the project, but they are now well metered and support continuing conservation efforts on that campus. Residential advanced metering infrastructure (AMI) system installations have been completed throughout six of the project's demonstration communities, and this infrastructure was finished, in part, using support from the U.S. Department of Energy and PNWSGD. Altogether, some 31 thousand AMI end points worth about $21M were installed by the project, and the project utilities reported that another 46 thousand existing meters participated directly or indirectly in the demonstration. Innovative distribution control features and systems were installed at seven of the project's distribution sites.

The project achieved several noteworthy results, including the following:

- The transactive system was deployed, tested, and validated, providing region-wide connection from the transmission system down to individual premises equipment, enabling dynamic response by assets at the end points.
- The participating utilities gained valuable experience in the challenges of deploying and operating smart grid equipment and in the benefits of the equipment in their systems. This experience is guiding their ongoing smart grid investments.
- The basic functionality of the transactive system was confirmed and scale-up analysis using modeling and simulation showed potential for 8% reduction of regional peak load with 30% penetration of demand responding to a transactive system.

Generally, the installations were not easy. Many of the participating utilities reported among their lessons learned that the communications capabilities of various system components were not interoperable. The source of the incompatibility was sometimes different versions of rapidly evolving communication standards, but even system components that were said to use the same standard were not easily integrated.

Some of the product vendors in the smart grid space, too, were found to be immature companies and were at risk of failing. Sets of skid-mounted battery energy storage systems were installed by two of the project's utilities but were unsupported and abandoned when the products' vendor ran into financial difficulties. Several vendors of small, renewable wind and solar generation systems were unable to deliver their products or delivered products that never generated significant energy.

Utilities were free to select their own preferred AMI systems. Not all of the selected AMI systems were found to be equal. In the Pacific Northwest (PNW), where time-of-use retail tariffs are not commonly used, utilities have been selecting their retail meter systems to remotely read meters, remotely disconnect and reconnect service, or automatically report customer outages. Interval power metering is perhaps of secondary importance. The meters' limitations became evident as the project requested from its utilities relatively fine-resolution power data for each premises. In the worst cases, a utility's power line carrier-based AMI system could not collect its customers' interval data at intervals shorter than 1 day.

Limitations were also found for distribution metering. While the smart grid community is promoting AMI, many utilities do not yet have complete supervisory control and data acquisition systems. Distribution metering, where it existed, sometimes included an incomplete set of measurements that did not even support measurement of the impacts that were to be demonstrated.

These challenges suggest that there is a continued need for work on interoperability standards and conformance testing to reduce the cost of integrating smart grid equipment. Third-party testing may be useful to provide independent verification of vendor claims. These general results also underscore the importance of practical, affordable upgrade paths for smart grid systems. Current research on integration of distributed energy resources should identify functional and architectural requirements that utilities can use to plan these system upgrades. As utilities respond to these new requirements, it is desirable that their recent smart grid investments have appropriate upgrade possibilities rather than becoming stranded assets.

6.2 The PNWSGD Transactive System

The PNWSGD featured a transactive system that was designed to incentivize dynamic, distributed changes in electric load that would, in turn, improve the scheduling and dispatch of the region's energy supply. The system was specified, designed, implemented, and ran for nearly two years. During the two-year period the transactive algorithms were tested and refined. Observation of the dynamics of the transactive signals relative to regional grid conditions verified the basic correct functionality of the transactive system. The experience of the project in deploying, testing, and operating the transactive system helped prepare the region to deal with an increasingly distributed grid capable of making maximum use of renewable energy resources and demand-side solutions.

It proved extremely difficult to demonstrate a distributed transactive system in the PNW. The region does not have a structured electricity market that could provide a starting point through, for example, locational marginal prices in the transmission system. Due to the predominant use of bilateral agreements for power purchase, much of the information needed to create the transactive incentive signals at the regional level was difficult to obtain. In spite of this, through the efforts of the Bonneville Power Administration and 3TIER, enough information was available to enable sufficient creation of regional signals using the Alstom models that represented the changing nature of resource availability to demonstrate functionality of the transactive system. Based on the understanding gained through this activity, the region is much better prepared to identify specific operational objectives and opportunities for applying a transactive system, for example, to engage demand-side systems to support wind balancing reserves.

The PNWSGD represented the region's generation and transmission using an "informed simulation." The informed simulation received some real-time status information, including accurate wind generation, but much regional status information had to be derived from representational season trends. The informed simulation had to infer the scheduling tradeoffs and priorities where specific information was lacking and for all of its hour-ahead and day-ahead predictions. A set of interim parameters were defined, by which the influences of multiple resources and incentives could be declared and blended into a single incentive signal. These parameters should be considered as a useful tool at this point, a potential interoperability boundary. The outputs of the informed simulation included a dynamic, location-specific incentive signal that was to represent the delivered cost of electricity at each location and time.

In order to conduct the planned experiment, the project members had to effectively simulate the equivalent of an organized regional market such as PJM Interconnection or Midcontinent Independent System Operator. This is not a trivial task in view of the large investments required to create those markets. According to the project's conceptual model, each of the region's generator sites should have been represented by its own transactive system node, not in aggregate, as occurred in the informed simulation. The project simplified its nodal topology for expediency. But this simplification also allowed the project to defer the solution to an unsolved technical challenge: in a meshed transmission network, the power flow solution must be integrated with the transactive system and must be solved in a distributed fashion. Each site in the transactive system's topology may be assumed to know only its local status. There is no universal reference for voltages in a truly distributed calculation. If this technical challenge is unsolved, a node in a meshed network cannot accurately allocate its export of power to more than one of its neighbors.

Analysis of the transactive system's incentive signals confirmed that they exhibited meaningful responses relative to the resource information used in the informed simulation. Comparison to actual events in the BPA system confirmed that where the informed simulation was capable of representing such events, the events had been represented by the transactive system. Further, the corresponding events advised by the transactive coordination systems at the utilities' responsive assets were often observed to be sensible, though the utilities were often not able to dispatch the corresponding asset system(s).

The PNWSGD transactive system, as implemented in the PNW, could not, in fact, directly influence the region's resource mix at all due to the use of the informed simulation to represent the bulk power system. That meant that part of the conceptual control loop could not be demonstrated. However, a simulation by International Business Machines Corp. closed the control loop and allowed the PNWSGD to simulate the impacts of much higher penetrations of transactive assets and wind generation than achieved and existing in the PNW. The simulation showed that the region's peak load might be reduced by about 8% if 30% of the region's loads were responsive to the transactive system. The simulation also showed that battery energy storage also took advantage of the lowest-cost time periods in a transactive system to recharge its batteries. The interplay between wind energy, seasonal variations, and the impacts of the transactive system was complex and warrants further study.

Unlike previous transactive system designs, the PNWSGD system included a predicted future dimension. All of the system's signals were to include predictions up to several days into the future. We believe this was an important advancement, allowing both supply and load resources to not only react, but also to plan their strategies. In practice, the future predictions were error prone. The incentive signals generated by the informed simulation, for example, exhibited a persistent bias prediction error for predictions more than about 3.5 hours into the future. The responsive asset systems that reviewed the incentive signals to plan their future responses were, of course, confused by the incentive signal's bias errors. Early in the project, many of the daily-event asset systems would review the future incentive signals that they received at the start of a new day, conclude that the future costs were only going to get higher (based on the prediction biases in the signals they had received), and opt to respond now (at midnight) rather than wait.

Utilities largely relied on functions that were designed, configured, and provided to them by the project. One such function predicted the utility sites' bulk electric load. The training of the function was done in bulk, using historical electric load files that had been provided by the utilities. The project analyzed both the relative and absolute accuracies of these load predictions. The absolute accuracies were poor when the training set had been small or unavailable. More future work is recommended to achieve accurate load predictions for distribution utility systems.

A set of functions was also developed to represent the systems of responsive assets that had been installed at the PNWSGD utility sites. These functions determined event periods and automatically advised the asset systems when they should respond. The functions' configuration helped tailor the advice to the asset owners' preferences and objectives. For example, a set of demand-response units (DRUs) could be configured to allow no more than five responses in a month if that were the number of responses promised to the DRU households by its utility. System models estimated the change in load that would accompany the responses. This functional approach for representing the responsive asset systems in the transactive system, while challenging to implement, proved remarkably flexible and resilient. The quality of the resulting advice and modeled impact corresponded to the care with which the functions had been created and configured. The timing of the advised events was found to correspond pretty well to the times that the transactive incentive signals had been relatively high. These functions and their prediction algorithms are a rich area for future research.

Relatively few events were found to have been conducted coincident with the times that the transactive system had requested events. Some of the utilities' reluctance to accept advice from the transactive system was understandable. Early in the PNWSGD, the quality of the incentive signal was poor. This early performance resulted in mistrust of the incentive signal that was not later re-earned. In addition, the transactive incentive signal was not used for revenue purposes, so responses to the incentive signal were not financially rewarded. Furthermore, some of the largest responsive systems lacked automation and relied on human intervention to dispatch events. Functions could be designed to better accommodate systems that lack automation, but the responses of such systems probably will not provide the flexibility that will be needed in future smart grids.

The commercially available responsive asset systems that were implemented by the PNWSGD, while appreciated, probably fell short of the smart grid capabilities that could be supported by a transactive system. First, there were simply too few responsive assets. If the smart grid community truly wishes to avoid dispatching its last resource, for example, the aggregate magnitudes of the available responses must be comparable to both the power and energy of the resource that is to be deferred. Second, each device must offer more responses and more dynamic responses. One surprise during the PNWSGD was that the project's battery system vendors advised or specified that their batteries not be charged and discharged more than about one cycle per day. This limitation potentially limits the grid services that can, in fact, be provided by the batteries. Third, the devices should be designed to take advantage of *both* high-cost disincentive periods and low-cost incentive periods. Especially in the PNW, balancing authorities need more resources that can usefully consume additional energy on demand.

The PNWSGD transactive system design was formalized as a state machine model with corresponding formal definitions of the transactive signals. The design was instantiated in a reference implementation with a corresponding test harness. These project products provide valuable tools for further research, development and deployment of transactive systems.

The PNWSGD also recommends that future transactive systems facilitate dashboards that show the status of the local transactive signals and local responsive assets. Anecdotally, the utilities that had developed their own dashboards became better-informed participants. In its second demonstration year, the PNWSGD developed such dashboards for each of its utility participants and displayed them on Webpages that were accessible by the utilities. This access to the previous day's information seemed to educate participants and rejuvenated their interest in the transactive system.

Based on the experience of the PNWSGD, several further research and development topics associated with the deployment of transactive systems are listed here:

- development of improved load modeling and forecasting techniques
- methodologies for translation of operational objectives into monetized form as the basis for creating transactive incentive signals
- development of libraries of asset system models to be used in construction of asset-specific transactive algorithms
- technical and policy research identifying value streams for utilities and their customers based on continuous engagement of responsive assets in response to signals from a transactive system
- control systems analysis of transactive systems to identify stability and convergence requirements.

6.3 Data and Data Collection Processes

The project analyzed impacts from the asset systems that had been installed at the project's utility sites. The PNWSGD strove to objectively confirm anticipated benefits using the meter data that the project collected.

Early in the project term, project staff met individually with the utilities to resolve what was to be tested and how the project might objectively confirm anticipated benefits. It was surprisingly challenging to resolve with the utilities precisely how many systems were to be tested and what the systems comprised. Some utilities accepted advice about how the demonstration components might be refined to improve the likelihood that impacts would be observed and would not be confounded by the behaviors of their other asset systems. Not all of the participating utilities were convinced that rigorous tests of assets' performances were necessary, preferring instead to test the ease with which the systems could be installed and the levels of satisfaction that were reported afterward by their customers.

Especially the smallest utilities preferred to contract out their data expertise. This worked in some cases, but not in others. Most participating utilities seemed challenged to access or accurately represent the data that they had at their disposal. The smart grid community should perhaps be concerned that in the midst of the vast amounts of new data that has begun to flow into utilities, the utilities' ownership and knowledge of its own data and data processes is often lacking. The most common errors encountered among the data received from utilities were mistaken applications of units of measure, incorrect meter scaling, and timestamp errors. Accurate data dictionaries are recommended at every stage of data collection to state the provenance of the data and to reduce uncertainties about its correct interpretation.

Project analysts were eventually able to resolve many, but not all, of the discrepancies. The project had limited automated data checking, primarily for the transactive system data. For the other test cases, the process was primarily manual. As a result, the analysts found it challenging to review the data as it was received, and often had time delays in resolving missing data or other inconsistencies with the utilities. This underscores the value of applying automated data checking whenever practical.

Time interval data records are inherently challenging. The project operated across multiple time zones. Therefore, the project had specified that data should be submitted using the coordinated universal time standard, which is independent of time zone and daylight standard time transitions. Utilities should indeed use the universal time standard, but the advice possibly caused as many errors as it avoided. The data collection team could not confidently assert which of the received data had been converted or not. The uncertainty was renewed near changes in daylight savings time, which might, or might not, have been correctly addressed by the sender.

One conclusion of the project is that better tools and techniques are needed for utilities to operate and maintain smart grid equipment. They must be able to observe that the intelligent end devices and other system components are operating correctly and providing valid data. There is a corresponding need for improved data management and decision support tools to get full benefit from the newly available data. As an example of such a tool, the project implemented a visualization tool as a means of making the transactive system data easier to evaluate for other researchers.

Research that can support improved means for utilities to deal with the onslaught of data from smart grid technology includes the following:

- standardized approaches to data quality, including methods and tools for continuous monitoring of data streams to assure that devices and systems are operating as intended
- distribution system situational awareness tools for operator monitoring of the operational status of smart grid systems

- model-based assessment of sensor-system and intelligent end-device operation, providing a basis for detecting abnormal operation.

6.4 Reliability Assets

Six of the PNWSGD utilities established fault detection, isolation, and restoration systems or took advantage of features of their AMI systems to avoid outages and reduce outage durations. The project attempted to verify that these systems had significantly improved their corresponding circuits' reliability. Toward this end, the utilities submitted one or more of the standard reliability indices chosen from among the System Average Interruption Frequency Index, System Average Interruption Duration Index, and Customer Average Interruption Duration Index. The utilities reported that their operational experience with the reliability improvements was positive.

Service reliability and power quality are already good in the PNW, and reliability events are infrequent. Project analysts were not especially successful at confirming improvements from these reported indices. For the few utilities that reported monthly calculations and supplied their indices from well before the systems had become installed and useful, significant improvements could not be detected. This is attributable, in part, to the unpredictability and natural randomness of outages, but there were other challenges, too. At least one utility was found not to have calculated the indices according to accepted practices. Little historical data was made available from long before to the installations. And uncertainty remained about precisely when and where the utilities were reporting their systems to have become activated.

There is nothing fundamentally wrong with the present set of reliability metrics. If they are to be used to validate trends and changes in service quality, as was the intention here, the utilities should calculate the indices monthly and for each circuit. Where monthly data was available, the project performed a Student's t test to objectively compare the service reliability before and after historical months. This method found some significant trends, but the trends were either contrary to expected outcomes or occurred at times other than when the utilities had reported their systems became active.

Some utilities reported outage minutes that they had avoided, a calculation derived, sometimes automatically, from their outage management systems. These numbers were quite favorable toward the applied technologies. However, this derived index begs the question, why don't these avoided outages appear to have affected the conventional index calculations?

Given that reliability events are infrequent, making it difficult to gather field data, there is an ongoing need for standard approaches to modeling and simulation of reliability improvements, with models validated using live data. This can improve the consistency of the calculations done in back-office systems and aid utilities in evaluating the benefits of reliability-related investments in smart grid technology.

6.5 Conservation / Efficiency Assets

Approximately one-third of the PNWSGD asset systems were tested for the impacts of long-term conservation and efficiency that they offered.

Efficient equipment. Two asset systems were implemented by Avista Utilities at the Pullman, Washington site to replace less-efficient equipment with new, efficient replacements. By replacing about 2 miles of inadequate distribution feeder lines, the utility estimated it will conserve about 29.6 MWh/yr. The utility also replaced aging transformers with efficient, smart transformers, which also offered useful new voltage and power meter points to the utility.

AMI. Several PNWSGD utilities wished to learn whether the installation of AMI itself or in combination with AMI, Web portals, or other devices affected premises energy consumption. By installing AMI in Pullman, Washington, Avista Utilities estimated it will save $235 thousand per year, mostly through operational efficiencies like reduced meter reads and truck rolls. In Idaho Falls, Idaho, the installation of AMI appeared to have reduced premises consumption by about 92 kWh per year, but the decrease could not be found for residents who had received both AMI and an in-home display (IHD). Lower Valley data suggested that its members conserved 270 W, on average, upon receiving AMI, but less (210 W) when they also received an IHD.

Similarly, the UW evaluated whether its building managers would conserve energy if informed by either its real-time facility energy management services displays or by simpler monthly reports made available to them.

Power factor correction. Both Idaho Falls Power and Lower Valley Energy invested in equipment that would improve their feeders' power factors. These efforts were successful and should reduce line losses from 7 to 30% on those feeders. Much of the impact was available from simple, one-time reviews and corrections of the affected feeders.

Voltage management. Six PNWSGD utilities demonstrated voltage management alone or integrated with reactive power management. Avista Utilities was confirmed to be able to conserve about 2% of its load in Pullman, worth approximately $0.5 million per year, using Integrated Volt/VAr Control. Idaho Falls and Milton-Freewater also demonstrated strong conservation savings on their distribution feeders. The performance of the Lower Valley Energy system was mixed and was found to have diminished after a strong project start. As was the case in Milton-Freewater, the short-term voltage reductions were calculated to have increased, not decreased, premises consumption. This preliminary finding warrants further investigation.

Renewable generation. The PNWSGD demonstrated 4 solar photovoltaic (PV) and 12 residential- or commercial-scale wind turbines. All of the PV systems performed well and generated power and energy commensurate with their system ratings. That was not the case for the wind turbines. Approximately half, once installed, generated significant amounts of energy, but the others never demonstrated their nameplate potentials. Two of the PV arrays and 11 of the wind turbines had been installed at an innovative community solar park in Ellensburg, Washington. Residents were able to buy shares of the park's renewable generators instead of installing their own. Regrettably, one of the turbine towers failed during the demonstration, and the city elected to remove all of the wind turbines, fearing danger to foot traffic in the park.

In general, conservation and efficiency is an area that is mature and well understood, particularly in the PNW. As smart grid technology is used for conservation and efficiency purposes, however, the challenges related to data quality and situational awareness apply. Research in improving the ability of utilities and asset owners to operate information-enabled conservation and efficiency technology is needed to help assure the quality and integrity of the data generated by these systems.

6.6 Dynamically-Responsive (Transactive) Assets

The PNWSGD demonstrated several classes of assets that may be dynamically controlled. The project established a transactive system and preferred that these assets respond to the transactive system's advice. The project intentionally did not prescribe to the utilities that they directly respond to the transactive system. In most cases, the utilities chose to have a conventional demand-response system, often with a "person in the loop," respond to asset control signals from their local transactive system node. In several cases, the conventional demand-response systems included customer participation agreements that limited the frequency and duration of responses. These systems could also be dispatched by the utility independent of the transactive system. The project analysts worked to quantify the assets' change in power consumption during events, regardless of how events had been initiated. The following classes of assets were demonstrated by the PNWSGD utilities:

Portals and IHDs. Participating utilities sent either binary event indicators or tiered pricing information to Web portals and IHDs. Building occupants, upon receiving these notifications, were to respond by voluntarily shutting off or deferring the operation of electric loads. An interesting finding at Flathead Electric Cooperative was that while a small power reduction occurred during IHD events, the impact seemed to continue past the end of the events. It was a *softer* response than what might be observed from systems that directly engaged electric loads. Unfortunately, Flathead Electric Cooperative chose to remove its IHDs amid concerns that audible beeps from the devices were irritating its members.

Thermostat systems. Three utilities installed communicating thermostats alone or as part of a larger suite of premises devices. The thermostats moved the temperature set points up or down by a couple degrees during events to reduce premises power consumption. The calculated impact, on average, was 52 W per premises at the Idaho Falls, Idaho site. The calculated impact might have been higher had there not been questions about the timing of the events and data available for additional months.

Heating, ventilation, and air conditioning (HVAC) control. At the two Washington universities, components of the buildings' HVAC systems were made responsive. Short-term curtailment of air circulating fans on the Washington State University (WSU) campus achieved a 240 kW reduction, and reducing chiller load yielded a 380 kW reduction. The UW campus implemented similar control on some of its buildings' HVAC systems.

DRU control of water heaters and air conditioning. At least five utilities tested load switches (DRUs, load-control modules, etc.) for the control of water heaters and other 240 V premises loads. This technology has become quite mature, and more than 2,200 such switches were installed by PNWSGD utilities. The confirmed curtailment impacts for these devices ranged from about 200 W to 370 W per device during the utilities' events. However, no significant impacts could be determined in Idaho Falls, Idaho, or on Fox Island, Washington. Fox Island premises data was unavailable for intervals shorter than

1 day, so it is understandable that impacts from relatively short events could not be observed. Idaho Falls Power had subdivided its 200 water heater locations into four groups that were sequentially engaged from hour to hour during events; this process diminished the net per-premises impact and made it harder to observe the impact.

Smart appliance suite. Flathead Electric Cooperative and NorthWestern Energy demonstrated suites of residential smart appliances, including thermostats, water heater controllers, IHDs, and even plug-load switches. The project reviewed the impacts from the suite as a whole based on premises-level metering. The Flathead Electric suite achieved reduction of 170 W per premises during events, on average, for the 118 members who received the suite.

Dynamic voltage management. Two of the PNWSGD utilities reduced feeder voltages to conserve energy during short-term (hours-long) events. While the infrastructure needed to conduct dynamic voltage control is similar to that used in conventional conservation voltage reduction, the purpose of conservation voltage reduction is long-term conservation, not short-term demand responses. No impact could be confirmed on Fox Island. Surprisingly, consumption appeared to *increase* in Milton-Freewater for these short events. Analysts hope to review this surprising preliminary finding as time permits.

Melding some of the best features of dynamic voltage management and DRUs, Milton-Freewater demonstrated grid-friendly, voltage-responsive water heater controllers. These water heater controllers were reliably engaged by feeder voltage reductions and achieved impacts comparable to systems that had required communications to DRUs.

Battery systems. The PNWSGD demonstrated battery energy storage systems at four of its utilities. The largest battery system was the Salem, Oregon, 5 MW, 1.25 MWh system. The project received test data from Portland General Electric that confirmed the capacity and capability of this battery system. Two utilities installed skid-mounted systems, but the systems' vendor ran into financial difficulties before these units' performance could be confirmed. The utilities and their remaining vendors limited their battery systems' responses to no more than one full charge cycle per day.

Distributed generators. Six distributed steam and diesel generators were controllable by the PNWSGD—three at each of the WSU and UW campuses. The distributed generators largely remained under the direct control of human operators at the two universities. The UW generators' operator normally checked the status of the transactive signals once per day in the morning to decide if they needed to change their generation schedule. WSU established a handshake mechanism with Avista Utilities with which the utility could request and the university could confirm their generators' responses.

The PNWSGD demonstrated most of the classes of responsive assets that are commercially available today. Utilities observed that the communications of the systems were not especially interoperable out of the box. Additional engineering integration was required. Many loads are still made controllable in a smart grid by "tacking on" the control system to existing electric loads. The devices are not yet smart enough to cleverly manage the tradeoffs between customer comfort and the grid's needs. The controllability is usually limited to switching the load off. There are very few assets that can *increase* load or smoothly transition throughout a continuum of available responses. Finally, the largest controllable loads maintain human control, which often limits the availability and reliability of the assets' responses.

A key to the successful application of transactive systems is the use of automation to coordinate the decision making and action of the responsive assets. Research and development is needed to further develop and deploy distributed, automated systems, both within the utility infrastructure and in customer premises. The performance of the automated systems must be demonstrated to be at a high enough level that utilities and their customers are comfortable with the results. Otherwise, there will continue to be significant use of person-in-the-loop approaches that limit the effectiveness of the technologies in delivering full value to the asset owner and the electric power system.

Research is also needed into the policy dimensions of incentivizing customers to respond to a dynamic cost or price signal. The PNWSGD transactive incentive signal is a dynamic representation of cost, but it was not used in a tariff. The participating utilities were asked to respond, and to have asset systems, generally involving their customers, provide the response. For large scale deployment, there is still work to be done on whether to use the dynamic cost signals as a dynamic tariff, or whether an approach based on periodic compensation, such as monthly capacity payments for which customers agree to respond to the dynamic signal, is better.

7.0 Avista Utilities Site Tests

Additional chapter coauthors: D Johnson and C Kirkeby − Avista Utilities

Avista Utilities is an investor-owned utility that serves about 680 thousand customers over 30,000 square miles (Avista Corporation 2015). The utility's headquarters are in Spokane, Washington, but it invested in modernization of the Pullman, Washington distribution system during the Pacific Northwest Smart Grid Demonstration (PNWSGD).

The following asset systems were demonstrated at the Pullman, Washington, site. A representation of these tests overlaid on the site's 13 distribution circuits is shown in Figure 7.1.

- volt/VAr optimization (Section 7.1)
- reconductoring (Section 7.2)
- smart, efficient transformers (Section 7.3)
- communicating thermostats (Section 7.4)
- completion of advanced metering infrastructure (Section 7.5)
- fault detection, isolation, and restoration (FDIR) and other reliability enhancements (Section 7.7)
- cooperative control of Washington State University (WSU) facilities
  - heating, ventilation, and air conditioning (HVAC) air handlers (Section 7.8)
  - chiller loops (Section 7.9)
  - diesel generator (Section 7.10)
  - two natural gas generators (Section 7.11)

The performance of these listed systems will be discussed further in the sections of this chapter.

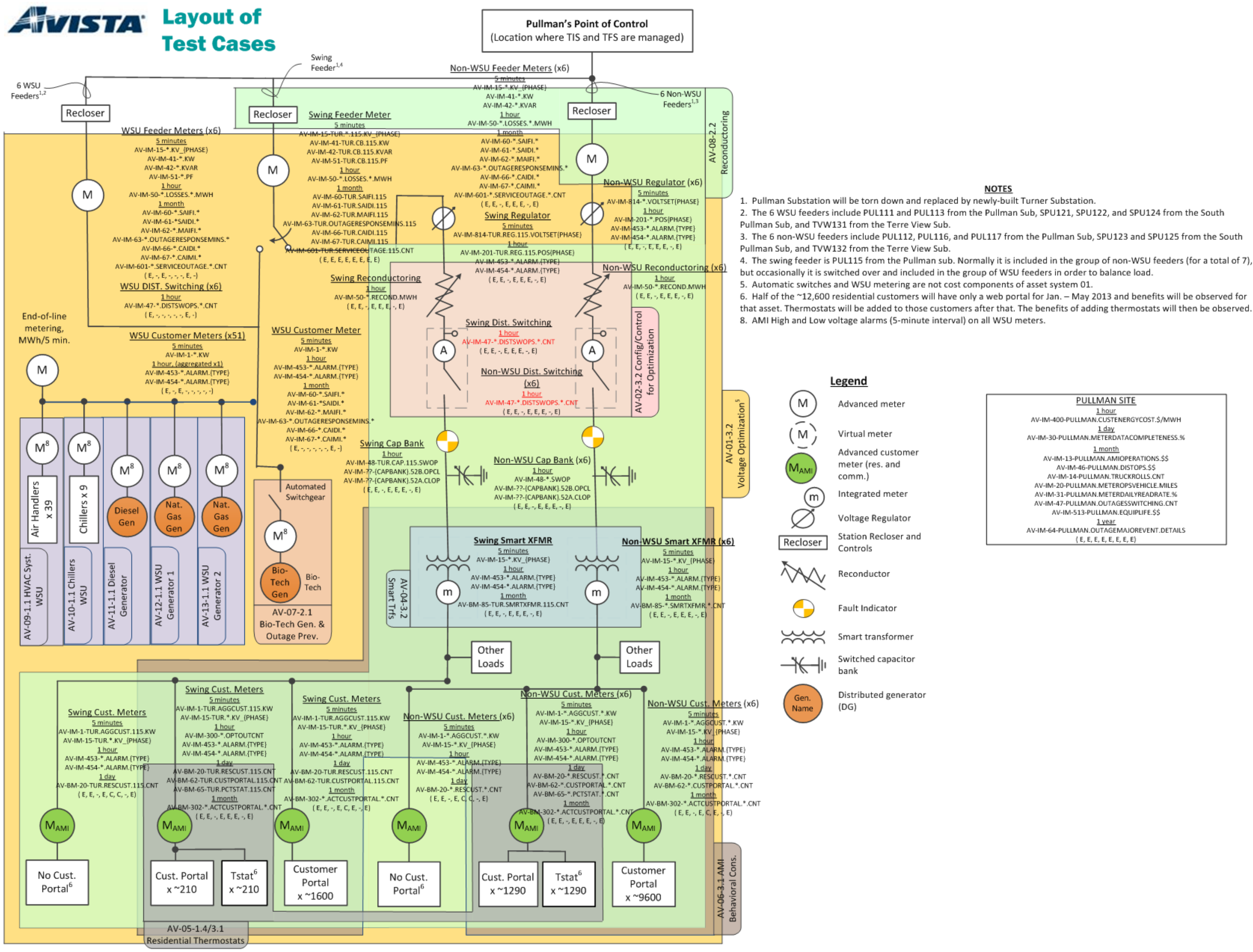


Figure 7.1. Layout of the Avista Utilities Test Groups Overlaid on their Distribution Circuits in Pullman, Washington

Locations within Figure 7.1 refer to data that was expected from the utility for the evaluation of these asset systems that were being demonstrated. The project developed abbreviations for the naming of data series, and most of these abbreviations may be found in Table 7.1. These abbreviations were prepended by “AV-” to indicate that they referenced data from Avista Utilities. The abbreviations were appended by the names of various feeders, substations, customer types, or units of measure to ensure that the names were unique in the project’s databases. The data interval column gives the anticipated time interval represented by a single record from the data stream, and the submit interval was the negotiated time between bulk updates received from Avista Utilities concerning the data stream. The project’s version of this table included many additional columns that specified the relationships between this data and the various asset systems.

Table 7.1. Representative Data Offered by Avista Utilities to the PNWSGD Project. Some of these data-stream naming conventions are found in Figure 7.1.

Data Stream	Data Interval	Submit Interval	Description
BM-20	1 day	1 day	Customer count
BM-62	1 day	1 day	Customer portal count
BM-65	1 day	1 day	Communicating thermostat count
BM-302	1 month	1 month	Active customer portal count
IM-1	5 minutes	1 day	Customer meter real power
IM-13	1 month	1 month	Meter operations cost
IM-14	1 month	1 month	Truck roll count
IM-15	5 min.	1 day	Voltage (phase)
IM-20	1 month	1 month	Meter operations vehicle miles driven
IM-30	1 day	1 month	Customer interval data read
IM-31	1 month	1 month	Customer meter reads by 02:00 daily
IM-41	5 min.	1 day	Distribution meter real power
IM-42	5 min.	1 day	Distribution meter reactive power
IM-46	1 month	1 month	Distribution system operations cost
IM-47	1 hour	1 day	Feeder distribution switching operations
IM-47	1 month	1 month	Distribution outage switch events
IM-48	1 hour	1 day	Capacitor switching count
IM-50	1 hour	1 day	Calculated losses
IM-51	5 min.	1 day	Distribution power factor
IM-60	1 month	1 month	Reliability index - SAIFI (feeder)
IM-61	1 month	1 month	Reliability index - SAIDI (feeder)
IM-62	1 month	1 month	Reliability index - MAIFI (feeder)
IM-63	1 month	1 month	Reliability index - outage response time (feeder)
IM-66	1 month	1 month	Reliability index - CAIDI (feeder)
IM-201	1 hour	1 day	Regulator tap changes
IM-400	1 year	1 year	Description of major system events

Table 7.1. (cont.)

Data Stream	Data Interval	Submit Interval	Description
IM-453	1 hour	1 day	Meter low-voltage alarms
IM-454	1 hour	1 day	Meter high-voltage alarm
IM-601	1 month	1 month	Customer service interruption count (feeder)
IM-622	1 month	1 month	Customer avoided outage minutes
IM-814	5 min.	1 day	Regulator voltage set point

CAIDI = Customer Average Interruption Duration Index
MAIFI = Momentary Average Interruption Frequency Index
SAIDI = System Average Interruption Duration Index
SAIFI = System Average Interruption Frequency Index

A misunderstanding was allowed to persist in Figure 7.1 until quite late in the project. The Pullman, Washington, distribution circuit comprises 13 distribution circuits. Six of these were referred to as "WSU feeders" by utility staff because they supplied the WSU campus in Pullman. Another six "non-WSU feeders" did not. Also, another "swing feeder" could be configured to either supply the campus or not. These terms and this level of understanding were applied in Figure 7.1.

What was not initially understood was that the distribution circuits were not necessarily radial, and the "WSU feeder" circuits may supply both WSU and other customers. A greatly simplified representation of the distribution circuits is shown in Figure 7.2. The project's analysis was limited by its limited model of the distribution circuit and by its imperfect understanding of the locations of asset systems and their components within the city's distribution circuit.

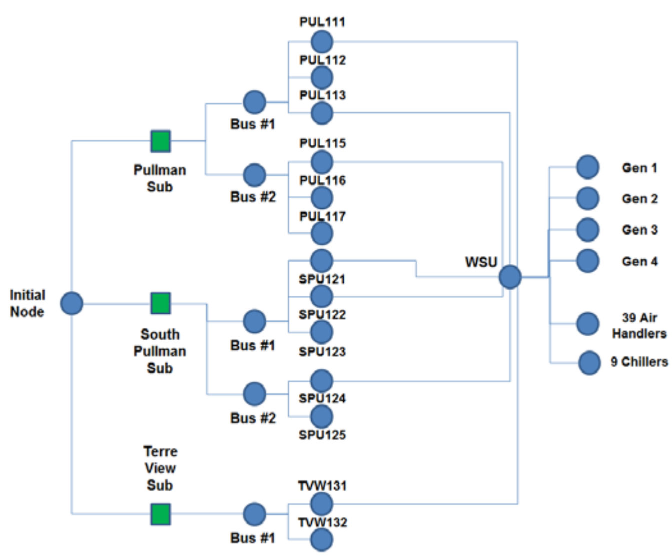


Figure 7.2. Pullman, Washington, Distribution Circuits

Avista Utilities also demonstrated a high level of integration among the demonstrated asset systems during the project, as is demonstrated in Figure 7.3. While the integration of systems is encouraged in a smart grid, the integration made it more difficult for the project to validate the effectiveness of the system's component subsystems. A type of unit testing of the individual subsystems might have better verified their performance apart from the larger integrated system. Particularly in the distribution automation subsystem components (e.g., voltage optimization, configuration control), the software system itself was granted the responsibility by the utility to compile and state its benefits.

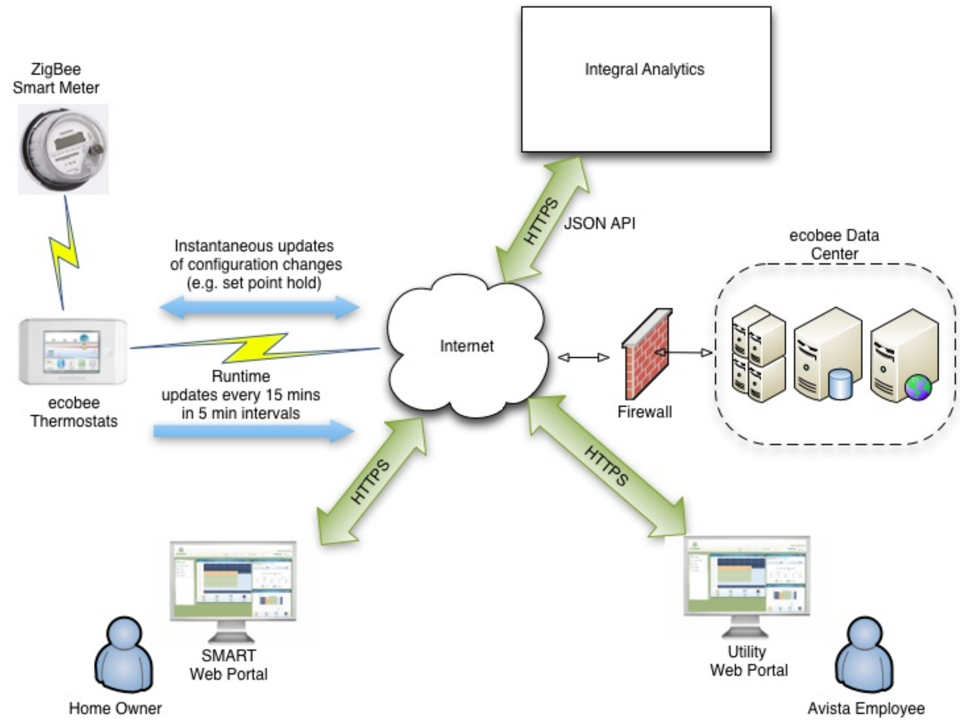


Figure 7.3. The Avista Utilities Customer Equipment (Thermostats), Customer Web Portals, and Distribution Automation Systems were Highly Integrated

7.1 Voltage and Reactive Power Optimization

Avista Utilities installed an integrated volt/VAr[1] control (IVVC) system to optimize voltages and improve power factors in the Pullman, Washington, circuits. It procured and installed Schweitzer Engineering Laboratories (SEL) (SEL 2015) voltage-regulator controllers to control Cooper Industries (Cooper Power Systems 2013) step-voltage–regulator banks on each phase of its 13 feeders. It also controlled the statuses of as many as 60 300 kVAr switched capacitor banks. Advanced Control Systems (ACS) (ACS 2015) customized its predictive voltage management and VAr management applications to provide an integrated solution for use with the utility's ACS distribution management system (DMS) for fully automated reactive power and voltage optimization.

[1] VAr = volt-ampere reactive

The project now believes testing of voltage and reactive power control affected all 13 Pullman, Washington, feeders. An early misunderstanding, evident in Figure 7.1, had caused the project to understand that it affected only the seven feeder circuits that did not supply the WSU campus. However, evidence of voltage and VAr control was found for almost all the feeders.

One purpose of this system was to manage distribution voltages to conserve power while maintaining satisfactory service voltage levels. After lowering distribution system voltage, some electric loads consume less power, often resulting in energy conservation. Voltage regulators respond to DMS requests by stepping the voltage up or down in multiple 1/2% increments. With this new capability, Avista Utilities targeted an average 1.85% (600 kW) power reduction.

Additionally, power factor correction allows the same power to be supplied with less distribution line current, thus reducing resistive line losses. The automation of system capacitors dynamically reduced the reactive power levels that must be supplied through the distribution circuits. It will be shown that the process began with static improvements during 2012. Reactive power supplies were significantly reduced even before the IVVC automation began.

If end-of-line voltages are monitored by the IVVC system, the distribution system may operate quite close to the lower voltage limits without impacting customer service. The advanced metering infrastructure (AMI), provided by Itron (Itron 2015) and the smart transformers, provided by Howard Industries (Howard Industries 2015), supplied the end-of-line voltage measurements for the system. Smart transformers were preferred for the end-of-line voltages because they streamed data every 4–10 seconds, eliminating the need for requests to the AMI collection system, responses from the meter concerning metered voltages, and subsequent retrieval of those responses from the collection system.

The step voltage regulators and capacitor banks were configured to automatically adjust voltage and reactive power in both local and remote manners. In the remote mode, the DMS asserted complete control of the voltage regulators and capacitor banks. In the local mode, which may come about as a result of maintenance testing or loss of communication, the SEL controls operated in a predetermined manner to apply line-drop compensation for voltage management while keeping VAr management static per the last known configuration prior to entering the local-control mode.

The DMS communicates with the step-voltage regulators and capacitor bank controllers using an internet protocol via an 802.11 wireless metropolitan area network (MAN). The DMS uses the utility’s fiber optic network backbone to communicate with a bank of remote terminal units (RTUs) that are located in the Spokane, Washington, central office. The majority of the fiber backbone existed prior to the project, except for a 7–15 mile section from the Shawnee substation to the Pullman substation. The 802.11 wireless MAN was newly designed and installed for this project.

Initially, Avista Utilities had intended to further reduce its distribution voltages to minimal acceptable levels when advised to do so by the project’s transactive system, thus achieving additional reductions in dynamic load and system loss. Perhaps another 1.85% reduction of average power might have been achieved utilizing the remaining margins of the accepted voltage supply range. Up to 600 kW of dynamic power reduction might have been available for a few hours at a time. This goal was abandoned. Significant delays were encountered by the utility as it tested and confirmed the accuracy of its end-of-line voltage monitoring points. The utility was unable to engineer the transactive response of this system by the time the accuracies had been determined and improved.

The IVVC methodology had to be developed as it was not an available vendor product at the beginning of the PNWSGD. Some automation was achieved during the project. In the future, the IVVC system may be made even more efficient after a history of end-of-line voltages has been collected and analyzed. The system may then know which end-use locations are statistically likely to have low or high voltages in given operating modes. The number of points metered by the system may then be reduced, checking locations less frequently if their voltages never approach high or low limits. Successful use of AMI or smart transformers for volt/VAr optimization may further reduce the cost of deployment for IVVC and facilitate the additional operational voltage margin needed by a transactive system for dynamic demand responses.

Avista Utilities' modernization of the Pullman, Washington, distribution circuits was very integrated. The utility worked with the Port of Whitman (Port of Whitman 2014) to improve its fiber backhaul communications infrastructure. This system also relied on upgrades to the DMS.

The annualized costs of the system and its components are listed in Table 7.2. The greatest costs were allocated to finalize installation of the advanced metering system. The costs of the wireless network and efforts to integrate the system with the project's transactive system were also significant. The total annualized cost was just under $1.5 million.

Table 7.2. Components and Annualized Component Costs of the Avista Utilities IVVC System

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)	
Advanced Metering System		655.5	
• Software and Systems	25		316.0
• Operations and Maintenance	25		100.3
• Residential Equipment			
o Control Group	33		39.2
o Target Group	33		29.7
o Target Group with DR	25		7.1
• Engineering	25		7.7
• Commercial Equipment			
o Control Group	33		5.2
o Target Group and DR	33		4.3
o Target Group	25		0.7
• Training	25		1.9
DMS Software and Hardware for 700-1000 End Points	25	420.8	
Wireless Network	25	173.2	
Transactive Node System	33	114.4	
Voltage Regulators and Controls	100	76.9	

Table 7.2. (cont.)

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
Fiber Network Communications	17	53.4
Smart Transformers with Sensors and Wireless Comms.	25	37.3
Switched Capacitor Bank (with SEL controls) Installation	100	29.7
Evaluation, Measurement and Validation	13	22.8
Project Management Services	13	12.9
Subcontractor – Volt/VAr Software	33	12.7
Reconductor	33	11.8
Total Annualized System Cost		**$1,477.9K**

DR = demand response

7.1.1 System Operation and Data Concerning the Voltage Optimization System

Voltage data was critical to the evaluation of the IVVC system's performance. Figure 7.4 is an example of the quality of distribution voltage data that was provided to the project by Avista Utilities for Turner Feeder 111. For most of the 13 feeders, the utility provided 5-minute voltage measurements for each of the three phases. The data period extended from April 2012 through August 2014. Data quality was good by the end of 2012.

As was its practice, the project divided the distribution voltages by their base distribution voltages, resulting in per-unit representations of the distribution voltages. The project graphically reviewed the raw phase voltages like those shown in Figure 7.4. The individual phases have been offset from one another by 0.04 per unit so that they may be compared without overlap. For all 13 feeders, the individual phase voltages were observed to be similar. Observe that the voltage became actively managed at this feeder starting in late 2013. Even under dynamic voltage management, the phase voltages were found to have been controlled simultaneously, not separately. Therefore, the project felt justified averaging the phase voltages and used these averages for the remaining analysis.

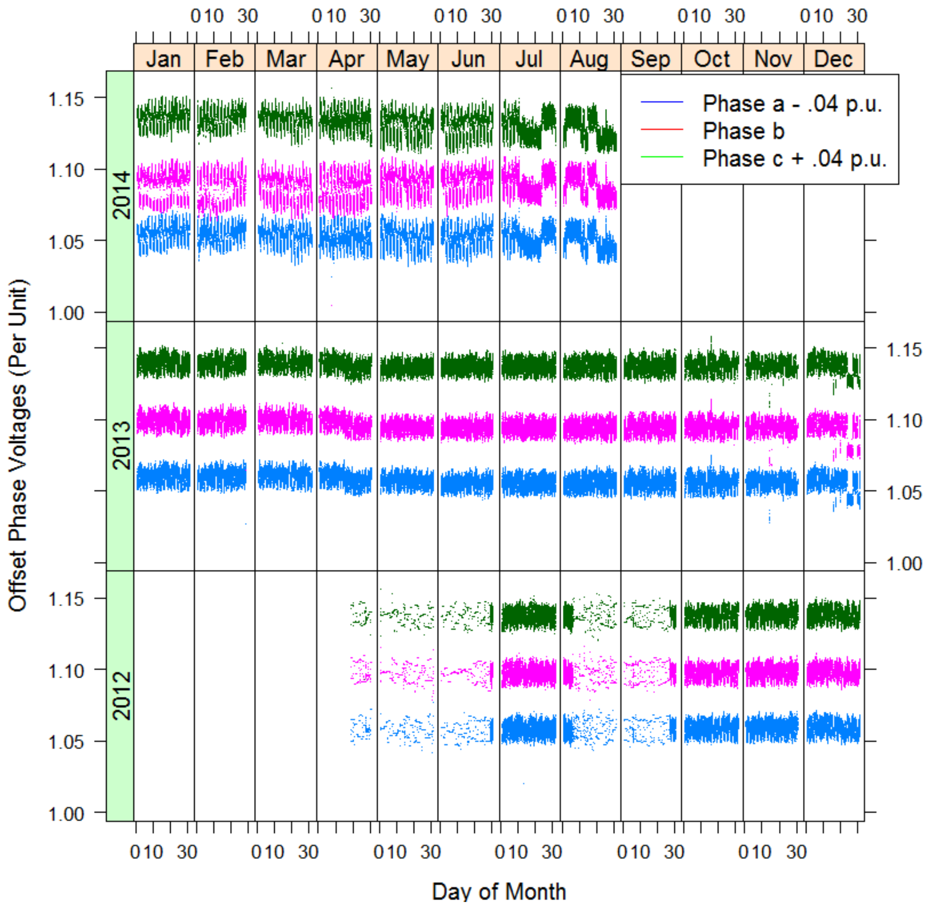


Figure 7.4. Head-End Phase Voltages on Turner Feeder 111

Figure 7.5 shows the same 2014–2014 data as was shown in Figure 7.4 after the individual phase voltages had been averaged. Because the phases were managed identically, the evidence of active voltage management appears to have been preserved. The project found sets of data for each feeder that correlated strongly with the observed voltage levels. For each of the 13 feeders, time series of this type were found to be identical among the three phases.. The status was binary, reporting value "120" when the voltage was at its normal level and value "118" when the voltage had been reduced. The three identical indicator time series were collapsed into a single event indicator for each feeder, stating when voltage management was active and when not. The active ("reduced") and normal statuses have been shown in Figure 7.5 using red and blue colors. The reported status was very well correlated with the managed voltage level on this feeder.

In the calculation of average feeder voltage, phase voltages below 1.0 per unit were generally discarded as outliers.

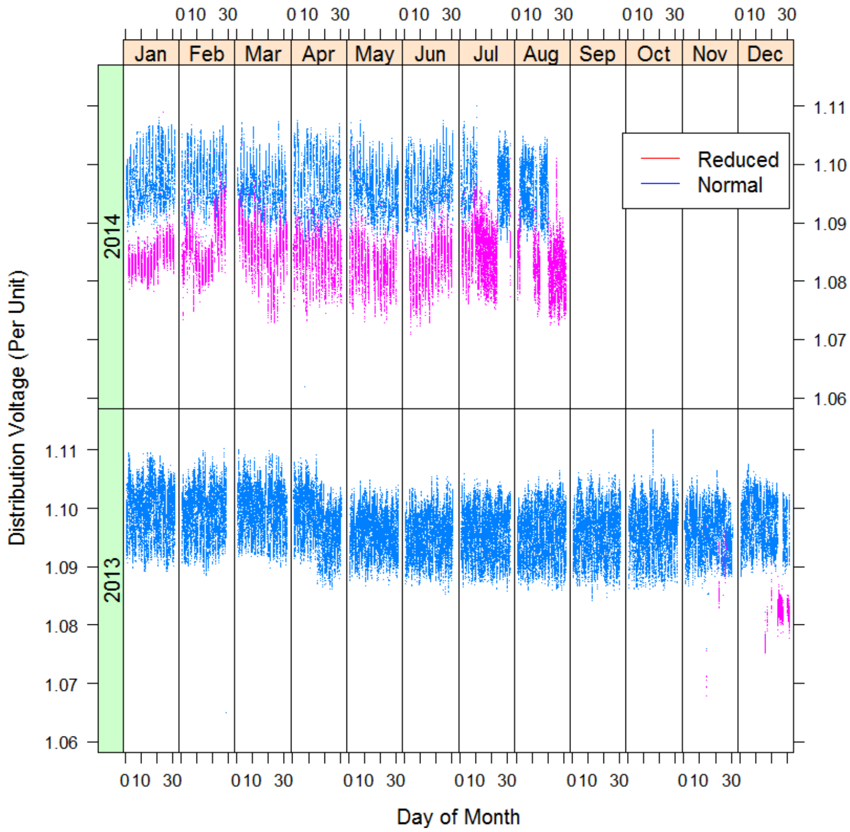


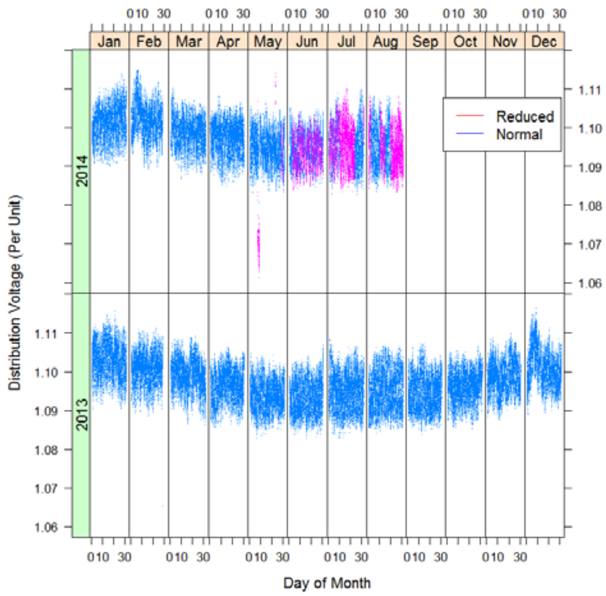
Figure 7.5. Average of Head-End Phase Voltages at Turner Feeder 111. The legend refers to the reported status of the IVVC system, whether it is active (reduced) or normal.

The average head-end distribution circuit voltages of the remaining 12 feeders, marked similarly according to the reported statuses of voltage management on the feeders, are shown in Figure 7.6. Including Turner Feeder 111 from Figure 7.5, nine feeders show clearly that voltage had been substantially reduced and with good correlation to the feeders' reported voltage management indicators.

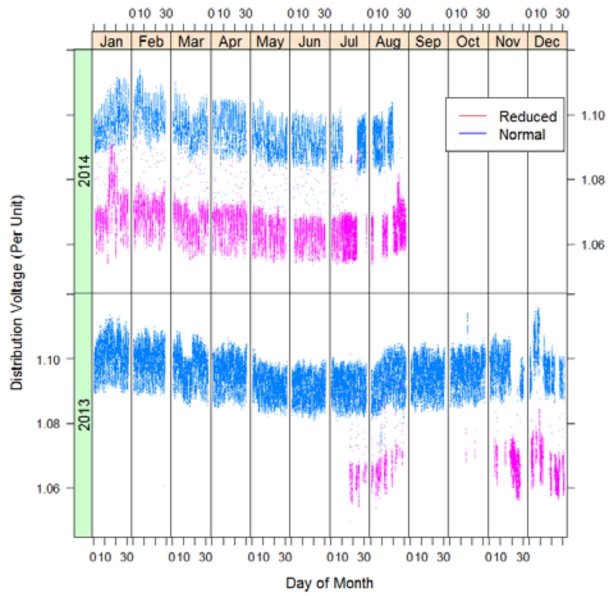
The four feeders with unclear voltage management included Turner Feeders 112 and 115 and South Pullman Feeders 122 and 124. The change in voltage at South Pullman Feeder 125 was greatly reduced for some reason during July and August 2014. The accuracy of the voltage management indicators on the two Terre View feeders was poor prior to April 2014, showing an almost random application of the voltage management status to normal and reduced voltages before then. The voltage management at South Pullman Feeder 122 was actually reversed, showing an *elevated* voltage at times the voltage management system was reported to be active.

Upon reviewing these observations of feeder performance, Avista Utilities responded that they had been challenged by the WSU feeders, which had additional voltage transformations within the WSU campus distribution system. Some of these campus transformers had fixed tap settings, so adjustments to voltage downstream from the Avista delivery point (i.e., the campus meter) were not possible. This resulted in low voltages within the campus that prevented further voltage reduction by the IVVC system.

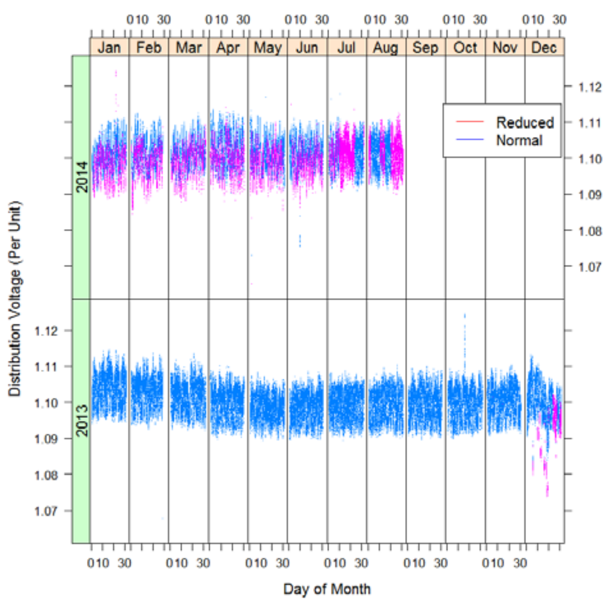
The project had been led to believe that feeders would be managed according to whether they were among the six feeders that serve the WSU campus. That did not appear to be the case. All the feeders were assigned voltage management indicators and all Pullman, Washington feeders were managed by the IVVC system. The feeders that had significant changes in managed voltages included both WSU and non-WSU feeders.



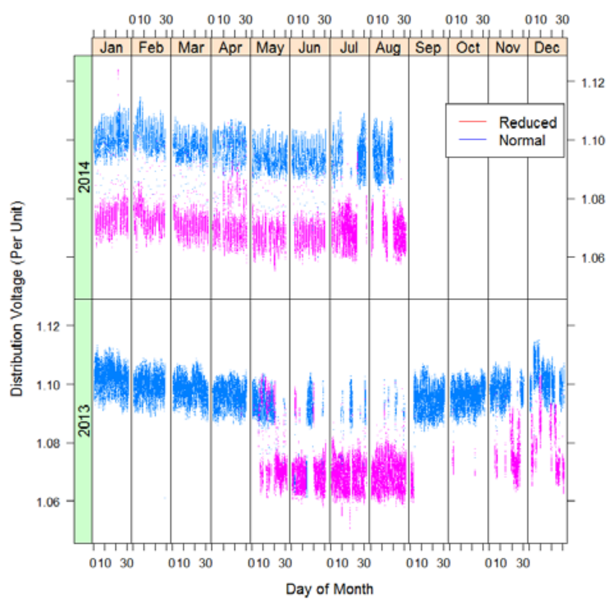
(a) Turner Feeder 112



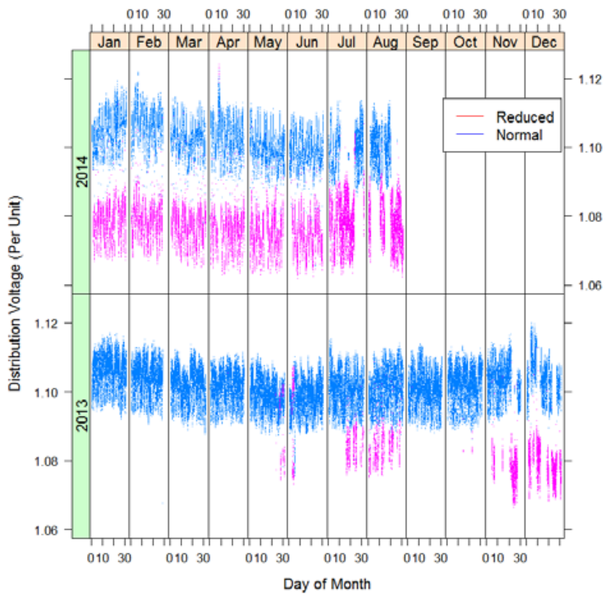
(b) Turner Feeder 113



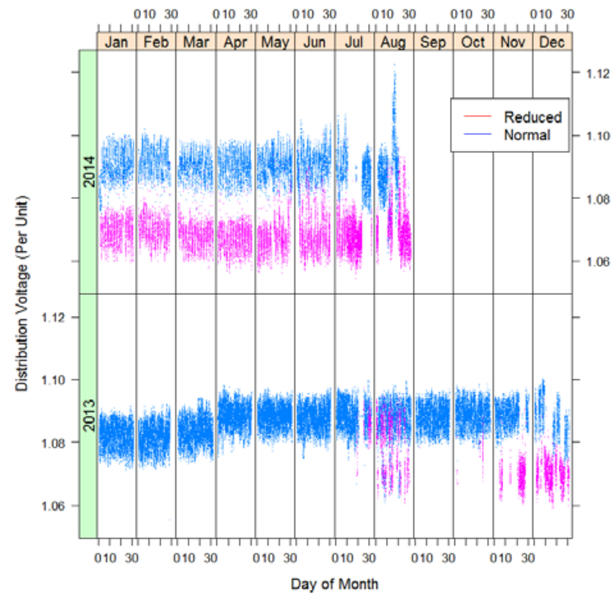
(c) Turner Feeder 115



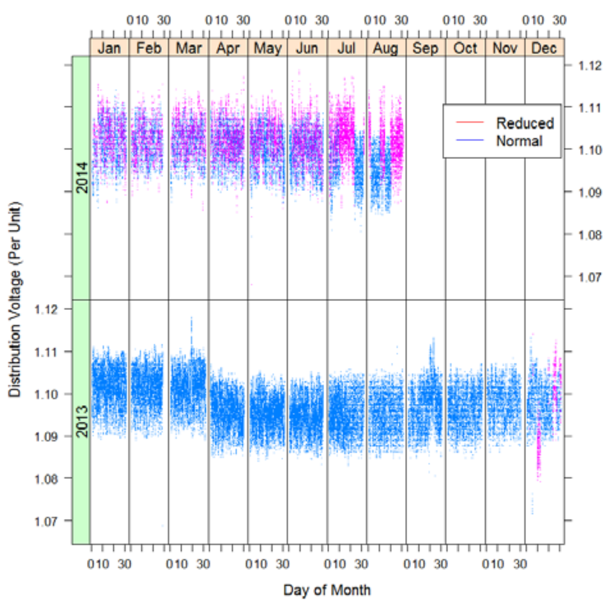
(d) Turner Feeder 116



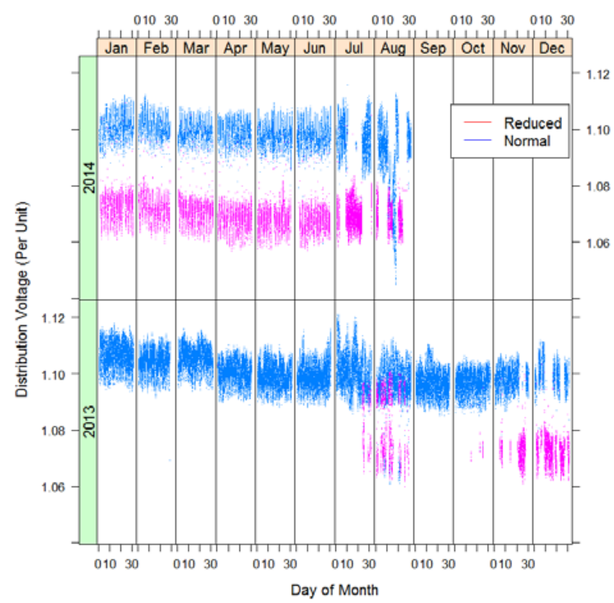
(e) Turner Feeder 117



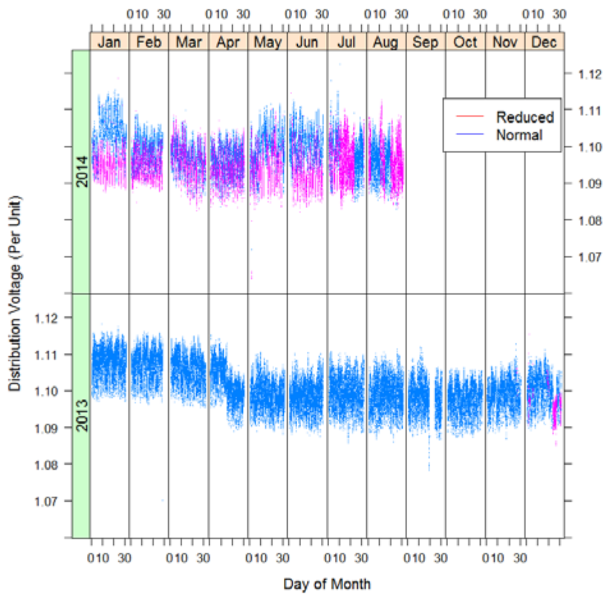
(f) South Pullman Feeder 121



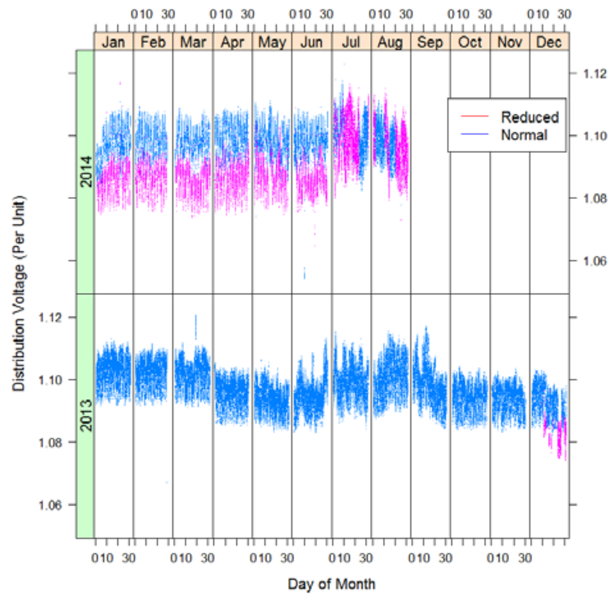
(g) South Pullman Feeder 122



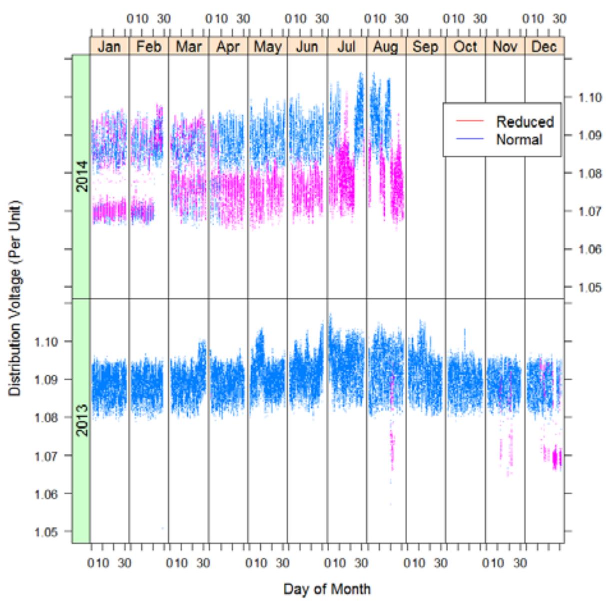
(h) South Pullman Feeder 123



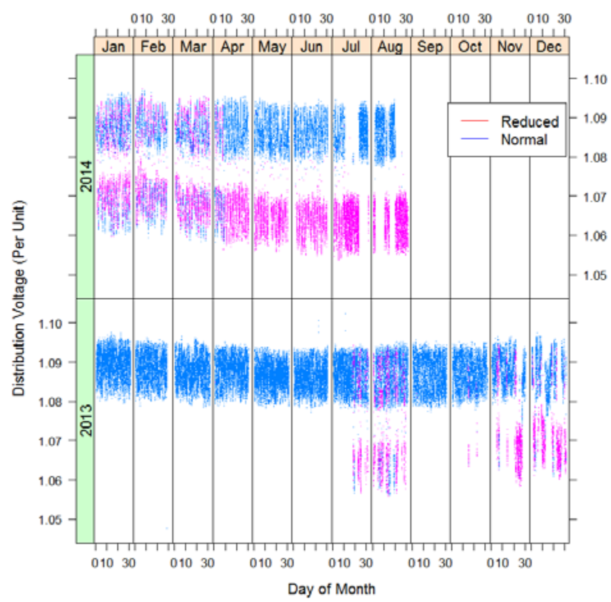
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.6. Average of Head-End Phase Voltages at Pullman Site Feeders. The legend refers to the reported status of the IVVC system, whether it is active (reduced) or normal.

The performance of distribution voltage management is sometimes based on changes in average end-of-line voltage rather than head-end distribution voltage. Avista Utilities measured end-of line phase voltages at a sample of its newly installed smart transformers (Section 7.3) and customer meters (Section 7.5). A sample is shown in Figure 7.7, which shows the averaged end-of-line phase voltages from Turner Feeder 111. The per-unit voltages of the individual phases have been offset from one another by 0.05 per unit so that they might be better viewed and compared. The availability of end-of-line voltages was sparse at this and other feeders. The Phase "b" voltage was entirely unavailable through much of 2013 and early 2014. Avista Utilities responded that smart transformers were placed at locations where low voltage was most likely. Phase "b", in this case, simply happened to not be such a location.

The head-end and end-of-line representations of system voltage should mostly rise and fall in parallel for passive distribution systems. The two may differ somewhat with electrical loading that induces voltage drops across conductors and transformers and that counteracts the natural tendency for voltage to increase due to system capacitance. The differences would be more pronounced where the profile of voltage down a feeder's length is being actively managed.

Active voltage management is evident in the end-of-line phase voltages as it was for head-end phase voltages. However, the end-of-line voltages exhibit some management of individual phases that was not evident from the head-end phase voltages. Both the normal and reduced voltages of Phase "a" have been increased during the first three weeks of February 2014, but the change did not occur in Phase "c." There are weeks during 2014 when the magnitudes of the end-of-line phase voltages were changed independently.

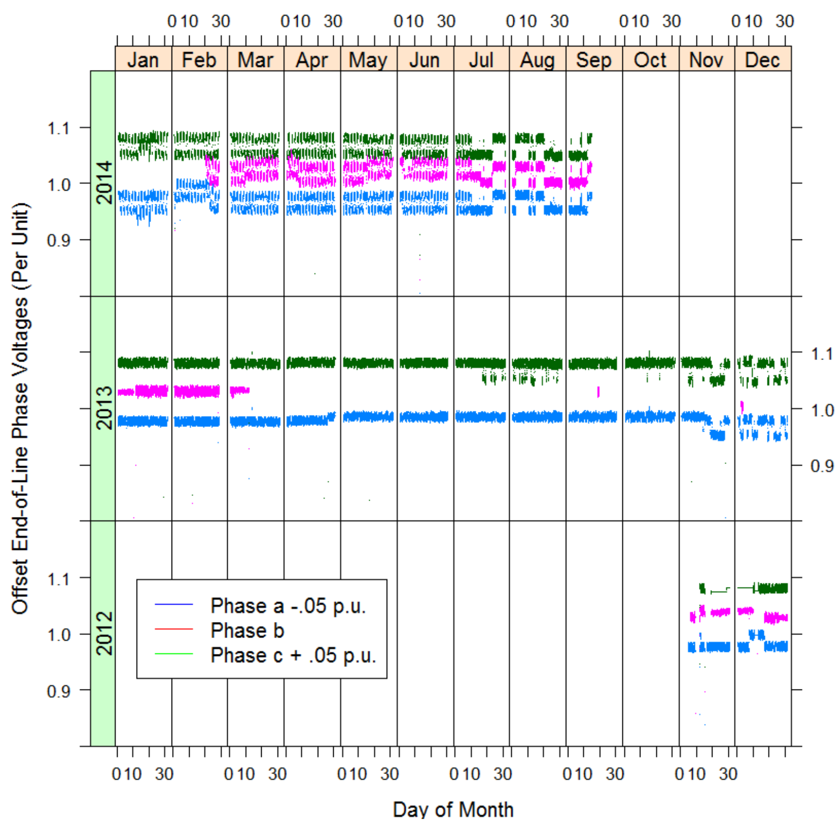
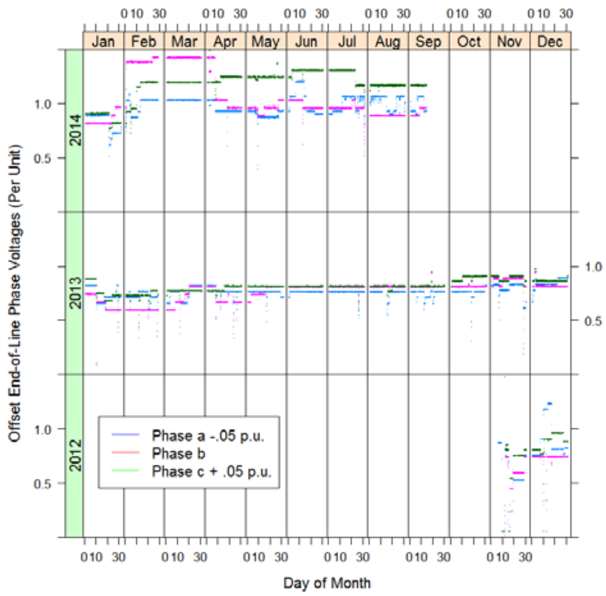
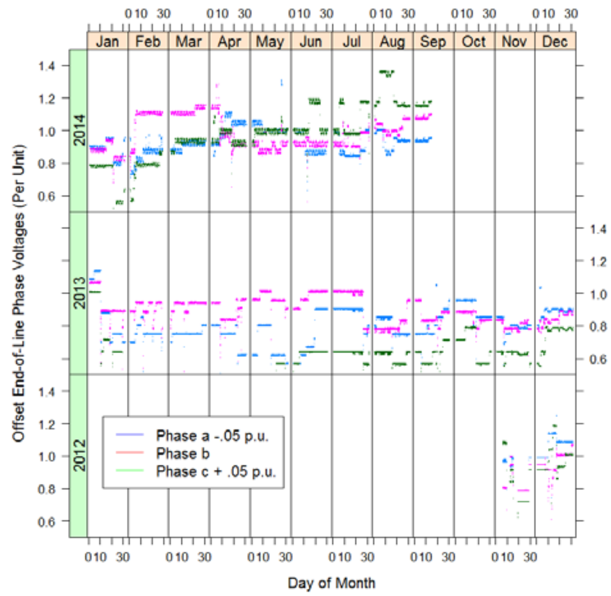


Figure 7.7. Averaged End-of-Line Phase Voltages from Turner Feeder 111. Per-unit values have been offset by 0.05 p.u. for readability.

Avista Utilities reported during the project that the measurement sources of the end-of-line voltages had been difficult to calibrate and integrate. While the phase-voltage magnitudes of Figure 7.7 for Turner Feeder 111 seemed reasonable, the measurements at the phases of other feeders were not as credible. See Figure 7.8. Many of the phase voltages were found to have not been metered, and were therefore unavailable. No end-of-line phase voltages were available for South Pullman Feeders 122 and 125 or Terre View Feeder 131. Where available, magnitudes of the per-unit end-of-line voltages were often found to be far outside an acceptable voltage range.[1] Furthermore, the typical voltage magnitudes of individual phases were found to have changed over time. For these reasons, the project opted to use average head-end voltages, not end-of-line voltages, for its evaluations of IVVC system performance.

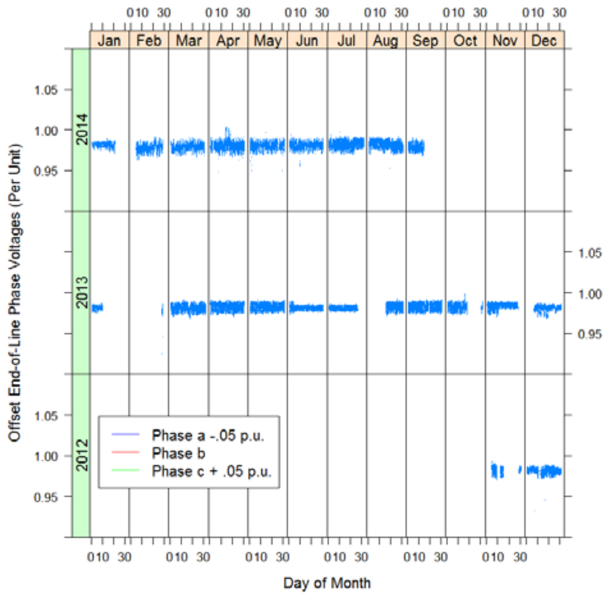


(a) Turner Feeder 112

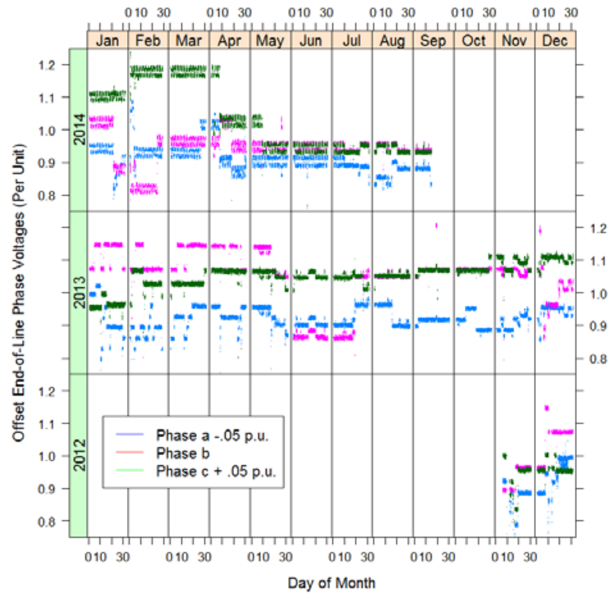


(b) Turner Feeder 113

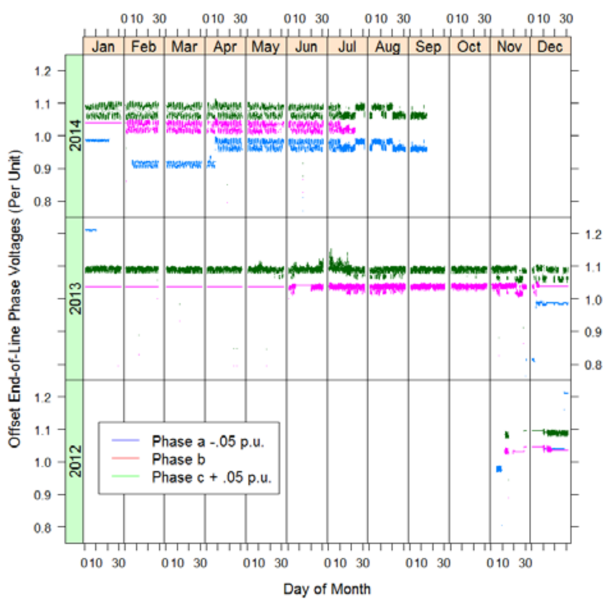
[1] On a 120 VAC basis, the per-unit voltages 0.95 and 1.05 correspond to the voltages 114 and 126 VAC, respectively.



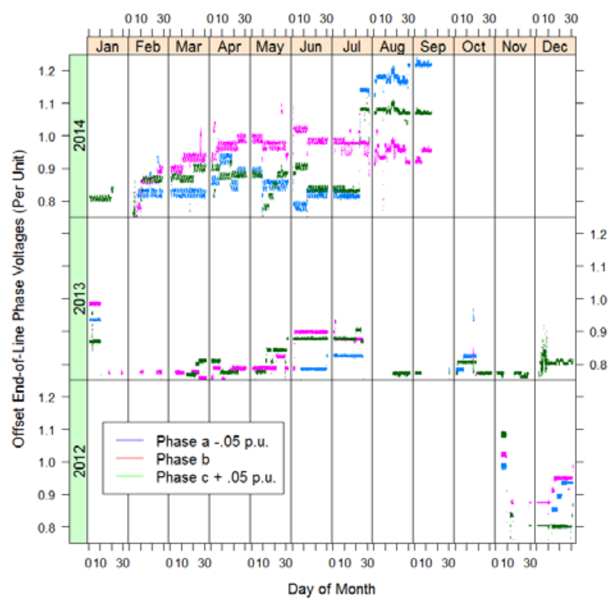
(c) Turner Feeder 115



(d) Turner Feeder 116



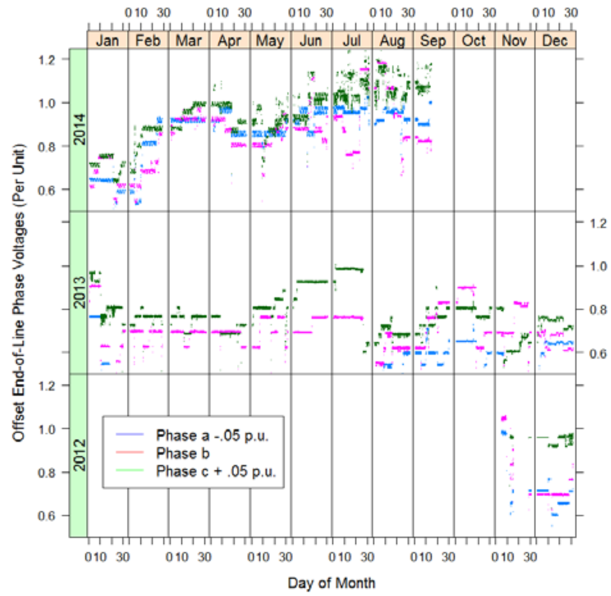
(e) Turner Feeder 117



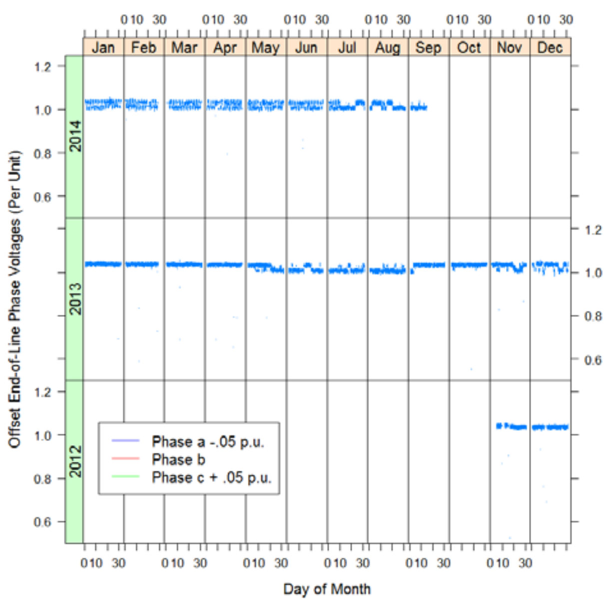
(f) South Pullman Feeder 121

NA

(g) South Pullman Feeder 122



(h) South Pullman Feeder 123

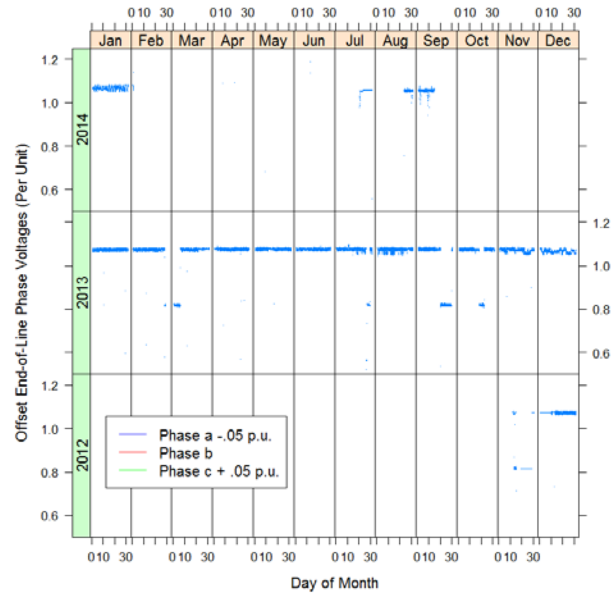


(i) South Pullman Feeder 124

NA

(j) South Pullman Feeder 125

NA



(k) Terre View Feeder 131

(l) Terre View Feeder 132

Figure 7.8. Averaged End-of-Line Phase Voltages from Turner Feeder 111. Per-unit values have been offset by 0.05 p.u. for readability. (NA = not available)

The other critical measurements important for evaluating the performance of IVVC are real and reactive powers. Avista Utilities supplied 5-minute feeder power data for a period from April 2013 into September 2014. An example of this time-series data from Turner Feeder 111 is shown in Figure 7.9. The power at this feeder has moderate variation by season. The feeder peaks in winter. A strong weekly consumption pattern is evident because consumption is less during weekends. No impact on power consumption from voltage management—expected to be only about a 2% change—is evident by inspection of the power time series.

Reactive power remained steady through 2012 with a moderate inductive load. After several trials and missteps, the reactive power was well corrected by May 2013 and remained good through 2013. It seems that experimentation resumed in 2014, allowing several changes in reactive power levels. Dynamic VAr control was evident during May 2014 and from late July into early September 2014, when the reactive power was modified frequently, perhaps on a daily basis. Avista Utilities confirmed that the testing was attributable to alternate-day testing that Navigant Consulting was completing on its behalf.

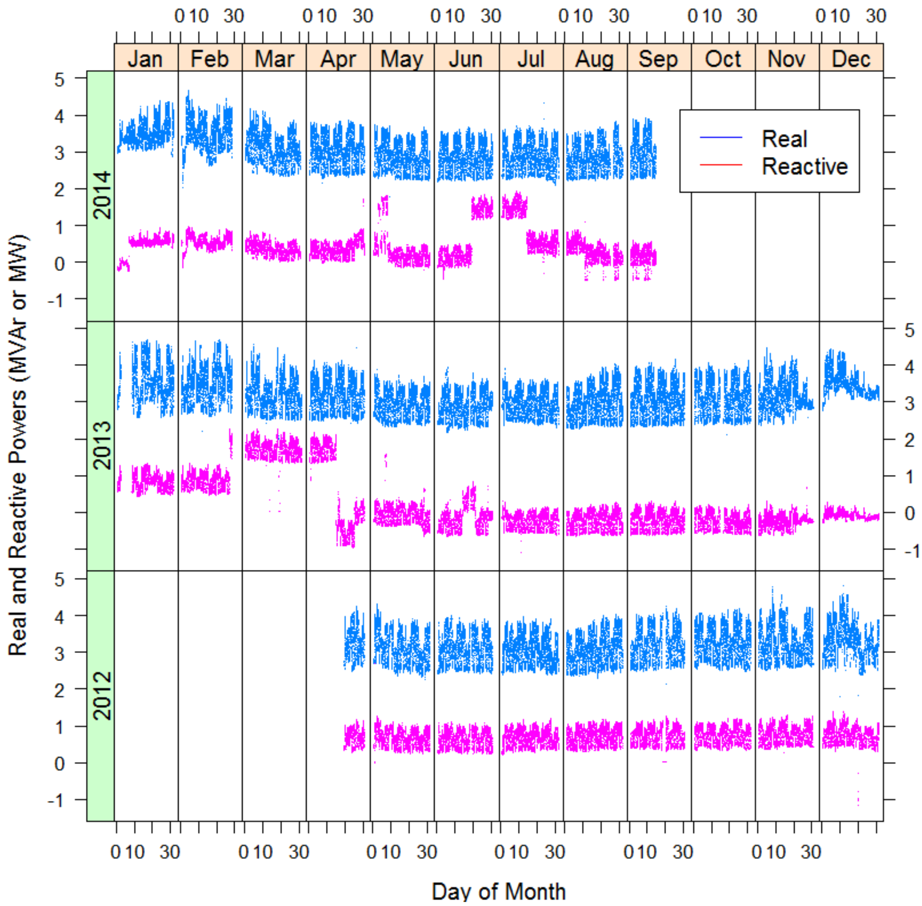
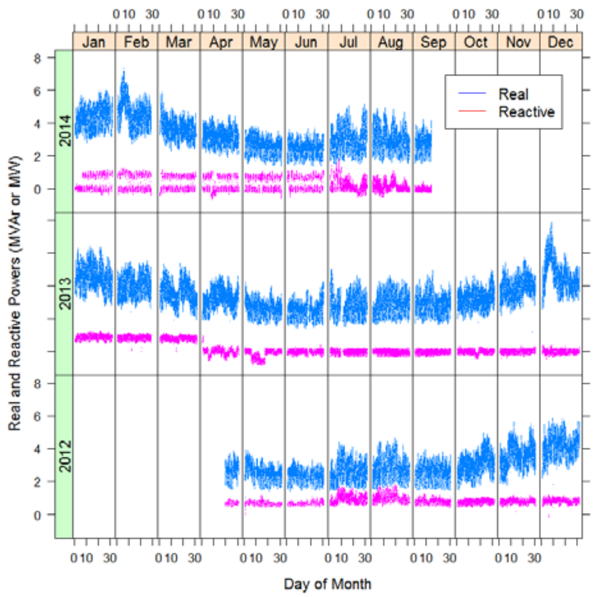


Figure 7.9. Real and Reactive Power Time Series for Turner Feeder 111

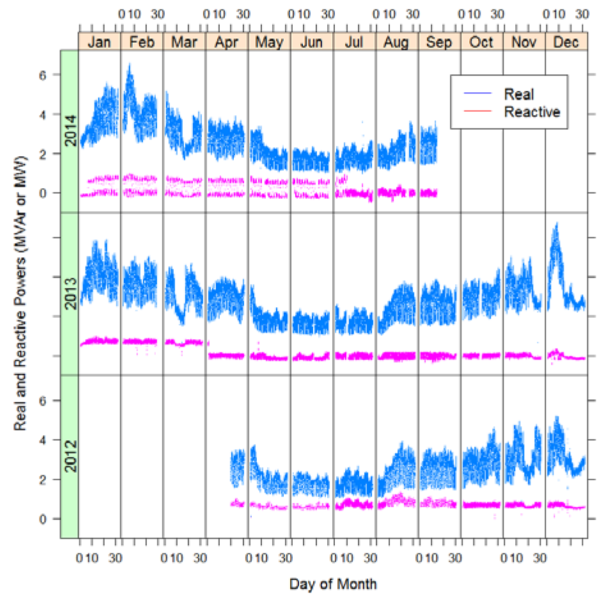
Real and reactive power time series for the remaining 12 Pullman site feeders are shown in panels of Figure 7.10. The diversity of the power consumption at the various feeders is intriguing. All the feeders except South Pullman Feeder 125 and Terre View Feeder 131 experienced their peak during winters. Like Turner Feeder 111, Turner Feeders 115 and 117 and South Pullman Feeder 124 exhibited strong weekly patterns with greatly reduced consumption during weekend days.

The reactive powers of all but four Pullman site feeders appear to have been corrected from small inductive levels starting in April 2013. The project does not know the details of these improvements, but they are likely the result of careful correction of static capacitor settings and circuit topology in those months. At South Pullman Feeder 121, moderate capacitive load was corrected. The reactive powers at Turner Feeder 117 and at both the Terre View Feeders 131 and 132 were already small and were probably not changed in April 2013.

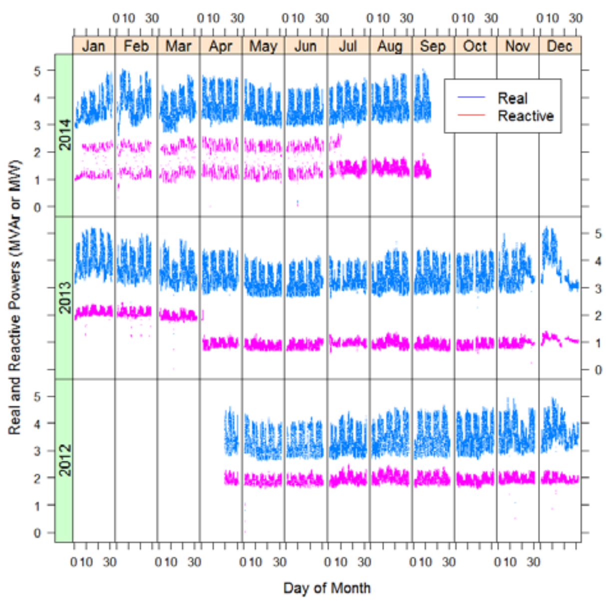
The reactive powers of all but the two Terre View feeders were dynamically managed at times during 2014. This is inferred from the periods in Figure 7.10 when the reactive power appears to have two values. In fact, these are rapid transitions, perhaps day-on/day-off transitions, between two reactive power levels.



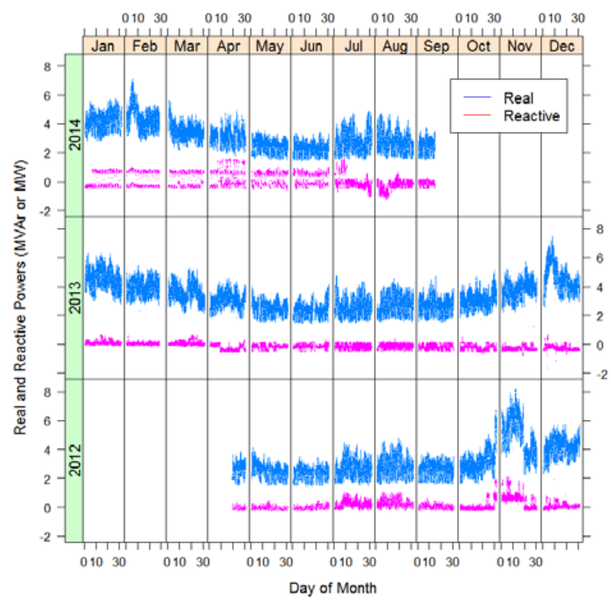
(a) Turner Feeder 112



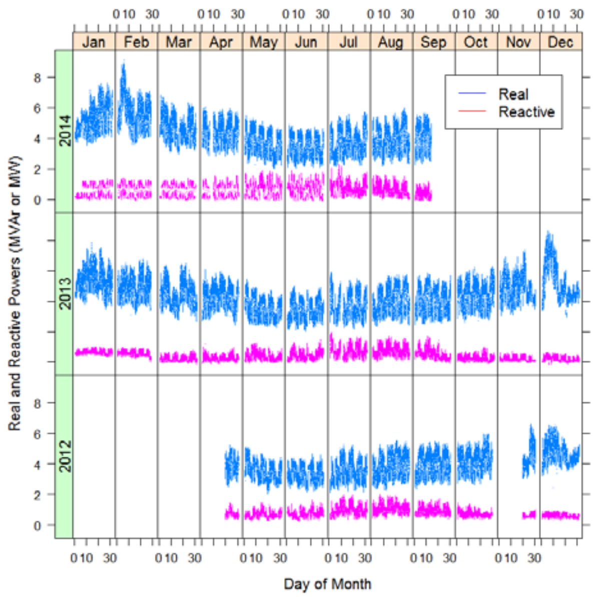
(b) Turner Feeder 113



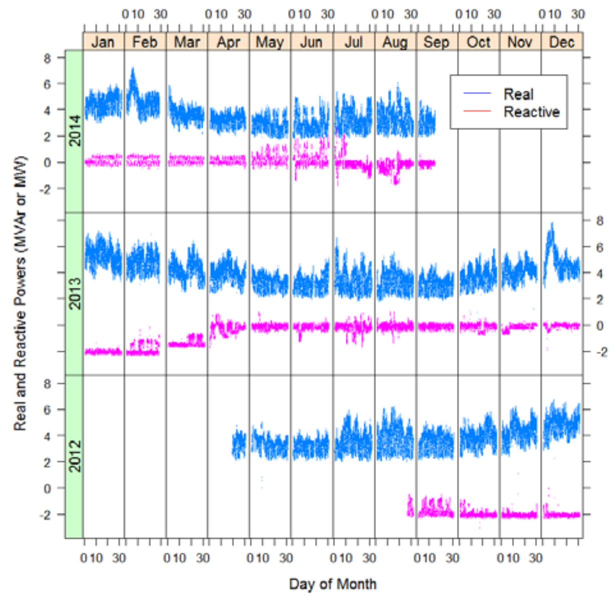
(c) Turner Feeder 115



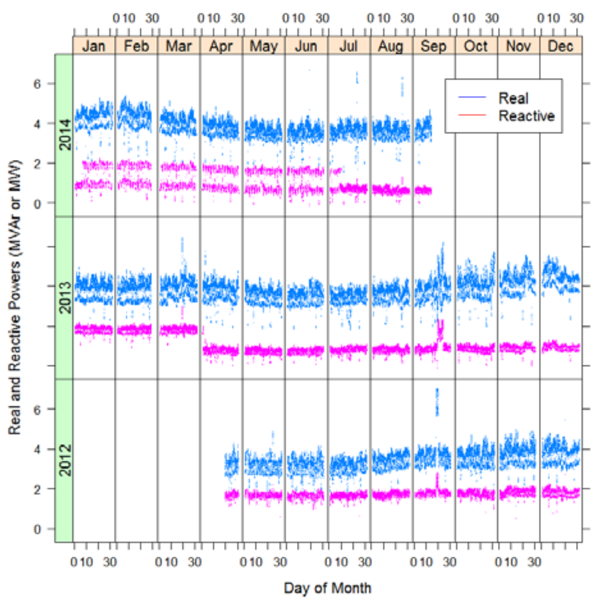
(d) Turner Feeder 116



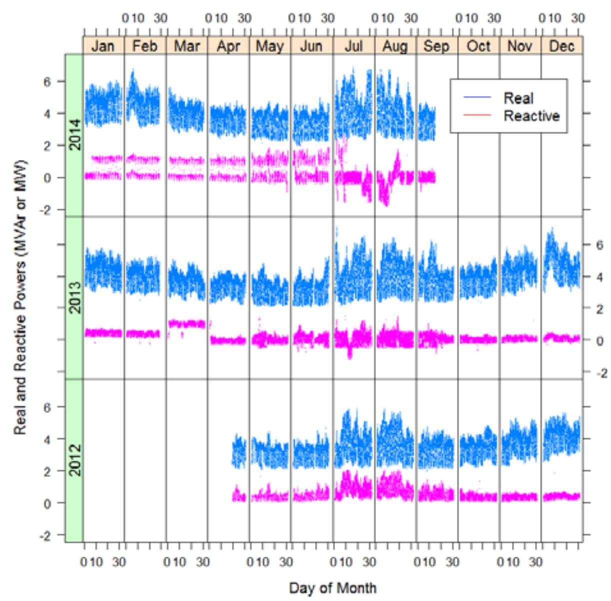
(e) Turner Feeder 117



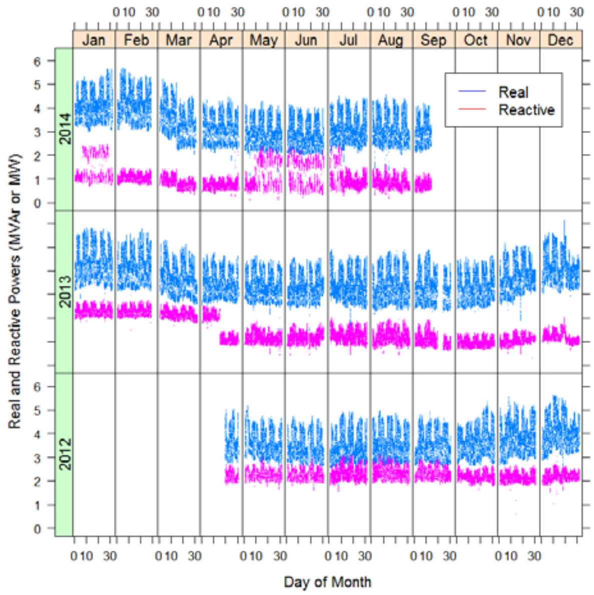
(f) South Pullman Feeder 121



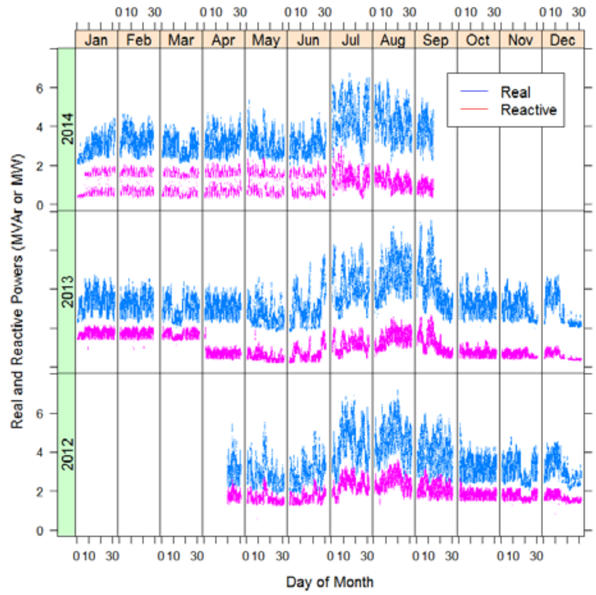
(g) South Pullman Feeder 122



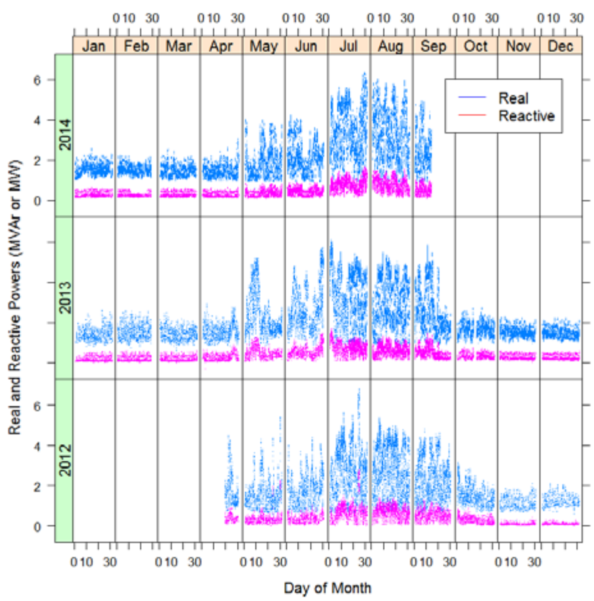
(h) South Pullman Feeder 123



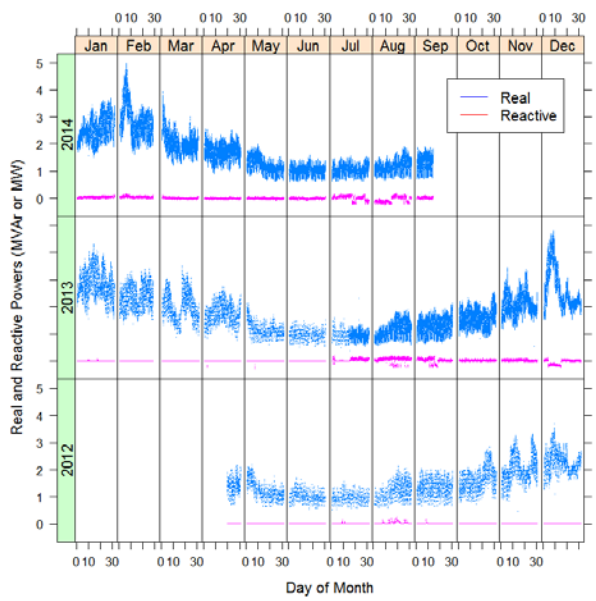
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.10. Real and Reactive Power Time Series for Pullman Site Feeders

Two of the three regression methods that were used in the analysis of the Pullman IVVC system incorporated temperature correction. A time series of ambient temperature data was found from weather station KPUW that is located at the Pullman-Moscow Regional Airport. The raw, sampled time series had missing intervals after it was moved to the project's 5-minute interval data frame. The data also possessed outliers at and near 0°F. To fix these shortcomings, a small band of data was first removed within the range −1.4°F to 1.4°F. This range was adjusted incrementally until the outliers disappeared upon visual inspection. The indiscriminate filter admittedly removed some valid data, as this is a relatively cold site. This data and data in many other missing data intervals were recovered by simple interpolation. The interpolation was permitted where the missing data interval was shorter than 6 hours.

The resulting time series of measured and interpolated temperatures is shown in Figure 7.11.

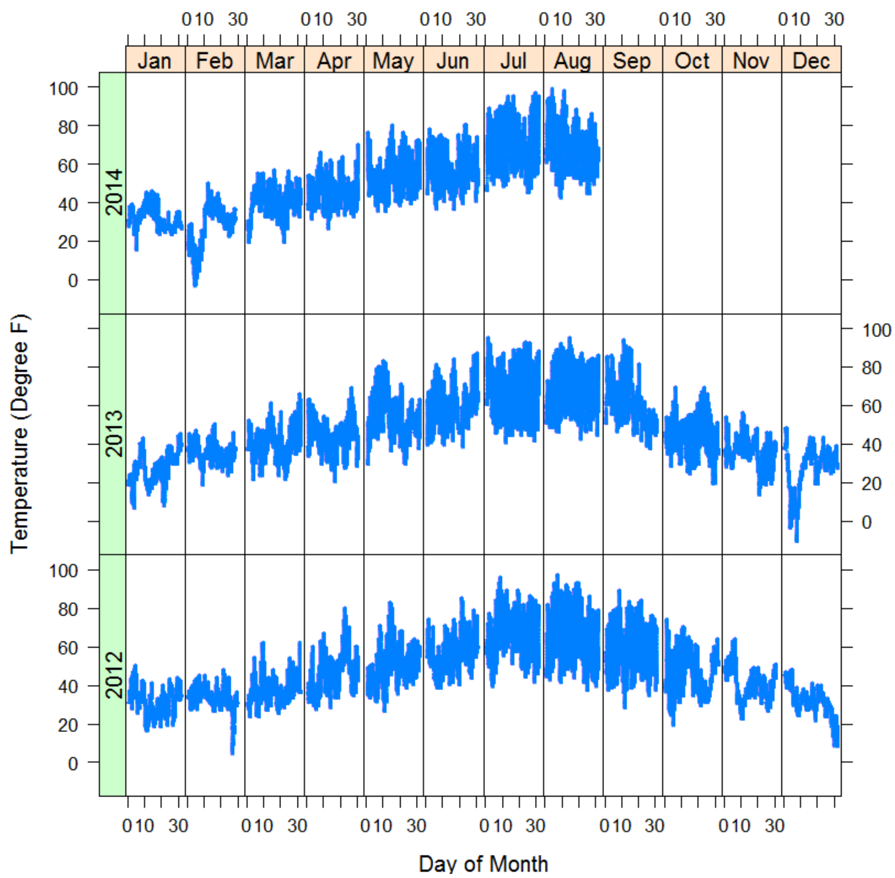


Figure 7.11. Series of Temperature Data from Weather Station KPUW at the regional Pullman-Moscow Regional Airport

IVVC might be expected to increase the number of switching events incurred by regulators and by controllable capacitors. The increased numbers of switching events may stress and shorten the life of affected distribution switch equipment. The data supplied to the project did not support a count of regulator switching actions that might have been then correlated with dynamic voltage management. However, the project received the counts of capacitor switching operations that had occurred each hour at each of the five South Pullman feeders. These sum counts were further aggregated by month and are shown in Figure 7.12. With the exception of a single outlier month, March 2012, for South Pullman Feeder 121, the sum counts of monthly switching operations were small before April 2013. The counts were observed to increase for all five feeders in 2014 as tests of VAr management were peaking. The counts at South Pullman Feeders 121 and 123 were strongly increased in 2013 and 2014, reaching counts of hundreds of switching events per month.

Based on Figure 7.12, there might be a valid concern that IVVC is stressing controllable capacitor banks.

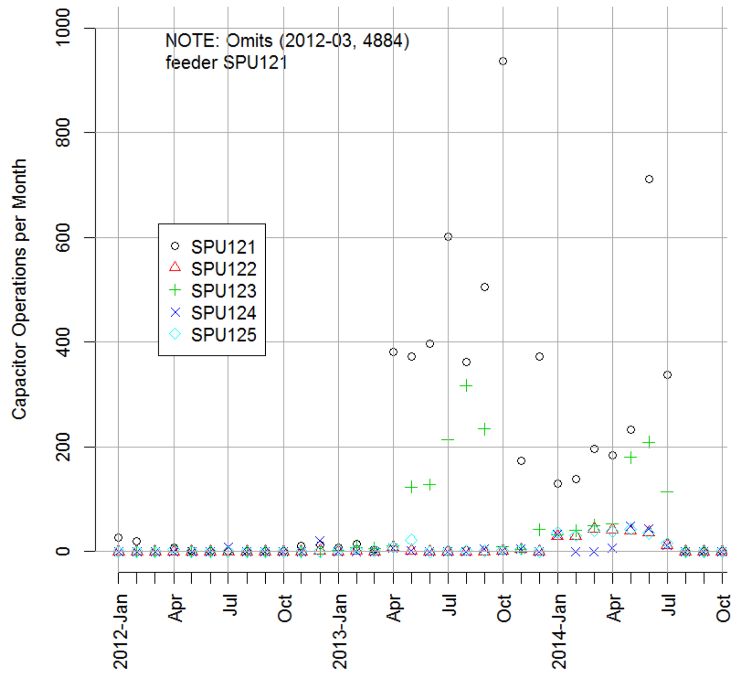


Figure 7.12. Monthly Counts of Capacitor Switching Operations, South Pullman Feeders

7.1.2 Analysis of the Avista Utilities Voltage Optimization System

Having observed evidence of voltage management among the raw phase-voltage data in late 2013 and in 2014, the project constructed distributions of the averaged phase voltages like the one shown in Figure 7.13 for Turner Feeder111. The histogram includes the counts of data intervals from only 2014. The histogram clearly shows a combination of two populations of voltage magnitudes on this feeder in 2014.

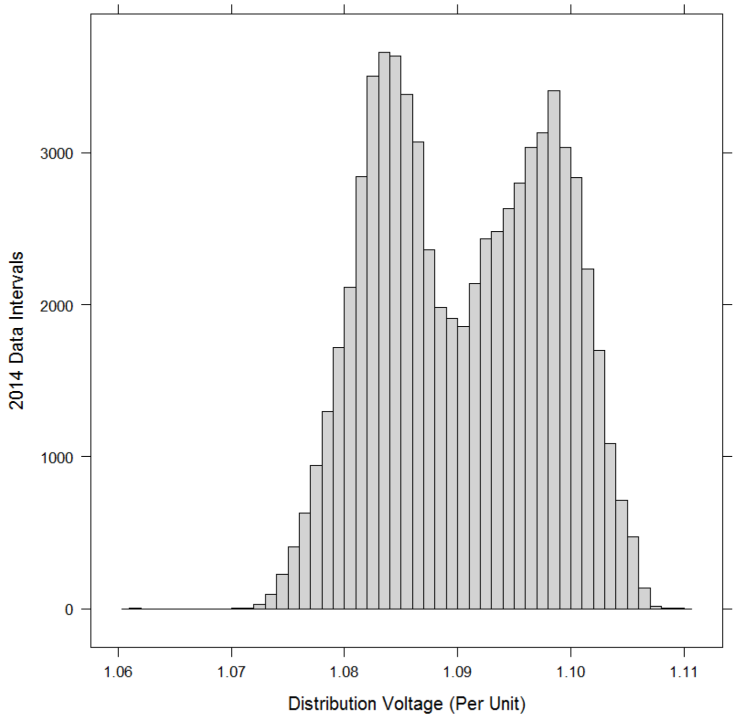
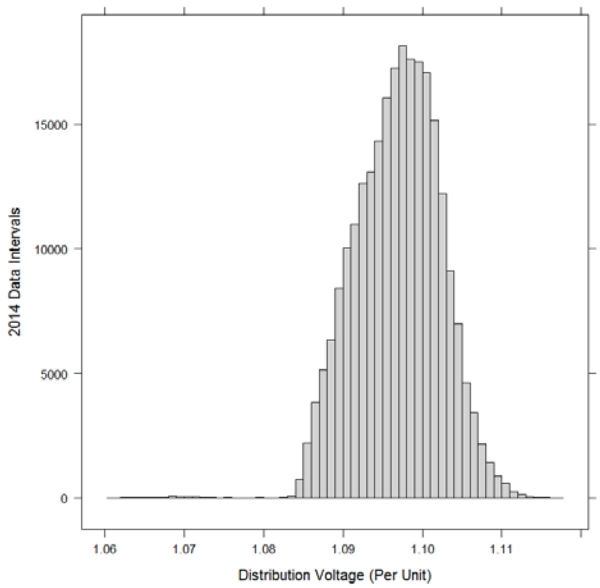


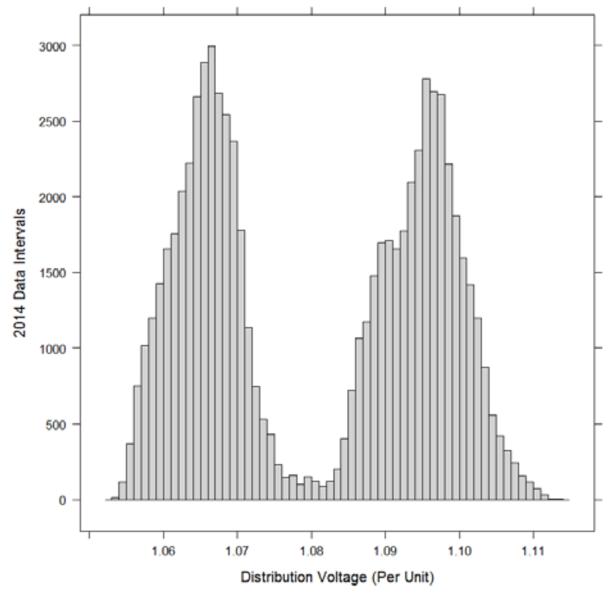
Figure 7.13. Histogram of Averaged Per-Unit Phase-Voltage Measurements for Turner Feeder 111 during 2014

The averaged phase-voltage histograms for the remaining 12 Pullman site feeders are shown in Figure 7.14. In addition to Turner Feeder 111, two or more distinct operational voltage levels are evident from these histograms on nine feeders: Turner Feeders 113, 116, and 117; South Pullman Feeders 121, 123 and 125; and both the Terre View Feeders 131 and 132. The separation of the voltages at South Pullman Feeder 125 was small, and there was much overlap between the voltages of the two operational modes. A third voltage level was suggested by the distribution for Terre View Feeder 131.

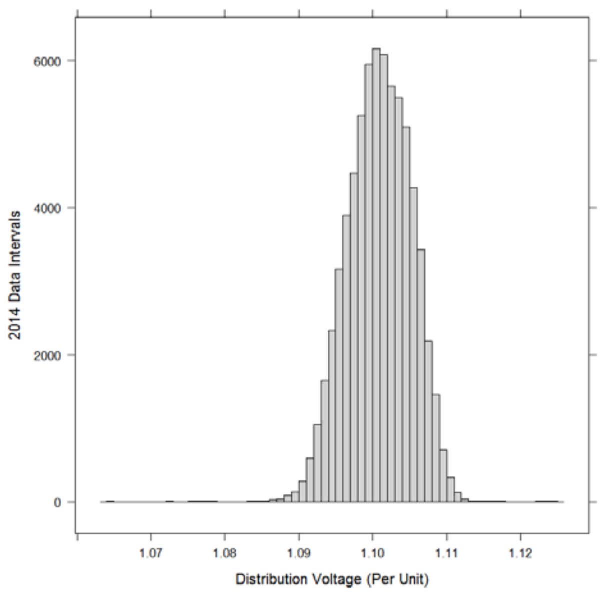
Thus, during 2014, distinct voltages might have been accurately identified at eight of the feeders based solely on a voltage threshold between the data populations. Fortunately, the project did not need to do so because the utility supplied a relatively accurate indicator of its voltage management intentions.



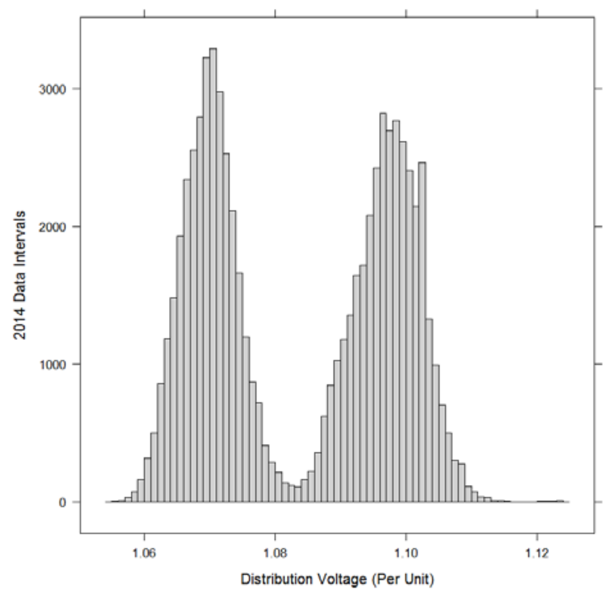
(a) Turner Feeder 112



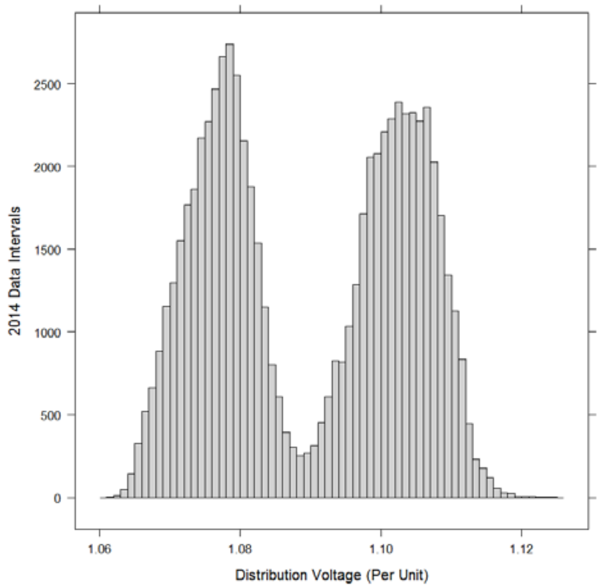
(b) Turner Feeder 113



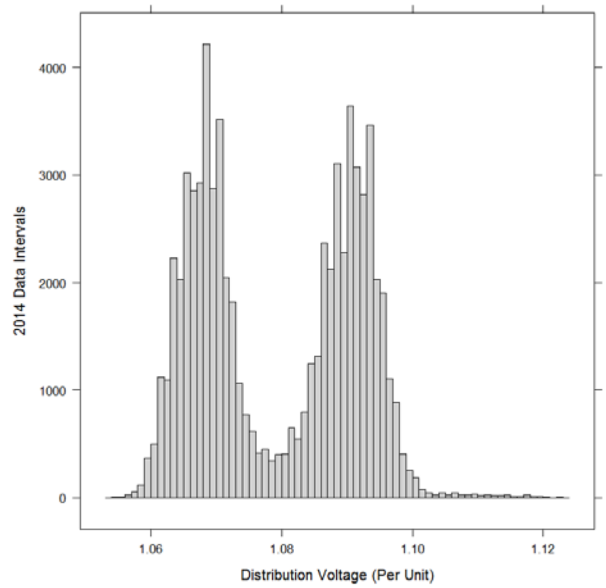
(c) Turner Feeder 115



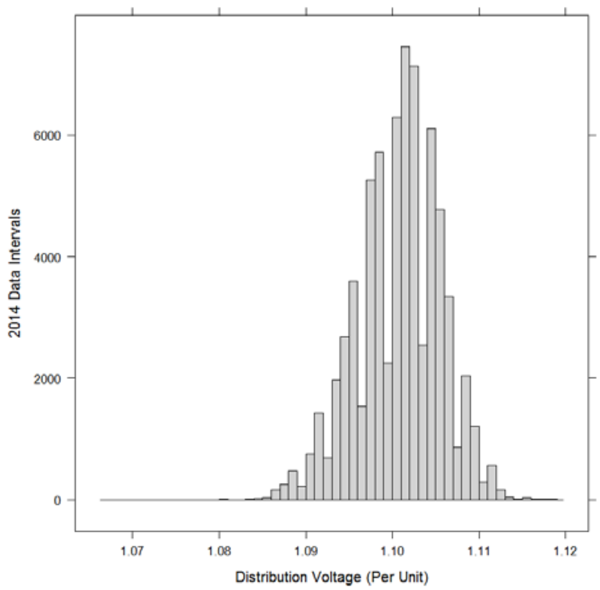
(d) Turner Feeder 116



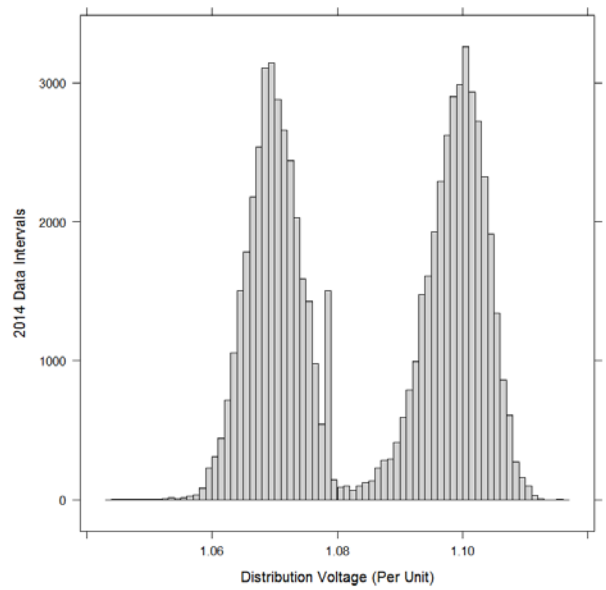
(e) Turner Feeder 117



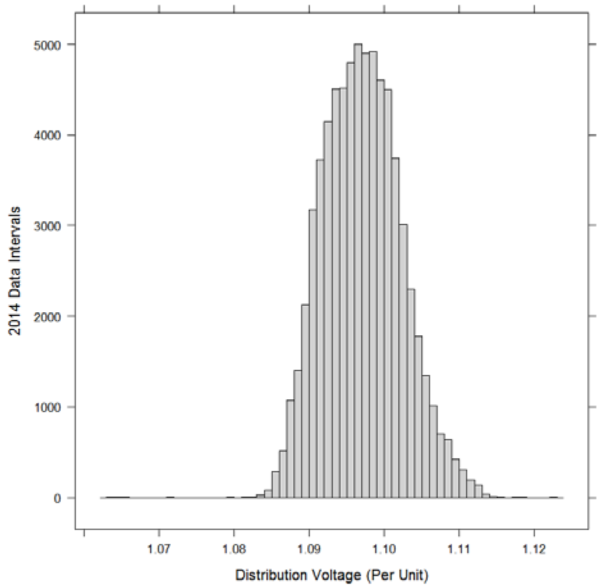
(f) South Pullman Feeder 121



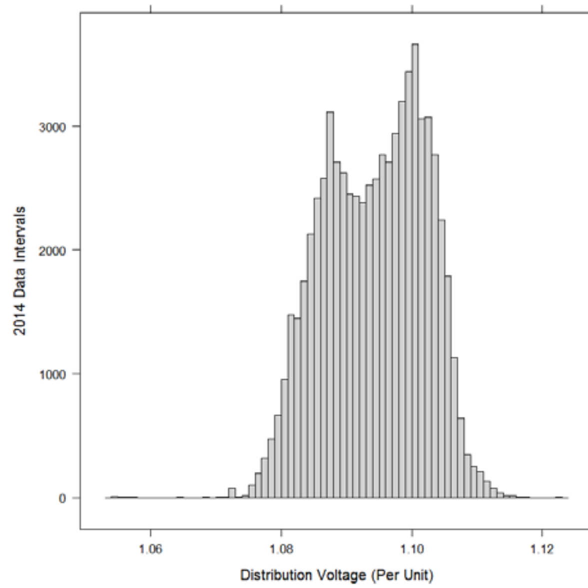
(g) South Pullman Feeder 122



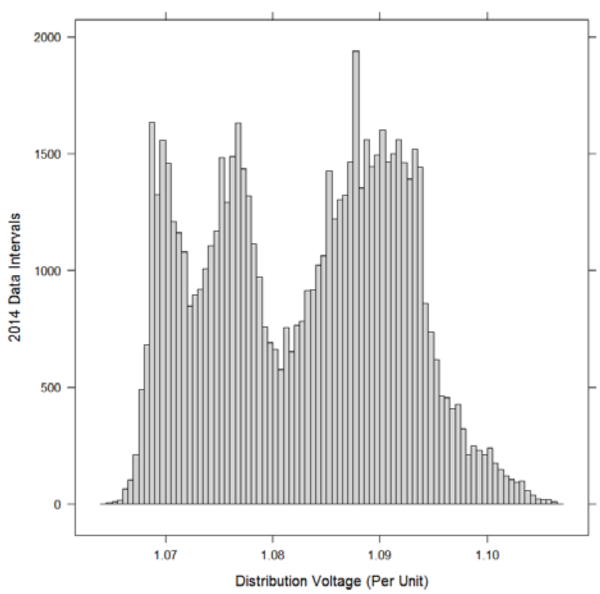
(h) South Pullman Feeder 123



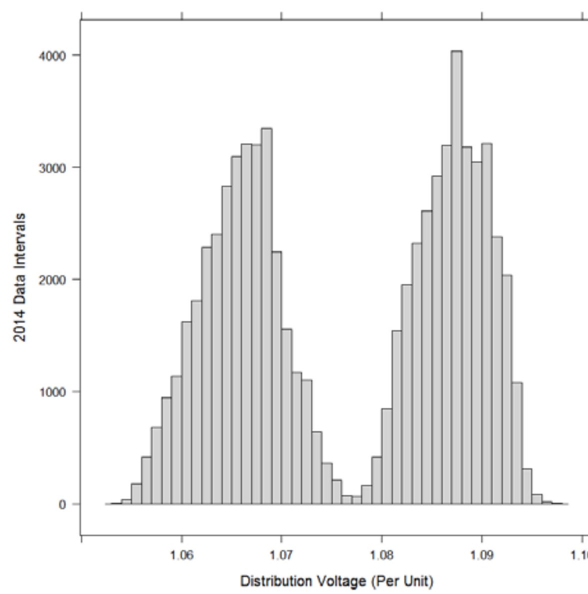
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.14. Histograms of the Averaged Per-Unit Phase-Voltage Measurements for 12 Pullman Site Feeders during 2014

Figure 7.15 shows information that is similar to that in histogram Figure 7.13, but using a quartile plot. Both figures are constructed for Turner Feeder 111, but the quartile plot includes all project data, whereas the prior histogram showed only data from 2014. Additionally, the separation between the two data populations in the quartile plot is based on the reported status of the feeder's voltage management that was reported to the project by the utility. Voltage is being managed (reduced) on the right ("Active") side, not on the left ("Normal") side. Any inaccuracy in the reporting of voltage management status for this feeder would affect the accuracy of the distributions shown in this plot. Specifically, such inaccuracies would typically lessen the distinction between the two data populations.

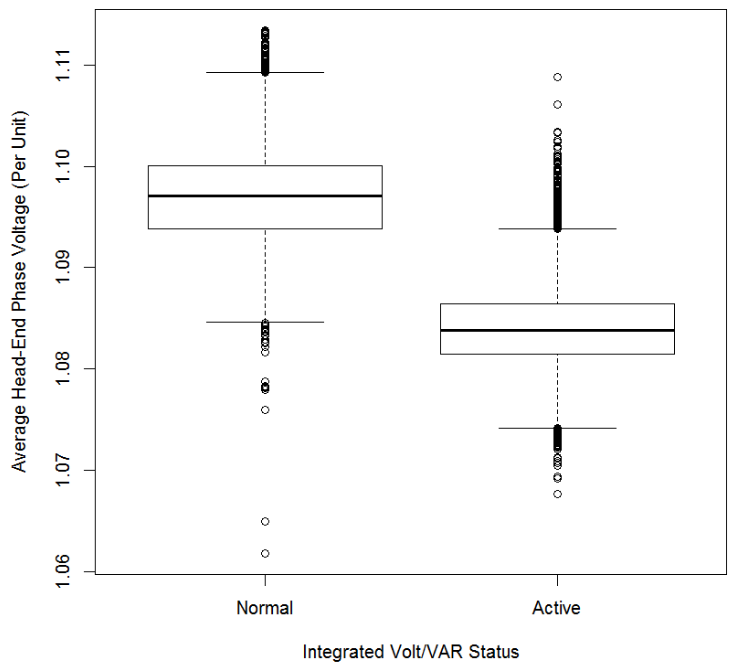
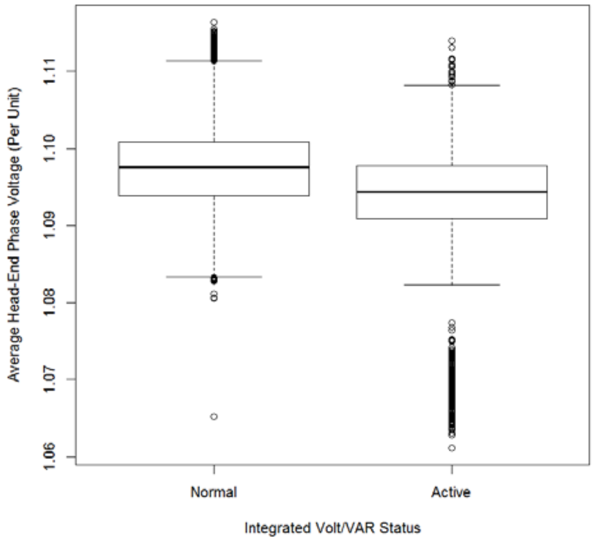
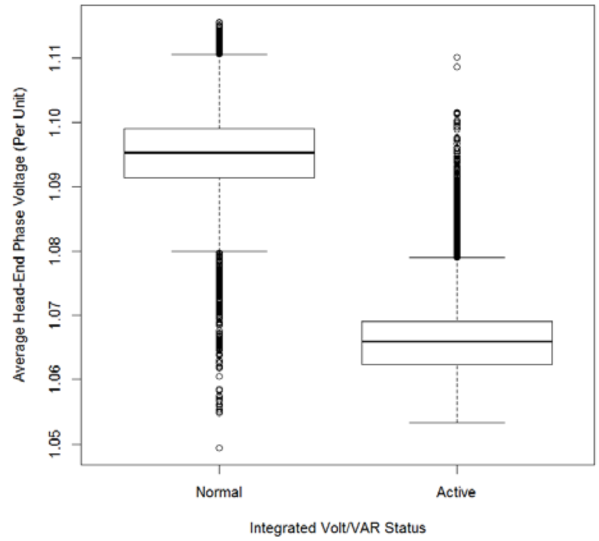


Figure 7.15. Quartile Distributions of Average Head-End Phase Voltages at Turner Feeder 111

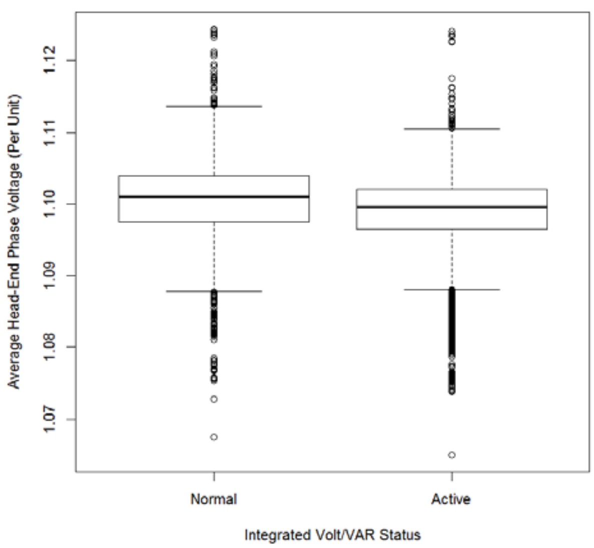
The quartile plots of active and normal head-end voltage data for the remaining 12 feeders are shown in Figure 7.16. The conclusions to be drawn are similar to those that were drawn from the histograms of Figure 7.14. It is noteworthy that the head-end feeder voltages at South Pullman Feeder 122 *increased* during times that voltage management was reportedly active. This is the only anomaly in that respect.



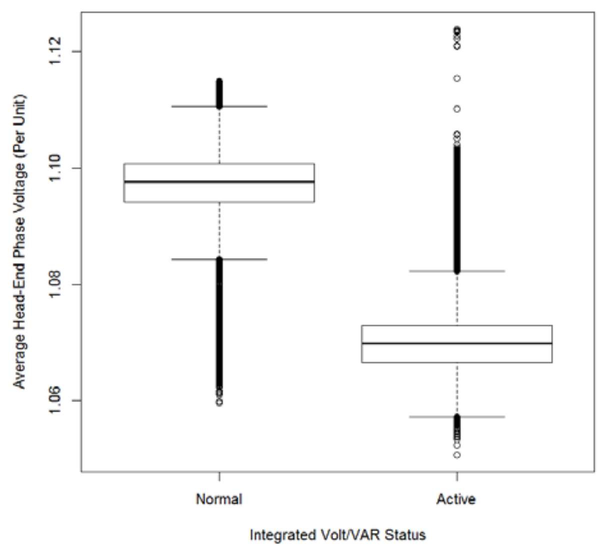
(a) Turner Feeder 112



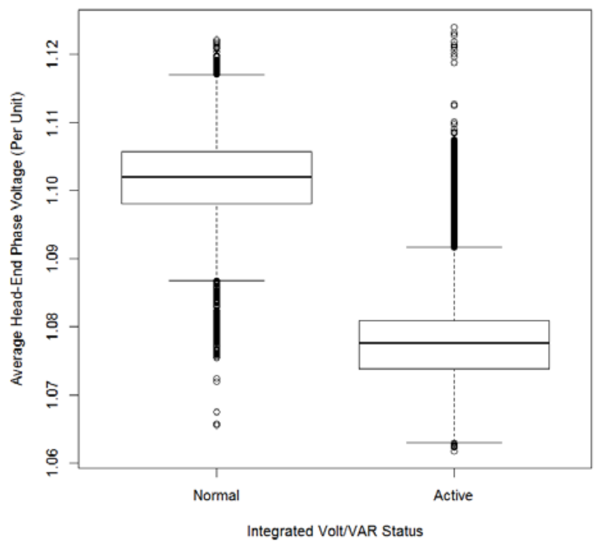
(b) Turner Feeder 113



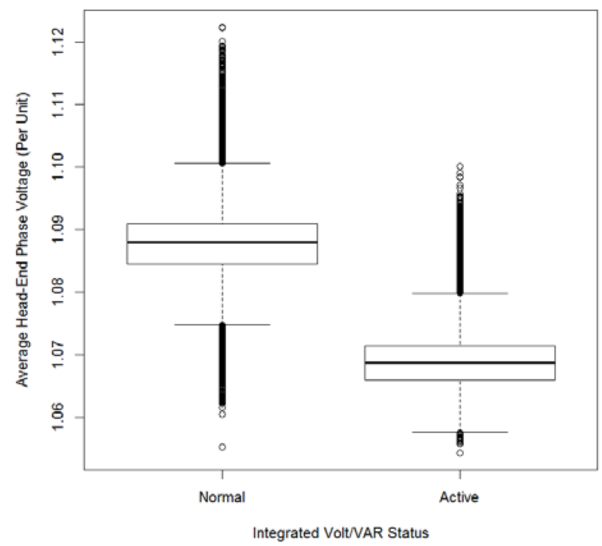
(c) Turner Feeder 115



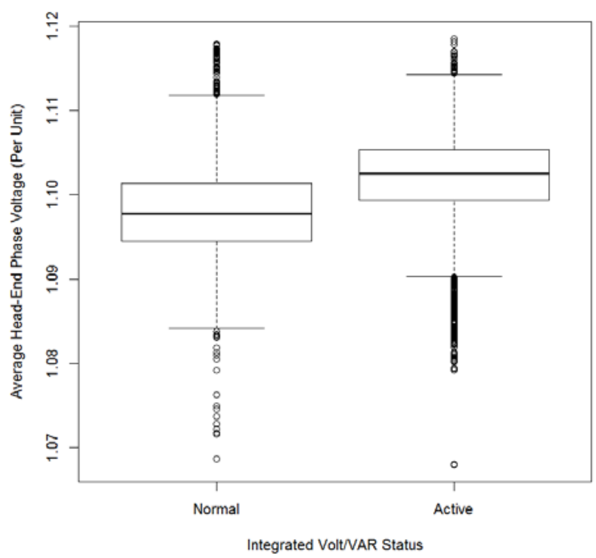
(d) Turner Feeder 116



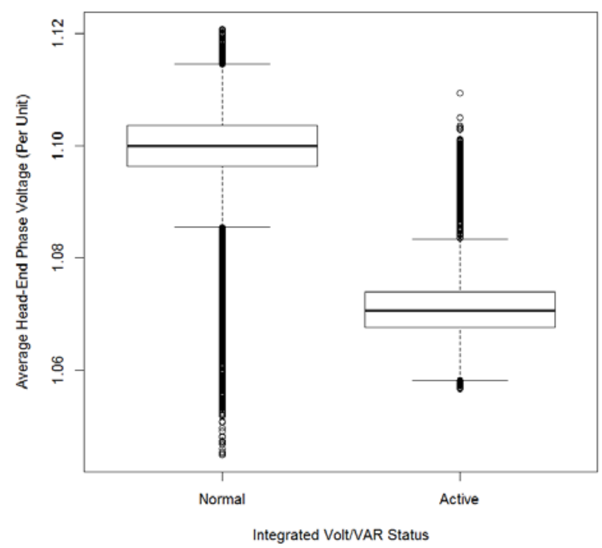
(e) Turner Feeder 117



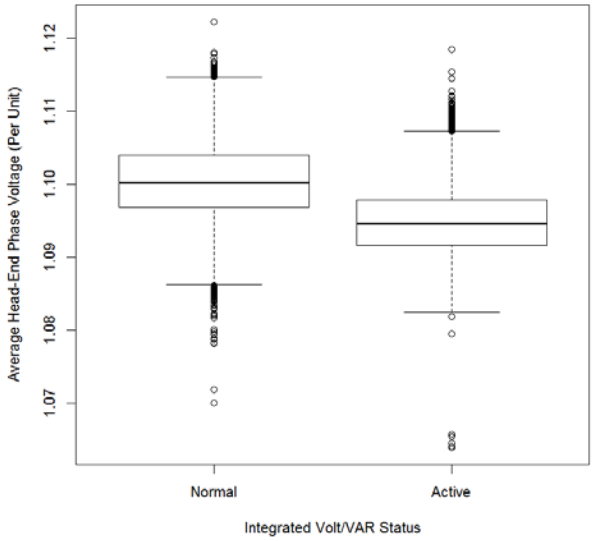
(f) South Pullman Feeder 121



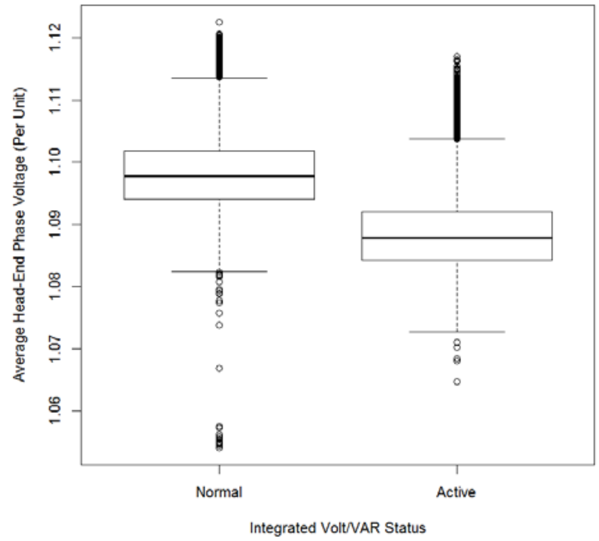
(g) South Pullman Feeder 122



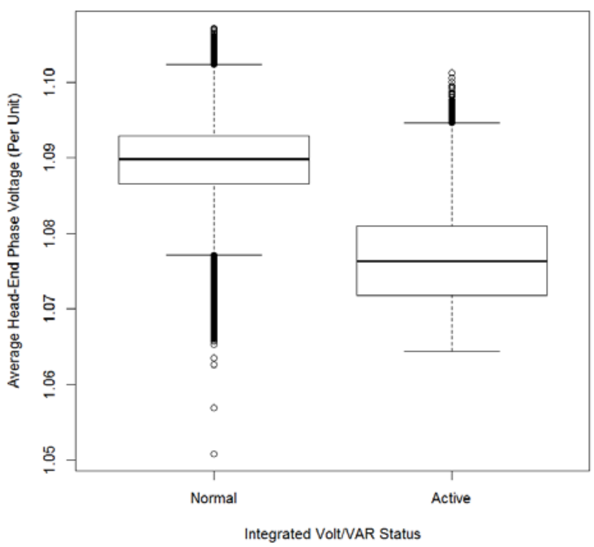
(h) South Pullman Feeder 123



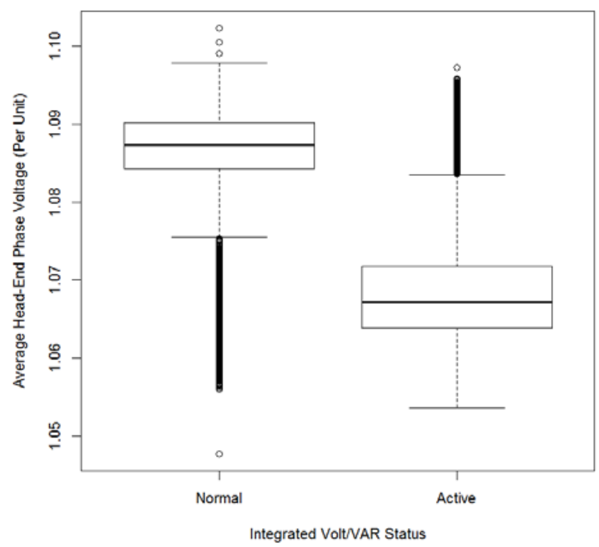
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.16. Quartile Distributions of Average Head-End Phase Voltages when the Integrated Volt/VAr System is Normal (not active) and Active

While the project might have directly analyzed reactive power, power factor is probably a better indicator of the success of an IVVC system. It is nicely normalized, a metric that always lies between zero and unity. At unity power factor, no reactive power is being supplied, either capacitive or inductive, and the minimum amount of conductor current is being used to supply the power needed on the feeder. Distribution line losses are thereby minimized, too.

Figure 7.17 is the time series of calculated power factors for Turner Feeder 111. Power factor is a function of real and reactive power. The project calculated the power factor for each data interval for which both valid real and reactive powers had been reported. The power factor on this feeder was observed to be reasonable through 2012. The power factor was good in 2012, but it never reached unity. After a precipitous drop in March and April 2013, the power factor improved and remained improved through the rest of 2013. Testing appears to have intermittently taken place during 2014, causing the power factor to sometimes return to the 2012 and early 2013 management standards.

The project received no useful indicator when reactive power was being managed and not on the feeders. Color was applied in Figure 7.17 according to the indicator that had proven accurate and useful concerning voltage management. The correlation between power factor level and this indicator is weak at this feeder, suggesting that VArs and volts were individually controlled. Possessing no strong indicator of the utility's intentions for VAr management on this feeder, the project's analysis of these impacts was diluted and imprecise.

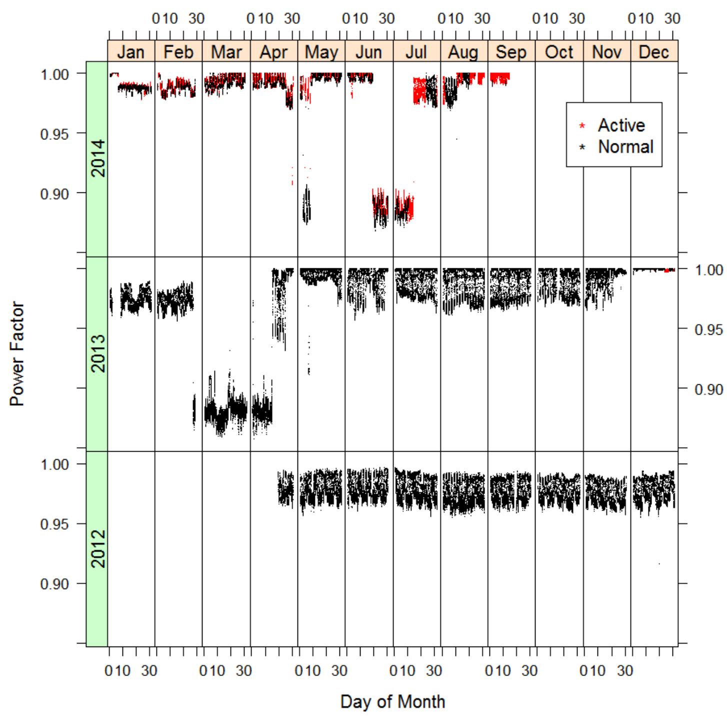
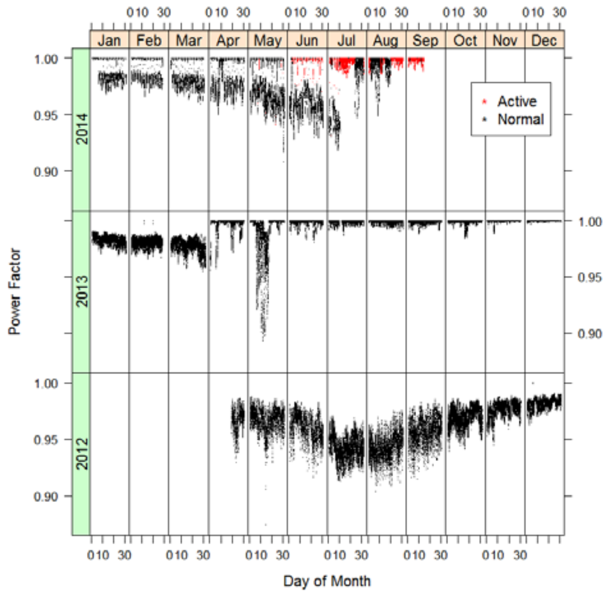
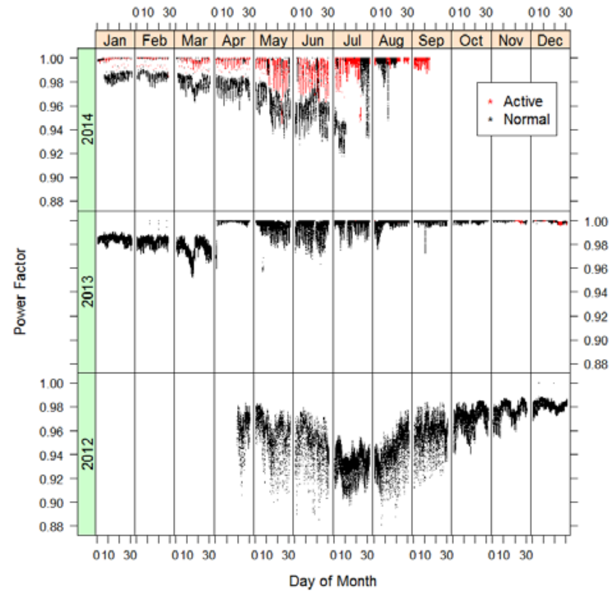


Figure 7.17. Calculated Power Factor for Turner Feeder 111

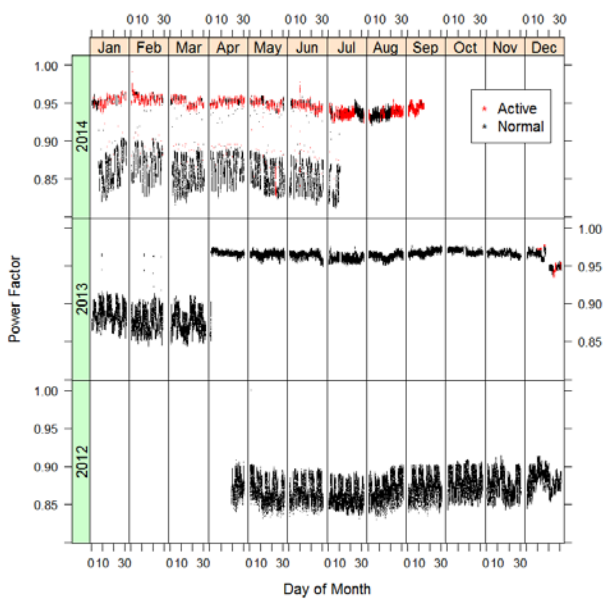
The calculated power factors on the other 12 feeders are shown in the panels of Figure 7.18. Marked improvements in feeders' power factors were observed beginning in April 2013 at all but four feeders—Turner Feeder 116, South Pullman Feeder 123, and Terre View Feeders 131 and 132. This observation had already been made based on reactive power levels. Some degree of reactive power management testing was evident at all of the Pullman site feeders, except perhaps South Pullman Feeder 121 and Terre View Feeder 132. Although the accuracy of the correlation was always questionable, some degree of correlation between the calculated power factors and the reported status of the voltage management system existed at all the feeders except South Pullman Feeder 121 and Terre View Feeder 132. The analyzed impacts of reactive power dynamic management were diluted by the lack of a clear signal that indicates when the utility is actively managing VArs and when it is not.



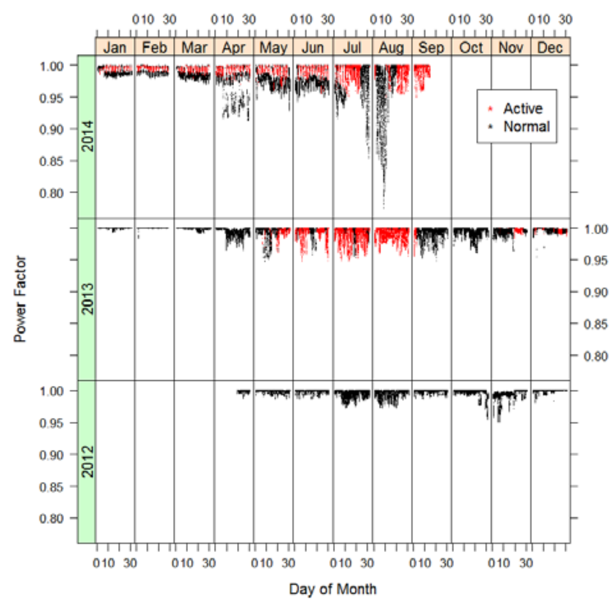
(a) Turner Feeder 112



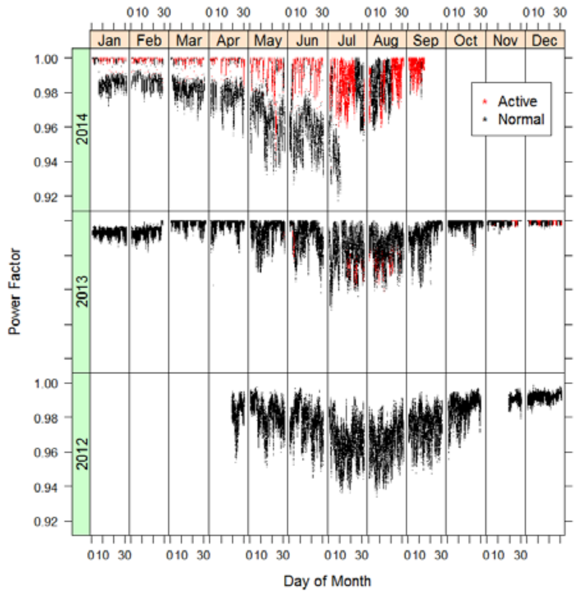
(b) Turner Feeder 113



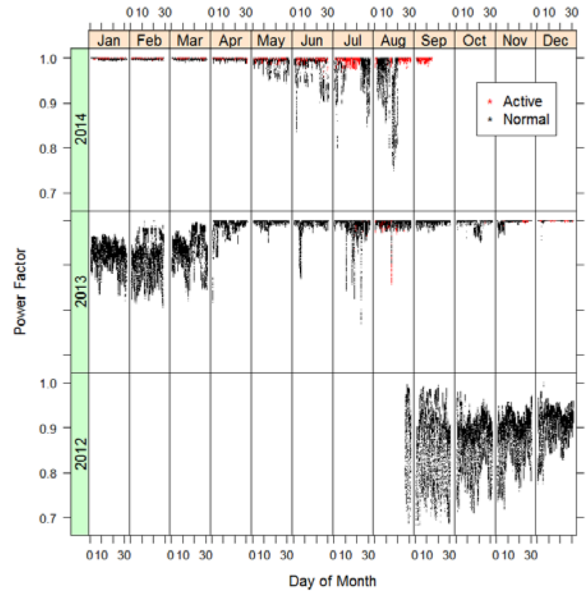
(c) Turner Feeder 115



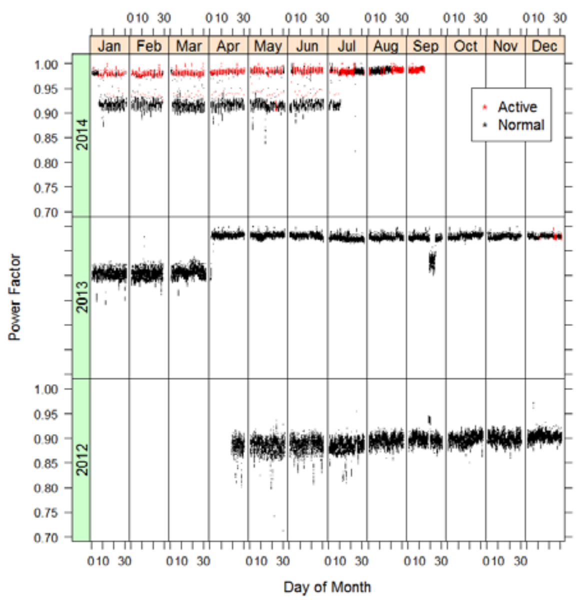
(d) Turner Feeder 116



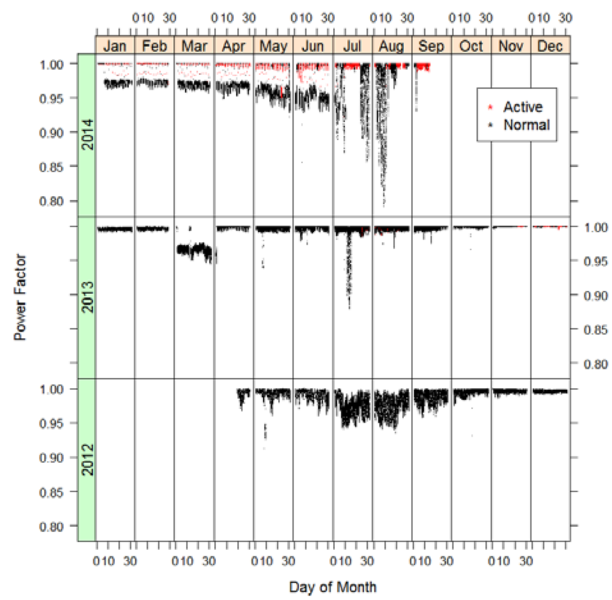
(e) Turner Feeder 117



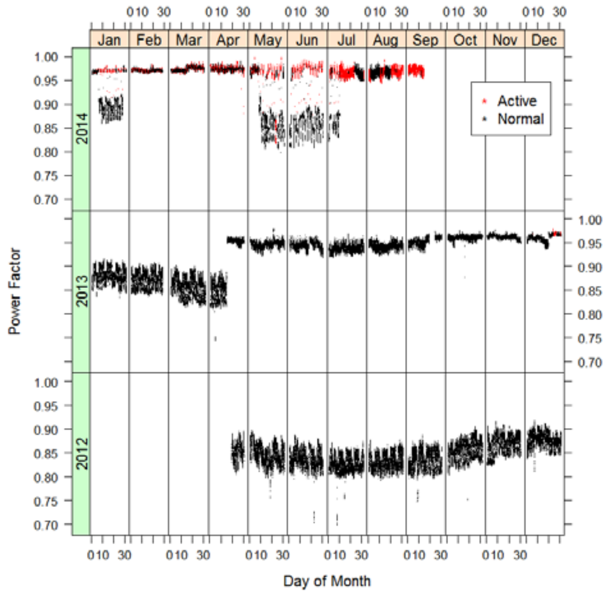
(f) South Pullman Feeder 121



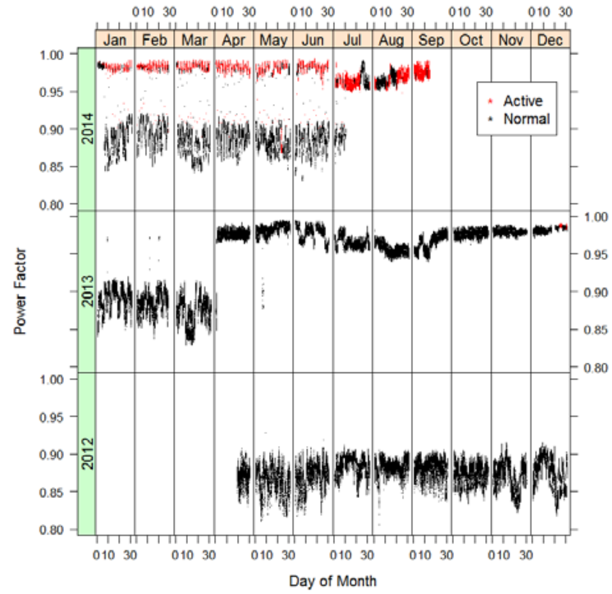
(g) South Pullman Feeder 122



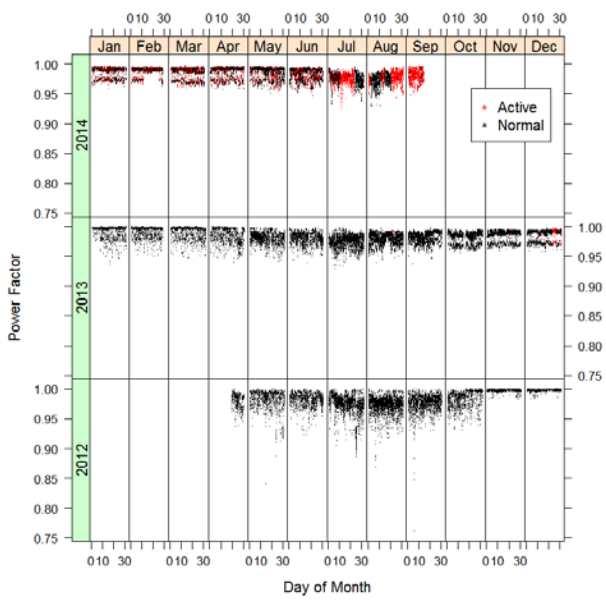
(h) South Pullman Feeder 123



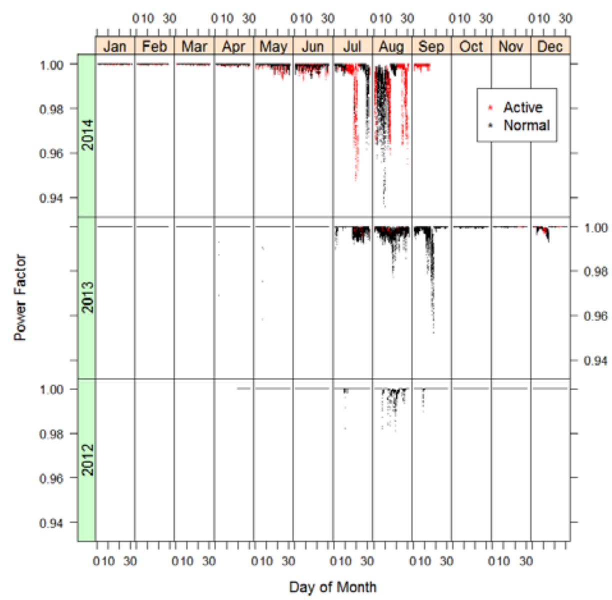
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.18. Calculated Power Factors for Pullman Site Feeders

It has been pointed out several times that the reactive power management practices at the Pullman site appear to have been changed several times during the PNWSGD. This observation is quantified in Figure 7.19, which shows the quartile distributions of calculated power factors at Turner Feeder 111 separately for years 2012, 2013, and 2014. The 2012 values preceded the utility's efforts to correct power factor, which became fully effective in April 2013. After the correction of April 2013 had taken place, the utility maintained these calibrations and configurations through the remainder of 2013. Power factor was markedly better and would have appeared even more improved if 2013 data had excluded its first four months. The power factors became worse in 2014 as the utility appeared to conduct various reactive power management experiments and tests. The project could not discern for certain whether the changes to power factor were a passive byproduct of intentional voltage management, or whether the reactive power had been intentionally and independently controlled. Upon its review, Avista Utilities confirmed that voltage and reactive power could be independently controlled by its IVVC system, and that no data tag had been created for the times that the IVVC system had controlled reactive power.

The above observations about how power factor was managed hold similarly for nearly every Pullman feeder. Quartile plots are not offered for the other 12 feeders.

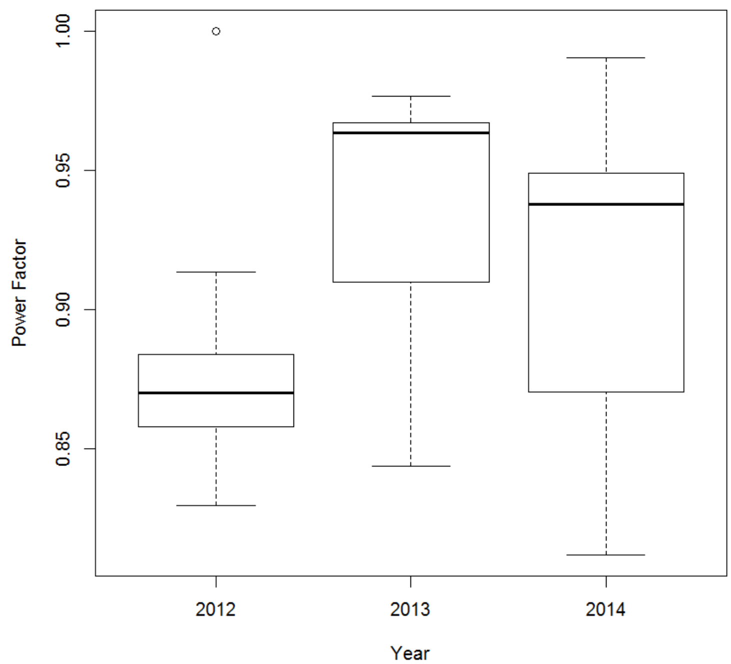


Figure 7.19. Quartile Distributions of Calculated Power Factor by Project Year for Turner Feeder 115. On this feeder, the reduction of power factor in Year 2014 is a pronounced example of what was observed for all Pullman site feeders.

Quartile plots like the example of Figure 7.20 were generated for the 13 Pullman site feeders. This plot compares the populations of the feeder's power factors when the voltage management had been reported to be inactive (false) against when it was reported to have been active (true). The power factors were improved when the voltage management indicator was active, but the differences are small.

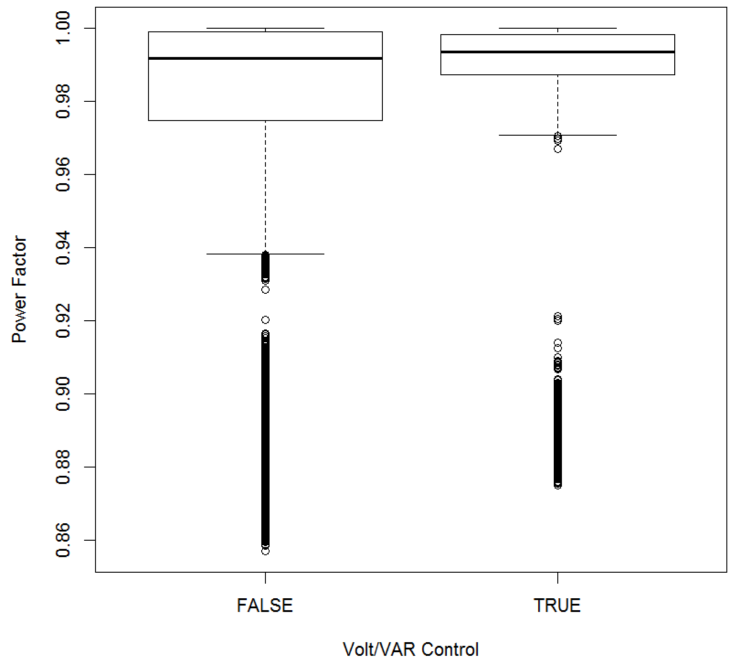
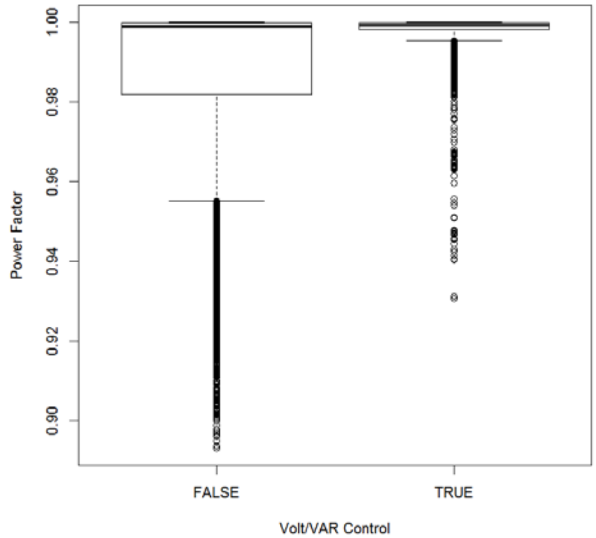
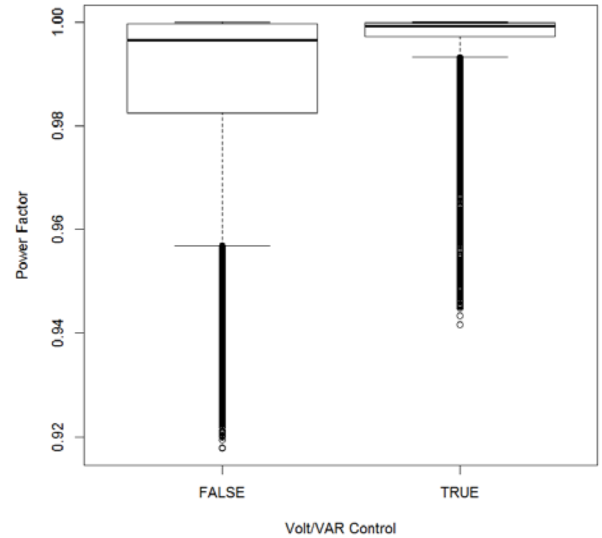


Figure 7.20. Quartile Distributions of Power Factor of Turner Feeder 111 when the IVVC System was Active (True) and Not (False)

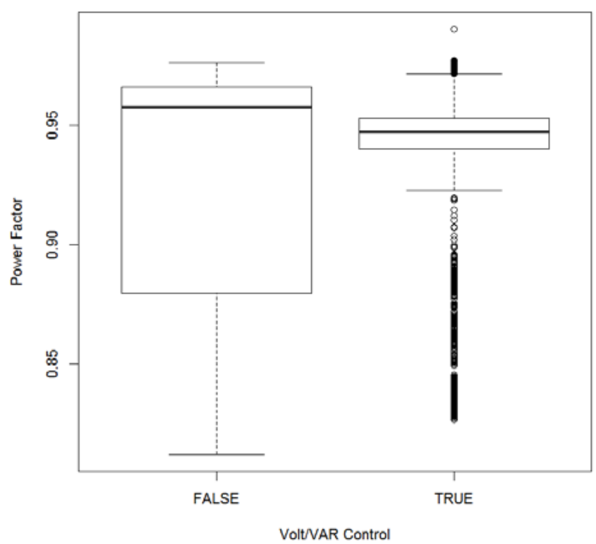
The quartile plots showing the change in power factors for the remaining 12 Pullman site feeders are shown in the panels of Figure 7.21. Small improvements are perhaps evident for all but three of the feeders. Virtually no improvement was evident at the two Terre View Feeders 131 and 132. The power factor at Turner Feeder 115 actually got worse at times the voltage was reported to be managed.



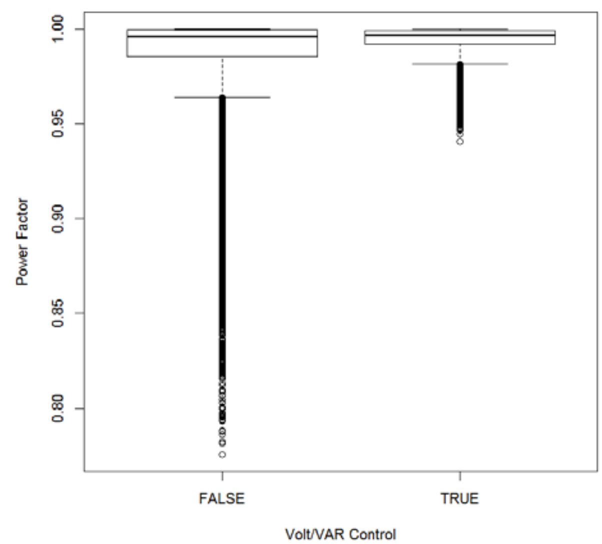
(a) Turner Feeder 112



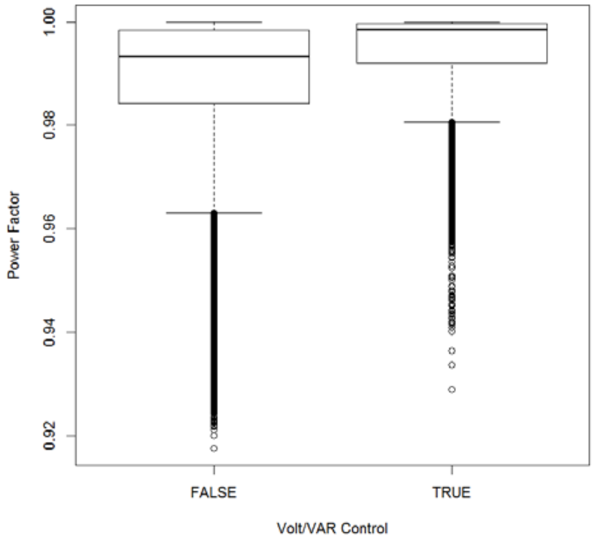
(b) Turner Feeder 113



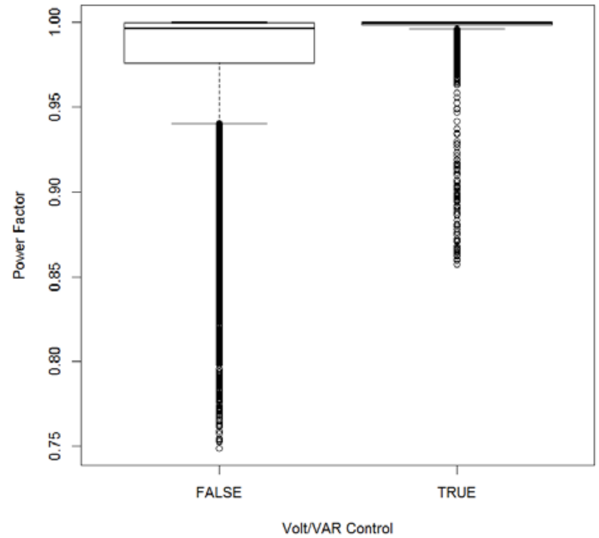
(c) Turner Feeder 115



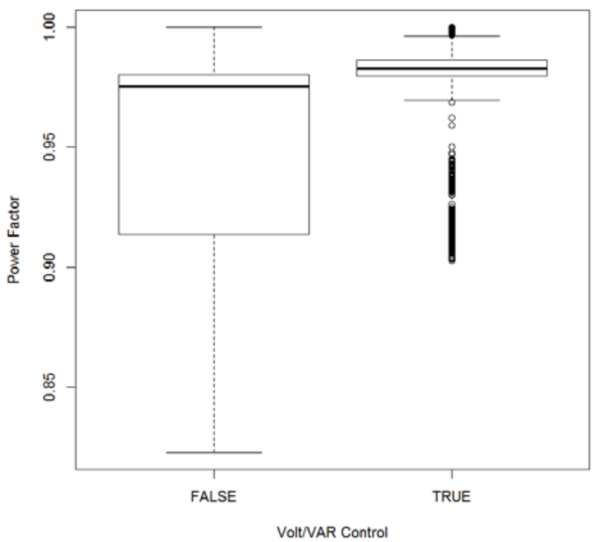
(d) Turner Feeder 116



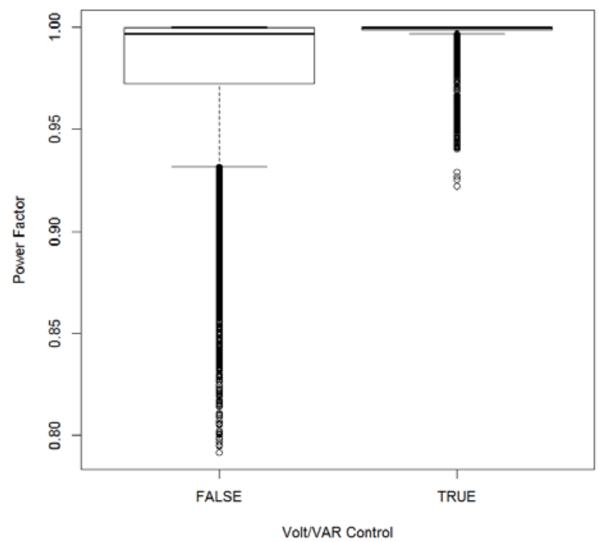
(e) Turner Feeder 117



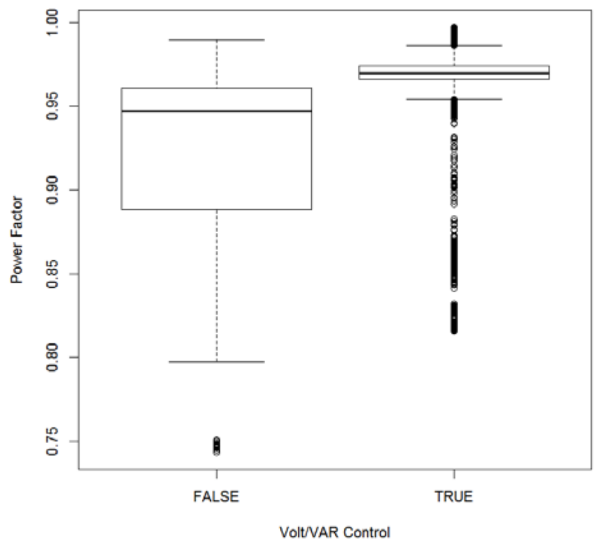
(f) South Pullman Feeder 121



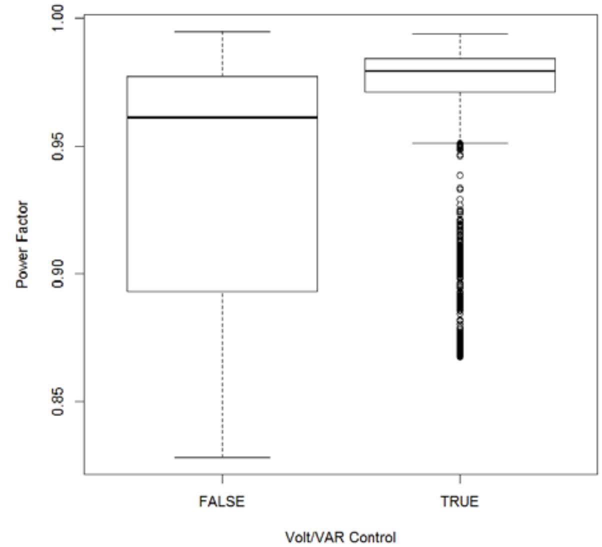
(g) South Pullman Feeder 122



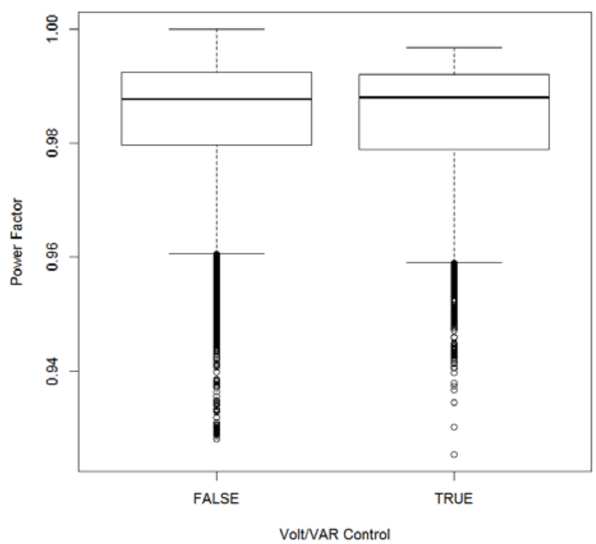
(h) South Pullman Feeder 123



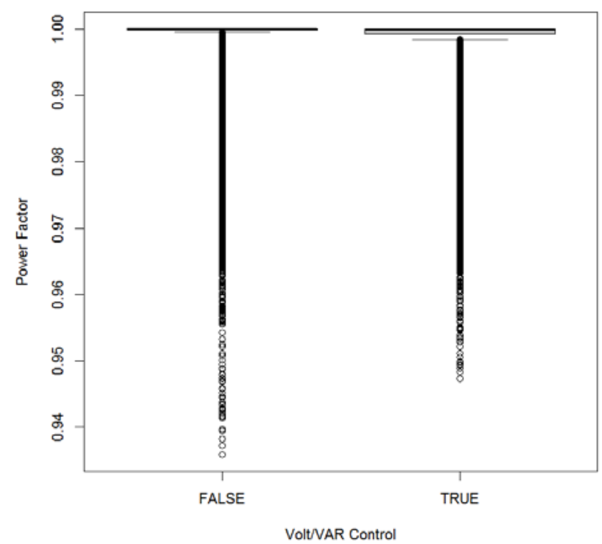
(i) South Pullman Feeder 124



(j) South Pullman Feeder 125



(k) Terre View Feeder 131



(l) Terre View Feeder 132

Figure 7.21. Quartile Distributions of Power Factor of Pullman, Washington, Feeders when the Feeder's IVVC System was Active (True) and Not (False)

Project analysts devised and completed three analysis methods to estimate the seasonal, weekday and weekend impacts of voltage management on the Pullman feeders. A data period from September 1, 2013, through August 31, 2014, was used for each method. Because this is an IVVC system, the individual power impacts from voltage and VAr (or power factor) management cannot be fully separated. The results of analysis are likely to exceed the conservation that is normally available from voltage management alone (i.e., conservation voltage reduction, or CVR).

Method 1 directly compared consumption when voltage management was reported against that when the system was not reported to be under voltage management. This method was not temperature corrected. Temperature correction may not be essential when long periods of day-on/day-off testing are conducted. No regression methods were used. Average consumption during reported voltage management was simply compared against that of normal periods. Separate assessments were made for each season by weekend and weekday.

Method 2 was similar to Method 1, but it employed temperature correction and used regression methods. The fit was made to season, local hour of day, weekday type, and all permutations of these variables with ambient temperature. Additional parameters were introduced for all permutations of the voltage-control status with season and weekday type. R software was used for the linear regression (R Core Team 2013). The regression fit's coefficients that included the status of the voltage management system were reported as analysis results.

Method 3 may be novel. First, both voltage and distribution power each month were normalized by subtracting the month's average value and then dividing by the average. A linear regression was then conducted to model the normalized, relative power as a linear function of all the permutations of season, hour of day, and weekday type with ambient temperature. Additional variables were defined for the permutations of season, weekday type, and normalized voltage. As was the case for Method 2, the coefficients of the fit produced using regression in R software were reported for the parameters that included the status of the voltage management system. A principal advantage of Method 3 is that it directly yields the CVR factor as the coefficient of the term that was applied to the relative voltage change. That is, these terms state change in relative power or energy as a function of change in relative voltage. This method was found to be somewhat robust even when voltage management status was inaccurately reported and when irregular test periods occurred, whereas Methods 1 and 2 became less trustworthy and yielded wilder estimates when day-on/day-off tests were not used.

An interesting interplay was expected with Method 3 between the impacts of intentional voltage management and passive voltage management. The CVR impact is expected where different voltages were intentionally applied, and power is expected to have some proportionality to the applied voltage. However, a natural fluctuation in voltage might accompany changes in load in passive systems. In this case, voltage drops increase across distribution lines and transformers as load rises, which has a downward influence on voltage. These two potential impacts are contrary. Feeders that are not conducting intentional voltage management might, therefore, exhibit negative CVR coefficients.

An emerging protocol for assessing CVR impacts is available from the Regional Technical Forum, a subcommittee of the Northwest Power and Conservation Council (Regional Technical Forum 2015). None of the three methods are claimed to strictly follow that protocol.

Table 7.3 lists the findings for the 13 Pullman site feeders using novel Method 3. The analysis was conducted separately for weekdays and weekend days. This table combines the impacts from all four seasons. The columns include the difference between median relative voltages when voltage management was reported active and not (ΔV), the product of CVR factor and the difference of median voltages (ΔP), the CVR factor itself, and the change in energy that season and weekday type calculated as though voltage management been continuous (ΔE).

The calculated CVR factors and relative changes in power are larger and more dramatic at feeders that had little or no change in voltage. Increased voltage was observed at South Pullman Feeder 122 when voltage management was reported, which affected the signs of the changes in power and energy. Interestingly, Method 3 ignored the anomalous changes in voltage with system status and still calculated a credible CVR factor for that feeder.

The project determined that the total load of the Pullman feeders during September 1, 2013, through August 31, 2014, was about 375 GWh. Of this total, 273 GWh was consumed on weekdays, and 102 GWh was consumed on weekend days. The sum of the weekday conservation from Table 7.3 was 6.53 GWh per year for weekdays, and conservation for weekend days was 1.26 GWh per year. These constitute an estimated total conservation of 7.79 GWh per year if IVVC were practiced throughout the year as it was demonstrated intermittently on all the Pullman feeders. The calculated conservation was about 2.1% of total load, just a little less than Avista Utilities' prediction of 1.85%.

Table 7.3. Summary of Estimated Volt/VAr Management Impacts using Method 3

	Weekdays				Weekends			
Feeder	ΔV (%)	ΔP (%)	CVR Factor	ΔE (MWh/y)	ΔV (%)	ΔP (%)	CVR Factor	ΔE (MWh/y)
TUR111	−1.23	−1.9	1.5	−378	−1.11	−1.2	1.0	−84
TUR112	−0.29	−1.7	5.9	−369	−0.38	−3.5	9.2	−306
TUR113	−2.74	−3.5	1.3	−616	−2.69	−1.1	0.4	−78
TUR115	−0.19	−1.1	5.8	−260	−0.14	−0.6	4.4	−52
TUR116	−2.46	−2.7	1.1	−540	−2.46	−1.5	0.6	−123
TUR117	−2.30	−2.7	1.2	−782	−2.38	−0.2	0.1	−19
SPU121	−1.95	−2.7	1.4	−626	−2.01	0.0	−0.0	2
SPU122	0.38	1.3	3.5	327	0.38	1.1	2.8	102
SPU123	−2.55	−1.9	0.7	−469	−2.56	−0.2	0.1	−20
SPU124	−0.38	−1.9	5.1	−431	−0.38	−1.1	3.0	−90
SPU125	−0.85	−7.6	8.9	−1682	−0.81	−4.0	4.9	−308
TVW131	−1.21	−5.1	4.2	−617	−1.24	−7.4	6.0	−344
TVW132	−1.84	−0.8	0.4	−85	−1.83	1.3	−0.7	58

MWh = megawatt hour

Much more detail is supplied in Table 7.4 for impacts from individual seasons, weekdays, and feeders. This table includes analysis results from all three analysis methods that were applied by the project. Sub-tables were created for each feeder.

The first five rows of each sub-table list some general measurements and metrics that were useful. The first row ($P_{avg.}$) is the average power during the given season and weekday type. The second row ("DODO") is a metric devised by the project to indicate how closely the utility had adhered to a strict day-on/day-off regimen during the season on that feeder. First, each day was alternately given a value of either 1 or −1. Next, the applied values were added for days on which voltage management was active and not active for the given season. Finally, the magnitude of that difference was divided by the sum calculated as though all the days had been given the value 1.0. The formula for the new metric is given in Eq. 7.1.

$$DODO = \frac{\left| \sum_{active}\{1.0,-1.0\} - \sum_{normal}\{1.0,-1.0\} \right|}{\sum_{active} 1.0 + \sum_{normal} 1.0} \qquad \text{Eq. 7.1}$$

If voltage management were randomly applied, or if voltage management were never applied, the value of the new DODO metric would be about zero. If alternate days were strictly designated for voltage management, the metric would be near unity. Because Avista Utilities did most of its day-on/day-off testing in spring 2014, the metric is high in the spring season. This metric is potentially important because less robust methods like Methods 1 and 2 will perform better when this metric is near unity.

The metric row ΔT indicates the average difference between ambient temperatures when voltage management was reported and not reported for the given season and day type. Positive values mean that the temperature tended to be higher during voltage management. Negative values mean the temperatures were higher without voltage management. If voltage management periods were fairly or randomly applied during the period, the difference between the average temperatures would be small. Also, if the temperatures were similar, less sophisticated analysis methods might be valid. If the temperatures were different, then temperature correction was more critical and necessary for the analysis.

The fourth row states the average per-unit voltage ($V_{avg.}$) for the given season and day type while voltage management was not being applied. That is, this is a representation of normal voltage without voltage management. The fifth row states the difference between median voltages when voltage management is being applied and not (ΔV). As stated earlier, these voltages are based on average distribution phase voltages. The end-of-line voltages were not found to have been consistently measured and calibrated.

For both Methods 1 and 2, the change in average power was directly calculated, and the CVR factors and projected energy impacts were calculated from the change in average power using the differences in median voltages and the sums of hours of each season and day type. Method 3 directly calculated CVR factor, and the change in average power and energy were then calculated based on the difference in median voltage and numbers of each type of hour each season and day type.

Table 7.4. Summary of Feeder CVR Metrics

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder TUR111	$P_{avg.}$ (kW)	3,602	3,270	3,085	2,807	2,918	2,635	3,193	2,873	3,220	2,911
	DODO	0.56	0.63	0.93	0.92	0.41	0.36	0.03	0.08	0.48	0.50
	ΔT (°F)	2.9	2.2	−0.7	−2.6	1.4	−0.5	−9.1	-	4.6	2.9
	$V_{avg.}$ (p.u.)	1.099	1.096	1.097	1.096	1.097	1.096	1.097	1.095	1.097	1.095
	ΔV (%)	−1.41	−1.13	−1.17	−1.14	−1.23	−1.24	−0.55	-	−1.23	−1.11
	**** Method #1 ****										
	ΔP (%)	−4.0	−1.7	-0.6	−0.9	1.3	1.1	10.6	-	−2.6	−2.6
	CVR Fact.	2.8	1.5	0.5	0.8	−1.1	−0.9	−19.2	-	2.2	2.3
	ΔE (MWh)	−225	−32	−29	−17	59	19	526	-	−530	−191
	**** Method #2 ****										
	ΔP (%)	−3.5 ± 0.1	−1.3 ± 0.7	−0.6 ± 0.1	−0.7 ± 0.8	1.2 ± 0.1	0.8 ± 1.0	−5.8 ± 0.4	-	−1.0 ± 0.0	−0.2 ± 0.1
	CVR Fact.	2.5 ± 0.1	1.2 ± 0.6	0.5 ± 0.1	0.6 ± 0.7	−1.0 ± 0.1	−0.7 ± 0.8	10.6 ± 0.6	-	0.8 ± 0.0	0.2 ± 0.1
	ΔE (MWh)	−196 ± 4	−26 ± 13	−28 ± 3	−13 ± 14	54 ± 3	14 ± 16	−289 ± 17	-	−205 ± 8	−17 ± 5
	**** Method #3 ****										
	ΔP (%)	−4.9 ± 0.1	−2.8 ± 0.1	−1.6 ± 0.1	−1.0 ± 0.1	0.8 ± 0.1	0.2 ± 0.1	−1.9 ± 0.1	-	−1.9 ± 0.0	−1.2 ± 0.1
	CVR Fact.	3.5 ± 0.1	2.5 ± 0.1	1.4 ± 0.1	0.9 ± 0.1	−0.6 ± 0.1	−0.2 ± 0.1	3.5 ± 0.1	2.5 ± 0.2	1.5 ± 0.0	1.0 ± 0.1
	ΔE (MWh)	−273 ± 4	−54 ± 2	−76 ± 3	−18 ± 2	34 ± 3	3 ± 2	−97 ± 3	-	−378 ± 8	−84 ± 4
Feeder TUR112	$P_{avg.}$ (kW)	4,428	4,516	3,054	3,129	2,786	2,739	3,259	3,247	3,475	3,486
	DODO	0.02	0.04	0.04	0.04	0.41	0.36	0.02	0.08	0.12	0.13
	ΔT (°F)	5.7	-	5.8	−0.2	1.4	−0.5	-	-	22.2	20.9
	$V_{avg.}$ (p.u.)	1.102	1.101	1.097	1.097	1.095	1.095	1.097	1.096	1.098	1.097
	ΔV (%)	0.16	-	−2.32	−0.11	0.03	−0.21	-	-	−0.29	−0.38
	**** Method #1 ****										
	ΔP (%)	−2.4	-	−16.0	−21.4	3.7	−2.3	-	-	−17.3	−23.2
	CVR Fact.	−15.1	-	6.9	194.7	124.7	10.8	-	-	59.5	61.1
	ΔE (MWh)	−166	-	−762	−434	163	-40	-	-	−3743	−2039
	**** Method #2 ****										
	ΔP (%)	−4.7 ± 6.7	-	4.7 ± 0.4	−20.8 ± 9.5	0.2 ± 0.1	−1.4 ± 1.6	-	-	0.6 ± 0.1	−1.3 ± 0.2
	CVR Fact.	−29 ± 42	-	−2.0 ± 0.2	190 ± 90	5.3 ± 4.7	6.5 ± 7.6	-	-	−2.1 ± 0.5	3.4 ± 0.6
	ΔE (MWh)	−330 ± 460	-	225 ± 20	−420 ± 190	7 ± 6	−24 ± 28	-	-	132 ± 28	−114 ± 19
	**** Method #3 ****										
	ΔP (%)	1.5 ± 0.0	-	−1.1 ± 0.4	−1.0 ± 0.0	0.3 ± 0.0	−1.7 ± 0.1	-	-	−1.7 ± 0.0	−3.5 ± 0.1
	CVR Fact.	9.4 ± 0.3	9.9 ± 0.4	0.5 ± 0.2	9.1 ± 0.4	9.5 ± 0.2	8.1 ± 0.3	9.0 ± 0.2	10.8 ± 0.4	5.9 ± 0.1	9.2 ± 0.2
	ΔE (MWh)	104 ± 3	-	−53 ± 19	−20 ± 1	13 ± 0	−30 ± 1	-	-	−369 ± 7	−306 ± 6

Table 7.4. (cont.)

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder TUR113	$P_{avg.}$ (kW)	3,832	3,595	2,611	2,512	1,840	1,726	2,928	2,812	2,835	2,729
	DODO	0.61	0.61	0.92	0.92	0.41	0.36	0.02	0.08	0.49	0.49
	ΔT (°F)	0	0.2	-0.6	−2.6	1.4	−0.5	−16.3	−22.4	−0.3	0.4
	$V_{avg.}$ (p.u.)	1.100	1.098	1.096	1.095	1.092	1.092	1.096	1.095	1.096	1.095
	ΔV (%)	−2.81	−2.61	−2.71	−2.67	−2.63	−2.72	−2.54	−2.57	−2.74	−2.69
	**** Method #1 ****										
	ΔP (%)	−3.1	6.9	−1.4	1.9	4.6	2.8	17.3	9.9	−1.9	−4.3
	CVR Fact.	1.1	−2.7	0.5	−0.7	−1.7	−1.0	−6.8	−3.8	0.7	1.6
	ΔE (MWh)	−184	150	−55	30	131	31	788	173	−331	−295
	**** Method #2 ****										
	ΔP (%)	−3.1 ± 0.2	4.7 ± 1.5	−2.6 ± 0.2	−0.5 ± 1.8	2.7 ± 0.2	3.1 ± 2.5	2.6 ± 0.4	-	−0.6 ± 0.1	2.3 ± 0.2
	CVR Fact.	1.1 ± 0.1	−1.8 ± 0.6	0.9 ± 0.1	0.2 ± 0.7	−1.0 ± 0.1	−1.1 ± 0.9	−1.0 ± 0.1	-	0.2 ± 0.0	−0.8 ± 0.1
	ΔE (MWh)	−184 ± 13	101 ± 31	−104 ± 9	−9 ± 29	77 ± 6	34 ± 27	118 ± 16	-	−108 ± 21	156 ± 13
	**** Method #3 ****										
	ΔP (%)	−7.0 ± 0.2	−0.5 ± 0.3	−5.3 ± 0.2	−2.0 ± 0.3	1.8 ± 0.2	1.9 ± 0.3	−2.0 ± 0.3	−9.6 ± 0.6	−3.5 ± 0.1	−1.1 ± 0.2
	CVR Fact.	2.5 ± 0.1	0.2 ± 0.1	2.0 ± 0.1	0.8 ± 0.1	−0.7 ± 0.1	−0.7 ± 0.1	0.8 ± 0.1	3.7 ± 0.2	1.3 ± 0.0	0.4 ± 0.1
	ΔE (MWh)	−417 ± 12	−11 ± 7	−215 ± 8	−33 ± 5	51 ± 6	21 ± 4	−92 ± 14	−168 ± 10	−616 ± 19	−78 ± 13
Feeder TUR115	$P_{avg.}$ (kW)	3,940	3,433	3,823	3,372	3,748	3,341	3,629	3,234	3,759	3,330
	DODO	0.54	0.63	0.88	0.92	0.41	0.36	0.02	0.08	0.46	0.5
	ΔT (°F)	2.8	2.2	−0.9	−2.6	1.4	−0.5	−9.2	-	4.2	2.9
	$V_{avg.}$ (p.u.)	1.102	1.099	1.103	1.101	1.102	1.101	1.101	1.098	1.102	1.100
	ΔV (%)	−0.41	−0.17	−0.31	−0.26	−0.11	−0.27	−0.07	-	−0.19	−0.14
	**** Method #1 ****										
	ΔP (%)	−5.6	−3.3	−1.2	0.6	1.6	0.8	18.9	-	0.4	1.1
	CVR Fact.	13.8	19.2	3.8	−2.2	−14.3	−3.1	−269.4	-	−1.8	−7.9
	ΔE (MWh)	−347	−67	−70	13	92	18	1068	-	82	92
	**** Method #2 ****										
	ΔP (%)	−4.9 ± 0.1	−1.1 ± 6.3	−0.7 ± 0.1	0.2 ± 6.3	1.1 ± 0.1	0.5 ± 6.3	7.4 ± 4.4	-	−1.4 ± 0.1	0.2 ± 0.1
	CVR Fact.	11.9 ± 0.2	7 ± 37	2.2 ± 0.3	−1 ± 24	−9.6 ± 0.8	−2 ± 23	v106 ± 63	-	7.4 ± 0.3	−1.1 ± 0.6
	ΔE (MWh)	−299 ± 6	−20 ± 130	−41 ± 5	0 ± 140	62 ± 5	10 ± 140	420 ± 250	-	−331 ± 14	13 ± 8
	**** Method #3 ****										
	ΔP (%)	−3.9 ± 0.1	−1.6 ± 0.0	−1.1 ± 0.0	−0.4 ± 0.1	−0.4 ± 0.0	−0.3 ± 0.1	−0.3 ± 0.0	-	−1.1 ± 0.0	−0.6 ± 0.0
	CVR Fact.	9.5 ± 0.1	9.6 ± 0.2	3.6 ± 0.1	1.5 ± 0.2	3.7 ± 0.2	1.2 ± 0.2	4 .0 ± 0.2	4.9 ± 0.2	5.8 ± 0.1	4.4 ± 0.1
	ΔE (MWh)	−238 ± 3	−34 ± 1	−66 ± 2	−9 ± 1	−24 ± 1	−7 ± 1	−16 ± 1	-	−260 ± 2	−52 ± 2

Table 7.4. (cont.)

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder TUR116	$P_{avg.}$ (kW)	4,348	4,338	2,959	2,949	2,616	2,605	3,034	3,003	3,231	3,243
	DODO	0.61	0.61	0.89	0.92	0.41	0.36	0.02	0.00	0.48	0.47
	ΔT (°F)	−0.1	0.2	−1.4	−2.6	1.4	-0.5	−9.7	−6.5	0.5	1.4
	$V_{avg.}$ (p.u.)	1.102	1.101	1.097	1.097	1.094	1.095	1.096	1.095	1.097	1.097
	ΔV (%)	−2.57	−2.44	−2.56	−2.48	−2.39	−2.53	−2.11	−2.32	−2.46	−2.46
						**** Method #1 ****					
	ΔP (%)	−2.7	−1.2	−0.2	0.5	1.2	−5.3	24.0	19.1	1.9	−3.6
	CVR Fact.	1.0	0.5	0.1	−0.2	−0.5	2.1	−11.4	−8.2	−0.8	1.5
	ΔE (MWh)	−180	−31	−11	10	50	−89	1135	358	379	−294
						**** Method #2 ****					
	ΔP (%)	−3.2 ± 0.1	2.3 ± 1.0	−1.2 ± 0.1	−1.7 ± 1.2	−2.4 ± 0.1	−4.4 ± 1.6	7.0 ± 0.2	-	−1.0 ± 0.1	0.1 ± 0.1
	CVR Fact.	1.2 ± 0.1	−-0.9 ± 0.4	0.5 ± 0.1	0.6 ± 0.5	1.0 ± 0.1	1.7 ± 0.6	−3.3 ± 0.1	-	0.4 ± 0.0	−0.0 ± 0.1
	ΔE (MWh)	−216 ± 9	60 ± 26	−55 ± 6	−32 ± 23	−96 ± 6	−74 ± 27	330 ± 9	-	−210 ± 16	7 ± 10
						**** Method #3 ****					
	ΔP (%)	−4.2 ± 0.1	0.9 ± 0.2	−3.2 ± 0.1	−1.4 ± 0.2	−3.7 ± 0.1	−5.6 ± 0.2	3.5 ± 0.2	3.5 ± 0.3	−2.7 ± 0.1	−1.5 ± 0.1
	CVR Fact.	1.6 ± 0.1	−0.4 ± 0.1	1.2 ± 0.1	0.6 ± 0.1	1.6 ± 0.1	2.2 ± 0.1	−1.7 ± 0.1	−1.5 ± 0.1	1.1 ± 0.0	0.6 ± 0.1
	ΔE (MWh)	−282 ± 9	22 ± 6	−146 ± 6	−27 ± 4	−151 ± 6	−94 ± 3	165 ± 9	65 ± 6	−540 ± 14	−123 ± 10
Feeder TUR117	$P_{avg.}$ (kW)	5,576	4,882	4,424	3,734	3,923	3,040	4,569	3,857	4,625	3,922
	DODO	0.61	0.61	0.90	0.92	0.41	0.36	0.03	0.08	0.48	0.49
	ΔT (°F)	0.0	0.3	−1.3	−2.6	1.4	−0.5	−13.9	−22.4	0.4	0.4
	$V_{avg.}$ (p.u.)	1.107	1.103	1.104	1.100	1.101	1.098	1.103	1.099	1.103	1.100
	ΔV (%)	−2.48	−2.37	−2.38	−2.43	−2.08	−2.40	−2.19	−2.22	−2.30	−2.38
						**** Method #1 ****					
	ΔP (%)	−1.2	4.9	−1.3	1.0	3.1	3.4	11.0	12.4	0.5	−1.2
	CVR Fact.	0.5	−2.1	0.5	−0.4	−1.5	−1.4	−5.0	−5.6	−0.2	0.5
	ΔE (MWh)	−102	144	−88	24	189	67	782	299	144	−115
						**** Method #2 ****					
	ΔP (%)	−0.9 ± 0.1	2.6 ± 1.0	−2.4 ± 0.1	−0.8 ± 1.2	1.3 ± 0.1	2.5 ± 1.6	−1.5 ± 0.3	-	−0.7 ± 0.1	1.5 ± 0.1
	CVR Fact.	0.4 ± 0.1	−1.1 ± 0.4	1.0 ± 0.1	0.3 ± 0.5	−0.6 ± 0.1	−1.0 ± 0.7	0.7 ± 0.1	-	0.3 ± 0.0	−0.6 ± 0.1
	ΔE (MWh)	−75 ± 11	76 ± 28	−162 ± 10	−20 ± 28	79 ± 8	49 ± 31	−107 ± 19	-	−211 ± 23	151 ± 12
						**** Method #3 ****					
	ΔP (%)	−3.1 ± 0.1	−0.1 ± 0.2	−3.8 ± 0.1	−0.7 ± 0.2	0.1 ± 0.1	1.4 ± 0.2	−6.9 ± 0.2	−4.1 ± 0.4	−2.7 ± 0.1	−0.2 ± 0.1
	CVR Fact.	1.2 ± 0.1	0.0 ± 0.1	1.6 ± 0.1	0.3 ± 0.1	−0.1 ± 0.1	−0.6 ± 0.1	3.1 ± 0.1	1.8 ± 0.2	1.2 ± 0.0	0.1 ± 0.1
	ΔE (MWh)	−265 ± 10	−2 ± 6	−263 ± 8	−18 ± 5	7 ± 7	28 ± 4	−488 ± 16	−98 ± 9	−782 ± 20	−19 ± 12

Table 7.4. (cont.)

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder SPU121	$P_{avg.}$ (kW)	4,676	4,690	3,259	3,156	3,317	2,838	3,574	3,336	3,673	3,496
	DODO	0.61	0.61	0.93	0.92	0.41	0.36	0.02	0.08	0.49	0.49
	ΔT (°F)	0.6	3.0	−0.7	−2.6	1.1	−0.5	−13.4	−22.4	−0.2	-0.5
	$V_{avg.}$ (p.u.)	1.090	1.090	1.091	1.090	1.089	1.091	1.089	1.088	1.090	1.089
	ΔV (%)	−1.91	−1.85	−2.17	−2.09	−1.91	−2.28	−1.70	−1.79	−1.95	−2.01
						**** Method #1 ****					
	ΔP (%)	−1.8	−3.9	−1.4	−0.0	1.0	−2.0	17.4	31.0	2.3	−1.4
	CVR Fact.	0.9	2.1	0.6	0.0	−0.5	0.9	−10.2	−17.3	−1.2	0.7
	ΔE (MWh)	−130	−109	−70	−1	52	−36	970	646	525	−122
						**** Method #2 ****					
	ΔP (%)	−2.8 ± 0.2	1.9 ± 1.0	−1.7 ± 0.2	−2.0 ± 1.3	−0.6 ± 0.1	−0.8 ± 1.7	0.8 ± 0.3	-	−1.6 ± 0.1	1.0 ± 0.1
	CVR Fact.	1.5 ± 0.1	−1.0 ± 0.6	0.8 ± 0.1	0.9 ± 0.6	0.3 ± 0.1	0.3 ± 0.8	−0.5 ± 0.2	-	0.8 ± 0.0	−0.5 ± 0.1
	ΔE (MWh)	−207 ± 11	53 ± 29	−88 ± 8	−40 ± 26	−28 ± 7	−14 ± 31	42 ± 15	-	−355 ± 18	88 ± 11
						**** Method #3 ****					
	ΔP (%)	−3.2 ± 0.2	0.3 ± 0.2	−3.2 ± 0.2	−0.1 ± 0.2	−3.2 ± 0.1	−1.1 ± 0.2	1.6 ± 0.2	5.4 ± 0.4	−2.7 ± 0.1	0.0 ± 0.1
	CVR Fact.	1.7 ± 0.1	−0.1 ± 0.1	1.5 ± 0.1	0.1 ± 0.1	1.7 ± 0.1	0.5 ± 0.1	−0.9 ± 0.1	−3.0 ± 0.2	1.4 ± 0.0	−0.0 ± 0.1
	ΔE (MWh)	−233 ± 11	7 ± 6	−164 ± 8	−3 ± 4	−167 ± 7	−20 ± 4	87 ± 12	113 ± 8	−626 ± 18	2 ± 11
Feeder SPU122	$P_{avg.}$ (kW)	4,355	4,218	3,788	3,629	3,610	3,413	4,014	3,891	3,976	3,827
	DODO	0.55	0.63	0.92	0.92	0.40	0.36	0.02	0.08	0.47	0.50
	ΔT (°F)	2.4	2.2	−0.9	−2.6	1.5	−0.5	-	-	4.3	2.9
	$V_{avg.}$ (p.u.)	1.100	1.098	1.101	1.100	1.097	1.097	1.097	1.096	1.098	1.098
	ΔV (%)	0.23	0.32	0.13	0.23	0.53	0.40	-	-	0.38	0.38
						**** Method #1 ****					
	ΔP (%)	−1.5	−0.7	−0.5	0.9	1.2	−0.4	-	-	−2.7	−3.9
	CVR Fact.	−6.4	−2.3	−3.7	4.0	2.3	−0.9	-	-	−7.1	−10.2
	ΔE (MWh)	−99	−18	−28	22	69	−8	-	-	−670	−372
						**** Method #2 ****					
	ΔP (%)	−0.9 ± 0.1	0.8 ± 0.8	−0.5 ± 0.1	0.4 ± 1.0	1.1 ± 0.1	−0.8 ± 1.3	-	-	−0.1 ± 0.1	0.1 ± 0.1
	CVR Fact.	−3.7 ± 0.5	2.5 ± 2.4	−4.1 ± 0.9	1.9 ± 4.2	2.2 ± 0.2	−2.0 ± 3.3	-	-	−0.2 ± 0.2	0.3 ± 0.3
	ΔE (MWh)	−58 ± 8	20 ± 20	−31 ± 7	10 ± 23	64 ± 7	−18 ± 29	-	-	−17 ± 17	12 ± 11
						**** Method #3 ****					
	ΔP (%)	0.3 ± 0.0	0.4 ± 0.1	0.3 ± 0.0	0.7 ± 0.1	2.0 ± 0.1	0.2 ± 0.1	-	-	1.3 ± 0.0	1.1 ± 0.1
	CVR Fact.	1.3 ± 0.1	1.2 ± 0.3	2.5 ± 0.2	3.0 ± 0.3	3.8 ± 0.1	0.5 ± 0.2	6.8 ± 0.2	7.7 ± 0.3	3.5 ± 0.1	2.8 ± 0.1
	ΔE (MWh)	20 ± 2	9 ± 2	19 ± 1	16 ± 1	112 ± 3	5 ± 2	-	-	327 ± 7	102 ± 5

Table 7.4. (cont.)

Feeder		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder SPU123	$P_{avg.}$ (kW)	4,690	4,605	3,748	3,644	3,967	3,727	3,921	3,762	4,043	3,907
	DODO	0.61	0.61	0.93	0.92	0.36	0.29	0.02	0.08	0.48	0.47
	ΔT (°F)	0.6	3.0	−0.7	−2.6	1.0	−0.1	−13.4	−22.4	−1.2	−2.5
	$V_{avg.}$ (p.u.)	1.101	1.100	1.100	1.099	1.096	1.094	1.097	1.096	1.098	1.097
	ΔV (%)	−2.64	−2.56	−2.75	−2.72	−2.50	−2.54	−2.26	−2.19	−2.55	−2.56
	**** Method #1 ****										
	ΔP (%)	−2.2	−2.7	−1.3	−2.3	0.1	−1.3	13.1	16.6	1.9	0.1
	CVR Fact.	0.8	1.1	0.5	0.9	−0.0	0.5	−5.8	−7.6	−0.8	−0.0
	ΔE (MWh)	−162	−75	−78	−55	7	−32	802	390	479	8
	**** Method #2 ****										
	ΔP (%)	−2.7 ± 0.1	0.6 ± 0.7	−1.5 ± 0.1	−2.4 ± 0.9	−1.5 ± 0.1	0.9 ± 1.2	4.1 ± 0.2	-	−1.4 ± 0.1	0.6 ± 0.1
	CVR Fact.	1.0 ± 0.0	−0.2 ± 0.3	0.6 ± 0.0	0.9 ± 0.3	0.6 ± 0.0	−0.3 ± 0.5	−1.8 ± 0.1	-	0.5 ± 0.0	−0.2 ± 0.0
	ΔE (MWh)	−194 ± 7	17 ± 20	−88 ± 6	−57 ± 21	−90 ± 6	21 ± 29	248 ± 12	-	−341 ± 15	59 ± 9
	**** Method #3 ****										
	ΔP (%)	−3.1 ± 0.1	−0.0 ± 0.2	−1.9 ± 0.1	−1.7 ± 0.2	−2.0 ± 0.1	0.2 ± 0.2	2.0 ± 0.2	4.4 ± 0.3	−1.9 ± 0.1	−0.2 ± 0.1
	CVR Fact.	1.2 ± 0.0	0.0 ± 0.1	0.7 ± 0.0	0.6 ± 0.1	0.8 ± 0.0	−0.1 ± 0.1	−0.9 ± 0.1	−2.0 ± 0.1	0.7 ± 0.0	0.1 ± 0.0
	ΔE (MWh)	−226 ± 8	−1 ± 4	−109 ± 6	−41 ± 4	−123 ± 6	5 ± 4	124 ± 10	103 ± 7	−469 ± 13	−20 ± 8
Feeder SPU124	$P_{avg.}$ (kW)	4,284	3,797	3,298	2,893	3,142	2,690	3,542	3,161	3,598	3,173
	DODO	0.57	0.63	0.92	0.92	0.42	0.36	0.01	0.08	0.48	0.50
	ΔT (°F)	2.4	2.2	−0.9	−2.6	1.8	−0.5	−1.9	-	4.5	2.9
	$V_{avg.}$ (p.u.)	1.102	1.100	1.099	1.097	1.099	1.097	1.099	1.097	1.099	1.098
	ΔV (%)	−0.61	−0.50	−0.29	−0.28	−0.30	−0.48	0.53	-	−0.38	−0.38
	**** Method #1 ****										
	ΔP (%)	−2.8	0.6	−1.4	0.0	1.1	−0.2	20.6	-	−3.5	−4.7
	CVR Fact.	4.6	−1.3	4.7	−0.0	−3.8	0.5	38.8	-	9.3	12.3
	ΔE (MWh)	−186	14	−70	0	55	−4	1136	-	−790	−373
	**** Method #2 ****										
	ΔP (%)	−2.8 ± 0.1	0.1 ± 3.6	−1.1 ± 0.1	−0.6 ± 3.6	−0.0 ± 0.1	−1.0 ± 3.7	−6.0 ± 2.5	-	−1.3 ± 0.1	−0.3 ± 0.1
	CVR Fact.	4.6 ± 0.2	−0.3 ± 7.2	3.6 ± 0.3	2.2 ± 1	0.1 ± 0.3	2.1 ± 7.8	−11.2 ± 4.8	-	3.5 ± 0.2	0.7 ± 0.2
	ΔE (MWh)	−189 ± 7	3 ± 82	−54 ± 5	−12 ± 68	−2 ± 5	−18 ± 65	−330 ± 140	-	−301 ± 13	−21 ± 7
	**** Method #3 ****										
	ΔP (%)	−3.5 ± 0.1	−0.7 ± 0.1	−2.0 ± 0.0	−1.4 ± 0.1	−0.6 ± 0.0	−1.2 ± 0.1	3.1 ± 0.1	-	−1.9 ± 0.0	−1.1 ± 0.0
	CVR Fact.	5.7 ± 0.1	1.4 ± 0.2	7.0 ± 0.1	4.9 ± 0.2	2.1 ± 0.1	2.4 ± 0.2	5.9 ± 0.2	4.6 ± 0.3	5.1 ± 0.1	3.0 ± 0.1
	ΔE (MWh)	−231 ± 5	−16 ± 2	−105 ± 2	−25 ± 1	−30 ± 2	−20 ± 2	171 ± 6	-	−431 ± 7	−90 ± 3

Table 7.4. (cont.)

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder SPU125	$P_{avg.}$ (kW)	3,331	2,718	3,233	2,807	3,971	3,574	3,647	3,214	3,552	3,080
	DODO	0.55	0.63	0.91	0.92	0.40	0.36	0.02	0.08	0.47	0.50
	ΔT (°F)	3.1	2.2	−1.0	−2.6	1.6	−0.5	-	-	4.4	2.9
	$V_{avg.}$ (p.u.)	1.097	1.094	1.100	1.098	1.099	1.098	1.096	1.094	1.098	1.096
	ΔV (%)	−0.98	−0.8	−1.17	−1.16	−0.49	−0.67	-	-	−0.85	−0.81
	**** Method #1 ****										
	ΔP (%)	−7.8	7.0	−0.9	−0.3	5.2	3.9	-	-	−0.3	3.5
	CVR Fact.	8.0	−8.8	0.7	0.3	−10.6	−5.9	-	-	0.3	−4.3
	ΔE (MWh)	−405	114	−43	−5	320	91	-	-	−62	272
	**** Method #2 ****										
	ΔP (%)	−7.6 ± 0.2	5.0 ± 1.3	−0.4 ± 0.2	0.3 ± 1.6	0.5 ± 0.2	1.5 ± 2.3	-	-	−2.4 ± 0.1	2.4 ± 0.2
	CVR Fact.	7.7 ± 0.2	−6.2 ± 1.7	0.4 ± 0.2	−0.3 ± 1.4	−1.0 ± 0.4	−2.3 ± 3.4	-	-	2.8 ± 0.1	−2.9 ± 0.2
	ΔE (MWh)	−394 ± 11	81 ± 22	−21 ± 10	6 ± 29	31 ± 12	35 ± 53	-	-	−525 ± 27	182 ± 14
	**** Method #3 ****										
	ΔP (%)	−10.6 ± 0.2	−2.2 ± 0.2	−4.1 ± 0.2	−1.5 ± 0.2	−4.0 ± 0.1	−3.9 ± 0.2	-	-	−7.6 ± 0.1	−4.0 ± 0.1
	CVR Fact.	10.8 ± 0.2	2.7 ± 0.3	3.5 ± 0.1	1.3 ± 0.2	8.2 ± 0.2	5.8 ± 0.3	28.4 ± 0.3	24.6 ± 0.4	8.9 ± 0.1	4.9 ± 0.1
	ΔE (MWh)	−552 ± 8	−36 ± 3	−205 ± 8	−27 ± 4	−250 ± 6	−90 ± 4	-	-	−1682 ± 18	−308 ± 9
Feeder TVW131	$P_{avg.}$ (kW)	1,506	1,412	1,629	1,476	2,992	2,802	1,893	1,815	1,950	1,838
	DODO	0.56	0.57	0.68	0.64	0.41	0.36	0.03	0.08	0.42	0.41
	ΔT (°F)	3.0	1.2	−0.9	−1.2	1.5	−0.5	−12.2	-	4.0	2.8
	$V_{avg.}$ (p.u.)	1.086	1.085	1.087	1.086	1.093	1.092	1.090	1.090	1.089	1.088
	ΔV (%)	−1.56	−1.42	−1.11	−1.09	−1.37	−1.52	−0.72	-	−1.21	−1.24
	**** Method #1 ****										
	ΔP (%)	−1.1	0.6	−3.0	−9.9	6.1	−9.3	−20.2	-	10.7	−0.5
	CVR Fact.	0.7	−0.4	2.7	9.1	−4.4	6.1	28.0	-	−8.8	0.4
	ΔE (MWh)	−26	5	−77	−94	283	−169	−596	-	1301	−24
	**** Method #2 ****										
	ΔP (%)	−1.1 ± 0.4	−1.2 ± 2.8	−2.2 ± 0.3	−5.4 ± 3.1	−0.7 ± 0.3	−9.0 ± 4.1	12.0 ± 1.2	-	−1.0 ± 0.2	−5.3 ± 0.3
	CVR Fact.	0.7 ± 0.2	0.8 ± 1.9	2.0 ± 0.3	5.0 ± 2.9	0.5 ± 0.2	5.9 ± 2.7	−16.7 ± 1.7	-	0.9 ± 0.2	4.3 ± 0.2
	ΔE (MWh)	−25 ± 8	−10 ± 23	−56 ± 8	−52 ± 30	−33 ± 15	−163 ± 75	355 ± 36	-	−125 ± 23	−246 ± 14
	**** Method #3 ****										
	ΔP (%)	−2.2 ± 0.3	−0.4 ± 0.5	−4.4 ± 0.3	−6.2 ± 0.4	−7.1 ± 0.3	−11.9 ± 0.5	−13.1 ± 0.4	-	−5.1 ± 0.2	−7.4 ± 0.2
	CVR Fact.	1.4 ± 0.2	0.3 ± 0.4	4.0 ± 0.2	5.7 ± 0.3	5.2 ± 0.2	7.8 ± 0.3	18.2 ± 0.5	26.0 ± 0.8	4.2 ± 0.1	6.0 ± 0.2
	ΔE (MWh)	−51 ± 7	−4 ± 4	−113 ± 7	−59 ± 4	−332 ± 14	−216 ± 9	−386 ± 10	-	−617 ± 18	−344 ± 11

Table 7.4. (cont.)

		Winter		Spring		Summer		Fall		All Seasons	
		M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S	M–F	S–S
Feeder TVW132	$P_{avg.}$ (kW)	268	2,604	1,581	1,650	1,050	1,024	1,569	1,571	1,685	1,732
	DODO	0.60	0.63	0.67	0.64	0.41	0.36	0.04	0.08	0.43	0.43
	ΔT (°F)	−0.1	−0.6	−0.9	−1.2	1.5	−0.5	−14.9	−22.4	−0.3	0.5
	$V_{avg.}$ (p.u.)	1.084	1.084	1.085	1.084	1.086	1.086	1.087	1.087	1.086	1.086
	ΔV (%)	−1.45	−1.24	−1.81	−1.72	−2.09	−2.17	−1.64	−1.78	−1.84	−1.83
	**** Method #1 ****										
	ΔP (%)	1.2	5.6	0.6	2.3	3.4	2.9	28.8	35.5	5.1	−0.8
	CVR Fact.	−0.8	−4.5	−0.3	−1.3	−1.6	−1.3	−17.6	−19.9	−2.8	0.4
	ΔE (MWh)	48	88	14	24	55	19	704	349	538	−35
	**** Method #2 ****										
	ΔP (%)	−0.2 ± 0.2	5.3 ± 1.3	−1.2 ± 0.2	0.2 ± 1.5	2.0 ± 0.2	3.3 ± 2.1	−0.4 ± 0.3	-	0.1 ± 0.1	2.8 ± 0.2
	CVR Fact.	0.2 ± 0.1	−4.3 ± 1.0	0.7 ± 0.1	−0.1 ± 0.9	−1.0 ± 0.1	−1.5 ± 1.0	0.2 ± 0.2	-	−0.1 ± 0.1	−1.5 ± 0.1
	ΔE (MWh)	−9 ± 7	83 ± 20	−30 ± 4	2 ± 16	33 ± 3	22 ± 14	−9 ± 8	-	13 ± 11	123 ± 7
	**** Method #3 ****										
	ΔP (%)	−2.4 ± 0.1	2.6 ± 0.2	−0.3 ± 0.2	0.1 ± 0.2	1.5 ± 0.2	2.7± 0.3	−3.8 ± 0.3	−3.0 ± 0.5	−0.8 ± 0.1	1.3 ± 0.2
	CVR Fact.	1.6 ± 0.1	−2.1 ± 0.2	0.2 ± 0.1	−0.0 ± 0.1	−0.7 ± 0.1	−1.2 ± 0.1	2.3 ± 0.2	1.7 ± 0.3	0.4 ± 0.1	−0.7 ± 0.1
	ΔE (MWh)	−96 ± 5	41 ± 4	−8 ± 4	1 ± 3	24 ± 3	18 ± 2	−92 ± 6	−29 ± 5	−85 ± 9	58 ± 7

The impact of VAr management on the Pullman feeders was difficult to independently assess. Review of the calculated power factors in 2014 revealed that control was being intermittently engaged and then released. These periods were not perfectly correlated with the times that voltage had been managed (reduced). Therefore, the project concludes that VAr management was often engaged independently from voltage management. Regardless, the project used the only indicator available to it to estimate the impact of VAr management.

First the median power factors were calculated at times that the IVVC status indicator (a binary status that had been attributed to a condition of regulator tap settings for each feeder) was active and not. The poor correlation between this indicator and power factor means that the differences between the two calculated medians will be conservative. The results of these calculations have been listed in Table 7.5, where "before" indicates the times that the binary status was inferred to be in its normal condition, and "after" indicates what is inferred to be the state of active IVVC control. The inverse ratio of these power factors may be used to infer the impact of distribution line currents compared to the "before" status. The implication for line losses is the square of this ratio, because line losses are proportional to the square of the electrical current the lines conduct. The far right column of Table 7.5 states the change in inferred line losses compared to the "before" condition when VArs were not being actively controlled.

From this table, none of the power factors change greatly. The implications for relative line losses are small. Four of the feeders likely reduce line losses by 1% or more. The greatest estimated change shows a 4.6% reduction in line losses.

This comparison does not give the utility due credit for the static improvements that were apparently made in 2012. Refer back to Figure 7.19, for example, which shows the distributions of power factor in 2012, 2013, and 2014 for Turner Feeder 115. That example shows that the power factor was only about 0.87 during 2012, much lower than any of the power factors in Table 7.5. The power factor was increased to about 0.97 the following year. This improvement might have reduced electrical distribution currents by fully 10%, and distribution lines losses might have been reduced by 20%. These are valuable improvements. The project understands that, while valuable, the improvements should probably be attributed to static equipment updates and not the operations of the IVVC system.

Table 7.5. Summary of the Observed Changes in Power Factor and the Inferred Impacts from Power Factor Correction on the Pullman Feeders

Feeder	Power Factor Before	Power Factor After	Current Ratio	Line Loss Ratio	Line Loss Change (%)
TUR111	0.9918	0.9936	0.998	0.996	−0.359
TUR112	0.9988	0.9992	1.000	0.999	−0.091
TUR113	0.9965	0.9993	0.997	0.995	−0.544
TUR115	0.9577	0.9474	1.011	1.022	2.166
TUR116	0.9962	0.9969	0.999	0.998	−0.151
TUR117	0.9933	0.9986	0.995	0.990	−1.040
SPU121	0.9964	0.9995	0.997	0.994	−0.616
SPU122	0.9753	0.9827	0.992	0.985	−1.513
SPU123	0.9966	0.9995	0.997	0.994	−0.572
SPU124	0.9472	0.9699	0.977	0.954	−4.635
SPU125	0.9613	0.9794	0.981	0.963	−3.672
TVW131	0.9878	0.9880	1.000	0.999	−0.055
TVW132	1.0000	0.9999	1.000	1.000	0.026

Based on data received from Avista Utilities during the PNWSGD project, the project was able to observe active management of both voltage and reactive power on the Pullman site feeders. Voltages for many of the Pullman feeders were observed to have been periodically reduced by up to 2.7%. Many of the feeders revealed periods of day-on, day-off testing, especially through spring 2014, as was stipulated by the Regional Technical Forum simplified protocol for evaluation of CVR impacts (Regional Technical Forum 2015). The utility had contracted Navigant Consulting, Inc., to evaluate the performance of voltage management on these feeders, and the results of that evaluation had been in line with the utility's projections.

The project also observed that site power factors were corrected significantly during early 2013, and power factors then varied with what the project infers to be the periodic engagement of IVVC.

The utility provided the project an indicator of a binary status of the regulator tap settings on the Pullman feeders. The project found very good correlation between this reported status and voltage magnitudes, where one status corresponded to normal voltages and the other corresponded to periods when the voltage had been measurably reduced. The correlation of this indicator was weaker for reactive power management. No independent indicator was found for times that VArs might have been managed at times different from voltage management.

The project used three methods to estimate the impacts of voltage management on these feeders. The first was similar to the Regional Technical Forum protocol using no temperature correction. The second was similar to the first in that it was based on discrete periods that the voltage had been reduced. The second method corrected for temperature impacts. The third was a continuous method that directly calculated seasonal CVR factor and required no reporting of discrete voltage management periods. All three methods worked adequately in seasons that day-on, day-off testing had been extensively used and when the changes in voltage had been great. The continuous method was found to be robust at other times when testing was irregular and when changes in voltage were small or had been perhaps reported erroneously. Even so, calculated impacts were highly variable with respect to methods, testing practices, data practices, season, feeder, and day type.

Using the third method, the project estimated that 2.1% of the Pullman electricity consumption might be conserved if the demonstrated IVVC control were applied continuously and across all 13 Pullman feeders. This estimate was near, but somewhat exceeded, Avista Utilities' prediction of 1.85% conservation versus before the demonstration.

Reactive power management was observably effective. Power factors were observed to improve markedly after 2012, but degraded again in 2014 as the VAr management was being actively tested. The project looked for evidence of additional improvements that would accompany activation of the automated IVVC system. Reactive power management contributed to the estimated conservation impact that was stated for voltage management, but a change in power from reactive power management cannot be independently determined apart from the impacts of voltage management. The times that power factor correction was employed were found to be correlated with times of voltage management, but the correlation was imperfect. Four of the 13 feeders were likely to have further reduced distribution line losses by more than 1% with the application of VAr management. The greatest impact was a reduction of line losses of around 4.6%.

Avista Utilities supplied the project a count of capacitor switching operations for each of its South Pullman feeders. Capacitor switch actuations increased significantly for several of the feeders in spring 2013, about the time that voltage and VAr management became active.

At the conclusion of the PNWSGD project, Avista Utilities stated that one-third of the Pullman, Washington, site customers were under IVVC. Based on its preliminary findings, Avista Utilities plans to enhance all 13 Pullman, Washington, feeders with IVVC. The utility estimates that optimization of distribution voltage alone will save the utility $0.5 million dollars annually, based solely on the value of the energy that will be conserved.

7.2 Reconductoring

This test case will involve reconductoring of approximately one mile of key feeder segments using 795 all aluminum conductor to reduce system losses and provide operational flexibility. Alternative circuit configurations were limited prior to this improvement in power capacity on these feeder segments. The project's understanding is that two feeders—Pullman 112 and South Pullman 123—were improved by this upgrade.

Table 7.6 lists the annualized costs of the system and its components. The greatest cost was for upgrades to the DMS, followed by line switches and fiber network communications upgrades. The total annualized system cost was about $0.6 million.

Table 7.6. Components and Annualized Component Costs of the Avista Utilities Reconductoring Effort

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
DMS Software and Hardware for 700–1,000 End Points	25	420.8
Automated Line Switches	50	72.6
Fiber Network Communications	17	53.4
Evaluation, Measurement & Validation	13	22.8
Project Management Services	13	12.9
Subcontractor – Volt/VAr Software	33	12.7
Reconductoring	33	11.8
Total Annualized System Cost		**$607.1K**

7.2.1 Data Concerning the Reconductoring

The reconductoring was reported by the utility to have been completed by the end of October 2010. The PNWSGD received no measurements from Avista Utilities from which the impacts of the reconductoring could be directly estimated. Instead, the utility submitted and the project must rely on estimates of these savings that were calculated by Avista Utilities' distribution engineers and planners, based on data from the DMS and SynerGEE, an engineering software tool, each month. The line losses are apparently estimated from each month's line currents and the difference in resistivity between the new and replaced conductors. The received data is shown in Figure 7.22. Avista Utilities reports that the missing data months are artifacts of its rebuild of its Pullman substation, which became the Turner substation during the project. During this construction, feeders were supplied from alternative substations, creating the data artifacts. No calculated data is missing.

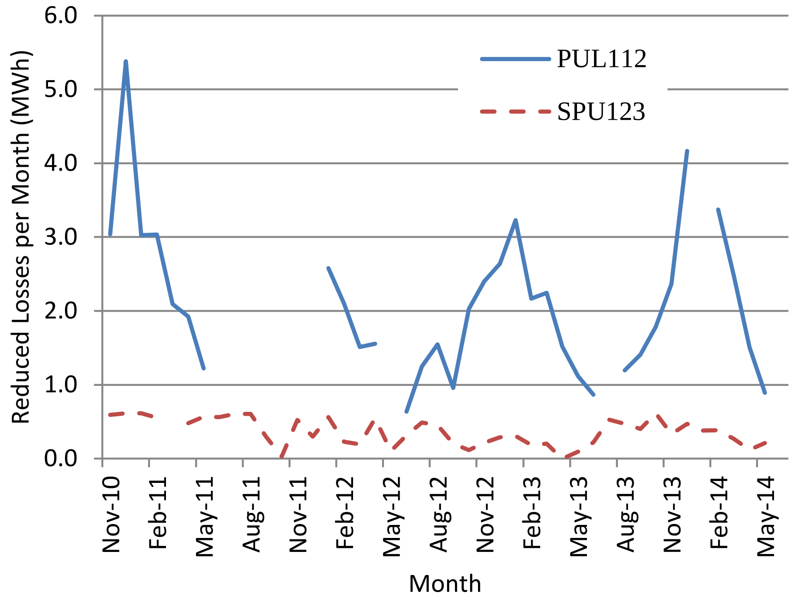


Figure 7.22. Calculated Reduction in Distribution Energy Losses on Two Pullman, Washington, Distribution Feeders each Month

7.2.2 Analysis of the Impact from Reconductoring

Based on the calculations made by Avista Utilities and shown in Figure 7.22, the utility will conserve 29.6 ± 0.6 MWh each year by having upgraded the conductors on the two feeders. Most of this conservation, 25.2 ± 0.3 MWh per year (average 2.1 ± 0.2 MWh per month) occurred on Pullman Feeder 112, while 4.4 ± 0.1 MWh per year (average 0.36 ± 0.03 MWh per month) is saved on South Pullman Feeder 123. These estimates were based on reported data, excluding any impacts from months on which no conservation savings had been reported by the utility.

The value of the conserved energy is less than $3,000 per year. However, the capability of new distribution automation features in Pullman, Washington, might have been constrained had these upgrades not been completed.

7.3 Smart, Efficient Transformers

Avista Utilities replaced ~383 of Pullman’s 1200 distribution transformers with smart transformers that are equipped with advanced sensors and telemetry for the remote measurements of voltage, current, and transformer temperature. The utility piggy-backed onto existing collaborative research between Howard Industries (Howard Industries 2015) and Southern California Edison to develop and test improved distribution transformers. The transformers to be replaced were those that had been installed before 1983. An economic analysis determined that distribution transformers installed before 1983 did not meet the utility’s present efficiency standards and should be replaced. The purpose of this report section is simply for the project to confirm the improved efficiency performance of the new transformers.

The high efficiency design and construction of these smart transformers was anticipated to provide a constant reduction in both load and no-load losses. Additionally, the electrical metering of the smart transformers was available for use in conjunction with the utility's integrated volt/VAr management system (Section 7.1), and the power passing through the distribution transformers may be compared against measurements of aggregated power from the AMI at customers' premises to detect electricity theft. The temperature of the new transformers may be monitored to detect imminent failures and thereby avoid customer power outages (Section 7.7).

The estimated annualized costs of the system of smart transformers and its components are listed in Table 7.7. The efficiency impact of these new transformers was assigned a small fraction of the annualized costs of many of the components that were shared among the assets. Among the greatest component costs were those of the improved demand-management system, communication upgrades, and the transformers themselves.

Table 7.7. Components and Annualized Component Costs of the Avista Utilities System of Smart Transformers

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
Demand Management System Software and Hardware for 700–1,000 End Points	25	420.8
Fiber Network Communications	17	53.4
Smart Transformers Equipped with Sensors, Current Transformers, and Wireless Communications	25	37.3
Evaluation, Measurement and Validation	13	22.8
Project Management Services	13	12.9
Subcontractor – Integrated Volt/VAr Software	33	12.7
Total Annualized System Cost		**$560.0K**

According to the utility's calculations prior to the PNWSGD project, the anticipated energy savings from transformer upgrades in Pullman was an average 130 kW, or 1,120 MWh annually, equating to the energy use of about 50 homes and a value of over $111 thousand. If correct, these loss reductions are on the order of 1.4–4.5% of the average customer load. The project was unable to confirm these savings. The utility did not provide metadata to identify which customers' transformers had been replaced, and the replacements were not consolidated on a single or a limited number of distribution circuits where the impacts might have been estimated by comparing historical and recent circuit loads. The utility responds that the transformers' no-load losses were validated at the factory

In short, the project was unable to confirm the energy efficiency performance of the Howard Industries smart transformers that Avista Utilities installed at the Pullman, Washington, site.

7.4 Residential Thermostats

Avista Utilities provided a group of test residences with Ecobee smart thermostats (Ecobee 2015) to launch a residential load response program in Pullman, Washington. Avista planned to place an emphasis on customer education, customer participation and energy management. Customers who volunteered to participate in the larger project and allow control of their thermostats would create a virtual power plant when the regional value signal warranted a response.

The utility originally targeted obtaining 1,500 program participants. The Avista Utilities Smart Thermostat Pilot (STP) was a voluntary program offered to a select group of customers in Pullman and Albion, Washington. Eligibility requirements were narrow, with the intent of selecting those consumers who were likely to maintain their current living arrangements throughout the study period (2012–2014). Selection criteria for programmable communicating thermostat (PCT) candidates were that the applicant must be an Avista Utilities customer; not be a student; own and occupy a single-family residence; be able to place the thermostat near the AMI (and near the gas meter, too, for gas customers); use electric forced air heating, heat-pump, or central air conditioning; possesses a secure wireless router; and make a six-month minimum commitment to remain in the program. These eligibility criteria reduced the available candidates to 650 homes.

After considerable review of market-available smart thermostats and their communications, Avista Utilities chose Ecobee's Smart Thermostat as the target PCT for deployment. The Smart Thermostat has a dual-radio capability permitting communications with either whole-house consumption meters via ZigBee (IEEE 802.15.4) or with authorized Wi-Fi networks (IEEE 802.11). The ZigBee interface, as well as serving a role during the "pairing" process between the PCT and the AMI meter, is also the communications pathway to display quasi real-time electric consumption information to the consumer. The consumer's Wi-Fi/internet interface is the direct communications path between the PCT and the PCT vendor, Ecobee.

When the PCT is paired with the AMI meter, the display of the Smart Thermostat's consumer interface graphically showed a number of useful energy consumption parameters, including real-time energy consumption, the premises' electricity usage over the last hour, total electricity used so far that day, and hourly, daily, weekly, and projected cost reports.

With Wi-Fi, customers can view weather forecasts and other useful information from the same device. The integrated display of the PCT addressed Avista's concern that a separate in-home display would not be cost-effective over the entire program period, while an integrated display in the PCT would provide value on an ongoing basis. Customers may access their thermostats using their smart tablet or smart telephone independent of the utility. This smart-device connectivity is directly to Ecobee and will continue without cost to the customer after the STP program has ended. Smart-device access to the Ecobee thermostat also allows the user to remotely adjust their thermostat settings and/or view the operation of their furnace. Additional online information through the Ecobee portal includes the following: monetary value of historical electric usage; ability to set a budget amount and be alerted when usage meets or exceeds the set amount; HVAC operational information; ability to set furnace maintenance alerts, such as filter replacements, annual maintenance, etc.; ability to export usage history; and consumer insights on HVAC operation related to weather and month-over-month data.

The utility had also intended to control electric water heaters, but that part of the system was not successfully developed. Gas water heaters are more prevalent in the Avista Utilities service territory than electric ones.

The utility offered to make the system of smart thermostats responsive to the PNWSGD project's transactive system that advised systems like these when to curtail load.

Avista Utilities conducted a survey to assess various recruitment practices for residential-load customer participation, and a survey concerning customer acceptance of the load-control devices and the incentives provided. Surveys, customer focus groups, demographic studies and profiles for controllable devices at each premises were leveraged to further shape concepts and staging of this two-pronged residential load control program. Avista will maintain a sharp focus to achieve success and customer satisfaction.

Residential demand-response (DR) programs historically have had a high level of interaction between the utility and the customer, primarily due to the DR event notification process. However, the STP events were automated, which allowed the program to function more like an energy efficiency program with limited interaction between the customer and the utility. This resulted in improved customer satisfaction by demonstration of the closeout survey.

To entice participants, a number of incentives were offered to potential participants: an HVAC system inspection was provided at no cost, the PCT was provided and installed at no cost, and a $100 per year "appreciation payment" was given participants during the project term. Although various communication channels were used to engage customers—including a concentrated direct marketing push over the summer of 2012—by the end of September 2012, only 36 thermostats had been installed, and no overwhelming interest by customers was being observed. The lessons learned were

- Strict participation criteria had narrowed the pool of potential participants.
- The utility possessed limited tracking tools and no customer-relationship–management database.
- Once the program was explained, people were receptive.
- Personal contact was the most effective method in securing participation.

In mid-October 2012, Avista Utilities decided to suspend active recruitment of Pullman customers for the STP and use the number of current enrolled participants to evaluate the program's value against the objectives of the STP. The program team executed the no-cost outreach efforts and speaking engagements that were already in the works. One such activity that proved successful was an email posting at SEL in early October that resulted in 11 Schweitzer employees signing up to participate. This is an example of engaging the right target audience. By the September 2013 enrollment deadline, recruitment efforts achieved 75 participants in the STP.

Avista Utilities had to coordinate the efforts of multiple vendors to integrate the system of smart thermostats. Close working partnerships with vendors led to much greater likelihood that products would meet the utility's needs. The system integration challenge is portrayed by Figure 7.23. Players in the integration included

- Ackerman Heating and Air Conditioning, who conducted all field work for thermostat installation and maintenance and managed thermostat inventory
- Ecobee, who provided and integrated thermostats and hosted central connections to the thermostats
- Integral Analytics, who conducted predictive analytics for the command and control of the thermostats during DR events and worked with Avista (via Spirae, Inc.) and Ecobee to integrate these commands
- Spirae, who completed an interface with the PNWSGD project to process transactive control signals.

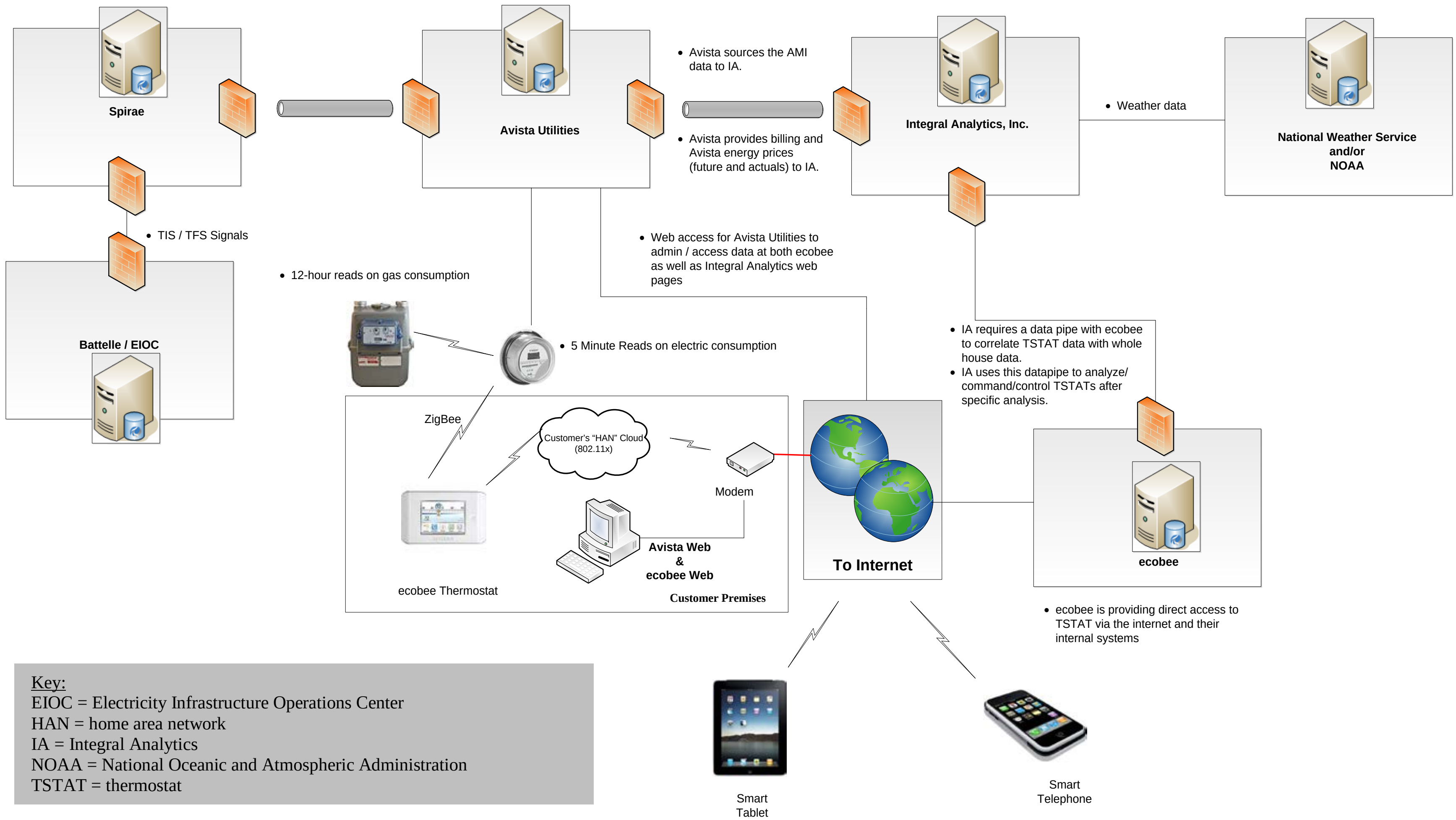


Figure 7.23. Subsystems that had to be Integrated to Complete Avista Utilities' Smart Thermostat System

Avista Utilities addressed physical security through the use of an internal security audit of its vendors and established a direct virtual private network with them. The audit determined that a combination of authentication requirements and Secure Sockets Layer certificates ensured that unauthorized entry into its infrastructure was extremely low. Avista Utilities allowed no customer-identifiable information to be part of the data exchange process.

The annualized costs of the smart thermostat system and its components are listed in Table 7.8. The most costly components were the allocated fraction of AMI costs, the cost of implementing the DR control system, the thermostats, and customer portal software.

Table 7.8. Components and Annualized Component Costs of the Avista Utilities Communicating Thermostat System

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)	
Advanced Metering System		433.6	
• Software and Systems	25		316.0
• Operations and Maintenance	25		100.3
• Engineering	25		7.7
• Residential Equipment - Target Group with DR	25		7.1
• Training	25		1.9
• Commercial Equipment - Target Group	25		0.7
Demand-Response Control System	100	413.1	
Demand Response - Thermostats	100	342.2	
Customer Portal - Software		195.3	
• Engineering	50		77.7
• Hosted Software Costs (Target Group with DR)	50		60.0
• Software and Systems Installed Costs	50		37.6
• Operations and Maintenance	50		20.0
Evaluation, Measurement and Validation	13	22.8	
Customer Service	25	10.5	
Outreach and Education	25	7.9	
Total Annualized System Cost		**$1,816.8K**	

7.4.1 Data concerning the Residential Thermostats

Project analysts attempted to verify the impact of residential load control in Pullman using aggregated residential metering. Metered power data was averaged from 57 premises that had received controllable load-control devices like thermostats. This number differs from the 75 premises that Avista Utilities reported they had recruited. The difference might be attributable to miscommunication concerning the feeders on which these tests were conducted and not. Project analysts had been led to believe the test premises would be on the seven non-WSU feeders only, which might not have been the case. The project also identified a larger set of 9,037 premises that never received residential load control devices and might serve as a comparison baseline.

Upon comparing the raw power data from the test and baseline groups, the project observed what might be a significant selection bias. The test group premises might be larger than average and seem to consume somewhat more energy than the baseline group. The difference is most evident in warm summer months, as is shown in Figure 7.24, when the test members consume three times more electricity than the baseline members. Perhaps the test group members have air conditioning that is not common among the rest of the population in Pullman. Interestingly, the two lobes of the fall season comparison were evident in two of the three years in which data was collected. For these reasons, the comparison group could not be used.

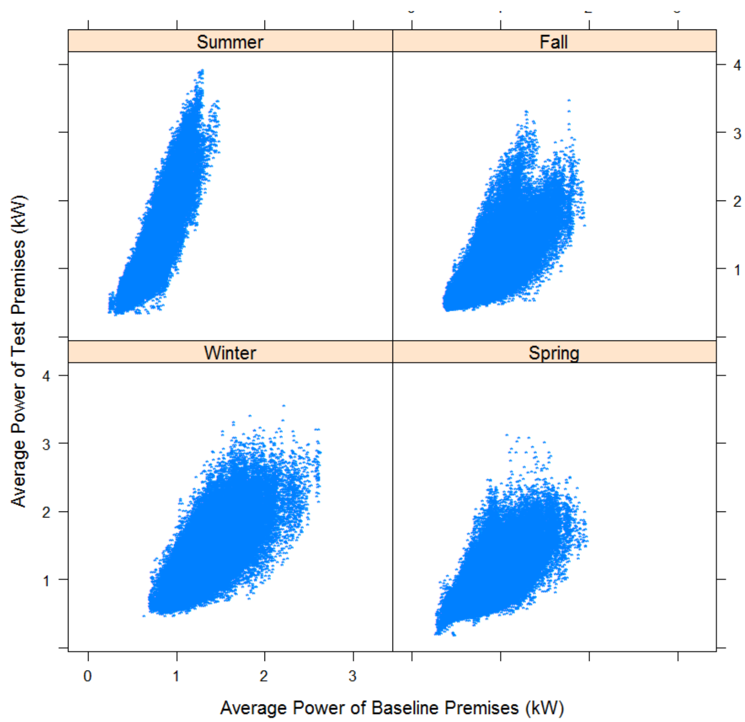


Figure 7.24. Comparison of the Average Power of Premises that Received Residential Load Control Devices and Others that Did Not, by Season

The averaged premises power data from the test premises that received residential DR equipment is shown in Figure 7.25. The legend refers to the marking of this power data according to whether the transactive system was actively advising that the system curtail load (active) or not (normal). The premises do not exhibit much weekly variation, and they exhibit relatively small variation by season. Data was available from January 2011, but the transactive signal was not defined until 2013. Data was intermittently available in 2013. Data collection continued through August 2014.

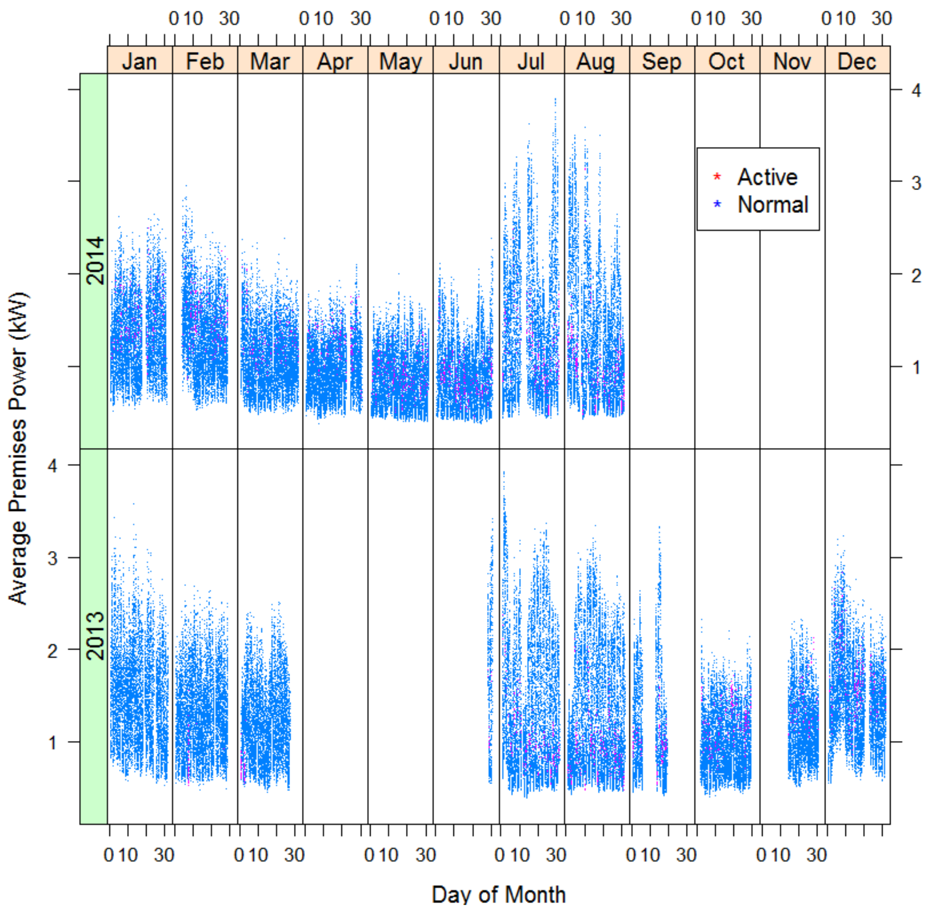


Figure 7.25. Average Residential Premises Power Data Collected from Avista Utilities Concerning Customers that had Received STP Thermostats

Avista Utilities' STP participants received a total of 636 DR event requests over the course of two years. Events averaged two hours in duration and consisted of a two-degree temperature increase or decrease, depending on the season. The PNWSGD project's transactive system initiated 405 events. The Avista-generated signal (AGS) DR events were called 231 times. A breakout by year is shown below in Table 7.9.

Table 7.9. Counts of Thermostat DR Events that were Initiated by Avista Utilities (AGS) and the Transactive System (TIS), as Reported by Avista Utilities

Year	AGS	TIS	Grand Total
2013	104	54	158
2014	127	351	478
Grand Total	**231**	**405**	**636**

AGS = Avista generated signal
TIS = Transactive incentive signal

Figure 7.26 breaks down the utility's event counts further by both year and month.

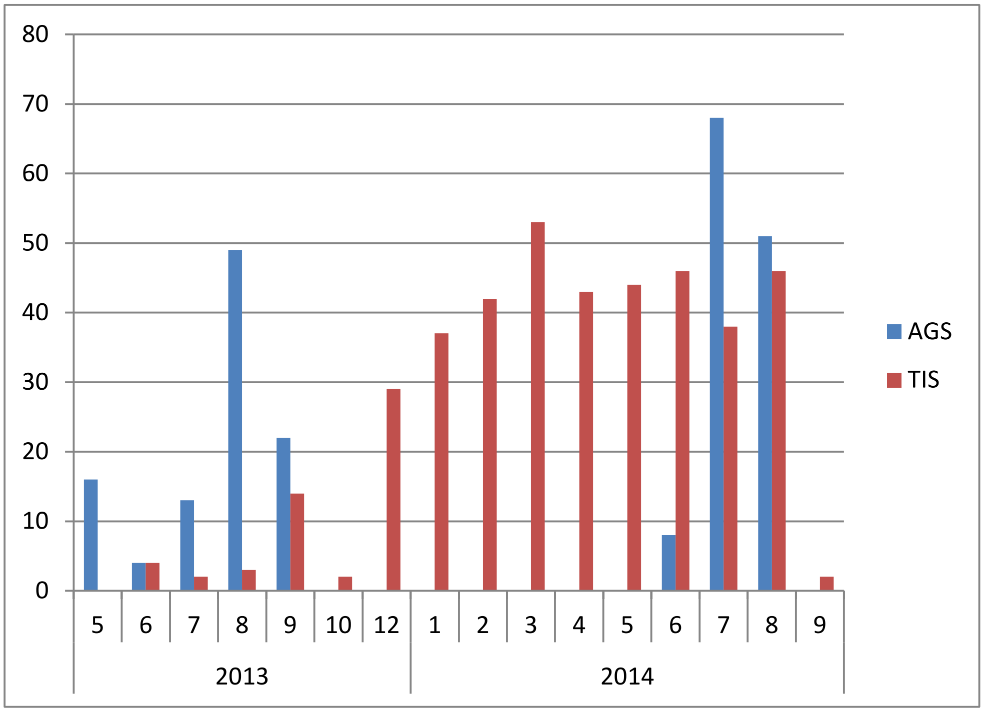


Figure 7.26. Utility (AGS) and Transactive System (TIS) Events by Year and Calendar Month

The project received complete information through the project's transactive data collection system concerning the times and durations of all the events that had been advised by the project's transactive system. However, the project did not receive any information concerning the times and durations of the Avista-generated DR events. The following discussion will characterize the times that the transactive events were advised. Analysis will attempt to confirm an impact from these events on residential power consumption. These steps were not possible for the Avista-generated events. Furthermore, the Avista-generated events may have affected the presumed baseline data periods, when the project believed no demand responses were taking place.

The transactive system advised that the system respond about 97 hours in 2013 and 124 hours in 2014. The distributions of those 5-minute intervals by calendar month are shown in Figure 7.27.

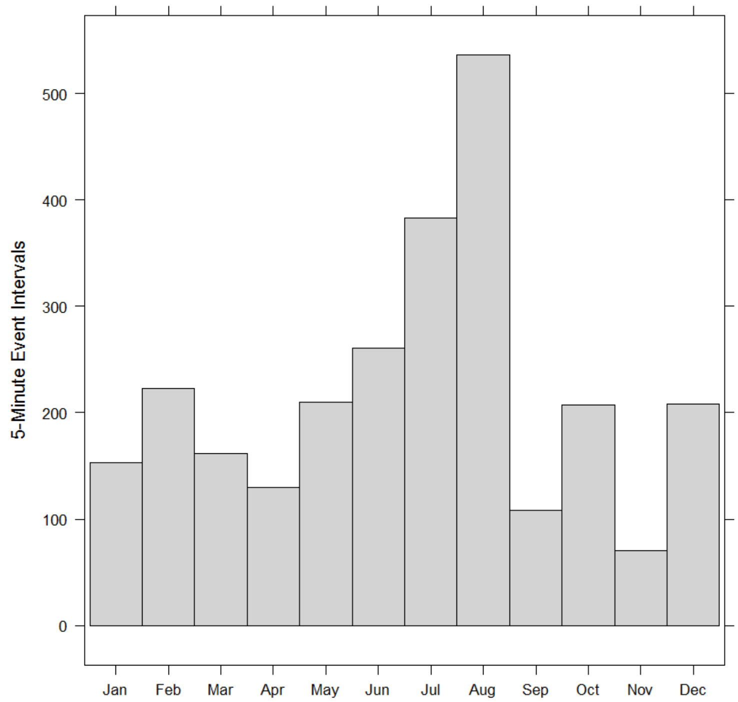


Figure 7.27. Counts of Advised Transactive System Event Intervals by the Months that those Intervals Occurred

The transactive system advised its events evenly across the days of week, as is shown by Figure 7.28. Avista Utilities had encouraged configuring the function by which these events were advised according to the utility's preferences.

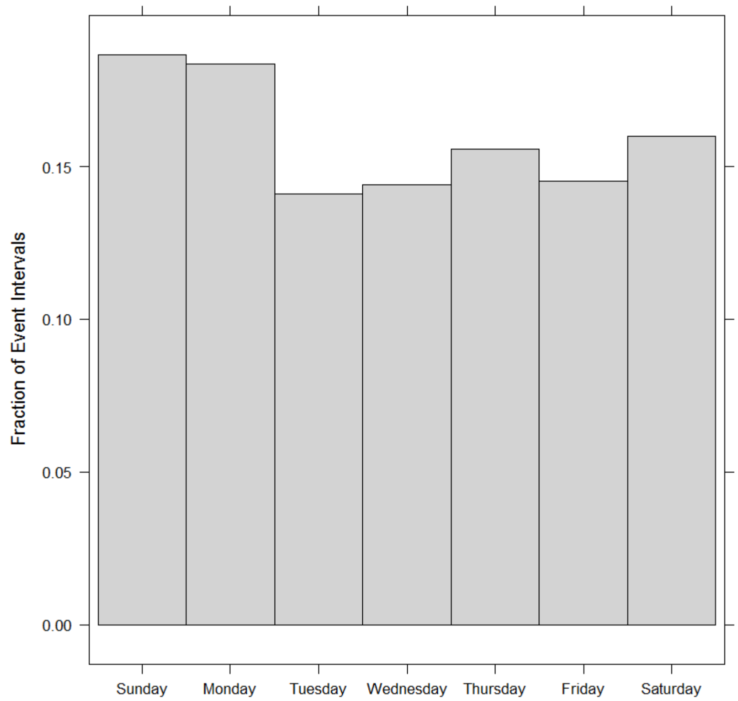


Figure 7.28. Relative Distribution of Advised Transactive System Event Intervals by the Days of Week that those Intervals Occurred

Most of the event periods were advised during between 08:00 and 10:00, as is shown in Figure 7.28.

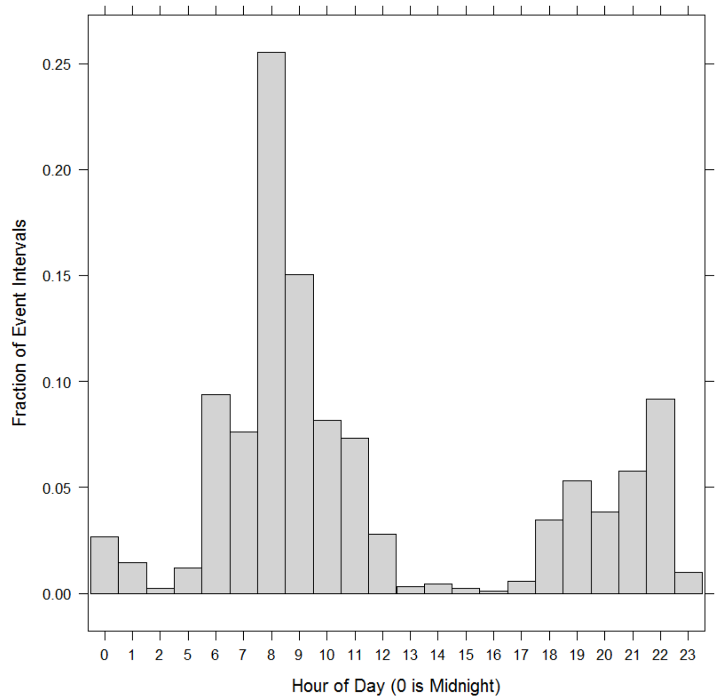


Figure 7.29. Relative Distribution of Advised Transactive System Event Intervals by the Hours of Day that those Intervals Occurred

7.4.2 Analysis concerning the Residential Thermostats

Regression analysis was conducted using the average power of the test premises that had been given the smart thermostats. The power data was modeled as a function of season, hour of day, and transactive event status in permutations with ambient temperature. The regression model was used to create a prediction of what the averaged power would likely have been had the transactive system not advised curtailment. The differences between the original averaged premises powers and the regression model (which emulated having no events) were compared both during event and non-event periods. A Student's t-test was used for this comparison, treating the event periods and non-event periods as independent populations.

Overall, there appeared to be a small reduction on the order of 18 W during events. However, the project's confidence in this result is low. There is approximately an 87% chance that any reduction occurred at all. The results from only two seasons were statistically significant. In summer, there was a reduction of 40 W, but in fall, there was an increase of 73 W. Recall that premises power data had been rather incomplete in fall 2013.

The project cautiously confirms that homes with smart thermostats reduced their energy consumption during advised transactive events, but the impact was small. The analysis lacked confirmations of which events had, in fact, been called. The analysis was confounded by lack of information about the timing and occurrences of DR events that were independently initiated by the utility for these thermostats; those events may also have polluted the baseline.

Avista Utilities gathered much information about how its customers had used the smart thermostats, how the program affected their energy consumption habits, and opinions about their electricity service.

From 31% to 71% of thermostat recipients were found to use the Ecobee mobile application on a weekly basis. However 29% of the thermostat recipients had never used the mobile application during the course of the Smart Thermostat Program. Of those who had used the mobile application, over 70% rated the application as “very useful.”

Avista Utilities surveyed its thermostat program participants to understand customer acceptance of the ecobee thermostats and the DR events. During the course of the PNWSGD, Avista Utilities received three requests from customers to remove the ecobee thermostat from their homes. Two had found the thermostat were too difficult to use (touch screen and drill-down menu options), and one customer felt the thermostat negatively affected his HVAC system. No evidence was found to support this latter claim. About 43% of respondents said they had been able to detect the set-point changes being made to their thermostats, but about 55% said they rarely or never noticed these changes (Table 7.10). Of the thermostat recipients, 88.64% said they had been very satisfied with the utility’s Smart Thermostat Program.

Table 7.10. Survey Responses to the Question, “During the STP Program were you able to detect when Avista made set point changes?”

Answer Choices	Responses	Response (%)
All the time	3	6.82
Sometimes	16	36.36
Rarely	9	20.45
Not sure	1	2.27
Never	15	34.09

Low opt-out levels imply that there was no noticeable change in customers’ comfort. Customers always had the choice to opt out of approaching DR events if they wanted or needed to do so. That choice perhaps helped drive high satisfaction levels.

The program’s customer incentives had been designed generously to gain the highest level of program participation in the least amount of time. The survey results indicate that these incentives were needed for about half of the customers for participation.

Table 7.11. Survey Responses to the Question, "If Avista had not provided the product, installation, and incentives for the ecobee thermostat, how likely would you be to install the ecobee thermostat on your own?"

Answer Choices	Responses	Response (%)
Extremely likely	4	9.9
Somewhat likely	12	27.27
Neutral	9	20.45
Somewhat unlikely	17	38.64
Not at all	2	4.55

7.5 Advanced Metering Infrastructure, Web Portals

Avista Utilities used the PNWSGD to replace all of its manually read utility meters—about 14,000 electric meters and 6,000 gas meters—with AMI. They selected Itron Open Way advanced meters (Itron 2015). The utility also installed a 900 MHz radio frequency mesh network throughout Pullman, Washington, to communicate with the new meters. In this section, the project reviews energy and operational efficiencies that directly or indirectly accompany advanced metering. For example, Avista no longer must send personnel to read customer meters, and fewer truck rolls may needed to read or check up on the newer meters.

Itron's Open Way AMI replaced all meters for the customers served by the Pullman, South Pullman, and Terre View substations. These meters use a 900 MHz multichannel mesh radio network, allowing every meter to act as a router to get information to a gateway device at 45 of the 802.11-type access points. It should be noted, Itron has very advanced security designed into this system. Meters are manufactured with an embedded key that is generated by Avista's security key device. The keys cannot be duplicated and can only be backed up on redundant hardware at Avista. Any device attempting to control a meter must supply the hardware-generated key.

The meters store usage data at 5-minute intervals for up to 90 days. Voltage measurements are available and may be used during the optimization of distribution voltages. A ZigBee gateway is included for communication with home area networks, which allows customers to obtain usage information directly from the meter. The meters are read remotely using software from Itron, the Open Way Collection System, that provides meter data management and meter communication.

All new meters were read remotely, eliminating two meter reader positions. It should be noted that although two meter reading positions were eliminated, new back-end system support was needed. The three support positions were required regardless of the scale of deployment, meaning that when AMI becomes deployed for all Avista customers in the state of Washington, few additional staff should be required. With the remote metering capability, high-bill complaints and other billing questions can be answered without requiring visits from service personnel. Customer calls initiated for power outage reasons can be validated remotely, eliminating the dispatch of service personnel and allowing the call representative to walk the customer through the process of checking their in-home breakers or fuses for quickest return to service for the customer. The average number of calls that fall into this category annually is 50.

Because Avista Utilities may remotely query the advanced meters, more accurate determination of fault locations and power status are possible. This superior information may reduce travel and trouble-assessment time for crew resources. Another benefit for AMI is the ability to validate that restoration efforts were successful by remotely checking status after repairs are made. This makes sure that customers with unresolved service problems are not overlooked.

By reducing the need for visits to customer locations, employee safety may have improved. The service personnel were less likely to encounter dangerous dog and hostile customer situations.

Smart transformers and AMI provided for detailed load and loss evaluation. Transformer usage that does not match the corresponding customer load usage indicates unidentified losses and theft. Studies suggest that for the United States as a whole electricity theft could be as high as 2–5% (source Itron). Avista estimated that 0.07% of total load for the included meter installs—220 MWh per year, the energy usage of 10 homes—may be saved.

The new meters include a service switch that allows connect/disconnect operations to take place remotely without dispatching service personnel. Given the student population in Pullman, utility accounts are opened and closed frequently. Meters can be connected, disconnected, or read remotely, freeing service personnel for other work and improving billing accuracy.

Partner Hewlett-Packard Company (HP®) provided computer hardware, services and monitoring software to support the Itron solution.

Perhaps most importantly, smart meters allow customers to participate in and learn about their energy consumption. Five-minute electric usage and one-hour gas usage intervals can be displayed over the web. Customers may compare themselves against other customers, groups, or regions of the country. Customer renewable generation, if installed, can be profiled along with energy usage. The web portal provides a wealth of information to educate customers and create interest in energy management. Most of the project's effort in this section was spent trying to validate whether this reduction in load had, in fact, accompanied the education of customers made available to them via their web portals.

The annualized costs of the entire system and its components are estimated in Table 7.12. The costs include a fraction of costs of the AMI system, a fraction of the costs of upgrading the fiber optic communications system, a fraction of the costs of evaluation, measurement and validation, and other smaller cost components. The total annualized cost was estimated at about $1.2 million per year.

Table 7.12. Components and Annualized Component Costs of the Avista Utilities System of Advanced Premises Metering Displays

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)	
AMI		511.9	
• Software and Systems	25		316.0
• Operations and Maintenance	25		100.3
• Residential Equipment - Control Group	33		39.2
• Engineering	25		7.7
• Training	25		1.9
• Commercial Equipment - Target Group	25		0.7
Customer Portal - Software		435.3	
• Hosted Software Costs - Control Group	100		120.0
• Hosted Software Costs - Target Group	100		120.0
• Engineering	50		77.7
• Hosted Software Costs - Target Group with DR	50		60.0
• Software and Systems Installed Costs	50		37.6
• Operations and Maintenance	50		20.0
Fiber Network Communications	17	53.4	
Project Management Services	13	12.9	
Evaluation, Measurement and Validation	13	22.8	
Customer Service	25	10.5	
Outreach and Education	25	7.9	
Total Annualized System Cost		**$1,228.0K**	

7.5.1 Data Concerning AMI and Web Portal Efficiencies

Avista Utilities defined test and baseline groups to review the impacts of web portals on customers' energy consumption in Pullman, Washington. The random selection of these customers and other details about the comparison were detailed in a Freeman, Sullivan and Company report[1] that analyzed the impact of web portals for Avista Utilities. The project did not necessarily receive the same data and information about the conduct of the experiment as was used in that report. Several possible discrepancies will be pointed out.

The project received 5-minute power data for these premises, which the project aggregated into two time series of averaged premises power. The counts of participating residents rose steadily between February and April 2011, which probably points to a period that AMI metering was completed in

[1] Sullivan MJ, CA Churchwell, MM Blundell, and CV Hartmann. 2013. "Avista Smart Grid Demonstration Project Study and Analysis of Customer Energy Usage." Report prepared for M Dillon, Avista, by Freeman, Sullivan & Co., 101 Montgomery St., 15th Floor, San Francisco, CA 94104, October 22, 2013.

Pullman. The project did not receive historical monthly data from these premises. Eventually, the premises counts rose to about 4,306 test premises and 4,276 baseline premises. Industrial and commercial premises were not included, leaving only residential premises. The project discarded data intervals if fewer than 95% of either the test or baseline premises were reporting their data. This practice removed much partial data from before May 2011 and also removed periodic intervals when there might have been data communication problems.

The project's understanding was that the test premises were provided access to Avista Utilities' web portal. Some in this group may have viewed hourly consumption, too, from their smart thermostats. The baseline premises were unable to access and view their hourly energy consumption from a web portal or from any other device. The project's understanding was augmented by the Freeman, Sullivan and Co. report, which said this was not necessarily the case. According to that report, the test population (their "treatment" group) was granted access to web portals in April 2012, but all customers, including the baseline (their "control" group) were granted access to energy Web portals in April 2013, after the study ended. These distinctions were not evident from the utility or from the supplied data.

The two aggregated and cleaned data sets are shown in Figure 7.30. Even from this raw time-series data, the baseline ("control") group's energy consumption appears to be greater than that of the test ("experimental") group. The average of the project's baseline group time series was 970.1 ± 0.6 W, and that of the test group was 916.3 ± 0.6 W. The difference between the two populations is unusual for randomly selected memberships. This difference was also recognized in the Freeman, Sullivan and Co. report (p. 9), but that report said that energy consumption of the control group was around 8–10 kWh per month *less* than that of their treatment group.[1] This contradiction calls into question the quality of the data collection process and both the project's and the cited report's analysis and conclusions.

[1] The comparison will be completed and the contradiction confirmed later in this section when the project's assessments of monthly energy will show the same bias as was suggested from the power plots.

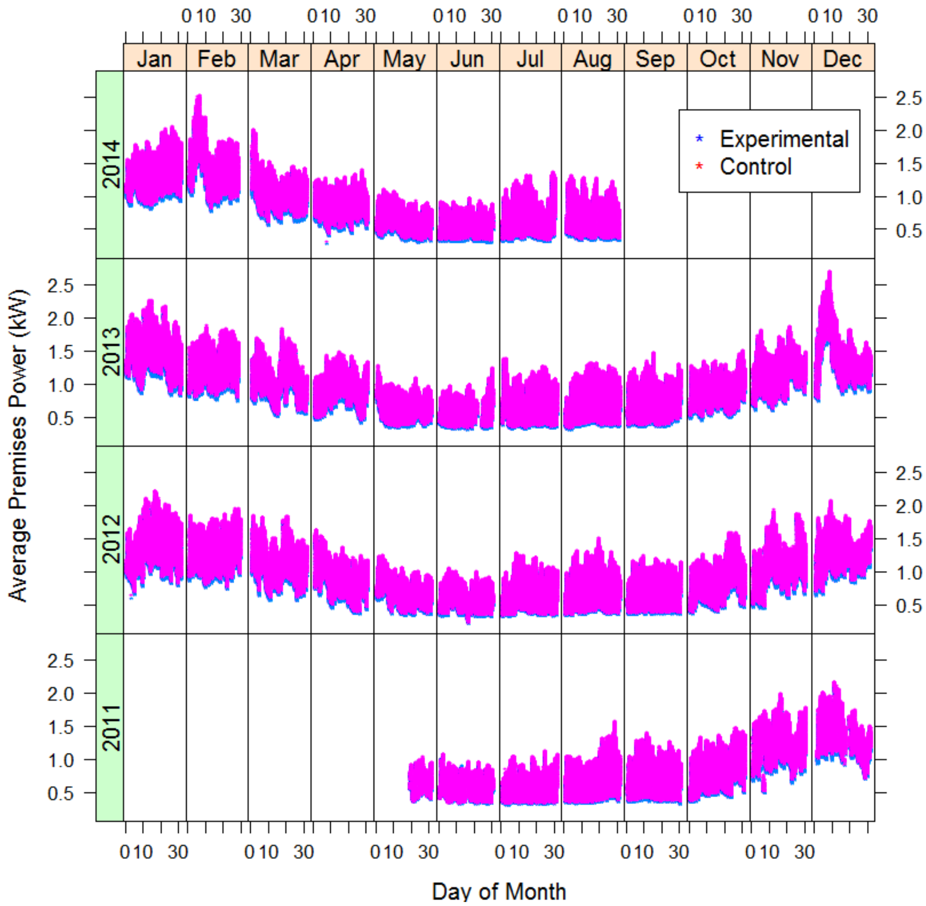


Figure 7.30. Average Premises Power Data from Test and Baseline Residence Groups

A time series of ambient temperatures from weather station KPUW was available to the project and is shown in Figure 7.31. This weather station is located at the Pullman-Moscow Regional Airport. The temperature data was found to be fairly complete, but several lone outliers were identified at and near 0°F. To improve the completeness of the data, temperatures between −1.4 and 1.4°F) were deleted. Then, the missing data, including where the near-zero values had been removed, were interpolated. Interpolation was allowed where data was found to be missing for less than 6 hours. This method recovers most of the values that were legitimately close to 0°F, as these cold temperatures sometimes occur at this site.

The information from web portals might have a small impact on the voluntary energy behaviors of residents. The project will apply temperature corrections as it strives to identify this impact. Therefore, the quality of ambient temperature data is critical to this analysis.

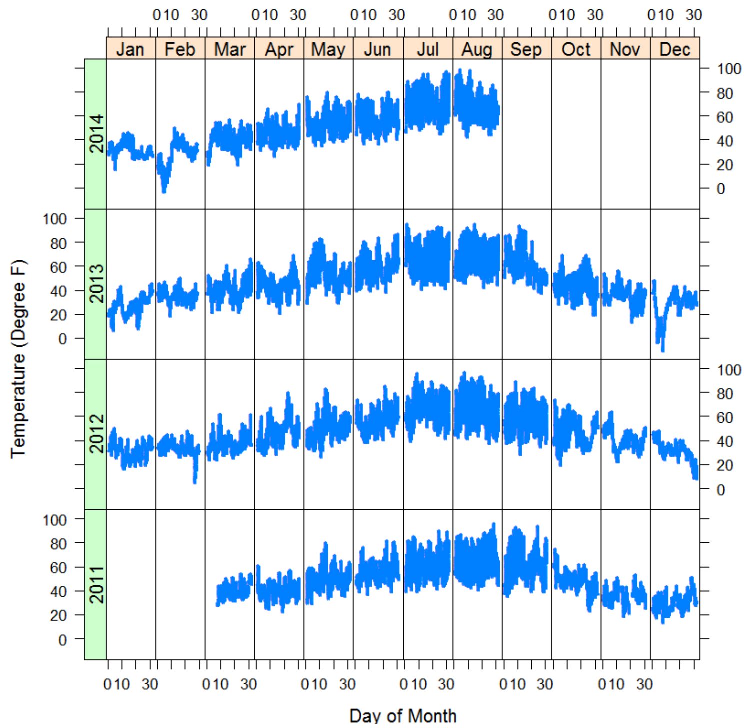


Figure 7.31. Ambient Temperature Data from Station KPUW (Pullman-Moscow Regional Airport)

Figure 7.32 previews the relationship between power consumption of the test and baseline groups as a function of ambient temperatures. A relationship is demonstrated and the familiar "V" shape is observed. Minimum consumption occurs when the ambient temperature is in the spring and fall comfort ranges. At extreme cold (left side) and hot (right) temperatures, the premises consume more energy. This figure again shows that the control residences consume more than the test ones at the same temperatures. This relationship between power consumption and temperature will be critical for analysis.

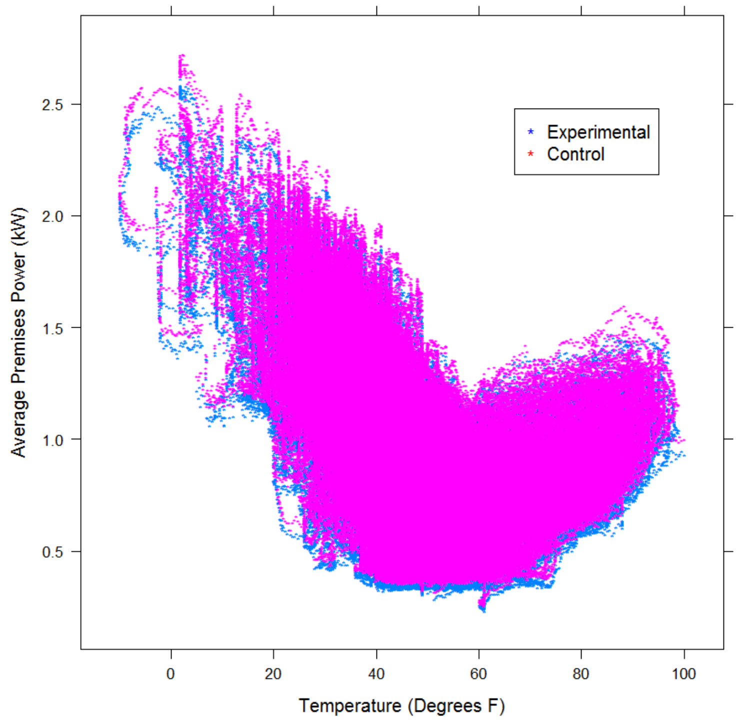


Figure 7.32. Average Premises Powers of the Test ("Experimental") and Baseline ("Control") Groups as Functions of Ambient Temperature

Avista Utilities compiled and submitted several metrics concerning the performance of its new AMI system at Pullman, Washington. Figure 7.33 presents the percentage of AMI meter reads that were successfully completed by 02:00 the next day. Using available data, these reported daily percentages were placed in increasing order and were plotted against the percent of all the available measurements. Based on available data, 100% of the meters were successfully read by 02:00 only 1.2% of the time. However, this figure shows that 98% or more of meters are successfully read 95% of the days.

The above paragraph was qualified several times by saying that it refers only to those intervals for which data was available. In fact, reported data for this metric was quite incomplete. The project looked at the days that AMI meter data had been reported and compared those counts to the days that this metric was calculated and reported. The metric was reported only 33% of the days that AMI meters were actively reporting premises energy consumption.

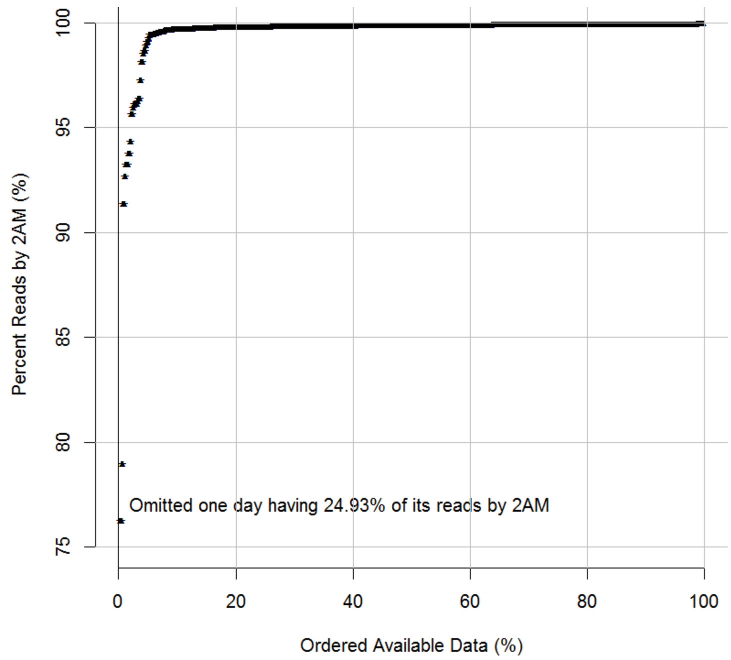


Figure 7.33. Distribution of the Available Data for the Percent of AMI Meter Reads Completed by 2 AM

Avista Utilities also estimated the numbers of truck rolls that had been avoided by its AMI meter operations department. These counts are listed my month and year in Table 7.13. The project understands these avoided truck rolls to have been automatically calculated based on types of service calls received that would have previously required a service visit that was made unnecessary by the features of the new AMI. For example, truck rolls are now unnecessary to shut off and restart electric service as college students leave and return to rental properties. And when a customer calls, the utility can remotely determine whether their meter is electrically “live” or not.

Avista Utilities also reported the avoided number of driven miles for meter operations. It turned out that this was not a unique calculation. Each avoided truck roll had been presumed to avoid exactly 15 driving miles for meter operations.

The utility’s internal business case includes not only the direct costs of staff and vehicle maintenance, but also includes the unlikely but potential costly impacts should the vehicle have an accident while it is being used.

Table 7.13. Count of Avoided Truck Rolls Reported by Avista Utilities for Project Months

	2011	2012	2013	2014
Jan	-	311	205	252
Feb	-	239	261	245
Mar	0	276	288	182
Apr	0	224	281	201
May	0	270	357	222
Jun	0	217	230	0
Jul	3	263	276	0
Aug	0	219	251	0
Sep	0	146	151	-
Oct	1	160	214	-
Nov	141	177	200	-
Dec	162	199	195	-

7.5.2 Analysis of AMI and Portal Efficiencies

The project attempted to observe a change in premises energy consumption attributable to customers' access to energy web portal information, but the project did not duplicate all the facets of the web portal program that were well addressed in the Freeman, Sullivan and Co. report. In addition to energy impacts, that report reviewed how, when, and whether customers used the web portal; impacts of the web portal on gas consumption; qualitative feedback from focus group members, and customer survey findings. Among the report's highlights, 68% of survey respondents said they visited the Avista website monthly (Freeman, Sullivan and Co. report, p. 3). Only 5% of the treatment group ever accessed the pertinent website content (Freeman, Sullivan and Co. report, p. 14).

The project accepted the statement in the Freeman, Sullivan and Co. report that the test group was first given access to web portal information in April 2012. If any change occurs in the behavior of the test group, its energy consumption should change after that month. The baseline group should not have received access to web portal information, so its behaviors should not change after that month. The difference in any observed changes after April 2012 between the two groups might be attributable to the availability of web portal information.

The project carefully summed the average monthly energy consumption by each group. A simple sum might underreport the energy consumption in a month that data was incomplete. Therefore, the project first calculated each month's average power, then average powers were multiplied by the precise number of hours each month to estimate total energy consumption per premises in that month.

The month's average premises energy consumptions have been plotted against time in Figure 7.34. More than three years' data are included. The dashed vertical line marks the project's new understanding of when the treatment—access to a web portal—began for the test group. The project wished to analyze full years both before and after the treatment, lest the analysis be corrupted by seasonal variations. April 2012 was considered pretreatment to achieve this goal and have an entire year of data before the treatment.

Again, the energy consumption of the baseline premises is consistently greater than that of the test premises, based on data provided to the project. This is inconsistent with observations made in the Freeman, Sullivan and Co. report.

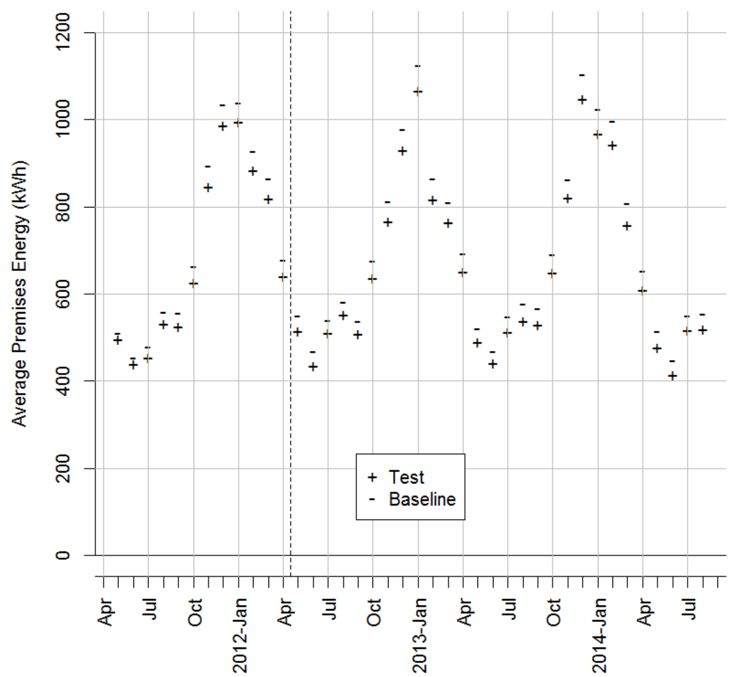


Figure 7.34. Monthly Average Energy Consumption by the Test and Baseline Premises

The monthly energy consumptions from year to year in Figure 7.34 appear to be similar. The sum energy consumption from three consecutive project years has been tabulated in Table 7.14. The years are selected to last from May through April, consistent with the years that were available and used in the project's analyses. The standard errors of the years' energy consumptions were estimated from the standard deviation of the months' energy consumptions that year. The groups' energy consumptions are similar from year to year. The differences between the yearly energy consumptions of the test and baseline groups are persistent and significant.

Table 7.14. Average Premises Energy Consumption of the Test and Baseline Groups over Three Consecutive Project Years

	Average Premises Energy (kWh)	
	Test Group	Baseline Group
May 2011 – April 2012	8246 ± 60	8666 ± 63
May 2012 – April 2013	8158 ± 56	8637 ± 58
May 2013 – April 2014	8310 ± 60	8826 ± 63

Net degree hours, heating degree hours, and cooling degree hours were calculated for each month. Again, caution was used to make sure that the calculations were not adversely affected by missing data intervals. Net degree hours were calculated by multiplying the average difference between ambient temperature and 55°F by the actual number of total hours each month. The “hot” hours add to make the net degree hours greater than zero; the “cold” hours subtract to reduce the net degree hours below zero. The calculation is “net” because many of the positive- and negative-valued intervals cancel one another, especially during shoulder spring and fall seasons.

The distinction between cooling and heating regimes was determined as the temperature at which the two lines that best represent the relationship between both groups’ monthly energies and net degree hours intersected. “Best” here refers to the linear regression model having minimal sum residual error. The intersection occurred at precisely 55°F.

Heating degree hours were determined as 55°F, minus the average of temperatures lower than 55°F, multiplied by the sum number of hours that the temperature was below 55°F that month. A similar calculation was conducted for cooling degree hours, but this calculation used temperatures and time intervals while the temperature was higher than 55°F.

If the sum of heating hours and cooling hours in a month was not equal to the actual hours in a month, the heating and cooling hours were accordingly scaled to make sure that all hours were represented in the heating and cooling degree-hour calculations.

The monthly energy usages of the test and baseline groups have been plotted against their months’ net degree days[1] in Figure 7.35. The legend, in this case, distinguishes both the group memberships and whether the months were before or after the test group’s exposure to web portal information. A vertical dashed line marks zero net degree days (or hours), where the average temperature would have been 55°F. The energy of baseline premises is again shown to be consistently greater than that of test ones. The impact of the treatment is not evident by inspection.

[1] Degree days are degree hours divided by 24.

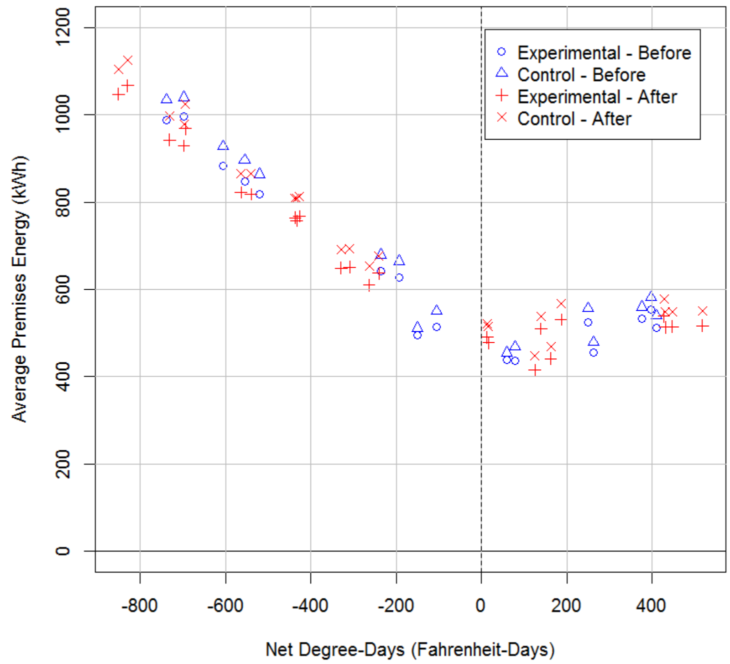


Figure 7.35. Monthly Average Premises Energies as a Function of Net Degree Days

Regression analysis was then conducted from this model. Each group's monthly energy consumptions were modeled using linear regression and R software programming tools (R Core Team 2013). The parameters included heating degree hours, cooling degree hours, and a flag indicating whether the month lay before or after the treatment.

The project first tried to emulate the experimental approach that had been used in the Freeman, Sullivan and Co. report, in which the treatment was stated to have lasted only from April 2012 to April 2013. The treatment flag parameter was modified to indicate this time period, after which all residents were said to have been given access to web portal information.[1] The baseline group's energy usages were calculated to have been reduced by 1 ± 17 kWh per month in the treatment period, and the test group energy was reduced 8 ± 13 kWh per month. The difference between the two changes that might be attributable to the access to web portal information would be a reduction of 5 ± 23 kWh per month. As was the case in the study by Freeman, Sullivan and Co., the change is not statistically significant, but it is a reduction, whereas the early study reported the opposite. If this magnitude were real and significant, it would represent a reduction of about 0.7% of the premises' energy consumption.

The project also performed the regression fit, but while presuming an additional full treatment year until April 2014. Interestingly, the presumption of an additional treatment year made virtually no difference in the end result.

The project was unable to confirm a significant change in energy consumption for residential customers who had been granted access to information from an energy web portal. A small reduction of

[1] It should also be noted that Sullivan et al. had at least another year's worth of historical data to use from 2009.

about 0.7% energy consumption was found, but the result was not statistically significant. An unusual difference between the test and baseline members' average energy consumption was noted. The Freeman, Sullivan, and Co. report observed this difference, too, but in the opposite direction.

The utility internally assessed the monetary impacts of its new AMI system features as follows:

- meter reading savings – $157,000
- customer service savings – $70,000
- servicemen callout reduction – $8,000.

The sum savings was estimated at $235 thousand per year. The project did not review or confirm these savings.

7.6 WSU Bio-Tech Generator for Outage Prevention

Avista Utilities proposed that the 800-kW Bio-Tech diesel generator at the WSU Pullman campus would become responsive to requests from the utility and would assist in outage prevention. The Bio-Tech generator had been installed and configured for parallel operation and might be the main resource in a campus microgrid. A control design was initiated to recommend when parallel operation should commence, but approval was always required from a human site operator.

New Washington State regulations regarding particulate emissions for diesel generators potentially applied to this generator, rendering it unavailable. The asset was not completed.

Table 7.15 lists estimated annualized costs for the system. Automated switchgear hardware was required and installed. It was estimated that almost $50 thousands would be needed each year to control this asset and measure and confirm its operation.

Table 7.15. Components and Annualized Component Costs of the WSU Bio-Tech Generator System

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
Evaluation, Measurement and Validation	13	22.8
Automated Switchgear	100	14.0
Project Management Services	13	12.9
Total Annualized System Cost		**$49.7K**

7.7 Configuration Control for Optimization (FDIR)

In addition to the ability of AMI meters to identify faults or outages, Avista Utilities implemented FDIR within its DMS to help it rapidly detect faults and improve its outage recovery process. The premise is that the utility becomes alerted soon after an outage as to which customers are affected. In some instances, the precise fault circuit location is identified. The utility can then respond rapidly and send the right resources to restore customer service, which has an economic benefit for the utility and its customers. The FDIR system was fully automated by August 2013.

Toward this end, Avista Utilities installed four sets of switchgear, 45 distribution line switches, 47 G&W Viper® smart circuit reclosers, and 354 Schweitzer (SEL 2015) smart fault circuit indicators, one at each primary trunk fuse location. These fault circuit indicators report outages to the DMS and the Avista Outage Management Tool (OMT). Most of these devices include voltage and current measurement points, making them even more useful for monitoring circuit status. All installed devices of this system communicate via the 802.11 MAN to RTU devices located in Spokane, Washington.

The utility subcontracted ACS (ACS 2015) to implement its DMS software with the FDIR application. Partner HP also provided integration resources and hardware.

At the beginning of the PNWSGD, Avista Utilities anticipated a decrease in the Customer Average Interruption Duration Index (CAIDI) and an increase in the Momentary Average Interruption Frequency Index (MAIFI) reliability measures. A minimum reduction of 20% was expected for CAIDI. The OMT calculates these IEEE indices, which have been reported to the Washington Utilities and Transportation Commission since 2004, potentially providing a comparison baseline of over six years of relevant reliability indices.

The estimated value that was derived from the application of FDIR was measured by the utility in customer avoided-outage minutes, translated to dollar impacts on customers. During 40 prior months, 24 incidents had led to lockout of service. Those outages corresponded to some 88,210 customer-outage hours that would be valued at $882,100, allowing $10 per customer-outage hour. If 20% of these outages had been avoided, the annual value would be just under $62 thousand per year. Avista Utilities thought they might yield even twice this benefit in Pullman because of its circuit characteristics.

Table 7.16 lists the estimated annualized costs of the FDIR system and its components. The major expenses were an allocation of some of the costs of customer advanced metering and the software upgrades needed for the DMS. The total annualized system costs were estimated to be about $1.4 million.

Table 7.16. Components and Annualized Component Costs of the Avista Utilities FDIR System

System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
Advanced Metering Infrastructure		511.9
• Software and Systems	25	316.0
• Operations and Maintenance	25	100.3
• Residential Equipment		
o Control Group	33	39.2
o Target Group	33	29.7
o Target Group with DR	25	7.1
• Engineering	25	7.7
• Commercial equipment		
o Control Group	33	5.2
o Target Group with DR	33	4.3
o Target Group	25	0.7
• Training	25	1.9
DMS Software and Hardware for 700–1,000 End Points	25	420.8
Wireless Network	25	173.2
Automated Line Switches	50	72.6
Fiber Network Communications	17	53.4
Smart Transformers Equipped with Sensors, Current Transformers, and Wireless Communications	25	37.3
Fault Indicators	100	26.8
Evaluation, Measurement and Validation	13	22.8
Station Reclosers and Controls	100	20.5
Project Management Services	13	12.9
Subcontractor – Integrated Volt/VAr Control Software	33	12.7
Reconductoring	33	11.8
Customer Service	25	10.5
Outreach and Education	25	7.9
Total Annualized System Cost		**$1,395.4K**

7.7.1 Data Concerning Pullman Site Reliability

The project attempted to observe improvements in the site's reliability based on the reliability indices SAIFI, SAIDI, and CAIDI that were calculated by Avista Utilities and submitted to the project for each project month. These indices were calculated separately for each of the 13 Pullman, Washington, feeders, but the project's analysis used aggregated indices that had been calculated for all 13 site feeders.

None of the indices were submitted from the months of 2011. The project does not know the reason for this omission.

Figure 7.36 shows the site's SAIFI metric from January 2009 through September 2014. These calculations were completed by the utility for these project months except for 2011. February and March 2009 had unusually high SAIFI values, the magnitudes of which have not been exceeded since.[1] The greatest SAIFI is about 0.75 outages per customer that month. The following months of 2009 had much lower values. The average month's SAIFI for the site is 0.085 ± 0.021 sustained outages per customer over these 57 months. The median is 0.020 sustained outages[2] per customer. These calculated statistics did not include 2011 data.

No improvement in SAIFI should be claimed based on inspection of this figure. In fact, the last project months had larger values than usual. No data was received from 2011.

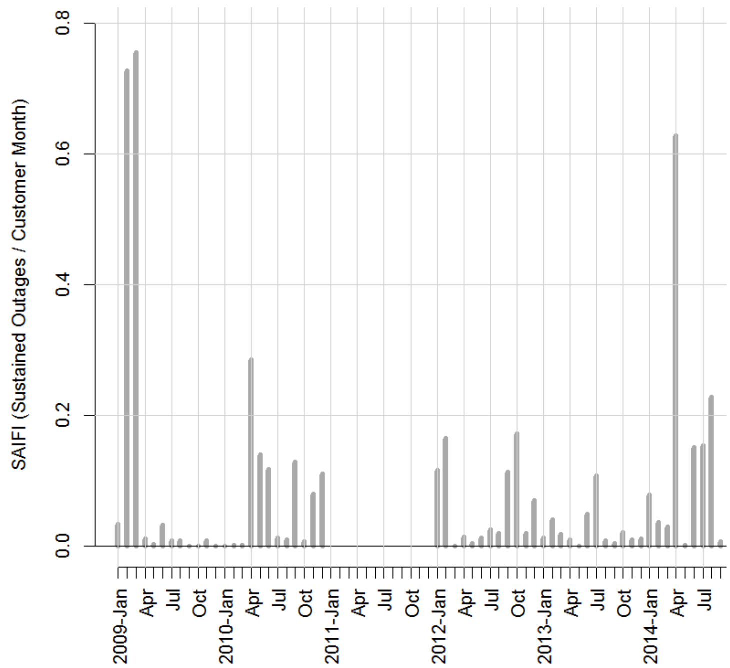


Figure 7.36. Monthly SAIFI Reliability Index for the Combined 13 Pullman Site Feeders

Figure 7.37 shows the calculated SAIDI metric for all of Pullman, Washington, from January 2009 through September 2014. The greatest SAIDI value was 94 minutes per customer in November 2010. The average month's SAIDI in Pullman, Washington, was 8.8 ± 2.3 minutes per customer, and the median was 2.3 minutes per customer per month. Again, no calculations were supplied for 2011.

[1] An analyst researched these months and found that there had been exceptional storms those months—an ice storm February 26, 2009 and a wind storm March 15, 2009.
[2] A "sustained" outage is almost always defined as one that exceeds 5 minutes.

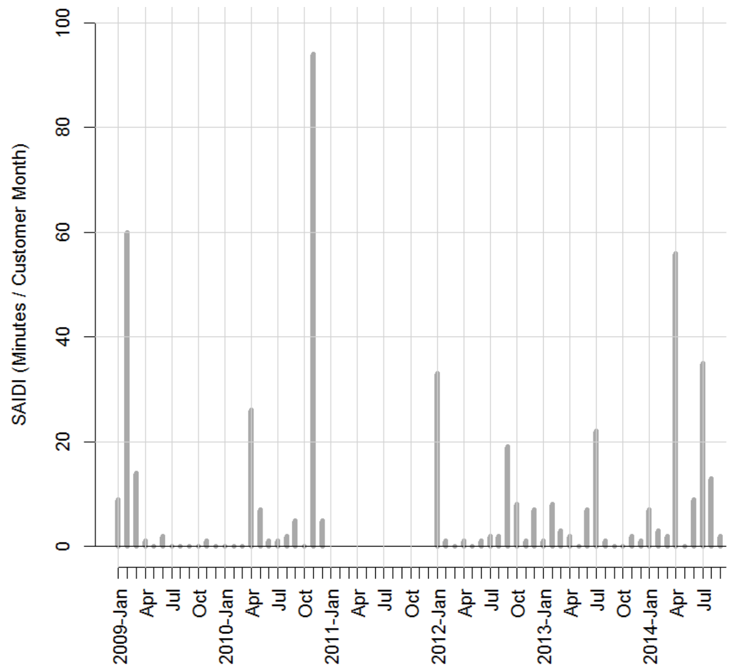


Figure 7.37. Monthly SAIDI Reliability Index for the Combined 13 Pullman Site Feeders

Figure 7.38 shows CAIDI for all of Pullman, Washington. A very large, uncharacteristic spike occurred in November 2010, when the typical customer outage was over 19 hours long. The cause of these outages was a wind storm November 16–17, 2010. The average of the months' CAIDI was 141 ± 21 minutes per outage. The median of the monthly values was 103 minutes per outage. The utility believe that had FDIR been in place, the numbers for this event would have been greatly reduced. By inspection, with the exception of the very large spike for November 2010, the CAIDI values have become greater, not less, toward the end of the project. However, the utility reports that it has had no events in Pullman during the PNWSGD that have locked out service. Therefore, no FDIR responses have become initiated during the PNWSGD.

No indices were submitted by the utility for 2011.

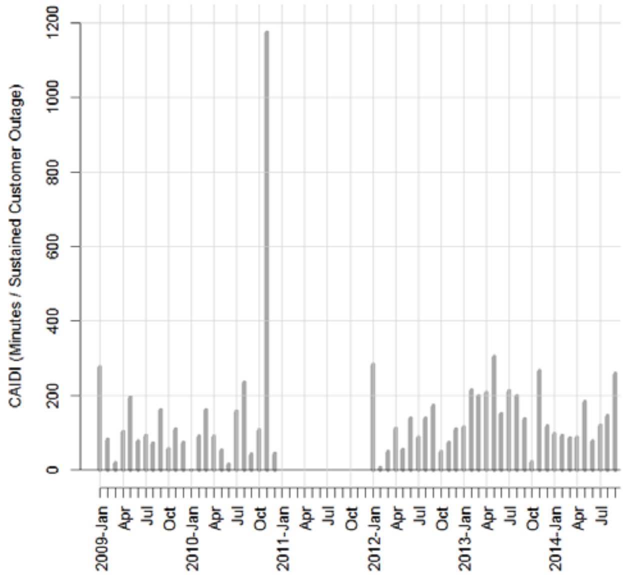


Figure 7.38. Monthly CAIDI Reliability Index for the Combined 13 Pullman Site Feeders

Recloser switches are critical components of the FDIR system, so the project reviewed a sample of recloser switch operation counts that had been submitted by Avista Utilities. Table 7.17 lists the aggregated counts by season for three of the South Pullman feeders—SPU121, SPU123, and SPU125. Data was listed only when the project had complete data for the seasons. The table also includes the sum count from the three feeders.

An exceptional number of recloser switch operations occurred during March 2012 on Feeder SPU123. There might be weak trend for fewer recloser operations during summers, but winter 2013 also had few operations. The use of smarter fault detection and recovery does not appear to be adversely affecting the counts of recloser operations. The utility confirmed that they had not observed any change in recloser operations. Anecdotally, the numbers of service lockouts has been small, but this fact might be attributable to weather.

Table 7.17. Recloser Operation Counts by Season for Three Representative South Pullman Feeders

Season	Feeder SPU121	SPU123	SPU125	Total
Spring 2012	28	2,579	8	2,615
Summer 2012	2	70	0	72
Fall 2012	30	20	40	54
Winter 2012	48	36	12	96
Spring 2013	48	36	12	96
Summer 2013	4	0	0	4
Fall 2013	32	24	6	62
Winter 2013	0	0	20	20
Spring 2014	17	12	4	33

7.7.2 Analysis of Pullman Site Electricity Reliability

Given that reliability indices are highly variable over time, the project has developed an objective method to observe whether significant changes might have occurred in a time series of index data. The method separates the indices by whether they occurred before or after a given data interval—a month, in this case. The populations of indices on the two sides of the time demarcation are treated as independent sets, and Student's t-tests are applied to objectively compare the two populations. The process marches through the successive months and reports whether the indices in the following months have a significantly reduced value when compared against the preceding months. This may be novel to the project and should be considered as a practice to continuously observe whether changing distribution utility practices are improving or harming customer service.

Figure 7.39 is the result of such analysis, where these results are based on the SAIFI metrics that were shown in Figure 7.36. The first SAIFI values from early 2009 had been unusually large. Therefore, this analysis approach determined that SAIFI had, indeed, improved. The vertical axis represents a statistical p-value, in this case interpreted as the percent likelihood that following months' SAIFI value is smaller than in previous months. A horizontal, dashed red line has been placed on the figure to indicate the normal threshold at which one may have 95% confidence in the premise. Conversely, the red dashed line at 5% suggests the threshold at which the latter months' indices appear to be *greater than*, not smaller than, the indices of the preceding months.

The SAIFI performance was so good in the second half of 2009 that the calculated trend projected that SAIFI was becoming worse in the future. The t-test discounted the impacts from the two initial spikes, concluding that these were possibly outliers. In the remainder of the project, the method indicated the index was neither improving nor degrading. The fact that the likelihood values remain in the bottom half of the range suggests that SAIFI values are tending to become slightly worse.

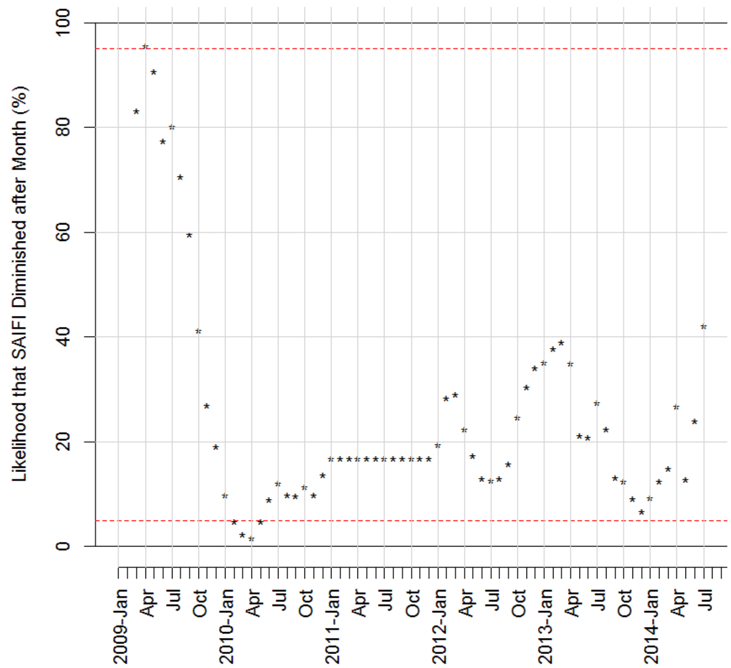


Figure 7.39. Likelihood that the SAIFIs for the following Months are Significantly Lower than those in the Preceding Months

The methods used to create Figure 7.40 are the same as was described above, but this figure is based on the site's monthly SAIDI indices. The sawtooth patterns on the two sides of 2011 were likely caused by the uncharacteristic peak index for November 2010. At no time does the likelihood exceed the 5% or 95% thresholds. No change can be confidently stated concerning the utility's management of SAIDI these months. The downward trends through much of 2012 and 2013 are troubling.

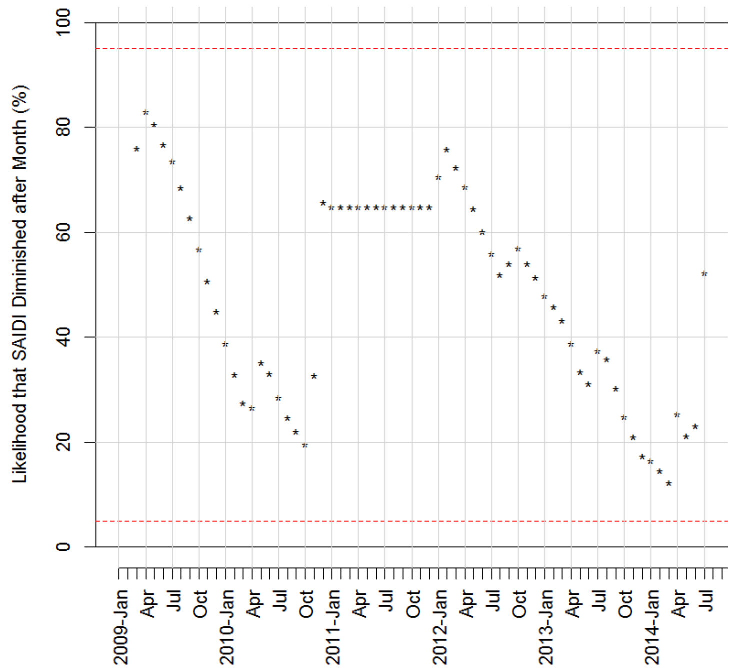


Figure 7.40. Likelihood that the SAIDIs for the following Months are Significantly Lower than those in the Preceding Months

The same analysis methods were applied in Figure 7.41 as the project reviewed trends in the CAIDI metric. The likelihood was strongly affected again by a peak CAIDI value in November 2010. While this outlier remained in the future, the method concluded that the index was getting worse. As soon as the peak month was in the past, the method's output jumped to a more reasonable likelihood value. The likelihood rose and fell predictably, based on what had been observed in Figure 7.38, but the t-tests never closely approached thresholds at which convincing changes could have been verified.

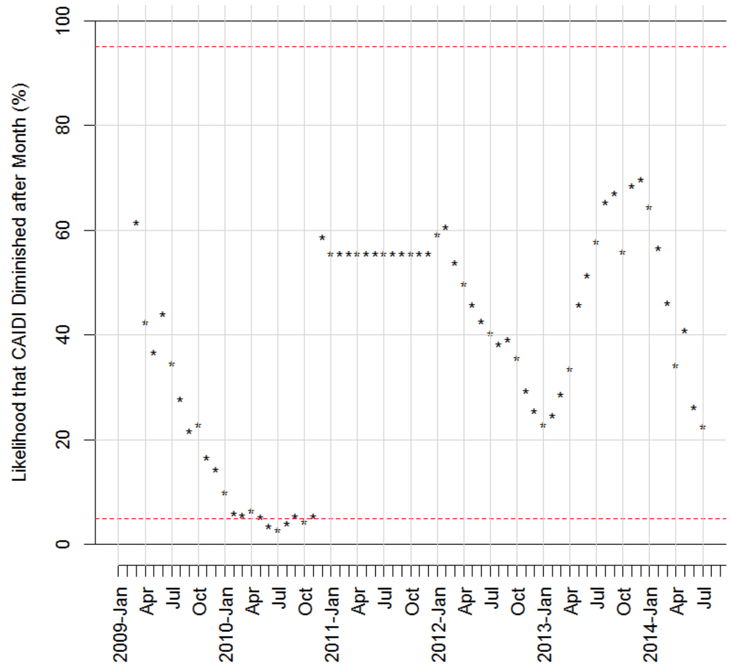


Figure 7.41. Likelihood that the CAIDIs for the Following Months are Significantly Lower than those in the Preceding Months

The project was not able to verify that the new FDIR system, or any other distribution management practices, for that matter, had significantly impacted the CAIDI reliability index that had been targeted for improvement. Similarly, no significant improvement in the site's SAIFI or SAIDI indices could be verified. Avista reported substantial improvements in reliability with 353,336 avoided outage minutes for customers beween August 2013 and December 2014. Customers also experienced an annual average of 17 percent fewer outages and more than 12 percent shorter outages during the same time period. Further, Avista believes a lack of severe weather-related outages during the grid demonstration project prevented full exercising of the FDIR system.

7.8 Controllable HVAC Fan Load at 39 Campus Buildings

The negotiated interaction between Avista Utilities and the WSU campus, including system integration was performed by Spirae. (Spirae, Inc. 2015), was documented in the Spirae-Washington State University Interface Control Document.[1] This document defined five response tiers that corresponded to five campus assets, of which Avista would be allowed to request control:

- Tier 1 – HVAC load shed (discussed in this section, 7.8)
- Tier 2 – Chilled water load shed (discussed in Section 7.9)

[1] Unpublished engineering document authored by Spirae, Inc., 320, East Vine Drive, Suite #307, Fort Collins, CO 80524, USA. Last known version 1.5 was revised April 6, 2015.

- Tier 3 – Grimes Way steam plant diesel generator dispatch (discussed in Section 7.10)
- Tier 4 – Grimes Way steam plant first natural gas generator dispatch (discussed in Section 7.11)
- Tier 5 – Grimes Way steam plant second natural gas generator dispatch (Section 7.11).

These assets were to remain under manual control. The campus's assets may at times be unable to change their operations upon receipt of requests from the utility. The parties defined a set of four signals with which responses could be requested, acknowledged, and informed between the parties:

- Avista-generated request signal (AGRS)—a utility request to the campus for the engagement of one of the asset "tiers"
- AGRS acknowledgement signal—the campus's acknowledgement upon receipt of an AGRS request from the utility
- AGRS response signal—further indication from the campus back to the utility that the campus either intends to act on the request or cannot respond
- Asset active signal—confirmation from the campus to the utility that the asset is indeed responding.

As described, the process may be initiated by Avista Utilities. The PNWSGD project had asked that the requests to the campus be made responsive to the transactive system. Transactive toolkit functions were established and configured for each of the five tiers. The utility was invited to further define its own objectives for the Pullman, Washington, site, which would have further refined the times at which the transactive system would have advised responses.

The five university assets were initially treated as a single asset system by the project. Table 7.18 lists the estimated annualized costs needed to make the five campus assets responsive to Avista Utilities and the PNWSGD project's transactive system. As these campus asset systems are discussed in the remaining sections of this chapter, the reader will be referred back to this table.

Table 7.18. System Components and Annualized Costs for the Combined WSU System, Including Controls of HVAC Load, Chiller, Diesel Generator, and Two Gas Generators on the WSU Campus in Pullman, Washington

Asset System Component	Component Allocation (%)	Allocated Annual Component Cost ($K)
Transactive Node System	33	114.4
WSU Engineering Labor	100	60.1
Evaluation, Measurement and Validation	13	22.8
Project Management Services	13	12.9
Outreach and Education	25	7.9
Total Annualized Cost		**$218.1K**

The remainder of this section addresses only Tier 1, concerning control of 39 HVAC systems on the WSU campus. Early in the project, the utility estimated that 145–552 kW of daytime load could be reduced in the summer by changing the operation of campus HVAC circulation fan systems. In winter, daytime power was projected to be reducible by 345–369 kW.[1]

Some conservation was anticipated through reduction of fan energy during unoccupied building hours. Unoccupied hours are typically considered 19:00 to 06:00, but may vary by building.

Because the utility had additionally requested demand responses for up to 50 hours per year, the campus planned to cycle through available HVAC fan loads upon receiving these requests, including during buildings' occupied periods, for short, 15–20-minute periods. They estimated that total fan loads could be reduced about 25% without adversely affecting air quality for the buildings' occupants. The requested reductions were to last 15, 30, or 60 minutes. Subsequent requests were not allowed within 3–4 hours after the prior event had concluded.

7.8.1 Data Concerning Control of the WSU HVAC Fan Loads

The project reviewed the statuses of the four DR signals that had been developed collaboratively by Avista Utilities, WSU, and Spirae. The AGRS turned out to be more of a permissive signal than targeted DR requests were. The signal remained fixed in its active ("1") state or in the special status, "Engagement with transactive control." In the end, there were only 39 5-minute intervals when all four signals were in their active ("1") states. The status of the final indicator alone—the active signal confirmed by WSU—was adequate to indicate whether the fan power reduction should be active or not.

The system was exercised only four months during 2014—January, February, June, and July. Two-thirds of the events occurred during February 2014.

The 39 intervals represent 3 hours and 15 minutes of engagement, spread over 12 event periods. These 12 events' starting times and durations are listed in Table 7.19. The shortest duration was 5 minutes; the longest, 30 minutes. The average duration was about 17 minutes. The events occurred exclusively on work weekdays between 10:35 and 15:50 local Pacific Time.

---

[1] These power reduction estimates and further information here about the anticipated response of the WSU HVAC system were found in the unpublished project document, Avista Utilities Subproject Description.

Table 7.19. Times and Durations of the Twelve Events when WSU HVAC Fan Usage was Reduced

Event	Year	Month	Day	Day of Week	Local Starting Time (hh:mm)	Duration (h:mm)
1	2014	Jan	30	Thursday	10:35	0:05
2	2014	Feb	6	Thursday	13:50	0:05
3	2014	Feb	7	Friday	13:05	0:15
4	2014	Feb	11	Tuesday	10:00	0:15
5	2014	Feb	12	Wednesday	13:50	0:15
6	2014	Feb	19	Wednesday	10:00	0:15
7	2014	Feb	20	Thursday	11:00	0:15
8	2014	Feb	21	Friday	12:00	0:15
9	2014	Jun	9	Monday	13:55	0:15
10	2014	Jun	23	Monday	15:05	0:30
11	2014	Jun	24	Tuesday	15:20	0:30
12	2014	Jul	28	Monday	12:20	0:30

Avista Utilities compiled a set of WSU campus meter readings for the observation of impacts from the 39 campus HVAC systems. McKinstry installed these meters for the utility and campus. Five-minute aggregated power data was supplied to the project covering a period from late April 2013 until September 2014. This data time series is shown in Figure 7.42. Data quality was generally good, but the data was found to have “stuck” on nonzero values throughout much of December 2013 and January 2014. These “stuck” intervals were removed from the data set prior to analysis and are not shown in the figure.

The power data has a strong weekly pattern. Power consumption was significantly reduced on weekends. Upon focusing in on individual months and weeks, analysts also observed very different consumption patterns on national holidays and certain other days, such as the Friday following Thanksgiving Day. By simple inspection, the four calendar months for which both 2013 and 2014 data exists are different. Power consumption in 2014 appears to have increased significantly above the levels in 2013.

Based on all the reported power data, the average power consumption was 2.795 ± 0.002 MW. The standard deviation of the power measurements was 0.56 MW.

The effect of temperature on power consumption, though noticeable, was small.

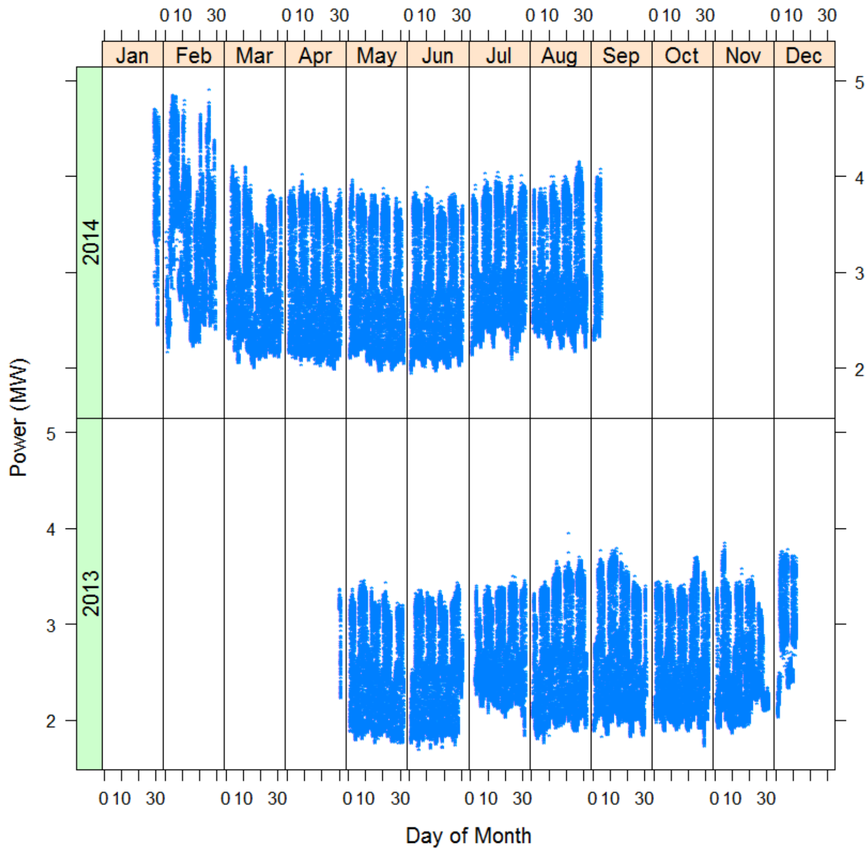


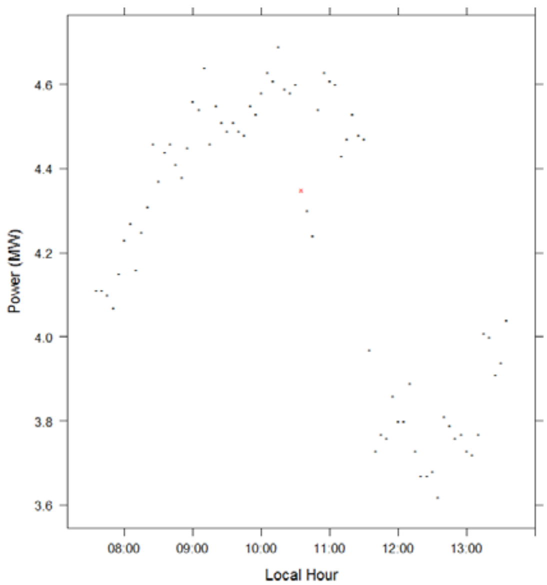
Figure 7.42. Power Data Supplied to the PNWSGD by Avista Utilities from which WSU HVAC Fan Reductions were Analyzed

7.8.2 Analysis of the WSU HVAC Fan Loads

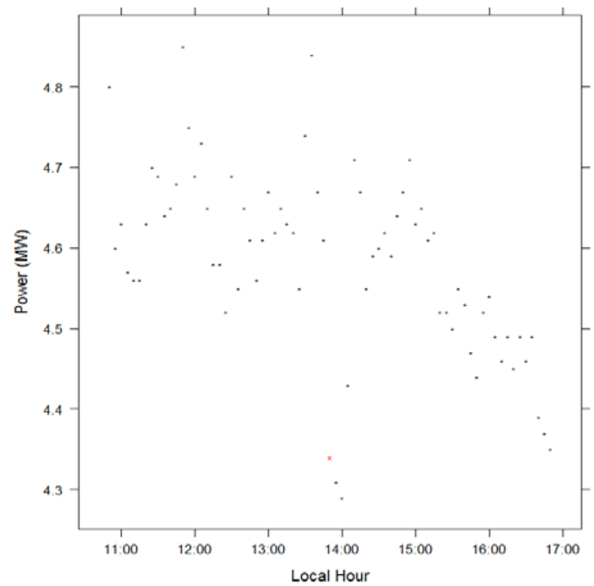
The power consumption during the 12 events, plus and minus about 3 hours each side of the event, are shown in Figure 7.43. This time series is the same that had been shown in Figure 7.42 above, but only narrow time windows around each reported event are shown in the panels of Figure 7.43(a-l). The power during event intervals is marked by a red "x," as is shown in the single legend in the last panel (l).

It was reassuring to analysts that the reduction in load was often evident by inspection of these plots. The only exception is Event 10, Panel (j), where no event intervals appear to have reduced power. However, a reduction of similar magnitude and the right duration appears to have occurred one hour earlier that event. It is likely that the time of that event was misreported by one hour. By inspection, the power reductions appear to be typically on the order of 0.2–0.3 MW.

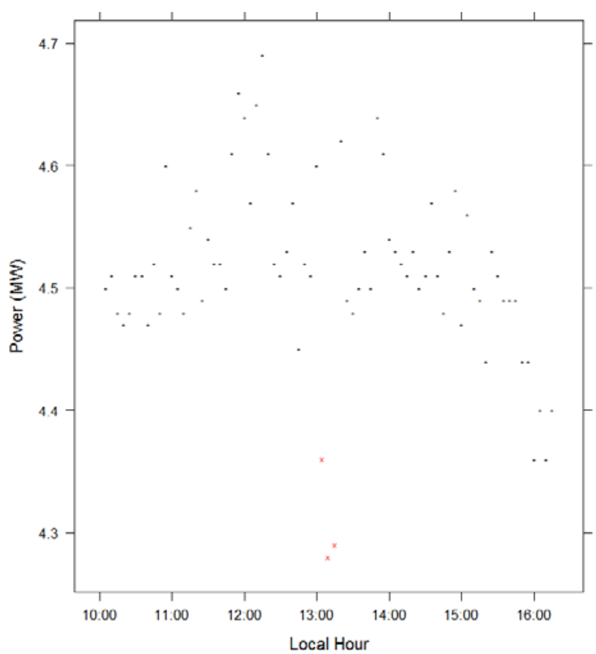
Other events in this set also appear to include reporting errors. For Events 1 and 2 (Panels (a) and (b)), power reduction appears to have extended beyond the intervals that had been reported. Event 12 (Panel (l)) appears to have been terminated earlier than was reported. All these types of reporting errors could adversely affect verification of the impacts of demand responses using this DR asset.



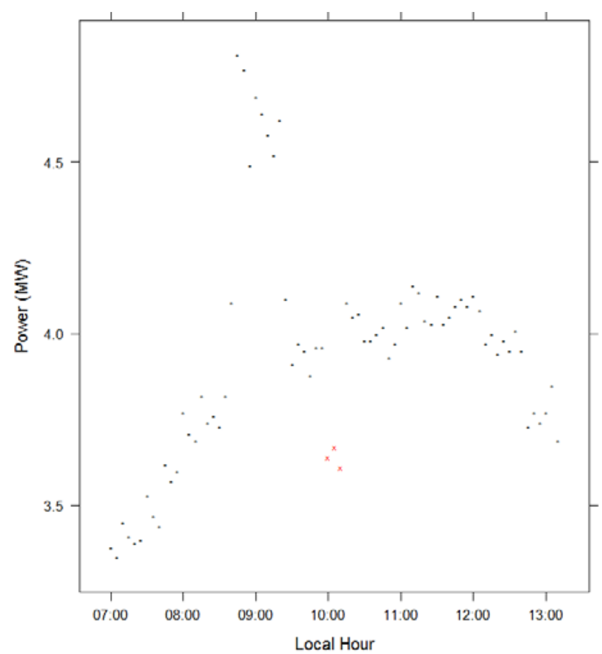
(a) Event 1: January 30, 2014



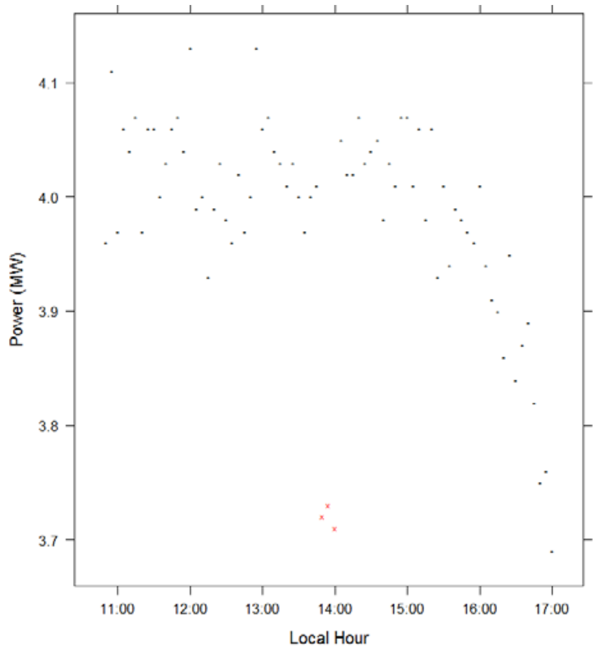
(b) Event 2: February 6, 2014



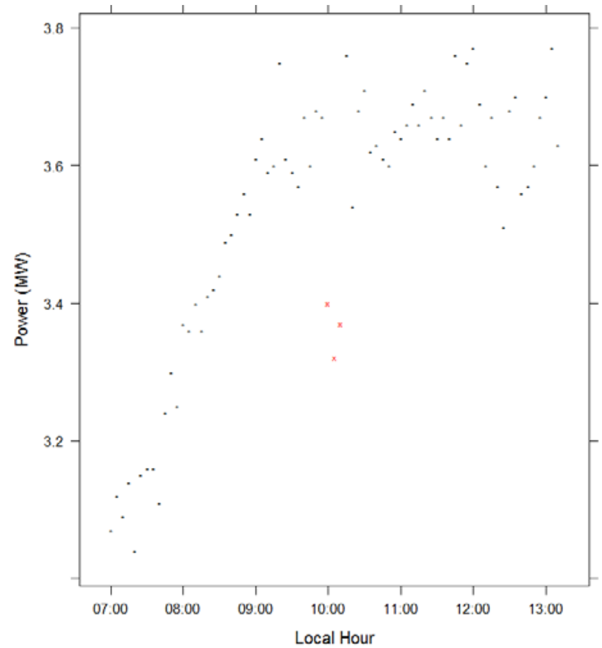
(c) Event 3: February 7, 2014



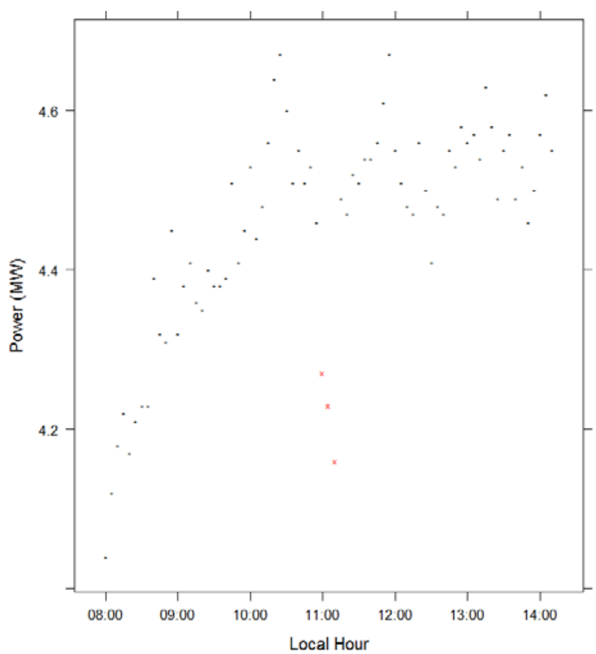
(d) Event 4: February 11, 2014



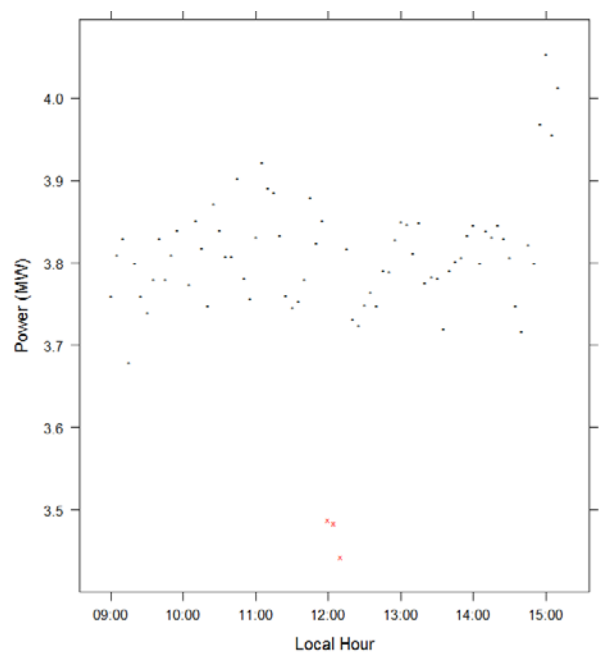
(e) Event 5: February 12, 2014



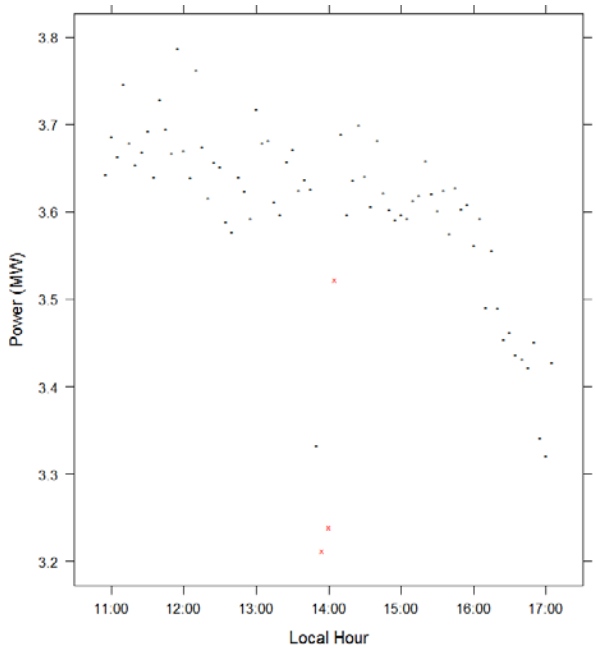
(f) Event 6: February 19, 2014



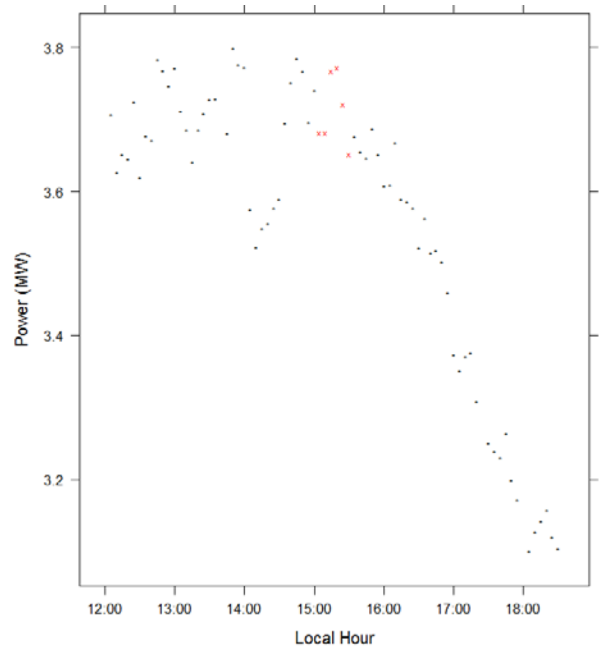
(g) Event 7: February 20, 2014



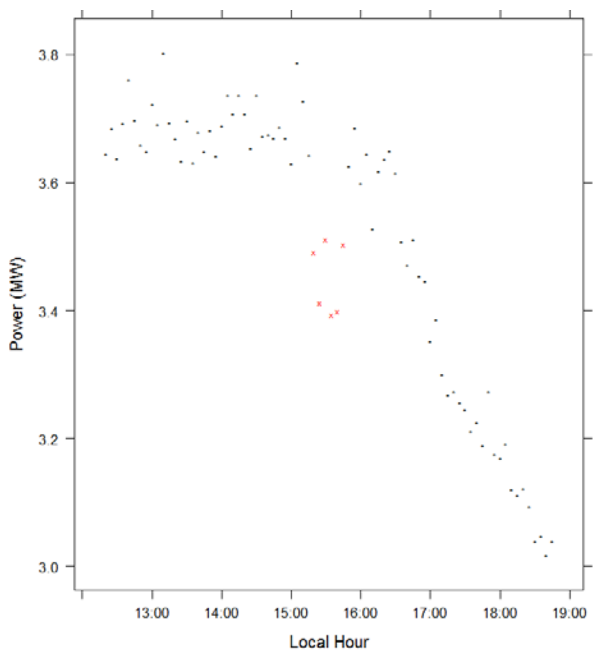
(h) Event 8: February 21, 2014



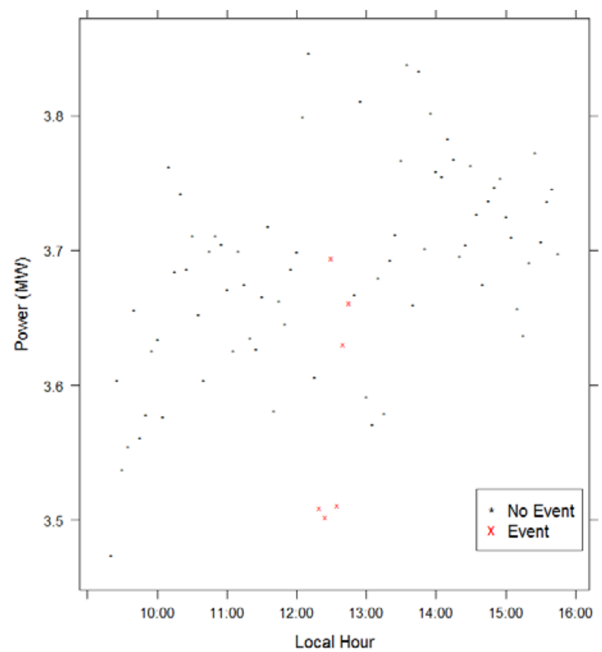
(i) Event 9: June 6, 2014



(j) Event 10: June 23, 2014



(k) Event 11: June 24, 2014



(l) Event 12: July 28, 2014

Figure 7.43. Power Time Series from 3 Hours Prior to the Reported Reduction in WSU HVAC Fan Load to 3 Hours after the Events. Event data intervals have been marked and colored differently according to the legend that is shown in the last panel (l).

To more rigorously quantify the magnitude of the HVAC fan power reductions, project analysts created a regression model of the reported power time series. The regression model was greatly improved and simplified after some interesting characteristics of this time series had been identified. First, the aggregated power on the campus was significantly reduced during weekends. Fortunately, no events occurred during weekend days, so weekends may be omitted from analysis. Holidays, too, were found to have very reduced and different consumption patterns. Additionally, consumption during days surrounding holidays, such as the day after Thanksgiving Day, were abnormal. Again, no events occurred on these days, so they could be omitted from analysis. There was no clear impact evident from the changes between student semester terms and student vacation periods. Removal of weekends and abnormal days was probably more impactful that temperature for this aggregated power time series.

The importance of considering day types and holidays for this analysis is demonstrated by Figure 7.44. In this figure, daily power load has been plotted a function of local time of day, Pacific Time. The days of the week have been shown in seven panels from left to right. The special days, including weekends, holidays, and days following holidays, are plotted in the top seven panels. The remaining "normal weekdays" are plotted in the bottom seven panels. The patterns are remarkably similar for the "normal" weekdays, although there might be a small reduction on Fridays. The data has been further parsed by season, which shows the remaining seasonal and temperature dependence of the data.

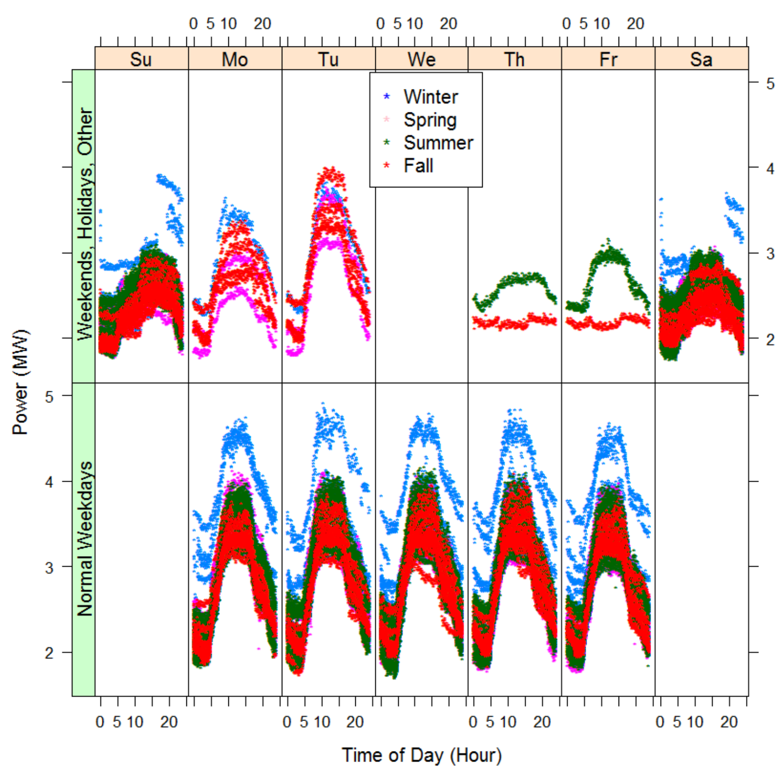


Figure 7.44. WSU Power Data as a Function of Time of Day, Grouped by Weekday and Season. The data for "normal weekdays" (bottom strips) is quite regular and predictable after weekends, holidays, and other unusual workdays have been excluded (top).

Only the "normal weekday" data was used for the regression analysis. A linear regression model was created in software tool R as a function of temperature and by event status, year, month, and hour. Fitting to year was determined to be necessary because the power levels in 2014 were significantly greater than those in 2013. The reason for this load growth is not known to the analysts. The regression fit was strong. Based on the regression that R performed on this data, the impact of events was a power reduction of 239 ± 21 kW.

The regression model was then used to create a comparison baseline that emulates the aggregated power as if the events had not occurred. The baseline was in good agreement with the measured power levels, as is demonstrated by Figure 7.45.

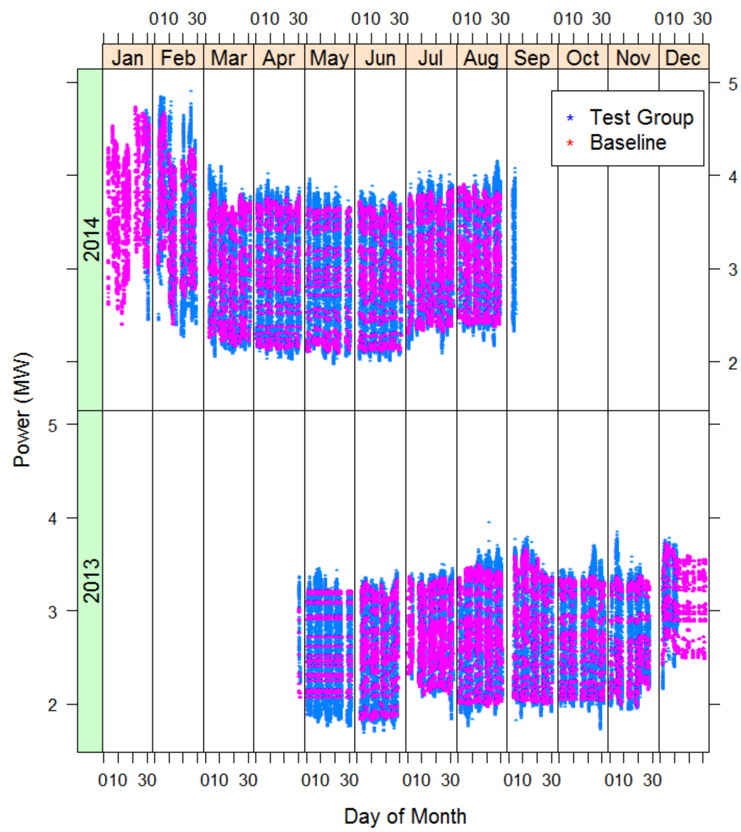


Figure 7.45. Power Measurements and the Modeled Power Measurements that Resulted from Regression Analysis

Student's t-tests were then used to compare the change in power during events against the change in power during non-event periods. The change in power here refers to the difference between the measurements and the baseline modeled powers. The impacts during events, during the rebound hour following events, and during entire event days were analyzed using Student's t-tests.

Based on a Student's t-test comparison between measured power and the regression fit on this power time series that emulates having no events, power was reduced by 239 ± 41 kW during events, on average. The 95% confidence interval is estimated to be from −157 to −321 kW. This estimate reproduced the average magnitude that had been stated by the R model, but the variability was more conservatively calculated. The average magnitude of the power impact is probably conservatively estimated here because of the multiple instances of misreported event periods, as was discussed in Section 7.8.1.

The system was active during only four calendar months, but the impact during these months has been estimated and is shown in Table 7.20. The estimated conserved energy is simply the product of the numbers of hours that the system was reported to have been reducing HVAC fan usage multiplied by the estimated reduction in fan power during the events.

Table 7.20. Estimated Impacts on Power and Energy during Times that the HVAC Fan Usage was Reduced, by Month and for All Months

	Duration (h:mm)	Δ Power (kW)	Δ Energy (kWh)
January	0:05	−14.6	−1.22
February	1:35	−354 ± 72	−561 ± 114
…	-	-	-
June	1:15	−109 ± 43	−136 ± 54
July	0:30	−236 ± 38	−118 ± 19
…	-	-	-
All Months	**3:25**	**−239 ± 41**	**−816 ± 140**

A similar analysis was conducted to estimate any rebound impact that might have occurred during the hours that followed the conclusions of the 12 reported events. No rebound impact should be reported because the impact was not statistically meaningful. The rebound impact might be anywhere between an increase of 32 kW and a continued reduction of 49 kW (i.e., between −49 and +32 kW), based on an estimated 95% confidence interval.

Analysts further looked at the overall impact when comparing days that events had and had not occurred. Surprisingly, a small but significant power reduction was observed throughout days that events had occurred compared with power consumption on days that events had not occurred. On average, the reduction was 43 ± 4 kW throughout these event days. This is about 1.5% of the average aggregated power measurement. Because the typical event lasted only about 17 minutes, the reduction in power during events can account for only several of these average kilowatts during event days. Perhaps other measures may have been taken on these days, in addition to the reduction of HVAC fan loads, to further reduce consumption at the WSU buildings where these measurements were taken.

In conclusion, the project was able to confirm that significant load reduction accompanied the reduction of campus HVAC fan loads. The estimated magnitude of the power reduction closely matched the magnitude that had been anticipated by Avista Utilities early in the PNWSGD project. The project's estimates may be conservative because of occasional misreporting of event periods, which misreporting would also affect the utility's efforts to validate DR from this and other WSU assets. Avista Utilities estimates that energy had been reduced 1,500–3,000 MWh per year through the more efficient management of the WSU air handlers, a reduction worth $87,500–$175,000.

7.9 Nine WSU Controllable Chiller Loads

Avista Utilities and WSU identified nine building chiller loads that could be made responsive to DR requests from the utility. The chillers are used to cool campus buildings. The load can be deferred for short periods without noticeably affecting the comfort of building occupants. The collaboration between Avista Utilities, WSU, and Spirae to request, acknowledge, and confirm the response from this and four other assets was described at the beginning of Section 7.8. The controllable WSU chiller load was the second tier of the five controllable WSU assets within the engineering design documentation.

WSU would allow its chiller loads to be deferred for 30 or 60 minutes. After a successful event, the chillers require 1 hour to recover and recool their building spaces.

The project requested that the demand responses be aligned with the automated requests from the transactive system at the Pullman site. The utility was invited to configure the toolkit function that represented this asset so that it would automatically request responses at the times the utility desired.

The annualized costs for the control of this asset were included in Table 7.18.

7.9.1 Data Concerning the WSU Controllable Chiller Loads

There were five events during the project when WSU confirmed that they had decreased chiller load. According to the signal handshakes that had been established between the utility, campus, and system integrator Spirae, all four signals were necessarily set to "1" for a successful DR event. The project had expected to see targeted utility requests for these responses, but the utility's requests remained in a permissive state much of the time. The status of the confirmatory "active" signal from the campus was adequate to track whether the chillers had, in fact, become engaged.

The starting times and durations of the five events are listed in Table 7.21. The first event, in September 2013, was only 10 minutes long and was probably a test of the system. Each of the remaining four events was conducted in June 2014 and was 1 hour long.

Table 7.21. Starting Times and Durations of the Five Events Reported to the Project Concerning WSU Controllable Chiller Loads. The first appears to be a test event.

Event	Year	Month	Day	Day of Week	Local Starting Time (hh:mm)	Duration (h:mm)
1	2013	Sep	3	Tuesday	15:45	0:10
2	2014	Jun	5	Thursday	14:10	1:00
3	2014	Jun	9	Monday	12:00	1:00
4	2014	Jun	23	Monday	14:00	1:00
5	2014	Jun	24	Tuesday	15:10	1:00

Avista Utilities submitted a series of aggregated power measurements that included the chiller loads. Data was collected from late April 2013 to September 2014. This data is shown in Figure 7.46. As one might expect, the chiller load is very seasonal. It falls to almost nothing from late fall through early spring. The load is active some of the day during shoulder months, and the load is quite large throughout summer days.

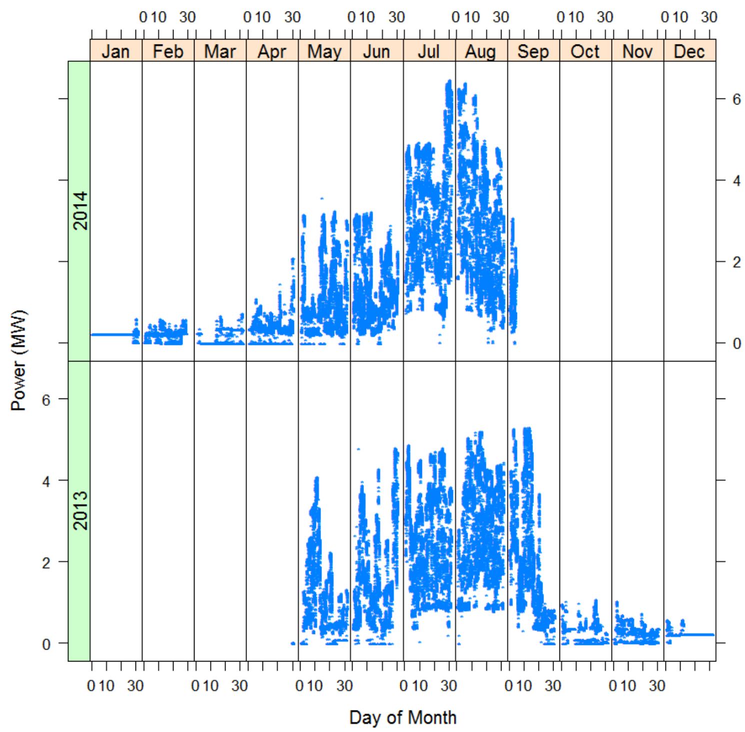


Figure 7.46. Aggregated Power Data Time Series of 5-Minute Data Supplied to the Project Concerning the Controllable WSU Chiller Load

7.9.2 Analysis of the WSU Controllable Chiller Loads

The first event was considered a trial engagement. Project analysis narrowed the investigation to June 2014, the month the remaining four events had been reported. Figure 7.47 displays the aggregated chiller load for all the days of June 2014. The reported event periods are colored red. Even at this resolution, some load reduction is evident.

However, the diurnal patterns of the load are quite irregular, perhaps not easily predictable. Discontinuities occur in midafternoons, when the load jumps 1 MW or more. The load as abruptly returns to lower levels in the evenings. The jumps and drops in load do not happen in the same hours during the month. The unusually low, flat power load in the middle of the month was confirmed to correspond with relatively cold days that month. The last days of the month did not return to the patterns of the first days, even though the temperatures in late June became similar to those of early June. Summer school sessions were launched and continued through this month, so it did not seem that the different patterns could be attributed to different building occupancies.

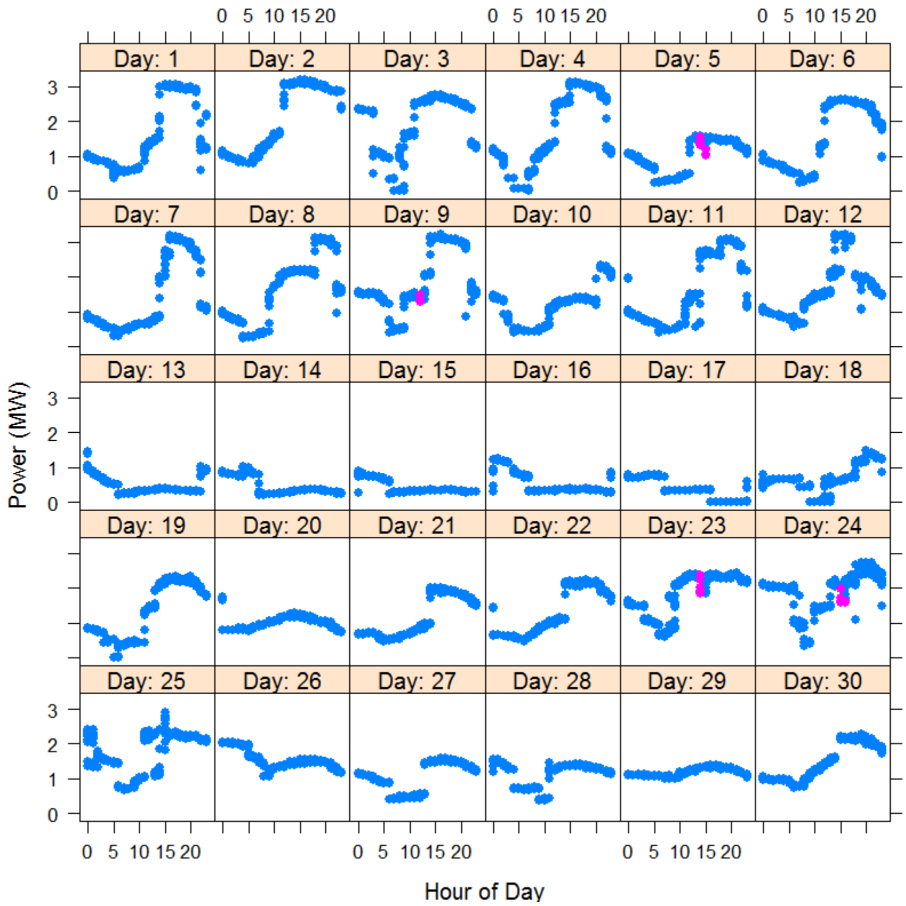


Figure 7.47. Aggregated Power Time Series for Days of June 2014, when the Events were Reported to have Occurred. The event periods have been colored red.

An interesting representation of chiller load emerged when the project tried to understand the connection between local hour of day, ambient temperature, and the aggregate chiller loads. Figure 7.48 is a contour plot of the aggregate chiller load as functions of local hour (horizontal axis) and ambient temperature (vertical axis). All available data was used in creating this graphic, including months of cold Pullman, Washington, weather that were uninteresting and were cropped from the bottom of the figure. If a trajectory of paired hours and temperatures is tracked for any given day, the trajectory's path through the contours creates a decent model of the power that the chillers consume, in aggregate. There will be inaccuracies to the degree that the discontinuities may create variability in the modeled power.

What this all means for the analyst is that the chiller power is extremely difficult to predict or model accurately.

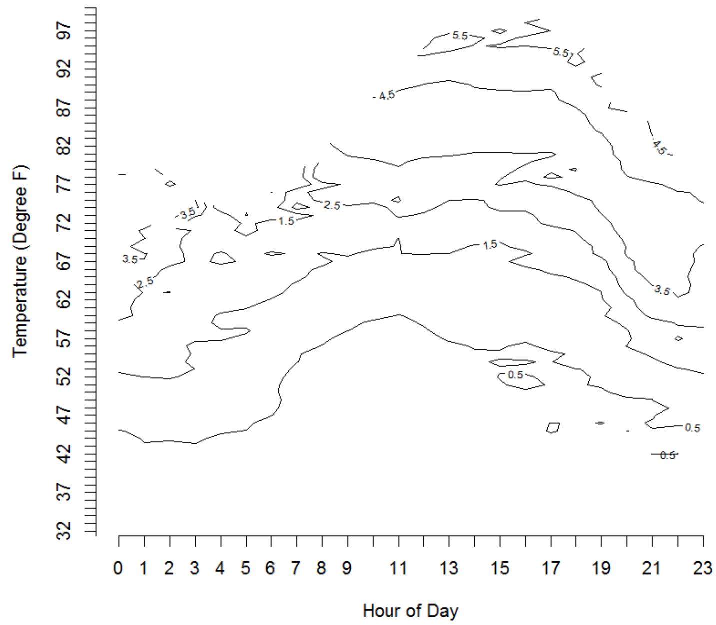


Figure 7.48. Contour Plot of Aggregate Chiller Power (MW) as Functions of both the Local Hour (Pacific Time) and Ambient Temperature

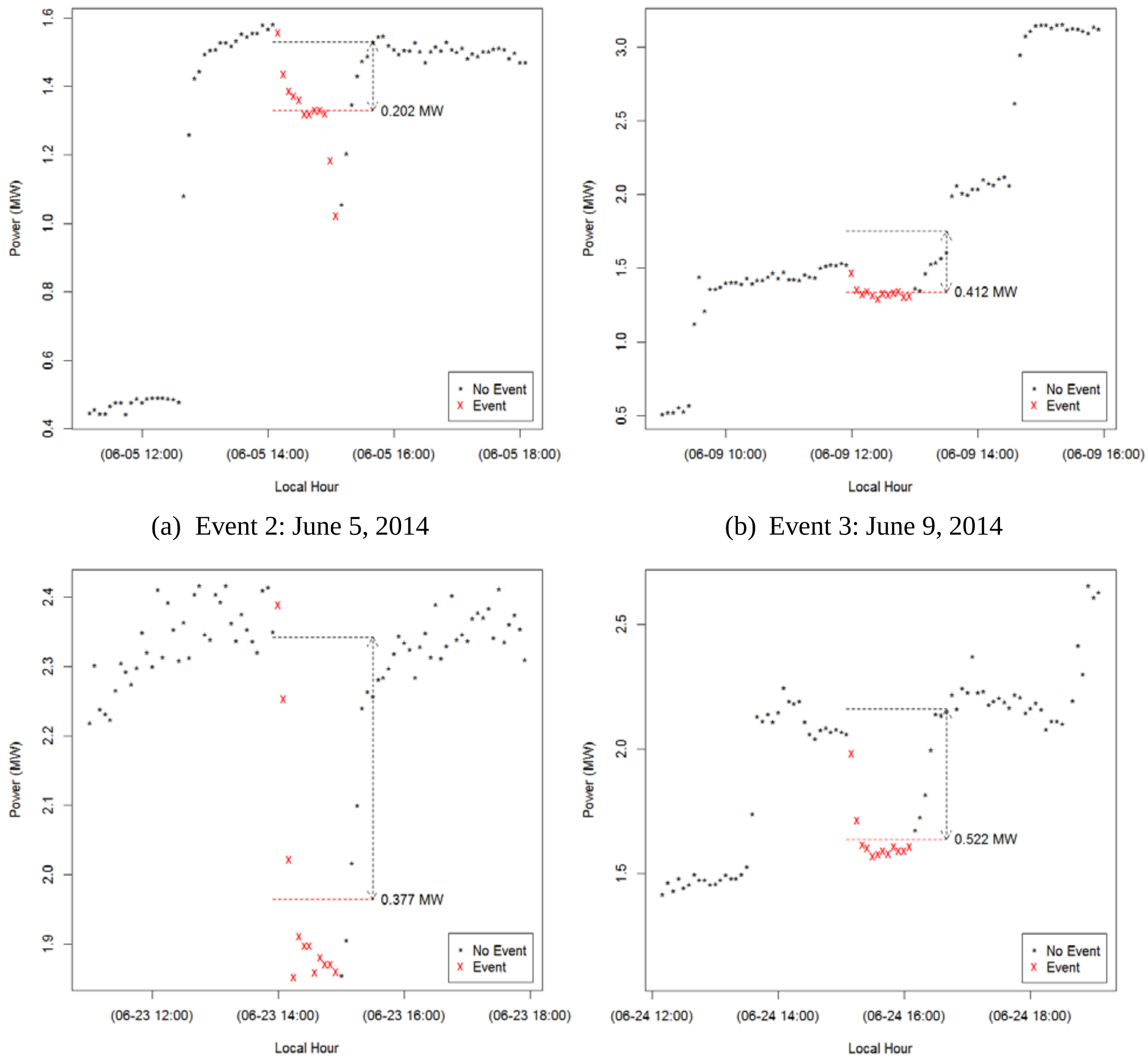
Reluctantly, analysts explored using a notch approach, a direct measurement of the change in power that occurs during events. Such methods are notoriously subjective, but proved fruitful for estimating the impact of the WSU chiller events.

Figure 7.49 focuses still more narrowly on the event periods and the 3 hours before and after the events. The four June 2014 events are shown. Data during the reported event periods is indicated by a red "x." Power reductions are evident by inspection.

Some delay is evident in the initiation and termination of the events, based on the notched power reductions. It appears to take about 15 minutes (three 5-minute data intervals) before an event achieves its fully reduced power level. When the event is terminated, it takes about 35 minutes (seven 5-minute data intervals) before the power returns to the higher, normal power level.

Dashed red lines were drawn at the average event power levels in Figure 7.49, using all the reported event intervals in the averages. Dashed black lines were generated to estimate the normal power level, and each of these lines is the average of the aggregated power levels from 1 hour before the first event interval to another hour duration that began between 35 and 95 minutes after the last event interval had ended. The power differences between the two lines are shown for each event.

The precise method for defining the two levels was subjectively determined and is arguable. Regardless, the representations appear reasonable. The red line might underestimate the depth of the curtailment, but that conservative impact might be fair if the asset required a "warmup" period, as appears to be the case. The black line (normal power level) provided an adequate measure when the power was changing during an event, as was the case for Event 3, Figure 7.49(b). It estimates the normal, unreduced power as an average of the prior and following power levels.



(a) Event 2: June 5, 2014

(b) Event 3: June 9, 2014

(c) Event 4: June 23, 2014

(d) Event 5: June 24, 2014

Figure 7.49. Power Time Series from 3 Hours before Reported Events until 3 Hours after Reported Events. The first, short event in September 2013 was likely a trial event and has been omitted.

The average of calculated impacts from Figure 7.49 is 0.38 ± 0.07 MW. The standard deviation of these differences was 0.13 MW.

The project explored regression models to confirm the estimated power curtailment, but the regression method was rendered inaccurate by the irregular seasonal and diurnal variations in the aggregate chiller power loads. Given that there were very few events to observe, the regression models could not be trusted to calculate impacts in line with those that could be directly observed in for the events in Figure 7.49. The project could not determine how the utility might eventually deploy this asset, but the project confirmed that this asset can defer about 0.38 MW of load for an hour at a time through its responses.

7.10 1.4 MW WSU Diesel Generator

Avista Utilities worked with WSU to develop and communicate DR signals for the control of a 1.4 MW diesel generator at the Grimes Way steam plant on the Pullman, Washington, university campus. The engineering design of this collaboration was described above in Section 7.8. The control of the diesel generator was Tier 3 of the five sets of control signals that were developed jointly by Avista Utilities, WSU, and Spirae. The agreement between the utility and campus laid out mutually acceptable expenses that would be reimbursed by the utility when the generator became activated by the demand responses.

Each engagement was for a 60-minute period. Successive hourly engagements were permitted, but a 6-hour wait was required after any request if the request were denied or if the engagement of the generator was unsuccessful.

The PNWSGD project worked with Avista Utilities to have the DR requests correspond to the advisory signals of the transactive system. A transactive toolkit function was established to anticipate and automate control of the asset based on the transactive system’s incentive signal. The project encouraged the utility to configure the toolkit function to help it determine useful DR events for the diesel generator.

If the utility could control the diesel generator, its generation might displace energy that would otherwise need to be procured by the utility.

The annualized cost for the control of this asset was included in Table 7.18.

7.10.1 Data Concerning the WSU Diesel Generator

The utility submitted to the project the status of each of the four DR signals by which requests, acknowledgements, and confirmations of demand responses were conveyed. Given that the utility had requested 50 or fewer responses from the asset, the project had expected to observe relatively infrequent active requests. That was not the case. The request signal seemed to be more of a system status signal that remained constant for extended periods.

Based on the condition of the Tier 3 asset active signal, the project inferred that control of the diesel generator might have been modified by the DR system no more than twice. The starting times and durations of these two engagements are listed in Table 7.22.

Table 7.22. Generation Events that were Initiated by the Transactive System for the WSU Diesel Generator

Start Time (yyyy-mm-dd hh:mm)	Day of Week	Duration (h:mm)
2014-06-06 10:00	Friday	1:00
2014-07-16 11:15	Wednesday	1:15

Power generation data from the WSU diesel generator is plotted in Figure 7.50. Data was provided for this generator from May 2013 until September 2014. A nonstandard data practice was employed by Avista Utilities, representing all of what the project presumes to be periods of non-generation as not available ("NA"). The project replaced these missing data intervals with zeros. There is some risk that the times that the generator was idle cannot be clearly distinguished from periods of truly unavailable data.

The two short events of Table 7.22 have been marked in Figure 7.50, but there was no generation during the two events. The project cannot explain the discrepancy or the overall lack of successful DR events. The utility was not terribly surprised by this lack of events. Given its portfolio of available resources, the generator was unlikely to often have been an economical resource during the PNWSGD.

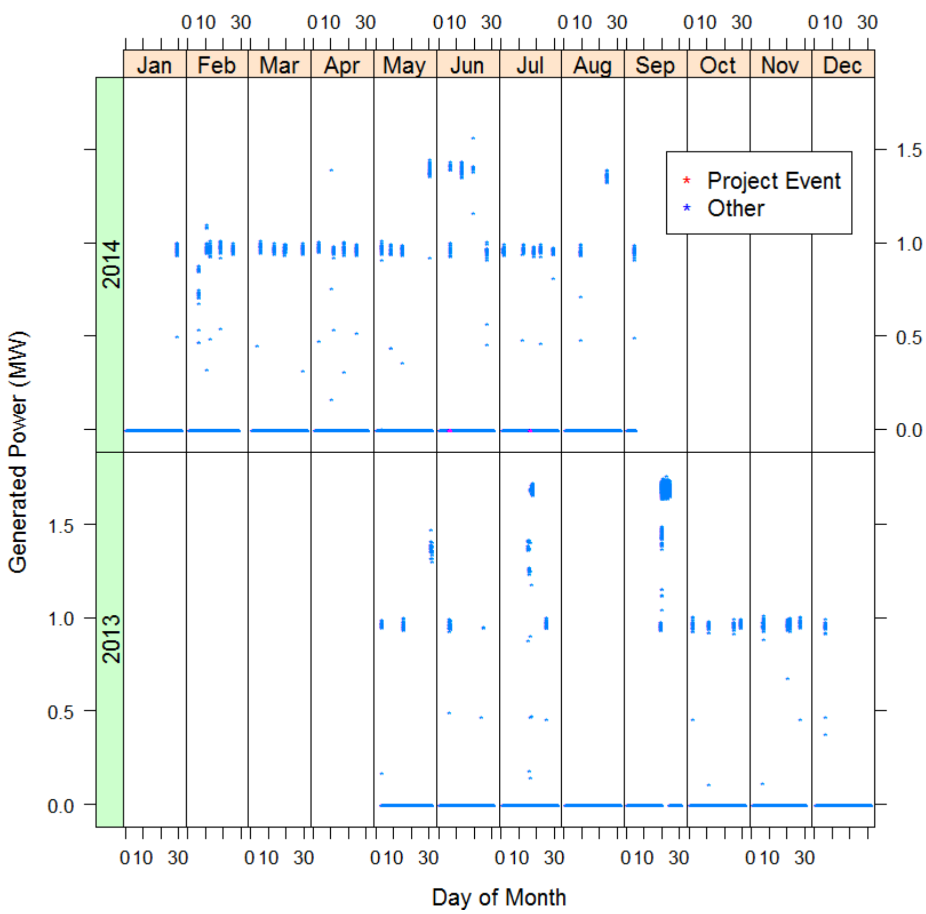


Figure 7.50. Power Generated by the WSU Diesel Generator. Two events were identified, but the generator did not generate during these times.

7.10.2 Analysis of the WSU Diesel Generator Performance

Analysts investigated the distribution of nonzero generated power during the project's 5-minute data intervals. Discrete generation levels were evident in Figure 7.50 and were confirmed in the histogram of Figure 7.51. While the generator had been understood to have 1.4 MW power generation capacity, the generator's power data was as great as 1.76 MW in a 5-minute interval. Four distinct operational power levels are evident, centered at about 1.7, 1.4, and 0.9 MW, with a remaining bin of intervals below 0.8 MW. The vertical red lines in Figure 7.51 separate the four operating modes.

The diesel generator is off, not generating, most of the time, but the overwhelming numbers of intervals having zero power generation were not shown in the distribution of Figure 7.51. The project has assumed that intervals to which "NA" was applied during the data collection period were, in fact, intervals having zero power generation.

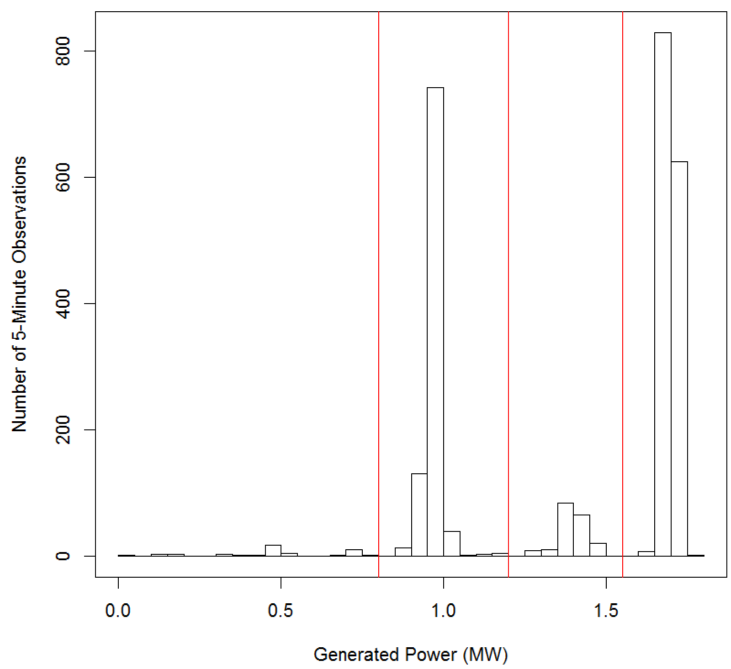


Figure 7.51. Distribution of Nonzero Power Levels that were Generated each Five Minutes by the WSU Diesel Generator. The vertical red lines divide what appear to be four distinct operational modes for this generator.

No significant difference was found between the operation of the diesel generator on weekends and weekdays.

The diesel generator was not energized by the DR signals during the project, but the project reviewed the correlation between generation and the transactive systems' advisory signal for this asset. Figure 7.52 is a side-by-side comparison of the diesel generator's power generation histograms at times that the transactive system had advised no response (i.e., the advisory control signal was zero, left) and had advised increased generation (i.e., the advisory control signal was 127, right). No compelling difference between the histograms is evident.

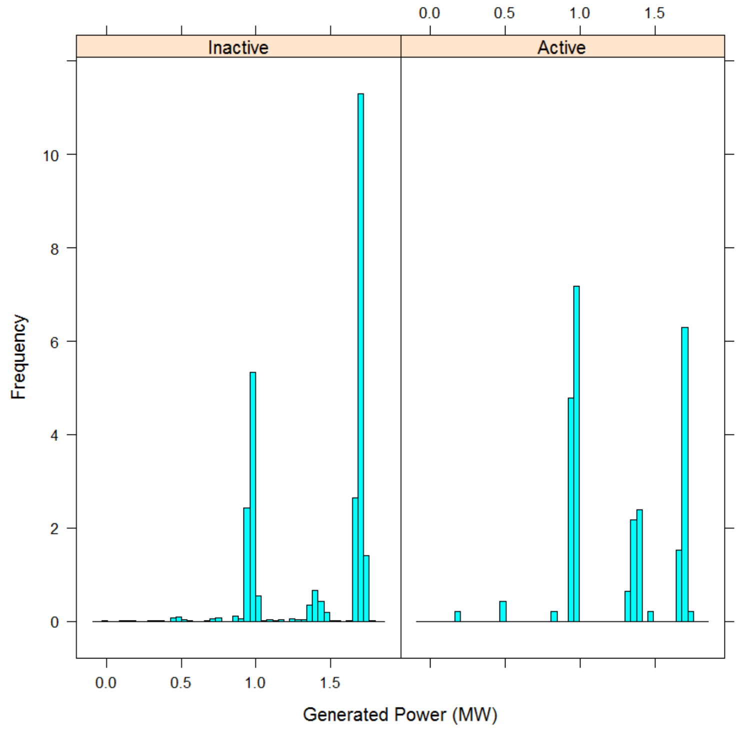


Figure 7.52. Histograms of Nonzero Power Levels Generated by the WSU Diesel Generator when the Transactive System was Actively Requesting Generation (right) and Not (left)

The campus's control strategy is evident from Figure 7.53. This is a contour plot of the average generated power (kW) as a function of month (horizontal axis) and local hour of the day (vertical axis). The hours extend from 0 to 23. The hour 0 is the local hour that begins at midnight, local time. Based on available data, generation peaked in September. Only the September of 2013 is represented in the data. The generator was engaged similarly throughout all hours of the day that month. The generator was used much less other months, but there was some tendency for the campus to engage the diesel generator between 09:00 and 13:00 other months.

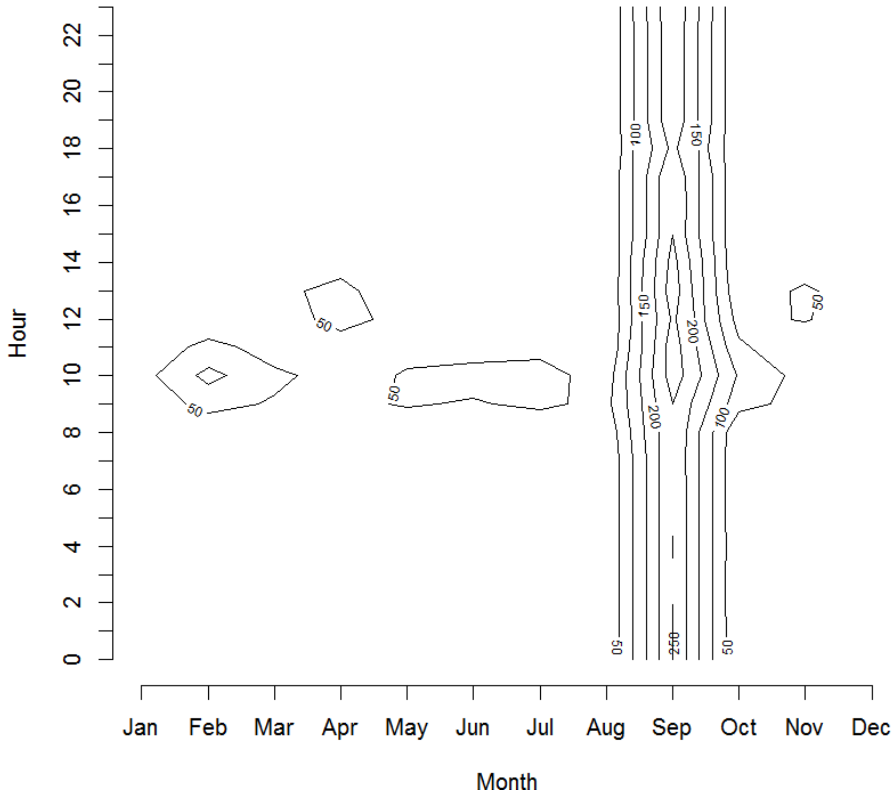


Figure 7.53. Contour Plot of Average Power Generation (kW) of the WSU Diesel Generator as a Function of Calendar Month and Local Hour of Day

In conclusion, the project has little evidence that the WSU diesel generator was ever engaged by the DR mechanisms that were developed jointly by Avista Utilities, the WSU campus, and Spirae. The connection between the asset and the PNWSGD project's transactive system was weak or nonexistent. The project collected operational data concerning the DR system's signals and the generated power for 16 project months, and some operational trends were observed from that data.

If the utility can affect control of the diesel generator, the control of the asset could displace up to 1.75 MW of electrical load, providing that the campus will agree to modify its existing schedules and purposes for dispatching the generator. If 50 hours of operation were successfully procured and timed by the utility, it could displace up to 87.5 MWh of the utility's most expensive energy supply per year. The value is even greater if the generation permits the utility to protect equipment or avoid outages.

7.11 Two 1.1 MW WSU Natural Gas Generators

The project has elected to combine discussion of the performance of the two natural gas generators at the Grimes Way steam plant on the WSU campus. Avista Utilities, WSU, and Spirae designed and implemented a set of DR control signals to request, acknowledge, and confirm generation from these two generators. Details about the DR system are discussed in Section 7.8. The two gas generators were represented by the fourth and fifth of the five asset response tiers of the DR system.

The two gas generators are similar. The DR specification refers to them as generators #2 and #3, but they will be simply described as the first and second WSU natural gas generators in the remainder of this section. The DR agreement stated that responses were to be addressed one hour at a time. Subsequent events were allowed after the successful completion of a prior event, but events were not to be requested within 6 hours after a request was either denied or unsuccessfully initiated.

As was the case for the WSU diesel generator (Section 7.10), the project invited Avista Utilities to make the WSU natural gas generators responsive to the PNWSGD transactive signals. Transactive toolkit functions were established for each of the two generators. The utility was invited to configure the functions so they would automatically advise reasonable events to which the generators could respond.

The annualized costs for the control of this asset were included in Table 7.18.

7.11.1 Data Concerning the Two WSU Natural Gas Generators

The utility submitted all four of the DR system signals with which the demand responses could be requested, acknowledged, and confirmed. As was the case for the WSU diesel generator (Section 7.10), the project had expected relatively few DR requests from the utility to WSU and these assets. Instead, the request signal was mostly static. The full handshake ran to completion only three times for the first WSU natural gas generator, and there were no complete, confirmed DR events for the second. The local starting times, days of week and durations of the three confirmed DR events of the first natural gas generator are listed in Table 7.23.

Table 7.23. Generation Events that were Initiated by the Transactive System for the First WSU Natural Gas Generator

Start Time (yyyy-mm-dd hh:mm)	Day of Week	Duration (h:mm)
2014-01-30 13:40	Thursday	1:00
2014-06-06 10:00	Friday	1:00
2014-07-16 11:15	Wednesday	1:15

Figure 7.54 shows a time series of all power generation data received from Avista Utilities for the first gas generator, and Figure 7.55 is the power generation data for the second. Data was provided for a period from May 2013 to September 2014. The project was supplied “NA” for the data intervals when the generators were idle. This is a poor data practice because it prevents analysts from differentiating periods of no generation from intervals when data was truly unavailable. The generators are believed to have been idle, not generating, most of the time.

Of the three reported events in Figure 7.54, the first gas generator appears to have been generating power during only two of the three events. The generator was likely idle in late January 2014 when the first event occurred. The utility provided some insights why there had been so few events: First, one of the gas generators was out for 3 months due to an emissions problem. The utility was reluctant to use the PNWSGD transactive signal because it was difficult for them to test and validate. They implicitly trusted the AGS signal that they generated themselves. Unfortunately, the AGS was not completed until the month before the PNWSGD ended collecting data. Avista Utilities will always dispatch assets that maintain lowest portfolio cost with best result for customers.

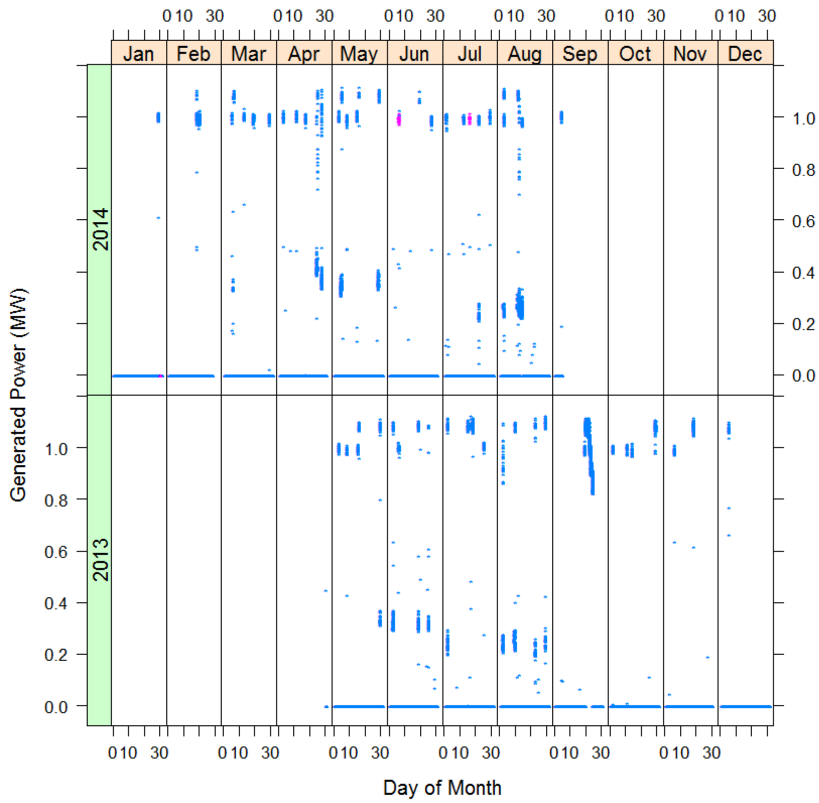


Figure 7.54. Power Generated by the First WSU Natural Gas Generator. Three of the events, marked in red, were reported to have been initiated by the project's transactive system.

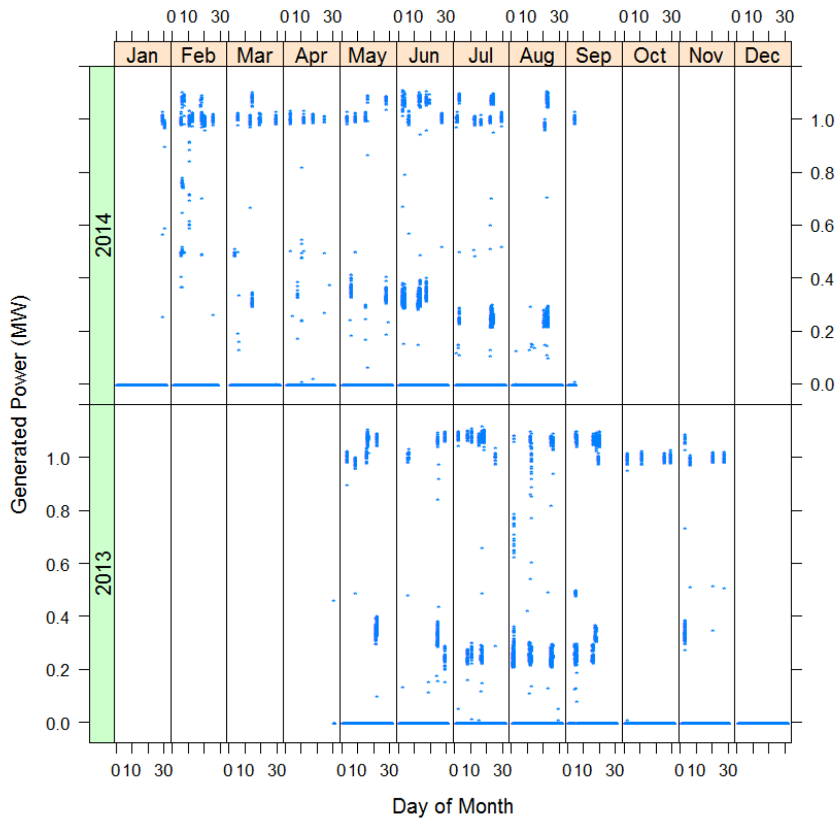
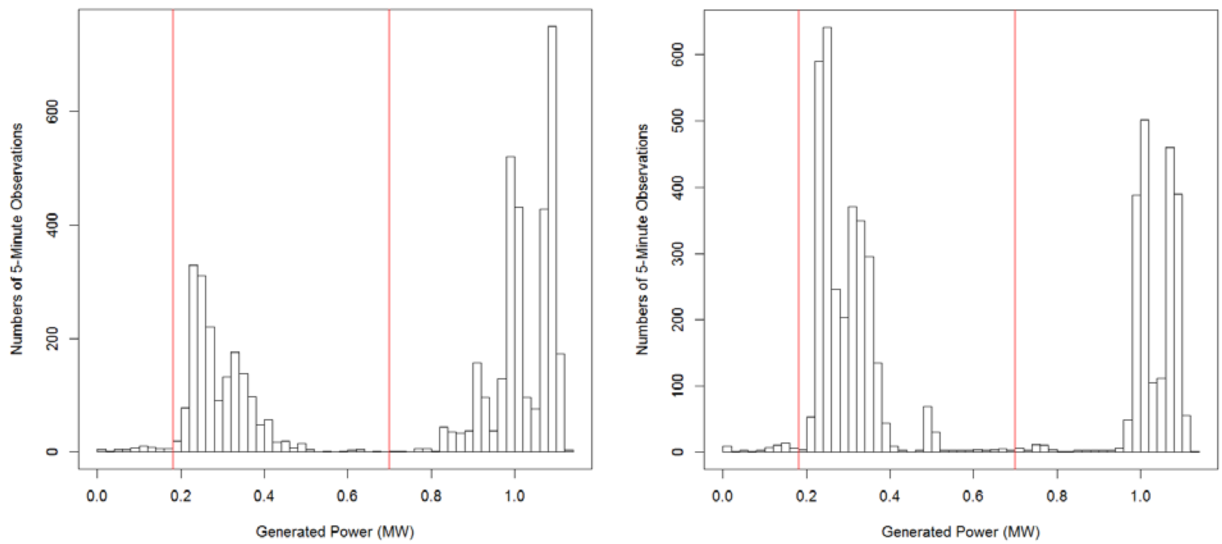


Figure 7.55. Power Generated by the Second WSU Natural Gas Generator. No events were reported to have been initiated by the project's transactive system for this generator.

Transactive event periods were advised by the transactive system for these generators with roughly equal frequency by day of work week. No events were advised during weekends by the transactive system, in accordance with the way the advisory function had been configured. Over 90% of the advised event periods occurred during 2013, and most of the event periods occurred between May and September that year. The periods that transactive responses were being requested did not overlap at all with the three "confirmed" events that were understood to have occurred for the first WSU natural gas generator.

7.11.2 Analysis of the Two WSU Natural Gas Generators

As was the case for the WSU diesel generator (Section 7.10), WSU tended to operate the gas generators at discrete power generation levels. These levels were evident from the time series of Figure 7.55, but they are more evident in the histograms of Figure 7.56. The overwhelming numbers of 5-minute data intervals when the generators were idle have been omitted from Figure 7.56. The remaining intervals reveal that each of the two generators is operated at three power levels—very low and idle, generation between about 0.2 and 0.4 MW, and full power generation of about 1 MW or more. The vertical red lines have been added to the histograms to emphasize the separation of these apparent operational modes.

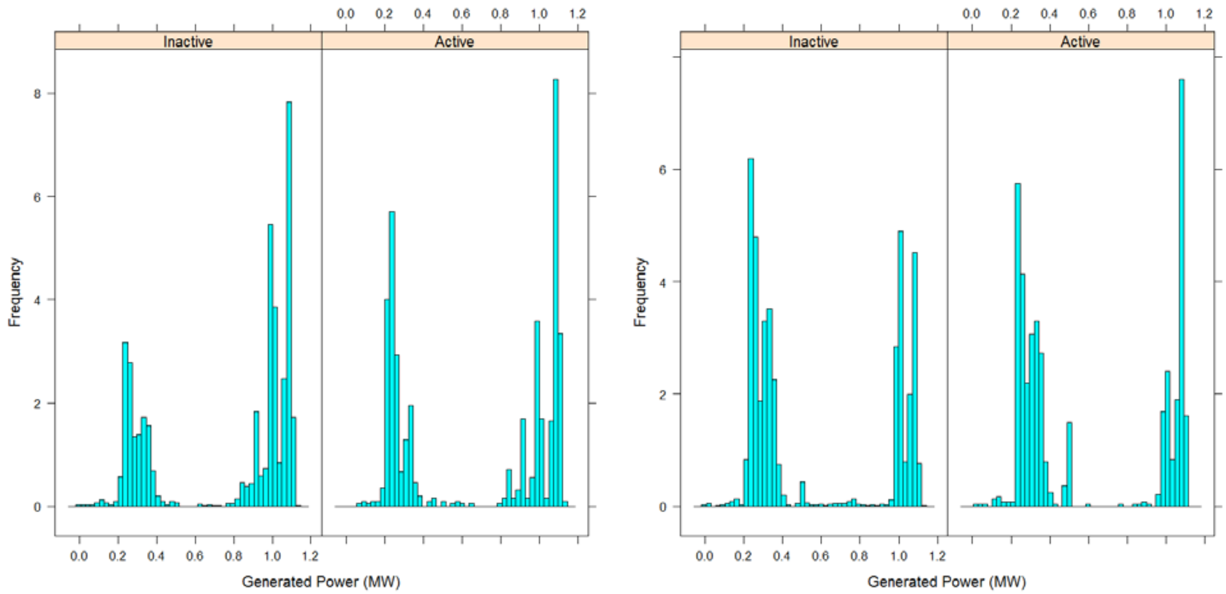


(a) First WSU Natural Gas Generator

(b) Second WSU Natural Gas Generator

Figure 7.56. Distribution of Nonzero Power Levels that were Generated each Five Minutes by the (a) First and (b) Second WSU Natural Gas Generators. The vertical red lines divide what appear to be three distinct operational modes for these generators.

Analysts reviewed the correlation between operation of the WSU natural gas generators and the project's transactive advisory signals that had been generated for these assets. Side-by-side comparisons of histograms are made in Figure 7.57. The first generator is addressed in panel (a) and the second in (b). For each of the two generators, two histograms are shown. The left histogram represents the active power generation at times that the transactive system is advising no response, and the right hand side histograms represent intervals when the transactive system has advised the assets to generate power. The differences between the two paired histograms suggest little or no correlation between the times the generators operated and the advice from the transactive system.



(a) First WSU Natural Gas Generator (b) Second WSU Natural Gas Generator

Figure 7.57. Histograms of Nonzero Powers Generated by the (a) First and (b) Second WSU Gas Generators when the Transactive System was Actively Requesting Generation (right) and Not (left)

The contour plots of Figure 7.58 and Figure 7.59 show that different operational strategies were employed by WSU for the engagement of the two generators. Each shows average power generation by month (horizontal axis) and local hour of the day (vertical axis). The first WSU natural gas generator (Figure 7.58) was apparently left operational for long periods during September 2013. There is almost no difference in the average hourly usage that month. The generation is also engaged during morning and early afternoon hours in early spring months and summer.

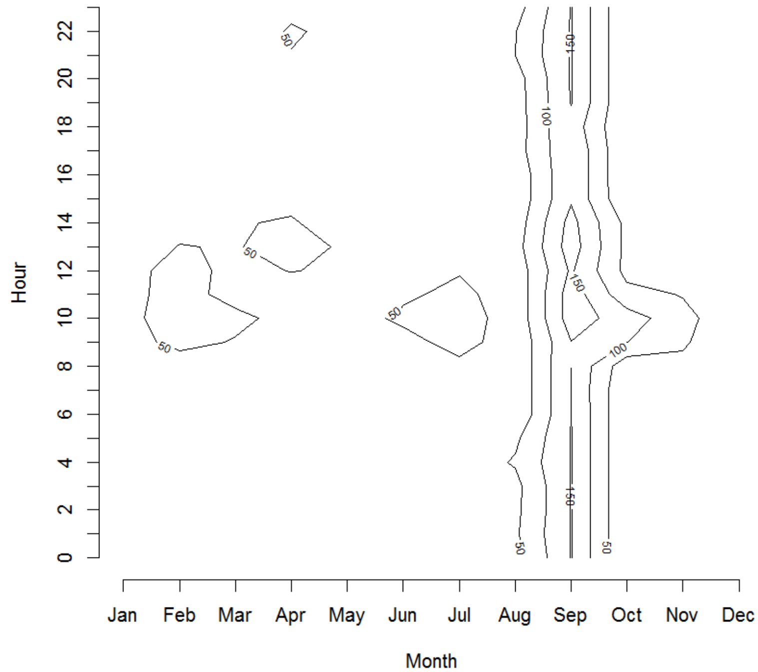


Figure 7.58. Contour Plot of Average Power Generation (kW) of the First WSU Natural Gas Generator as a Function of Calendar Month and Local Hour of Day

Unlike the first WSU natural gas generator, the second (Figure 7.59) was not heavily used in September 2013. It was employed heavily, however, in late winter months of 2014 in the late morning and early afternoon.

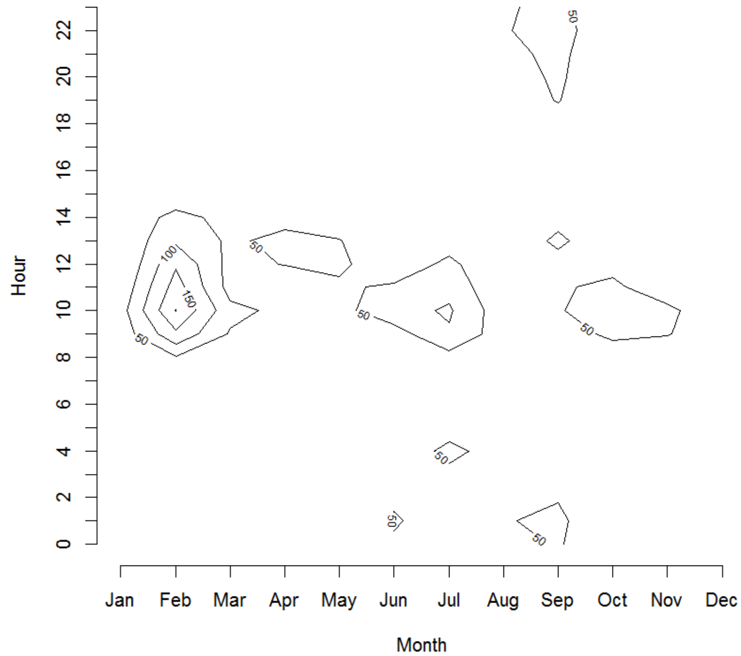


Figure 7.59. Contour Plot of Average Power Generation (kW) of the Second WSU Natural Gas Generator as a Function of Calendar Month and Local Hour of Day

The project's conclusions from this section are very similar to those for the WSU diesel generator (Section 7.10). Based on its data, the project cannot confirm that the natural gas generators were usefully engaged during the project by the DR system that was established by Avista Utilities, WSU, and Spirae. The connection between these generators and the project's transactive system was weak or nonexistent.

The project collected a set of DR system signals and interesting data concerning power generation from the two gas generators. Some existing operational strategies were gleaned from the power generation time series.

If Avista Utilities can modify the operation of these two generators for 50 hours each year, it might displace up to 110 MWh of its most expensive electricity supply each year. This presumes that the university campus has the flexibility to modify the scheduled dispatch of the generators and would accept such DR requests, which was not demonstrated.

7.12 Other Project Activities and Assets

Avista Utilities' participation in the PNWSGD was diverse and extensive. They wish to highlight some additional project activities and project assets that were not already discussed in this chapter.

7.12.1 Distribution Management System

In 1999, Avista initiated a project to complete an accurate field inventory and populate a geographic information system with electric and gas facility models. The inventory process was very thorough and yielded an accurate electric and gas model. This model is referred to as "AFM." Avista also created digital tools for editing and designing against the model as well as the outage management system, which allows distribution dispatch personnel to represent field operation of equipment within the model. Currently, the outage management system does not directly control field devices. This model provides the basis for another key component of the smart grid infrastructure, the DMS.

Avista, as a part of its Smart Grid Investment Grant project, purchased a DMS provided by ACS. The PNWSGD funded implementation of the DMS for Pullman and integration with other back-end systems such AFM, Spirae black box, AMI and DR virtual power plant. The funding for each project, the Smart Grid Investment Grant and PNWSGD, is separated by contract and by product(s). Only software license costs were borne by the PNWSGD project in the form of a purchase agreement and a software license agreement. Software license costs are for products that provide the required functionality as an out-of-the-box solution for the PNWSGD. The PNWSGD project requires a higher level of capability and substantial integration that was not yet available from vendors in final product form. Therefore, PNWSGD functionality was provided contractually via a professional services agreement. The PNWSGD project covered these additional costs, which include integration with the virtual power plant system, the AMI system, smart transformers, smart faulted circuit indicators, and the transactive signal.

The DMS communicates and controls smart devices without human intervention. Dynamic transactive system commands and configuration control for system optimization originated with the DMS either directly or as a result of a request from the Spirae black box and data from the meter data management system that is a part of the AMI.

7.12.2 Fiber Backhaul Communications

Field and customer devices communicated locally via the site's 802.11 wireless network. The 802.11 network, in turn, reached Avista's Spokane headquarters by traversing a fiber backhaul network. That backhaul network path was already complete to the Shawnee substation, which is within seven miles of Pullman as measured by the transmission corridor. Avista partnered with the Port of Whitman to jointly fund the Shawnee-to-Pullman segment parallel to railroad rights-of-way, the total distance of which was up to 15 miles. The project was scoped for as many as four access points along this corridor, possibly located at the three substations—Pullman, South Pullman, and Terre View—as well as at the utility's Pullman service center. Up to 25 additional miles of fiber were required to connect these additional backhaul sites. Routing occurred on existing transmission structures, distribution structures or WSU conduits.

The fiber communication backhaul was a critical component required to provide measurement and status data for the DMS, the AMI back-end systems, and the DR system, and direct communication to customer displays and devices. Communication is a very important enabling technology for smart devices, and it is probably the most critical set of smart grid enabling assets. The fiber backhaul communications network provides for minimal latency and maximum reliability, security, and bandwidth for future growth such as security and mobile workforce applications.

The utility subcontracted with the Port of Whitman for siting, trenching and deployment of the fiber. Avista personnel designed and terminated the fiber.

7.12.3 802.11 a/b/g Wireless Communications

Avista procured and installed an 802.11 a/b/g wireless network provided by Tropos. The wireless network provided coverage for all field assets and AMI meters connected to the feeders sourced out of the Pullman, South Pullman, and Terre View substations.

The 802.11 wireless type is used heavily by business and consumers and is considered a mature technology. Approximately 90 wireless access points were installed on utility poles, some of which were colocated with field devices. All smart switches, fault circuit indicators, smart transformers, and capacitor bank controls communicate via this wireless network with the DMS and /or RTUs at Avista central headquarters in Spokane, Washington.

The Itron AMI meters used a bridge device to transition from the 900 MHz Open Way radio frequency to the 802.11 wireless network.

7.12.4 Avista-WSU Curriculum Project

It is critical to Avista Utilities that there are talented, educated engineers and technicians available to hire. Avista worked closely with WSU to modernize power electrical engineering laboratory courses in Pullman during the five-year program. These improvements were thoroughly described in an unpublished report from the university to the utility.[1] The highlights of the report discuss new laboratory classes “Renewable Energy” (EE492) and “Power System Protection” (EE494). Additionally, a new professional science master’s degree program is offered, and online teaching classroom capabilities have been improved.

7.13 Conclusions and Lessons Learned

Avista greatly modernized the Pullman site distribution system and considers its participation in the PNWSGD to have been very successful. During the project, the utility implemented IVVC on many of the 13 feeders. The project was able to confirm that these efforts would indeed conserve about 2% of the electrical load in Pullman. Power factors were significantly improved on at least 9 of the 13 feeders. Avista values this conservation at over $0.5 million per year, based solely on the value of avoided energy purchases. The utility initially encountered delays as it calibrated the system’s sources of end-of-line voltages, but they were eventually able to measure customer voltage within the 0.5% accuracy that was needed by the voltage optimization system.

A couple of miles of reconductoring was necessary to reduce system losses and maintain the flexibility needed for optimal circuit topology. The utility estimated that 29.6 MWh will be conserved each year due to the improved conductors.

[1] A Bose, CC Liu, R Olsen, V Venkatasubramanian, A Srivastava, A Mehrizi, B Carper, R Zamora, J Opheim, and J Yates. 2014. “Final Report: Avista-WSU Curriculum Project.” Washington State University, Pullman, Washington, September 25, 2014 (Unpublished).

The utility replaced its oldest, least efficient distribution transformers with about 400 smart transformers. Regrettably, the transformers were not monitored in a way that would have permitted the project to confirm such energy savings from improved energy efficiency. The smart transformers provided new voltage and status metering points. The newly available information now facilitates transformer health assessment, finding of energy loss and theft, and operation of the distribution system closer to acceptable voltage limits.

About 70 smart, communicating ecobee thermostats were supplied to a group of Pullman residential customers. Recruitment of these participants was challenging. The project was able to tentatively confirm a very, very small conservation during the project's transactive events. Questions remain about when and whether these events were, in fact, communicated to the thermostats and Avista conducted additional DR events that were unknown to the project. Regardless, the utility learned much about recruitment and customer acceptance of this type of program. Those customers who had received thermostats were generally satisfied with their program experiences.

Avista investigated how its customers would use energy web portals and whether they would conserve energy given transparent information about their own energy consumption habits. Small, but statistically insignificant, energy conservation was found for customers who were provided access to a customized energy web portal. This finding was consistent with that in the contracted Freeman, Sullivan, and Co. report. Regardless, by Avista Utilities' assessment, the modern features of AMI were attributed by them with saving $235 thousand per year in Pullman through a combination of remote meter reading, improved customer services, and reduced service site visits. By the utility's estimation, 2,714 truck rolls per year are being avoided with the AMI's ability to confirm power status and remotely open and close accounts.

The utility installed an FDIR system to more quickly respond to outages and reduce the duration of outages that its customers experience. The project observed that these improvements were not evident in the reliability metrics SAIFI, SAIDI, or CAIDI. The utility's conclusion may be more optimistic based on automated reports of avoided customer outages from its upgraded DMS. By the utility's estimation, the FDIR system reduces 12,000 to 16,000 customer outage hours per year, valued at $10 per customer outage hour. The more efficient identification of and response to outages also reduces vehicle miles and emissions.

The utility worked closely with WSU to make a set of campus loads responsive to DR requests from the utility. The assets included reduction of building air circulation fan load, reduction of cooling-loop pump load, and control of three onsite diesel and gas generators. The project confirmed that about 240 kW was conserved by the curtailments of air circulation fans, and about 380 kW was conserved through control of the chiller loops. The project was able to find no evidence that the times that the generators were operated had been influenced by project signals, but if Avista can procure control of these assets, it might procure up to 3.7 MW of distributed generation.

Overall, the utility estimated that its activities under the PNWSGD project reduced greenhouse gas emissions by 2,367 tons of CO_2.

While Avista Utilities encountered immaturity among the smart grid assets that it deployed during the PNWSGD, these challenges were mostly overcome, and the Pullman, Washington, distribution system has been significantly modernized by its participation in the PNWSGD project.

8.0 Benton PUD Site Tests

Additional chapter coauthors: K Subbarao – Battelle; B Scherer − Benton PUD

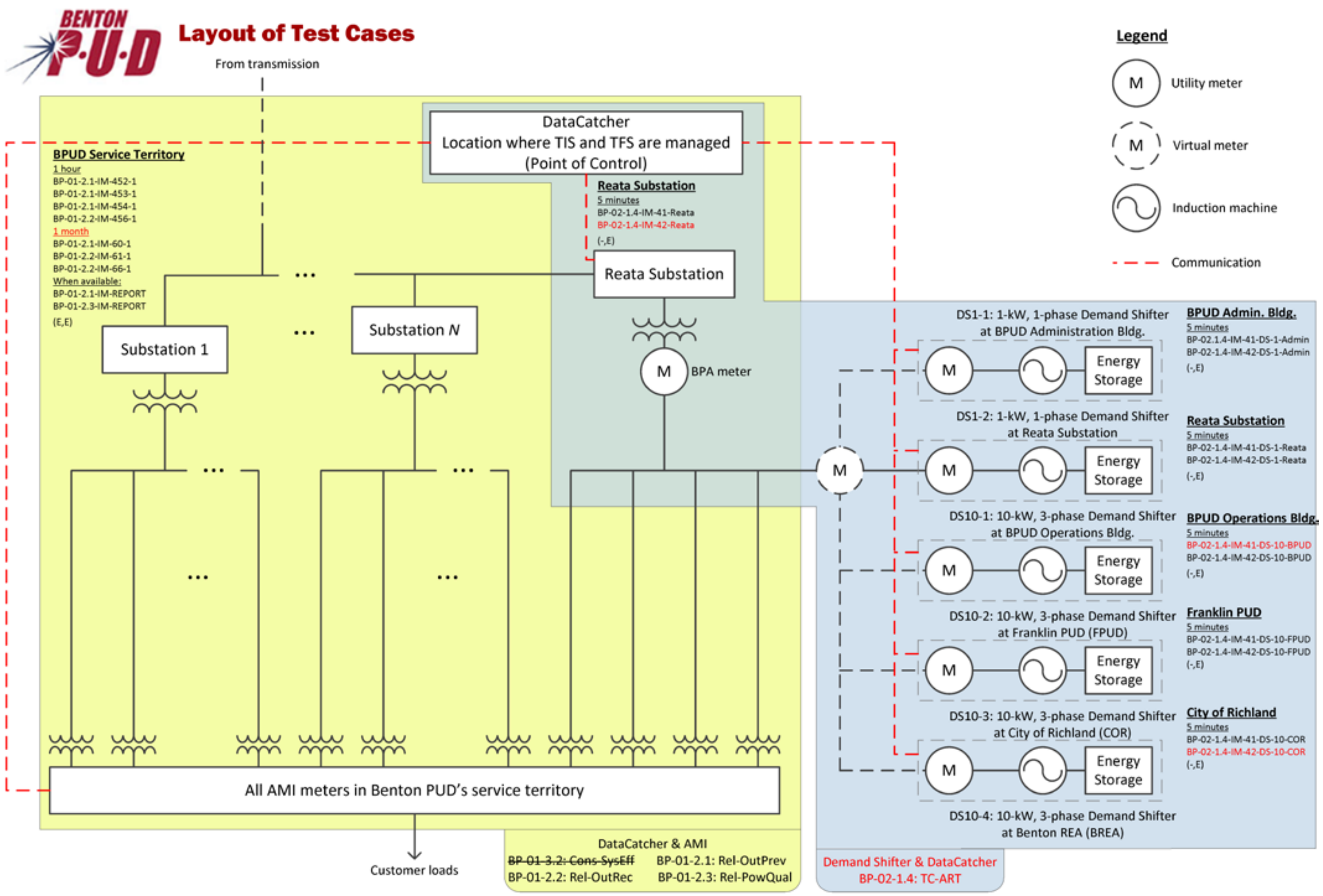
Benton PUD is a public utility district (PUD) that serves almost 50 thousand customers. It serves 939 square miles, including Kennewick, Washington, and has summer and winter peak loads of about 400 MW (Benton PUD 2014). Benton PUD had already installed smart meters at most of its customer locations by the beginning of the Pacific Northwest Smart Grid Demonstration (PNWSGD) project and completed the installations by 2012. The utility was eager to demonstrate the capabilities and benefits of the approximately 48,000 advanced customer meters.

The utility initially defined two demonstration components within the project:

- DataCatcher™ and advanced metering infrastructure (AMI) advance meter capabilities. These track data collected in Benton PUD's "5-bit" program, where the 5 bits represent five power-quality alerts that are communicated back to the utility. The alerts include low voltage, high voltage, hot socket, and outage, (and could include tamper). Information from the installed meters might reduce response time by the PUD to outages.
- Demand Shifter™ and DataCatcher energy storage. Two 1 kW and three 10 kW battery energy storage units were installed by the PUD and by its neighboring utilities. These units were to be responsive to the project's transactive control system.

These two asset systems are shown overlaid on the Benton PUD distribution circuits in Figure 8.1. The investigation of the alerts that are made available from advanced metering (DataCatcher and AMI) covers the entire Benton PUD service territory. The investigation of the energy storage response to transactive control was to be evaluated in reference to a transactive feedback signal representing the load served from the utility's Reata substation.

The layout diagram references several of the shorthand names applied to data series (or "data streams") that were to be collected from the utility by the project. The U.S. DOE sponsor of the PNWSGD had requested that the project measure impact metrics ("IM"), which list was the basis of the shorthand naming practices that were employed by the project. A compressed list of the Benton PUD data is shown in Table 8.1. The table includes the negotiated data intervals at which the data series were collected and a description of each data series. Within the data stream names, asterisks ("*") represent wildcards, where additional text or numbers were appended to specify multiple instantiations of the data series.



	AMI 5 Bits				
Test Case	Low Voltage	High Voltage	Hot Socket	Outage	~~Tamper~~
~~BP-01-3.2~~					X
BP-01-2.1	X	X	X		
BP-01-2.2				X	
BP-01-2.3	X	X			

Figure 8.1. Benton PUD Layout Diagram

Table 8.1. Names Used for the Data Series that were Submitted to the PNWSGD Project by Benton PUD. Some of these names are referenced in the Benton PUD layout diagram.

Data Stream	Data Interval	Description
BP-02-1.4-IM-41-Reata	5 min.	Real Power at Reata substation
BP-02-1.4-IM-41-DS-1-*	5 min.	Real Power at a 1 kW Demand Shifter
BP-02-1.4-IM-41-DS-10-*	5 min.	Real Power at a 10 kW Demand Shifter
BP-02-1.4-IM-42-Reata	5 min.	Reactive Power at the Reata Substation
BP-02-1.4-IM-42-DS-10-*	5 min.	Reactive Power at a 10 kW Demand Shifter
BP-01-2.1-IM-60-1	1 year	SAIFI
BP-01-2.2-IM-61-1	1 year	SAIDI
BP-01-2.2-IM-66-1	1 year	CAIDI
BP-01-2.1-IM-452-1	1 hour	Number of abnormal meter temperature occurrences
BP-01-2.1-IM-453-1	1 hour	Number of abnormally low meter voltage occurrences
BP-01-2.1-IM-454-1	1 hour	Number of abnormally high meter voltage occurrences
BP-01-2.2-IM-456-1	1 hour	Number of outage report occurrences

CAIDI = Customer Average Interruption Duration Index
SAIDI = System Average Interruption Duration Index
SAIFI = System Average Interruption Frequency Index

8.1 DataCatcher and AMI

Benton PUD contracted Resource Associates International, Inc., (RAI) to install its DataCatcher software product integrated with the utility's system of advanced premises meters. This software acquires meter event data from Benton PUD's existing set of Sensus Flexnet™ two-way wireless AMI meters (Sensus 2015). This asset system focused on five indicators that are available from the existing AMI customer meters, which Benton PUD refers to collectively as its "5-bit system:"

- abnormal-temperature alarm (hot socket)
- outage alarm (loss of voltage)
- high-voltage alarm
- low-voltage alarm
- tamper alarm.

Benton PUD intended to use these indicators toward reaching three closely related reliability objectives:

- Use reports of high temperature and low or high voltage from AMI meters to anticipate and prevent customer outages.
- Use the AMI outage indicator to more rapidly detect and restore customer outages.
- Use reports of low and high voltages to correct voltages and reduce cases where customers are supplied their electricity outside accepted voltage ranges.

The tamper alarm is useful to Benton PUD, but it was not employed for the objectives to be tested.

Table 8.2 estimates the annualized costs of the system and its components. The costs of the system's components were to be shared equally between the utility's two asset systems. The systems' component costs were for software system integration and for the DataCatcher software product from RAI. The total annualized cost of the system was estimated to be $30.6 thousand per year.

Table 8.2. Estimated Annualized Costs of the DataCatcher System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Software System Integration	50	38.2	19.1
DataCatcher	50	23.0	11.5
Total Annualized Asset Cost			**$30.6K**

8.1.1 Analysis of Reliability Indices for This Asset System

This asset system was applied to the entire distribution utility circuit. Only indices aggregated for whole years and for the entire distribution system were available, and these values are summarized in Table 8.3.

Table 8.3. Yearly Reliability Indices over a Five-Year Period

	2010	2011	2012	2013	2014[(a)]
SAIFI (outages per customer per year)	0.35	0.33	0.60	0.36	0.26
SAIDI (outage minutes per customer per year)	40.4	42.3	74.9	53.4	28.7
CAIDI (minutes per outage)	116.1	126.5	124.6	147.5	108.9

(a) All months of calendar year 2014 are included in the calculated indices even though the project's formal data collection period ended September 1, 2014.

While 2014 yielded the best system reliability numbers in recent years, the project cannot conclude from this limited data that system reliability has improved with the new information that is available from advanced metering and the coordination of this information with other utility systems. If improvements in system reliability had been evident, they might have been attributable to improvement in standard utility operations and practices.

The following charts summarize the counts of the alerts that were made available from the utility's metering upon the meter detecting high temperature, low voltage, high voltage, or an outage. Benton PUD worked with the project to assemble numbers of each type of alert per hour. The project stored these data in its database as counts per interval, which means that 5-minute data intervals within an hour are each allocated one-twelfth of the count. While this seems awkward at first, it facilities combination of time series that have different base-interval durations, and it allows summing of counts over increasingly long data intervals.

The project's ability to analyze the five years of data (2010–2014) and draw conclusions is limited due to configuration changes that occurred during the project. From 2010 to 2012, the AMI system configuration was consistent, but in 2013 the AMI communications network was reconfigured to utilize a priority channel for all AMI meter alerts, significantly increasing the count of meter alerts by improving the reliable transmission of the messages. Prior to this change, events were likely occurring; however the alert messages were not being reliably delivered. In addition, the configuration changes in 2013 resulted in the DataCatcher collecting duplicate messages for high- and low-voltage alerts for several months before the issue was recognized and corrected. For these reasons, the data from 2013 is invalid for analysis and trending of voltage alerts.

8.1.2 Abnormal-Temperature Alerts Reported by Advanced Meters

Figure 8.2 shows the count of abnormal-temperature alerts collected by Benton PUD from all its meters each project month. These alerts were infrequent. No alerts were received during many of the months. The most alerts, 23, occurred during July 2014, which had several weeks of extreme heat that contributed to counts higher than normal. The utility says these were false alerts caused by the ambient conditions rather than by electrical issues.

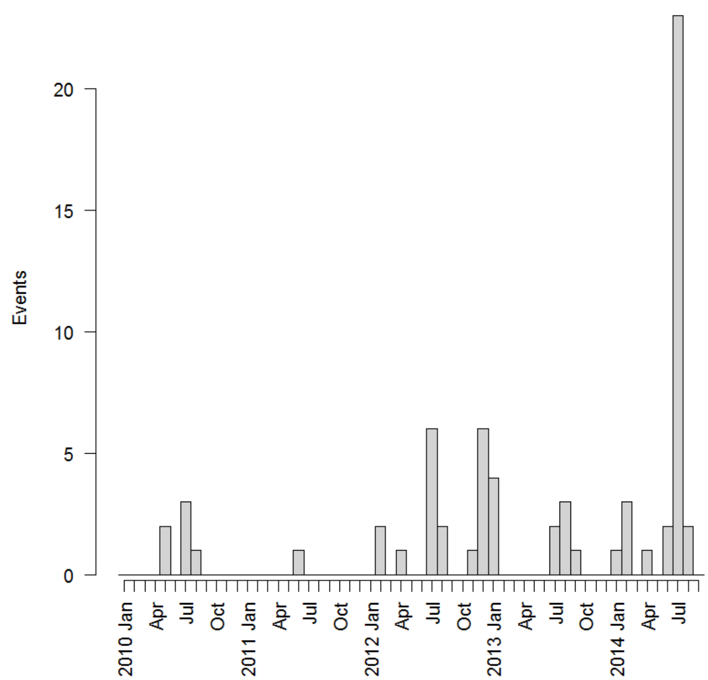
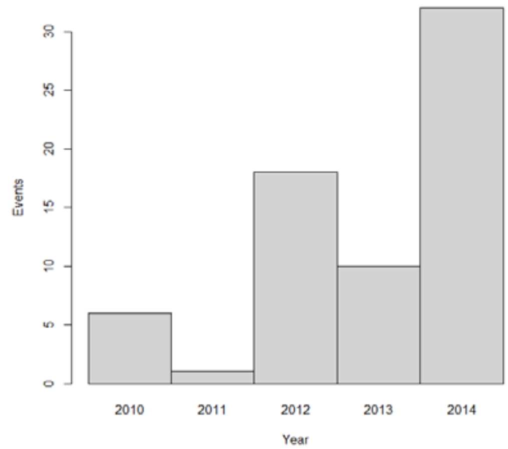


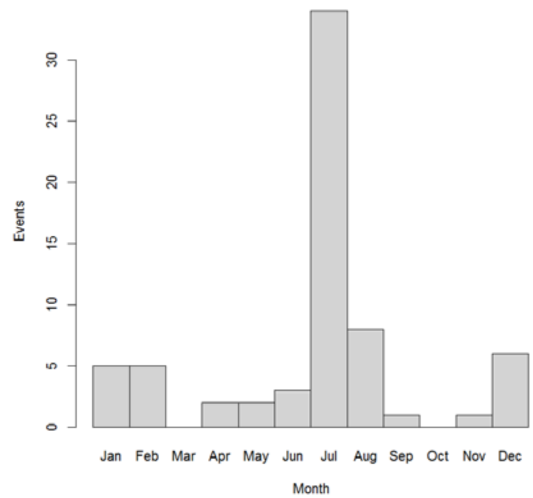
Figure 8.2. Counts of Meters Reporting Abnormal Temperature each Month

Next, analysts looked at the distributions of these alerts across several additional dimensions to see whether interesting trends might be observed. Figure 8.3 presents the same alerts in Figure 8.2, but they are here grouped according to the year, month, day of week, or local hour in which they occurred. Most of the counts had been shown in Figure 8.2 to have occurred during July 2014. That month of 2014 also caused July to be the calendar month on which most alarms were received, as shown in Figure 8.3b.

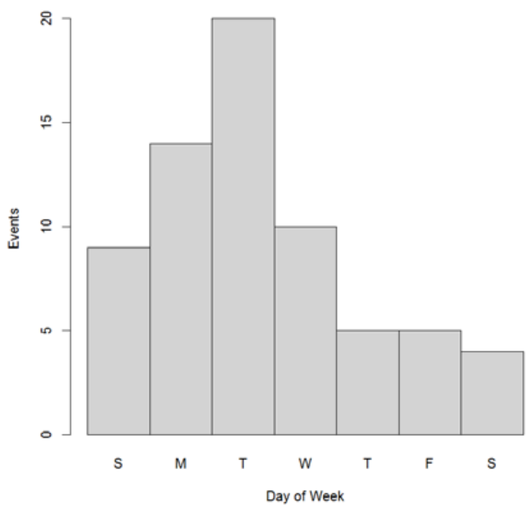
Surprisingly, more events happen in the first half of the work week than in the latter half, as shown in Figure 8.3c. The project has no strong hypothesis why this was the case. Tuesday was the day of week on which most abnormal-temperature alerts occurred. Based on Figure 8.3d, the alerts are more likely to occur in late afternoon. The value 0 on the horizontal axis represents the hour beginning at midnight local Pacific Time. Fourteen events were tabulated during each of the consecutive hours 16:00 and 17:00, local Pacific Time.



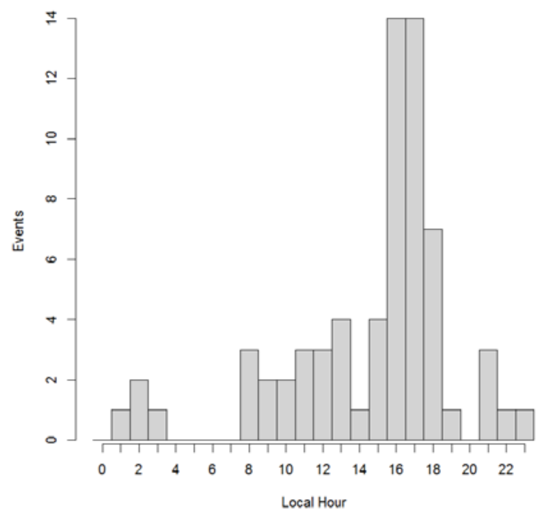
(a) By Year[1]



(b) By Month



(c) By Day of Week



(d)

By Local Hour

Figure 8.3. Distributions of Abnormal-Temperature Events by (a) Calendar Year, (b) Calendar Month, (c) Day of Week, and (d) Local Hour

[1] Data for year 2014 includes January–August 2014, inclusive.

8.1.3 Low-Voltage Alerts Reported by Advanced Meters

The project next looked at the low-voltage alert. This alert should be generated by any meter that encounters a voltage lower than the accepted supply range. These alerts were summed each project month in Figure 8.4. These alerts are apparently common. The vertical axis was changed to report thousands of occurrences, in this case. The top of this bar was cropped in the figure so that variations for the other months might be better seen.

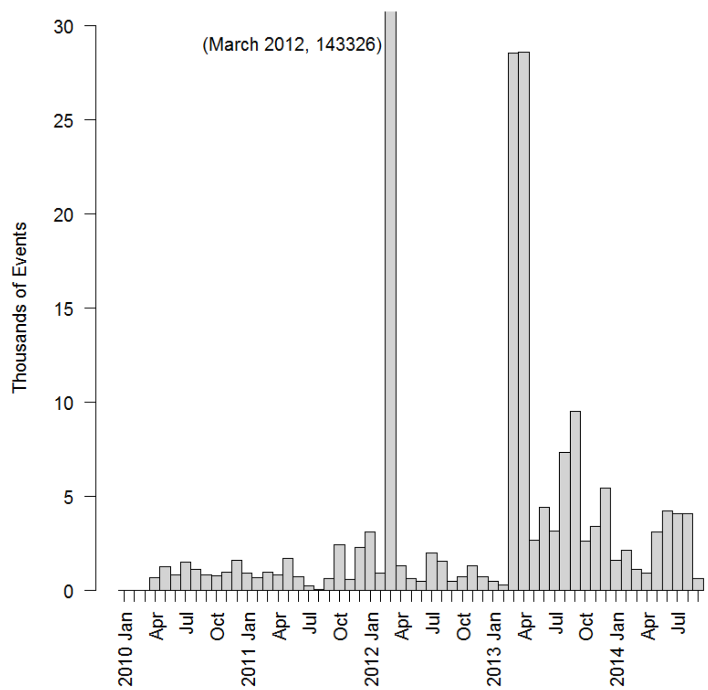
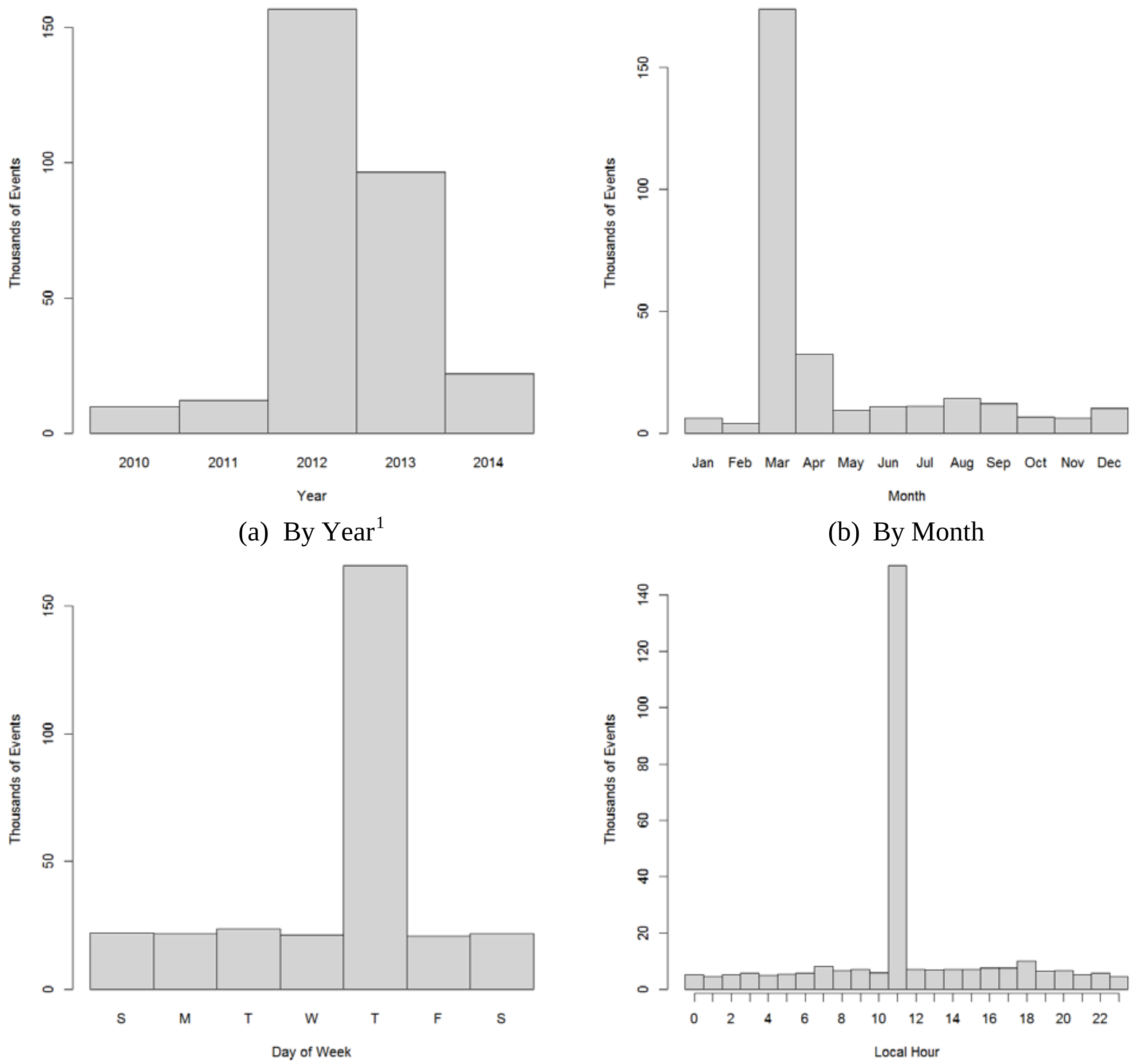


Figure 8.4. Counts of Meters Reporting Abnormally Low Voltage Each Month. The top of this figure has been cropped due to the outlier month March 2012, when 143,326 abnormal low-voltage occurrences were reported.

As reported in the introduction to this section, the low-voltage counts for 2013 are not valid for analysis due to an issue with duplicate alert messages being received during a portion of the year. The 2014 counts are valid, but they are expected to be higher than the counts for 2010 to 2012.

The very large number of alerts from March 2012 was also found to greatly influence the four distributions in Figure 8.5. The year 2012 and the month of March exhibited the greatest numbers of these occurrences. Upon further investigation, a single event on March 15, 2012, was found to have occurred during hour 11:00, and that day was a Thursday. These are precisely the hour and day of week when, overall, the most of these low-voltage alerts were found to have occurred. It was discovered that these alerts were all generated by a group of nine meters that were erroneously repeating their alarm messages and flooding the system with invalid alerts.



(a) By Year[1]

(b) By Month

(c) By Day of Week

(d) By Local Hour

Figure 8.5. Distribution of Low-Voltage Events by (a) Calendar Year, (b) Calendar Month, (c) Day of Week, and (d) Local Hour

[1] [1] Data for year 2014 includes January–August 2014, inclusive.

8.1.1 High-Voltage Alerts Reported by Advanced Meters

Figure 8.6 shows the counts of high-voltage alerts received from advanced metering each project month from 2010 through the end of August 2014 when the project's formal data collection period ended. As reported in the introduction to this section, the high voltage counts for 2013 are not valid for analysis due to an issue with duplicate alert messages being received during a portion of the year. The 2014 counts are valid, but they are expected to be higher than the 2010 to 2012 counts.

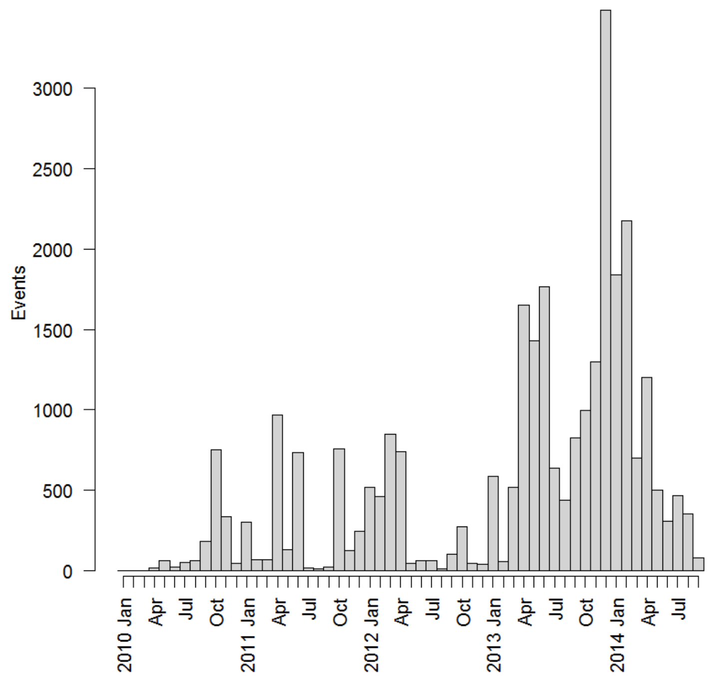
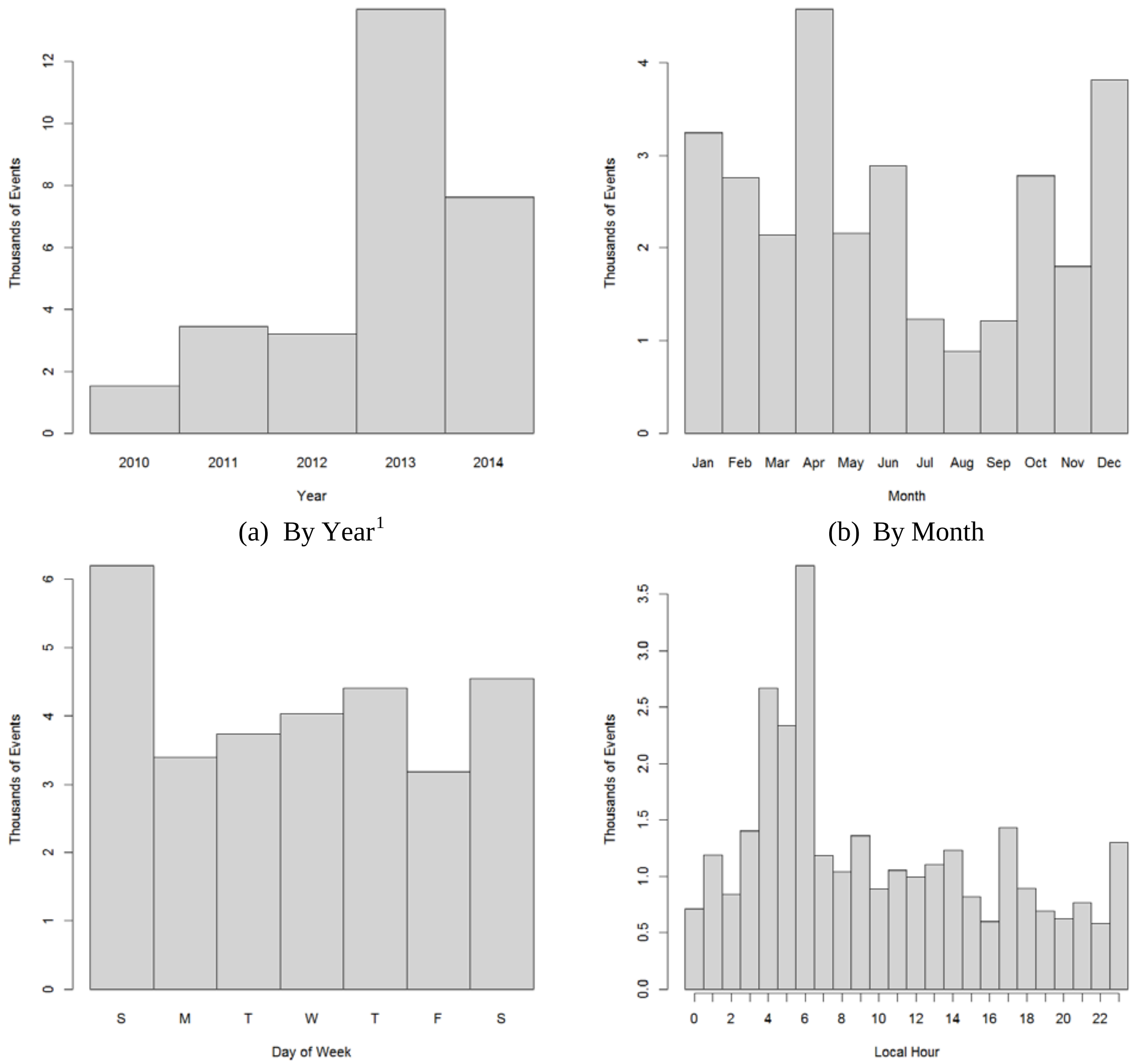


Figure 8.6. Counts of Meters Reporting Abnormally High Voltage Each Month

Figure 8.7 shows distributions of these same high-voltage alerts by the calendar year, calendar month, day of week, and local hour, Pacific Time. According to panel (a), the high-voltage alerts peaked in 2013. Based on panel (b), high-voltage alerts are at their minimum during summer months. This might indicate a relationship between these occurrences and the utility's yearly voltage management practices. High-voltage alerts are most prevalent on Sundays according to Figure 8.7c, but the occurrences are otherwise evenly distributed among the days of the week. Figure 8.7d suggests that high-voltage events occur most often from 04:00–06:00 in the morning, perhaps related to management of voltage in preparation for peak load hours.



(a) By Year[1]

(b) By Month

(c) By Day of Week

(d) By Local Hour

Figure 8.7. Distribution of High-Voltage Events by (a) Calendar Year, (b) Calendar Month, (c) Day of Week, and (d) Local Hour

8.1.1 Outage Alerts Reported by Advanced Meters

Figure 8.8 shows the counts of outages that are reported by advanced premises meters each month from 2010 through August 2014.

[1] The year 2014 included data from January through August 2014.

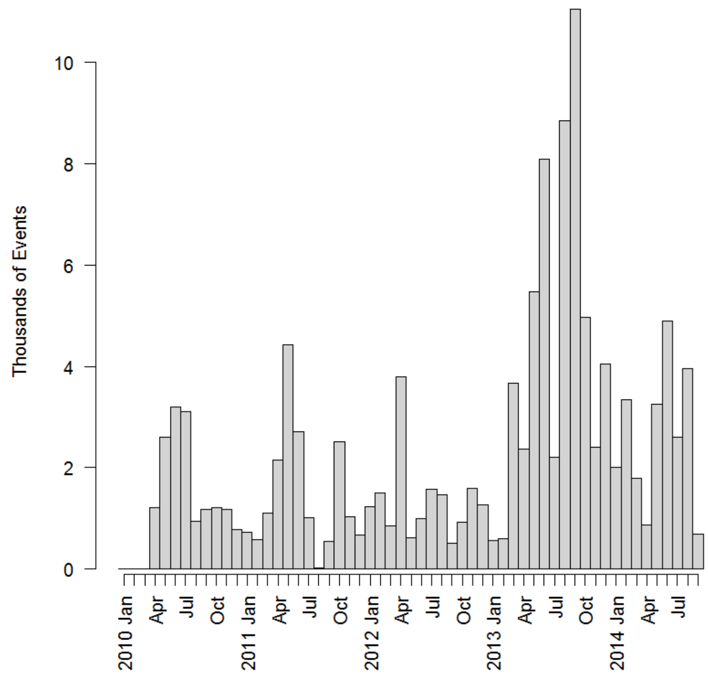


Figure 8.8. Counts of Meters Reporting Power Outages each Month

As reported in the introduction to this section, the counts for 2013 and 2014 are greater than those for the previous years (2010–2012), as expected, due to the configuration changes. An unexpected result of reviewing the data is a realization that the magnitudes of the counts are far greater than expected and are not valid. It appears that the test case's data stream delivered more alerts to Battelle than expected. For example, Benton PUD's own DataCatcher database analysis indicates that the most alarms occurred in 2013, which is in agreement with the project's data analysis; however, Benton PUD's total outage alert count for 2013 is only 13,759, while the project's count for the same year is more than 50,000.

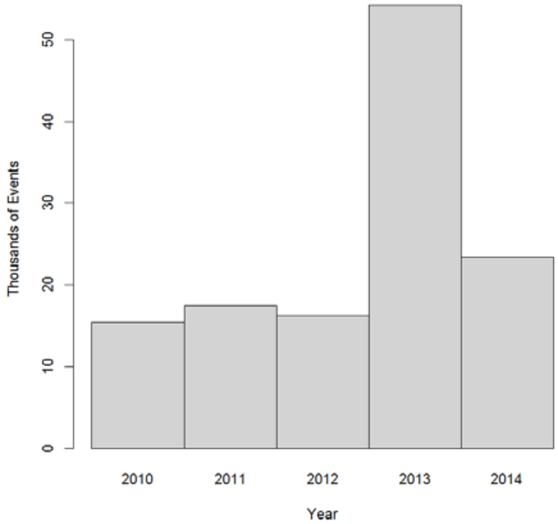
One possible explanation for the project receiving too many outage alerts is that the data stream was not properly configured to filter out duplicate messages. It is common during an AMI meter outage event for the meter to send up to five or six "last gasp" outage alerts to increase the probability that at least one message will be reliably transmitted back to the head-end system. The AMI communications network uses four base station transceivers located on nearby mountain tops that listen for these "last gasp" outage alerts. To further ensure reliable transmission of messages to the head-end system, the outage alerts may also be repeated from multiple base stations back to the head-end system. The DataCatcher integration to the AMI head-end system was designed with logic to filter out the repeat outage alerts and to only store a single outage event. It is possible that this filtering logic was not being applied within the coding that generated the outage alert data stream being sent to Battelle.

Although the AMI meters and the communications system are designed to repeat the outage alerts to improve the reliability of successfully transmitting the message back to the head-end database, the system is still not expected to always receive outage alerts from 100% of the affected meters. For an outage involving only a few meters, it would not be uncommon to receive 100%, but as the meter count increases the percentage decreases. For example, in a typical outage involving several hundred customers, it may drop to around 80%, and for a few thousand customers it may drop to around 50%. The DataCatcher's outage alert data, when properly filtered for repeat alarms, provides an approximation of the number of customers who experienced outages over a given time period, but the total count will always be lower than the number of customers who actually experienced an outage.

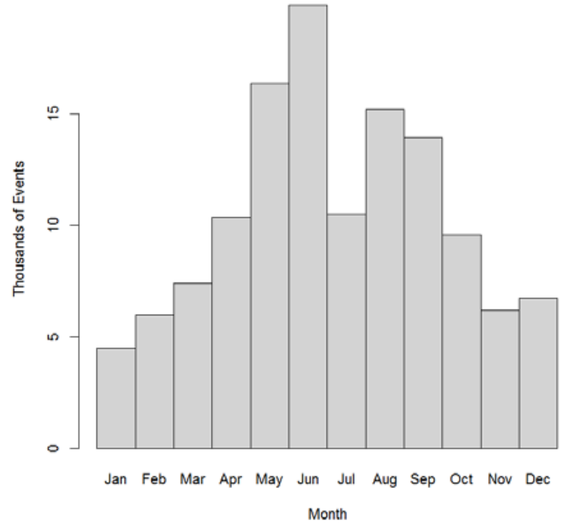
It is expected that outage alert counts should correlate with SAIFI if the alerts are being received with relatively high reliability and if they are being properly filtered to exclude duplicates. Prior to 2013, the outage alerts were not being reliably transmitted and there were repeat alarms. Therefore, correlation with SAIFI is not valid before 2013. Data for 2013 and 2014 should better correlate with SAIFI because the configuration improvements should result in a higher percentage of outage alerts being received. However, the data still contains duplicate alerts and cannot be compared to the previous years (2010–2012) because of the configuration change.

The distributions of these outage alerts according to the calendar year, calendar month, day of week, and local Pacific Time hour on which the alerts occurred are shown in Figure 8.9. Based on Figure 8.9b, the occurrences of outage alerts roughly correspond to outdoor temperature. The greatest numbers of outages were reported in June, and the fewest in January. Outage alerts were fairly evenly distributed across all days of the week, according to panel (c). Perhaps there is a tendency for outages to have occurred midweek, since the days with the greatest number of alerts were Tuesdays, Wednesdays, and Thursdays. Because of the unknown distribution of duplicate alerts, it is difficult to draw any firm conclusions.

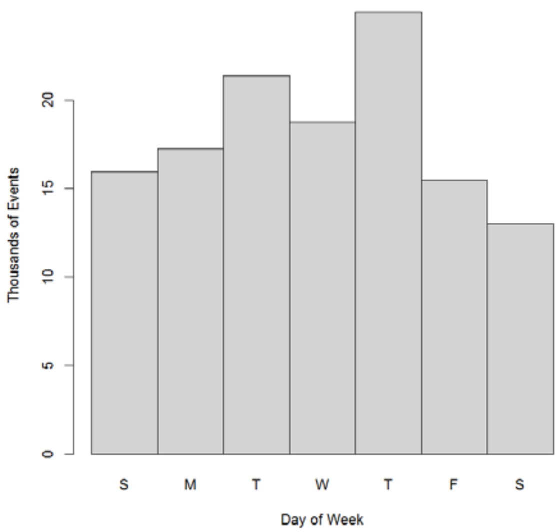
According to Figure 8.9d, most outages are reported by advanced metering during daylight hours.



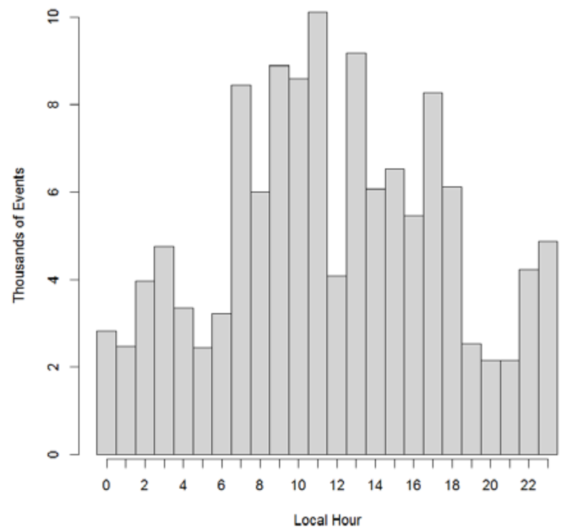
(a) By Year[1]



(b) By Month



(c) By Day of Week



(d) By Local Hour

Figure 8.9. Distribution of Outage Events by (a) Calendar Year, (b) Calendar Month, (c) Day of Week, and (d) Local Hour

8.2 Demand Shifter and DataCatcher

Benton PUD, collaborating with neighboring utilities Franklin PUD and the City of Richland, Washington, installed five battery energy storage units: three had ratings of 10 kW, 40 kWh and two had ratings of 1 kW, 5 kWh. The 10 kW energy storage units were made by Demand Energy Networks (Demand Energy Networks, Inc. 2014) who called the systems Demand Shifters. The 1 kW energy storage units were prototypes developed by RAI, which were integrated with their DataCatcher software

[1] The year 2014 included data from January through August 2014.

application for monitoring and control. RAI and Demand Energy Networks worked together to enable the 10 kW units to also be managed by the DataCatcher. Benton PUD wished to demonstrate that these units could charge when the nearby Nine Canyon Wind farm was producing wind energy, and then discharge this energy during the PUD's peak demand periods. Wind energy would then be better used and the utility's demand curve would also be flatter.

Of these five battery storage systems, the two smaller 1 kW systems were not reliable enough to keep working, and since they were prototypes, they were not worth any continued efforts to keep them running. Data from these two smaller units faltered and stopped during the project's data collection period. The capabilities of these small 1 kW units could not be confirmed by the project.

Benton PUD installed one 10 kW storage module at its headquarters in Kennewick, Washington, and it coordinated with two neighboring utilities to install and monitor two more 10 kW units at these neighbors' sites. The three 10 kW units were installed and unit tested, but they never truly became responsive to the project's transactive control system. First, the site's transactive node never achieved full function, and the energy storage devices never became automatically controlled by the transactive system. Benton PUD opted to code its own implementation for the transactive system, an effort that proved more challenging than had been anticipated by them. While the Benton PUD transactive site eventually achieved the ability to exchange conformant signals with the larger transactive system, its participation faltered in 2013. The site never again communicated with the transactive system. Demand Energy Networks, Inc. stopped supporting these energy storage products around October of 2013. The energy storage products could not be operated without web-based software operated by this vendor.

Table 8.4 estimates the annualized costs of the energy storage system and its components.

Table 8.4. Estimated Annualized Costs of Demand Shifter System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Demand Shifter	100	46.5	46.5
Transactive Control	100	26.3	26.3
Substation BPA Meter Interface	50	0.4	0.2
Total Annualized Asset Cost			**$84.5K**

BPA = Bonneville Power Administration

8.2.1 Data from the Energy Storage Modules

The project received no useful data concerning status of any of the five battery energy storage modules. Therefore, little can be said about the intentions of the utilities as they operated these devices. No connection was completed between the devices and the project's transactive system. While Benton PUD had once indicated that they would coordinate the charging and discharging of the storage modules with utility-owned wind generation resources, the project believes this connection was not automated or completed.

The project did, however, receive data concerning the power exchanged by the modules. Figure 8.10 shows the power exchanged between the three 10 kW modules and their distribution systems. Positive power represents charging of the modules, and negative power represents their discharge. Data was collected from most of the three modules from late March 2012 into October 2013. Even though the modules were rated for 10 kW, they typically operated at only about 1 kW or less, per the data received. This discrepancy is likely related to a problem with the data's' units not having been reported correctly. The charging rate appears to have been controlled, creating a continuum of power charging rates. Discharge power was more constant at a few discrete discharge power magnitudes.

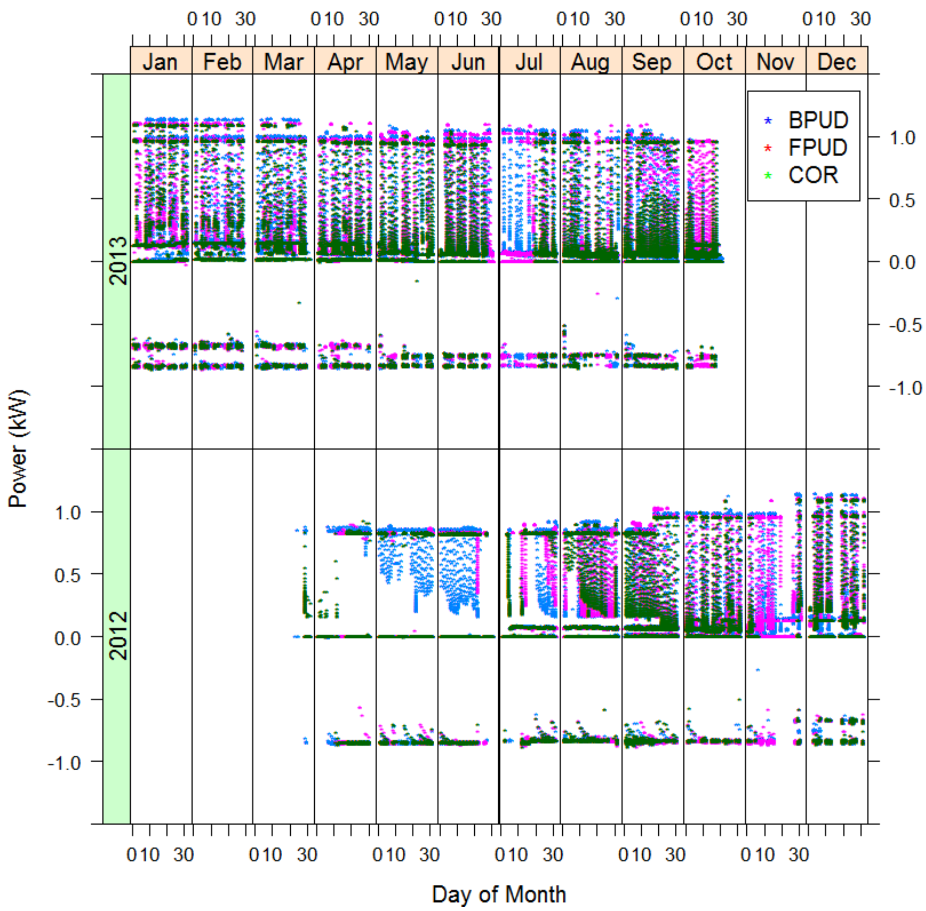


Figure 8.10. Power Data Received from Benton PUD Concerning the Performance of Three 10 kW Energy Storage Modules

Power data was also available from the two 1 kW modules, and is shown in Figure 8.11. This data is believed to be the sum power exchange from the two 1 kW modules. The data period was from late March 2012 to early November 2013. There were month-long periods within this range for which data was not available. Data was delivered sporadically until the end of August 2014 when the project's formal data collection period ended, but most of this data was either zero or entirely missing.

Although these two units were rated at 1 kW, they never charged or discharged at more than one tenth of that rating (~100 W), per the data received. This discrepancy it likely related to a problem with the data's units not having been reported correctly. The utility had stated that positive power values represent charging of the batteries, but that will be called into question in the next section.

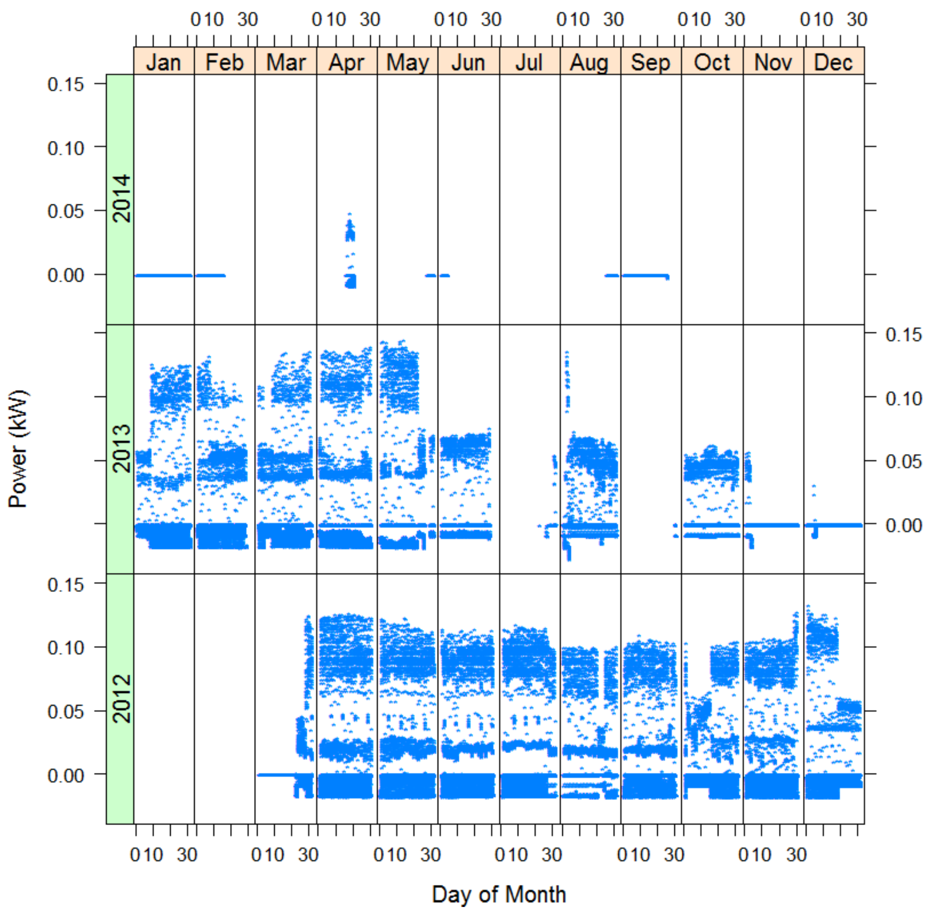


Figure 8.11. Power Data Received from Benton PUD Concerning the Sum Power Conversion at Two 1 kW Energy Storage Modules

8.2.2 Performance of the Energy Storage Modules

The project analyzed patterns in the operation of the battery storage modules. Figure 8.12 shows the power of the 10 kW modules as a function of time of day. The value 0.0 on the horizontal axis represents midnight local Pacific Time. While there is some variability in the results, the modules' recharging typically began abruptly late in the evening and continued into the morning. The charging rate declined as the batteries were recharged overnight. The batteries were typically discharged around hours 06:00 and 07:00 local Pacific Time.

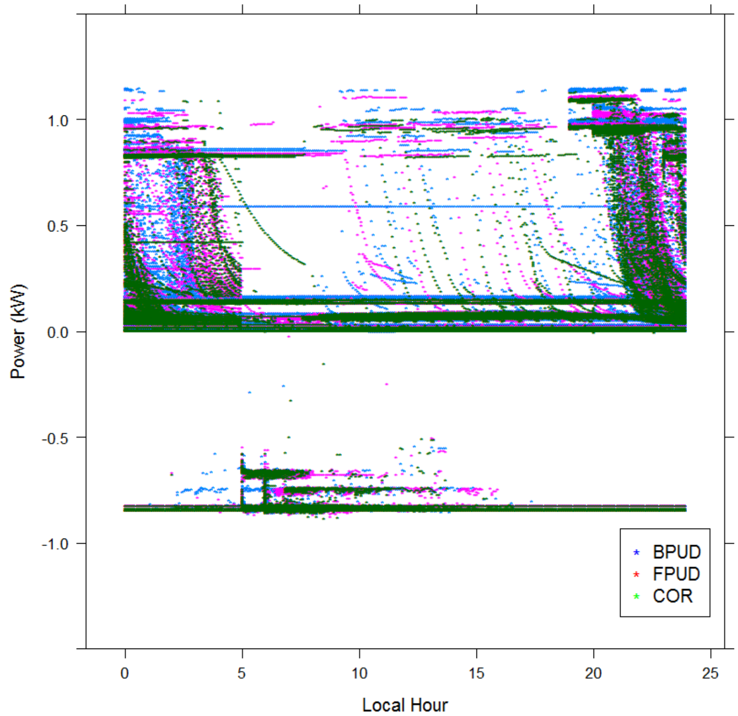


Figure 8.12. Power Generation of the Three 10 kW Energy Storage Modules versus Local Pacific Time. Positive power indicates charging of the batteries.

The hourly charge and discharge patterns are perhaps more easily seen in Figure 8.13, which shows the median power and quartiles of operation of the Benton PUD 10 kW battery energy storage module during the project versus the local Pacific Time hour. In these quartile plots, the two boxes above and below the median and the extended bars above and below those boxes represent approximately one fourth of the data points. Some outliers are shown, as well above and below the extended bars. The systems were often discharged during the hours starting 06:00 and 07:00. The plots for the remaining two 10 kW units were similar but are not shown.

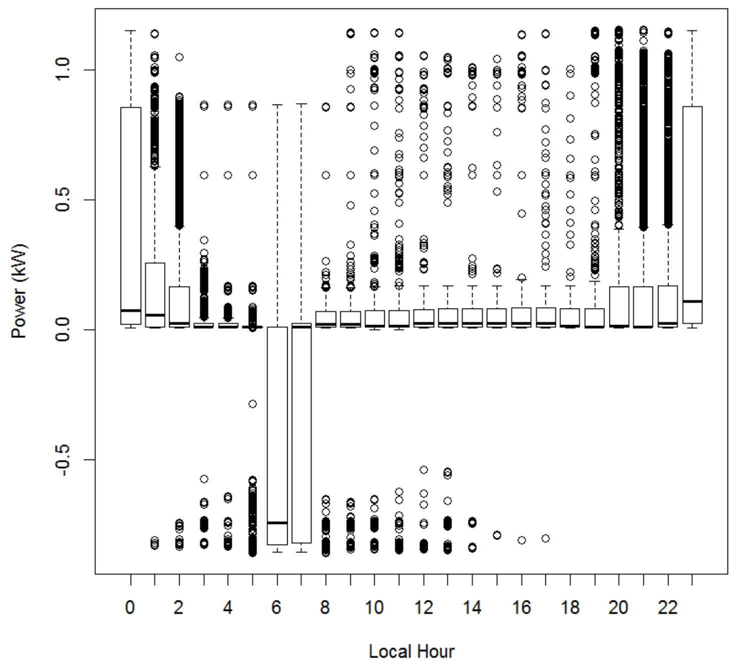


Figure 8.13. Quartile Plot of the Charging (Positive) and Discharging (Negative) of the Benton PUD 10 kW Battery Energy Storage Module throughout the Project

The power of the smaller, 1 kW battery energy storage modules is plotted against time of day in Figure 8.14. According to this data, the modules sometimes charged during blocks of time in midmorning or late afternoon. The modules discharge in the late evenings and into the mornings. This pattern of usage does not seem sensible. The project must hypothesize that either the interpretation of the signs of the power has been misstated, or there exists a time shift in the data that was submitted to the project concerning the power of these 1 kW units.

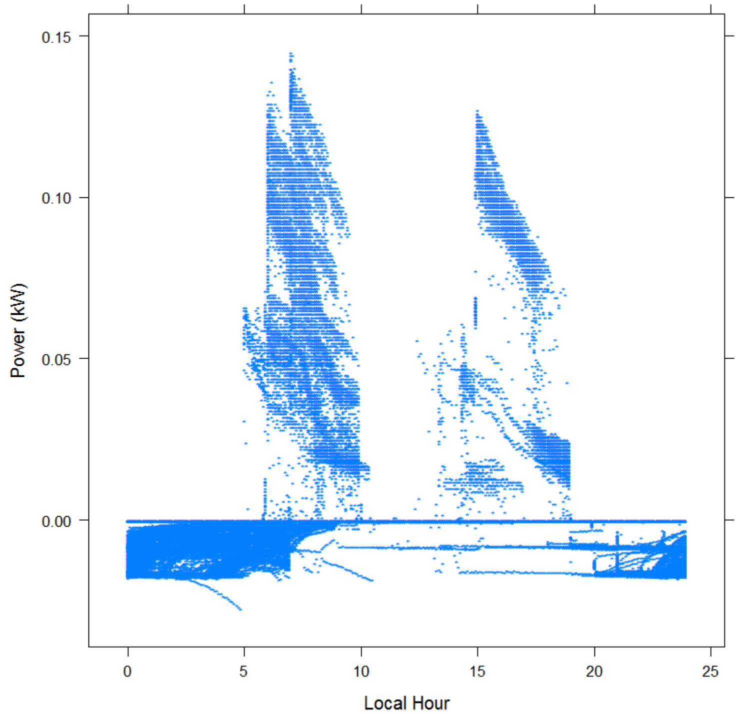


Figure 8.14. Sum Power Generation of Two 1 kW Energy Storage Modules versus Local Pacific Time. Benton PUD responded that positive power indicated charging the batteries, but that might be incorrect for these 1 kW modules.

Given that the project's understanding of the control of these devices was limited and the devices became obsolete early in the project, the project conducted no further analysis on the performance of these battery energy storage modules.

8.2.3 Conclusions and Lessons Learned

Benton PUD worked with the PNWSGD project to demonstrate two smart grid technologies—power-quality alerts that were being generated by a system of advanced premises meters, and small commercial- and residential-scale battery energy storage.

The utility was able to demonstrate the usage of alerts from its advanced premises metering—its 5-bit project—and was able to collect interesting operational data, including counts from four of the five alert types. Over the life of the project and still ongoing today, the DataCatcher has been a valuable tool being utilized by Engineering and Operations for visibility into real-time system operations and after-the-fact analysis. The standard reliability indices appeared to remain similar throughout the project term. The patterns in the meters' alerts were discussed in this chapter, but no significant improvements in these metrics can be attributed to the project at this time.

Benton PUD's efforts to install and demonstrate a reserve of battery energy storage referenced to the load profile from its Reata substation were partially successful. The modules were installed at the Benton PUD's and two neighboring utilities' facilities. The smaller, 1 kW storage devices were never very productive, but some data was received from the larger, 10 kW modules before the modules' vendor experienced financial difficulties and stopped supporting the devices in 2013.

The utility's attempts to create its own software instantiation and site within the project's transactive system were unsuccessful. While the first system conformance tests were eventually passed early in the project, the utility's vendors were not able to pass later, more complex conformance tests as the transactive system matured.

Benton PUD submitted the following "lessons learned" based on their experiences with the PNWSGD project and the implementations of the two asset systems:[1]

- The discipline of configuration control and change management principles must be applied to AMI meters and communications systems prior to trying to evaluate meter alarms.
- Participation in the PNWSGD project improved Benton PUD's awareness within and between its Engineering and Information Technology staff regarding cyber security best practices.
- As the PNWSGD was a demonstration sponsored by the federal government, project reporting and project management requirements required much more work and were more challenging than had been expected.
- Distributed energy storage technologies are not yet mature, and, as Benton PUD experienced, there is an increased risk that its vendors will go out of business during a project.
- Benton PUD's efforts to develop and implement its own transactive control interface became too complex. The setup of transactive systems will have to become less complex if small utilities like Benton PUD are to participate without being fully dependent on consultants and vendors.[2]
- As a project with a significant research and development component, the PNWSGD project initially required flexibility in its scope of work. As the project tasks and expectations became better defined, Benton PUD should have established payment milestones for its contractor. As it was, contractors struggled with the complexity of the project, which depleted project budget and resulted in several deliverables not being completed.
- Technology continued to evolve over the life of the PNWSGD project. Now, vendors offer software modules and interfaces for handling advanced meter alerts that will take the place of Benton PUD's custom solution that it and its vendors developed during the project. The utility developed several of its functional requirements for implementing this new technology during the course of the PNWSGD project.

[1] The lessons discussed in these paragraphs have been paraphrased from the unpublished presentation "Benton PUD - Lessons Learned Template.docx" that was last modified by Blake Scherer, Benton PUD, for the PNWSGD project on October 13, 2014.
[2] This bullet refers to the fact that Benton PUD did not accept the reference software implementations that had been developed by IBM and offered by the project. Instead, the utility's vendor attempted to develop its own instantiation based solely on the systems' design specifications.

9.0 City of Ellensburg Site Tests

Additional chapter coauthors:
S Rowbotham − City of Ellensburg; S Elbert − Battelle Memorial Institute

The City of Ellensburg, Washington, is an historic municipality that serves about 10,000 electric and 5,500 gas customers. Starting in 2006, the city launched the first community solar project in the United States. Through their participation in the Pacific Northwest Smart Grid Demonstration (PNWSGD) Project, the city added renewable generation capacity of 153 kW to the existing renewable energy park, including both renewable solar and wind generation. The solar generators are shown installed at the renewable energy park in Figure 9.1 from high above the park. The array on the left is polycrystalline panels, and the array on the right is the thin-film panels.

Figure 9.1. Polycrystalline (left) and Thin-Film (right) Solar Panel Arrays at the City of Ellensburg Renewable Energy Park, Ellensburg, Washington[1]

The site's wind generators are shown in Figure 9.2. From left to right, the nine wind generators are the Ventera Wind, Urban Green Energy, Tangarie, Bergey, Windspire, Honeywell WindTronics, Wing Power, Energy Ball, and Southwest Windpower Skystream wind turbines.

[1] Courtesy City of Ellensburg, e-mail from S Rowbotham to DJ Hammerstrom, January 12, 2015.

Figure 9.2. Wind Generators at the City of Ellensburg Renewable Energy Park, Ellensburg, Washington (City of Ellensburg 2013a)

The community renewable energy park consolidates citizens' efforts to test and use more renewable resources. Residents may buy into the projects without having to construct and operate the generators themselves. The residents can take advantage of economies of scale by building larger and more cost-effective generators than they might construct on their own properties. Furthermore, the city believes that the centralized park generation resources are safer and are more safely managed than would be the case with many, more distributed renewable generators located randomly throughout the city. The city and its residents may learn about and compare the renewable generator technologies that will inform their future energy decisions (City of Ellensburg 2013a). As shown in Figure 9.3, the park is close to and highly visible from Interstate Highway 90. The site is at a multipurpose community park that is publicly accessible. The diagram in Figure 9.3 labels the four installation phases for the arrays of solar panels and indicates the approximate locations of the solar arrays and nine wind turbines. The weather metrology tower was installed just beyond the upper right corner of this diagram. Public walkways lie to the north of and among the wind generator sites and lead to more park land on the other side of the highway.

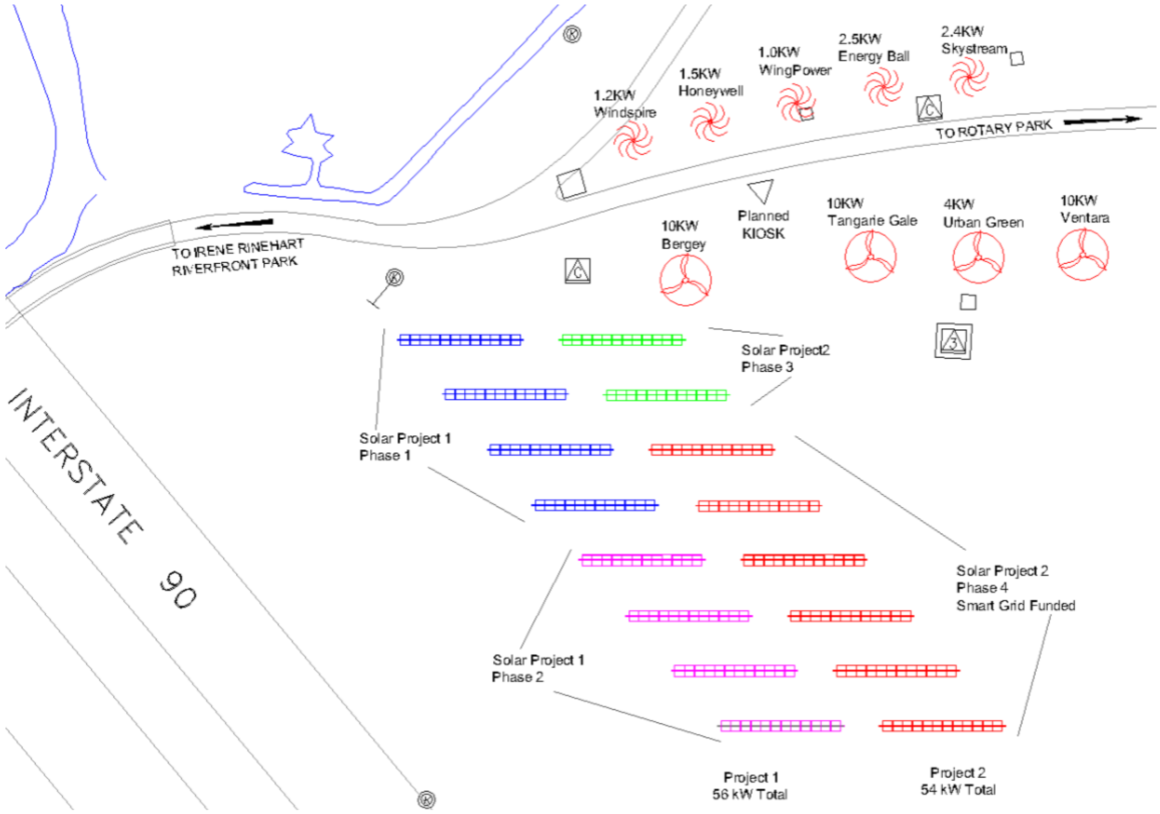


Figure 9.3. Layout of Renewable Generation at the Ellensburg Renewable Energy Park (City of Ellensburg 2013b)

The city had intended to make the data created by the project at the renewable park available to its residents, to researchers at Central Washington University, which resides in Ellensburg, and even to local teachers and their K–12 curricula, but these features were not successfully implemented in the city's supervisory control and data acquisition (SCADA) system by the city's chosen vendor. The City of Ellensburg received some qualitative value from its very visible investment in green energy resources and describes the park as an "eco-tourism" site. (City of Ellensburg 2013a)

The City of Ellensburg installed metrology equipment and made SCADA and other general site improvements. The major focus of their project participation was the installation and testing of two renewable solar photovoltaic (PV) generation systems, five residential-class wind turbine systems, and four larger commercial-class wind turbine systems. The new and existing solar and wind generation resources have been listed in Table 9.1. In this list, the names of the city's data metering points (e.g., "MP-1") have been mapped to each metered renewable generator. These renewable generation systems and their performance will be described in detail in the remainder of this chapter. The assets' corresponding chapter sections have been included in Table 9.1.

Table 9.1. Existing and New Renewable Solar and Wind Generation

Type/Make/Model	Meter Point	Section	Existing	New
Solar PV arrays:			69.5 kW	40.5 kW
Polycrystalline	MP-1	8.2	56.0	-
Thin-film	MP-2	9.3	13.5	40.5
Residential wind turbine generator systems:				8.6 kW
Honeywell WindTronics	MP-5	9.4	-	1.5
Windspire	MP-4	9.5	-	1.2
Energy Ball V200	MP-6	9.6	-	2.5
Skystream	MP-15	9.7	-	2.4
Wing Power	MP-7	9.12	-	1.0
Commercial wind turbine generator systems:				34.0 kW
Bergey	MP-8	9.8	-	10.0
Tangarie	MP-9	9.9	-	10.0
Urban Green Energy	MP-10	9.10	-	4.0
Ventera Wind	MP-11	9.11	-	10.0

The city was unable to establish and operate a transactive node and participate in the project's transactive system. None of its assets were represented in the transactive system. The City of Ellensburg was one of three utility sites that elected to design its own transactive node according to project specifications and using a proxy server instead of the software platform that was offered from project participant IBM. This effort proved more challenging than had been anticipated and was not completed. The city and project jointly decided to terminate the activity after it became seriously delayed.

9.1 Recloser Switch for Reliability and Outage Prevention

The City of Ellensburg purchased and installed a remote recloser switch at the interface between all the renewable generators and the city distribution system. The switch could be remotely opened using the site's SCADA. During an unlikely regional overgeneration event, the City of Ellensburg offered to use SCADA-level metering and control to quickly disconnect its renewable generators at the renewable energy park, thus improving system grid reliability. Fiber optic cable was installed to tie the renewable energy park communications to the city's electricity distribution operations center.

The Bonneville Power Administration (BPA) occasionally encounters overgeneration scenarios when wind generation is high, electric load is small, and base-load generation cannot be further reduced. During these scenarios, "dec" (decreased) balancing reserves can become depleted, and the region becomes challenged to manage frequency and enforce its exchange obligations.

It was determined early in the project that the project would not engage this disconnect switch through the project's transactive control system. Because the transactive system was only weakly connected to the region's operational objectives and was not aligned with real energy costs and incentives, the project could not reimburse the city for its loss of generation.

The project was not successful in its request to connect the operation of the switch with mitigation of overgeneration events. There was no signal or program available to the city for that purpose. In 2013, BPA solicited participation in a demonstration of commercialized demand response that might have dispatched this resource during overgeneration events. The city did not engage in this solicitation.

Recloser switch operation was successfully tested by the City of Ellensburg via the SCADA system in December 2012.

9.2 Polycrystalline Flat-Panel 56 kW PV System

The 56 kW polycrystalline flat-panel PV system, shown in Figure 9.4, at the Ellensburg community renewable energy park, Ellensburg, Washington, existed prior to the PNWSGD project, but the City of Ellensburg offered its data for evaluation by the project. The City of Ellensburg supplements its power and energy requirements, and thereby displaces its need for BPA energy supply with the power generated by the existing PV system.

Figure 9.4. Arrays of Standard Polycrystalline PV Panels at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The city chose not to include the expense of the existing PV panels in its estimation of annualized system costs. The remaining annualized costs, summarized in Table 9.2, were for site improvements and for improved monitoring of the generator and local weather conditions.

Table 9.2. Annualized Costs of the 56 kW Polycrystalline Flat-Panel PV System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
SCADA and Monitoring	8	33.2	2.7
Fiber Optic Communication	8	16.4	1.3
Climate Data Equipment	8	6.7	0.5
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Fencing	8	4.6	0.4
Consultants	8	18.5	1.5
56 kW PV Polycrystalline Solar Panels (existing)	100	0.0	0.0
Total Annualized Asset Cost			**$8.6K**

9.2.1 Baseline Approach

The baseline for this renewable generation system is the hypothetical absence of the system. The system is given credit for the value of the energy that is being generated at the times of active generation.

9.2.2 Data and Data Collection for the Polycrystalline PV Panels

The City of Ellensburg submitted 5-minute SCADA data concerning this PV system from its metering point “MP-1.” The raw generation data from the city stated the energy generated every 5 minutes. The project converted this data into average power for each 5-minute interval. The data period began August 2, 2012, and continued through August 31, 2014, the end of the project’s data collection period. Analysts removed obvious outliers—very negative generation values, for example. They also removed nonzero “stuck” data values from five time periods that ranged from 8 hours to over 17 days in duration. From March 31 to April 18, 2014 (17 days, 16 hours), no data was received while fiber optic cable was being changed. Most of the analysis used averaged power and will therefore be minimally degraded by the removal of these few periods when the data was questionable.

The city also collected and submitted meteorological data from its onsite weather station, including solar irradiance data. This onsite weather data, which was never calibrated, was supplemented by data from nearby Ellensburg weather stations. The data collected by the project permitted a characterization of the average hourly production from the 56 kW PV system as a function of measured solar irradiance. Figure 9.5 plots the average hourly power as a function of the average hourly solar irradiance.

Each point on Figure 9.5 represents the average power output for a solar irradiance range that is 1.0 W/m^2 wide (e.g., from 431–432 W/m^2). Considerable variability is evident, but some of this variability must be attributed to the irradiance meter. There is some evidence that birds perching on or near the meter influenced its output. Furthermore, the meter was not perfectly colocated with the PV system and therefore could be differently affected by intermittent cloud cover. The metrology tower was approximately 400 feet northeast of the center of the PV array, and the arrays themselves span about 350 feet from their northwest corner to their southeast corner.

The maximum hourly generation from the PV system was about 50 kW, somewhat less than the 56 kW nameplate capacity. This correlation provides some insight concerning the fixed orientation, quality, and design of the PV system, but it was not directly used for benefit analysis.

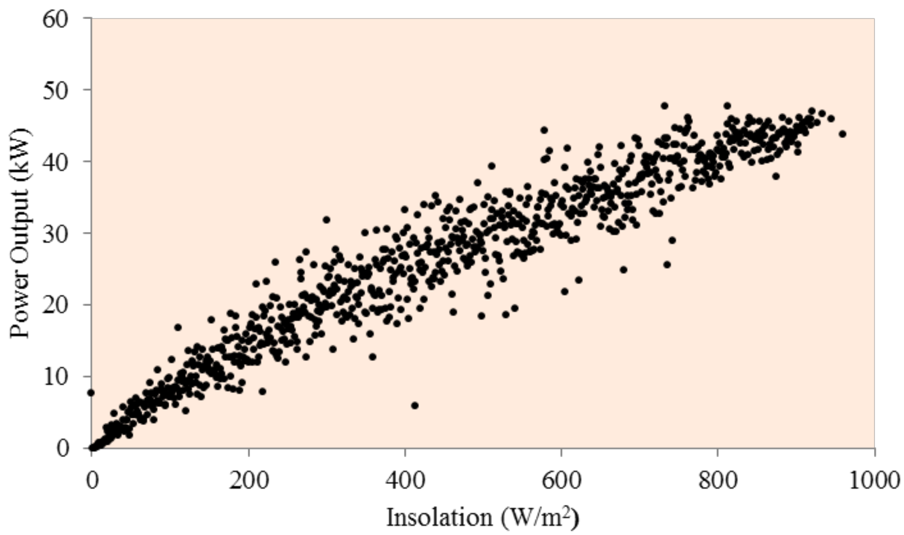


Figure 9.5. Power Curve Calculated for the 56 kW Polycrystalline PV Generator System. (This calculation used available averaged hourly production data from August 2, 2012, through March 14, 2014.)

9.2.3 Performance of the Polycrystalline PV System

The value of the displaced energy supply may be assessed from costs described within the BPA load-shaping service. This service differentiates unit energy costs by month and by heavy-load hour (HLH) and light-load hour (LLH). The BPA tiered-rate methodology is discussed in Appendix C.

The component HLH and LLH energy usages and their average impact on the city's energy supply costs are listed by calendar month in Table 9.3. The average energy usages were calculated for each calendar month from the average power generation for each of the two hour types that month and the numbers of HLHs and LLHs in the months of 2013. The variabilities in these energy calculations were estimated from the differences between the average power levels generated in the same calendar month but in different project years. The totals are simply the sums of the results from the HLHs and LLHs, but their variability is the square root of the squares of the variability in the data for the two hour types.

Table 9.3. Average Monthly Power Generation and Value of Displaced Supply According to BPA Load-Shaping Rates for the Polycrystalline PV Array

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	2,300 ± 400	87 ± 15	460 ± 190	14 ± 6	2,800 ± 450	101 ± 16
Feb	4,300 ± 850	160 ± 31	610 ± 150	19 ± 5	4,900 ± 870	179 ± 32
Mar	5,700 ± 200	170 ± 6	1,300 ± 190	32 ± 5	7,000 ± 280	204 ± 8
Apr	7,600 ± 1,600	190 ± 41	1,300 ± 220	26 ± 4	8,800 ± 1,600	220 ± 41
May	7,800 ± 580	160 ± 12	1,200 ± 53	16 ± 1	9,000 ± 580	179 ± 12
Jun	7,400 ± 600	170 ± 14	1,700 ± 140	24 ± 2	9,100 ± 620	193 ± 14
Jul	8,200 ± 360	250 ± 11	1,500 ± 220	37 ± 6	9,700 ± 420	287 ± 12
Aug	8,000 ± 500	270 ± 17	1,300 ± 110	34 ± 3	9,200 ± 510	304 ± 17
Sep	6,300 ± 1,100	210 ± 36	1,600 ± 220	45 ± 6	8,000 ± 1,100	259 ± 36
Oct	5,900 ± 1,500	190 ± 48	800 ± 180	22 ± 5	6,700 ± 1,500	209 ± 48
Nov	2,900 ± 1,200	100 ± 42	770 ± 340	24 ± 11	3,700 ± 1,200	127 ± 43
Dec	2,500 ± 980	98 ± 38	460 ± 270	15 ± 9	3,000 ± 1,000	114 ± 39

As shown in Figure 9.6, most of the solar energy is generated during HLHs. Almost 4 times as much energy is generated in the summer months, when the sun is high in the sky and daylight is longer, as in winter, when the sun remains low and is often hidden by clouds. Based on the calculated energy values in Table 9.3, this array of polycrystalline PV panels could be expected to generate 81.9 ± 3.3 MWh each year. The sum value of the annual generated energy from the PV system was found to be $2,377 ± $104, based on the value of the energy supply that the city would otherwise need to purchase for this energy and using the most recent BPA load-shaping rates.

The variability in the stated value (i.e., $104) was estimated by comparing monthly values from one year to the next. By the end of the project, two complete years' data were collected. The total variability should be the square root of the sum of the squared variabilities for the 12 calendar months. The total energy and total value of the energy produced each calendar month was remarkably similar from year to year during the project.

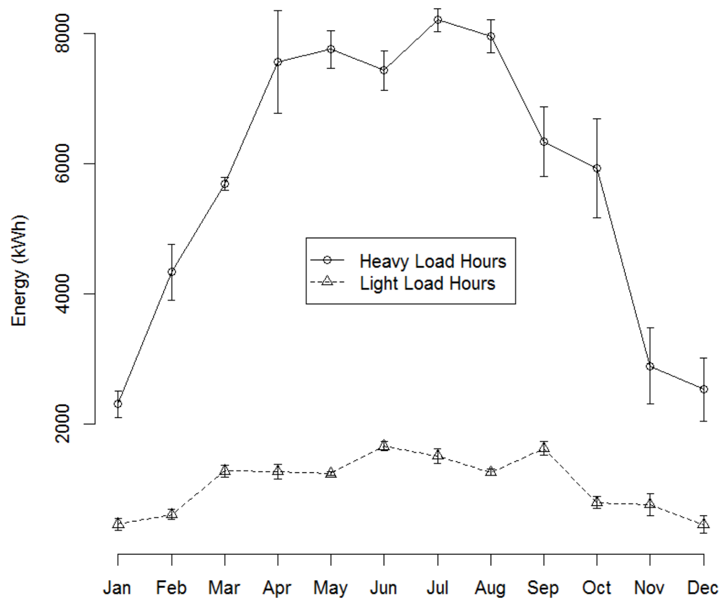


Figure 9.6. Average HLH and LLH Energy Production for the Polycrystalline PV Array by Calendar Month

Figure 9.7 shows the average generated renewable power by hour for all hours of the project. In this figure, the x-axis lists the Pacific Time hour on which the hour-long interval began. The pattern of power generation is quite symmetrical from 06:00 until 19:00 Pacific Time. One should expect production of about 30 kW during the hour that begins at noon.

The variability shown by the error bars represents the distribution range from the 16th percentile to the 84th percentile. This range was chosen because, for a normal distribution, it would represent the span between one standard deviation above and below the average. The distributions of hourly power production are not normal distributions, but this representation of variability is useful to analysts who have worked often with standard populations.

Even in this figure that has aggregated all the project hours, one can see that the variability of production in the afternoon is greater than that in the morning. This trend will be more evident for individual seasons.

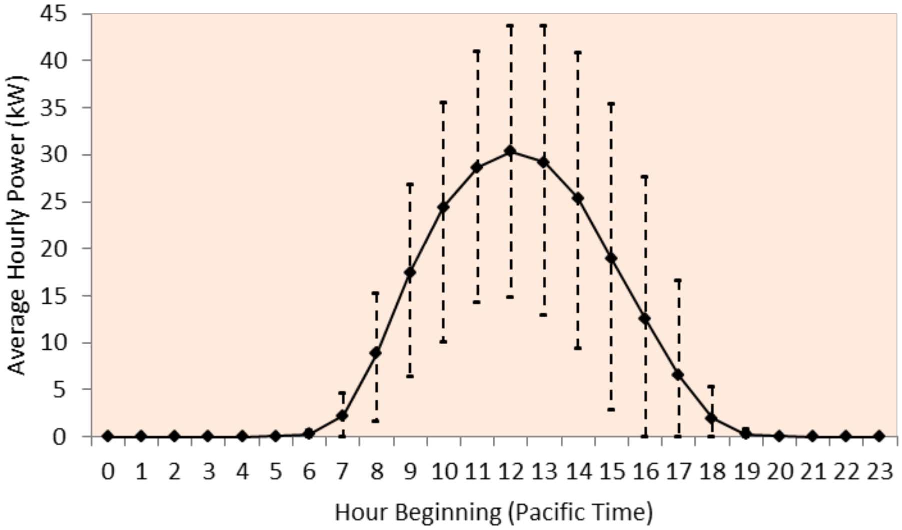
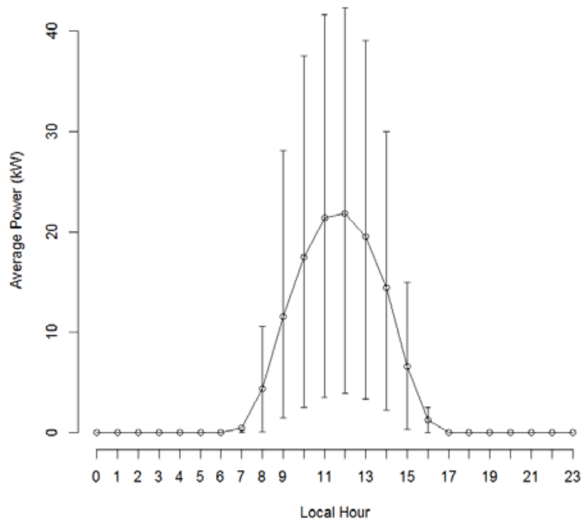


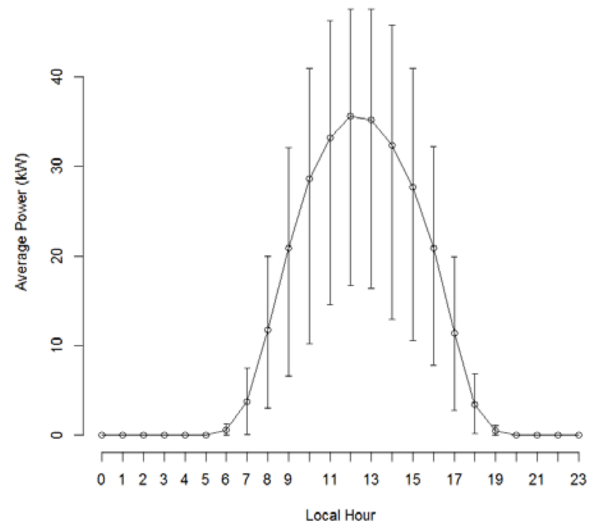
Figure 9.7. Average Hourly Power Production of the 56 kW Polycrystalline PV System for All Project Hours. The error bars represent the data range of the hourly production from the 16th through the 84th percentiles.

Figure 9.8 separates hourly generation by hour for winter (Dec.–Feb.), spring (Mar.–May), summer (Jun.–Aug.), and fall (Sep.–Nov.) seasons. The production differs by numbers of hours during which energy is produced—about 11 hours during winter compared to about 15 hours during summer. The average peak power production ranges from about 22 kW in the winter to about 39 kW in the summer.

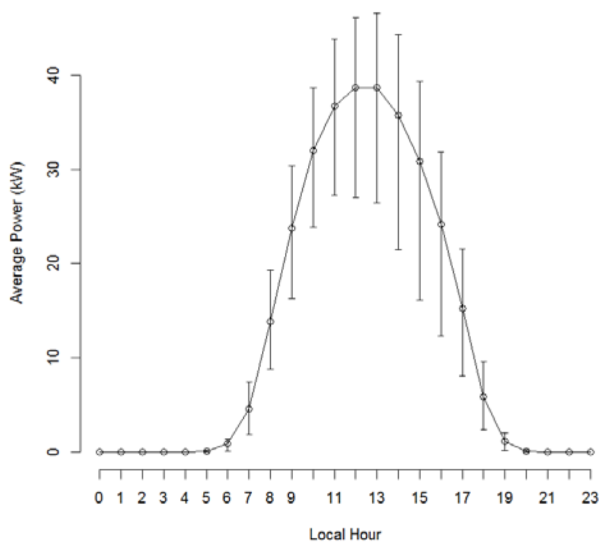
The variability represented by the 16th and 84th percentile error bars also differs significantly from season to season. Generation during the summer is relatively reliable, with average hourly production relatively narrowly distributed around the average. The distribution of average hourly production is wider in the other three seasons. During winter, the variability is especially large compared to the relatively small expected generation. It is fall that drives the trend of having more variability in the afternoon than in the morning.



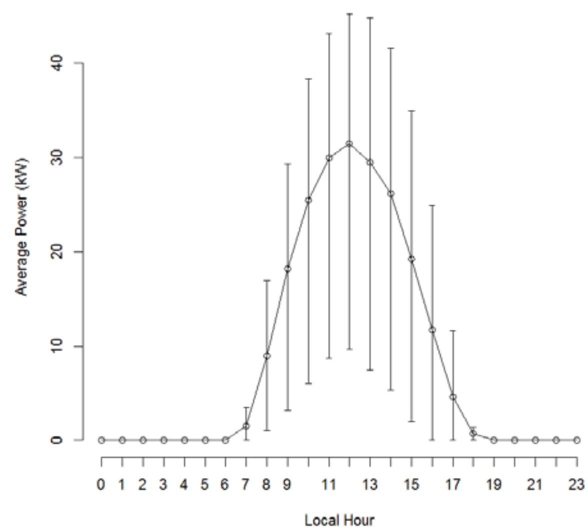
(a) Winter



(b) Spring



(c) Summer



(d) Fall

Figure 9.8. Average Hourly Production and Variability of Production of the 56 kW Polycrystalline PV System by Season. The error bars represent the range between the 16th and 84th percentiles.

The City of Ellensburg is subject to BPA demand charges that are determined at the conclusion of each month from the city's peak HLH, the average hourly HLH load, and a contract demand quantity allowance that has been calculated for the month. Generation from renewable sources may affect two of these—the month's peak load during the peak HLH and the average load during all HLHs that month. BPA's bills to its customers are complex. There may be other corrections in the complete billing method that are not accounted for here.

To estimate the impact on peak load in a month, one must know or infer the utility's peak hours. The City of Ellensburg submitted to the project a history of their months' peak hours. The project used the most recent 24 months to represent typical peak hours by calendar month. Analysts determined how the generation resource during an example peak hour would have affected the demand for that particular hour. This was performed for each calendar month. The result is therefore a statistical result and does not necessarily reflect the outcome during any specific month or year. As was shown in Figure 9.7, actual production for any given hour is highly variable. The variability was estimated by propagating the standard deviations of the exemplary peak hours each month.

Because the formula for determining BPA demand-charge determinants also subtracts average HLH power (i.e., “aHLH”), the impact of generation from the 56 kW polycrystalline PV system on average HLH power must be addressed. Renewable solar energy production decreases the city’s average HLH energy consumption and therefore slightly increases the determinant on which the demand charges are based. Referring now to Table 9.4, the formula for the billing determinant yields significant reductions in the demand charges during hot months when the sun shines for many hours and can affect peak load. In the other months, the PV site may actually *increase* the city’s demand charges. This is possible because the solar generation continues to displace HLH energy supply throughout much of the day, but the sun is not shining brightly during the months’ peak demand hours.

The overall cost impact of this system on BPA demand charges was calculated to be only $15 ± 37 per year. Solar renewable generation has a negligible influence on peak demand and peak demand charges at this site.

Table 9.4. Typical Monthly Impacts on Demand Charges Based on Example Peak Hours Each Month for the Polycrystalline PV Array

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Demand Charges ($)
Jan	0.8 ± 3	5.5 ± 1.0	53 ± 3
Feb	4.7 ± 8.7	11 ± 2	72 ± 9
Mar	4.5 ± 7.3	14 ± 1	82 ± 7
Apr	18 ± 12	18 ± 4	−1 ± 13
May	24 ± 13	19 ± 1	−31 ± 13
Jun	22 ± 14	19 ± 2	−25 ± 14
Jul	40 ± 14	20 ± 1	−180 ± 14
Aug	27 ± 14	18 ± 1	−87 ± 14
Sep	26 ± 15	17 ± 3	−98 ± 15
Oct	4.3 ± 6.4	14 ± 4	87 ± 7
Nov	0.4 ± 2.2	7.2 ± 2.9	71 ± 4
Dec	0 ± 0.3	6.3 ± 2.5	72 ± 2

9.3 Thin-Film Solar Panel 54 kW Array

During the project, the City of Ellensburg added 40.5 kW of nameplate generation capacity to its existing 13.5 kW thin-film PV power generation. The city refers to the added thin-film technology as its Phase-4 expansion. The array grew to 54 kW. As with the other renewable generation at this site, the city installed this resource to reduce demand from its energy supplier. A portion of the completed array is displayed in Figure 9.9.

Figure 9.9. Arrays of Thin-Film PV Panels at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

Table 9.5 lists the system's components and their annualized costs. The majority of the costs were for purchasing and installing the new 40.5 kW generation capacity at the renewable energy park. Remaining annualized costs were for SCADA system upgrades, consultants, fiber optic communication, outreach, and miscellaneous upgrades to the site. The total annualized system cost for the incremental set of thin-film solar panels was $39.4K. Many of the components' costs were shared with the other renewable generator systems that the city installed and tested during the project. The costs of the existing panels were not included in the estimate of annualized system costs.

Table 9.5. Annualized Costs of the Flat Thin-Film Solar Panel System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
40.5 kW Thin-Film Nanotechnology Solar Panels (new)	100	29.0	29.0
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Climate Data Equipment	8	6.7	0.5
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
13.5 kW Thin-Film Nanotechnology Solar Panels (existing)	100	0.0	0.0
Total Annualized Asset Cost			**$39.4K**

In a report to the City of Ellensburg city council, the one-time cost of the city's Phase-4 installation of thin-film solar generation was stated as $291,787. This is probably not directly comparable to the annualized system costs listed in Table 9.5 because the two sums might not include exactly the same subcomponents.

9.3.1 Data from the Thin-Film Solar Panel System

The City of Ellensburg submitted the energy that was generated every 5 minutes for a period from the beginning of July 2012 to the end of the project's data collection at the end of August 2014. The city referred to the site metering point for the thin-film solar panel array as "MP-2." The project converted these data into average power for the 5-minute intervals. Obvious outliers, such as large negative values, for example, were removed by the project. The project also removed from analysis several time periods that exhibited "stuck" data values—nonzero values that remained constant for many data intervals. About five periods with missing data were received, and these empty data periods ranged from 8 hours to more than 17 days. The project was informed that the longest period of missing data (beginning March 31, 2014) resulted from required maintenance. A fiber optic cable was being replaced.

9.3.2 Performance of the Thin-Film Solar Panel System

The City of Ellensburg evaluated their Phase-4 installation of additional thin-film PV generation and concluded that the unit cost of the energy produced by the solar system was $0.28 (City of Ellensburg 2013b). This is expensive energy compared to inexpensive wholesale electricity in the Pacific Northwest.

The remainder of this section presents independent analysis conducted by the project concerning the entire array of thin-film PV at the Ellensburg renewable energy park.

The generation by this system was found to be quite similar to that of the similarly sized 56 kW polycrystalline PV system (Section 9.2). Table 9.6 estimates the monthly energy generated by this system and the value of the energy according to recent BPA load-shaping rates, which are provided in Appendix C. The calculations of yearly energy production used in this chapter are based on average power generation during each calendar month's HLHs and LLHs. That is, the energy reported by the project is not simply the sum energy that was reported to the project for a given time period. The calculated energy is a statistical result that is based on average power generation each calendar month, which may include data from multiple years. This approach may overstate generation somewhat when data were unavailable. Often the loss of data may be attributable to power metering or data collection, but the solar generator operates well. Conversely, the method overstates energy generation when outages are genuine and no energy is, in fact, generated. The project rarely possessed accurate information concerning the specific nature of data outages.

Table 9.6. Displaced HLH and LLH Supply Energy Consumptions and Costs, Based on BPA Load-Shaping Rates for the Thin-Film PV Array

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	2,200 ± 410	83 ± 15	440 ± 160	13 ± 5	2,600 ± 440	97 ± 16
Feb	4,200 ± 790	150 ± 29	580 ± 140	18 ± 4	4,700 ± 810	171 ± 30
Mar	5,600 ± 140	170 ± 4.3	1,300 ± 180	31 ± 5	6,800 ± 230	201 ± 6
Apr	7,600 ± 1500	200 ± 39	1,300 ± 230	26 ± 5	8,900 ± 1500	222 ± 39
May	7,800 ± 510	160 ± 11	1300 ± 45	16 ± 1	9,100 ± 520	181 ± 11
Jun	7,600 ± 510	170 ± 12	1,700 ± 120	25 ± 2	9,300 ± 520	197 ± 12
Jul	8,100 ± 510	250 ± 15	1,600 ± 150	40 ± 4	9,700 ± 530	286 ± 16
Aug	7,700 ± 170	260 ± 5.8	1,200 ± 140	33 ± 4	8,900 ± 220	295 ± 7
Sep	6,100 ± 1100	210 ± 37	1,600 ± 230	44 ± 6	7,700 ± 1100	250 ± 37
Oct	5,900 ± 1300	190 ± 41	790 ± 160	22 ± 4	6,700 ± 1300	208 ± 41
Nov	2,800 ± 1100	100 ± 38	720 ± 300	23 ± 10	3,500 ± 1100	123 ± 39
Dec	2,400 ± 800	92 ± 31	440 ± 220	15 ± 7	2,800 ± 830	106 ± 32

Based on the data in Table 9.6, total annual energy generation is estimated by the project to be 80.7 ± 3.0 MWh. The total annual HLH and LLH energy usages are expected to be 68 ± 3 MWh and 12.9 ± 0.6 MWh, respectively. The annual displaced energy supply costs for HLHs and LLHs are $2,031 ± 92 and $305 ± 18, respectively, with a total displaced supply value of about $2,335 ± 94 per year.

The city estimated that the overall unit cost of the solar energy generated by its Phase-4 assets (that include only the added 40.5 kW of the thin-film PV system) was $0.28 per kWh. Of course, this does not yet compare favorably with either the cost of the city's BPA energy supply or even the average retail energy rate that Ellensburg residents now pay for their electricity (City of Ellensburg 2013b).

The generated HLH and LLH energy for each calendar month has been plotted in Figure 9.10. This figure emphasizes that most of the energy is generated during HLHs. Nearly four times more energy is generated in the summer when the sun is high in the sky than is generated during winter months, when the sun remains low on the horizon and is often hidden by clouds.

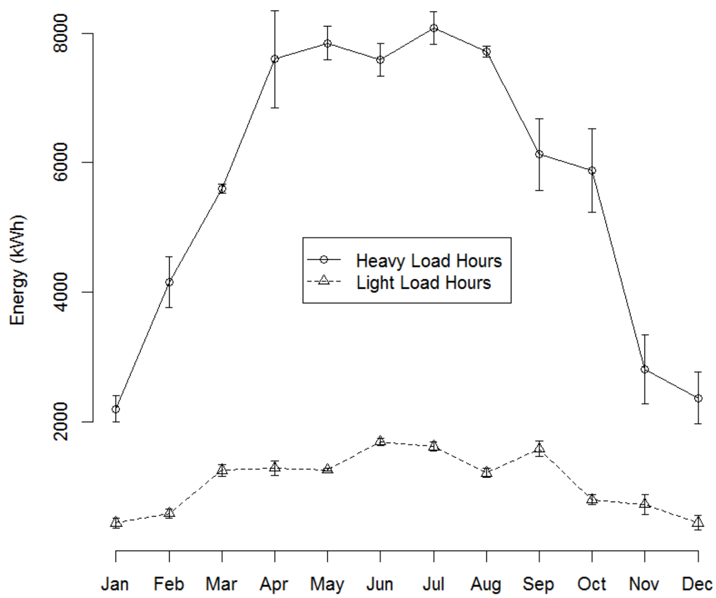
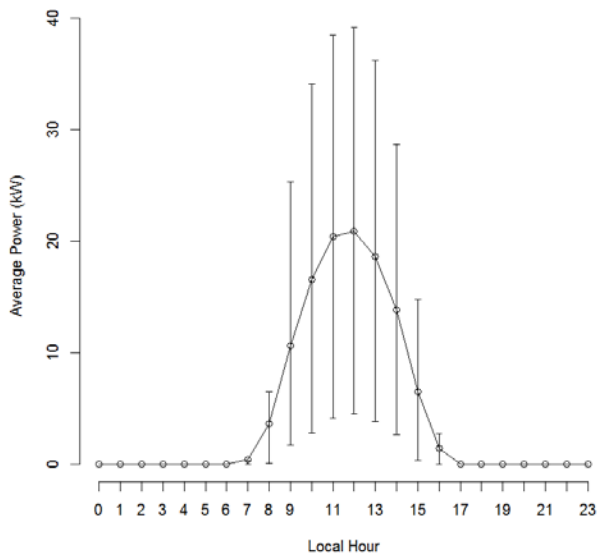


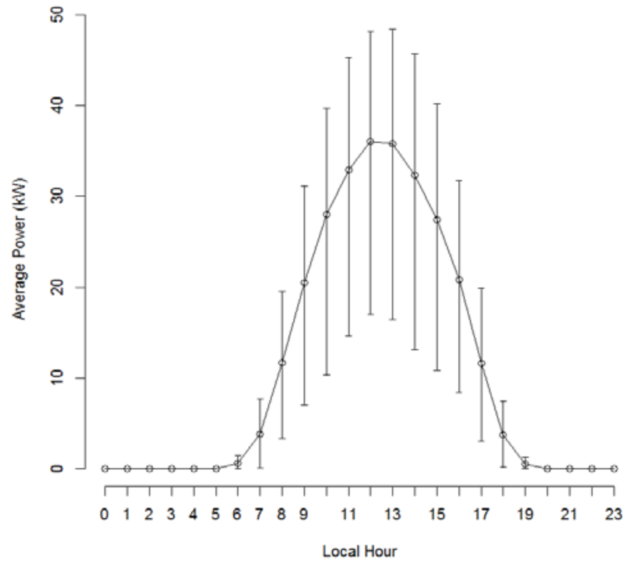
Figure 9.10. Average HLH and LLH Energy that is Generated each Calendar Month by the Thin-Film PV Array. Error bars are estimates of standard year-to-year variability.

Figure 9.11 shows average hourly diurnal patterns of the power that was generated by the complete system of thin-film solar panels. The hours are numbered such that "0" is the hour that began midnight, local Pacific Time. The error bars expand from the 16th to the 84th percentile of the data for these hours.

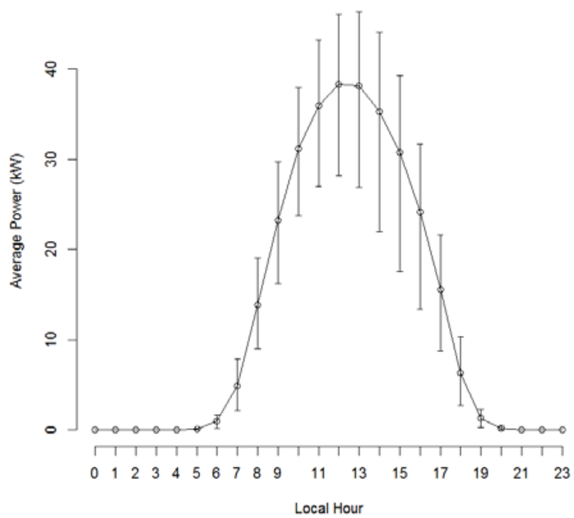
As was observed for the polycrystalline panel array in Section 9.2, summer peak power generation is approximately twice that of winter. The productive summer day includes more morning and evening hours than in other seasons. Power generation in the summer is more predictable than for other months. The error bars are shorter. The variability of generation is somewhat greater in the afternoon than during the morning hours, but this variability is perhaps not as pronounced as was observed for the polycrystalline panel array (Section 9.2).



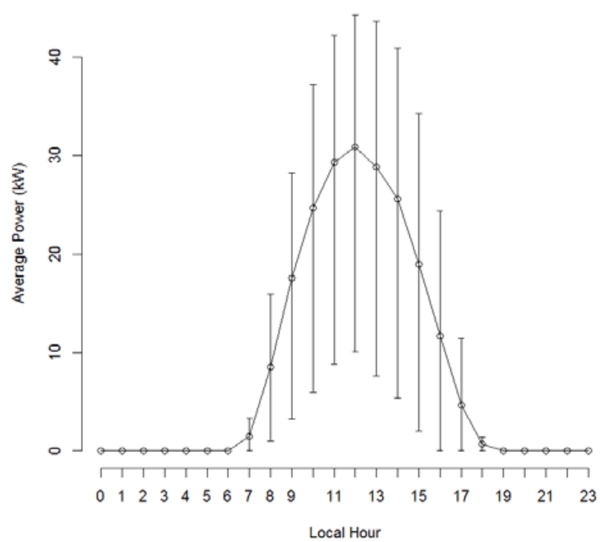
(a) Winter



(b) Spring



(c) Summer



(d) Fall

Figure 9.11. Average Solar Power Generation by Hour and Season for the Thin-Film PV Array

Table 9.7 presents the change in aHLH and the change in peak-hour demand that may be attributed to this thin-film system's power generation. These are the two main components of the demand-charge determinant from which a change in monthly demand charges may be calculated.

The city incurs demand charges nearly every month. The project received from Ellensburg a history of their peak hours. The most recent 24 of these examples (i.e., two years' worth) were used to estimate typical hours of the city's peak electrical load. The normal generation and variation of generation for these hours were used to estimate the impacts during peak hours. The aHLH component is simply the average generated power during HLHs each month with an estimate of how this average might change from year to year.

Finally, the total monthly impact was estimated from these analysis results and the BPA demand rate (Appendix C). This monthly impact is shown in Table 9.7. The negative values that occur primarily during summer months represent *reductions* of the city's demand charges those months. The demand charges are *increased* for many other months because the solar power generation is unimpressive during the (typically) morning peak hours those months.

Table 9.7. Impact on Peak Demand Determinants and Demand Charges from Thin-Film PV System

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Expense ($)
Jan	0.6 ± 1.7	5.3 ± 1.0	52 ± 2
Feb	4.2 ± 7.7	11 ± 2	71 ± 8
Mar	4.6 ± 6.8	13.5 ± 0.3	80 ± 7
Apr	18 ± 1	18 ± 4	2 ± 12
May	24 ± 13	19 ± 1	−31 ± 13
Jun	23 ± 14	19 ± 1	−26 ± 14
Jul	39 ± 15	19 ± 1	−173 ± 15
Aug	26 ± 13	17.9 ± 0.4	−83 ± 13
Sep	25 ± 14	16 ± 3	−94 ± 14
Oct	4.2 ± 6.3	14 ± 3	87 ± 7
Nov	0.4 ± 1.9	7.0 ± 2.7	70 ± 3
Dec	0.0 ± 0.4	5.9 ± 2.0	67 ± 2

The total impact of the solar generation from the thin-film PV system on the municipality's demand charges is only $22 ± 36 per year. Note that this is an overall *increase* in the demand charges the city would pay. Regardless, the magnitude is relatively insignificant.

9.4 Honeywell WindTronics 1.5 kW Model WT6500

The City of Ellensburg hoped to supplement its power and energy requirements (effectively reducing its demand from its supplier) with the power generated by a 1.5 kW Honeywell WT6500 wind generator (WindTronics, Inc. 2013) located at its renewable energy park. This is among the set of five residential-class wind systems tested by the city. This turbine has a unique design with the generator's stator and rotor located distal from the turbine's hub. The turbine is shown installed in Figure 9.12.

Figure 9.12. Residential-Class Honeywell 1.5 kW Turbine Installed at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

Electrical generation from this wind turbine stopped January 12, 2013, and was not restored. A wing failed due to an object (perhaps a bird) passing through the spoked generator wheel, which bent it enough to prevent it from rotating. The unit was de-energized as repair parts were not available. In a November 1, 2013, city report, the cause was attributed to “wing failures” (City of Ellensburg 2013c).

The annualized costs of the system and its components are listed in Table 9.8. The total system cost $16.0K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Table 9.8. City of Ellensburg Costs of 1.5 kW Honeywell WindTronics System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
1.5 kW WindTronics Wind Turbine	100	5.6	5.6
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Climate Data Equipment	8	6.7	0.5
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
Total Annualized Asset Cost			**$16.0K**

9.4.1 Data for the Honeywell WindTronics System

Power data from mid-November 2013 until mid-March 2013 was received from the city. The city's source for this data was their site metering point "MP-5." The power generation data in Figure 9.13 from this period is discretized because the raw data was reported to the nearest watt-hour each 5-minute interval. Therefore, the power is represented by whole-number products of 12 W. Maximum generation seldom, if ever, approached the nameplate value of the wind turbine—1.5 kW.

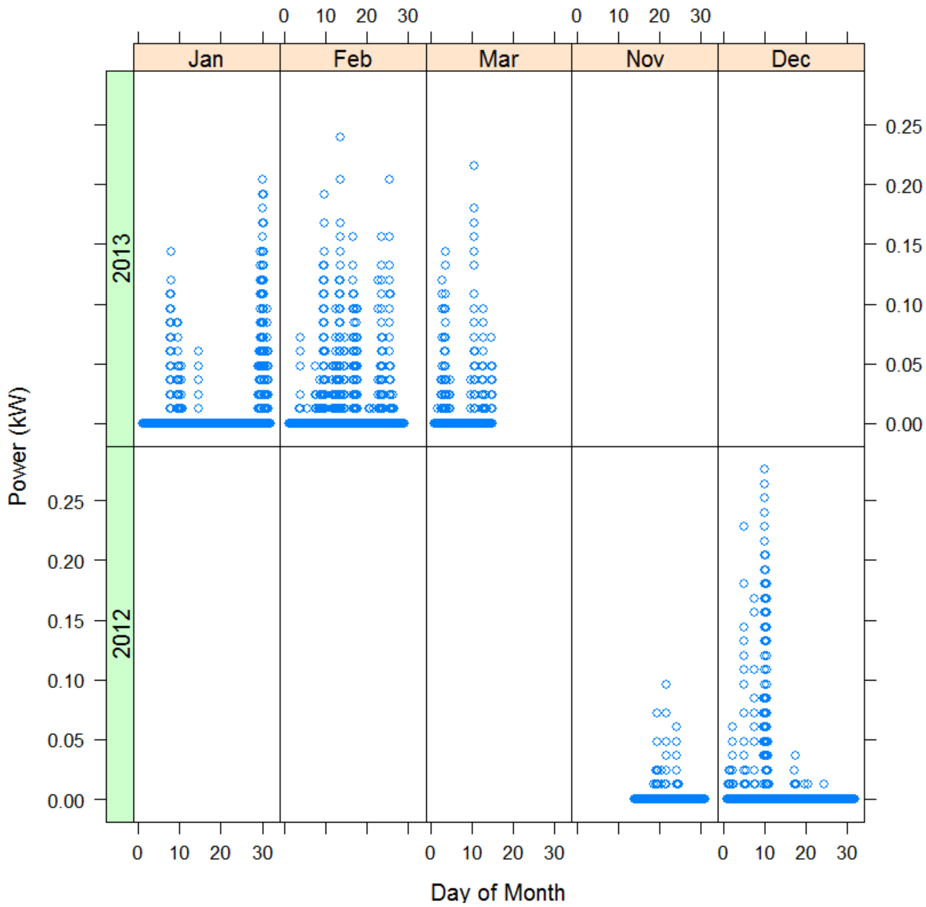


Figure 9.13. All Data Received Concerning Power Generation for the Honeywell WindTronics System

9.4.2 Performance of the Honeywell WindTronics System

The characteristic power generation as a function of wind speed was calculated and is presented in Figure 9.14. This calculation used all the power data that was available from 5-minute intervals and compared that power against the corresponding wind speeds that were reported 36 feet above ground at the site's weather metrology tower. The wind speeds from this sensor were found to have been discretized into the irregular set of wind speeds that were plotted in this figure. The error bars again represent the range of generated power data between the 16th and 84th percentiles at each wind speed. The characteristic curve shape is interesting, but the project is not confident that the meter source of the reported wind speeds had been calibrated.

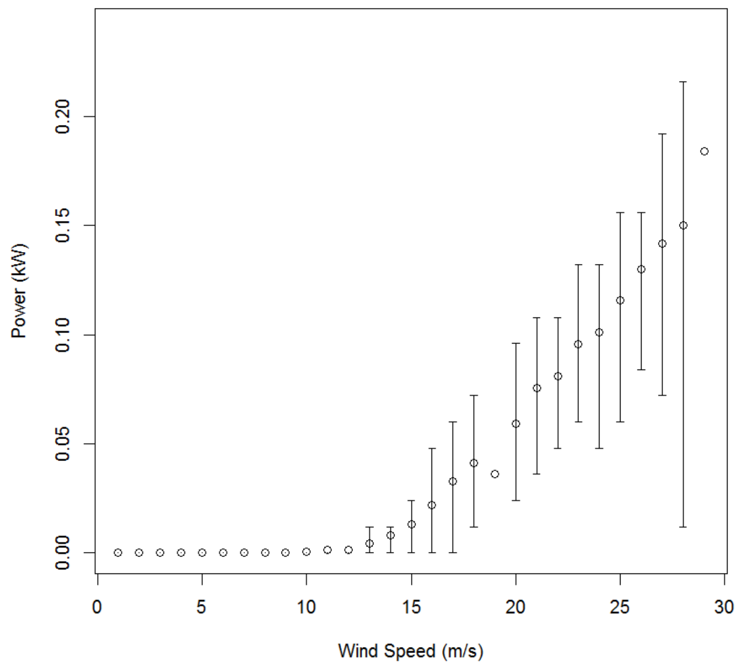


Figure 9.14. Generated Wind Power from the Honeywell WindTronics Wind System as a Function of the Wind Speed that was Measured at the Site at Height 36 Feet

The monthly energy generation each month is shown separately for HLHs and LLHs in Figure 9.15. The uncertainty of these monthly sums cannot be determined because the system ran less than one full year. Because generation was intermittent and was somewhat randomly distributed over time, the generation could occur during either HLHs or LLHs each month.

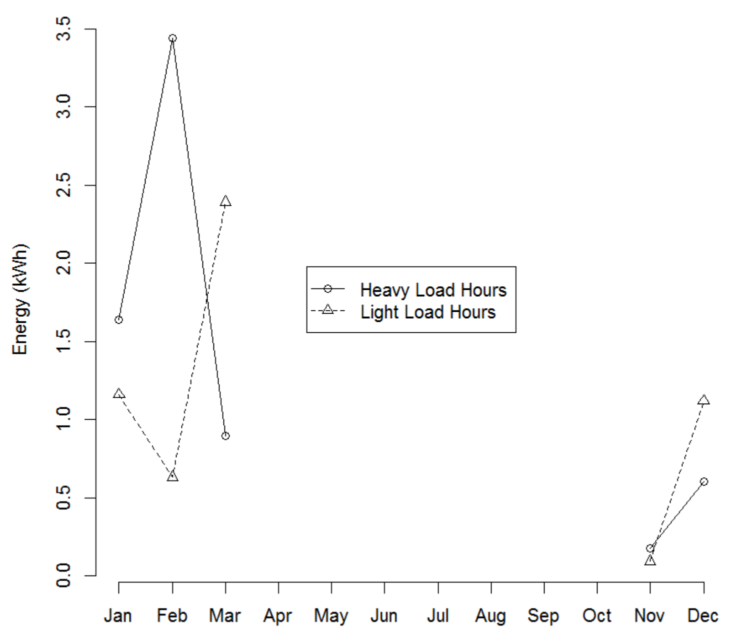
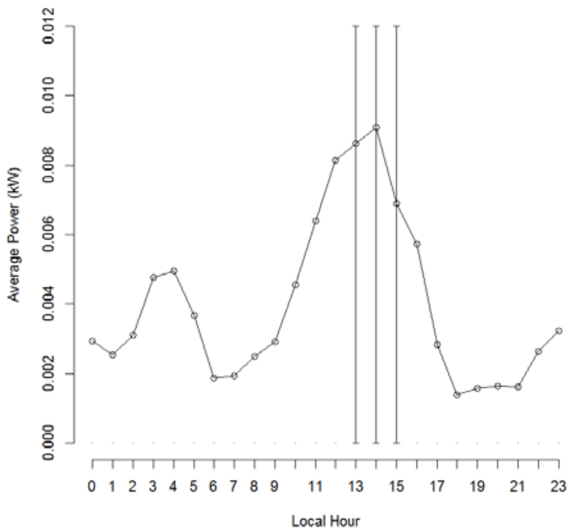
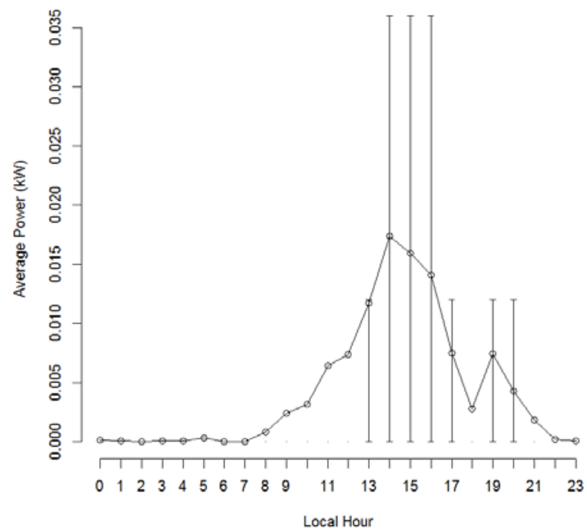


Figure 9.15. Average HLH and LLH Energy by Calendar Month for the Honeywell WindTronics System. Data was collected during five of the calendar months.

The diurnal power generation patterns were determined for winter and spring seasons and are shown in Figure 9.16. Wind generation is strongest during early afternoons. The error bars again represent samples between the 16th and 84th percentiles in this figure. The average power generation was very small.



(a) Winter



(b) Spring

Figure 9.16. Average Power Generation by Hour and Season for the Honeywell WindTronics System. Seasons summer and fall had inadequate data and are not shown.

The average monthly energy generation and the values of the amounts of supply energy displaced by the renewable resource are listed in Table 9.9. Data was received during only five calendar months. The monthly energy generation and the values of these quantities of energy, according to BPA load-shaping rates, are miniscule. Even if the generator had operated similarly for a full year, all the energy produced over a year would be expected to displace no more than about $1 of energy that the City of Ellensburg would otherwise have purchased.

Table 9.9. Energy Generated Each Month and the Value of Supply Energy that it Displaced for the Honeywell WindTronics System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	1.6	0.06	1.2	0.04	2.8	0.10
Feb	3.4	0.13	0.6	0.02	4.1	0.15
Mar	0.9	0.03	2.4	0.06	3.3	0.09
…	-	-	-	-	-	-
Nov	0.2	0.01	0.1	0	0.3	0.01
Dec	0.6	0.02	1.1	0.04	1.7	0.06

The project analyzed the impact that this asset system had on peak demand; the value was inconsequential. The typical power generation during peak hours was small. Because the resource is intermittent, generation was unlikely to be coincident with a month's peak demand hour.

9.5 Windspire® 1.2 kW Wind Turbine

The City of Ellensburg further complemented its power and energy requirements (effectively reducing its demand from its supplier) with the power generated by a 1.2 kW Windspire wind generator (Windspire Energy Inc. 2010) located at its renewable park. This is among the set of residential-class wind systems tested by the city. The turbine is shown installed in Figure 9.17.

This wind turbine was declared failed on March 15, 2013. In a report November 1, 2013, posted on the city website, the cause was described as a generator and inverter failure. The turbine eventually would not rotate. The city understood the manufacturer to no longer be in business (City of Ellensburg 2013c). Late July that same year, vandals damaged a $1,500 meter that had been used to monitor this turbine system.

The annualized costs of the system and its components are listed in Table 9.10. The total system cost $15.4K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Figure 9.17. 1.2 kW Windspire Wind Turbine at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

Table 9.10. City of Ellensburg Costs of 1.2 kW Windspire Wind Turbine System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
1.2 kW Windspire Wind Turbine	100	5.0	5.0
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Climate Data Equipment	8	6.7	0.5
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
Total Annualized Asset Cost			**$15.4K**

9.5.1 Data for the Windspire System

Data was collected at 5-minute intervals from the beginning of July 2012 to January 12, 2013, at which time the generator and inverter failed and the turbine would not rotate. The city's source for this data was their site metering point "MP-4."

All this data is shown in Figure 9.18. Observe from the scale of the power axis that the generator never generated more than 1 kW. Generation was very intermittent, as might be expected.

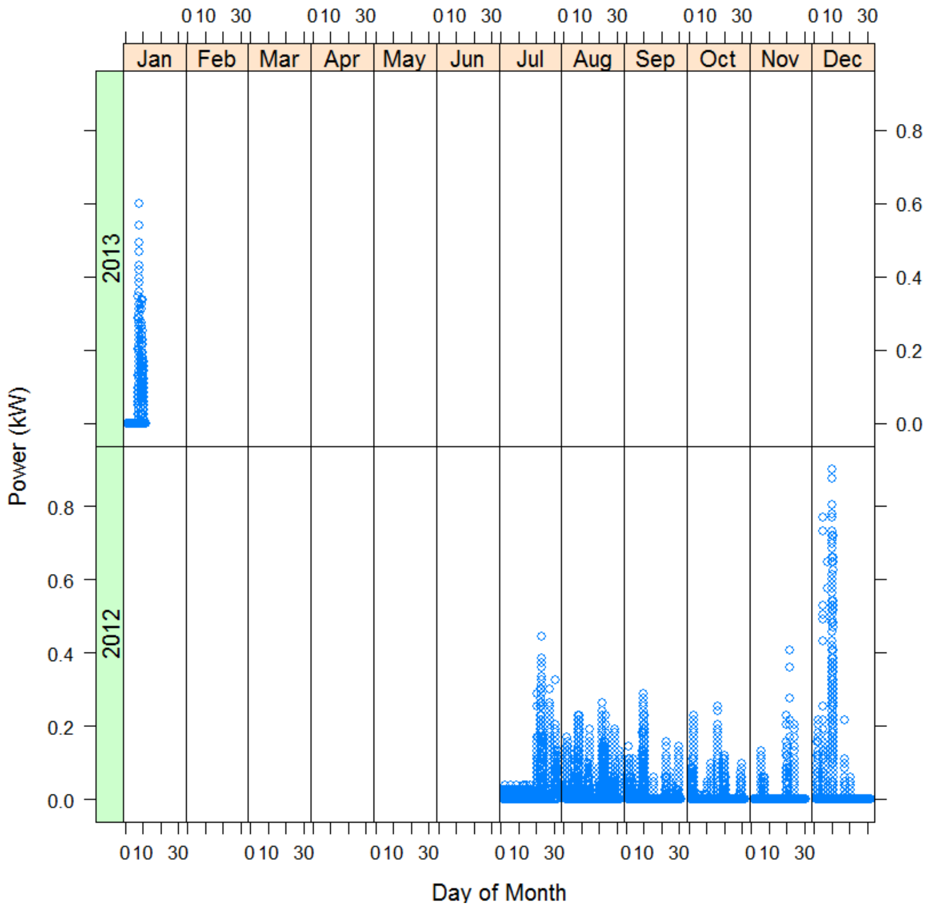


Figure 9.18. Power Generation from July 2012 through January 2013 for the Windspire System

9.5.2 Performance of the Windspire Turbine System

The project calculated the characteristic power generation by this system as a function of the wind speed measured 36 feet above ground at the renewable energy park's weather tower. The result is summarized by Figure 9.19, which includes all the 5-minute data received by the project. The error bars represent the range of measured power intervals from the 16th to 84th percentile at each wind speed.

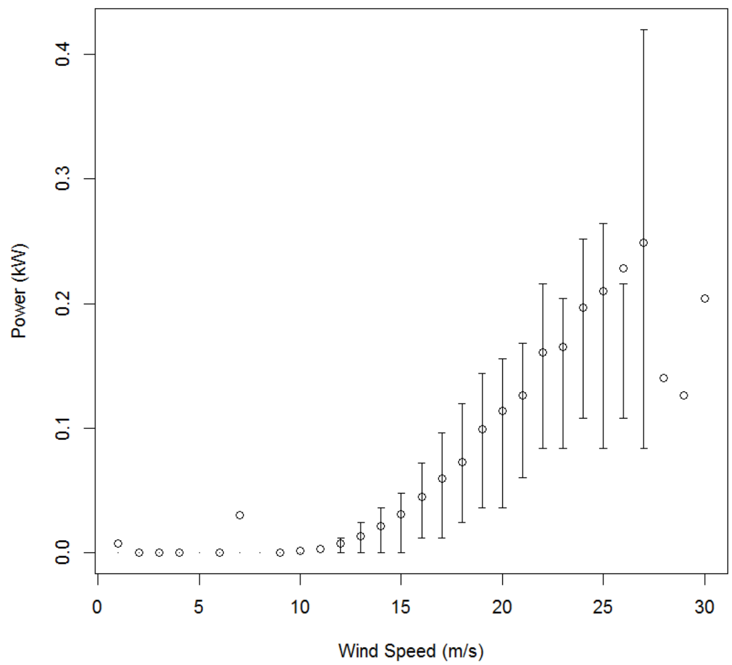
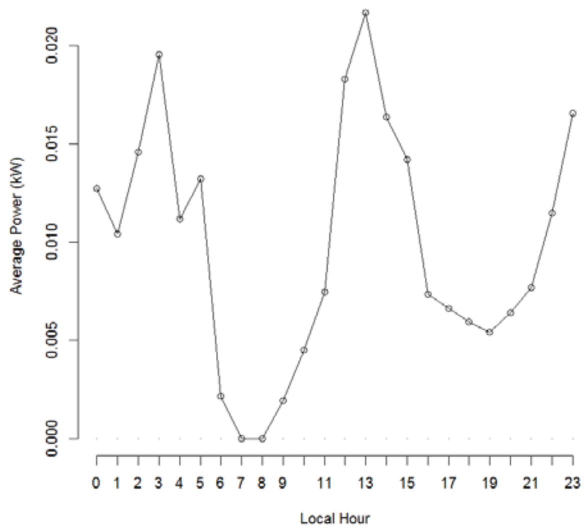


Figure 9.19. Characteristic Power Generation as a Function of Metered Site Wind Speed 36 Feet above the Ground for the Windspire System

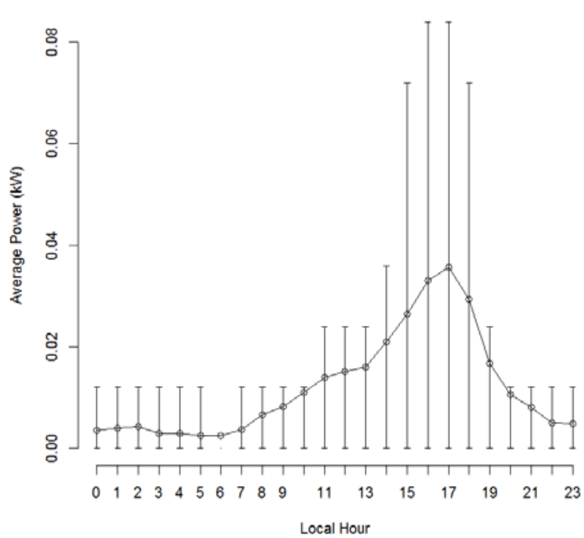
The average diurnal power generation patterns are shown for each season in Figure 9.20. Wind generation typically peaked in the early afternoon, but the typical average power was never more than 50 W for any hour of any season. Data was not reported for spring because generator data was unavailable those months. The error bars estimate the standard range of the data from the 16th to the 84th percentile. Because the generation was very intermittent, the 84th percentile generation was often zero for many of the hours and seasons. That simply means that the wind generator produced power less than 16% of the time.



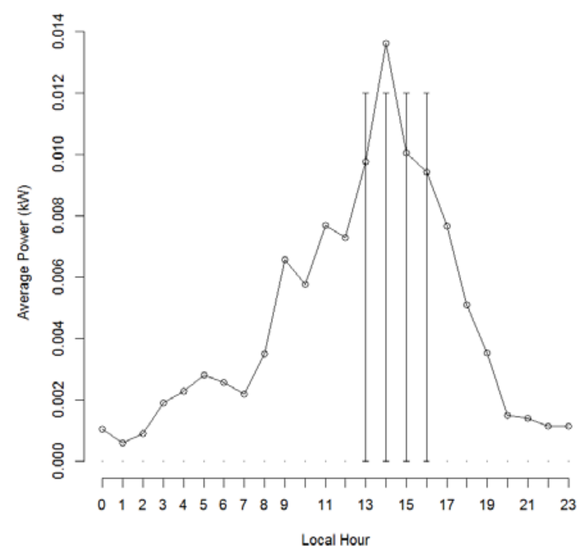
(a) Winter

NA

(b) Spring



(c) Summer



(d) Fall

Figure 9.20. Average Power Generation by Season and Pacific Time Zone Hour for the Windspire System. There was inadequate spring data to create a figure.

Table 9.11 lists the amounts of HLH, LLH, and total energy production and the monetary values of these quantities of energy by calendar month. The value of displaced supply was based on BPA's most recent load-shaping rates. Of the seven months for which generation data was received, none included impressive quantities of energy production. No generation data was available for five calendar months, from February through June. The total value of the energy in monitored months was less than $1.00. The total projected value of the yearly generated energy would be on the order of $2.50. The project did not estimate the variability in these values because less than one year's data was collected.

Table 9.11. Monthly Energy Production and the Monetary Value of the Energy Supply Displaced by the Windspire Generator

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	7.0	0.26	2.6	0.08	9.6	0.34
…	-	-	-	-	-	-
Jul	6.4	0.20	2.8	0.07	9.3	0.27
Aug	8.0	0.27	0.7	0.02	8.7	0.29
Sep	2.8	0.09	2.5	0.07	5.3	0.16
Oct	2.7	0.09	0.4	0.01	3.1	0.10
Nov	1.2	0.04	0.4	0.01	1.6	0.06
Dec	2.7	0.10	3.9	0.13	6.6	0.23

The project reviewed the impacts that this generator would have on peak demand charges. Like the values of the displaced energy supply above, these impacts never exceeded a dollar for any calendar month.

9.6 Home Energy International 2.25 kW Energy Ball® V200

The City of Ellensburg further complemented its power and energy requirements with the power generated by a 2.25 kW Energy Ball wind generator (Home Energy International 2013) located at its renewable energy park. This is among the set of five residential-class wind systems tested by the city. The turbine is shown installed in Figure 9.21.

Figure 9.21. 2.25 kW Home Energy International Energy Ball V200 at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The City of Ellensburg decided quickly to not continue with the Energy Ball turbine system. In a November 1, 2013, report to its city council, it was reported that the system typically consumed more energy than it generated.

In Table 9.12, the annualized cost of the system and its components is estimated at $15.3K. Most of this expense was for the 2.25 kW Energy Ball wind turbine and upgrades to the SCADA monitoring subsystem. The next greatest costs were for consultancy, outreach, and equipment upgrades at the site.

Table 9.12. City of Ellensburg Costs of 2.25 kW Home Energy International Energy Ball V200 System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
2.25 kW Energy Ball Wind Turbine	100	4.9	4.9
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Climate Data Equipment	8	6.7	0.5
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
Total Annualized Asset Cost			**$15.3K**

9.6.1 Data for the Energy Ball System

The City of Ellensburg monitored and submitted data from this wind generation system from the middle of September 2012 through October 2013. It remained functional until the city opted to stop testing wind systems altogether and removed it. The city's source for this data was their site metering point "MP-6." They submitted the energy generated in each 5-minute interval, and the project converted this data to average power for each interval. All the data received by the project has been plotted in Figure 9.22. Although the generator capacity is rated at 2.25 kW, it never appears to have generated more than about 0.9 kW during the project period.

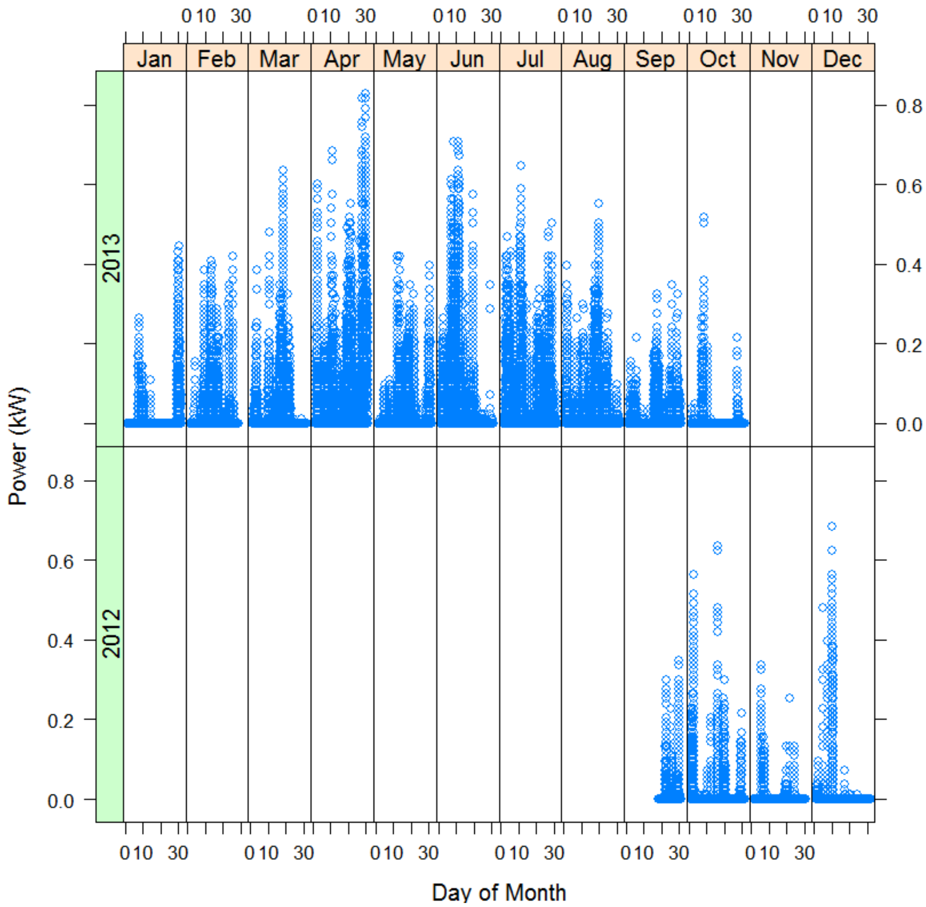
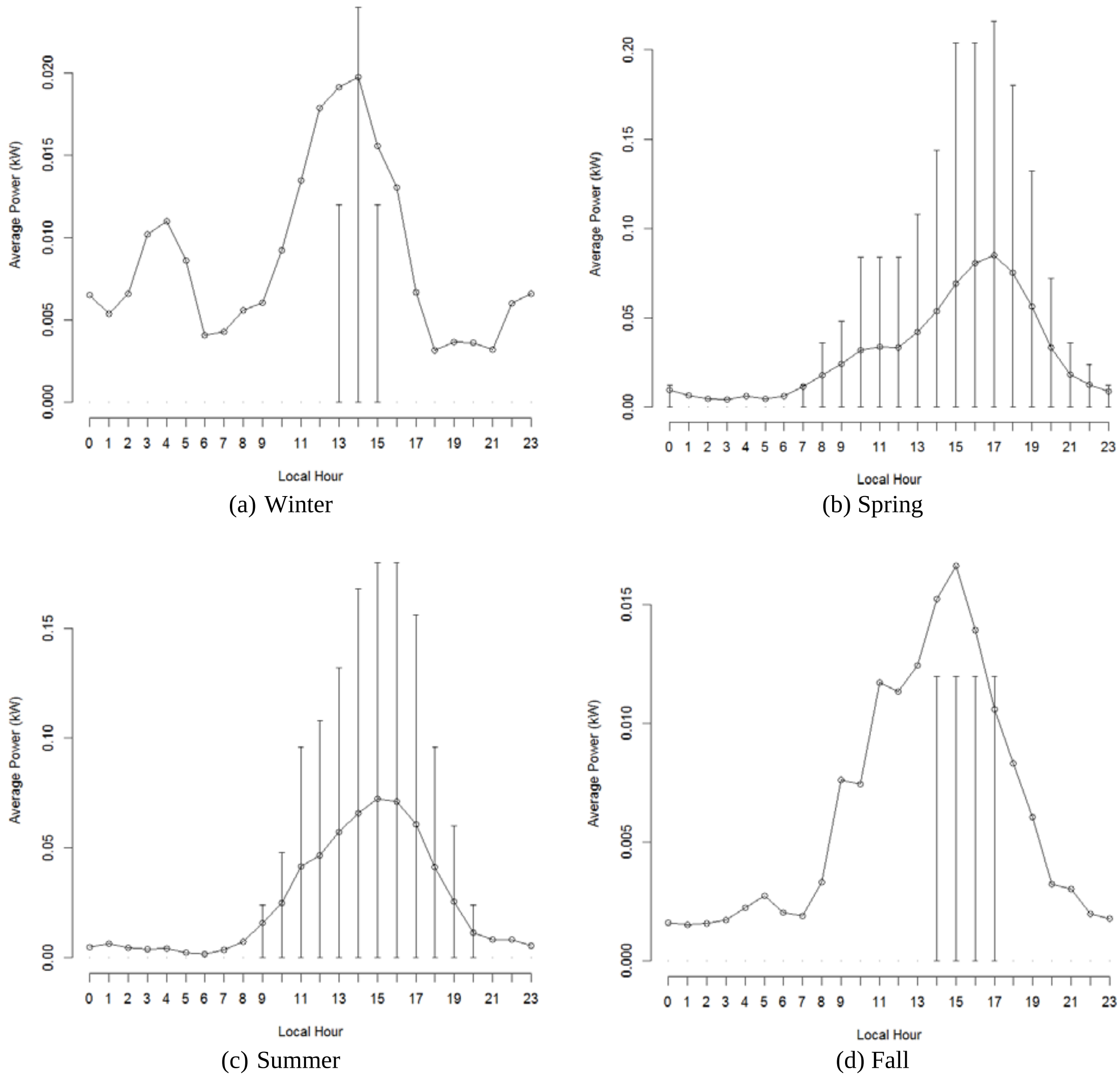


Figure 9.22. Power Generated by the Energy Ball V200 Wind Generator by Month

9.6.2 Performance of the Energy Ball Wind Generation System

The average seasonal diurnal power generation from this wind generator has been plotted in Figure 9.23. The generation is greatest in the afternoon during each of the four seasons. On average, 20 W is generated in winter during the hour that starts at 14:00 Pacific Time. Fall production is similar in magnitude. The other seasons' winds tend to produce more power, and the peak generation is somewhat later in the afternoons. The generation during winter and fall is so intermittent that the average generation does not often fall within the 16th to 84th percentiles. Generation in spring and summer is more predictable, so the average lies within this standard range.



(a) Winter (b) Spring (c) Summer (d) Fall

Figure 9.23. Diurnal Wind Power Generation Patterns for the Four Seasons for the Energy Ball System

The typical HLH and LLH energy generated each calendar month has been plotted in Figure 9.24. The uncertainty from one year to another could be estimated only for September and November because data was collected in both 2012 and 2013 for only these calendar months. The quantities of LLH and HLH energy track one another. The curves are quite jagged, which is probably due to natural wind variability within the year. The curve would likely have been smoother if data had been collected over multiple years.

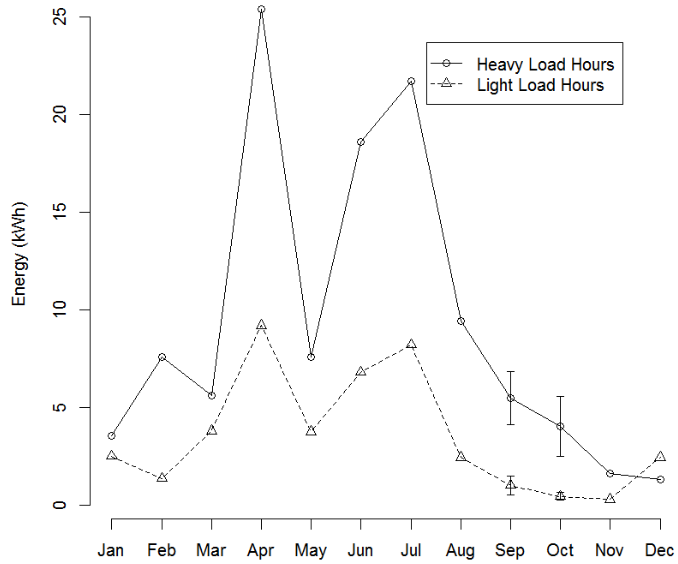


Figure 9.24. HLH and LLH Energy Generated Each Calendar Month by the Energy Ball V200 Wind Generation System

The energy generation from this wind generator has been summarized in Table 9.13. The value of the energy has been estimated using the HLH and LLH BPA load-shaping rates. Based on the 14 project months that this wind generator was monitored, it should be expected to generate 153 ± 10 kWh and thereby displace only about $4.16 ± 0.35 worth of electrical energy supply during a year, based on the BPA load-shaping rates and the energy supply that was displaced by the generator each month. The uncertainty in this calculation was estimated by extrapolating the uncertainty that was estimated for the two calendar months—September and October—that had data in both 2012 and 2013.

Table 9.13. Typical Calendar Month Energy Generation and its Monetized Value for the Energy Ball System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	4	0.13	3	0.08	6	0.21
Feb	8	0.28	1	0.04	9	0.32
Mar	6	0.17	4	0.10	9	0.26
Apr	25	0.66	9	0.19	35	0.84
May	8	0.16	4	0.05	11	0.21
Jun	19	0.42	7	0.10	25	0.52
Jul	22	0.66	8	0.20	30	0.86
Aug	9	0.32	2	0.07	12	0.39
Sep	5 ± 3	0.18 ± 0.09	1 ± 1	0.03 ± 0.03	6 ± 3	0.21 ± 0.10
Oct	4 ± 3	0.13 ± 0.10	0.5 ± 0.4	0.01 ± 0.01	4 ± 3	0.14 ± 0.10
Nov	2	0.06	0.3	0.01	2	0.07
Dec	1	0.05	2	0.08	4	0.13

The impact of this wind generation system on peak demand was evaluated, but it was determined that the impact was inconsequential—less than $1 per year.

9.7 Southwest Windpower 2.4 kW Skystream 3.7®

The City of Ellensburg still further complemented its power and energy requirements with the power generated by a 2.4 kW Southwest Windpower Skystream 3.7 wind generator (Southwest Windpower 2012) located at its renewable energy park. This is among the set of five residential-class wind systems tested by the city during the project. The turbine is shown installed in Figure 9.25.

The Windpower Skystream wind system remained functional until the city opted to stop testing wind systems altogether and removed it in late 2013.

The annualized costs of the system and its components are listed in Table 9.14. The total system was estimated to cost $14.9K on an annualized basis. The greatest cost was for the turbine generator itself, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

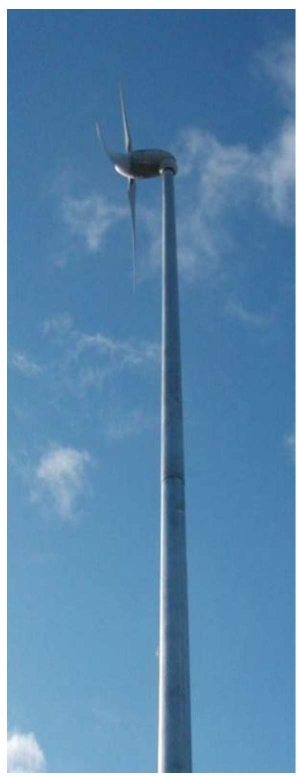


Figure 9.25. 2.4 kW Skystream Wind System at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

Table 9.14. City of Ellensburg Costs of the 2.4 kW Southwest Windpower Skystream 3.7 System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
2.4 kW Skystream Wind Turbine	100	4.5	4.5
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Climate Data Equipment	8	6.7	0.5
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
Total Annualized Asset Cost			**$14.9K**

In a report dated November 1, 2013, posted on the city's website, the one-time cost of the Skystream system was $24,770 (City of Ellensburg 2013b).

9.7.1 Data for the Southwest Windpower System

All the power data collected by the city from site metering point "MP-15" are shown in Figure 9.26. Data became available for the period from late August 2012 into October 2013. The power achieved and even exceeded the 2.3 kW nameplate rating many times over this period. However, only a fraction of the nameplate power rating was achieved during the first three months of data collection. If this was a problem with the early installation that was later fixed, this data may have caused the project to understate the energy production that should be expected during fall months.

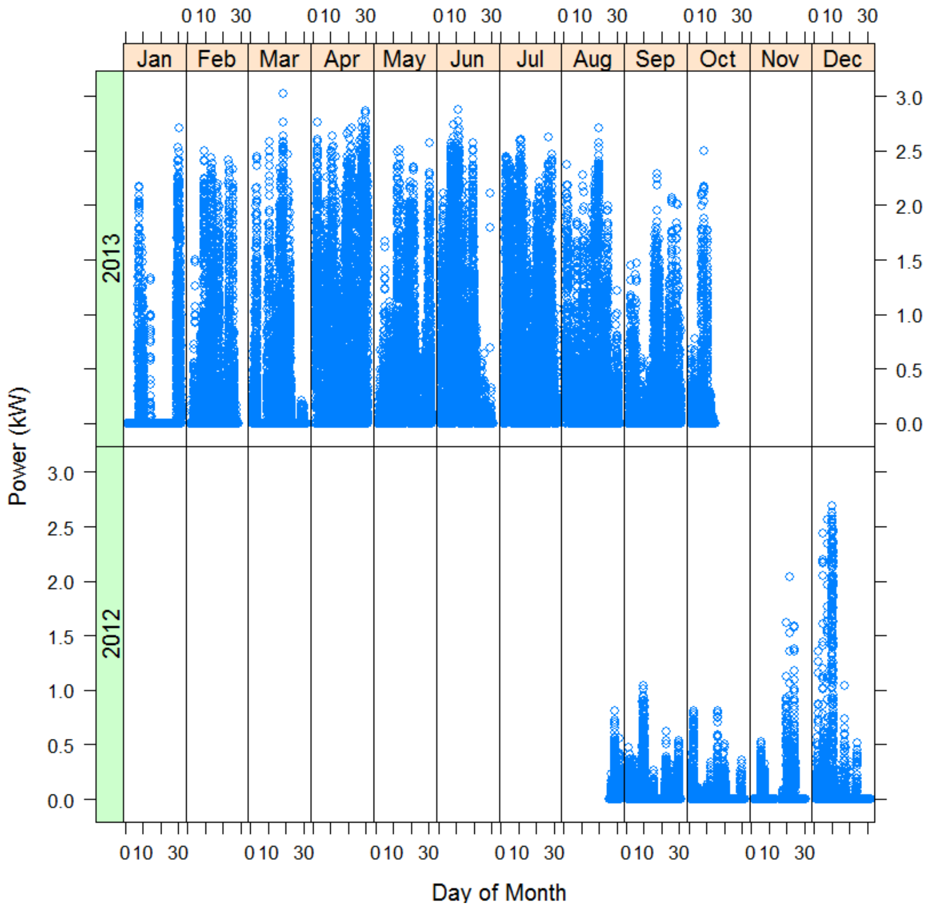


Figure 9.26. Wind Power Data Submitted by the City of Ellensburg for the Southwest Windpower System

9.7.2 Performance of the Southwest Windpower System

The power generated by the wind turbine system is plotted as a function of wind speed in Figure 9.27. All the project's 5-minute power data for this wind system was plotted against the corresponding wind speed data from the 85-foot metrology tower at the renewable energy park near the turbines. The error bars represent the range of power measurements from the 16th to 84th percentile at each wind speed. The wind speeds were found to have been discretized at the plotted wind-speed magnitudes. The characteristic curve is informative, but the project does not believe the wind speed sensors to have been thoroughly calibrated to ensure wind speed accuracy.

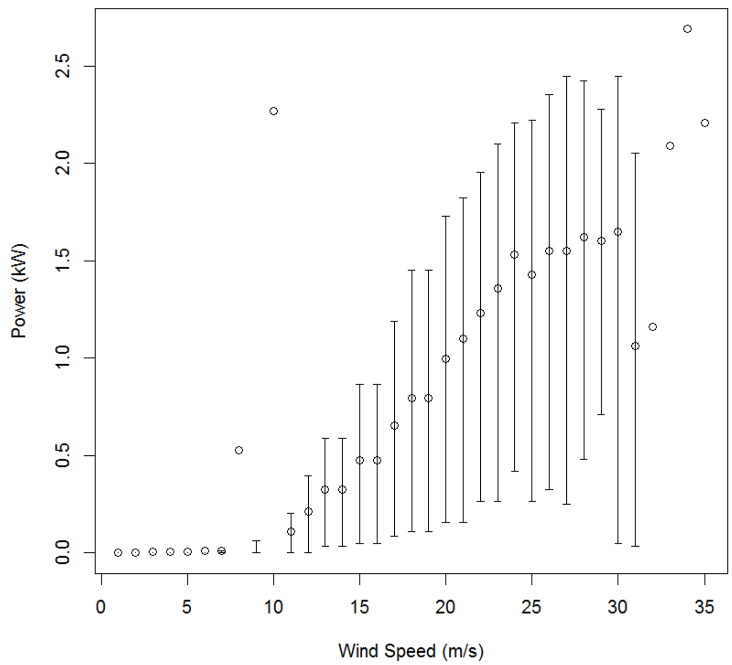
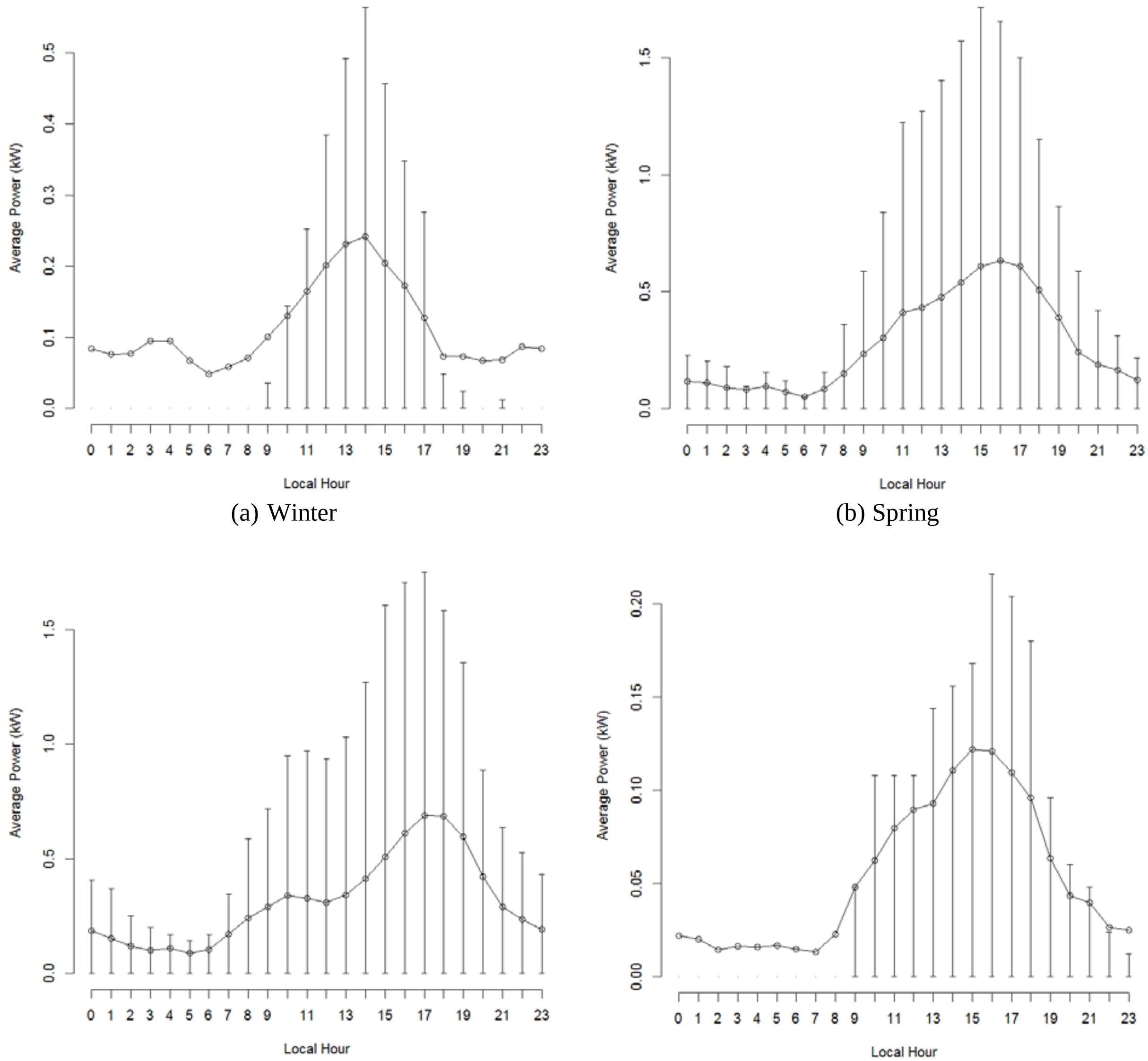


Figure 9.27. Power Generated by the Southwest Windpower Skystream 3.7 System as a Function of Wind Speed at 85 Feet

The typical hourly generation patterns for this wind turbine system are shown for each season in Figure 9.28. In this figure, Hour 0 is the hour that begins at midnight local Pacific Time. As has been shown for other of the site's wind turbine systems, wind production at the site peaks in the afternoon. Nighttime and morning wind generation are less reliable than afternoon generation.



(a) Winter (b) Spring

(c) Summer (d) Fall

Figure 9.28. Average Diurnal Wind Power Generation by Season for the Southwest Windpower Generator

Figure 9.29 shows the impact of these diurnal generation patterns on the total monthly HLH and LLH energy production by this wind system. For those several calendar months for which the project collected data for more than one year, the standard error bars have been included. It would be interesting to learn whether a longer data collection period would smoothen the pattern that is observed here during spring and summer months.

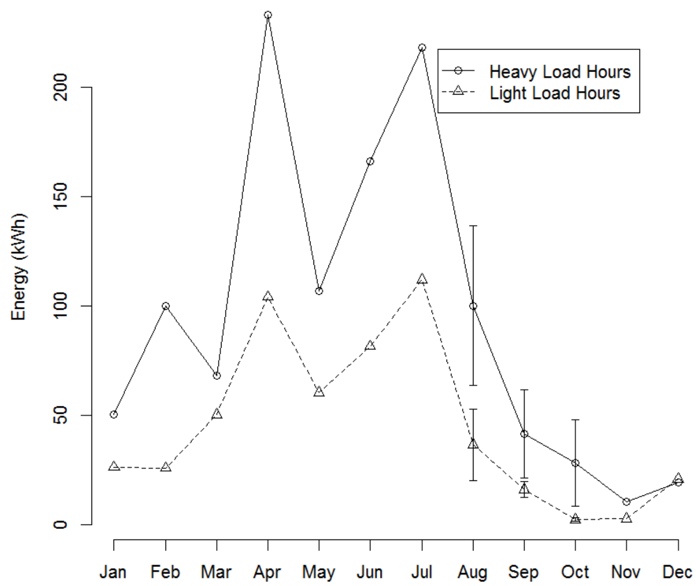


Figure 9.29. Observed HLH and LLH Energy Generated Each Calendar Month by the Southwest Windpower Generator

Energy generation each calendar month was compiled and is reported in Table 9.15 for HLH, LLH, and both hour types. Based on the monthly energy summary in this table, the wind generator system should be expected to generate about 1.7 ± 0.2 MWh per year. The annual value of this energy, based on the unit costs of HLH and LLH energy that would otherwise be supplied by BPA at its load-shaping rates is $45.13 ± 6.44.

The city's analysis led them to conclude that this turbine system would produce 1.33 MWh per year, somewhat less than what the project concluded (City of Ellensburg 2013c).

Table 9.15. Typical Energy Generated Each Month and the Monetary Value of the Displaced Energy for the Southwest Windpower System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	50	1.90	26	0.81	77	2.71
Feb	100	3.69	26	0.79	126	4.48
Mar	68.3	2.07	50	1.26	118	3.32
Apr	233	6.01	104	2.1	338	8.11
May	107	2.24	60	0.79	167	3.03
Jun	166	3.78	82	1.19	248	4.97
Jul	218	6.66	112	2.74	330	9.40
Aug	100	3.41 ± 2.48	37 ± 32	0.99 ± 0.87	137 ± 80	4.40 ± 2.63
Sep	41 ± 40	1.39 ± 1.35	16 ± 7	0.45 ± 0.2	58 ± 41	1.84 ± 1.37
Oct	28 ± 40	0.89 ± 1.25	2 ± 2	0.06 ± 0.05	31 ± 40	0.96 ± 1.26
Nov	10	0.37	3	0.09	13	0.46
Dec	20	0.76	21	0.69	40	1.45

As has been shown for other wind systems being tested by the City of Ellensburg, the impact of the generation on peak demand and demand charges is negligible. The monthly impacts are summarized in Table 9.16. Negative dollar values in this table represent reductions in the estimated demand charges that the city would incur. The sum impact is an increase in the total yearly demand charges by $0.60 ± 2.00.

Table 9.16. Typical Monthly Impact of Generation on Peak Demand for the Southwest Windpower System. Negative expenses are reductions in BPA demand charges.

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Expense ($)
Jan	0.1 ± 0.5	0.1	0.11
Feb	0.2 ± 0.5	0.3	0.65
Mar	0.1 ± 0.4	0.2	0.30
Apr	0.3 ± 0.6	0.6	2.24
May	0.3 ± 0.8	0.3	−0.55
Jun	0.6 ± 1.1	0.4	−1.02
Jul	0.6 ± 1.1	0.5	−0.32
Aug	0.3 ± 0.8	0.2 ± 0.2	−1.04 ± 0.85
Sep	0.2 ± 0.5	0.1 ± 0.1	−0.59 ± 0.50
Oct	0 ± 0.1	0.1 ± 0.1	0.33 ± 0.16
Nov	0 ± 0.1	0	0.17
Dec	0 ± 0.1	0	0.32

9.8 Bergey WindPower 10 kW Excel 10

The City of Ellensburg further complemented its power and energy requirements with the power generated by a 10 kW Bergey WindPower Excel 10 wind generator (Bergey WindPower 2012) located at its renewable energy park. This is one of the four commercial-class wind systems tested by the city. The system was functioning well at the time the city chose to remove all the site's wind generator systems in late 2013. The turbine is shown installed in Figure 9.30.

The annualized costs of the system and its components are listed in Table 9.17. The total system costs $29.9K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Figure 9.30. 10 kW Bergey Wind System at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

Table 9.17. City of Ellensburg Costs of 10 kW Bergey WindPower Excel 10 System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
10 kW Bergey Wind Turbine	100	15.2	15.2
SCADA and Monitoring	11	33.2	3.7
Consultants	11	18.5	2.0
Fiber Optic Communication	11	16.4	1.8
Outreach and Education	11	15.9	1.7
High-Voltage Equipment Installation	11	13.1	1.4
Low-Voltage Equipment Installation	11	7.8	0.9
Climate Data Equipment	11	6.7	0.7
Project Signs	11	7.4	0.8
Administrative	11	5.1	0.6
Fencing	11	4.6	0.5
Customer Service	11	1.0	0.1
Total Annualized Asset Cost			**$29.9K**

In a report dated November 1, 2013, posted on the city website, the one-time cost of the Bergey system was stated as $96,350 (City of Ellensburg 2013c).

9.8.1 Data for the Bergey WindPower System

All of the project's power generation data from the Bergey WindPower wind system is shown in Figure 9.31. The data was collected from the site metering point "MP-8." The system achieved and even exceeded its 10 kW nameplate power generation capacity often during this data collection period. Data was collected for almost a year, from mid-November 2012 until the end of October 2013.

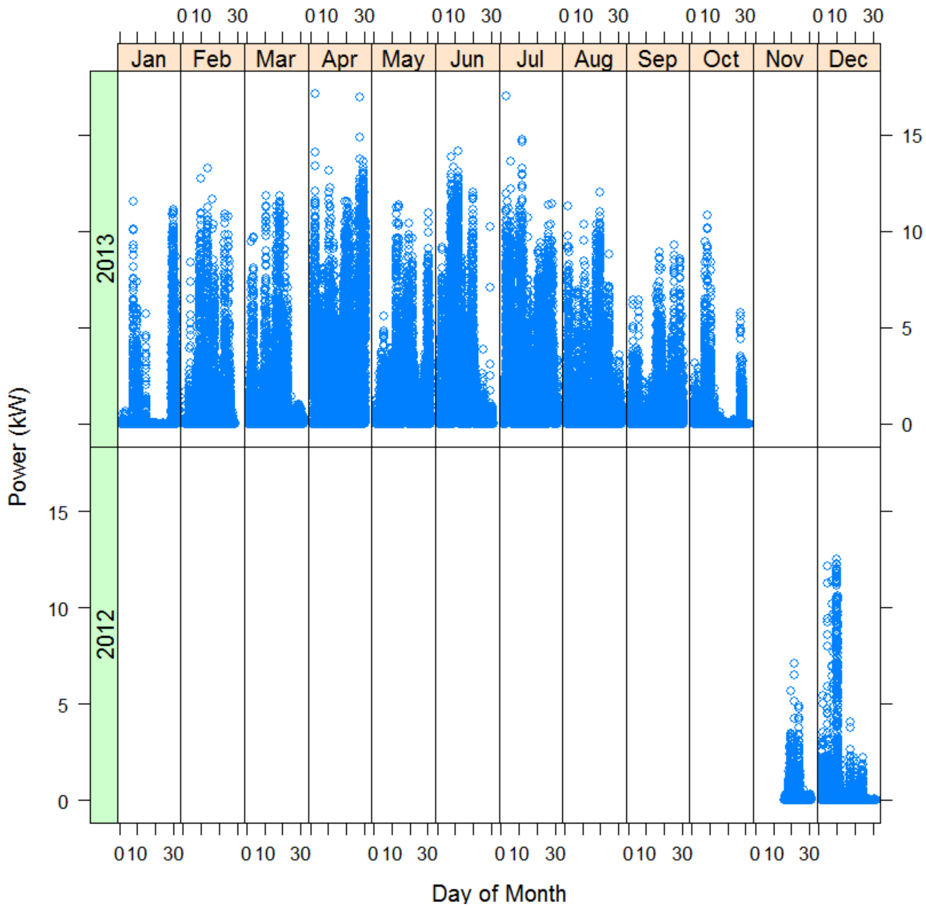


Figure 9.31. Power Generation Data for the Bergey WindPower Excel 10

9.8.2 Performance of the Bergey WindPower System

The project calculated the characteristic power generated by the Bergey wind generator as a function of wind speed. Figure 9.32 shows the result of this calculation. All the project's 5-minute interval power data was used along with the corresponding wind speeds that were measured 85 feet above ground at the project's metrology tower at the renewable energy park near the turbine. The markers are at the average generated power for the given wind speeds. The error bars represent the range of power data from the 16th through the 84th percentile. Wind speeds were found to have been discretized at 1 m/s increments.

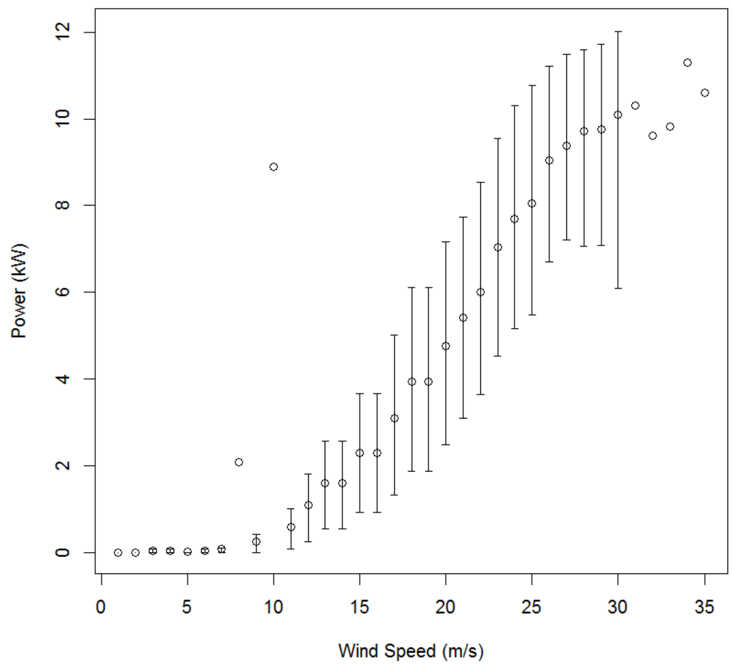
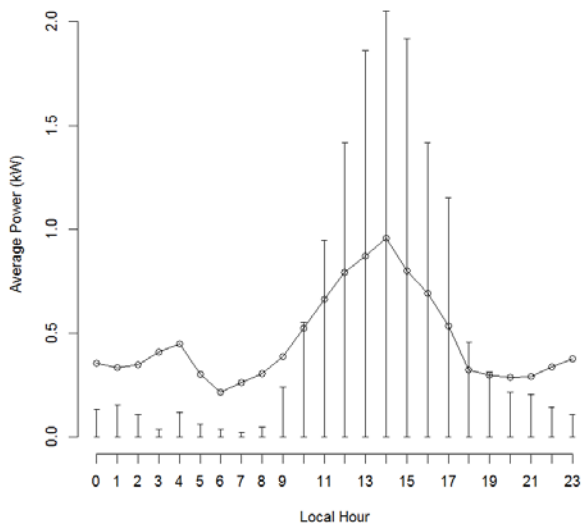
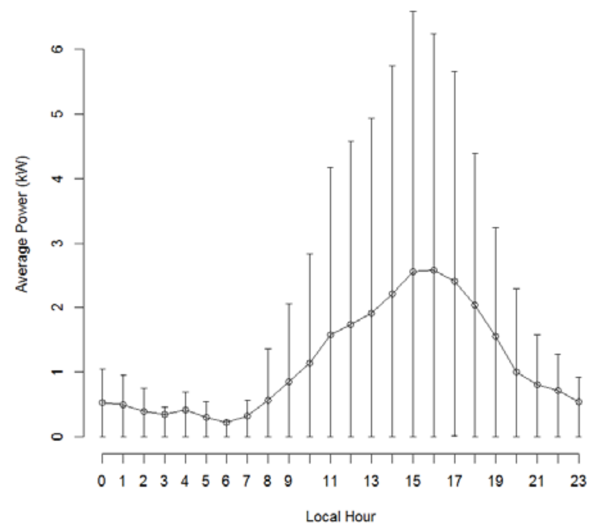


Figure 9.32. Characteristic Power Generation of the Bergey Windpower System as a Function of Wind Speed Measured at 85 Feet

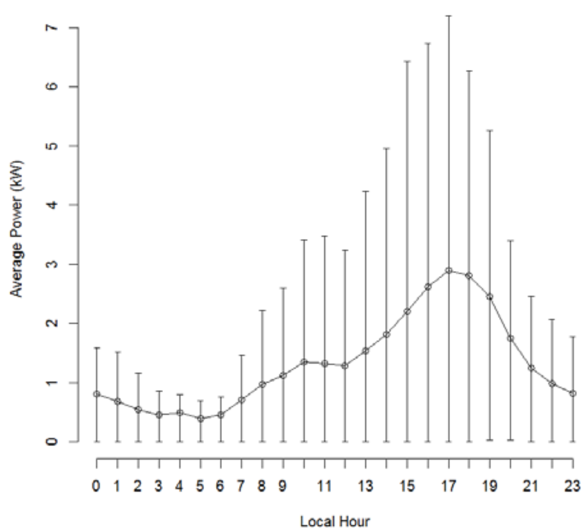
The average diurnal power generation patterns and variability of the output power have been plotted for each season in Figure 9.33. The hour value 0 represents the hour that begins midnight local Pacific Time. Morning power generation during winter and fall is so sporadic that those hours' average power generation magnitudes do not fall within the 16th and 84th percentile data range. Power generation is much more predictable the other months. Peak generation often occurs during afternoon hours. The average power generation is about 3 kW at the 17:00 hour during summer.



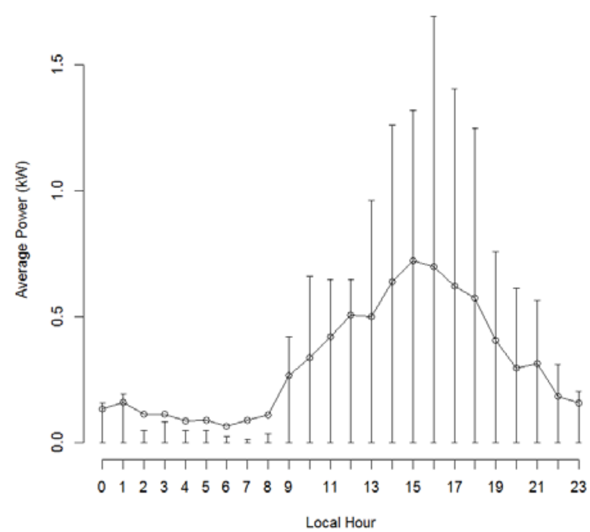
(a) Winter



(b) Spring



(c) Summer



(d) Fall

Figure 9.33. Hourly Power Generation of the Bergey Windpower System for Each Season

Figure 9.34 shows the impact of these diurnal generation patterns on the total monthly HLH and LLH energy production by this wind system.

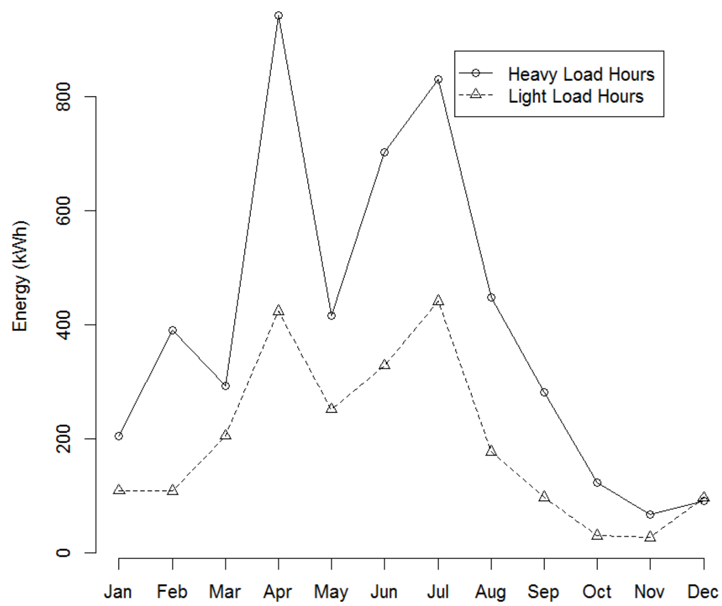


Figure 9.34. Amounts of HLH and LLH Energy Generated each Calendar Month by the Bergey Windpower System

Using the average power generation during HLHs and LLHs each month and the numbers of these hours each month of 2013, the project calculated the HLH, LLH, and combined energy generation for each calendar month. Based on the almost full year of operation that is represented in Table 9.18, this generator would generate 7.1 MW and thereby displace $191 worth of supply energy that the city would have otherwise purchased from BPA. The variability of this estimate from one year to another cannot be estimated well because less than one year of data was collected from the operation of this generator.

Table 9.18. HLH and LLH Energy Generation for Each Month and the Value of the Energy Supply that it Displaced for the Bergey Windpower System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	205	7.76	109	3.35	315	11.11
Feb	390	14.39	108	3.31	498	17.70
Mar	292	8.82	205	5.14	497	13.96
Apr	942	24.27	423	8.50	1360	32.77
May	415	8.71	251	3.29	666	12.00
Jun	702	15.95	328	4.78	1030	20.73
Jul	829	25.26	441	10.80	1270	36.07
Aug	447	15.18	177	4.78	623	19.96
Sep	281	9.45	97	2.70	378	12.15
Oct	123	3.89	30	0.82	153	4.72
Nov	68	2.41	27	0.84	94	3.24
Dec	92	3.56	96	3.21	188	6.77

In summer months, the operation of the wind turbine tended to reduce the determinant on which demand charges are applied, but the overall yearly net impact of the generation on incurred demand charges was estimated to be only $0.13. The use of wind generation neither helps nor hurts the calculation of demand charges throughout the entire year, as summarized in Table 9.19 for each calendar month.

Table 9.19. Estimated Monthly Impact on Peak Demand for the Bergey WindPower System

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Expense ($)
Jan	0.5 ± 2.1	0.5	0.19
Feb	0.8 ± 2.1	1.0	2.54
Mar	0.6 ± 1.9	0.7	1.31
Apr	1.0 ± 2.3	2.3	9.82
May	1.4 ± 3.1	1.0	−2.36
Jun	2.6 ± 4.9	1.8	−5.55
Jul	2.1 ± 4.0	2.0	−1.10
Aug	1.5 ± 3.5	1.0	−4.52
Sep	1.1 ± 2.3	0.7	−4.15
Oct	0.1 ± 0.6	0.3	1.34
Nov	0.0 ± 0.3	0.2	1.30
Dec	0.1 ± 0.6	0.2	1.31

9.9 Tangarie Alternative Power 10 kW Gale® Wind Turbine

The City of Ellensburg further complemented its power and energy requirements with the power generated by a 10 kW Tangarie Alternative Power Gale wind generator (Tangarie Alternative Power 2013) located at its renewable energy park. This is one of the four commercial-class wind systems tested by the city. The turbine is shown installed in Figure 9.35.

Figure 9.35. 10 kW Tangarie Wind System Installed at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The last credible data from this wind turbine was received August 8, 2012. The wind turbine's tower was blown over on April 29, 2013. See Figure 9.36. After this event, the City of Ellensburg chose to entirely halt its testing of wind systems and removed all its wind systems due to its concerns for the safety of pedestrians near the site.

Figure 9.36. Collapsed Tangarie Wind System

The annualized costs of the system and its components are listed in Table 9.20. The total system costs $34.2K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Table 9.20. City of Ellensburg Costs of 10 kW Tangarie Alternative Power Gale Wind Turbine System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
10 kW Tangarie Wind Turbine	100	20.0	20.0
SCADA and Monitoring	11	33.2	3.7
Consultants	11	18.5	2.0
Fiber Optic Communication	11	16.4	1.8
Outreach and Education	11	15.9	1.7
High-Voltage Equipment Installation	11	13.1	1.4
Low-Voltage Equipment Installation	11	7.8	0.9
Project Signs	11	7.4	0.8
Climate Data Equipment	11	6.7	0.7
Administrative	11	5.1	0.6
Fencing	11	4.6	0.5
Customer Service	11	1.0	0.1
Total Annualized Asset Cost			**$34.2K**

9.9.1 Data for the Tangarie System

Useful data were collected at site metering point “MP-9” during only two months of 2012. This power data is shown in Figure 9.37 for July and August 2012.

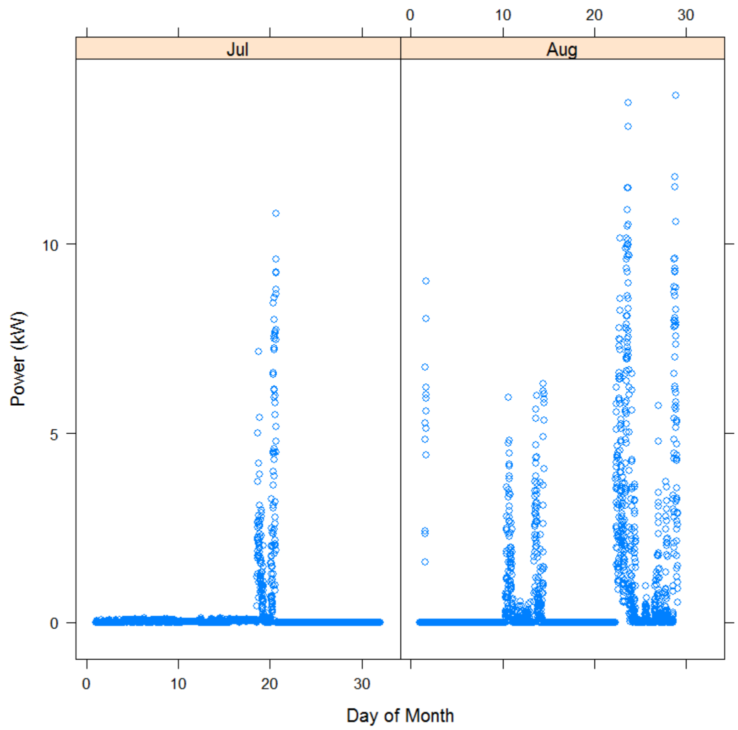


Figure 9.37. Tangarie Wind System Power Generation for the Two Months of 2012 that Data was Available

9.9.2 Performance of the Tangarie System

Figure 9.38 shows the average hourly power production from the two summer months that the wind turbine was operational.

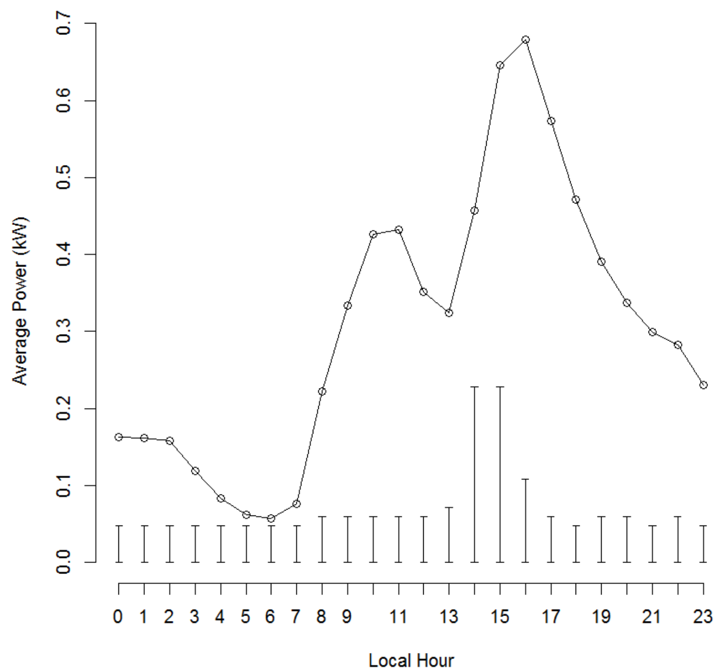


Figure 9.38. Average Diurnal Power Generation for July and August 2012 while the Tangarie Wind Turbine was Operational

Referring to Table 9.21, the wind system could have generated 474 kWh during July and August, and the value of this energy, based on the value of load-shaping supply energy that the city would otherwise purchase, would be $15.23. Given that the generator functioned for only two months before its tower toppled, the project will not estimate the total energy that might have been generated or the total value of the yearly energy it might have displaced.

Table 9.21. Quantities of HLH and LLH Energy Generated During the Two Months of Operation for the Tangarie System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jul	75	2.28	18	0.43	92	2.71
Aug	314	10.66	69	1.86	382	12.52

Referring to Table 9.22, the wind system could have reduced the city's demand charges somewhat, but the project will not estimate a yearly impact based on its limited operational data.

Table 9.22. Impact on Peak Demand for the Two Months of Operation of the Tangarie System

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Expense ($)
Jul	0.2	0.2	0.2
Aug	1.2	0.7	−4.84

9.10 Urban Green Energy 4 kW Wind Turbine

The City of Ellensburg further complemented its power and energy requirements with the power generated by a 4 kW Urban Green Energy (Urban Green Energy 2015) wind generator located at its renewable park. This is one of the four commercial-class wind systems tested by the city. The turbine is shown installed in Figure 9.39.

Figure 9.39. 4 kW Urban Green Energy Wind System at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The Urban Green Energy generator failed. The unit had a bearing failure causing a grinding noise while operating. The city's attempts to get it serviced failed. The unit ceased to generate electricity and was shut down.

The annualized costs of the system and its components are listed in Table 9.23. The total system cost $26.8K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Table 9.23. City of Ellensburg Costs of 4 kW Urban Green Energy Wind Turbine System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
4 kW Urban Green Energy Wind Turbine	100	12.5	12.5
SCADA and Monitoring	11	33.2	3.7
Consultants	11	18.5	2.0
Fiber Optic Communication	11	16.4	1.8
Outreach and Education	11	15.9	1.7
High-Voltage Equipment Installation	11	13.1	1.4
Low-Voltage Equipment Installation	11	7.8	0.9
Project Signs	11	7.4	0.8
Climate Data Equipment	11	6.7	0.7
Administrative	11	5.1	0.6
Fencing	11	4.6	0.5
Customer Service	11	1.0	0.1
Total Annualized Asset Cost			**$26.8K**

9.10.1 Data for the Urban Green Energy System

All the power generation data observed for the Urban Green Energy wind turbine system is shown in Figure 9.40. Usable data was gathered and delivered for a period from mid-July 2012 until mid-March 2013, a period of about eight months. The source of this data was site metering point “MP-10.” Spring is poorly represented, with less than one month’s data.

The generated power magnitudes in 2012 were greater than those in 2013. While this variability could potentially be caused by natural wind variability, it is more likely that the performance of the wind generator degraded over the months that it was monitored by the project. The reduction in wind power was not similarly observed for other of the Ellensburg wind turbines. The initial 2012 power had at times approached the turbine’s nameplate capacity, but it never did so in 2013.

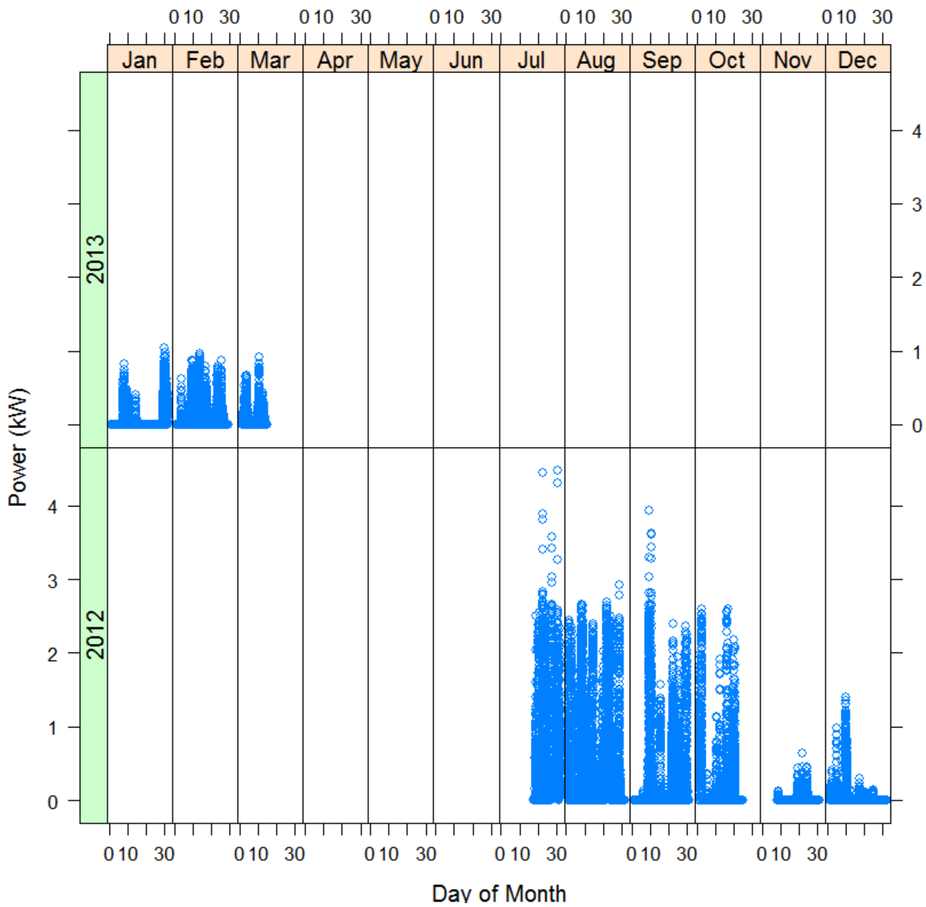
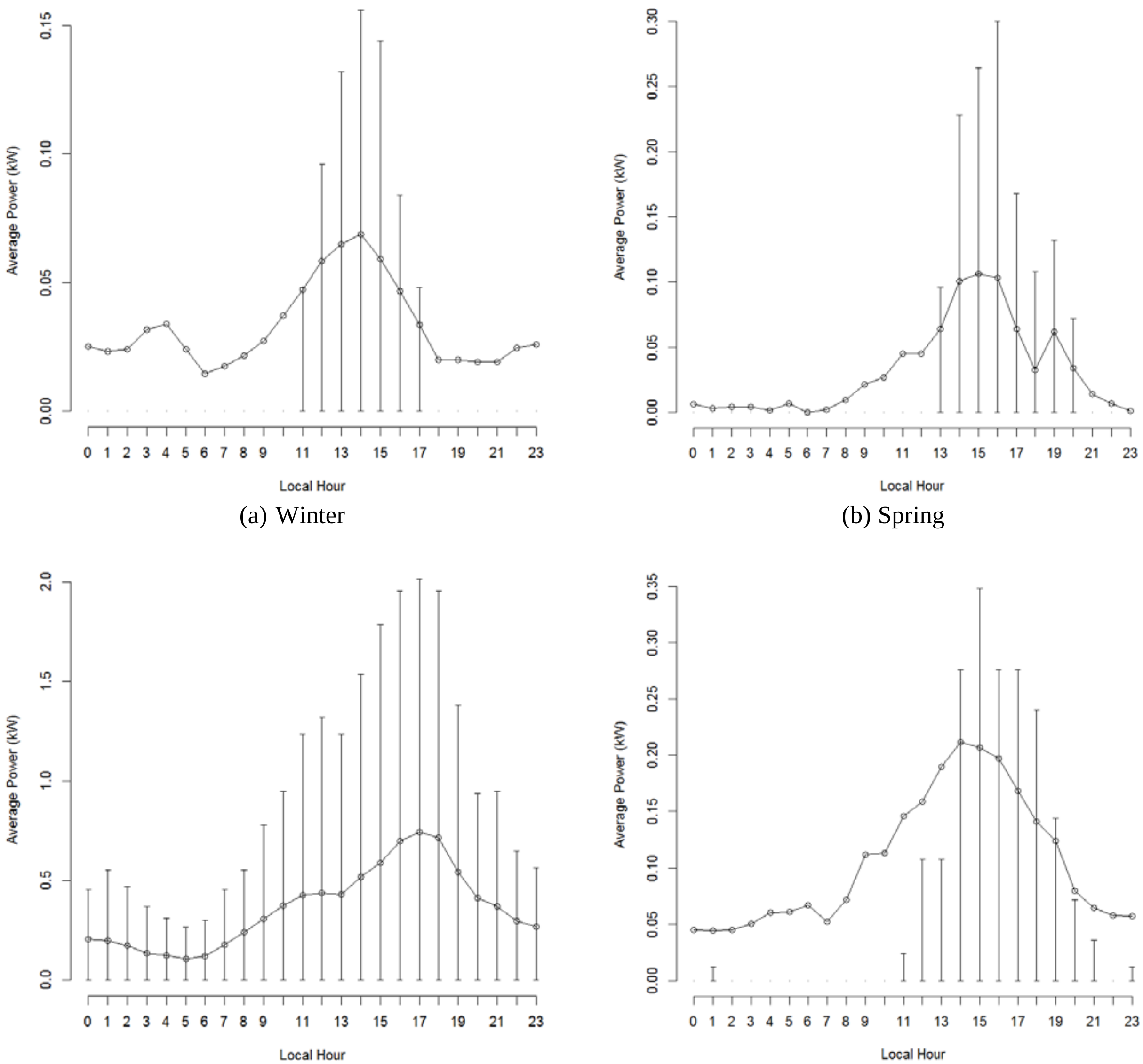


Figure 9.40. Power Generation for the Urban Green Energy Wind Turbine System

9.10.2 Performance of the Urban Green Energy System

Given the apparent change in the Urban Green Energy generator output after October 2012, analysts determined that a plot of the system's characteristic wind generation as a function of wind speed would likely be inaccurate, thus misleading. The project elected not to publish such a characteristic curve for this wind system.

The average seasonal diurnal power generation has been plotted in Figure 9.41. The hour 0 refers to the hour that begins at midnight local Pacific Time. The error bars span the range of data from the 16th to the 84th percentiles. The summer plot includes only the available late July and August 2012 data. The spring plot includes only the data that was available from early March 2013. Analysts suspect that the system's performance degraded significantly after October 2012, so the generated diurnal power levels reported for fall, winter, and spring are probably inaccurate due to the degradation of the system's performance.



(a) Winter (b) Spring

(c) Summer (d) Fall

Figure 9.41. Average Diurnal Power Generation by Season for the Urban Green Energy System

The impacts of the diurnal generation patterns affected the average monthly HLH and LLH energy generation as is shown in Figure 9.42. Data was available for only eight of the 12 calendar months.

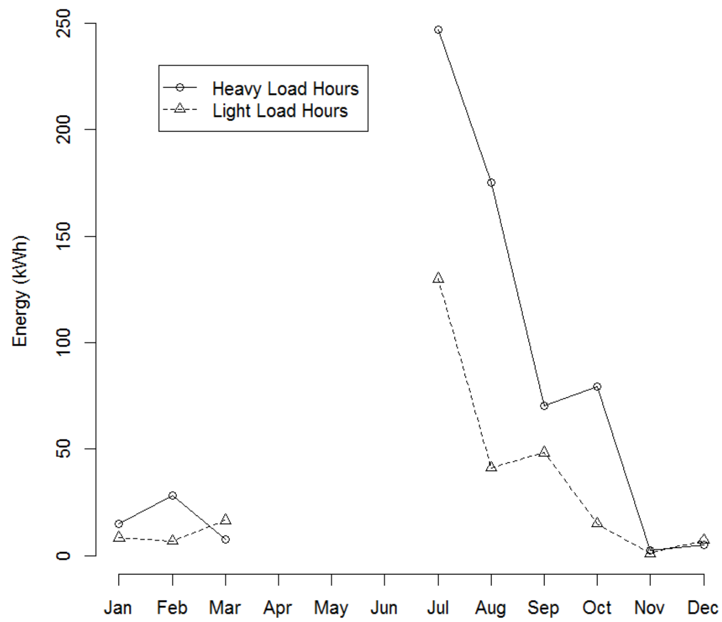


Figure 9.42. HLH and LLH Energy Production for the Urban Green Energy System, for Months that Data was Available

Annual generation would be 1.2 MWh, presuming the generator had operated throughout the year and the months of data collection were typical. The total annual value of displaced energy supply would be $26.93 if the generator had produced throughout the year and presuming the months of data collection can be used to represent the entire year. Table 9.24 lists the HLH, LLH, total energy, and the monetary values of these amounts of energy by calendar month. No estimate can be made for the variability in these calculations because data was collected for less than one year.

Table 9.24. Energy and Monetary Value of Displaced Energy Supply by Calendar Month for the Urban Green Energy System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	15	0.57	8	0.26	23	0.82
Feb	28	1.04	7	0.21	35	1.25
Mar	8	0.23	17	0.42	24	0.65
…	-	-	-	-	-	-
Jul	247	7.55	130	3.19	378	10.73
Aug	175	5.94	41	1.12	216	7.05
Sep	70	2.37	48	1.35	119	3.72
Oct	79	2.50	15	0.41	94	2.92
Nov	2	0.09	1	0.03	4	0.12
Dec	5	0.20	7	0.24	12	0.44

The monthly impacts of this wind generation on peak demand and demand charges have been listed in Table 9.25. The total impact of this renewable generation on peak demand might be a reduction of only about $2, based on the impacts during the nine calendar months that data was available to the project.

Table 9.25. Impact of Generation on Peak Demand for the Urban Green Energy System

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Expense ($)
Jan	0.0 ± 0.2	0.0	0.01
Feb	0.1 ± 0.2	0.1	0.20
Mar	0.0 ± 0.0	0.0	0.08
…	-	-	-
Jul	0.6 ± 1.2	0.6	0.10
Aug	0.6 ± 1.2	0.4	−1.96
Sep	0.2 ± 0.8	0.2	−0.61
Oct	0.1 ± 0.4	0.2	0.64
Nov	0.0 ± 0.0	0.0	0.05
Dec	0.0 ± 0.0	0.0	0.09

9.11 Ventera Wind 10 kW VT10 Wind Turbine

The City of Ellensburg installed and operated a 10 kW Ventera Wind VT10 wind generator (Ventera Wind 2015) at its renewable park. This is one of four commercial-class wind systems that were tested by the city. Again, the city was investigating how its need for energy supply and demand might be impacted by renewable energy generation. The turbine is shown installed in Figure 9.43.

Figure 9.43. 10 kW Ventera Wind System at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The annualized costs of the system and its components are listed in Table 9.26. The total system costs $27.8K per year on an annualized basis. The greatest cost was for the turbine generator, followed by the costs of communication upgrades, consultancy, electrical hardware upgrades, and other site upgrades.

Table 9.26. City of Ellensburg Costs of 10 kW Ventera Wind Turbine System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
10 kW Ventera Wind Turbine	100	13.6	13.6
SCADA and Monitoring	11	33.2	3.7
Consultants	11	18.5	2.0
Fiber Optic Communication	11	16.4	1.8
Outreach and Education	11	15.9	1.7
High-Voltage Equipment Installation	11	13.1	1.4
Low-Voltage Equipment Installation	11	7.8	0.9
Project Signs	11	7.4	0.8
Climate Data Equipment	11	6.7	0.7
Administrative	11	5.1	0.6
Fencing	11	4.6	0.5
Customer Service	11	1.0	0.1
Total Annualized Asset Cost			**$27.8K**

In a report to its city council, the one-time installed cost of the Ventera Wind system was stated as $110,660 (City of Ellensburg 2013b).

9.11.1 Data for the Ventera Wind System

Referring now to Figure 9.44, the City of Ellensburg supplied a data stream of the energy generated every 5 minutes for the period from the beginning of January until late October 2013. The source of this data was the city's site metering point "MP-11." The system never generated its 10 kW nameplate capacity, but it occasionally exceeded an 8 kW power output.

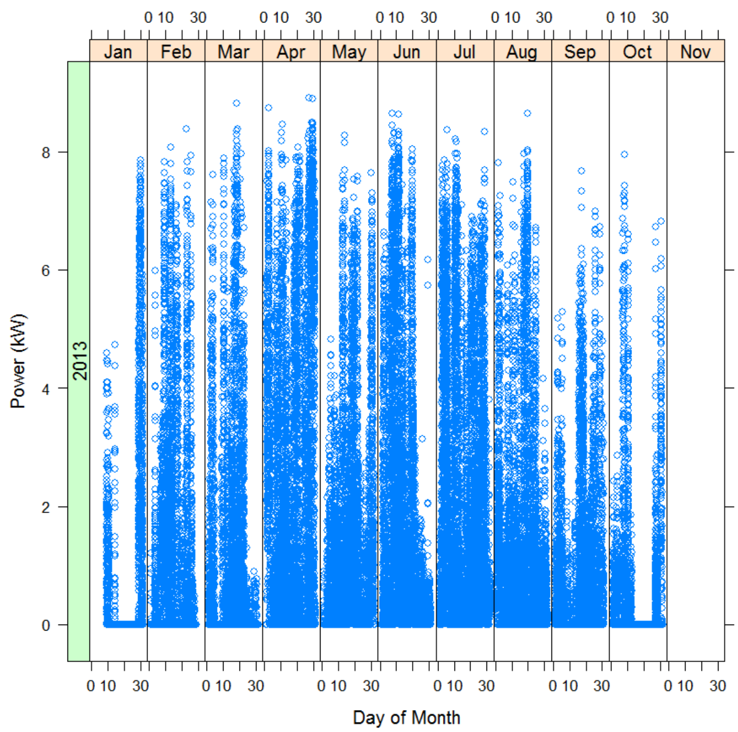


Figure 9.44. Available Power Generation Data from January through October 2013 for the Ventera Wind System

9.11.2 Performance of the Ventera Wind System

According to the Ventera Wind website, the generator is rated to start at winds of 2.7 m/s (6 mph) and generate 10 kW at wind speeds of 13 m/s (29 mph). It is advertised to withstand winds at 58 m/s (130 mph).

The characteristic power generation of the Ventera Wind system was checked by plotting power generation as a function of wind speed that was measured 36 feet above ground at the renewable energy park site. The results are shown in Figure 9.45. All of the available 5-minute power and wind-speed data were used for this figure. The markers represent average generated power at the given wind speed, and the error bars represent a span of data from the 16th to the 84th percentiles. Substantial power was generated at high winds, but the results fall short of the claims in the preceding paragraph.

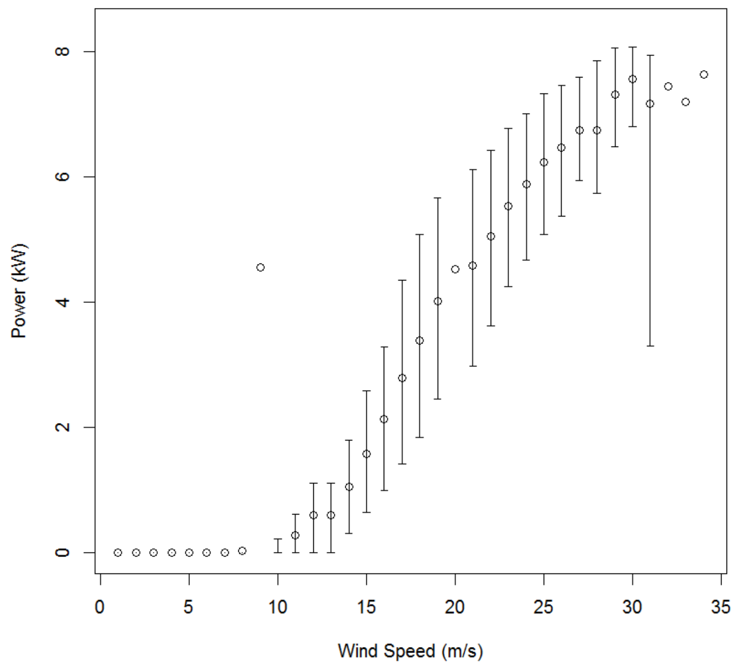
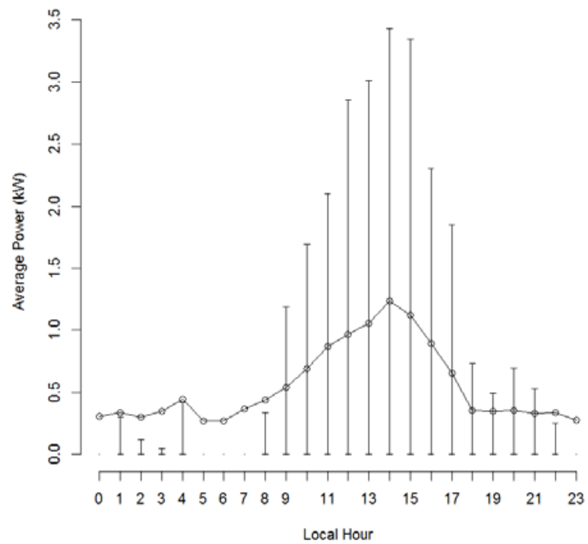
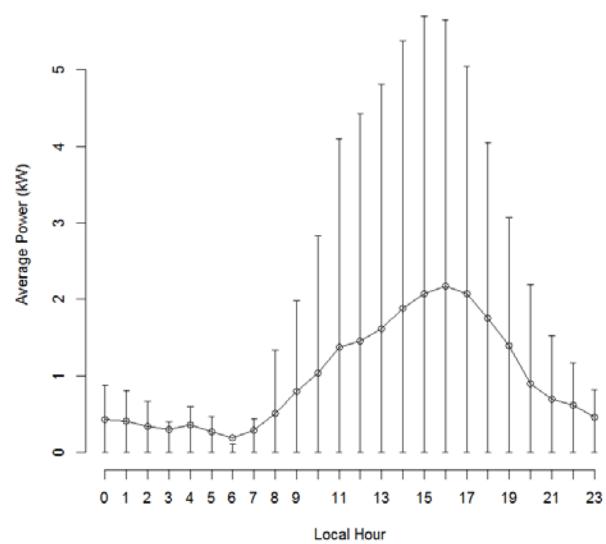


Figure 9.45. Characteristic Power Generation as a Function of Wind Speed at 36 Feet for the Ventera Wind System

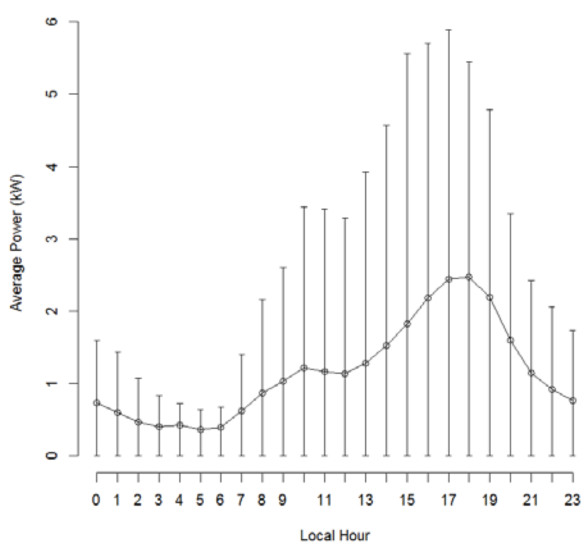
The average hourly power generation each season is shown in Figure 9.46 for the Ventera Wind system. Unlike what has been found for other of the wind systems, the average power generation in these figures often lies within the 16th to 84th percentile data range. It would appear that the generator does indeed activate and generate power at relatively low wind speeds as was claimed.



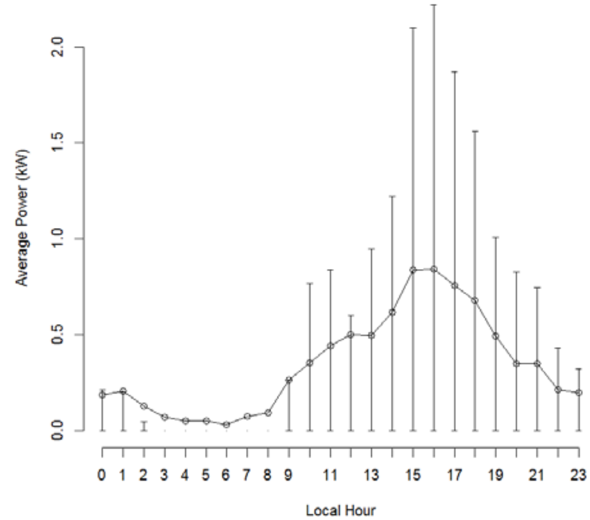
(a) Winter



(b) Spring



(c) Summer



(d) Fall

Figure 9.46. Hourly Power Generation Patterns by Season for the Ventera Wind System

The impact of these diurnal power generation patterns on the monthly energy production has been summarized in Figure 9.47. The amounts of energy production during HLH and LLH hours have been shown separately.

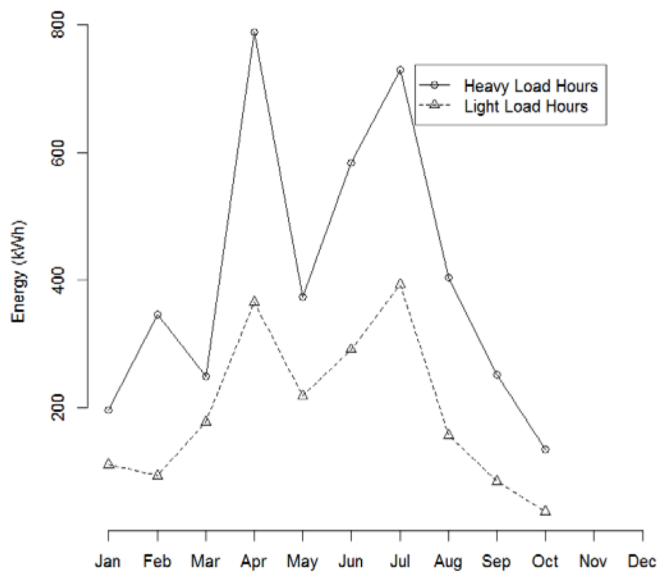


Figure 9.47. HLH and LLH Energy Generated as a Function of Calendar Month for the Ventera Wind System. No data was available for the months of November or December.

Table 9.27 lists the HLH and LLH energy that was generated each calendar month by the Ventera Wind generator system. If the 10 monitored months of generation can be meaningfully extrapolated, then the wind system might generate about 7.2 MWh per year. For comparison, the Ventera Wind website (Ventera Wind 2015) projected that this system would generate 24 MWh per year given a 6.5 m/s (14.5 mph) wind speed at its hub.

Extrapolating from the 10 calendar months for which data was available, the value of annual displaced energy supply would be about $192, based on recent BPA load-shaping rates. The variability in this projection will not be estimated because less than one year of data was available.

Table 9.27. Monthly HLH and LLH Energy Production and the Monetary Value of Displaced Supply Energy for the Ventera Wind System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	196	7.42	110	3.38	307	10.80
Feb	346	12.75	93	2.86	439	15.61
Mar	248	7.50	177	4.44	425	11.94
Apr	789	20.33	365	7.34	1,150	27.67
May	374	7.85	218	2.85	592	10.70
Jun	584	13.26	291	4.24	874	17.50
Jul	729	22.22	393	9.62	1,120	31.83
Aug	404	13.71	156	4.22	559	17.93
Sep	251	8.45	84	2.35	335	10.80
Oct	134	4.24	37	1.01	171	5.25
…	-	-	-	-	-	-

If we can extrapolate the estimated monthly change in demand charges from the 10 months that data is available (see Table 9.28), the result would be a reduction in these charges of only $2.65 for the year. In fact, the missing months were winter months, so it is likely that the impact would be even less. Wind generation does not significantly affect calculated BPA demand charges at this location.

Table 9.28. Impact of Generation on Peak Demand for the Ventera Wind System

	Demand (kW)	aHLH (kWh/h)	Expense ($)
Jan	0.5 ± 1.9	0.5	−0.15
Feb	0.7 ± 1.9	0.9	2.00
Mar	0.5 ± 1.5	0.6	1.20
Apr	0.9 ± 2.1	1.9	7.69
May	1.2 ± 2.7	0.9	−1.94
Jun	2.0 ± 3.6	1.5	−3.95
Jul	1.8 ± 3.5	1.8	−0.86
Aug	1.3 ± 3.0	0.9	−3.53
Sep	1.1 ± 2.2	0.7	−3.92
Oct	0.2 ± 0.8	0.3	1.25
…	-	-	-

9.12 Wing Power 1.4 kW Wind Turbine

The City of Ellensburg hoped to still further supplement its power and energy requirements with the power generated by a 1.4 kW Wing Power wind generator (Wing Power Energy 2012). This is among a set of five residential-class wind systems that were installed and tested by the City of Ellensburg. The turbine is shown installed at the renewable energy park site in Figure 9.48.

Figure 9.48. 1.4 kW Wing Power Wind System at the Ellensburg Renewable Energy Park (City of Ellensburg 2013a)

The city apparently needed to replace the Wing Power wind system several times during the project. In a November 1, 2013, report to the city council, two wing failures had occurred, and failed bolts were recurring issues. A third unit was installed by the city (City of Ellensburg 2013c). The city chose to remove all the wind turbine systems, including this one, in late 2013.

The annualized costs of the wind system and its components are listed in Table 9.29. The greatest costs were to update site SCADA and fiber optic communications. Technical consultants, too, were more expensive than the wind system itself.

Table 9.29. City of Ellensburg Costs of 1.4 kW Wing Power Wind Turbine System

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
SCADA and Monitoring	8	33.2	2.7
Consultants	8	18.5	1.5
Fiber Optic Communication	8	16.4	1.3
Outreach and Education	8	15.9	1.3
1.4 kW Wing Power Wind Turbine	100	1.3	1.3
High-Voltage Equipment Installation	8	13.1	1.0
Climate Data Equipment	8	6.7	0.5
Low-Voltage Equipment Installation	8	7.8	0.6
Project Signs	8	7.4	0.6
Fencing	8	4.6	0.4
Administrative	8	5.1	0.4
Customer Service	8	1.0	0.1
Total Annualized Asset Cost			**$11.7K**

9.12.1 Data for the Wing Power System

Power generation data from this wind turbine system was received from August 2012 through November 2013. The raw data was the energy generated every 5 minutes at the site's "MP-7" metering point. Data after December 10, 2013, remained zero and was removed from analysis. Figure 9.49 displays all the available data. Generation data greater than 5 kW—twice the nameplate generation—was discarded. Power generated in early in the test period during 2012 attained values greater than those in 2013. That the power generation became smaller over time might be a sign of generator fatigue. Generator output approached the 1.4 kW nameplate capacity into fall 2012, but never again through the remaining data collection period.

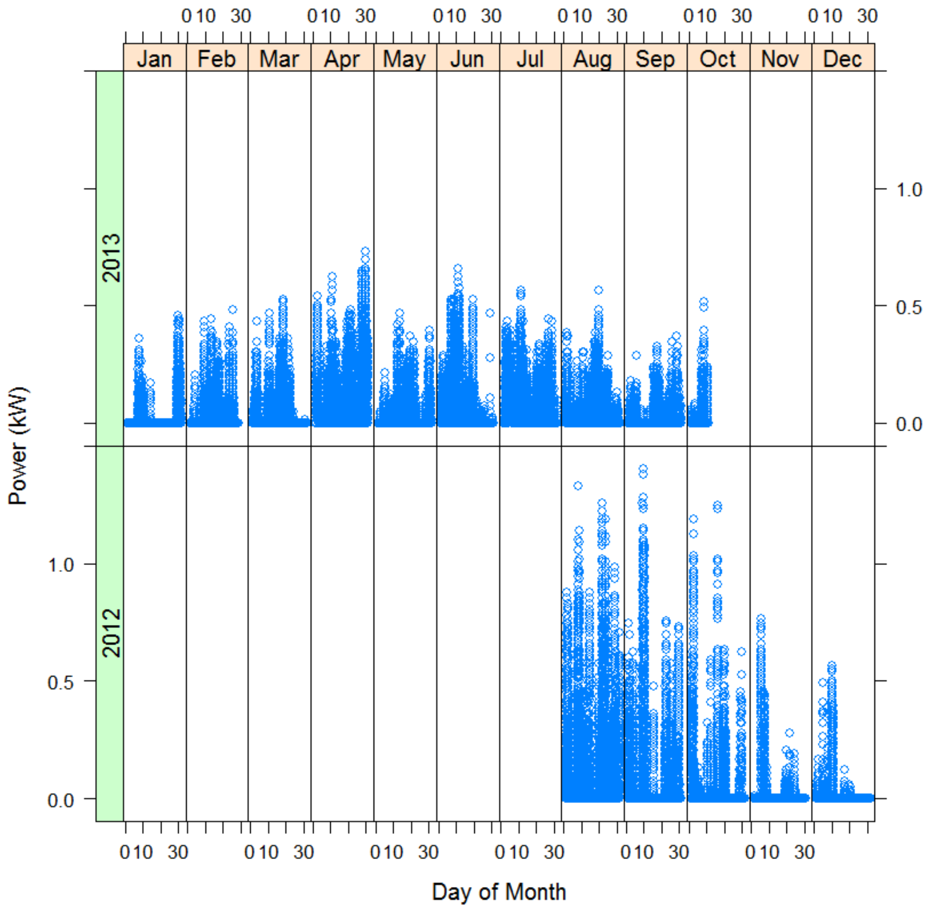
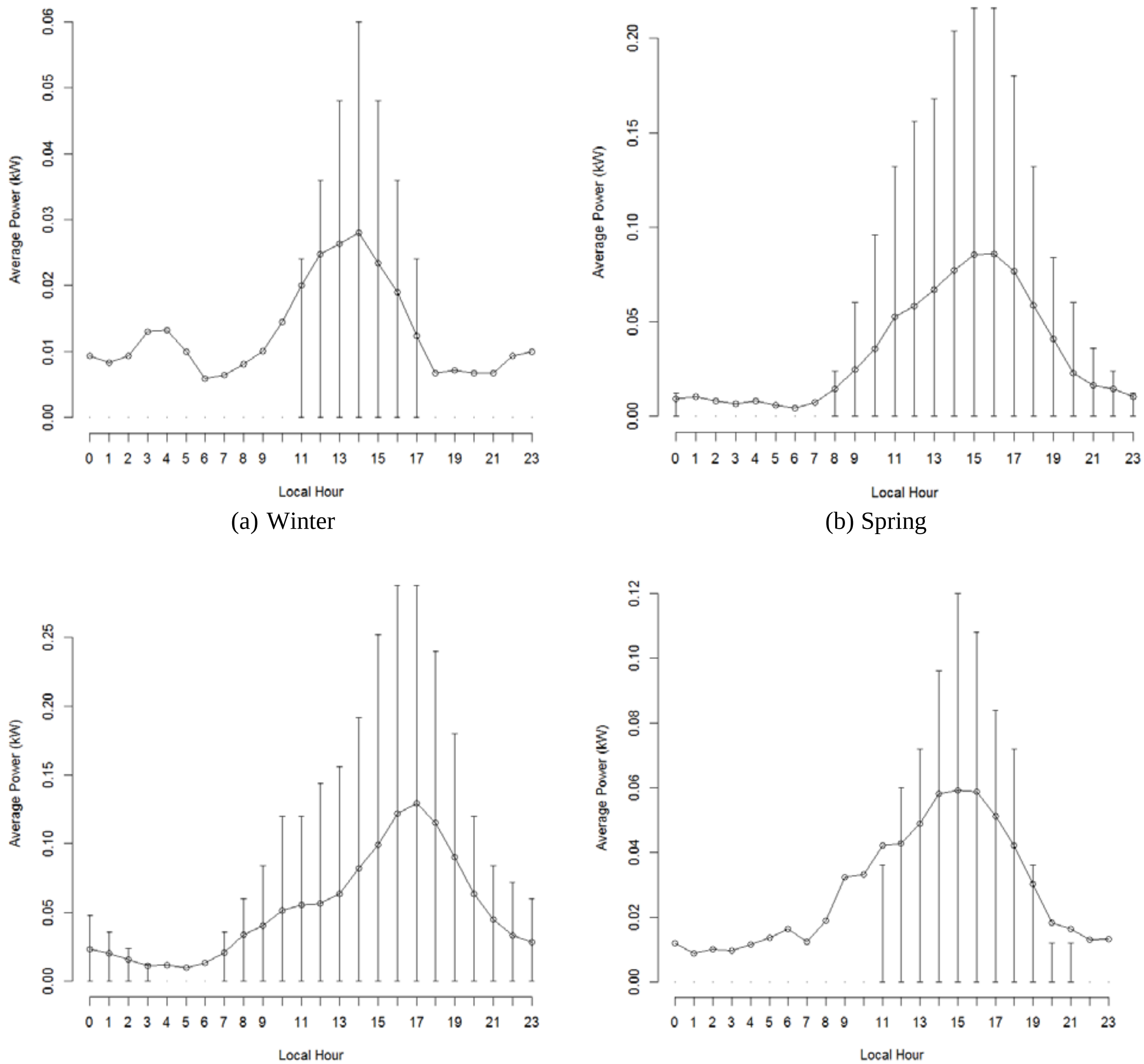


Figure 9.49. Wind Power Generation Data Received by the Project for the Wing Power System

9.12.2 Performance of the Wing Power Turbine System

Given the apparent reduction in power generation over time by this system, the project chose not to present a characteristic power curve as a function of wind speed. That characteristic curve would likely be inaccurate or misleading.

Refer to the average diurnal power generation for the four seasons in Figure 9.50. Hour 0 in these figures is the hour that begins midnight local Pacific Time. The greatest average generation occurred during the summer. About 125 W was generated, on average, during summer early afternoons. Wind generation is most productive and reliable in the early afternoon, regardless of season. The apparent generator fatigue discussed in Section 9.12.1 and evident in Figure 9.49 affected (reduced) the calculated seasonal power generation every season.



(a) Winter (b) Spring

(c) Summer (d) Fall

Figure 9.50. Hourly Generation Patterns by Season for the Wing Power System

The HLH, LLH, and combined energy production for each calendar month are provided in Table 9.30. The variabilities of the averaged energy and monetary values in Table 9.30 are quite large for those months that data was collected in both 2012 and 2013. This is probably caused again by the degradation in system performance that occurred between 2012 and 2013. Energy production in 2013 was nearly halved compared to that in 2012. Therefore, the ranges of variability have magnitudes similar to those of the energy production and monetized values themselves. Regardless, the system might be projected to generate 270 ± 80 kWh in a typical year. The total value of annual generated energy is projected to be only about $7.50 ± 2.40.

Table 9.30. Generated Energy and the Value of the Supply that it Displaced for the Wing Power System

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	6	0.22	3	0.10	9	0.32
Feb	11	0.42	2	0.08	14	0.5
Mar	8	0.25	6	0.14	14	0.39
Apr	31	0.79	12	0.25	43	1.04
May	11	0.24	6	0.08	17	0.31
Jun	22	0.50	9	0.13	31	0.63
Jul	25	0.76	11	0.27	36	1.03
Aug	35 ± 33	1.19 ± 1.11	7 ± 5	0.20 ± 0.15	43 ± 33	1.39 ± 1.12
Sep	15 ± 12	0.52 ± 0.41	11± 14	0.31 ± 0.38	27 ± 18	0.83 ± 0.56
Oct	17 ± 9	0.54 ± 0.3	3 ± 3	0.08 ± 0.08	20 ± 10	0.62 ± 0.31
Nov	7	0.23	2	0.05	8	0.28
Dec	2	0.07	3	0.10	5	0.17

The impact of the wind generation on peak demand was found to be trivial—less than $1.

9.13 Conclusions and Lessons Learned

The City of Ellensburg tested altogether two solar panel technologies and nine wind turbine generators during the PNWSGD project. The two solar technologies—polycrystalline and thin-film—produce significant, predictable quantities of energy and continue to operate today.

The wind generators were not as reliable and produced relatively small amounts of energy for the city. Altogether, four of the nine wind generators failed. Two of the five residential-class wind generators—the 1.2 kW Windspire and 1.5 kW Honeywell WindTronics turbines—failed to operate throughout the short demonstration period. Two of the four commercial-class wind generator systems—the 4.0 kW Urban Green Energy and 10 kW Tangarie Alternative Power turbines—also failed during the demonstration period. In the case of the Tangarie Alternative Power system, its tower toppled, after which the City of Ellensburg committed to quickly remove all its wind and metrology towers.

The projected annual energy generation and its monetary values, according to BPA load-shaping rates, have been summarized in Table 9.31. The solar arrays each generate about 80 MWh per year that is worth thousands of dollars, even using the modest value of the displaced wholesale electricity supply, as was done here. The commercial wind generators and the 2.4 kW Southwest Windpower Skystream 3.7, too, produced thousands of kWh of energy per year that was worth from $45 to under $200 each year, based on the value of displaced wholesale electricity that the city would otherwise buy. Excepting the 2.4 kW Southwest Windpower Skystream 3.7, the residential-class wind generators produced very little energy, which was worth less than $10 per year. This evaluation was conducted from the perspective of the utility. The generated energy might be valued more from the perspectives of customers, who pay a higher retail rate.

Table 9.31. Projected Annual Energy Generation and Monetized Value of the Energy for each Technology

Tested Renewable Generator Technologies	Cost ($/year)[a]	Generation (kWh/year)	Capacity Factor (%)	Energy Value ($/year)
Solar Technologies				
56 kW polycrystalline	8,600	81,900 ± 3,300	16.7	2,377 ± 104
54 kW thin-film	39,400	80,700 ± 3,000	17.1	2,335 ± 94
Residential-Class Wind Turbine Technologies				
1.5 kW Honeywell WindTronics WT6500[b]	16,000	29	0.2	~1
1.2 kW Windspire[b]	15,400	76	0.7	~2
2.25 kW Home Energy International Energy Ball	15,300	153 ± 10	0.8	4
2.4 kW Southwest Windpower Skystream 3.7	14,900	1,700 ± 200	8.1	45 ± 6
1.4 kW Wing Power	11,700	270 ± 80	2.2	8 ± 2
Commercial-Class Wind Turbine Technologies				
10 kW Bergey WindPower Excel 10	29,900	7,100	8.1	191
10 kW Tangarie Alternative Power Gale[b]	34,200	-[c]	-[c]	-[c]
4 kW Urban Green Energy[b]	26,800	1,200	3.4	27
10 kW Ventera Wind VT10	27,800	7,200	8.2	192

(a) This cost may include the costs of the installed generator, plus many system costs for metering, administration, signage, outreach, maintenance, system communications, etc. Refer to the individual sections to view a more complete listing of cost components.

(b) This wind generation system failed during the demonstration period.

(c) Annual production is not being estimated. Data was generated for only two project months.

Table 9.31 also includes the calculated capacity factor, which is the average generation over all hours stated as a percentage of the systems' declared nameplate capacity. The solar arrays were found to generate, on average, about 17% of their nameplate rating. The wind generators' capacity factors were lower: 4–8% for the Southwest Windpower and commercial-class generators, and less than 1 for the other residential-class wind systems.

The project analyzed the impact that these renewable generators would have on demand and the demand charges that are incurred by the City of Ellensburg. The impacts were small to negligible. The solar generator systems tended to reduce the utility's peak demand in the summers, when the monthly peak hour was likely to occur while the generators were producing power. But those gains were offset in winter when the coincidence was poor. The generators appear to increase demand charges in the winter. The net impacts were small increases of less than $25 in yearly demand charges for each of the two solar arrays.

Because wind generation produced less energy and is fairly randomly distributed over time, the impacts of the wind generators on peak and incurred demand charges were even less than calculated for the solar arrays.

Annualized costs of the polycrystalline system were 3.6 times greater than the annual value of the displaced BPA energy supply for the City of Ellensburg even though the solar panels of this system were preexisting and were not included in the system costs.

The City of Ellensburg received benefit from the visibility of the renewable technologies at its renewable energy park site. These benefits are indirectly realized, and the project did not attempt to monetize them.

The way that the project elected to report annualized system costs creates a pessimistic view of the return on investment for these technologies. The costs, summarized above in Table 9.31, generally included not only the costs of the installed generator technologies, but also many costs that the utility incurred to meter the performance of these technologies and communicate the performance and status back to the utility and to the project. Some of these expenditures and activities had been requested by the project and its clients for the purposes of the demonstration and might not have been necessary otherwise. The project had elected to account for benefits from the utility's perspective, which devalued the impacts on transmission, generation, and customers, which impacts do not directly accrue for the utility.

Following is a summary of the lessons learned as the City of Ellensburg implemented its renewables park as a utility site participant in the PNWSGD project.

Even having signed contracts with prepayments to vendors did not mean the products would be delivered. There are many vendors who only exist on the Web. Small wind turbines are finicky, and maintenance issues are frequent on some units. Local suppliers come and go and cannot be depended upon to provide ongoing maintenance. Our project site was originally intended to use two types of flat-panel solar panels, one concentrating-solar system, and eight small wind systems. The city had hoped to make real-world comparisons of reliability, efficiency and cost-effectiveness of a variety of small renewable systems. The city also hoped to demonstrate the viability of using the aggregated power from small renewable systems as a means to help alleviate some of the overgeneration issues the region faces at times.

The city wanted to test many diverse renewable generation technologies. It went through four concentrating-solar vendors, including signing contracts and paying a deposit with one of the vendors. The vendor went out of business, taking a large deposit with them. The city ultimately could not find a vendor who could provide a concentrating-solar product. For the eight small wind systems the city had originally identified, only half of them were still available in the marketplace by the time the project moved into its construction phase. The city finally found replacement vendors and installed nine small wind systems (one was experimental and was provided to the project at no charge), but it took over a year and review of more than a half-dozen additional vendors before the city could obtain the four replacement systems for the wind technologies that had become unavailable.

The city contracted with two electrical contractors who sell and install renewable products. The electrical contractors procured all of the small wind systems, so the city did not have a lot of direct contact with vendors. Most of the vendors were selected based on their internet presence, and this process was very frustrating. Many vendors did not actually have a product to sell or were so undercapitalized that they could not manage public procurement processes.

The city marketed only the output of the community solar portion of the project to its customers. They could contribute as little as $250 and could receive a credit on their utility bill commensurate with their contribution as compared with all customer contributions. The city had planned to also market the wind portion of the project, but the small wind generators proved to be unreliable, subject to repeated failures, and were ultimately taken down for safety reasons.

Few contractors or support firms are available to supply maintenance to equipment. Contractors only service a few product types, and because the city had difficulty finding vendors to sell products, it ended up with vendors from all over the country. Few of the renewable systems have local factory authorized dealers, so the city had difficulty finding qualified contractors to work on many of the systems.

In summary, the City of Ellensburg spent almost two years just finding products to be part of the project. This was very frustrating and caused significant delays in meeting project milestone dates. The small renewables industry is very much fledging. Vendors, suppliers and contractors come and go very quickly. There were great differences in reliability and efficiency of the various systems. Solar panels, while more expensive per nameplate kW than the wind systems, were more reliable and required little maintenance. Even so, solar panel glass broke and an inverter failed. The broken panels were left in place with crystallized glass and are still generating. The inverter was able to be replaced. There seems to be little correlation between an economically good product and its chances of surviving in the marketplace. SCADA software also proved to be problematic as it was continually evolving.

With the relatively short life span of many products, local or even regional contractors and suppliers hesitate to invest in parts supply or staff training unless the product has a long track record of successful installations. This scarcity of support, combined with the large variety of technologies involved, means that there are few, if any, qualified contractors to maintain many of the products that are on the market.

Table 9.32. The City of Ellensburg's Assessment of Generated Renewable Energy and the Effective Unit Cost of the Renewable Energy

Component	Projected Annual Generation (kWh)	Actual Annual Generation (kWh)	Cost ($K)	Average Unit Cost[(a)] ($/kWh)
Phase-4 PV	52,600	52,740	291.8	0.28
Bergey	-	5,362	96.4	0.90
Ventera Wind	-	5,285	85.0	0.80
Skystream	-	1,337	24.8	0.90
Wind Turbines	50,100	12,155	525.8	2.16
PNWSGD Project	1,020,700	64,895	1,481.0[(b)]	1.14
BPA Wholesale Power Cost – Tier-1				0.035
BPA Wholesale Power Cost – Tier-2				0.049
City Retail Residential Rate				0.065
Statistics on the other six wind turbines are not presented due to lack of performance.				

(a) Assumes 20-year financing, 0% interest rate, no operation and maintenance or other continuing costs.
(b) This is a sum cost for the city's participation. It includes the above asset costs and other operational and administrative costs.

10.0 Flathead Electric Site Tests

Flathead Electric Cooperative, Inc. is the largest electric cooperative in Montana and serves approximately 49,000 members (FEC 2014a). The cooperative worked with the project to define two demonstration sites within its service territory at the communities of Libby and Marion/Kila, Montana. Two sites were used because the cooperative wished to learn about the technologies as they might be applied in both urban (Libby) and rural (Marion/Kila) locations. Refer to Figure 10.1 for the boundaries from which the cooperative solicited participants for these two sites. The two sites became nodes ST07 (Libby) and ST08 (Marion/Kila) of the project's transactive system.

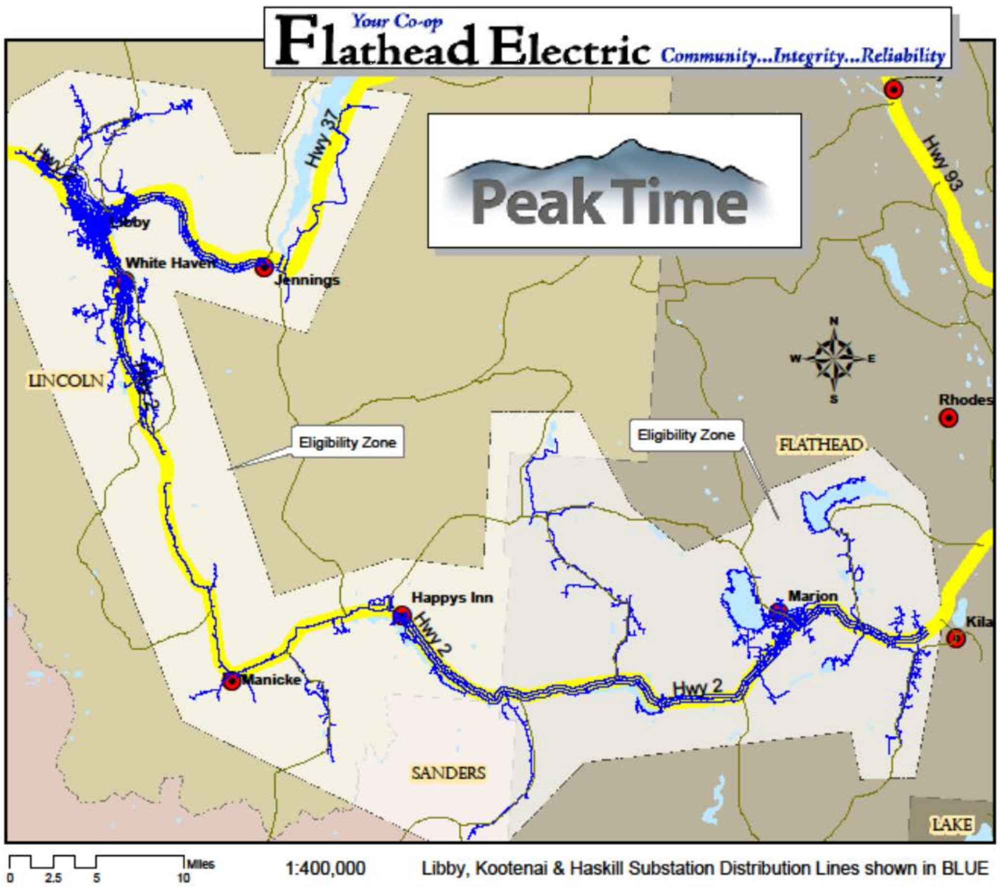


Figure 10.1. The Libby (left top) and Marion/Kila (bottom right) Sites within the Flathead Electric Cooperative Service Region in the Flathead Valley, Montana[1]

[1] In Flathead Electric Cooperative, Inc. (FEC). 2013. Flathead Electric Cooperative Demonstration Project: Peak Time. Unpublished slide presentation file Peak_Presentation_2013.pptx, February 2013, slide 5.

The cooperative is supplied wholesale electric power from the Bonneville Power Administration. An objective of the cooperative's participation in the Pacific Northwest Smart Grid Demonstration was to use the federal investment grant to finish deployment of their automated meter-reading system and develop tools to reduce its members' peak period power costs. This was an opportunity for the cooperative to upgrade substation equipment, install common two-way premises metering throughout the two project sites, improve system reliability, investigate the applicability of various demand-response technologies, prepare for anticipated load growth, and generally modernize their power grid.[1]

Flathead Electric also wished to better inform their members how the members could reduce their future energy costs. Toward this end, they designed and branded the Peak Time™ voluntary demand-response project. The project logo appears above in Figure 10.1. The cooperative hired a demand-response coordinator—a new staff position—to manage the Peak Time program and to recruit, educate, and interact with member participants. Cooperative members could benefit directly from receiving low cost appliances and project devices and corresponding incentive rebates, and they could benefit indirectly from improved service quality, rich energy usage information, shorter outages, and improved billing accuracy. Flathead reached out to its members using newspapers, newsletters, radio, its website, mailings, bill inserts, and community meetings. Ultimately, they were able to attract 290 member participants in Libby (97% of their target) and 49 in Marion/Kila (49% of their target).[2]

The program was anchored by the cooperative's investment in advanced premises metering for every member at the two site communities. Due to similar deployments in other areas of the local distribution system, the cooperative selected the Aclara Two-Way Automatic Communication System (TWACS®) meters (Aclara 2014) and other system components that were needed to gather and send the TWACS power-line-carrier signals. All members were required to accept advanced metering installations and, if they wished to participate in any of the four defined project participation groups, accept additional behind-the-meter technology deployments. Other unique communication protocols besides TWACS were needed in other parts of the system to incorporate General Electric (GE) appliances and to communicate with the project's transactive system. Figure 10.2 summarizes the communication pathways that Flathead Electric Cooperative established to make the component assets communicate and interoperate.

[1] Ibid.
[2] Ibid.

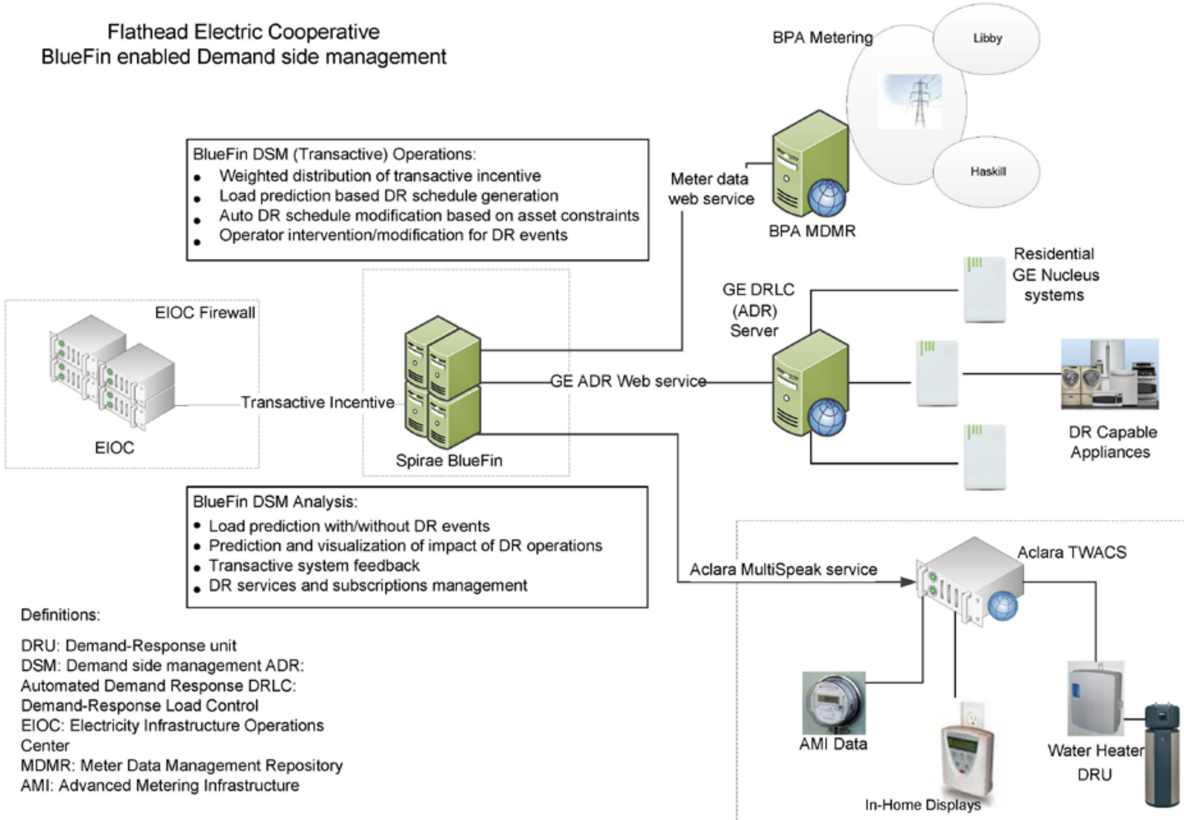


Figure 10.2. Flathead Electric Cooperative's Communication and Interoperability Design for Their Project Assets (Courtesy of Flathead Electric Cooperative)[1]

The following four participation groups were established at the two sites. Each will be discussed in detail in following subsections:

- Group A: These members received advanced premises meters, but they did not receive any of the displays or responsive equipment that those in the other three groups received. The primary purpose of this test group was to confirm that advanced metering can improve the speed with which customers recover after power outages. Aggregated premises metering from this test group provided a comparison baseline for the performance of the other three groups.
- Group B: These members received not only advanced meters, but also in-home displays. Members received signals from the displays and could choose to reduce energy consumption during Peak Time events.

[1] Flathead Electric Cooperative, Inc. (FEC). 2014. Email attachment "FEC design.pdf" from Teri Rayome-Kelly to DJ Hammerstrom Sept. 17, 2014. Unpublished.

- Group C: These members received not only advanced meters, but also demand-response units (DRUs). The DRUs permitted the cooperative to cycle these members' electric water heaters on and off for up to 2 hours during Peak Time events.
- Group D: Members paid $800 and received an advanced meter; energy display; 240 V water heater switch; GE Nucleus™ home energy gateway; and a suite of GE Profile Brillion™ dishwasher, clothes washer, and clothes dryer.

Figure 10.3 shows how these four test populations were laid out similarly at the two Flathead Electric Cooperative sites. The project reviewed reliability indices and outage data concerning the performance of Group A, the baseline group. The cooperative also submitted feeder data for the affected feeders, but premises meter data was the primary source that was used to confirm the performance of Groups B–D.

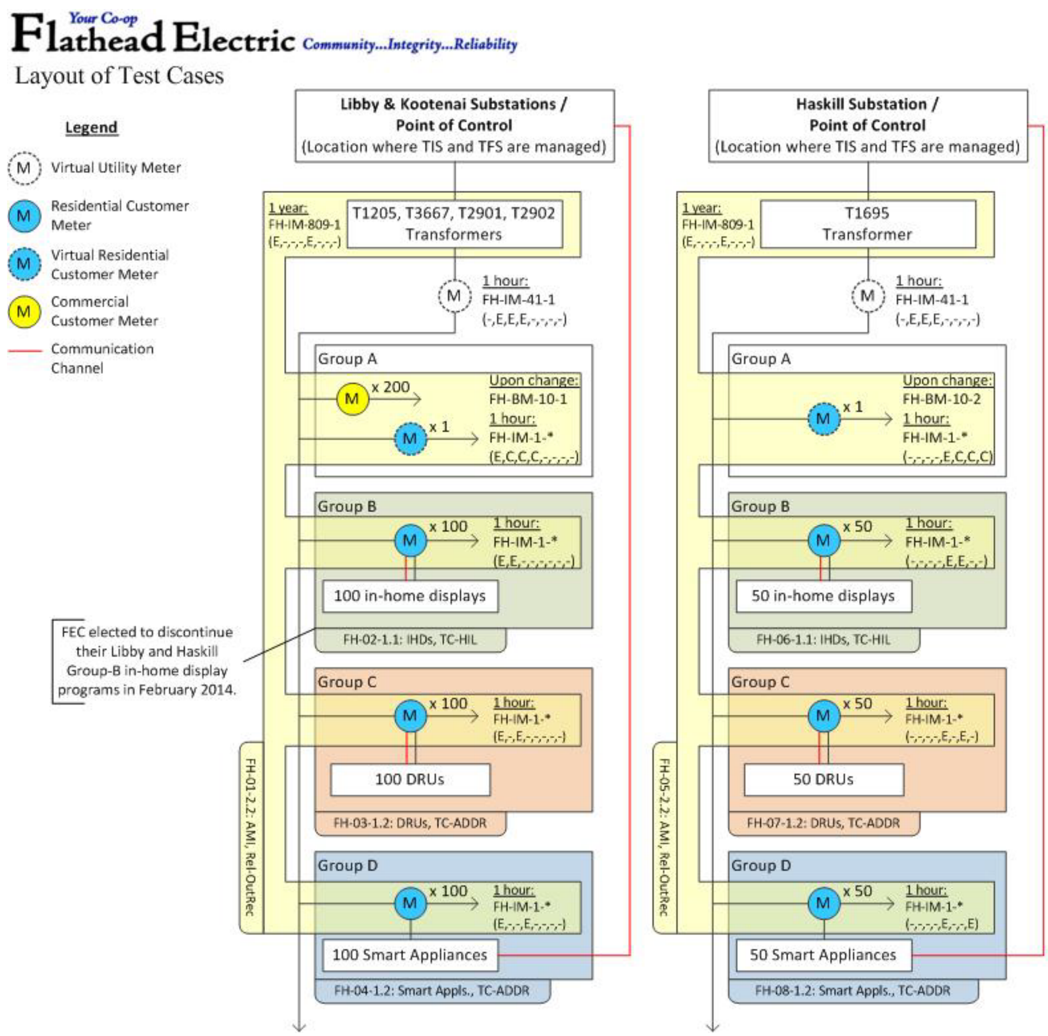


Figure 10.3. Layout of Flathead Electric Cooperative Asset Systems among the Two Sites and by Test Group. Groups A – D in Libby, Montana were served by the Libby and Kootenai Substations, and Groups A-D in Marion/Kila were served by the Haskill substation.

From the start, the cooperative avoided using the terms "smart grid" or "smart meters" with its members, thinking that these terms were perhaps too broad, did not correctly brand the technologies they would be applying, and might not engage their members as they wished. Flathead Electric Cooperative surveyed its members near the conclusion of the project period and compiled the survey results in a 2014 Flathead Electric technical report attributed to Teri Rayome-Kelly[1]. This report has been appended to this chapter (Appendix D). The report summarizes the types of electric loads that members possess and how members typically used these electric loads. Some of the survey questions asked members whether their usage of energy had changed as a result of their project participation. Most telling about the trust that members have for their cooperative is that 97% of respondents said they would participate in a similar program and would recommend participation to other members.

Among the highlights,

- 58% of participants said that electricity is their major source of heating.
- 50% have programmable thermostats.
- 72% said that they changed the way they managed their heating occasionally or more. 36% said they had changed their cooling.
- 58% had elected to conduct efficiency improvements.
- 48% and 52%, respectively, had changed their scheduled usage of their dishwasher and laundry appliances.
- 25% stated they had changed the times that they bathed.

Flathead Electric Cooperative reported that its members' interest level in the Peak Time project technologies varied greatly. Its members were curious whether these technologies would save energy and benefit the cooperative and its members. The Peak Time branding effort helped them recruit and retain participants, and these participants were perhaps better focused than might have occurred had the technologies been branded instead as "smart."

A key lesson learned for the cooperative was that the communication technologies were not easily integrated. Because "smart" technologies are advancing so rapidly, industry trends and these products change faster than a utility can react. Product models and features changed between the times the cooperative selected and implemented the technologies. Not all the technologies were as they had been described, and some had not been fully tested to confirm that they would perform in the project's configurations. Overall, the cooperative's staff became more involved in and knowledgeable about the installation of the vendors' products than it had anticipated.

[1] In Teri Rayome-Kelly. 2014. 2014 Peak Time Demonstration Project Member Survey Results. Technical report by Flathead Electric Cooperative, Inc., 121 W 4th St., Libby, MT 59923, September 24, 2014.

10.1 Advanced Metering Infrastructure for Outage Recovery

Flathead Electric Cooperative invested in installation of advanced residential interval power metering at all member premises that are served by its Kootenai and Libby, Montana substations and by the rural Haskill substation west of Kalispell, Montana. It was hoped that these advanced meters would improve the meter-reading frequency and billing accuracy. The meters enabled the cooperative to view complete sets of hourly interval data for each substation, but the cooperative was also interested in the real-time outage information that became available to them as a feature of the new advanced metering infrastructure (AMI). Outage notification continues to be through an automated phone-initiated outage management system, but the TWACS system allows the cooperative to verify outages and narrow exact outage locations for more efficient troubleshooting and restoration. The effectiveness of this improved troubleshooting and restoration was to be measured by changes in reliability indices before and after the asset system had been deployed.

The annualized component costs of the AMI system and its components are summarized in Table 10.1 (Libby, Montana site) and Table 10.2 (Marion/Kila, Montana site). The biggest cost component is the cost of the premises metering system, followed by the cost of utility staff support and the costs of TWACS system components that had to be updated at substations. The Marion/Kila site required new outage management software that was not needed at the Libby site.

Table 10.1. Annualized Costs of Group-A Advanced Metering Infrastructure at the Libby, Montana, Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Premises Metering			55.2
Group-A Single-Phase Meters	50	72.6	36.3
Polyphase Meters	100	14.7	14.7
Back-End Metering	13	11.7	1.5
Group-B Single-Phase Meters	50	1.5	0.7
Group-C Single-Phase Meters	50	1.5	0.7
Group-D Single-Phase Meters	50	1.5	0.7
Meter Operations and Maintenance	25	2.4	0.6
Staff Support	13	293.1	36.6
Substation TWACS Components			0.9
Modulation Transfer Unit (Model Y87363)	25	1.4	0.3
Inbound Pickup Unit (Model Y83760)	25	0.3	0.1
Outbound Modulation Unit (Model 303)	25	1.3	0.3
Control/Receiving Unit (Model 627)	25	0.9	0.2
Total Annualized Asset Cost			**$92.9K**

Table 10.2. Annualized Costs of Group-A Advanced Metering Infrastructure at the Marion/Kila, Montana Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Premises Metering			40.5
• Group-A Single-Phase Meters	50	72.6	36.3
• Back-End Metering	13	11.7	1.5
• Group-B Single-Phase Meters	50	1.5	0.7
• Group-C Single-Phase Meters	50	1.5	0.7
• Group-D Single-Phase Meters	50	1.5	0.7
• Meter Operations and Maintenance	25	2.4	0.6
Staff Support	13	293.1	36.6
Outage Management Software	100	17.6	17.6
Substation TWACS Components			0.4
• Modulation Transfer Unit (Model Y87362)	25	0.7	0.1
• Inbound Pickup Unit (Model Y83765)	25	0.2	0.0
• Outbound Modulation Unit (Model 303)	25	0.7	0.2
• Control/Receiving Unit (Model 627)	25	0.4	0.1
Total Annualized Asset Cost			**$95.3K**

10.1.1 Reliability Data

In order to begin understanding whether grid modernization at these two Flathead Electric Cooperative sites corresponded to measureable improvements in the reliability of the service they provide to their members, reliability metrics must be analyzed from both before and after the improvements were made. Table 10.3 presents a summary of these indices for affected feeders from September 1, 2011 to October 16, 2013. These indices were calculated by the utility. The metrics, while interesting, do not facilitate the comparison that was desired. The index "Average Service Availability Index" in this table is the average availability of service—the fraction of the year that remains after the System Average Interruption Duration Index duration has been removed.

Table 10.3. Reliability Indices for Affected Flathead Electric Cooperative Feeders from September 1, 2011 to October 16, 2013

Feeder	ASAI (%)	CAIDI (minutes/outage)	SAIDI (minutes/year)	SAIFI (outages/year)
Kootenai T2091	99.97	187	385	2.06
Kootenai T2092	99.97	85	377	4.43
Libby T1205	99.99	92	145	1.57
Libby T3667	99.99	90	66	0.73
Haskill T1695	99.86	143	1,538	10.77
Haskill T2093	99.93	132	739	5.59

ASAI = Average Service Availability Index
CAIDI = Customer Average Interruption Duration Index
SAIFI = System Average Interruption Frequency Index

Table 10.4 provides a detailed analysis of the causes of the outages during the same time period that was covered by Table 10.3. This analysis was compiled by the utility.

Table 10.4. Counts and Causes of Feeder Outages from September 1, 2011 to October 16, 2013

Substation / Metric	Power Supply	Planned Outage	Equipment Installation Design	Maint.	Weather	Animals	Public	Other	Unknown	Substation Total
Kootenai T2091										
Outages	0	4	1	1	0	3	0	0	1	**10**
Customers Out	0	20	2	3	0	196	0	0	51	**272**
Cust. Minutes	0	1,923	126	138	0	43,025	0	0	5,610	**50,822**
Kootenai T2092										
Outages	0	64	28	34	12	22	5	1	15	**181**
Customers Out	0	593	2,997	4,927	671	1,200	24	2	853	**11,267**
Cust. Minutes	0	29,930	153,050	607,811	47,358	13,374	1,431	116	106,625	**959,695**
Libby T1205										
Outages	0	43	11	16	7	33	4	2	8	**124**
Customers Out	0	395	303	495	263	255	55	28	84	**1,878**
Cust. Minutes	0	12,234	28,250	59,538	31,449	23,400	5,187	2,305	10,225	**172,588**
Libby T3667										
Outages	0	37	14	4	5	16	3	3	7	**89**
Customers Out	0	110	80	212	208	294	9	11	314	**1,238**
Cust. Minutes	0	6,899	7,266	16,822	20,178	16,920	732	1,717	40,357	**110,891**
Haskill T1695										
Outages	1	49	14	29	9	6	3	0	7	**118**
Customers Out	913	606	1,667	5,901	987	80	970	0	380	**11,504**
Cust. Minutes	17,347	42,631	234,055	931,112	292,921	7,151	83,443	0	33,526	**1,642,186**
Haskill T2093										
Outages	1	41	19	44	18	4	8	1	11	**147**
Customers Out	1,347	794	121	3,650	1,333	36	177	7	82	**7,547**
Cust. Minutes	25,593	68,782	18,701	570,729	235,928	3,685	59,921	1,477	13,349	**998,165**

10.2 In-Home Displays

Flathead Electric Cooperative next considered the incremental costs and benefits available from Aclara TWACS in-home displays (see Figure 10.4). These devices were easily provided to and installed by cooperative members. Members simply plugged the devices into a wall socket at their premises. The in-home displays communicate using the power-line-carrier communication system of the installed advanced metering at each premises. These devices were intended to display general information from the cooperative about the utility and project, and to emit an audible alarm and display the message “Peak Time” on their light-emitting diode screens during peak periods. Members, upon receiving this Peak Time message and its alarms and indicators, were expected to manually curtail their electricity use. A monthly credit (~$5 per month) and annual rebate based on peak period reductions were provided to cooperative members who accepted and used the in-home displays.

This test was halted by Flathead Electric Cooperative after only one year of operation. The cooperative believed that the audible alarms being emitted by the in-home displays were annoying to participating members. This annoyance was further increased by the challenges that the project encountered as it automated the transactive system events. The project initially misconfigured the automation of assets’ responses to the transactive system, and it took months for project participants to identify and correct the assets’ misconfigurations. Furthermore, the incentive signals generated by the project to engage distribution systems like the in-home displays took many months to correct. For example, a persistent system design problem caused the transactive system to at first invite assets to participate in erroneous “midnight” events. That was unfortunate.

Regardless, the performance and benefit of the in-home displays were evaluated by the project for the limited number of events that the in-home displays were allowed to operate. The project reviewed premises data supplied by Flathead Electric Cooperative and evaluated energy usage during events, after events, and during event days.

Figure 10.4. Aclara Model 110 In-Home Display of the Type Used by the Flathead Electric Cooperative Peak Time Project[1]

The annualized costs of the two sites' in-home display systems are summarized in Table 10.5 (Libby, Montana site) and Table 10.6 (Marion/Kila, Montana site) below. The entire annualized cost of the system in Libby was estimated as $113,500, and that at Marion/Kila was estimated as $102,800. Annualized system component costs are dominated by the costs of software, utility staff labor, and incentives. The systems also include a fraction of the TWACS communication substation components and a fraction of the cost of AMI. The 50-percent allocation of the cost of in-home displays refers to the split of that hardware cost between the Libby (Table 10.5) and Marion/Kila (Table 10.6) sites. Had the system of in-home displays not shared some of the component allocations with other of the cooperative's asset systems, the costs would have been greater.

[1] Flathead Electric Cooperative, Inc. (FEC). 2013. Flathead Electric Cooperative Demonstration Project: Peak Time. Unpublished slide presentation file Peak_Presentation_2013.pptx, February 2013.

Table 10.5. Incremental Annualized Costs of Installing and Operating 90 In-Home Displays at the Libby, Montana, Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Integration Software	17	293.6	49.0	
Staff Support	13	293.1	36.6	
Incentives	100	20.5	20.5	
In-Home Displays (Model 110)	50	6.4	3.2	
Back-End Metering	13	11.7	1.5	
Substation TWACS Components			0.9	
• Modulation Transfer Unit (Model Y87363)	25	1.4		0.3
• Inbound Pickup Unit (Model Y83760)	25	0.3		0.1
• Outbound Modulation Unit (Model 303)	25	1.3		0.3
• Control/Receiving Unit (Model 627)	25	0.9		0.2
Group-B Single-Phase Meters	50	1.5	0.7	
Meters Operations and Maintenance	25	2.4	0.6	
Demand-Response Software	33	1.1	0.4	
Total Annualized Asset Cost			**$113.5K**	

Table 10.6. Incremental Annualized Costs of Installing and Operating 12 In-Home Displays at the Marion/Kila, Montana, Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Integration Software	17	293.6	49.0	
Staff Support	13	293.1	36.6	
Incentives	100	10.3	10.3	
In-Home Displays (Model 110)	50	6.4	3.2	
Back-End Metering	13	11.7	1.5	
Group-B Single-Phase Meters	50	1.5	0.7	
Meter Operations and Maintenance	25	2.4	0.6	
Substation TWACS Components			0.5	
• Modulation Transfer Unit (Model Y87362)	25	0.7		0.2
• Inbound Pickup Unit (Model Y83765)	25	0.2		0.0
• Outbound Modulation Unit (Model 303)	25	0.7		0.2
• Control/Receiving Unit (Model 627)	25	0.4		0.1
Demand-Response Software	33	1.1	0.4	
Total Annualized Asset Cost			**$102.8K**	

It is very challenging to predict voluntary responses that will be offered by cooperative members. Unknowable conditions affect the willingness of members to respond to a given event. The overall willingness of members to respond may be influenced by the timing of educational information supplied from the cooperative. The project was able to marginally confirm members’ responsiveness at the Libby site, but little can be confidently said about the rural Marion/Kila site, which had few participating residences.

10.2.1 Characterization of In-Home Display System Responses

The starting times and durations of Peak Time in-home display events are shown in Table 10.7 (Libby site) and Table 10.8 (Marion/Kila site). The hours are stated in local Mountain Time. The in-home display program was halted in Libby after only four Peak Time events that occurred from February through September 2013. An additional three events were allowed through March 2014 at the Marion/Kila site. The events were all between 2 and 3 hours long. These events that are understood to have been sent by the utility to the in-home displays at the two sites will be referred to as the Peak Time events, regardless whether they coincided with utility peak load.

After reviewing the project’s analysis, the utility noted a couple discrepancies between their records of event times and the times that had been reported into the project’s database. For example, the first events at both sites failed, and the Peak Time messages had not, in fact, reached the targeted in-home displays. The utility reported that Event 5 at the Marion/Kila site had begun at 06:55, but the project’s records had shown the event to have begun at 12:55 that day.

The cooperative provided to the project a list of their actual monthly peak-demand hours from October 2012 until the demonstration project ended. Only one Peak Time event at the two sites coincided with an actual month’s peak-demand hour—equivalent to 25% of the Libby events and 14% of the Marion/Kila events. Seventy-eight percent of the total Peak Time event durations at Libby and 78% of those at Marion/Kila occurred during Bonneville Power Administration (BPA) heavy-load hours (HLHs).

Table 10.7. Starting Times and Durations of the Libby, Montana, In-Home Display Peak-Time Events

Event	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1[(a)]	2013	2	28	Thursday	6	50	2:20
2[(b)]	2013	3	5	Tuesday	6	50	2:10
3[(c)]	2013	8	15	Thursday	9	20	2:10
4	2013	9	2	Monday	19	0	2:00

(a) Flathead Electric said this was a manual event that was dispatched by them but failed to reach any of the in-home displays.
(b) Coincided with a Flathead Electric Cooperative monthly peak-demand hour.
(c) Coincided with an advised transactive system event for this asset system.

Table 10.8. Starting Times and Durations of the Marion/Kila, Montana, In-Home Display Peak-Time Events

Event	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1[(a)]	2013	2	28	Thursday	6	50	2:20
2[(b)]	2013	3	5	Tuesday	6	50	2:10
3[(c)]	2013	8	15	Thursday	9	20	2:10
4	2013	9	2	Monday	22	15	2:45
5[(d)]	2013	9	18	Wednesday	06	55	2:05
6[(a,c)]	2014	1	30	Thursday	9	30	2:00
7[(a.c)]	2014	2	11	Tuesday	9	0	2:00

(a) Flathead Electric Cooperative later stated that this event, which was included in project analysis, had been dispatched by the utility but failed to reach the in-home displays.
(b) Coincided with an actual Flathead Electric Cooperative monthly peak-demand hour.
(c) Coincided with an advised transactive system event for this asset system.
(d) There was a discrepancy in the timing of this event. Flathead Electric says that event ran from 06:55 to 09:00. Analysis was conducted from data that said the event ran from 12:55 to 15:00. The cause of the discrepancy is unknown.

There were altogether 56 events advised by the transactive system for the in-home displays at the Libby site from February 2013 through August 2014. Only one of the four Peak Time events of Table 10.7 coincided with one of the 56 advised transactive events. Three of the seven (43%) Peak Time events at the Marion/Kila site overlapped with advised transactive system events. The advised transactive events never, in fact, coincided with the cooperative's actual monthly peak-demand hours. Sixty-seven percent of the advised transactive event hours were during BPA HLHs. While 70% of the advised transactive events were precisely 2 hours long, the other events ranged from 1 hour long to almost 9 hours long. The longest events tended to occur early in the demonstration while the transactive system function for this asset system remained poorly configured.

The days on which transactive events were advised for the systems of in-home displays are shown by Figure 10.5. Early misconfiguration of the assets' responses accounted for the many weekend events, which never have HLHs and would typically not benefit the cooperative.

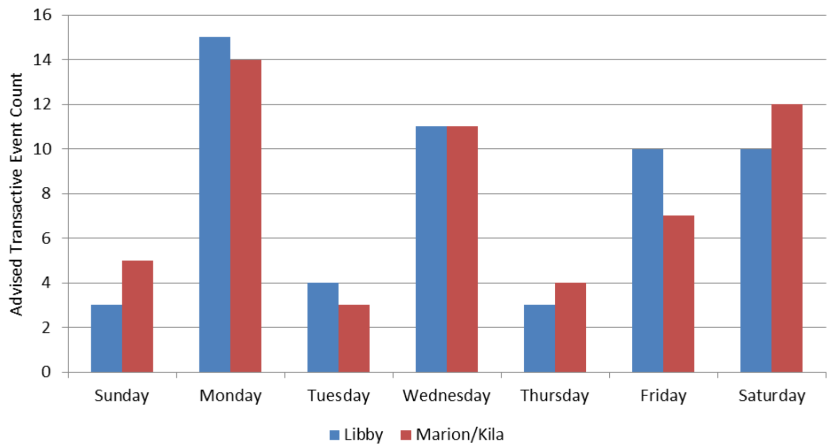


Figure 10.5. Week Days on which Transactive Events were Advised to the In-Home Displays

The starting hours on which the transactive events were advised for in-home displays at the two sites are summarized in Figure 10.6. The cooperative would be unlikely to deploy any assets for peak reduction during off-peak hours, but transactive signals were regionally focused. It was plausible that the transactive system's incentives might occur during off-peak hours. The events were eventually called during reasonable morning and afternoon hours, when they were likely to help reduce peak demand. Early on, the transactive incentive signals had suffered from a persistent prediction error that invited many erroneous late evening, early morning, and weekend events that are shown here.

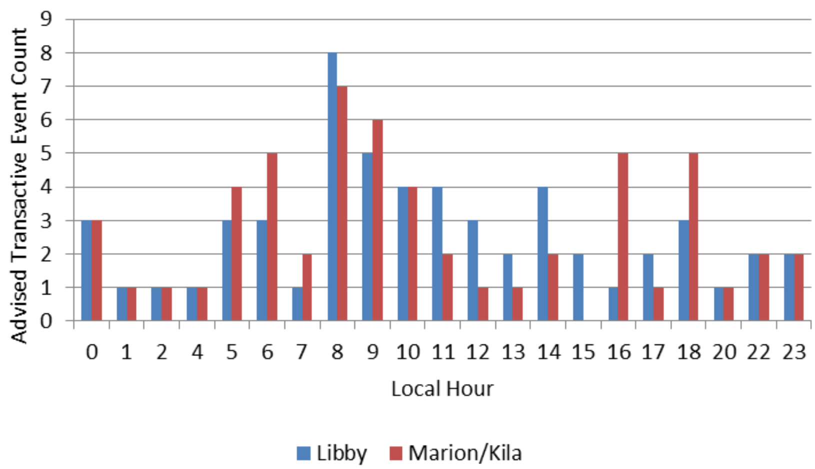


Figure 10.6. Hours on which Transactive Events were Advised for the In-Home Displays

Starting with August 2011, the test population of Libby in-home display premises was defined and remained consistent throughout the project. The typical number of in-home display participants in Libby was about 83. The count varied from about 65 to 90 on an averaged monthly basis. The recruitment of one hundred participants had been the cooperative's goal.

The Marion/Kila test population ranged from 8 to 12 members from January 2012 through August 2014.

10.2.2 In-Home Display System Performance

The project attempted to confirm impacts from the in-home display Peak Time events. Two baseline comparison approaches were used and compared—modeled and controlled. The baselines emulate data that is unaffected by in-home displays. The words “modeled” and “controlled” refer to the methods by which the baselines were constructed.

Modeled baseline. In the first, a linear model of the averaged premises power for each site’s test population was constructed using R statistical software (R Core Team 2013). Using regression methods, the average premises power of the test group was modeled as a function of temperature, evaluated separately by calendar month, day of week, and hour of day. A modeled baseline time series was then constructed from this linear model for comparison against the raw time-series data to determine whether the load was measurably affected during events, after events, and during event days.

Controlled baseline. The controlled baseline was constructed using a control group by scaling the average power from a comparable set of Group-A premises that had not been given in-home displays and was not informed about Peak Time events. By observation, the raw power data from the Group-A time series had a lower average load, suggesting that there was perhaps a selection bias between the two populations. The Group-A time series was scaled to have the same mean and standard deviation as the data from the test population on a month-by-month basis. Noting that the two populations still exhibited different hourly consumption patterns, the Group-A time series was further globally corrected on an hourly basis to have the same average hourly consumption as the test population.

Figure 10.7 may be useful to explain the project’s method for comparing time series against either baseline. In this example, the averaged 5-minute premises loads for Libby members who had in-home displays is plotted against similar 5-minute intervals that were created from the modeled baseline. If the baseline were perfect, then all the points would align perfectly on a line having unity slope. However, baseline inadequacies and natural load variability conspire to make the baseline diverge from the time-series data that it attempts to emulate. On average, however, the difference between the time-series data and its baseline is about zero.

Peak Time event data have been shaded red in Figure 10.7. The question posed by analysts is, is the difference between the experimental population and its baseline significantly different between event periods and non-event periods? The figure includes linear best fits of the Peak Time data (red) and from non-event periods (blue). The two sets of will be compared to estimate the mean difference, standard error (that is, the interval within which about 68% of differences would be expected to fall), and a 95% confidence interval. While these methods might yield results for even very small data sets, we will try not to overstate the significance of such results, which can be misleading.

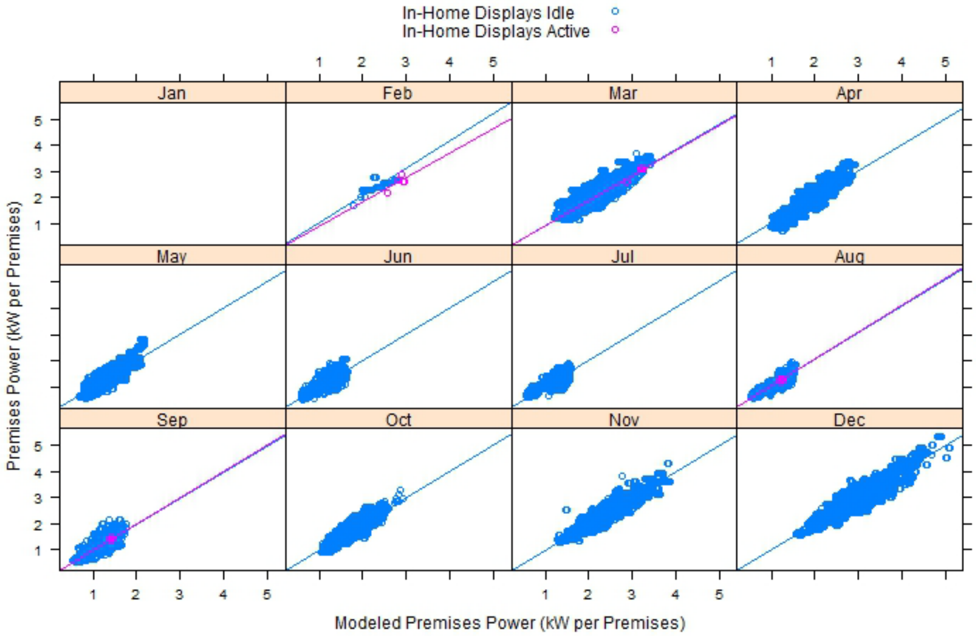


Figure 10.7. Averaged Load for Libby, Montana, Premises that have In-Home Displays Plotted against a Modeled Baseline of this Same Data for the Months of 2013. Data from Peak Time event periods are colored red.

The project will refer to these confidence intervals as *estimates* because they are adopted from statistical practices that are intended for statistically normal populations and independent observations. The project cannot assert that the small populations of differences have Gaussian distributions or that the data observations are entirely independent.

A load reduction may be reported for all on-peak and off-peak Peak Time events in Libby, as shown in Figure 10.8. The far right-hand side of this figure shows a statistical result for all the Libby Peak Time event periods. Using the modeled baseline (blue), there is a 94% likelihood that consumption was, in fact, reduced during events at Libby premises that have in-home displays, and the reduction is about 80 ± 50 W per premises. Using the controlled baseline population (black), there is 91% likelihood that power consumption was reduced in the homes with in-home displays during Libby events, and the reduction was 190 ± 140 W. The average of the results from both baseline approaches is a reduction of 140 ± 80 W per premises during the Peak Time events for those premises that had in-home displays.

The monthly results from the modeled baseline are shown slightly offset to the left of the month and the controlled baseline result is offset to the right. Individual months' results at Libby should be used cautiously because each month had few independent, hourly Peak Time measurements. However, some of the greatest impacts appear to have occurred when the program was new, suggesting that cooperative members were affected by the novelty of the device and by the education that they received from the cooperative at the beginning of the Peak Time program. One hypothesis is therefore that member enthusiasm waned rapidly with time. Alternative explanations include measurement clock errors and miscalibrations that would appear to soften the aggregated result or even cause the project to seek the result at the wrong times.

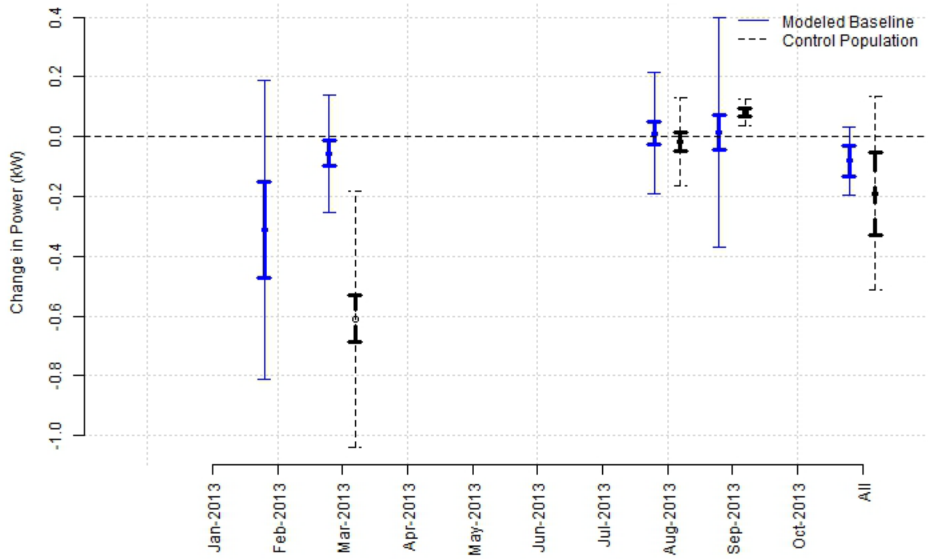


Figure 10.8. Measured Change in Power per Premises during Libby, Montana In-Home Display Peak-Time Events. Ranges include standard errors (bold bars) and 95% confidence intervals (thin bars). Blue results are from the modeled baseline and black dashed results used the controlled baseline.

During events at the Marion/Kila site, no significant reduction in member load can be reported. Both baseline methods suggested an *increase* in load had accompanied the in-home display events there, but statistical confidence was low. There were too few test premises and too few events at the Marion/Kila site to obtain significant analysis results.

A similar analysis was conducted to look at the hour immediately following Peak Time events to determine whether any rebound effect can be observed after in-home display events are terminated. Figure 10.9 shows the averaged results by month while using the modeled baseline (blue, offset just left of the corresponding month) and controlled baseline (black, offset just right of the corresponding month). The results from using all Peak Time data are shown on the far right.

Using the modeled baseline (blue in Figure 10.9), a *reduction* of about 130 ± 70 W per premises may be reported for the hour following events in Libby with 95% confidence that a reduction occurred. Using the controlled baseline approach, a similar load reduction was suggested (180 ± 160 W) (black in Figure 10.9) for Libby, but there is only about an 86% confidence that any reduction occurred. The average of the results from the two baselines is a reduction of 160 ± 90 W per premises that had in-home displays during the rebound hours following Peak Time events at the Libby, Montana, site.

This is not a typical rebound impact in that continued load *reduction* was observed rather than an *increase* in load that is typical for most demand-response systems. The demand reduction in the hour following events might be even greater than the reduction during events. In-home displays appear to induce voluntary responses that may have lingering impacts even after an event has ended.

No standard errors or confidence intervals appear for the individual months in Figure 10.9 because the number of measurements was insufficient to calculate and state such intervals.

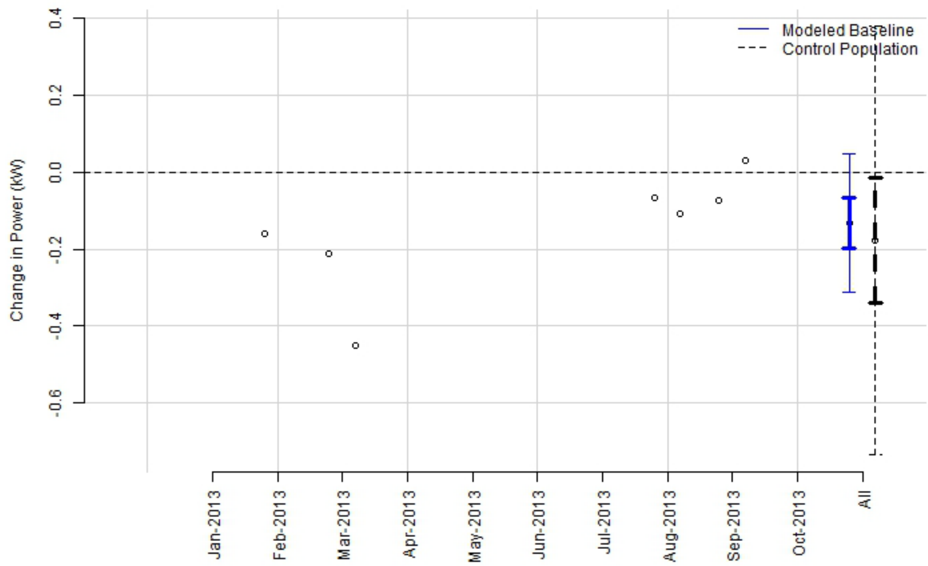


Figure 10.9. Measured Impact per Premises during Rebound Hours for Libby, Montana Premises having In-Home Displays Using the Modeled (blue) and Controlled (black) Baselines

Inconclusive results were observed during the rebound hours at the Marion/Kila site (not shown). Both baselines suggested that an increase in load might have occurred during rebound hours, but the project’s confidence is low that the increase is real.

The project additionally compared the entire days on which events had and had not occurred. A surprising finding was that both baselines suggested that significant reductions occurred the entire day of the Peak Time events. Figure 10.10 summarizes impacts at the Libby site during Peak Time event days. Using the modeled baseline, there is a 90% likelihood that a reduction occurred at premises having in-home displays, and the average reduction was 20 ± 20 W per premises throughout the days of the events. The controlled baseline yielded even stronger confidence that the days’ premises loads had diminished for those in Libby who had been notified via their in-home displays, and the average reduction was 60 ± 20 W.

The voluntary responses by in-home display owners extended through the entire event day, not just through the limited event duration. The members were more responsive to the March 2013 event than to events later in the program. The average of the results from the two baselines at Libby is a reduction of 40 ± 30 W per premises throughout days that Peak Time events had occurred.

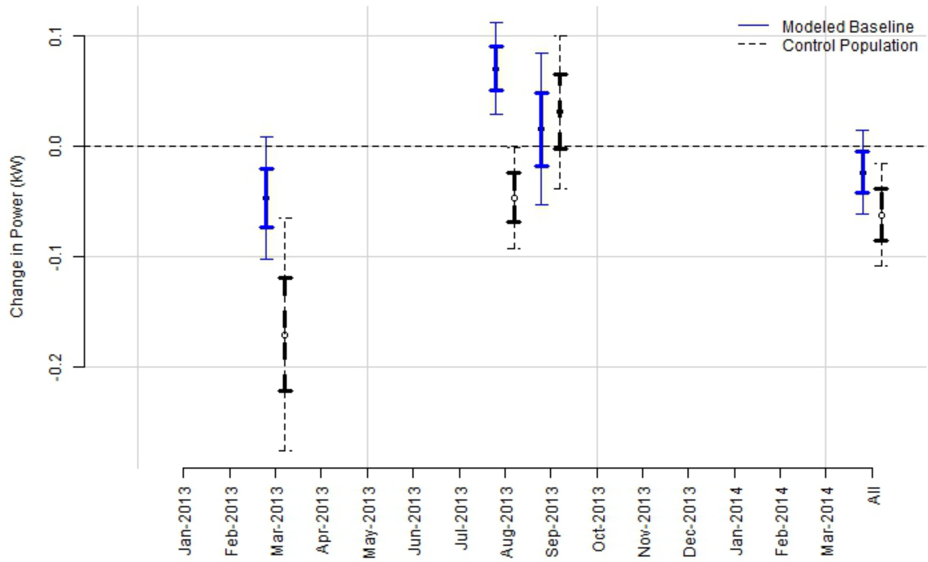


Figure 10.10. Measured Average Impact per Premises during Peak-Time Event Days for Libby, Montana Premises having In-Home Displays Using the Modeled (blue) and Controlled (black) Baselines

At the Marion/Kila site, using the modeled baseline, member premises used an average 30 ± 30 W less power during event days than during non-event days (Figure 10.11). The confidence that any reduction occurred was about 98%. A similar reduction was suggested by the controlled baseline, but the likelihood of the reduction cannot be stated with confidence. The averaged result from the two baseline approaches was a reduction of 20 ± 20 W per in-home display premises throughout the days that had Peak Time events at the Marion/Kila site.

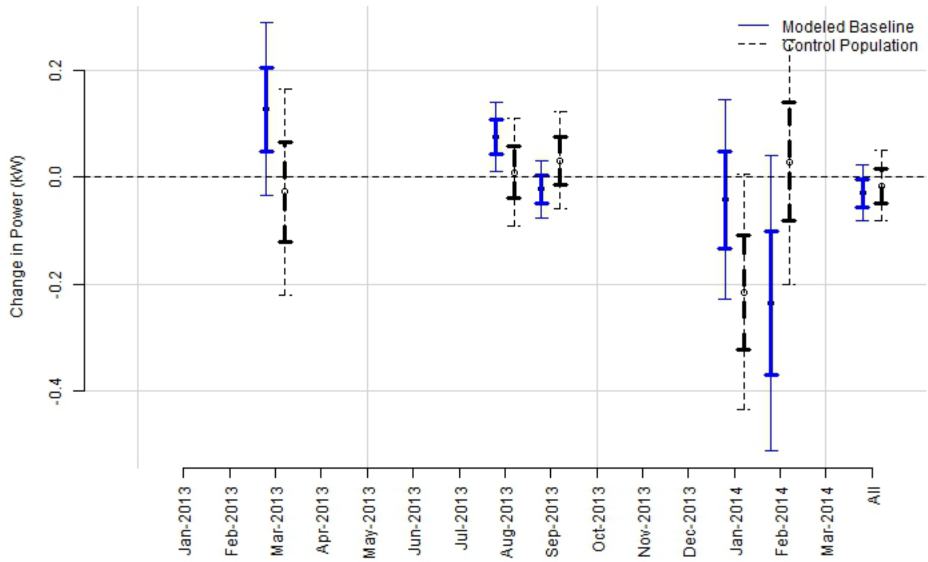


Figure 10.11. Measured Average Impact per Premises during Event Days for Marion/Kila, Montana Premises having In-Home Displays Using the Modeled (blue) and Controlled (black) Baselines

The project next estimated the value of the energy that was displaced as the system of in-home displays responded to Peak Time events. Flathead Electric Cooperative is a BPA supply customer, so the value of energy supply may be based on BPA's unit energy costs for heavy-load and light-load (LLH) hours. See Appendix C for additional detail about BPA's tiered rate methodology.

First, a table was created to compile the average differences between the Libby test group's average premises power and the modeled baseline that was created from the Libby test group power data. The differences were created for each calendar month and separately for HLHs and LLHs. This table provided the project a statistical estimate of the impacts by these hour types and months, including estimates of the standard deviations between the data and baseline. Then, the durations of the Peak Time events within HLH and LLH types was used to estimate the total energy and costs impacts.

Table 10.9 summarizes these estimates. Because there were few events, this benefit could be assessed only three calendar months. The value of the curtailed energy was miniscule. Even if the results from the active months were extrapolated to all the calendar months, the value of the displaced energy supply is only a couple dollars.

Table 10.9. Estimated Energy Curtailed by In-Home Display Premises each Calendar Month and the Supply Value of that Energy as the In-home Display Premises Responded to Peak Time Events

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
…	-	-	-	-	-	-
Mar	−33 ± 2	−0.7 ± 0.0	-	-	−33 ± 2	−0.7 ± 0.0
…	-	-	-	-	-	-
Aug	2 ± 1	0.0 ± 0.0	-	-	2 ± 1	0.0 ± 0.0
Sep	-	-	9 ± 2	0.23 ± 0.06	9 ± 2	0.2 ± 0.1
…	-	-	-	-	-	-

Analysis was conducted to estimate the potential impact of the Libby in-home display system on the utility's demand charges that are imposed on it as a customer of BPA. One of the components of the demand charges calculation is the change in average HLH energy. As was shown in the discussion about energy impacts, the system's impact on the HLH energy, and therefore its impact on average HLH energy, was negligible.

A table of impacts was generated for each calendar month and by HLH hour. Only HLH hours were considered because demand charges may be incurred only during those hours. This table estimates the statistical average by HLH hour each month, and the table included the standard deviations that were useful toward understanding the variability of the impacts. Then, this table was compared against a list of the utility's historical monthly peak hours. If the month's historical peak hours never coincided with the hours that Peak Time events were, in fact, called in a month, the utility was given no credit for changing its demand charges. If, however, the Peak Time events were demonstrated to have occurred during one or more of the historical peak hours in a given month, the estimated impact was estimated proportionate to the numbers of times that the hours were coincident.

This method of estimation will be somewhat optimistic because it presumes that the Peak Time events will be skillfully applied on the exact day that the monthly peak occurs. Had the project given credit for changing demand charges only if the hour and the day in a given month had coincided with the actual month's peak, the estimated impact on demand charges would have been even smaller, and the project would have been unable to apply any estimate of statistical variability of the impact.

The method of estimation is also affected by the scale of the demonstration. Libby had installed up to about 90 in-home displays. The impact should be expected to scale pretty linearly with the numbers of installations.

Table 10.10 summarizes the impact that the system of Libby in-home displays might have on typical demand charges each calendar month. The system had been shown to insignificantly affect the average HLH load during a March and August. The timing of the demonstrated Peak Time event in March coincided with historical March peak hours. If the system were to perform every month as it did in March, the project extrapolates that the utility might reduce its yearly demand charges by about $3,500.

Table 10.10. Estimated Impact of the System of Libby In-Home Displays on the Demand Charges that are Incurred each Month by Flathead Electric Cooperative

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Demand Charges ($)
…	-	-	-
Mar	−30 ± 1	~0	−290 ± 1
…	-	-	-
Aug	0	~0	~0
…	-	-	-

While looking at energy supply costs and impacts on demand charges, the project used only the demonstrated changes in power during events. The project did not explicitly consider the potential impacts of rebounds hours or event-day impacts on the costs.

10.3 DRUs

Flathead Electric Cooperative members who possessed advanced interval meters were candidates to participate in Group C, for which Aclara DRUs were installed to control residential electric water heaters See Figure 10.12. These devices communicate via the existing TWACS power-line-carrier system, and the cooperative could send a command to water heater DRUs to curtail water the heaters' electric load. Participating Group-C members who accepted the water heater DRUs received a monthly participation credit (~$8/month) on their monthly bills.

Figure 10.12. Aclara TWACS DRU that was Used to Cycle Water Heaters in the Flathead Electric Cooperative Peak-Time Project[1]

The benefit of the TWACS DRU technology versus the cost of providing it was to be evaluated by comparing incremental costs and benefits for the premises that accept DRUs against those that have only AMI. Table 10.11 summarizes the annualized system costs at the Libby site, and Table 10.12 summarizes the annualized system costs at the Marion/Kila site. The systems, of course, include the DRUs that are allocated between the two sites. The annualized system costs also include some of the shared costs of substation TWACS components, the metering systems, metering operations, demand-response software, and member incentives. The total annualized cost of the Libby DRU system was $113,000, and that of the Marion/Kila system was $104,900.

[1] Ibid.

Table 10.11. Flathead Electric Incremental Costs of DRUs at the Libby Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Integration Software	17	293.6	49.0
Staff Support	13	293.1	36.6
Incentives	100	15.0	15.0
DRU (two-way)	50	16.2	8.1
Back-End Metering	13	11.7	1.5
Substation TWACS Components			0.9
• Modulation Transfer Unit (Model Y87363)	25	1.4	0.3
• Inbound Pickup Unit (Model Y83760)	25	0.3	0.1
• Outbound Modulation Unit (Model 303)	25	1.3	0.3
• Control/Receiving Unit (Model 627)	25	0.9	0.2
Group-C Single-Phase Meters	50	1.5	0.7
Meter Operations and Maintenance	25	2.4	0.6
Demand-Response Software	33	1.1	0.4
Total Annualized Asset Cost			**$113.0K**

Table 10.12. Flathead Electric Incremental Costs of DRUs at the Marion/Kila Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Integration Software	17	293.6	49.0
Staff Support	13	293.1	36.6
DRU (two-way)	50	16.2	8.1
Member Incentives	100	7.5	7.5
Back-End Metering	13	11.7	1.5
Group-C Single-Phase Meters	50	1.5	0.7
Meter Operations and Maintenance	25	2.4	0.6
Substation TWACS Components			0.5
• Modulation Transfer Unit (Model Y87362)	25	0.7	0.2
• Inbound Pickup Unit (Model Y83765)	25	0.2	0.0
• Outbound Modulation Unit (Model 303)	25	0.7	0.2
• Control/Receiving Unit (Model 627)	25	0.4	0.1
Demand-Response Software	33	1.1	0.4
Total Annualized Asset Cost			**$104.9K**

10.3.1 Characterization of DRU System Responses

The number of members in the DRU Group-C test population at the Libby site ranged from 85 to 92 over the three years from August 2011 through August 2014. At Marion/Kila, the member count grew slowly and ranged from 15 to 21 from February 2012 through August 2014.

The cooperative provided the project with lists of the events that it initiated for this asset system, and these lists are reproduced here as Table 10.13 and Table 10.14. In the remainder of discussion about DRUs in this chapter, the events in these lists will be referred to as Peak Time events. There were 19 events called at Libby and 20 at Marion/Kila during the 19 months that this asset system was operated during the project. These listed events coincided only once (~6%) with actual monthly peak-demand hours at each of the two sites. Peak Time events overlapped advised transactive system events for this asset system 47% of the time at Libby and 60% of the time at the Marion/Kila site.

Two-thirds of the total Peak Time event durations at both sites occurred during BPA HLHs. The ratio was almost identical for events that had been advised to the DRUs by the transactive system (68% for Libby and 64% for Marion/Kila).

All of the Peak Time events were between 2 and 3 hours long.

Table 10.13. DRU Peak-Time Event Starting Times and Durations at the Libby Site

Event	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1	2013	2	28	Thursday	6	50	2:20
2	2013	3	5	Tuesday	6	50	2:10
3[c]	2013	8	15	Thursday	9	20	2:10
4	2013	9	2	Monday	19	0	2:00
5	2013	9	18	Wednesday	12	55	2:05
6[a,c]	2013	12	9	Monday	18	0	2:00
7	2014	2	10	Monday	17	30	2:00
8[b,c]	2014	2	11	Tuesday	9	0	2:00
9	2014	3	3	Monday	06	55	2:00
10[c]	2014	4	29	Tuesday	08	0	2:00
11[c]	2014	5	15	Thursday	09	45	2:00
12[c]	2014	6	10	Tuesday	10	25	2:05
13[c]	2014	6	12	Thursday	10	0	2:00
14[c]	2014	7	1	Tuesday	11	40	2:05
15[c]	2014	7	14	Monday	13	20	2:10
16	2014	7	16	Wednesday	16	0	3:00
17	2014	8	1	Friday	13	30	2:00
18	2014	8	1	Friday	17	0	2:00
19	2014	8	4	Monday	16	0	3:00

(a) This event was dispatched by the transactive system but was cancelled and not acted upon by the Flathead Electric Cooperative.
(b) The utility, upon review, had no record of this event having occurred.
(c) Coincided with an advised transactive system event for this asset system.

Table 10.14. DRU Peak-Time Event Starting Times and Durations at the Marion/Kila Site

Event	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1	2013	2	28	Thursday	6	50	2:20
2	2013	3	5	Tuesday	6	50	2:10
3[a]	2013	8	15	Thursday	9	20	2:10
4	2013	9	2	Monday	22	15	2:45
5	2013	9	18	Wednesday	12	55	2:05
6[a]	2013	12	9	Monday	18	0	2:00
7[a]	2014	1	30	Thursday	9	30	2:00
8	2014	2	6	Thursday	6	55	3:00
9[a]	2014	2	10	Monday	17	30	2:00
10[a]	2014	2	11	Tuesday	9	0	2:00
11[a]	2014	4	29	Tuesday	8	0	2:00
12[a]	2014	5	15	Thursday	9	45	2:00
13[a]	2014	6	10	Tuesday	10	25	2:05
14[a]	2014	6	12	Thursday	10	0	2:00
15[a]	2014	7	1	Tuesday	11	40	2:05
16[a]	2014	7	14	Monday	13	20	2:10
17	2014	7	16	Wednesday	16	0	3:00
18[a]	2014	8	1	Friday	13	30	2:00
19	2014	8	1	Friday	17	0	2:00
20	2014	8	4	Monday	16	0	3:00

(a) Coincided with an advised transactive system event for this asset system.

The project's transactive system advised 58 transactive events at the Libby site and 59 at the Marion/Kila site. The advised transactive event durations ranged from 50 minutes to 4 hours and 10 minutes. The advised transactive events never coincided during the project with either the listed Peak Time events or the actual monthly peak-demand hours for this asset system. Regardless, the next couple paragraphs will address some characteristics of the transactive events even though the Peak Time events were found to not have been coincident.

The weekdays of the advised transactive system events at the two sites for this asset system are shown in Figure 10.13. The weekend events transactive system events were ill-advised early in the project before the advising toolkit function had been thoroughly configured. The cooperative would unlikely desire curtailment events on Sundays and other off-peak hours because it receives no compensation for reducing peak demand during BPA lightly loaded hours.

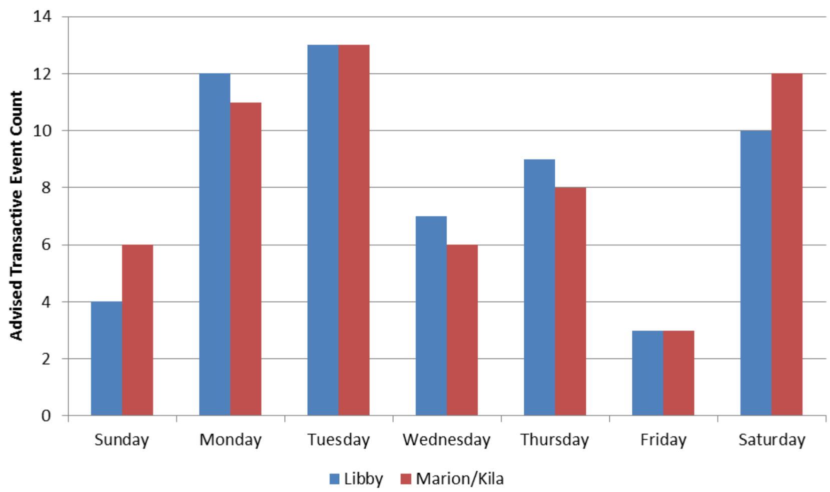


Figure 10.13. Days of Week on which Transactive Events Were Advised for the Libby and Marion/Kila DRUs

Figure 10.14 shows the starting hours (local Mountain Time) of the advised transactive system events at the two sites for this asset system. The late night and very early morning events resulted partly from the misconfigured advising function and partly from an erroneous incentive function early in the project that incentivized responses at such times.

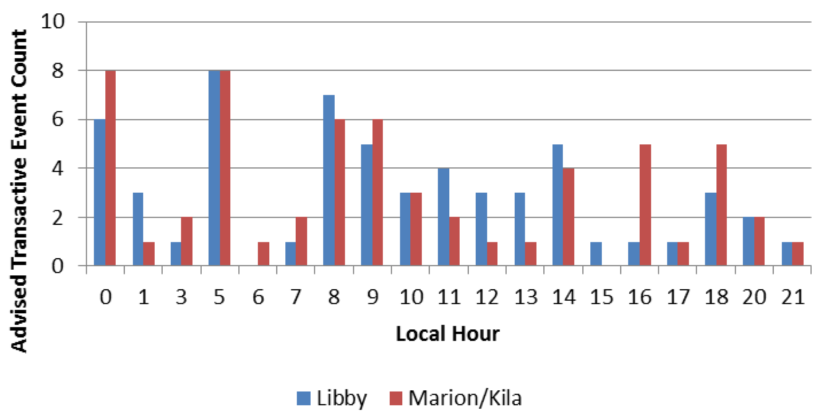


Figure 10.14. Local Starting Hours of the Advised Transactive Events for the Libby and Marion/Kila DRUs

10.3.2 DRU System Performance

The analysis for DRUs was very much like that used for the Flathead Electric Cooperative in-home displays (Section 10.1). Again, two baselines were created to emulate average premises power unaffected by the DRUs.

Controlled baseline. The controlled baseline was based on averaged hourly power from nearby Group-A premises. The data from this control group was scaled each month to have the same average and standard deviation as the premises that had DRUs controlling their water heaters. Additional global corrections were made to improve the comparison between hourly power profiles.

Modeled baseline. To create the modeled baseline, a linear regression was performed to model power consumption at times the power should not have been affected by Peak Time events as a function of ambient temperature and by month, hour, and day of week. The quality of these models was assessed by reviewing their residuals.

Several figures will now be presented to show the average difference between the baseline and test data. The results further take into account the differences between the baselines and test data both when Peak Time events were active and when they were not. The analysis was based on a Student's t-test, treating the differences between the baselines and test data as independent sets.

Figure 10.15 addresses the impact of DRU curtailment per premises at the Libby site. Impacts from Peak Time event periods are being compared to those when no events were active, which are expected to be near zero. The results using the modeled baseline for comparison (blue) are shown offset to the left of the corresponding month, and results from the controlled baseline (black) are offset to the right of the corresponding month. The aggregate results from all Peak Time periods are shown to the far right labeled "All."

The results are consistently negative, indicating that a *reduction* in load was consistently observed during events at homes that had DRUs. Based on the modeled baseline, the reduction was 226 ± 41 W per premises. A similar impact was estimated using the controlled baseline— a reduction of 252 ± 39 W per premises. The average of the analyses from both baselines is a reduction of 239 ± 28 W.

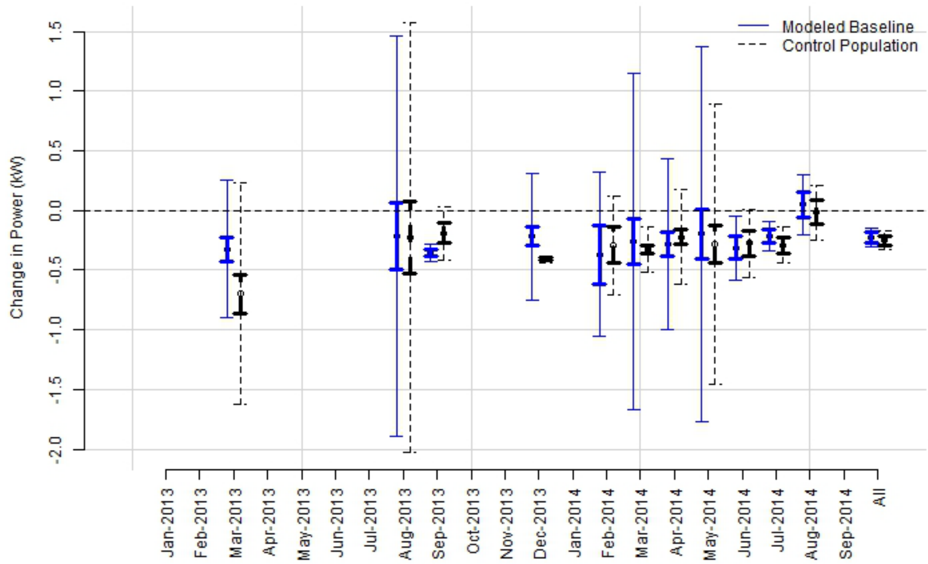


Figure 10.15. Average Impact of DRUs during Peak Time Events by Month at the Libby Site Using the Modeled (blue) and Controlled (black) Baselines

Similar results were found for the impact of DRUs during Peak Time events at the Marion/Kila site (not shown). Using the modeled baseline, a decrease of 112 ± 51 W per premises was estimated during the events. Using the controlled baseline, a decrease of 172 ± 61 W per premises was estimated. If the results from using the two baselines are averaged, the power was reduced by 142 ± 42 W at Marion/Kila premises having DRUs while the Peak Time events were active.

The project next analyzed the performance of the DRU premises in the 60-minute periods immediately following the termination of Peak Time events. Figure 10.16 shows the estimated per-premises impacts during these rebound hours at the Libby site, and Figure 10.17 shows the similar results for the Marion/Kila site. The results are shown by project month for any month that had Peak Time events. The aggregated results from the entire project are shown at the far right labeled “All.” The results appear similar at the two sites. The impacts are often positive numbers, meaning that additional energy was consumed these hours that followed the events.

Based on the modeled baseline at the Libby site, 398 ± 74 W additional average power was consumed the hour following Peak Time events at Libby premises that had DRUs. Using the controlled baseline, 417 ± 71 W more power was consumed per DRU premises. If the results from the two baselines are averaged, 408 ± 51 W more power was consumed during the rebound hour at DRU premises in Libby.

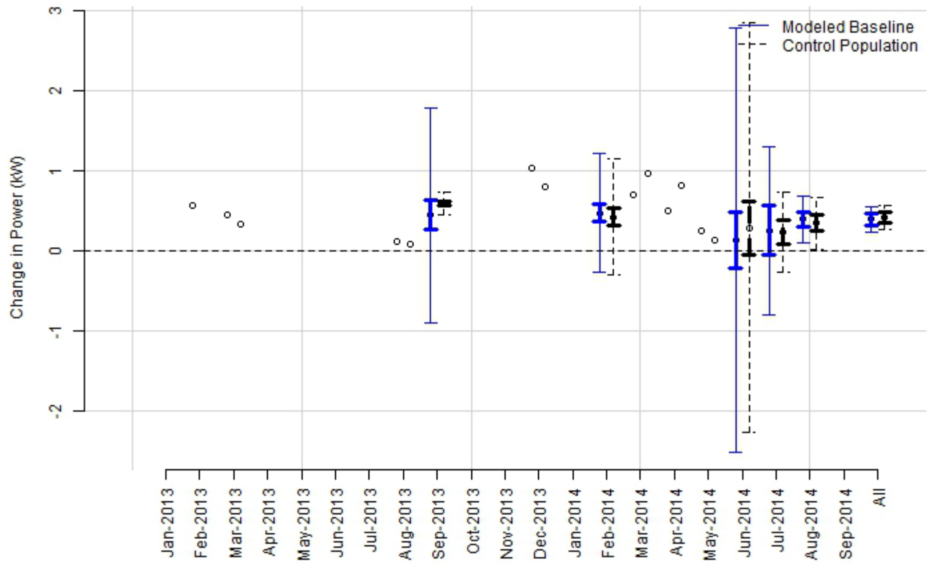


Figure 10.16. Averaged Monthly DRU Rebound Impacts per Premises at the Libby Site Based on the Modeled (blue) and Controlled (black) Baselines

At the Marion/Kila site, the modeled baseline estimate was 500 ± 110 W additional power consumed during the rebound hour, 387 ± 89 W using the controlled baseline. The averaged result from both baselines is that 441 ± 76 W additional power was consumed the rebound hour at the Marion/Kila site.

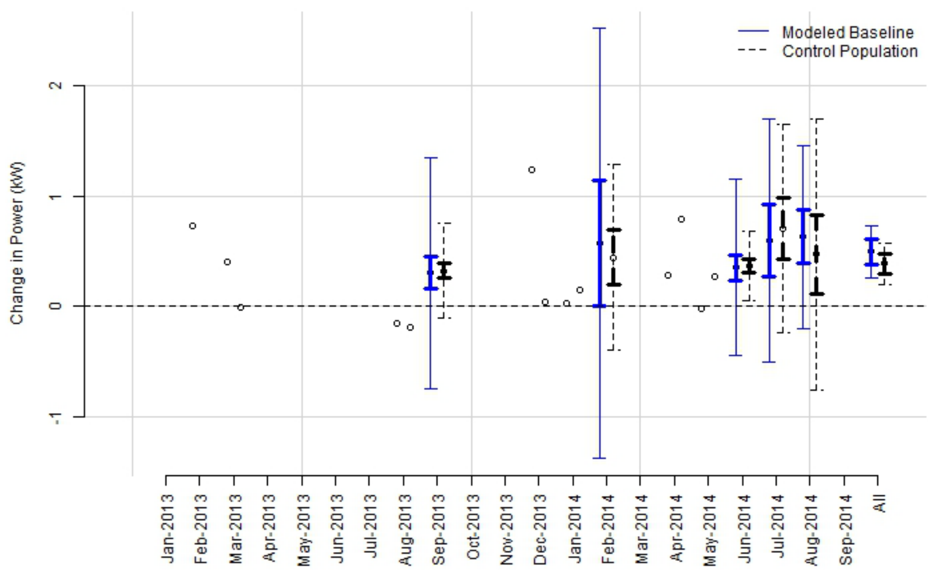


Figure 10.17. Averaged Monthly DRU Rebound Impacts per Premises at the Libby Site Based on the Modeled (blue) and Controlled (black) Baselines

Finally, the project estimated impacts of DRU events throughout the days on which Peak Time events had occurred. Figure 10.18 presents the average per-premises impact of DRU events on the day's average power consumption at the Libby site, and Figure 10.19 does the same for the Marion/Kila site.

The results are quite inconsistent from month to month. Many of the month's standard error ranges and 95% confidence ranges intersect zero. This uncertainty was evident, too, in the aggregated results for the entire project duration that is shown to the far right of these two figures. In Libby, DRU premises, on average, consumed 23 ± 12 W more throughout days that Peak Time events had occurred (i.e., 550 Wh more energy), according to the modeled baseline. The confidence of the result using the controlled baseline was poor. The combined estimate from both baselines, however, was the consumption of 15 ± 11 W more power throughout event days in Libby (i.e., 360 Wh more energy).

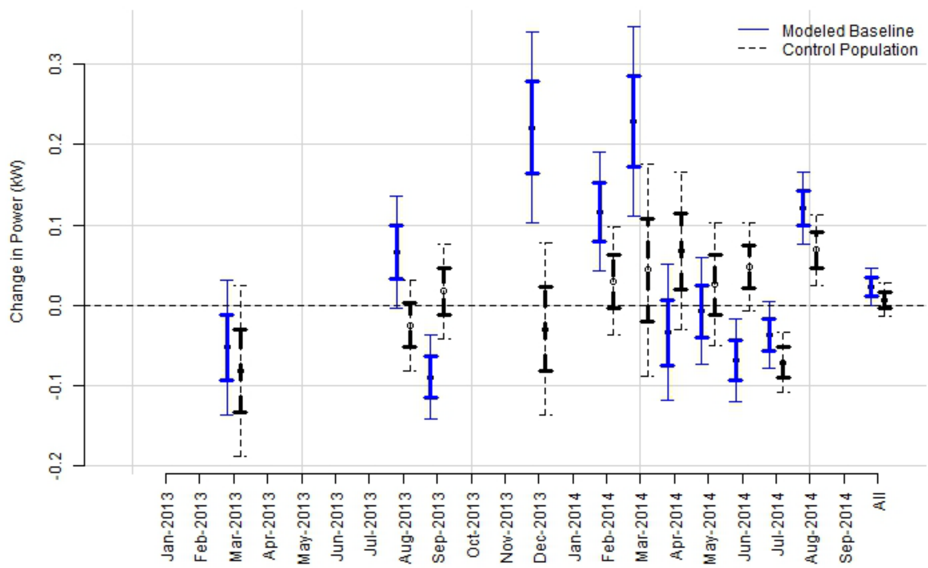


Figure 10.18. Averaged Monthly DRU Impacts per Premises at the Libby Site throughout Entire Days that Peak-Time Events had Occurred, Based on the Modeled (blue) and Controlled (black) Baselines.

Using the modeled baseline at the Marion/Kila site, DRU premises consumed 70 ± 15 W more power, on average, (i.e., 1.7 kWh more energy) throughout event days. The controlled baseline yielded a similar magnitude, but at marginal confidence levels. The combined estimate using both baselines was that Marion/Kila DRU premises consumed 46 ± 33 W more power, on average, (i.e., 1.1 kWh more energy) throughout days that Peak Time events had been called.

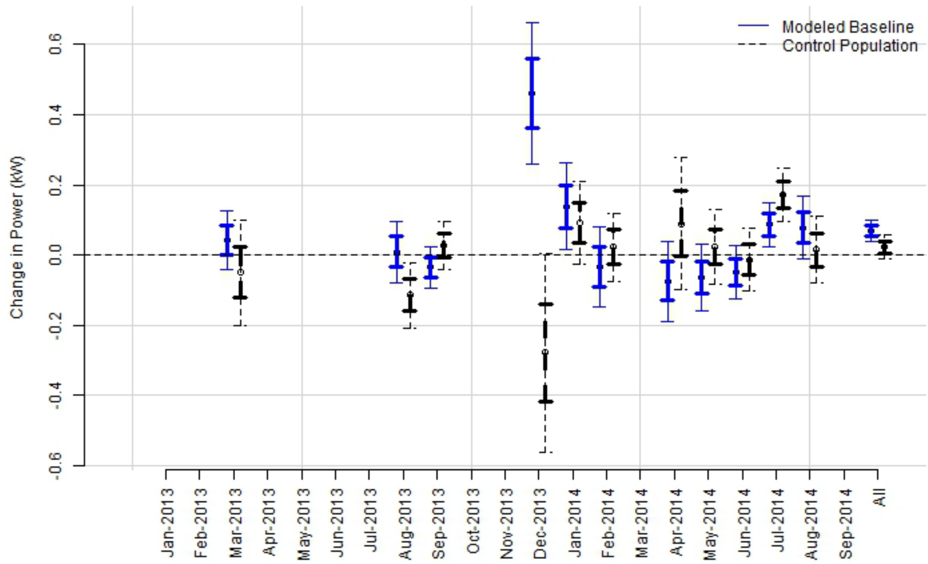


Figure 10.19. Averaged Monthly DRU Impacts per Premises at the Marion/Kila Site throughout Days that Peak-Time Events had Occurred, Based on the Modeled (blue) and Controlled (black) Baselines

Figure 10.20 presents a fairly prototypical event for the DRU premises. Event 2 from March 5, 2013 at the Libby site is the example event used in this figure. The horizontal axis includes 22 hours from this date, local Mountain Time. Each data marker shows the average per-premises power over 5 minutes for the test group at Libby that had received DRUs. Flathead premises metering was conducted at hourly intervals, so the measurements remained constant through each hour. Near the center of the figure, the blue data represents the power while the Peak Time event was reported to have occurred. The green data markers were for the rebound hour that followed the event. The average power prototypically decreased during the event and rebounded following the event.

Some analyzed DRU impacts may have become affected by event periods that did not perfectly align with the utility's hourly data collection intervals, as was often the case.

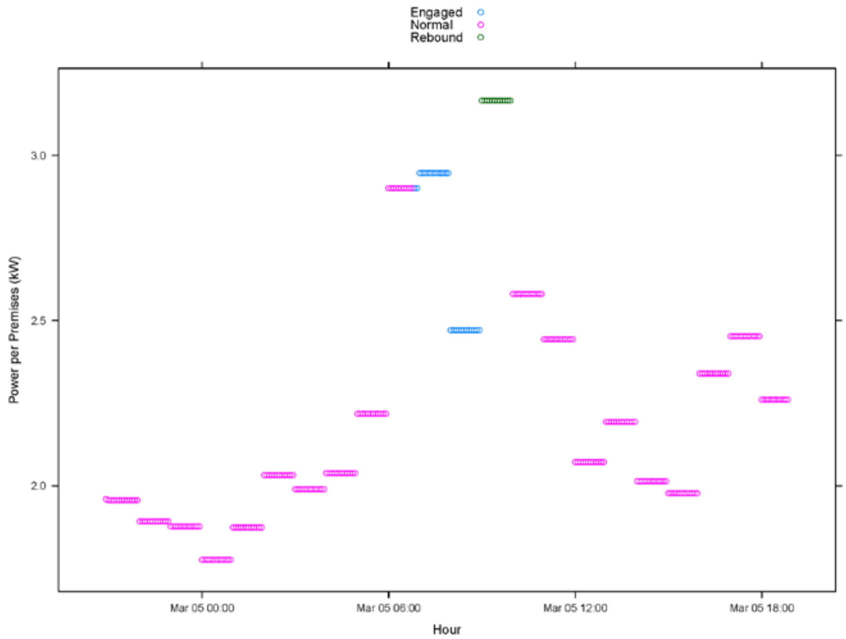


Figure 10.20. Average Premises Power for Libby DRU Owners Leading Up to and Following the Second Event. This result appears prototypical. This is Event 2 on March 5, 2013.

The project estimated the impacts of the system of DRUs at the Libby site on energy supply costs and on the demand charges that are incurred by the utility. The methods used here parallel the methods that were described in conjunction with Table 10.9 and Table 10.10 concerning the Libby in-home displays (Section 10.2.2). Those details will not be repeated here.

Table 10.15 summarizes the estimated impacts of the Libby DRUs on the utility's energy supply costs each calendar month. Presuming the utility were to operate the system as was demonstrated during the Pacific Northwest Smart Grid Demonstration, and further presuming that the utility were to also similarly use the system on the three calendar months during which the system was not actively demonstrated, the utility might avoid purchasing 775 ± 96 kWh of supply energy per year. The value of this energy is modest at $16 ± 2 per year.

Table 10.15. Estimated Energy Curtailed by Premises with DRUs each Calendar Month and the Supply Value of that Energy as the DRU Premises Responded to Peak Time Events

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	-	-	-	-	-	-
Feb	−119 ± 67	−2.3 ± 1.3	-	-	−119 ± 67	−2.3 ± 1.3
Mar	−90 ± 19	−1.8 ± 0.4	-	-	−90 ± 19	−1.8 ± 0.4
Apr	−32 ± 2	−0.7 ± 0.1	-	-	−32 ± 2	−0.7 ± 0.1
May	−26 ± 9	−0.6 ± 0.2	-	-	−26 ± 9	−0.6 ± 0.2
Jun	−65 ± 18	−1.6 ± 0.4	-	-	−65 ± 18	−1.6 ± 0.4
Jul	−80 ± 15	−1.4 ± 0.3	-	-	−80 ± 15	−1.4 ± 0.3
Aug	−9 ± 37	−0.2 ± 0.6	-	-	−9 ± 37	−0.2 ± 0.6
Sep	−48 ± 4	−0.8 ± 0.1	−55 ± 6	−1.5 ± 0.2	−103 ± 7	−2.2 ± 0.2
…	-	-	-	-	-	-
Dec	−57 ± 4	−1.2 ± 0.1	-	-	−57 ± 4	−1.2 ± 0.1

The impact of the Libby system of DRUs on its yearly demand charges are estimated in Table 10.16 for each calendar month. The DRUs demonstrated a small effect on average HLH for nine of the 12 calendar months. The Peak Time events coincided with historical peak hours four of those months. In sum, if the system were to be operated throughout a full year as was demonstrated by the utility, the demand charges might be reduced by $1,163 ± 11 per year.

This estimate would be expected to scale nearly linearly if additional DRUs were to be installed. This analysis used only the demonstrated impacts on energy consumption during Peak Time events. Rebound effects and event-day effects were not explicitly included in the results.

Table 10.16. Estimated Impact of the System of Libby DRUs on the Demand Charges that are Incurred each Month by Flathead Electric Cooperative

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Demand Charges ($)
Jan	-	-	-
Feb	-	−0.31 ± 0.17	3 ± 0
Mar	−36 ± 7	−0.21 ± 0.04	−341 ± 7
Apr	-	−0.08 ± 0.01	1 ± 0
May	-	−0.06 ± 0.02	1 ± 0
Jun	−16 ± 6	−0.16 ± 0.04	−150 ± 6
Jul	−26 ± 1	−0.20 ± 0.04	−243 ± 1
Aug	−15 ± 1	−0.02 ± 0.09	−145 ± 1
Sep	-	−0.12 ± 0.01	1 ± 0
…	-	-	-
Dec	-	−0.14 ± 0.01	1 ± 0

10.4 Demand-Response Appliances

Flathead Electric wished to investigate whether it is cost-effective for its members who already have AMI to additionally install a suite of communicating home appliances. The cooperative selected a suite of General Electric Profile Brillion™ appliances, a home energy gateway (Figure 10.21 and Figure 10.22), a 240 V water heater switch, and an energy display (GE 2014) and installed them at qualifying members' homes. Qualifying members were home owners who possessed electric water heaters, a home computer, and internet connectivity and who agreed to pay a deeply subsidized rate of $800 for the entire suite of devices. Participants committed to maintain the appliances in place or repay a pro rata value full appliance value if they removed the appliances from the program.

This system of home devices all communicated via the wireless ZigBee® specification (ZigBee Alliance 2014a). Flathead Electric Cooperative wished to send their Peak Time command to these ZigBee-enabled appliances (clothes washer, clothes dryer, dishwasher, and DRUs for water heaters and 240 V appliances) to conduct load curtailment.

An important lesson from this asset system was that the system components procured from the multiple vendors of the smart appliances, home gateways, and advanced premises metering were not interoperable. Flathead Electric led an intense effort to gradually integrate and test the system. While the GE equipment worked well together, the non-GE water heater switch and the connection to an Aclara meter was difficult. Some of the confusion appeared to result from the vendors' various stages of adopting and implementing the ZigBee Smart Energy Profile versions 1.0 or 2.0 (ZigBee Alliance 2014b). Eventually, an acceptable work-around solution was identified, but the communication routes were circuitous.

Figure 10.21. GE Nucleus™ Home Energy Gateway that was Used in the Flathead Electric Cooperative Peak-Time Project[1]

Figure 10.22. Example GE Home Energy Gateway Display[2]

Figure 10.23 is an example snapshot of the screen of Flathead Electric's Web portal that was available to its participating members. The portal is displaying the member's current rate for electricity, current power usage, an example of disaggregated energy cost information for a member's dishwasher, and the member's historical electricity consumption.

[1] Ibid.
[2] Ibid.

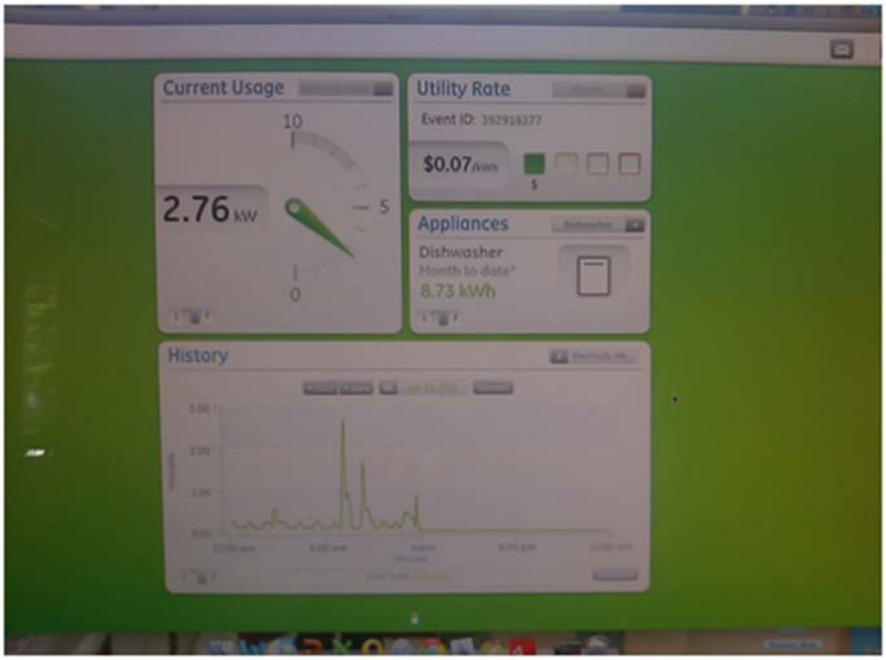


Figure 10.23. Example Web Portal Screen Available to Premises that Used the GE System of Communicating Appliances[1]

The benefit of the cost-additive technology of ZigBee wireless communication and smart appliances was evaluated by comparing costs and benefits of those members who install smart appliances against those who have only AMI. The annualized costs of the system and its components are summarized in Table 10.17 (Libby site) and Table 10.18 (Marion/Kila site). The ZigBee appliances, home energy gateways, and 240 V switches are the active hardware components of the system and account for much of the cost. Other cost components follow from software, utility staff labor, incentives, premises metering, and TWACS upgrades at substations. The total annualized cost of the Libby, Montana, demand-response appliance system was $207,100. The annualized cost at the Marion/Kila site was $174,500.

[1] Ibid.

Table 10.17. Incremental Annualized Costs of Demand-Response Appliances at the Libby, Montana, Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
ZigBee Appliances			158.4
• Washers/Dryers	100	41.6	41.6
• Dishwashers	50	31.2	115.6
• Washers/Dryers (spares)	100	0.8	0.8
• Dishwashers (spares)	100	0.4	0.4
Integration Software	17	293.6	49.0
Staff Support	13	293.1	36.6
Home Energy Gateway (includes energy display)	50	66.7	33.3
Incentives	100	20.0	20.0
DRU 240 V Switch	50	11.0	5.5
Back-End Metering	13	11.7	1.5
Substation TWACS Components			0.9
• Modulation Transfer Unit (Model Y87363)	25	1.4	0.3
• Inbound Pickup Unit (Model Y83760)	25	0.3	0.1
• Outbound Modulation Unit (Model 303)	25	1.3	0.3
• Control/Receiving Unit (Model 627)	25	0.9	0.2
Group-D Single-Phase Meters	50	1.5	0.7
Meter Operations and Maintenance	25	2.4	0.6
Demand-Response Software	33	1.1	0.4
Total Annualized Asset Cost			**$207.1K**

Table 10.18. Incremental Annualized Costs of Demand-Response Appliances at the Marion/Kila, Montana, Site

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Integration Software	17	293.6	49.0	
ZigBee Appliances			36.4	
• Dishwashers	50	31.2		15.6
• Washer/Dryer Sets	100	20.8		20.8
Staff Support	13	293.1	36.6	
Home Energy Gateway (includes energy display)	50	66.7	33.3	
Incentives (rebates)	100	10.0	10.0	
DRU 240 V Switch	50	11.0	5.5	
Back-End Metering	13	11.7	1.5	
Group-D Single-Phase Meters	50	1.5	0.7	
Meter Operations and Maintenance	25	2.4	0.6	
Substation TWACS Components			0.5	
• Modulation Transfer Unit (Model Y87362)	25	0.7		0.2
• Inbound Pickup Unit (Model Y83765)	25	0.2		0.0
• Outbound Modulation Unit (Model 303)	25	0.7		0.2
• Control/Receiving Unit (Model 627)	25	0.4		0.1
Demand-Response Software	33	1.1	0.4	
Total Annualized Asset Cost			**$174.5K**	

10.4.1 Characterization of the Demand-Response Appliance System Responses

On an average monthly basis, the number of premises participating in the demand-responsive appliance test ranged from 67 to 101 at the Libby, Montana, site between August 2012 and the end of August 2014. There were between 12 and 17 participating premises at the Marion/Kila site between January 2012 and the end of August 2014.

There were 19 Peak Time events called for the appliances at both sites. See Table 10.19 and Table 10.20 for summaries of these events' starting times and durations. The ridiculously long first event at the Libby site was omitted from most of the analysis. Some additional problems and discrepancies were found between the utility's records and the project's records upon review by the utility, as are noted in the footnotes of these tables. During the analysis, the events in these two tables will be referred to as the set of Peak Time events.

Table 10.19. Peak-Time Event Times and Durations for the Libby, Montana, Demand-Response Appliances

	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1[a]	2013	3	5	Tuesday	9	0	3873:45
2[b,c]	2013	8	15	Thursday	09	20	2:10
3[c]	2013	8	19	Monday	12	40	2:05
4[c]	2013	9	2	Monday	13	0	2:00
5	2013	9	3	Tuesday	12	0	2:00
6	2013	9	18	Wednesday	12	55	2:05
7	2013	12	9	Monday	1	0	2:00
8[c]	2014	2	10	Monday	17	30	2:00
9[c,d]	2014	2	11	Tuesday	9	0	2:00
10	2014	3	3	Monday	06	55	2:00
11[c]	2014	4	29	Tuesday	08	0	2:00
12[c]	2014	5	15	Thursday	09	45	2:00
13	2014	6	10	Tuesday	10	25	2:05
14[c]	2014	6	12	Thursday	10	0	2:00
15[c]	2014	7	1	Tuesday	11	40	2:05
16[c]	2014	7	14	Monday	13	20	2:10
17	2014	7	16	Wednesday	16	0	3:00
18[c]	2014	8	1	Friday	13	30	2:00
19[e]	2014	8	1	Friday	16	0	2:00

(a) The first event was "stuck" in its engaged state. This event period was excluded from analysis.

(b) The utility and project had discrepant records. Analysis was performed from database records that indicated this event began at 15:20.

(c) Coincides with an advised transactive event

(d) The utility, upon review, had no record of this event that was used in analysis.

(e) The utility and project had discrepant records. Analysis was performed from database records that indicated this event began at 17:00.

Table 10.20. Peak-Time Event Times and Durations for the Marion/Kila, Montana, Demand-Response Appliances

	Year	Month	Day	Weekday	Hour	Minute	Length (h:m)
1	2013	3	20	Wednesday	6	50	2:10
2[(a)]	2013	8	15	Thursday	9	20	2:10
3[(a,b)]	2013	9	2	Monday	16	15	2:45
4[(c)]	2013	9	18	Wednesday	06	55	2:05
5[(a)]	2013	12	9	Monday	18	0	2:00
6[(a)]	2014	1	30	Thursday	09	30	2:00
7	2014	2	6	Thursday	06	55	3:00
8[(a)]	2014	2	10	Monday	17	30	2:00
9[(a)]	2014	2	11	Tuesday	09	0	2:00
10[(a)]	2014	4	29	Tuesday	08	0	2:00
11[(a)]	2014	5	15	Thursday	09	45	2:00
12	2014	6	10	Tuesday	10	25	2:05
13[(a)]	2014	6	12	Thursday	10	0	2:00
14[(a)]	2014	7	1	Tuesday	11	40	2:05
15[(a)]	2014	7	14	Monday	13	20	2:10
16	2014	7	16	Wednesday	16	0	3:00
17[(a)]	2014	8	1	Friday	13	30	2:00
18	2014	8	1	Friday	17	0	2:00
19	2014	8	4	Monday	16	0	3:00

(a) Event coincides with an advised transactive event
(b) Project and utility records conflict. The project data caused analysis to look for this event starting at 22:15.
(c) Project and utility records conflict. The project data caused analysis to look for this event starting at 12:55.

The analysis of the performance of the suite of communicating appliances will be focused on the Peak Time events, when the appliances were reported to have been engaged by the utility. However, the next figures and paragraphs will refer to the transactive events. The project had requested that the assets should be engaged coincident with advice that was generated by the project's transactive system. Eleven and 12 of the 19 Peak Time events at the two sites (58 - 63%) were found to have overlapped the events that had been advised by the transactive system.

Figure 10.24 summarizes the days of week on which the transactive system advised its events at the two Flathead Electric sites. The events were pretty uniformly distributed across the days. The most events were advised on Tuesdays, and the fewest on Fridays.

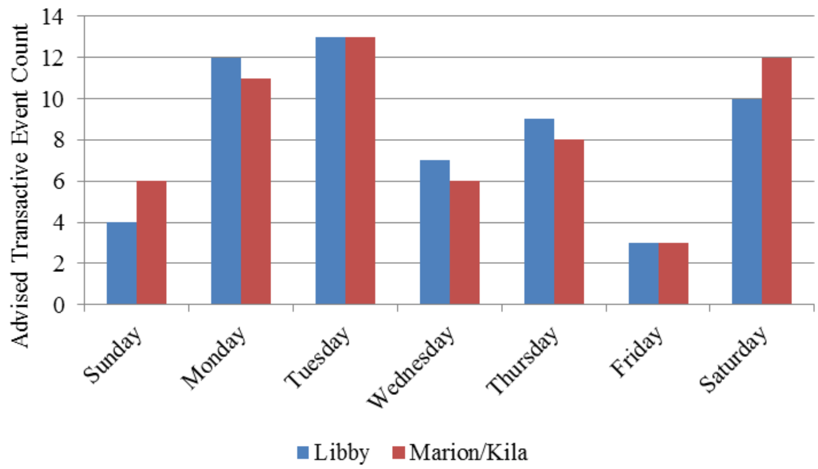


Figure 10.24. Days on which Transactive Events were Advised for the Group-D Premises in Libby and Marion/Kila

Figure 10.25 summarizes the local Mountain Time hours that the advised transactive events started at the two sites. An unexpectedly large number of events occurred at hour 0 just after midnight. These events likely occurred early in the project while the project was troubleshooting its transactive system's signals and before the utility had fully configured the transactive function that was used to advise events for this asset.

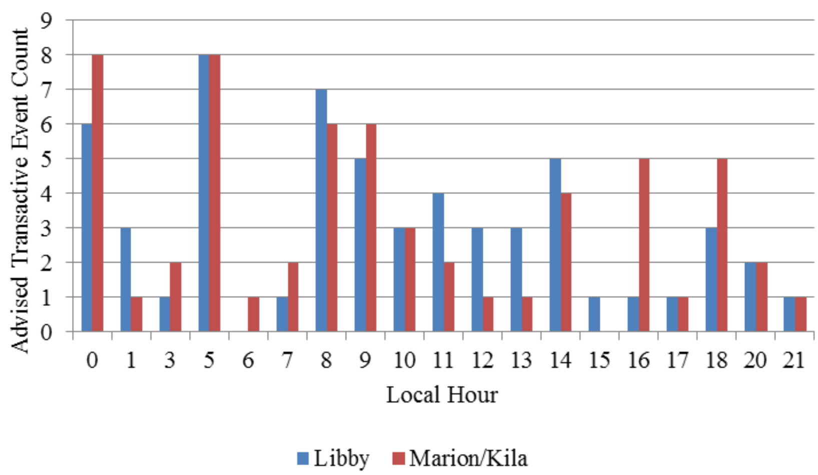


Figure 10.25. Hours on which Transactive Events were Advised for the Group-D Premises in Libby and Marion/Kila

10.4.2 Demand-Response Appliance System Performance

The cooperative installed and monitored the demand-response appliance asset system similarly at the urban Libby and the more rural Marion/Kila sites. One of the utility's objectives was to learn whether smart grid infrastructure is equally cost-effective in urban and rural settings.

Figure 10.26 estimates the average monthly per-premises impacts of the communication appliances during Peak Time events at the Libby site premises that had received these appliances. The modeled and controlled baselines were created the same as was done for the Group-B and Group-C analyses. The monthly ranges and aggregated results for all project months that are shown to the right of the diagram labeled "All" are perhaps more varied and uncertain than was observed for the system of DRU. The appliances include smaller loads that are less regularly used. Some are affected through the voluntary actions of their owners.

Using the modeled baseline at the Libby site, the suite of appliances was estimated to have reduced premises load during Peak Time events by 112 ± 34 W. Using the controlled baseline at this site, the reduction was estimated to be 168 ± 28 W. Combining the results from the two baselines, the appliance set reduced consumption by about 140 ± 40 W per premises during the Peak Time events in the Libby site.

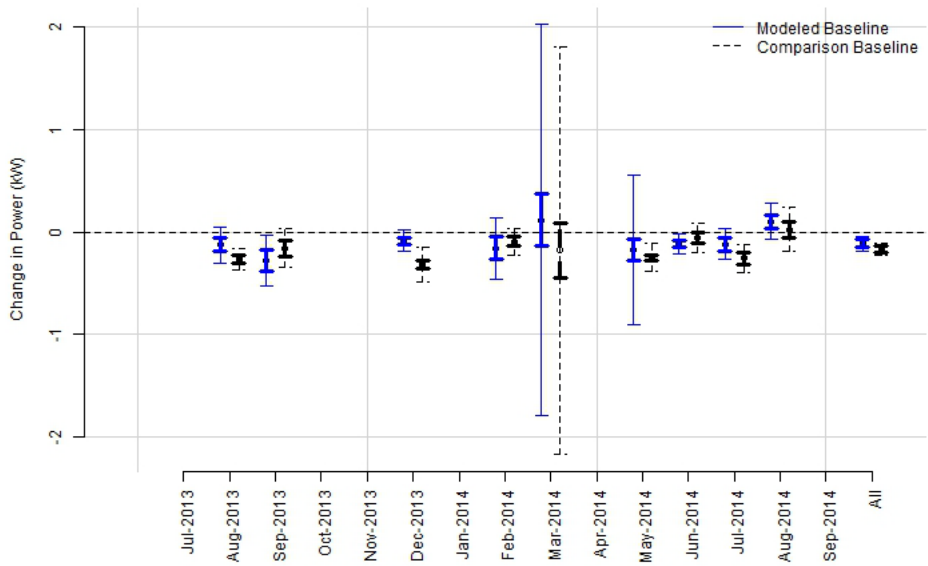


Figure 10.26. Change in Premises Power by Month during both On-Peak and Off-Peak Events at the Libby Site According to the Modeled (blue) and Controlled (black) Baselines

Greater reductions were estimated for the Marion/Kila site. The modeled baseline comparison showed power reduction of 198 ± 63 W, and the controlled baseline yielded reduction of per-premises load by 232 ± 59 W during the Peak Time events. The average from the two baselines was a reduction of 215 ± 43 W per premises during the Peak Time events.

Figure 10.27 summarizes the monthly results when the project looked at the impact on power consumption during the rebound hour at residences that possessed the communicating appliances. These results were inconclusive. The modeled baseline suggested that power consumption increased 75 ± 49 W during the hour following the Peak Time events, but no impact was found using the controlled baseline. If results from both baselines are averaged, the impact is a more modest 38 ± 51 W, reported with large uncertainty.

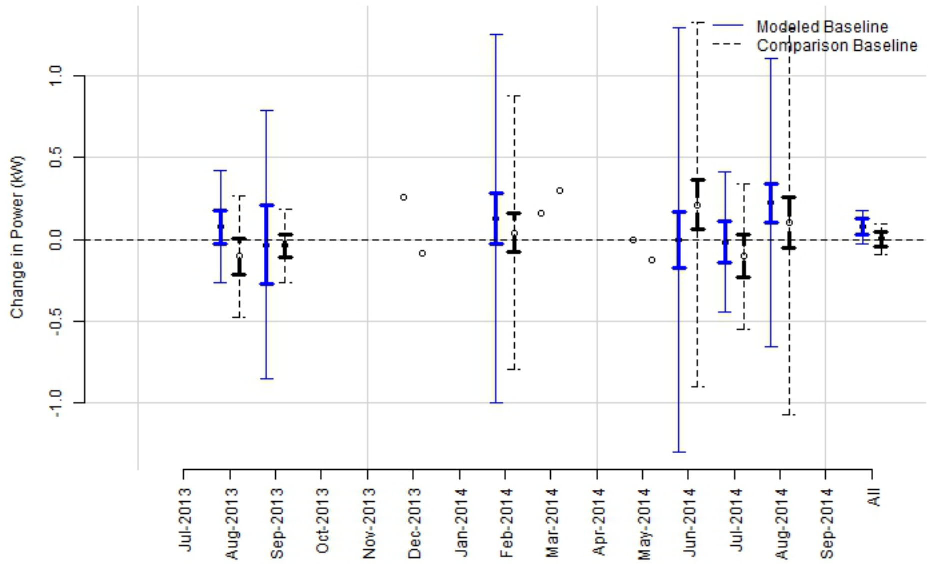


Figure 10.27. Change in Premises Power by Month during the Rebound Hour Following Events at the Libby Site According to the Modeled (blue) and Controlled (black) Baselines

Neither the modeled nor the controlled baselines at the Marion/Kila site suggested that any rebound impact had occurred.

Figure 10.28 summarizes the per-premises impacts that were observed at the Libby site throughout those days on which Peak Time events had occurred. Again, the results were highly variable from month to month. Using the modeled baseline, the impact was estimated as an average increase of 39 ± 11 W per premises on Peak Time event days at premises that possessed the appliances. If both baselines are used, the average is only about 12 ± 38 W, but this result is accompanied by great uncertainty.

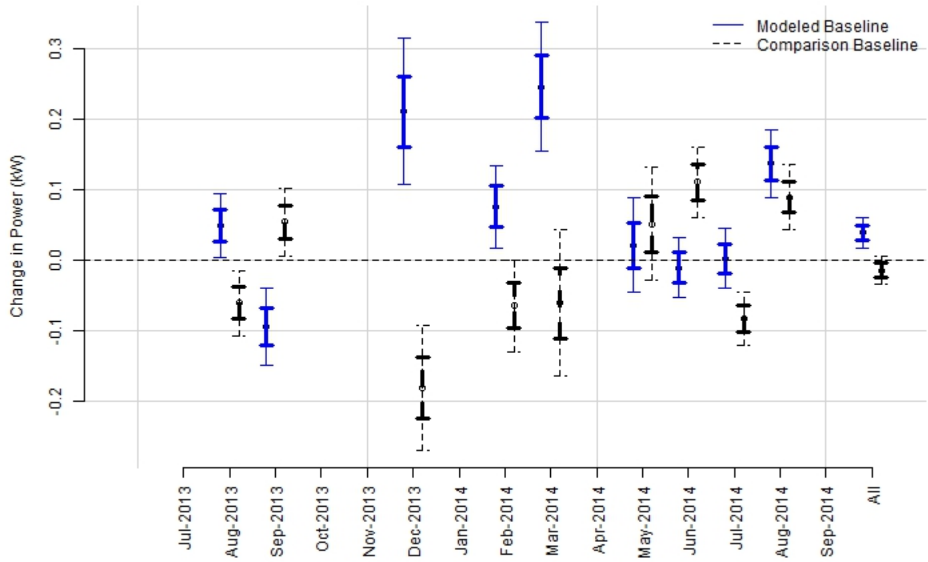


Figure 10.28. Change in Premises Power by Month during Following Event Days at the Libby Site According to the Modeled (red) and Comparison (blue) Baseline Approaches

Neither the modeled or controlled baselines resulted in event-day impacts at the Marion/Kila site with high enough certainty to report.

The project estimated the impact that the set of Libby communicating appliances had on energy supply costs and demand charges. The methods closely parallel those that were used and discussed in conjunction with Table 10.9 and Table 10.10 in Section 10.2.2 and will not be repeated here.

Table 10.21 summarizes the estimated impacts of the Libby system of communicating appliances on the costs of supply energy each calendar month. If the utility were to use the appliances all 12 calendar months as it demonstrated during eight project months, the project extrapolates that it would conserve about 800 ± 200 kWh per year with a supply value of $16 ± 4 per year. This estimate is based on the system’s performance during the events periods only.

Table 10.21. Estimated Energy Curtailed by Premises with Communicating Appliances each Calendar Month and the Supply Value of that Energy as the Premises Responded to Peak Time Events

	HLH		LLH		Total	
	(kWh)	($)	(kWh)	($)	(kWh)	($)
Jan	-	-	-	-	-	-
Feb	−44 ± 21	−0.8 ± 0.4	-	-	−44 ± 21	−0.8 ± 0.4
Mar	−3 ± 33	−0.1 ± 0.7	-	-	−3 ± 33	−0.1 ± 0.7
Apr	-	-	-	-	-	-
May	−45 ± 8	−1.1 ± 0.2	-	-	−45 ± 8	−1.1 ± 0.2
Jun	−30 ± 10	−0.7 ± 0.2	-	-	−30 ± 10	−0.7 ± 0.2
Jul	−116 ± 27	−2.1 ± 0.5	-	-	−116 ± 27	−2.1 ± 0.5
Aug	−62 ± 130	−1.0 ± 2.0	−62 ± 65	−2.0 ± 2.0	−124 ± 145	−2.7 ± 2.7
Sep	−107 ± 42	−1.8 ± 0.7	−31 ± 8	−1.0 ± 0.0	−139 ± 43	−2.6 ± 0.7
Oct	-	-	-	-	-	-
Nov	-	-	-	-	-	-
Dec	−35 ± 3	−0.7 ± 0.1	-	-	−35 ± 3	−0.7 ± 0.1

Table 10.22 estimates the demonstrated monthly impacts of the Libby communicating appliances on the utility’s demand charges each calendar month. The system had a small impact on the average HLH hour energy during the eight calendar months that the system was being demonstrated. The Peak Time events for these appliances coincided with historical peak hours four of these months. Presuming the system were operated all 12 months in the same way it was demonstrated, the utility might reduce its demand charges by only about $190 ± 10 per year.

Table 10.22. Estimated Impact of the System of Libby Communicating Appliances on the Demand Charges that are Incurred each Month by Flathead Electric Cooperative

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Demand Charges ($)
Jan	-	-	-
Feb	-	−0.11 ± 0.05	1 ± 0
Mar	4 ± 4	−0.01 ± 0.08	38 ± 4
Apr	-	-	-
May	-	−0.11 ± 0.02	1 ± 0
Jun	−1 ± 2	−0.07 ± 0.02	−5 ± 2
Jul	−21 ± 3	−0.29 ± 0.07	−198 ± 3
Aug	3 ± 3	−0.14 ± 0.30	33 ± 3
Sep	-	−0.27 ± 0.11	3 ± 0
Oct	-	-	-
Nov	-	-	-
Dec	-	−0.09 ± 0.01	1 ± 0

11.0 Idaho Falls Power Site Tests

Idaho Falls Power is a municipal electric utility that serves the 22.4 thousand residential and 3.7 thousand commercial customers in Idaho Falls, Idaho. In 2013, 42% of its retail power was supplied to residential customers, 39% to commercial, and 13% to industrial customers. In addition to its distribution customer services, the city also operates 37 miles of transmission lines, 410 miles of distribution lines and 53.5 MW of hydroelectric, wind, and solar generation (Idaho Falls 2014). The city purchases the majority of its power from the Bonneville Power Administration (BPA) and is a slice customer of the BPA.

Idaho Falls Power elected to demonstrate a great variety of asset systems of any utility participant in the Pacific Northwest Smart Grid Demonstration project. The following asset systems will be described in this report:

- voltage management (Section 11.1)
- power factor control (Section 11.2)
- distribution automation (Section 11.3)
- water heater control (Section 11.4)
- plug-in hybrid electric vehicle (PHEV), solar, and battery storage (Section 11.5)
- thermostat control (Section 11.6)
- in-home displays (IHDs) (Section 11.7).

The layout of these tests among the Idaho Falls Power distribution circuits is shown in Figure 11.1 and Figure 11.2.

In Figure 11.1 and Figure 11.2, asset systems are labeled with asset numbers assigned by the project. For example, "IF-01" refers to the voltage management system at Idaho Falls. The two digits that are appended to the asset number indicate whether the principal objectives of the asset system were applied toward demand response ("1.x"), improved reliability ("2.x"), or conservation and efficiency ("3.x"). The series of dashes, "E," and "C" reference the sequential numbered asset systems to which a data set is relevant as experimental data ("E"), control data ("C"), or neither ("-").

Additionally, Table 11.1 lists the data stream names that were negotiated with Idaho Falls Power for the data listed on the layout diagram. Faced with the need to organize many data time series, the project defined shorthand for the impact metrics ("IM") relevant to analysis of the various project assets. The asterisks represent unique text for the given asset system, device, or meter location. The table also lists the interval that each data series element represents and the interval at which the utility agreed to update the series. Not all the data streams listed in this table were, in fact, supplied by the utilities and at the requested intervals.

Table 11.1. Data Notation Shorthand used by the Project in Layout Diagram Figure 11.1 and Figure 11.2

Data Stream	Data Interval	Submit Interval	Description
IF-IM-1-*	15 minutes	1 day	Residential customer meter – power
IF-IM-3-*	1 month	1 month	Residential customer meter – monthly energy
IF-IM-13-*	1 month	1 month	System efficiency – meter operations costs
IF-IM-15-*	5 minutes	1 day	Distribution meter – voltage (end-of-line)
IF-IM-15-*	15 minutes	1 day	Residential customer meter – voltage (end-of-line)
IF-IM-20-*	1 month	1 month	System efficiency – meter operations miles driven
IF-IM-30-*	1 day	1 month	Residential customer meter – data completeness
IF-IM-40-*	1 year	1 month	Reliability events – feeder overload
IF-IM-41-*	5 minutes	1 day	Distribution meter – real power
IF-IM-42-*	5 minutes	1 day	Distribution meter – reactive power
IF-IM-48-*	1 hour	1 day	Distribution equipment – capacitor switch events
IF-IM-51-*	5 minutes	1 day	Distribution meter – power factor
IF-IM-52-*	1 month	1 month	System efficiency – truck rolls
IF-IM-61-*	1 year	1 month	System Average Interruption Duration Index
IF-IM-63-*	1 year	1 month	Reliability events – outage response time
IF-IM-66-*	1 year	1 month	Customer Average Interruption Duration Index
IF-IM-201-*	1 hour	1 day	Distribution equipment – tap changes
IF-IM-300-*	1 hour	1 day	Demand-response system – opt-out count
IF-IM-453-*	1 hour	1 day	Residential customer meter – low-voltage alarm
IF-IM-454-*	1 hour	1 day	Residential customer meter – high-voltage alarm
IF-IM-814-*	1 hour	1 day	Distribution equipment – target voltage

Two other asset systems were initially proposed—control of thermostats at commercial customer premises and a combined PHEV, solar, and battery energy storage system—but these never fully materialized. Commercial-customer–grade meters were installed and tested in February 2013, but they were found to not support the functionality that Idaho Falls Power had wanted to test at commercial premises. The project invested in the system of PHEV, solar-generation, and battery-storage assets, but this asset system ultimately failed to produce useful demonstration data for reasons that will be discussed later in this section.

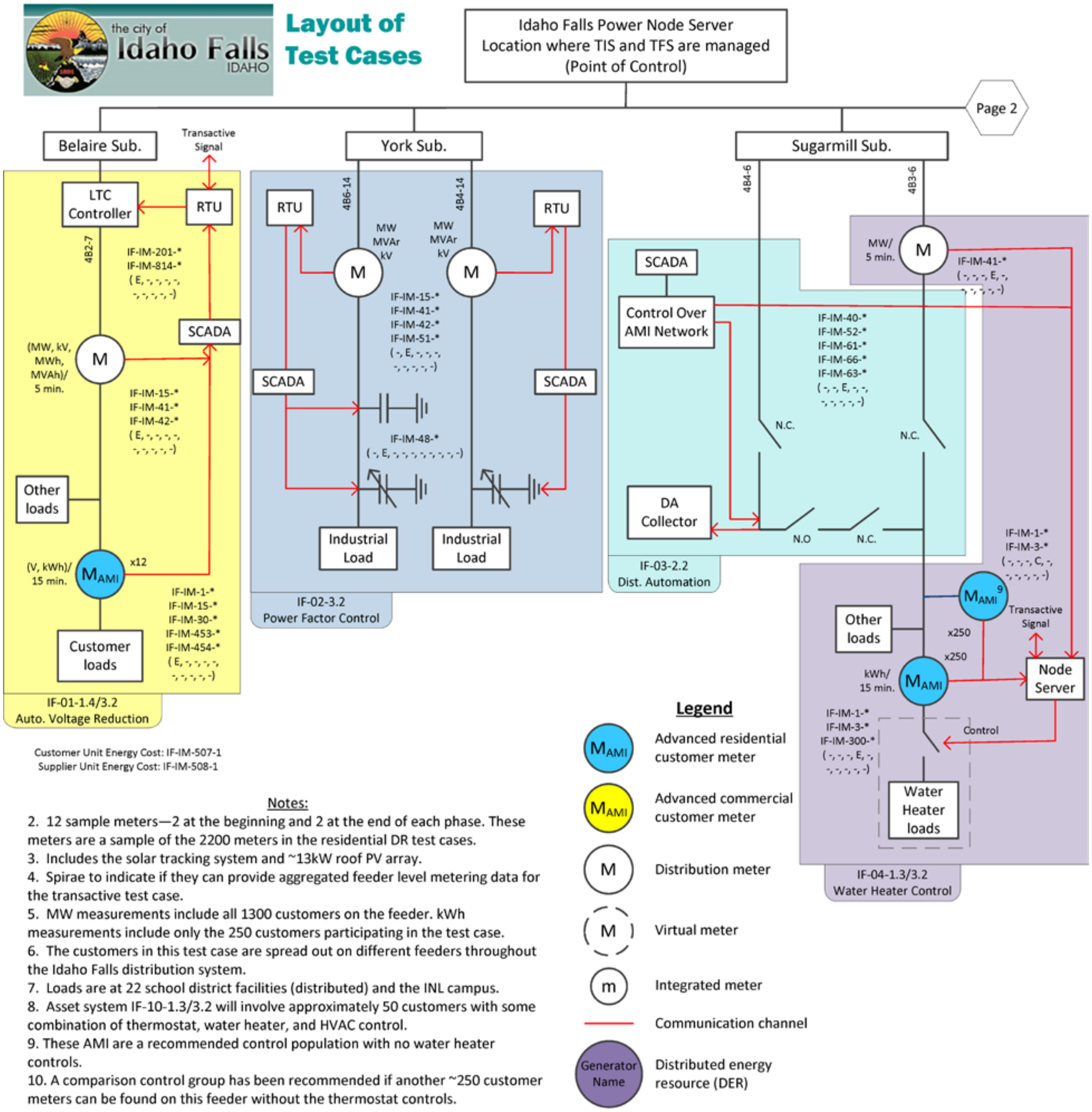


Figure 11.1. Idaho Falls Power Layout Diagram, Page 1

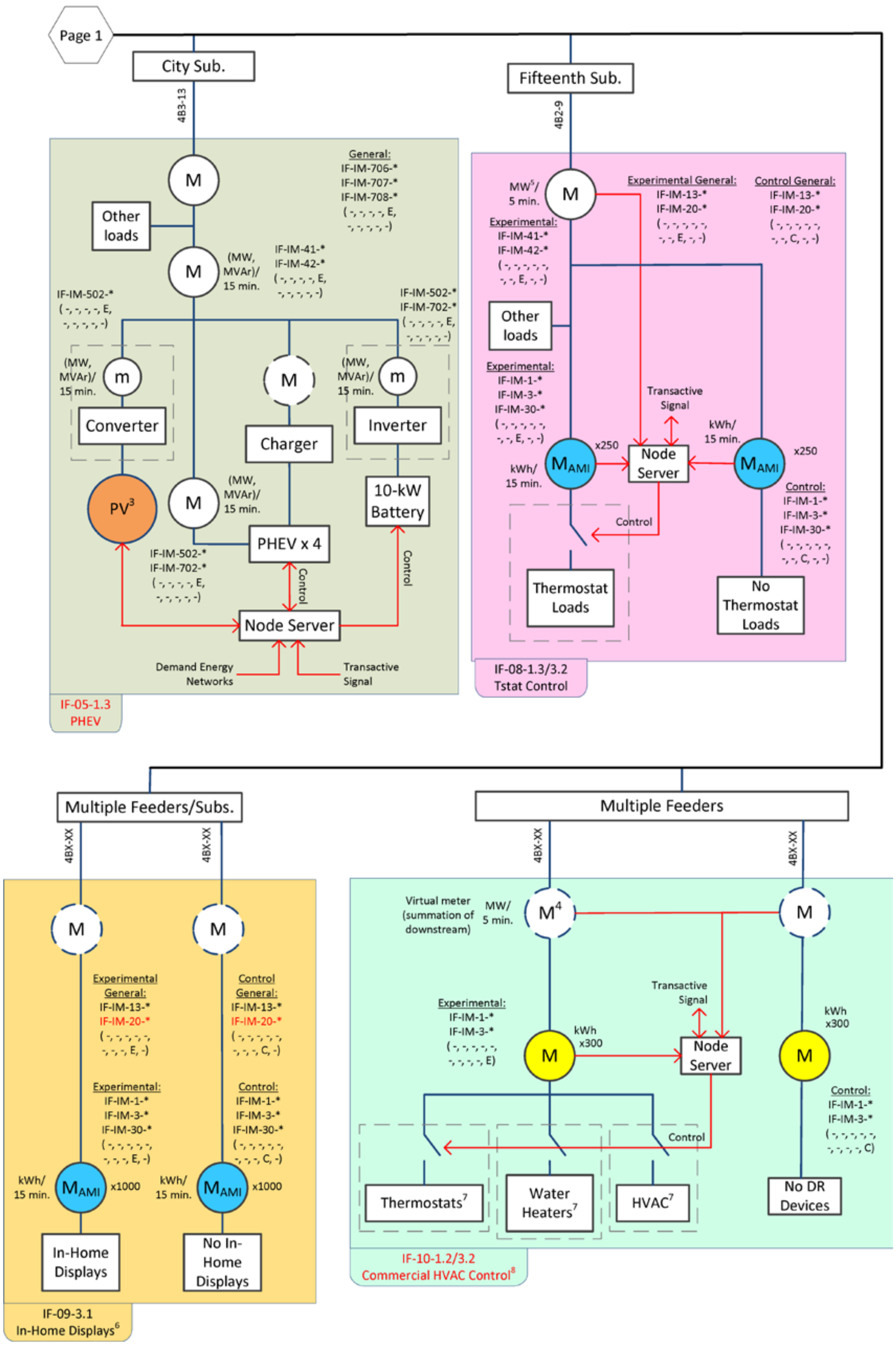


Figure 11.2. Idaho Falls Power Layout Diagram, Page 2

11.1 Conservation Voltage Regulation

Idaho Falls Power purchased and installed a load tap change controller at its Belaire substation to manage the feeder's voltage. The system was installed and useful as of June 29, 2012. One of the objectives was conservation voltage regulation, so the city expected to observe a reduction in feeder energy consumption after the system was installed and while applying a lower, managed distribution voltage to the feeder. The project monitored numbers of tap changes to address wear and tear on distribution equipment. The project also monitored high- and low-voltage alarms to address whether distribution voltage management degraded or improved the quality of delivered voltages.

The voltage control system was also configured to respond to the project's transactive system. The system was configured to conduct additional voltage reduction each day when the transactive incentive signal (TIS) was at its highest. The city asserted that it would respond to every event that was advised by the transactive system. No independent event status was made available to the project. However, this asset system allowed analysts to confirm events by observing periods when the feeder's voltage had been reduced.

The city's supervisory control and data acquisition (SCADA) system gathered 5-minute distribution power and voltage readings at the Belaire substation. Additionally, the system sampled 12 premises meters to monitor end-of-line voltages and thereby verify that customers were being supplied adequate power quality.

Table 11.2 summarizes the asset system components and estimated costs that were incurred to install and operate this system. The costs have been annualized so that they may be compared directly against annualized benefits. The project believes these annualized costs are those that would be borne by a Pacific Northwest municipality that reproduces similar voltage control capabilities. The system's total annualized cost is the sum of the individual component's annualized costs, based on the component's anticipated useful lifespan.

Table 11.2. Idaho Falls Power Costs of Voltage Management System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Transactive Node	14	317.1	45.3	
Idaho Falls Power Staff Labor	100	25.3	25.3	
Administrative	11	151.5	16.8	
Network Engineering for Transactive Control and Cyber Security	13	85.4	10.7	
<u>AMI</u>			<u>8.2</u>	
• Equipment	100	0.2		0.2
• Installation and Integration	100	0.1		0.1
• Testing (new and existing meters)	100	0.0		0.0
• Communication Network System	20	3.9		0.8
• Head-End Server	20	1.2		0.2
• System Applications (includes MDM)	20	19.4		3.9
• AMI Four-Year Maintenance Warranty	17	17.9		3.0
Vulnerability and Penetration Testing for AMI Network	14	48.8	7.0	
Engineering: AMI/SCADA integration, control algorithm development, modeling, and testing	100	2.1	2.1	
<u>Training</u>			<u>1.3</u>	
• AMI	17	2.7		0.4
• SEL Device Training (1 week)	33	1.8		0.6
• SEL Year-2 Refresher Training (2 days)	33	0.8		0.3
Distribution Automation Collector/Router	100	0.6	0.6	
SEL 351 Overcurrent Relay	100	0.4	0.4	
Load Tap Change Controller	100	0.3	0.3	
Total Annualized Asset Cost			**$118.0K**	

AMI = Advanced Metering Infrastructure
MDM = meter data management
SCADA = supervisory control and data acquisition
SEL = Schweitzer Engineering Laboratories

11.1.1 Project Data and the Operation of the Voltage Management System

The independent variable for analysis of conservation voltage regulation is feeder voltage. The city provided the project 5-minute feeder voltages from March 2013 through August 2014. The voltages did not reveal any dynamic control until February 2014, when the voltage was occasionally reduced by about 1.5%. The voltage was no longer reduced after the middle of July 2014, according to this data.

Figure 11.3 shows feeder voltage data for the test period. The legend notes the times that the transactive system had advised the system to reduce its voltage ("Engaged") and not ("Not Engaged"). The project had been informed that the voltage would be reduced coincident with the advice from the transactive system.[1] As can be seen in the figure, this was not the case. The transactive function began advising the system to engage by March 2013, long before the system was first exercised. Once the voltage was truly being reduced, the advice from the transactive system imperfectly aligned with the observed voltage magnitudes. Clearly, the system's status must be inferred from observations and the project should not rely on the transactive system advice to infer its status.

The project observed that the normal voltage setting of the system was increased in July 2014. This period late in project data collection was not included in the analysis. The higher-voltage period could pollute the formulation of a regression baseline if it were included in its training set.

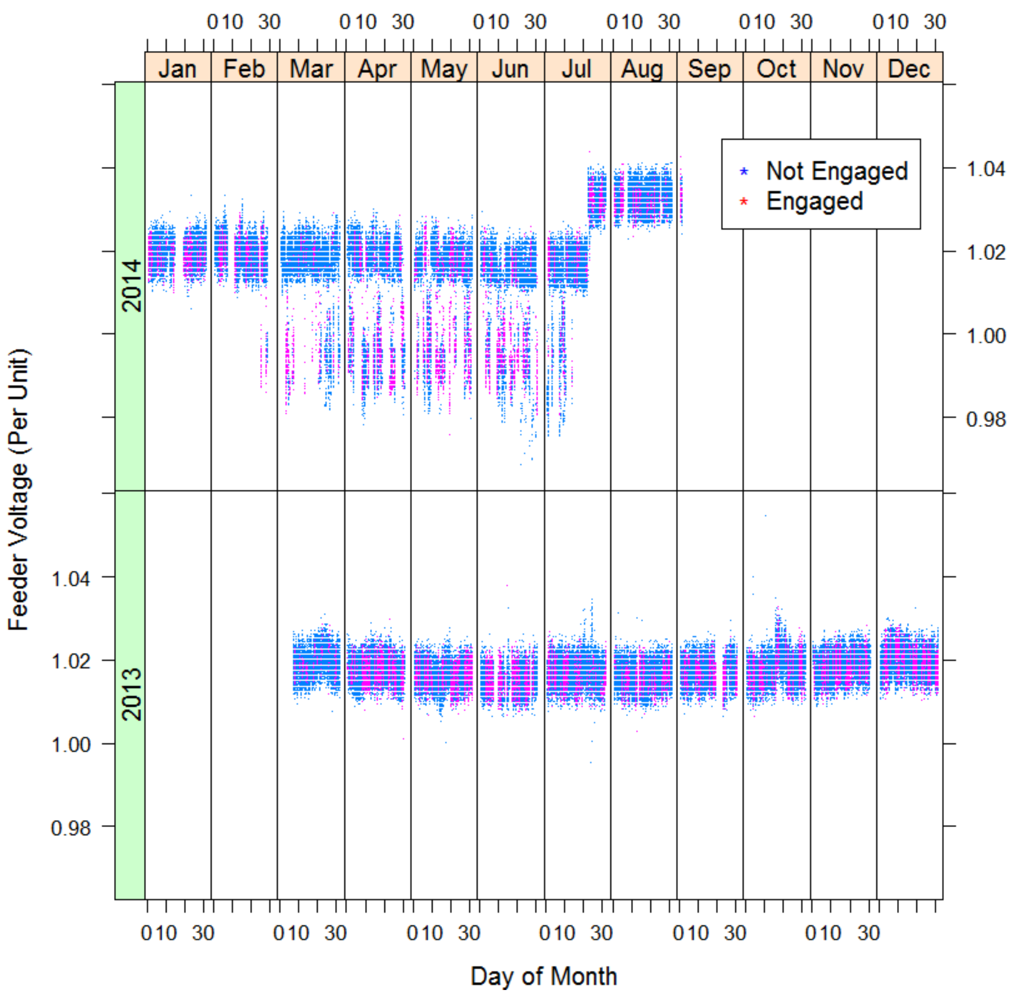


Figure 11.3. Managed Per-Unit Feeder Voltage during the Project

[1] "Advice from the transactive system" refers to the condition of the advisory control signal that was generated at the Idaho Falls utility site by its transactive load toolkit functions.

A representative sample of end-of-line feeder voltages became sporadically available in September 2013 and revealed evidence of voltage management similar to that in distribution voltage through 2014. The averages from these samplings are shown in Figure 11.4. These meters were polled sequentially, in a round-robin manner, due to limitations of the premises metering. This data confirms that voltage management was active from February to mid-July 2014. There is an unexplained inconsistency between the late July and August 2014 data in Figure 11.3 and Figure 11.4. While the distribution voltage appears to have been increased from mid-July forward, the average end-of-line voltages fell significantly after they had been initially increased.

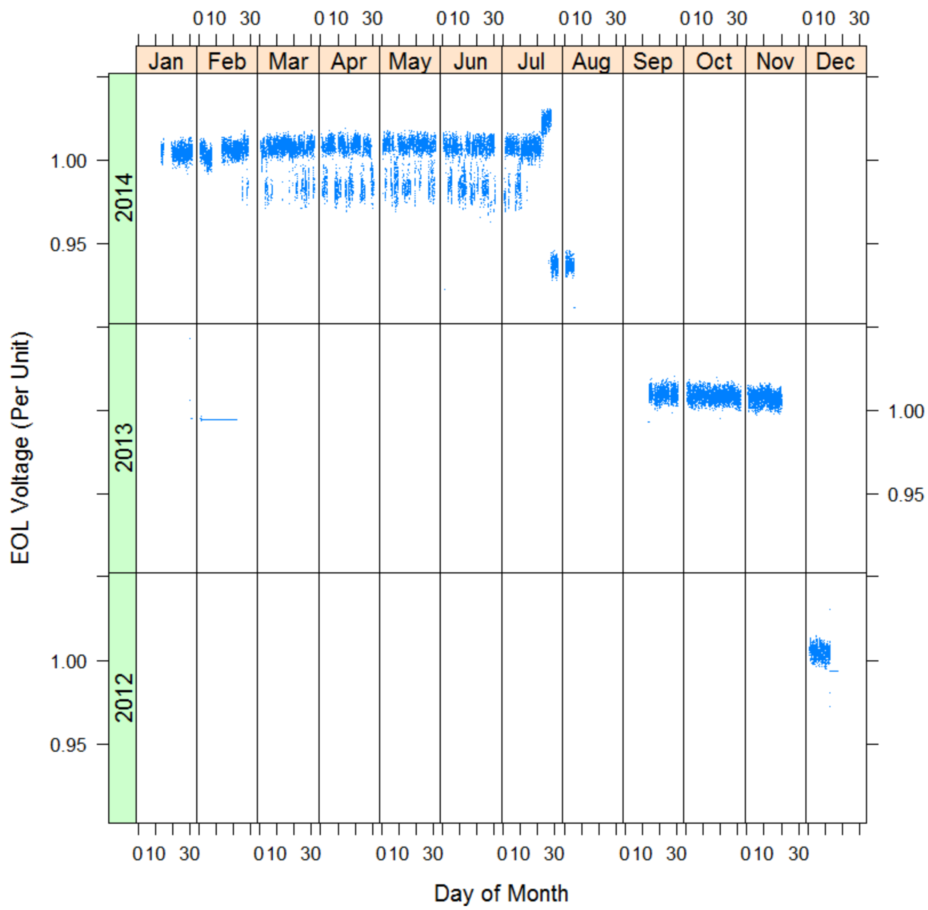


Figure 11.4. Per-Unit End-of-Line Voltage Measurements

Still further confirmation of the utility's intentions for the voltage management system may be gleaned from the target voltage settings that were provided to the project by Idaho Falls Power. The per-unit voltage settings were provided for much of 2014 and are shown in Figure 11.5. These settings appeared to closely correspond with the reported distribution voltages on the feeder.

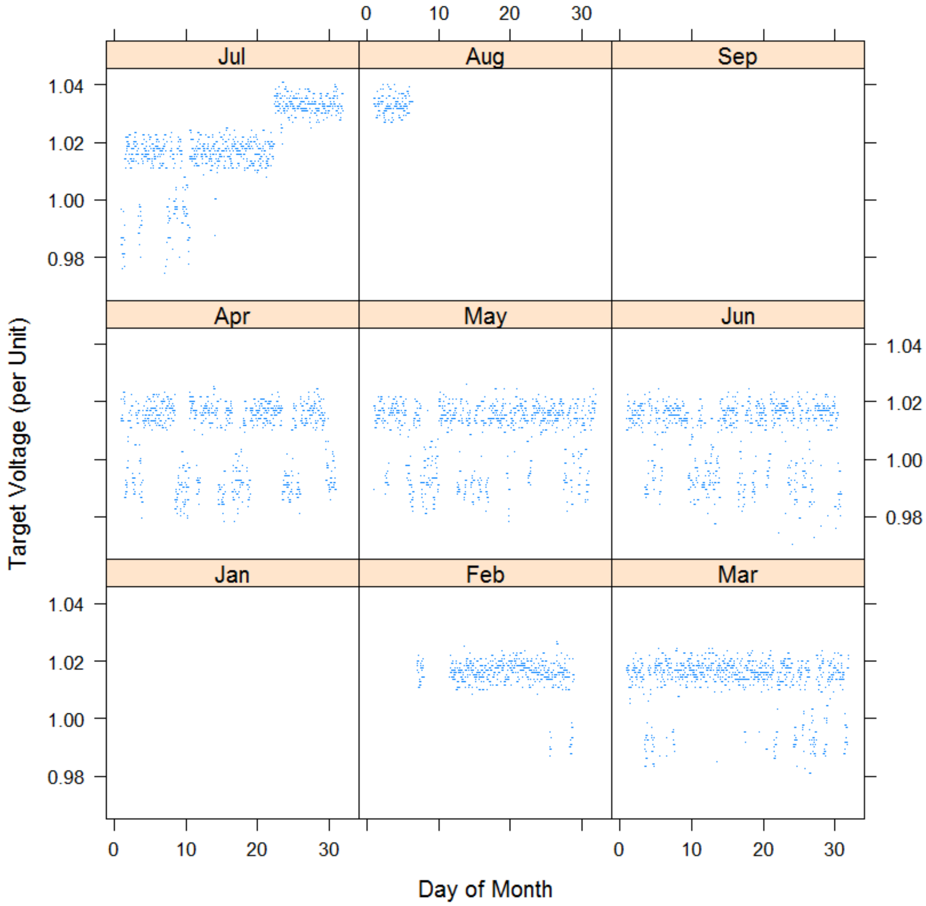


Figure 11.5. Reported Per-Unit Target Voltages in 2014

Project analysts searched 5-minute feeder real-power data for the effect of voltage reduction. The city provided this data from March 2011 until the conclusion of project at the end of August 2014. The entire set of feeder data received from Idaho Falls Power is shown in Figure 11.6. The average power of the Belaire feeder during the project, based on all the project data that is shown in Figure 11.6, was 5,593.2 ± 2.4 kW. Using the months of 2013 as an example year, the average monthly peak-hour demand on the feeder was 8.88 ± 0.37 MW.

Feeder power data quality was good. A clear weekly pattern was evident in the feeder power. The legend of Figure 11.6 distinguishes weekday periods from weekends. Feeder power was consistently lower during weekends. The yearly trends show that consumption peaks in winter but is also elevated in summer.

Residential premises power was also available to the project for about 12 residents who are supplied from the feeder, but the project spent most of its effort with feeder-level data that, unlike per-premises data, should reveal the entire impact of voltage reduction.

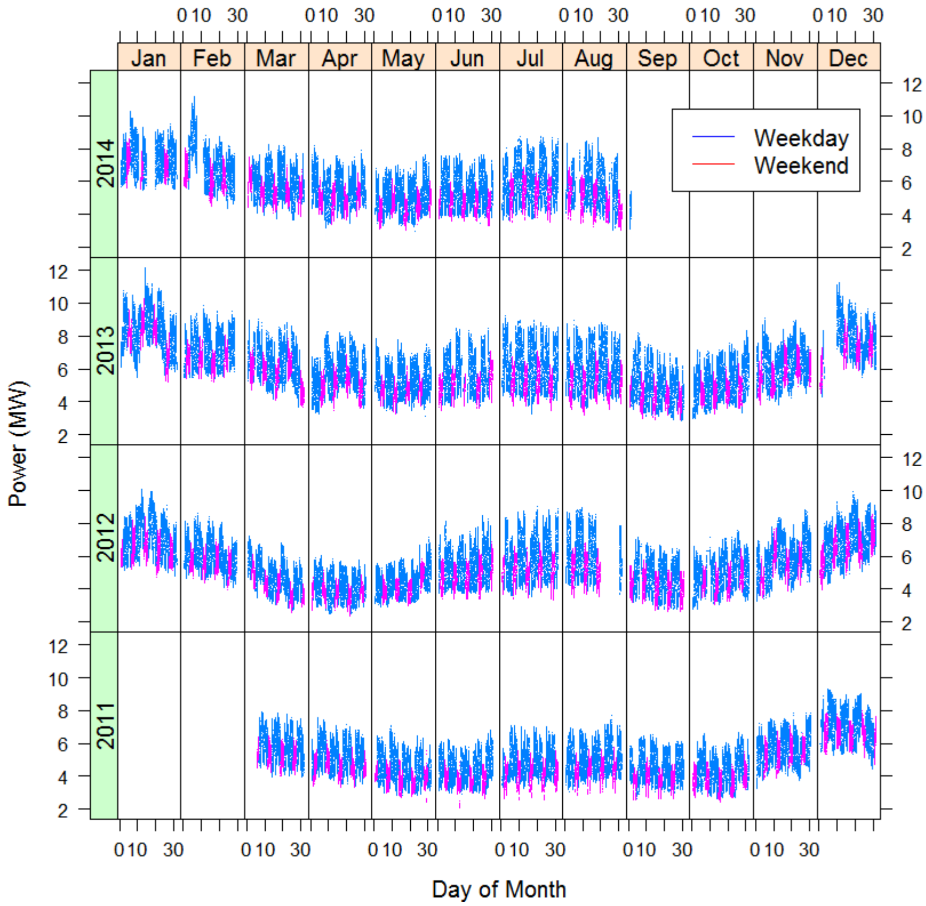


Figure 11.6. Feeder Power Data

11.1.2 Analysis of the Impact from Voltage Management

Idaho Falls Power did not provide independent confirmation of when they had and had not reduced feeder voltage. The first analysis challenge was therefore to infer engagement of the voltage management system from the available voltage data. Both the per-unit distribution voltage and reported target voltages had revealed evidence of voltage management during 2014.

Figure 11.7 compares actual feeder voltage and reported target voltage data. If the correlation between these two voltages were perfect, all the data points would have fallen on the dashed diagonal line in this figure. The correlation is not perfect, but three groupings of voltages lie on the diagonal. The three groups roughly correspond to the reduced, normal, and elevated sets of distribution voltages that were observed in both Figure 11.4 and Figure 11.5. Interestingly, the coincidence between the actual and target voltages was poorest when either the actual or target voltages were near 1.015 per unit. A hypothesis is that there was a significant delay between the times that the target voltage was changed to or from the normal and reduced voltage settings and the response of the system to actually change the voltage. Although the correlation between target and actual voltages is strong, the project elected to infer the status of voltage management from actual distribution voltage measurements.

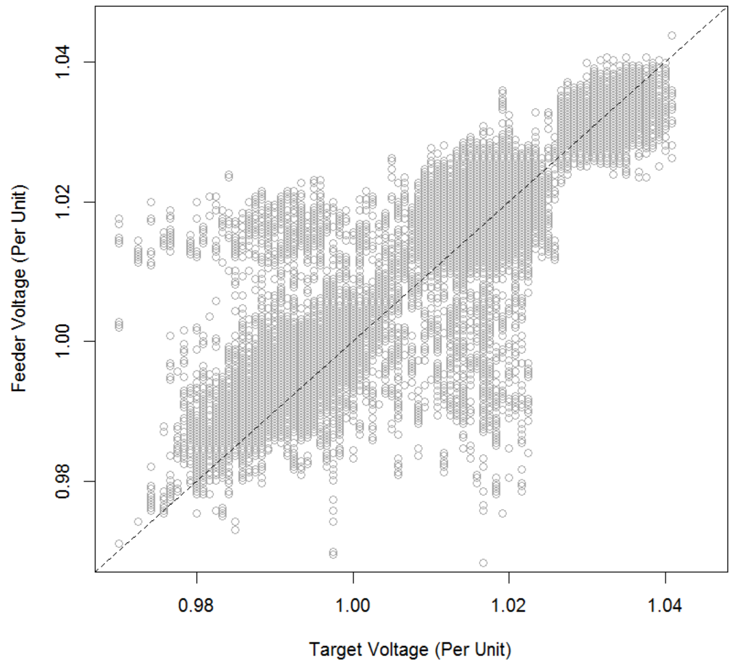


Figure 11.7. Feeder Voltage Plotted Against Target Feeder Voltage. Values on the dashed line would indicate perfect correlation between these two voltages.

Figure 11.8 is a histogram of the per-unit distribution voltages that were available to the project for 2014. The three populations of voltages—reduced, normal, and elevated—are again evident. By inspection, the value 1.0065 per unit was selected as the demarcation between the reduced and normal voltages. The voltage management system was therefore inferred to have been engaged any time that the distribution voltage was less than 1.0065 per unit.

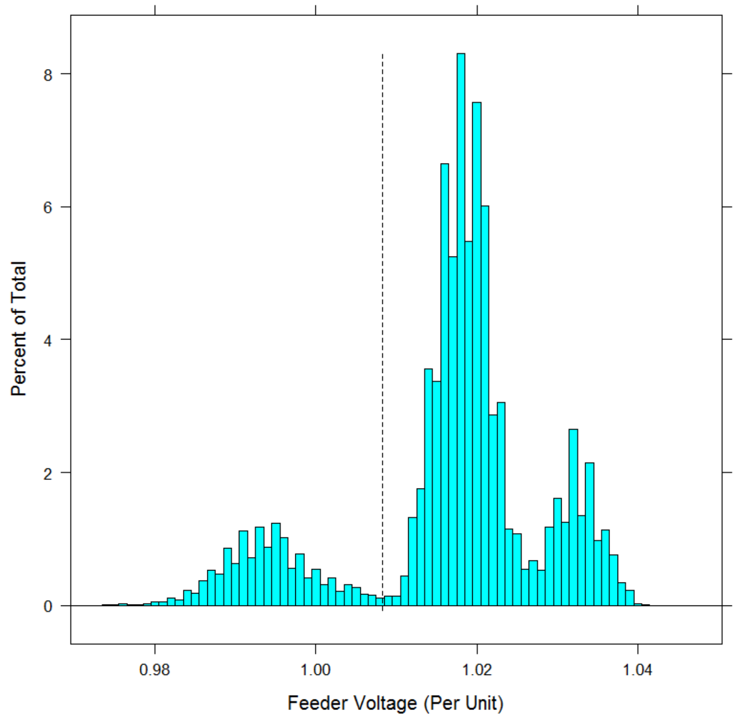


Figure 11.8. Histogram of 2014 Feeder Voltages. The separation between reduced and normal levels was assigned at 1.0065 per unit.

Several baseline control methods were considered, but the project chose to create a linear regression model of feeder power as a parametric function of temperature, cooling or heating regime, calendar month, day of week, and hour of day. The project used the R software (R Core Team 2013) environment for this analysis.

Cooling and heating regimes were determined for each calendar month. When distribution feeder power is plotted as a function of outdoor temperature, a “V” shape becomes evident. In the winter, more data lie to the left side of the “V,” representing an increase in heating power as temperature falls. In summer, feeder power rises with higher temperatures. Figure 11.9 shows, for all the month in the period August 2013 – July 2014, linear fits by hour to the cooling and heating temperatures. The “best” fit was determined at a temperature that separates the two linear regression fits such that the total sum of residuals between the modeled and actual powers is minimized. These temperatures that separate heating and cooling regimes are shown in Figure 11.9.

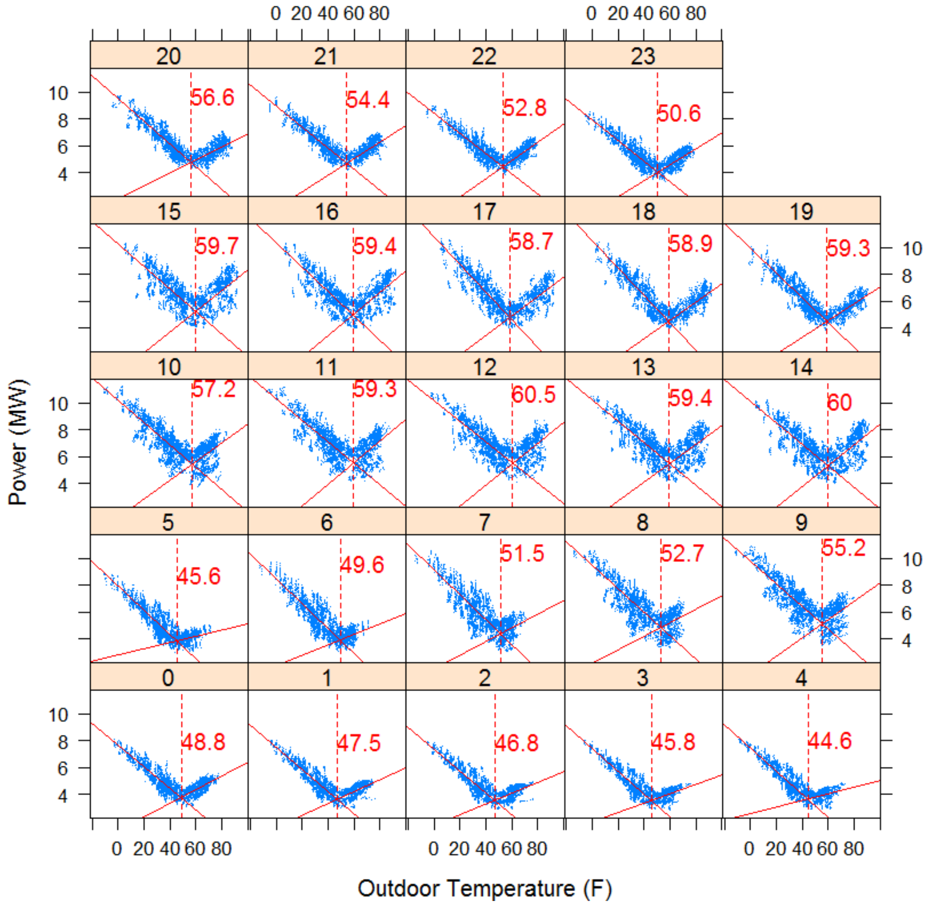


Figure 11.9. Calculated Cooling and Heating Regimes by Hour, Based on Feeder Power

A baseline was created from the regression model to emulate feeder power as if feeder voltage was unchanged. By comparing actual feeder power against this regression model baseline when the voltage was reduced and not, the impact of the reduced voltage operation could be estimated. Typically, based on all project data, the feeder's power was reduced by 137 ± 4 kW when the voltage was reduced.

Analysts also reviewed the impacts for each calendar month of the project's last year (August 2013 – July 2014), estimates of which are shown in Table 11.3. These results are based on a Student's t-test comparison of the differences between actual and baseline feeder power when the voltage had been reduced and not. Of the six months that voltage management was exercised well, data from four suggested that power had been significantly reduced. The system was not exercised much in January or during August through December, so the results from these months were probably not meaningful.

Table 11.3. Total Measured Power Impact when Voltage was Reduced

	Δ Power[b] (kW)
Jan[a]	−609
Feb	−475 ± 23
Mar	−269 ± 11
Apr	−64 ± 8
May	33 ± 11
Jun	−169 ± 8
Jul	95 ± 13
Aug[a]	−90 ± 770
Sep[a]	-
Oct[a]	−123
Nov[a]	-
Dec[a]	-
All data	−137 ± 4

(a) Few, if any, events occurred these months.
(b) The negative values in this column are costs that are avoided by the utility.

Based on the estimated change in power each month during voltage management that occurs during heavy-load hour (HLH) and light-load hour (LLH) hour types and the fraction of time that voltage was reduced during each hour type, the monthly impact on energy consumption was estimated. These results are in Table 11.4. The monthly cost impacts were then estimated by multiplying the changes in HLH and LLH energy by the unit costs of these energy usages, according to recent BPA demand rates. The impact from the two hour types was then summed for each month. The sum energy purchases avoided during the six months that the voltage management system was exercised were worth about $2,710 ± 120. If these benefits may be extrapolated to the remaining calendar months, the total annual displaced energy might be worth about twice as much, or $5,420 ± 170, to the utility.

These estimates of the value of energy purchases that may be avoided by Idaho Falls Power were based on the way that the utility practiced voltage management during six months of 2014. The project's understanding was that the utility was investigating voltage management as a dynamic resource, not a constant conservation voltage reduction resource. Results would, of course, differ if the system were exercised more or less often in the future or differently during HLHs or LLHs.

These calculations did not include the impact from lost energy sales revenues that would tend to reduce the monetary benefit. Yes, the utility does not need to purchase this energy from its supplier, but it also loses retail revenues from the sale of most of this energy to the city's electricity utility customers.

Table 11.4. Estimated Impact on HLH and LLH Energy Usage and Energy Cost Impacts, based on the period August 2013 – July 2014

	Δ HLH Energy[b] (MWh)	Δ HLH Cost[c] ($)	Δ LLH Energy[b] (MWh)	Δ LLH Cost[c] ($)	Δ Total Energy Cost[c] ($)
Jan[a]	0	0	−0.080	−2	−2
Feb	−8.80 ± 0.41	−326 ± 15	0	0	−326 ± 15
Mar	−33.6 ± 1.6	−1,017 ± 49	−8.45 ± 0.64	−212 ± 16	−1,229 ± 51
Apr	−20.0 ± 2.2	−516 ± 56	−0.7 ± 1.6	−13 ± 32	−530 ± 64
May	−4.0 ± 2.8	−84 ± 58	6.0 ± 1.2	79 ± 15	−5 ± 60
Jun	−28.2 ± 1.9	−640 ± 43	−15.2 ± 1.2	−221 ± 17	−861 ± 46
Jul	−4.2 ± 1.4	−127 ± 42	14.83 ± 0.93	363 ± 23	237 ± 48
Aug[a]	0.03	1	−0.065	−2	−1
Sep[a]	-	-	-	-	-
Oct[a]	−0.012	0	0	0	−0.012
Nov[a]	-	-	-	-	-
Dec[a]	-	-	-	-	-

(a) Voltage management was not routinely exercised these months.
(b) A negative energy value in this column refers to a reduction in electrical load.
(c) A negative cost value in this column means the utility’s supply costs have decreased.

The impact of voltage management on the demand charges that are incurred by Idaho Falls Power from its energy supplier has been estimated in Table 11.5. The utility’s demand charges are determined each month by its average HLH consumption and the month’s peak-hour demand. The example peak hours used in these calculations were determined from the Belaire feeder data by tabulating the hours on which demand peaked each project month. This method yielded two or three hours in which peak demand was likely to occur each calendar month.

The estimated total annual impact from the demonstration of voltage management was a reduction of $3,570 ± 620 for the utility. Energy was conserved, so the utility paid less for its energy supply. This number gives no credit for months on which no events occurred and months during which the example peak hours were not among those when the system was activated, but it does give credit on a statistical basis by month, even if the precise peak hours were not those reacted to during the project.

If the voltage management had been well exercised all months of the year, the utility might have reduced its demand charges by about $6,770 ± 680 per year. This projected number presumes that peak hours are always correctly identified throughout the year, including during the six calendar months that the system was, in practice, inactive.

Table 11.5. Estimated Changes in the Peak Demand Determinant and Resulting Demand Charges, based on the period August 2013–July 2014

	Δ aHLH (kWh/h)	Typical Demand Hours	Δ Peak Demand (kW)	Δ Demand Charges ($)
Jan[a]	−0.2	9, 10, 10	-	2
Feb	-	10, 9, 10	−147 ± 35	−1,600 ± 380
Mar	−26 ± 2	10, 12, 10	−167 ± 21	−1,260 ± 190
Apr	−2 ± 5	10, 9, 11	155 ± 25	1,200 ± 190
May	-	14, 11, 15	−114 ± 37	−710 ± 230
Jun	-	12, 15, 14	−77 ± 24	−520 ± 160
Jul	−10 ± 3	13, 13, 14	−65 ± 32	−500 ± 290
Aug[a]	−0.2	15, 14, 15	-	~0
Sep[a]	18 ± 4	15, 13	-	−180 ± 40
Oct[a]	-	11, 13	-	-
Nov[a]	-	17, 10	-	-
Dec[a]	-	10, 10	-	-

(a) Little, if any, voltage management was demonstrated these months.

The management of distribution voltage could either improve or harm distribution equipment life and customer power quality. The remaining figures in this section will show metrics that were collected by the project to assess these impacts.

First, the project requested Idaho Falls Power to help it monitor the numbers of transformer tap changes. As voltage control is automated, control actions may cause distribution equipment to engage more often or differently from how it was operated prior to the automation. Idaho Falls Power submitted hourly counts of tap changes to the project, Figure 11.10, for parts of three months in 2014. Tap changers were observed to change their setting up to nine times per hour. On the hours that tap settings were changing, 79% of these intervals coincided with times that the voltage had been reduced.

The project is unable to conclude anything about changes in tap change counts that might have been caused by the project's voltage management. No historical data about tap changes was provided from before the voltage was managed.

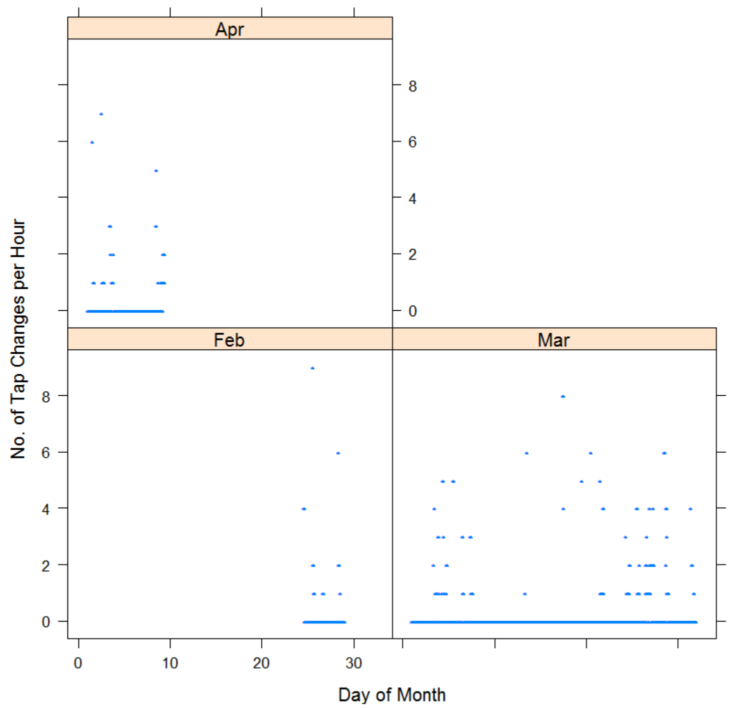


Figure 11.10. Tap Changes per Hour

The premises meters installed by Idaho Falls Power have a feature that records divergence of the delivered voltage above or below accepted thresholds. The project summed the numbers of these occurrences by hour for the premises on the Belaire feeder that were affected by voltage management. The low-voltage events are shown in Figure 11.11 and the high-voltage events in Figure 11.12. Up to three low-voltage events were received from customer premises during one hour in 2012. The high-voltage events occurred less often, and there has not been more than one in any hour.

No low- or high-voltage events were reported after the middle of February 2014 when Idaho Falls Power began exercising the voltage management system. It appears that the voltage management system has been quite effective toward improving the quality of delivered voltage for the premises on the Belaire feeder.

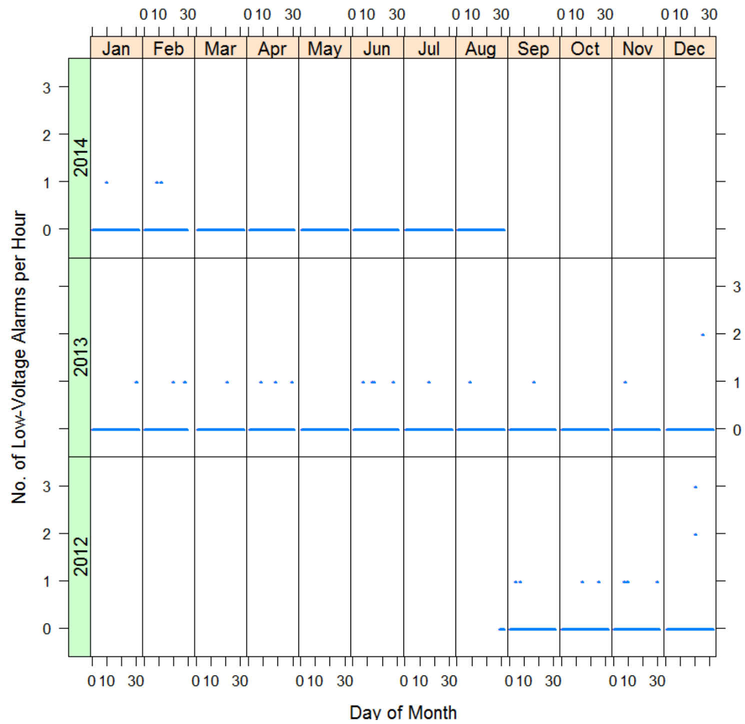


Figure 11.11. Residential Low-Voltage Alarms per Hour

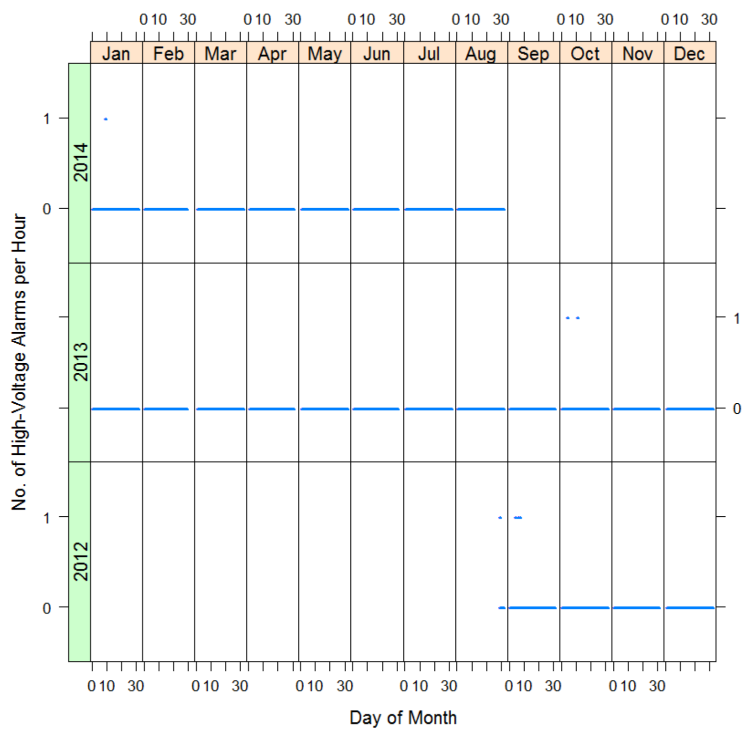


Figure 11.12. Residential High-Voltage Alarms per Hour

11.2 Automated Power Factor Control

Note. Upon its review of this section, Idaho Falls Power stated that the real power data and perhaps the reactive power data, too, are about 10 times as great as they should be. This critique, of course, calls the entire analysis in this section into question. The project was unable to confirm this possible scaling issue or rectify the inconsistency working with the utility. Regardless, the analysis text has been left in place. If the same scaling issue affected both the real and reactive power data in this section, then the calculations and conclusions may still be valid.

Idaho Falls Power automated the control of switched capacitor banks at two large breweries that are supplied from its York substation. The purposes were to reduce system losses and to improve feeder power factor. Local controllers at the industrial premises supervised the switched capacitor banks to make sure that power remained within acceptable parameters.

When preset reactive power thresholds were reached at the industrial sites, the controllers switched in or out the shunt capacitor banks. The system may be controlled remotely via the utility's SCADA system over an Ethernet network using Distributed Network Protocol version 3.0 and a fiber optic link between the substation and capacitor banks. Prior to the demonstration, Idaho Falls Power predicted that this system would conserve approximately 2% of the average feeder demand - about 140 average kilowatts - on the two affected feeders. That would have saved about 38 thousand dollars from Idaho Falls Power's annual electricity purchases. The system was declared to be installed and useful on September 30, 2011, but the data suggest that the capacitors were activated in December 2013.

Idaho Falls Power estimated annualized system costs. Refer to Table 11.6. The system components include the two capacitor banks and the communication system components that were needed to control the capacitor bank. Idaho Falls Power also applied fractions of the costs of their advanced meter system, cyber security consulting, and various training sessions.

Table 11.6. Idaho Falls Power Costs of Power Factor Control System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Idaho Falls Power Staff Labor	100	29.3	29.3	
Administrative Costs	11	151.5	16.8	
Network Engineering for Transactive Control and Cyber Security	13	85.4	10.7	
Engineering: Invensys, TriAxis	100	8.0	8.0	
Vulnerability and Penetration Testing for AMI Network	14	48.8	7.0	
AMI Meter System			4.9	
• System Applications (includes MDM)	20	19.4		3.9
• Communication Network System	20	3.9		0.8
• Head-End Server	20	1.2		0.2
Capacitor Bank	100	1.6	1.6	
SEL Device Training			0.9	
Communication Equipment (media converters, fiber)	100	0.6	0.6	
Communication Controller	100	0.5	0.5	
Total Annualized Asset Cost			**$80.2K**	

11.2.1 Project Data and Operation of the Automated Power Factor Control

Idaho Falls Power submitted reactive power measurements from the two York feeders on which the power factor was controlled. The data from March 2013 into July 2014 was made available. The sum of the reactive power on the two feeders is plotted in Figure 11.13. Based on a step change reduction in the two feeders' calculated reactive power, analysts inferred that capacitors were engaged on the two feeders on the 3rd and 9th of December 2013 and stayed engaged throughout the rest of project's data collection period. The project inferred that this was the month that power factor correction must have become operational on the York feeders. Prior to then, the power was strongly reactive. After that period, the reactive power was lower and even occasionally crossed below zero to become slightly capacitive. The legend of Figure 11.13 distinguishes the data prior to and after this date.

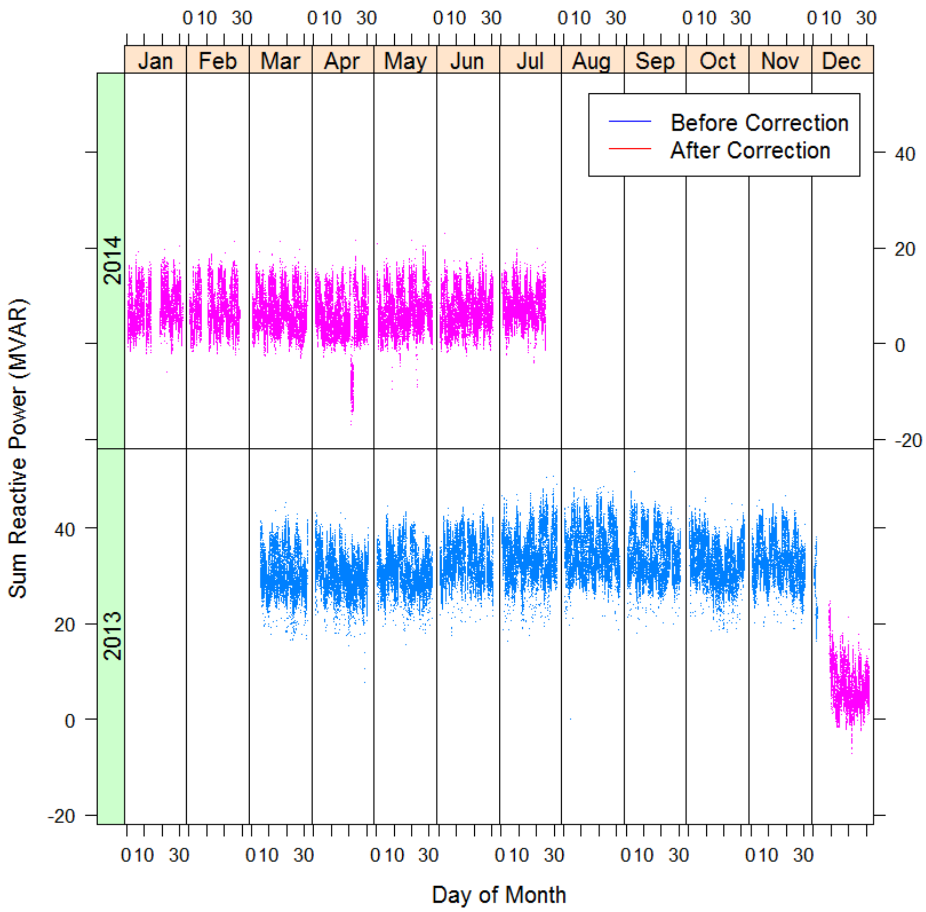


Figure 11.13. Sum Reactive Power by Month and Year for Available Data from the Two Feeders with Power Factor Control

Idaho Falls Power also submitted feeder real-power data for the two York feeders that were affected by its new power factor control. The data also covered the period from March 2013 into July 2014. The sum power from the two feeders has been plotted in Figure 11.14. The average power on these two feeders, based on the available data, was 88.86 ± 0.03 MW. When Idaho Falls Power reviewed this data, it said the magnitude is about ten times too great, but the source of the potential scaling error was not identified. The legend on this figure distinguishes the data prior to and after power factor correction had begun, according to changes that were observed in the reactive power. Total real power did not appear to change after the power factor correction began. The project did not attempt to quantify any change in the power measurement.[1]

[1] This might be an interesting extension for future analysis. Can any change in feeder power be attributed to the correction of power factor on these feeders?

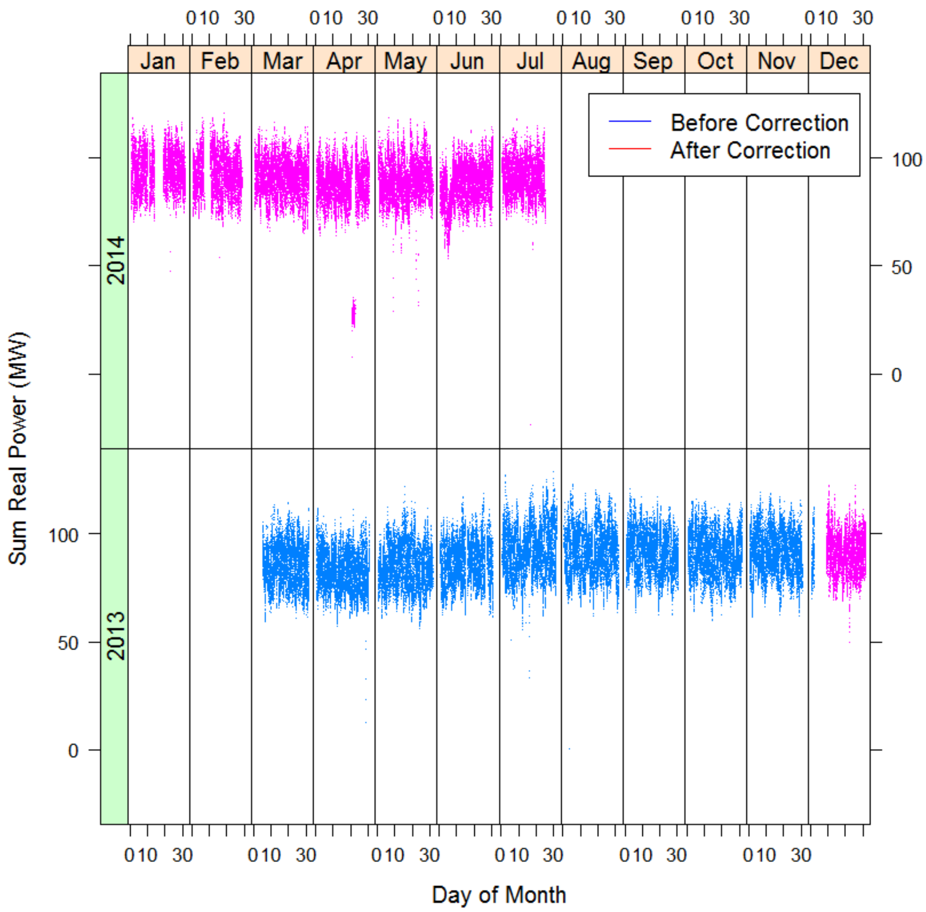
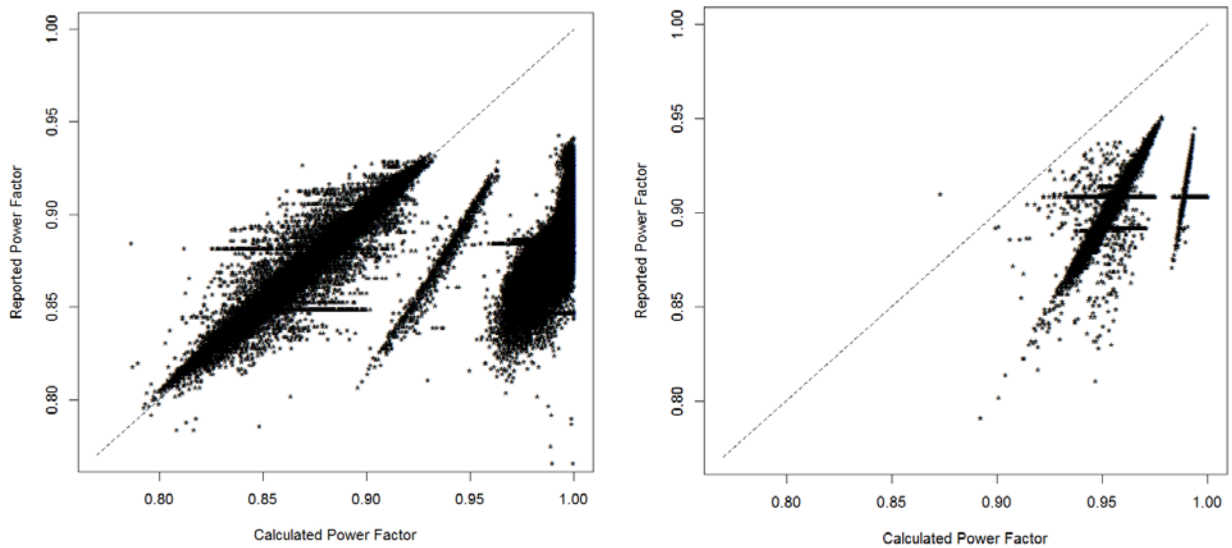


Figure 11.14. Total Real Power by Month and Year for Available Data from the Two Feeders with Power Factor Control

Idaho Falls Power submitted power factor measurements for the two York substation feeders from March 5, 2013 through August 31, 2014, but these values do not match those power factors calculated from the available feeder power data that was shown above. Figure 11.15 compares the reported power factors (vertical axis) against the calculated ones (horizontal axis). Had the reported and calculated values agreed, Figure 11.15 would have exhibited a nearly perfect linear correlation along the dashed diagonal lines that are shown in the figures. The measured and calculated values matched some months for Feeder 1, but never matched for Feeder 2. The calculated power factors were often greater than those that had been reported. Additionally, the reported power factors were found to “stick” on certain values, especially during times that capacitor bank switching events were being reported.

Upon its review, Idaho Falls Power stated that it believed its reported power factors were accurate. The project was unable to identify the source of the inconsistency. Project analysts opted to use the power factor calculated from the feeders’ real and reactive powers, rather than the reported power factor data, for its analysis.



(a) Feeder 1 (b) Feeder 2

Figure 11.15. Power Factors Provided by the Utility versus Power Factors Calculated from Feeder Data for the Two York Feeders. These graphs demonstrate that the feeder data did not always match calculated values.

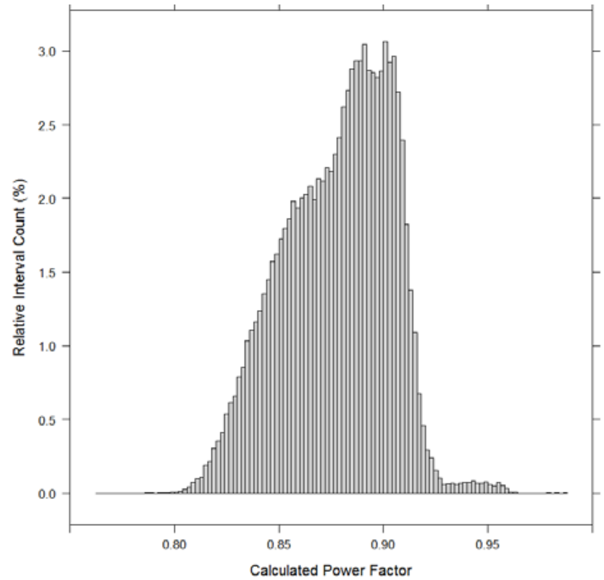
Capacitor switching events were reported to have taken place during September 2013 (2 hours), October 2013 (31 hours), and January 2014 (94 hours). The capacitors at the two industrial sites were always engaged simultaneously. These events do not appear to be meaningful amidst the significant correction that was observed in the first weeks of December 2013.

11.2.2 Analysis Results from the Automated Power Factor Correction

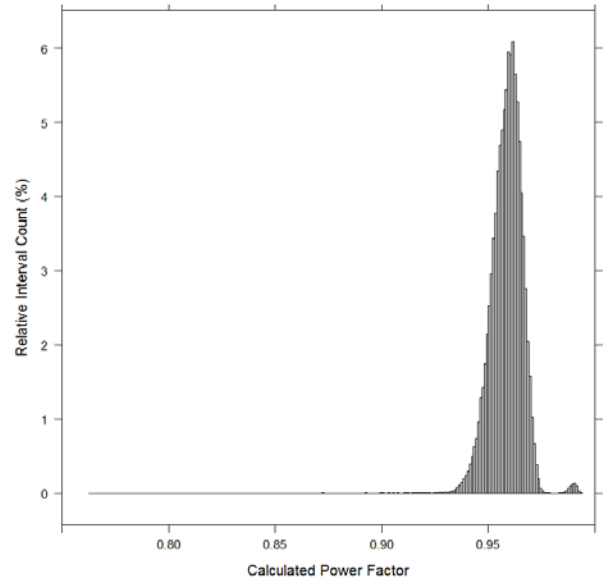
Comparing the power factors on the feeders before and after early December 2013, the average power factor of Feeder 1 improved from 0.878 to 0.993. The power factor of Feeder 2 improved from 0.959 to almost 0.997. The distributions of the calculated power factors on the two feeders before and after early December 2013 are shown in Figure 11.16.

This improvement means that the distribution currents now needed to supply the same electrical load on the two feeders are 88 and 96% of what was needed prior to the engagement of the capacitors. Line losses are proportional to the square of the line currents. Based conservatively on the average change in distribution line currents, the distribution losses on Feeder 1 should have been reduced by about 22%, and the distribution losses on Feeder 2 should have been reduced by about 7.5%.

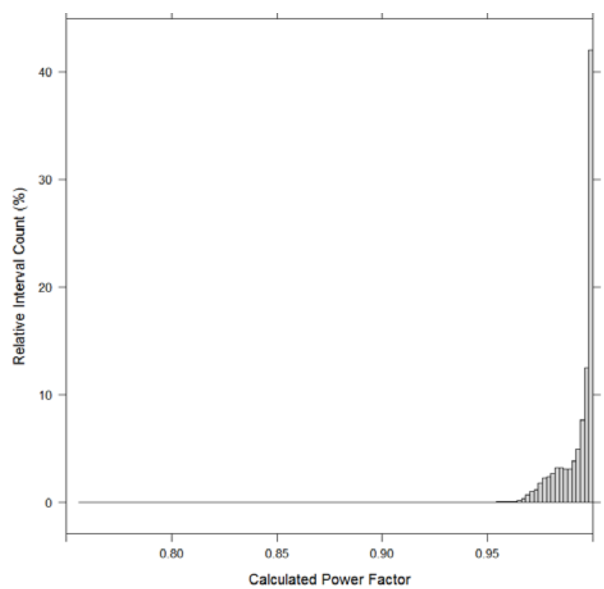
The project had no independent means to measure or estimate distribution losses, but if distribution system losses on these feeders were on the order of 5% of the total power supply, then the total impact would be on the order of a 0.5 MW reduction of distribution losses on these two feeders. This is about 0.6% of the average total feeder power.



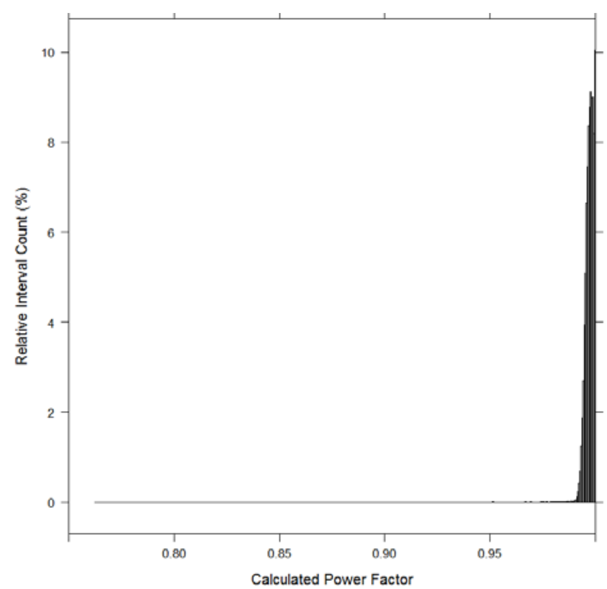
(a) Feeder 1 Power Factor before Correction



(b) Feeder 2 Power Factor before Correction



(c) Feeder 1 Power Factor after Correction



(d) Feeder 2 Power Factor after Correction

Figure 11.16. Histograms of York Feeder Power Factors Before and After Early December 2013

11.3 Distribution Automation

Using remotely controlled switch operators, its advanced metering infrastructure (AMI) system, and fault indicators, Idaho Falls Power installed a fault detection, isolation, and restoration system to quickly detect fault locations and isolate the faulted parts of two circuits that are supplied by its Sugarmill substation, thus reducing the duration of service outages. The system was installed and useful by November 9, 2012.

The annualized costs of the system and its components have been estimated in Table 11.7. The total cost of the system, as defined, is about $91.3 thousand per year. The greatest costs are for utility staff labor, administrative expenses, network engineering, and cyber security.

Table 11.7. Idaho Falls Power Costs of Distribution Automation System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Idaho Falls Power Staff Labor	100	52.1	52.1
Administrative	11	151.5	16.8
Network Engineering for Transactive Control and Cyber Security	13	85.4	10.7
Engineering: SCADA integration, control algorithm, modeling	100	4.9	4.9
Motorized Switch Operator	100	3.0	3.0
Fault Indication Device	100	2.0	2.0
Training			0.9
• SEL Device Training (1 week)	33	1.8	0.6
• SEL Year-2 Refresher Training (2 days)	33	0.8	0.3
Distribution Automation Collector/Router	100	0.6	0.6
SEL 351 Overcurrent Relay	100	0.4	0.4
Total Annualized Asset Cost			**$91.3K**

11.3.1 Available Reliability Metrics

Idaho Falls Power calculated and submitted yearly reliability indices and metrics for the two Sugarmill feeders for years from 2010 through the end of the project after August 2014. These indices and metrics have been compiled in Table 11.8.

Table 11.8. Yearly Reliability Indices Reported to the Project by Idaho Falls Power

Reliability Index	Units	Feeder	2010	2011	2012	2013	2014[(a)]
System Average Interruption Duration Index	minutes/customer/year	1	0.00	1.43	0.00	0.00	0.00
		2	1.05	1.54	0.00	1.26	0.00
Customer Average Interruption Duration Index	minutes/event	1	0.00	2.20	0.00	0.00	0.00
		2	1.50	3.35	0.00	-[(b)]	0.00
Outage response time	minutes/year	1	0.00	57	0.00	5,948	0.00
		2	0.00	0.00	0.00	42,975	0.00
Reliability events	count/year	1	0	0	0	0	0
		2	0	1	0	0	0

(a) Period from January 1–August 31, 2014.

(b) Values were submitted, but they were likely incorrect, given that the feeder's System Average Interruption Duration Index and outage minutes were nonzero.

11.3.2 Analysis of the Impact from Distribution Automation

The project will not report any conclusions regarding reliability based on the limited history of reliability metrics that have been collected. However, no outages had occurred during the last nine months of the project, which is very promising, providing this trend endures.

11.4 Water Heater Control

Idaho Falls Power installed 218 Tendril Networks (Tendril 2014) / Elster load control modules (LCMs) to curtail residential electric tank water heaters that are supplied energy from one of their Sugarmill substation feeders. These units were controllable by Idaho Falls Power via broadband communications. The system was declared installed and useful by December 21, 2012. Test events were conducted during 2013 and into February 2014, and the system was made automatically responsive to the project's transactive system briefly from late 2013 until early 2014.

Idaho Falls Power chose to remove all the LCMs abruptly in early 2014 due to a small number of catastrophic device failures and ensuing concerns about their customers' safety. According to the utility, the LCMs are no longer offered by the product's vendors.

Refer to Table 11.9 for a summary of annualized system and component costs. The system costs include the load controllers and all the labor and software needed to install and operate the LCMs, the cost of implementing the transactive site and its communications, a fraction (about 20%) of the cost of the AMI system that interacts with the LCM, and a fraction of the costs for reviewing and improving the utility's cyber security. One-fourth of the utility's costs for outreach and education were also included.

Table 11.9. Idaho Falls Power Costs of Water Heater Control System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)	
Transactive Node	14	317.1	45.3	
Idaho Falls Power Staff Labor	25	119.7	29.9	
Software for Demand Response	33	65.5	21.8	
Cyber Security Consulting			17.7	
• Network Engineering for Transactive Control and Cyber Security	13	85.4		10.7
• Vulnerability and Penetration Testing for AMI Network	14	48.8		7.0
Administrative	11	151.5	16.8	
Engineering	33	42.7	14.2	
AMI Meter System			7.7	
• Equipment	100	1.6		1.6
• Installation and Integration	100	1.0		1.0
• Testing (new and existing meters)	100	0.2		0.2
• Communication Network System	20	3.9		0.8
• Head-End Server	20	1.2		0.2
• System Applications (includes MDM)	20	19.4		3.9
Water Heater Controls	100	6.2	6.2	
Outreach and Education	25	24.4	6.1	
AMI Four-Year Standard Maintenance Warranty	17	17.9	3.0	
Total Annualized Asset Cost			**$168.7K**	

11.4.1 Characterization of the Water Heater Control System and Data

Idaho Falls Power gathered and delivered power data from premises that hosted responsive LCMs and water heaters. Data intervals included a mix of 1-hour and 15-minute time-series data from the individual premises. Typically 213 residential premises, mostly supplied by the Sugarmill feeder 4B3-6, were included in the test group. The project averaged these data across all the premises for analysis. Data were collected from August 2012 until the end of August 2014 from these premises. The average of this data stream was 2.2 kW. Figure 11.17 shows all the aggregated premises power data that was received by the project from Idaho Falls Power for the approximately 213 premises that received water heater load controllers.

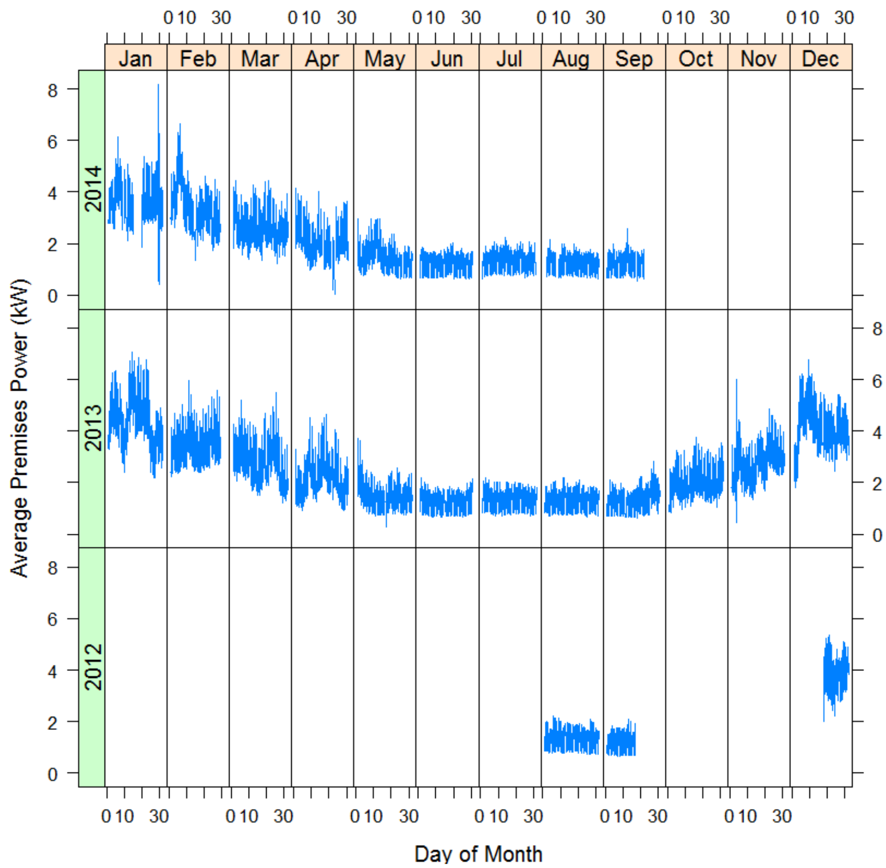


Figure 11.17. Average Premises Power for the 213 Idaho Falls Power Customers Who Received Water Heater Load Controllers

The utility also supplied real-power data from a set of similar premises that did not receive responsive LCMs or water heaters. A small set (~17) of these premises were located on the same Sugarmill substation feeder as the test group, but this data set was found to be inexplicably dissimilar to the experimental set. A set of data from a larger data set of 477 premises meters on multiple feeders—a set of premises that had received IHDs (Section 11.7) but did not receive water heater controllers—was preferred. Power data from these premises was collected from August 2012 until the end of August 2014. The averages of all the time-series data from these aggregated sets of power data were 1.25 kW for the Sugarmill comparison group and 1.53 kW for the alternative comparison group from multiple other Idaho Falls Power feeders.

Ambient temperature data was collected from Idaho Falls weather stations KIDA (airport) and IDA (central city). These temperatures were used by analysts for regression analysis. Linear interpolation was used to fill in small gaps in the temperature time series, providing that the gaps were less than 6 hours long.

Idaho Falls Power worked with the Pacific Northwest Smart Grid Demonstration project to set up and configure a toolkit function that would advise the system of water heater controllers when to curtail their loads. The function was operating and generating such advice by the beginning of 2013. Early transactive events for this asset were configured by the utility to remain almost always active. The toolkit function was revised and reconfigured in mid-2013 to advise events for no longer than a couple of hours, but events were allowed most workweek days. System installation and testing created delays, so the system was not responsive to the transactive system until at least December 2013.

Idaho Falls Power asserted to the project that the LCMs were to be engaged every time the transactive system advised[1] them to curtail their loads. However, caution had to be used. Advisory control signals had been generated by their corresponding function long before the LCMs became installed and controlled. Further, the advisory control signals continued to be generated after the LCMs had been disabled and removed from premises. An alternative set of test events was e-mailed to the project and will be described in this section.

Communications received from Idaho Falls Power led the project to believe that the system was being primarily manually controlled. A list of over 500 test event hours was sent to the project. Each hour-long event record stated the event's starting time and which of four premises subgroups was to have been engaged that hour. The utility had evenly subdivided the population of approximately 213 LCMs premises into four subpopulations. For event periods longer than 1 hour, the subpopulations were sequentially engaged and released each successive hour. Rarely was load at more than one of the subgroups curtailed the same hour.

This approach, in hindsight, was ill advised. Had all the water heaters been simultaneously curtailed, a reduction of between 0.2 and 0.8 kW per premises—a total reduction of 44 to 170 kW—might have been observed during the curtailment periods. Because only one-fourth of the total population was engaged the first hour of the curtailment period, only one-fourth of this impact may be observed among the entire population of premises that hosted controllable water heaters. After the first hour of each curtailment, the initial subpopulation was apparently released as another subpopulation became curtailed. Little or no net change in total demand should be expected between the first and subsequent hours. In fact, a rebound impact might occur after each transition as the prior subpopulation reheats its water after its hour of curtailment. The multiple, periodic energy rebounds add to the data variability.

The characteristics of the water heater test events are shown in the next several figures. The test events engaged the water heaters 559 hours between August 2013 and February 2014. After successive hours were discounted, there were 288 unique test events. The events were called regularly during this period, as is shown in Figure 11.18. On average, 41 unique test events were initiated each of the months in this period.

[1] The transactive system advised the asset systems to engage when the function that represented the asset at this transactive system site published a nonzero advisory control signal. The signal value 127 requested full curtailment by the asset.

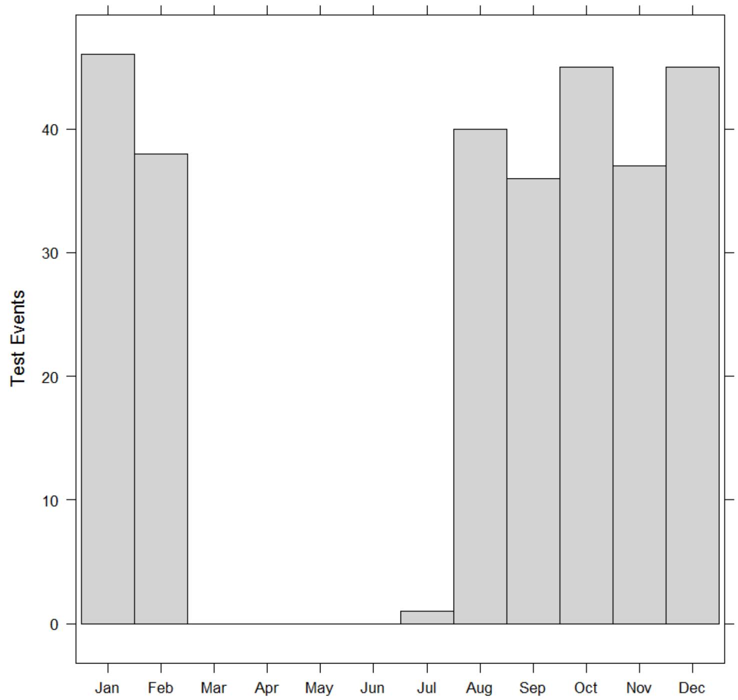


Figure 11.18. Count of Test Events According to the Events' Calendar Month. Events started in August 2013 and ended in February 2014.

The water heater test events were also applied evenly by workweek day, as is shown in Figure 11.19. This histogram counts the test events according to the weekdays on which they began. The test events were conducted almost exclusively on weekdays.

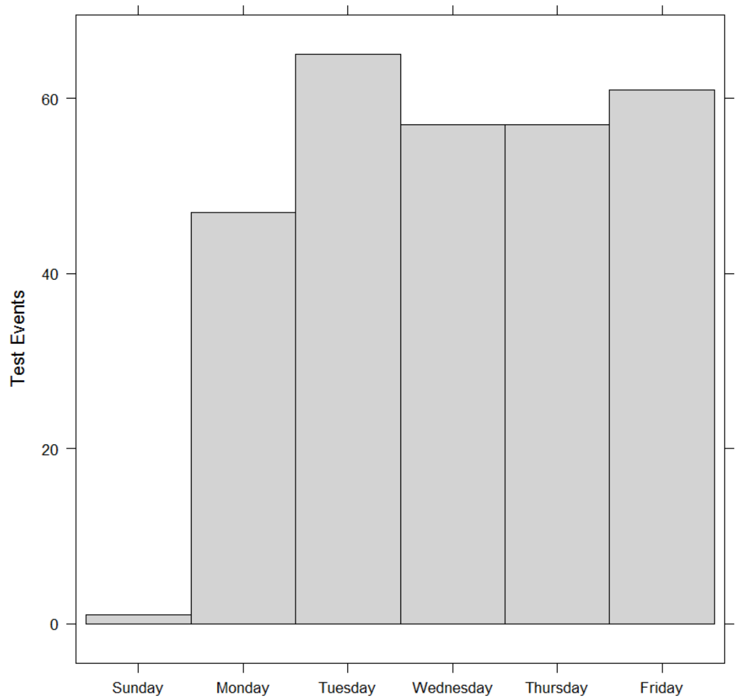


Figure 11.19. Count of Test Events According to the Day they Started

Test events were most often initiated at 07:00 and 17:00 local Mountain Time. A histogram of the hours on which the test events began is shown in Figure 11.20. Curtailment tests on a new group of LCMs that immediately followed a previous test were not counted as new events. Idaho Falls rotated through subpopulations of LCMs, each group experiencing only one hour of curtailment, in order to achieve 2-, 3- or 4-hour-long events.

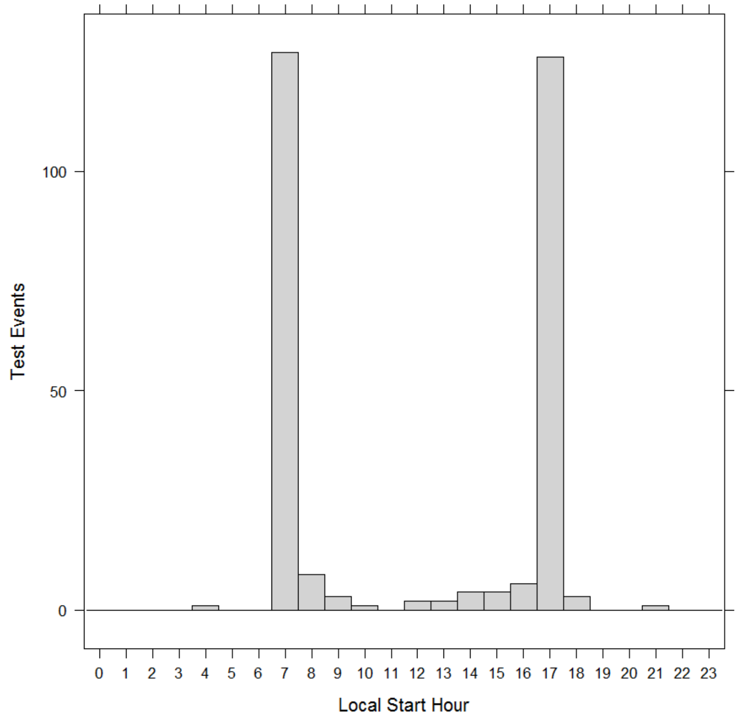


Figure 11.20. Count of Test Events According to the Local Hour they Began

The water heater load controllers permitted their homeowners to opt out of events. Data concerning occurrences of opt-outs were received for a period from December 2014 through March 2014. The controllers would ignore signals received from the utility for a period of an hour when directed to do so by an occupant. Figure 11.21 shows these opt-out occurrences per hour as a percentage of the total number of installed water heater controllers. At most, five occupants (~2.3%) opted out of an announced curtailment event.

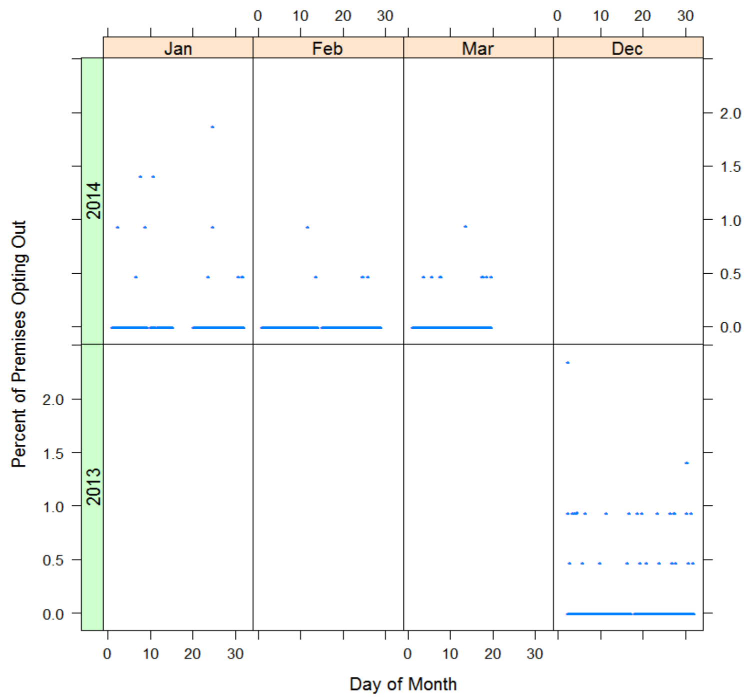


Figure 11.21. Percentage of Premises Reported to have Opted Out of Water Heater Events Each Hour

11.4.2 Water Heater Control Performance

Idaho Falls had projected to reduce yearly load by approximately 15,000 kWh and demand by 20 kW by engaging the LCMs on water heaters. The project was unable to confirm any significant change in average premises power during curtailment events. Several approaches were investigated. By observation near purported event periods, the time series never appeared to exhibit a definitive reduction "step" in load at the premises during either transactive or test event periods.

Analysts were unsuccessful at confirming any power reduction at the times the water heaters may have been commanded to curtail their loads. The utility's anticipated performance could not be confirmed. Table 11.10 summarizes the results of eight unsuccessful baseline comparisons. All eight comparisons used the aggregated power of the approximately 213 premises that had received water heater controllers as the test group. The first column of Table 11.10 states whether analysts compared the test group against a regression model baseline or against the average power of similar groups of premises that did not receive the project's water heater load controllers.

The second column further qualifies the regression and comparison methods. All the regression models fit the test-group power to month, heating or cooling regime, hour, day of week, and permutations of outdoor temperature with each of the previously listed variables. Because there was uncertainty in when the system was, in fact, commanded to curtail its load, the regression was first conducted without using the event period as an independent variable. Then the regression model was reconstructed to explicitly fit against the event periods. Regardless of whether regressions explicitly included the events, baseline time series were constructed to emulate what the test group's power might have been without water heater curtailments.

The third column states which defined event periods were assumed to have been responded to. Idaho Falls Power had originally stated that the system responded to all the transactive events. Based on communication received by the project in November 2013, it was believed the automation to make the system respond to the transactive signal was not yet completed but would be completed soon. The transactive events prior to December 2013 were therefore not used by analysts. Idaho Falls Power also submitted to the project a list of hours that were described at test events. Therefore, the project also looked for the impacts of water heater curtailment during these times.

The power impacts determined for the eight baseline analyses in Table 11.10 all suggested power had *increased* during curtailment events, regardless of the baseline methods and events. Only three of the eight results may be statistically relevant. The project cannot explain this outcome.

Table 11.10. Results of Many Unfruitful Analysis Investigations that were Attempted for Water Heater Curtailments

Events	Baseline Type	Baseline Qualifier	Power Impact (kW)	Confidence[a]
Transactive events (December 2013 – August 2014)	Regression	Ignoring transactive events	0.024 ± 0.020	0.55
		Including transactive events	0.024 ± 0.20	0.55
	Comparison	Same feeder, no LCM	0.061 ± 0.046	0.91
		Similar feeder, no LCM	0.012 ± 0.023	0.71
Water heater test events (August 2013 – February 2014)	Regression	Ignoring test events	0.029 ± 0.016	0.97
		Including test events	0.072 ± 0.016	1.00
	Comparison	Same feeder, no LCM	0.104 ± 0.028	1.00
		Similar feeder, no LCM	0.012 ± 0.011	0.86

(a) This value represents the approximate fraction of the distribution's tail that is above zero. Values in this column greater than 0.95 suggest there might be 95% confidence that the power impact was an *increase* in power

The project cannot confirm from available data that any reduction in power was achieved from the curtailment of Idaho Falls Power water heaters. In fact, there is evidence that load might have *increased* during test events that were reported to the project. Based on purely hypothetical impacts, the system, as implemented, might have reduced demand by 10–40 kW during curtailment events. Analysts determined not to seek the relatively small 10–40 kW impact among the feeder's power data, which was typically 8.2 MW for this Sugarmill feeder. The expected impact would be only about 0.1–0.5% of the total feeder measurements.

No further evaluation of benefits was conducted for this asset system.

Idaho Falls Power observed that it had been difficult with their system to determine whether the load controllers had, in fact, operated at specific times. Their customers could not tell whether they were working either. As the project analysts have observed, the utility said that event timing and programming of the devices were challenging. The 1-hour events used for testing were not nearly long enough to determine real energy reduction value. When queried about their involvement, 42% of the Idaho Falls Power customers rated the water heater control program as “least obtrusive.”[1]

11.5 Battery Storage (with PHEV and Solar)

Idaho Falls Power installed a 10 kW, 40 kWh Demand Energy Networks (Demand Energy Networks, Inc. 2015) battery storage system, which was to be charged and discharged based on the TIS. The battery system was located near four PHEV charging stations and a 1.73 kW photovoltaic (PV) solar panel system at the utility’s headquarters in Idaho Falls, Idaho. The system is shown installed in Figure 11.22.

The system was declared installed and operational by January 17, 2013.

Figure 11.22. Idaho Falls Power Battery Storage and PV Array

The annualized costs of the system and its components are listed in Table 11.11. It is estimated that the system would cost $158.7 thousand per year. The greatest costs were assigned to help set up the transactive functionality, purchased the electric vehicles, engineer system integration, and administer the project. Smaller costs were anticipated for utility staff labor, cyber security services, solar panels and the batteries.

[1] Information in this paragraph was extracted or paraphrased from a presentation named “IFP - Battelle 1-22-15.pptx” that Mark Reed presented to project participants January 29, 2015.

Table 11.11. Idaho Falls Power Costs of PHEV, Solar, and Battery Storage System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Transactive Node	14	317.1	45.3
PHEV Cars	100	43.9	43.9
Engineering Services (integrating solar, battery, and Demand Energy Networks application with SCADA)	100	18.3	18.3
Administrative	11	151.5	16.8
Idaho Falls Power Staff Labor	100	13.5	13.5
Cyber Security Consulting	13	85.4	10.7
10 kW Battery System	100	8.1	8.1
Solar PV Panels with Solar Tracking System	100	1.9	1.9
Data Acquisition (monthly recurring cost per charger, 4 chargers)	100	0.3	0.3
Total Annualized Asset Cost			**$158.7K**

11.5.1 Data from, and Performance of, the Battery Storage System

Data was never made available from the battery storage system. The battery's vendor, Demand Energy Networks, encountered financial difficulties and stopped supporting the device soon after it had been installed. The utility was left with no way to control the battery storage module.

11.6 Thermostat Control

Idaho Falls Power installed 42 programmable, controllable thermostats at premises supplied with electricity from its Fifteenth substation. The ZigBee Smart Energy Profile devices were installed and tested October 31, 2012, and the thermostat system was declared installed and useful by December 21, 2012.

The program was offered to residents who had one thermostat and used primarily electricity to heat and cool their occupied spaces. The municipality observed that a surprising number of their customers did not know what kind of heating system they had as they responded to the recruiters.

Startup was delayed by the additional steps necessary to integrate the thermostats with the vendor's advanced metering.

The annualized costs of this system and its components are listed in Table 11.12. The greatest costs were the cost for establishing the transactive node and its connection to this system and the utility staff labor working with the project to install this system. Intermediate costs were for demand-response software, administration costs, procured engineering cyber security help, and the AMI system. The cost of the thermostats themselves was relatively small.

Table 11.12. Idaho Falls Power Costs of Thermostat Control System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Transactive Node	14	317.1	45.3
Idaho Falls Power Staff Labor	25	119.7	29.9
Software for Demand Response	33	65.5	21.8
Administrative	11	151.5	16.8
Engineering	33	42.7	14.2
Network Engineering for Transactive Control and Cyber Security	13	85.4	10.7
AMI Meter System			8.4
• Equipment	100	0.3	0.3
• Installation and Integration	100	0.2	0.2
• Testing (new and existing meters)	100	0.0	0.0
• Communication Network System	20	3.9	0.8
• Head-End Server	20	1.2	0.2
• System Applications (includes MDM)	20	19.4	3.9
• AMI Four-Year Standard Maintenance Warranty	17	17.9	3.0
Vulnerability and Penetration Testing for AMI Network	14	48.8	7.0
Outreach and Education	25	24.4	6.1
Load-Controlling Thermostats (~42)	100	1.0	1.0
Total Annualized Asset Cost			**$161.2K**

11.6.1 Thermostat System Operation and Project Data

Idaho Falls Power recruited 42 residents to receive and help test programmable, communicating thermostats at their premises. They recruited another 29 residents who had received AMI and also were supplied by the Fifteenth substation to help baseline this study. The baseline group did not receive controllable thermostats from the utility. Residents programmed their preferred temperature set points. The utility was able to temporarily increase or decrease the test group’s set points during events. The project calculated averages of the power data from the test and baseline groups.

Idaho Falls, Idaho, is a relatively cold location, and the average premises power was found to have a strong winter morning peak. The morning peak completely disappears in the summer. The hourly weekday premises power levels for each season are shown in Figure 11.23 for the average of the premises with project thermostats. The mean premises power was 1.92 kW, including all days of the week and all project data.

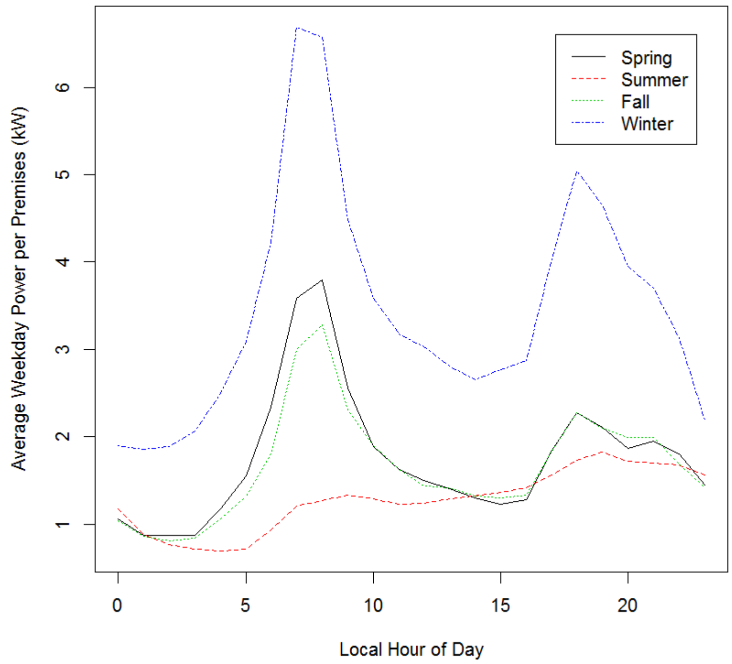


Figure 11.23. Seasonal Weekday Premises Power for the Idaho Falls Power Residents that had Project Thermostats

Some premises power data was received starting from May 2012, but several months of data were missing from fall 2012. Good premises power data was received from mid-December 2012 until the end of August 2014 when project data collection ended. The project's average premises power data series from those premises that received project thermostats is shown in Figure 11.24.

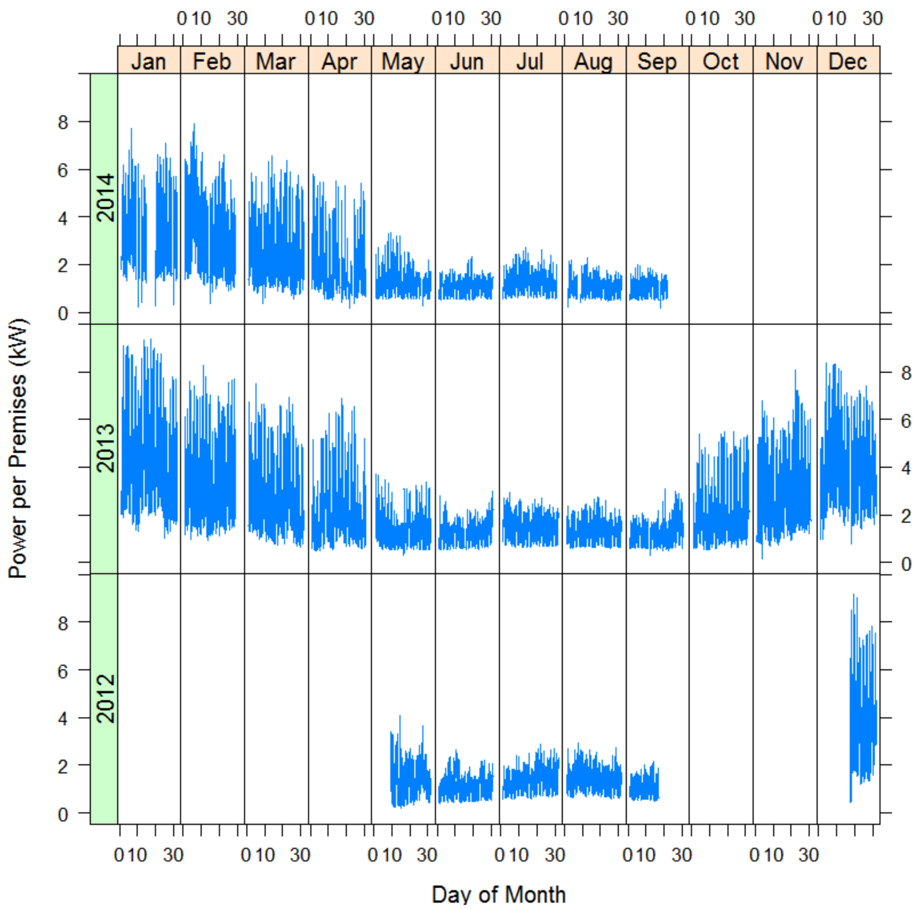


Figure 11.24. Power per Premises for Residences that Received Project Thermostats

Analysts observed that average premises loads had relatively large diurnal peaks, especially in winter. This was evident in both Figure 11.23 and Figure 11.24. The histogram of the average premises powers is shown in Figure 11.25, and this histogram confirms that a small number of premises have much higher power levels than most. Thermostatic load is clearly a driver of system peak demand in Idaho Falls.

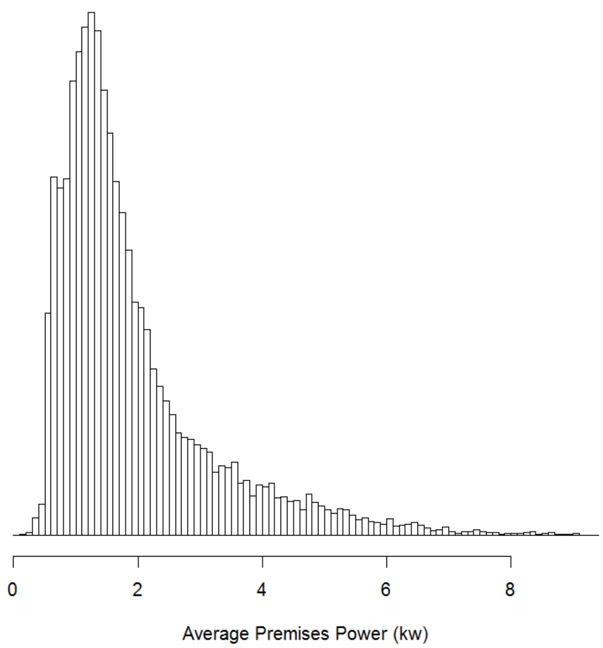


Figure 11.25. Relative Occurrences of Average Premises Power Levels for Residences that Received Project Thermostats

The transactive system began advising events for this asset in February 2013. There were altogether 410 events advised by the transactive system before the end of the project September 1, 2014. Of these, 241 occurred after September 2013, when the thermostat control began. The events were most often either exactly 1 hour long or 1 hour and 15 minutes long.

As shown in Figure 11.26, this asset was configured by the transactive system to generate events only on weekdays. Only the events following September 2013 were used in the creation of this histogram. The asset used the “daily” toolkit function that strove to place exactly one event during each weekday, coincident with the receipt of a TIS representing the highest unit cost of electricity.

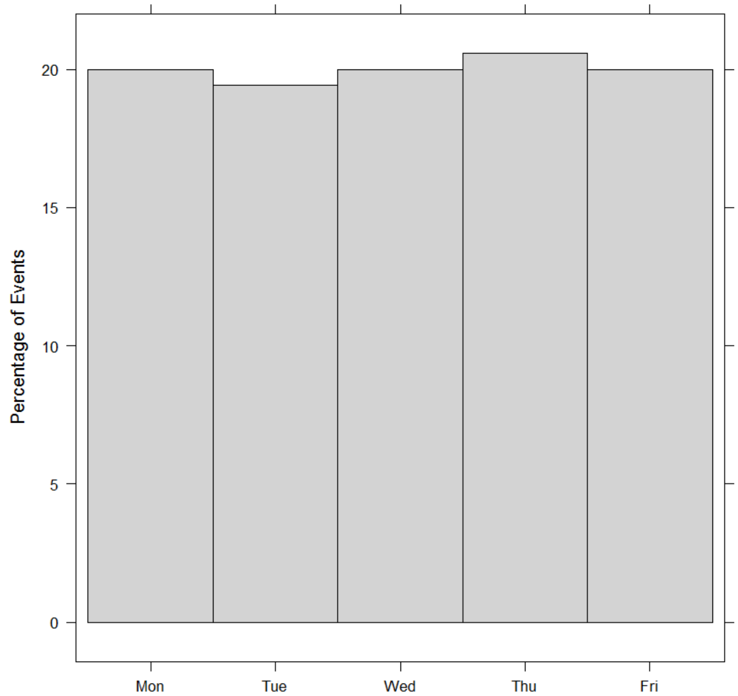


Figure 11.26. Weekdays of Events that Occurred after September 2013

Figure 11.27 uses all the transactive events that were advised to the thermostat control system by the transactive system, both before and after September 2013 when thermostat control began. Events were advised regularly throughout the year and during every calendar month.

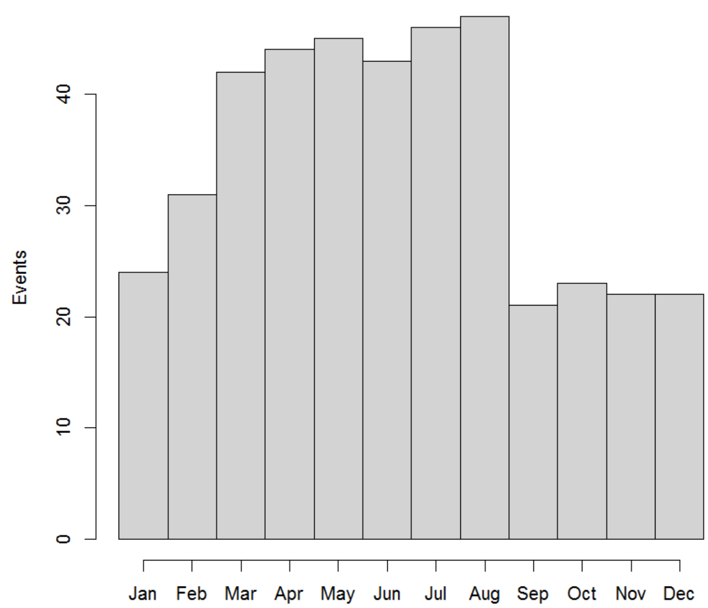


Figure 11.27. Count of All Thermostat Events by Calendar Month

Figure 11.28 is a histogram of the hours during which the thermostat control events were initiated. These events were believed to have been initiated by the project's transactive system, so the events were inferred to be coincident with the transactive system's advisory control signal for this asset. Only the events after September 2013 were used because communications from Idaho Falls Power led the project to believe that the thermostats were not controlled until then.

A startling number of transactive events began very late in the evening. The project struggled early on to make the TIS meaningful with a relevant diurnal pattern. Unfortunately, these problems persisted and may have caused assets like this one to become induced to respond at nonsensical times. The fact that events occurred far off peak hours may have reduced the magnitudes of the observed impacts as well.

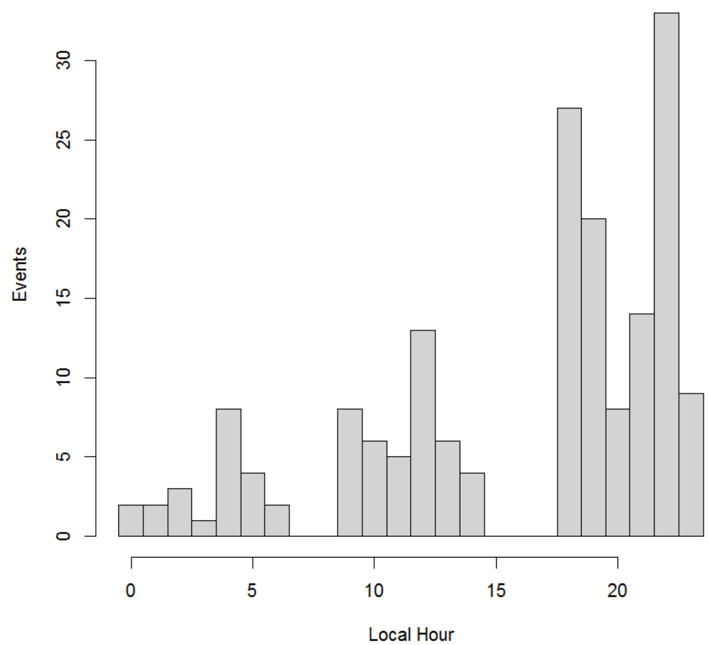


Figure 11.28. Count of Events after September 2013 by Their Local Starting Hour

11.6.2 Analysis of the System of Controllable Thermostats

Based on all the thermostat events and results of both the regression and comparison methods, the load was reduced by 0.052 ± 0.054 kW per premises during event periods. Even though the regression and comparison methods very closely agreed about the magnitude of the impact, the result has been assigned a greater uncertainty because the uncertainty in the comparison method was large. The regression model result had high confidence. Calculated results from the regression model approach are listed in Table 11.13. No results could be estimated for the months September, October, or November because the thermostats were not controlled these months.

Table 11.13. Average Change in Premises Power During Thermostat Events by Calendar Month, Based on the Period from December 2013 through August 2014

	Δ Premises Power (kW)[c]
Jan	0.11 ± 0.09
Feb	0.01 ± 0.16
Mar	−0.18 ± 0.08
Apr	−0.15 ± 0.07
May	−0.15 ± 0.07
Jun	−0.11 ± 0.05
Jul	0.02 ± 0.06
Aug	0.01 ± 0.05
…[a]	-
Dec[b]	0.02 ± 0.14

(a) The utility reported in November 2013 that the system was not yet responding to the transactive signal. Therefore, no results are being reported from September, October, and November 2013.

(b) This data was from December 2013. All other reported data were from months of 2014.

(c) A negative power in this column means that there had been a reduction in the average power consumption at the premises with the thermostats.

The value of the HLH and LLH energy that was potentially displaced by the thermostat events was small. The energy impacts and the cost impacts to the utility of the energy usages are shown in Table 11.14 for the impact of all the thermostats and the months that thermostat control was exercised. Only the results of the regression approach were used in the creation of this table. The total value of the annual avoided energy supply was only about $6 ± 9. The project was not able to determine how much of the energy that was conserved during events was actually conserved and how much was simply shifted within the day to non-event times, so even this estimate could be higher than it should be.

Table 11.14. Total HLH and LLH Energy Impact and Value of Avoided Supply Energy, Based on the Period from December 2013 through August 2014

	HLH		LLH		Total
	(Δ kWh)[(a)]	(Δ $)[(b)]	(Δ kWh)[(a)]	(Δ $)[(b)]	(Δ $)[(b)]
Jan	70 ± 77	2.70 ± 2.90	24 ± 75	0.70 ± 2.30	3.40 ± 3.70
Feb	−96 ± 93	−3.60 ± 3.50	103 ± 54	3.20 ± 1.70	−0.40 ± 3.80
Mar	−152 ± 73	−4.60 ± 2.20	−23 ± 32	−0.60 ± 0.80	−5.20 ± 2.40
Apr	−126 ± 54	−3.30 ± 1.40	7 ± 32	0.10 ± 0.60	−3.10 ± 1.50
May	−108 ± 54	−2.30 ± 1.10	−2 ± 25	−0.00 ± 0.30	−2.30 ± 1.20
Jun	−58 ± 32	−1.30 ± 0.70	−29 ± 21	−0.40 ± 0.30	−1.80 ± 0.80
Jul	44 ± 43	1.30 ± 1.30	−26 ± 36	−0.60 ± 0.90	0.70 ± 1.60
Aug	28 ± 40	1.00 ± 1.30	8 ± 12	0.20 ± 0.30	1.20 ± 1.40
…	-	-	-	-	-
Dec	−9 ± 141	−0.30 ± 5.50	49.4 ± 32.8	1.60 ± 1.10	1.30 ± 5.60
Totals[(c)]	**−410 ± 220**	**−10.40 ± 5.50**	**110 ±120**	**4.20 ± 3.40**	**−6.20 ± 8.60**

(a) Negative energy values in this column mean that load was reduced.

(b) Negative monetary values in this column mean that the utility's supply costs were reduced by this amount. The cost magnitudes have been rounded to the nearest dime.

(c) These are actual sums from the nine months that are listed.

A similar analysis was conducted to estimate the impact of the thermostat control on the municipality's peak monthly demands and demand charges. These findings are summarized in Table 11.15. Idaho Falls Power's demand charges are determined by the average monthly load during HLH hours and by their peak-hour demand each month. The utility's peak hours were modeled using hours that distribution power was found to be greatest each month that distribution data was available. If the thermostats were not controlled during those example hours in a given calendar month, no credit was granted that month. If the thermostats had been controlled for at least one of the example peak hours in a month, then the impact was calculated from the estimated change in power for that hour, averaging among the one or more coincident hours.

This approach is generous in that it presumes that not only the peak hour, but also the day of the peak hour, can be correctly identified each month. If credit had been given only when the utility correctly selected both the peak hour and its day, the correlation and calculated benefit would have been still lower.

Based on all the utility's demonstrated control of thermostats, the utility's control of thermostats reduced their demand charges by about −$473 ± 51 per year. If the demonstrated results may be extrapolated from the nine operational months to a full calendar year, perhaps the energy impact might have been a reduction of 400 ± 251 kW in the wholesale energy that the utility must purchase that would be worth $631 ± 59 reduction, based on BPA load-shaping rates (Appendix C). If the performance in March could be replicated throughout the year, the impact might be up to −$3,516 ± 132.

Table 11.15. Estimated Demand-Charge Determinants and the Estimated Monetary Impact of Thermostat Control on Demand Charges after September 2013

	Δ aHLH (kW)	Δ aHLH ($)	Δ Peak Demand (kW)[a]	Δ Peak Demand[a] ($)	Δ Demand Charges ($)
Jan	0.17 ± 0.18	−2 ± 2	0.0	0	−2 ± 2
Feb	−0.25 ± 0.24	3 ± 3	−11.7	−128	−125
Mar	−0.36 ± 0.18	3 ± 2	−33.2 ± 4.2	−296 ± 38	−293 ± 38
Apr	−0.30 ± 0.13	2 ± 1	4.0	30	33
May	−0.26 ± 0.13	2 ± 1	0.0	0	2 ± 1
Jun	−0.15 ± 0.08	1 ± 1	0.0	0	1 ± 1
Jul	0.11 ± 0.10	−1 ± 1	0.0	0	−1 ± 1
Aug	0.06 ± 0.09	−1 ± 1	2.3	23	22
…[b]	-	-	-	-	-
Dec	−0.02 ± 0.35	0 ± 4	−9.6	−110	−110

(a) A zero in this column may mean that the month's thermostat events never coincided with example utility peak hours.

(b) Data were not reported for September through November because the thermostat system was not demonstrated responsive to the transactive signal during any of these calendar months.

The municipality recorded the numbers of participants who elected to opt out of thermostat events. The project restated these as a percentage of respondents per hour, which is shown in Figure 11.29. This data was received for the months from December 2013 through much of March 2014. As many as five of the 42 participating premises (~12%) opted out of thermostat control one hour. The project looked at the coincidence of these actions with the event periods. Of the hours that at least one premises opted out of thermostat events, 6.4% of these times were coincident with event intervals.

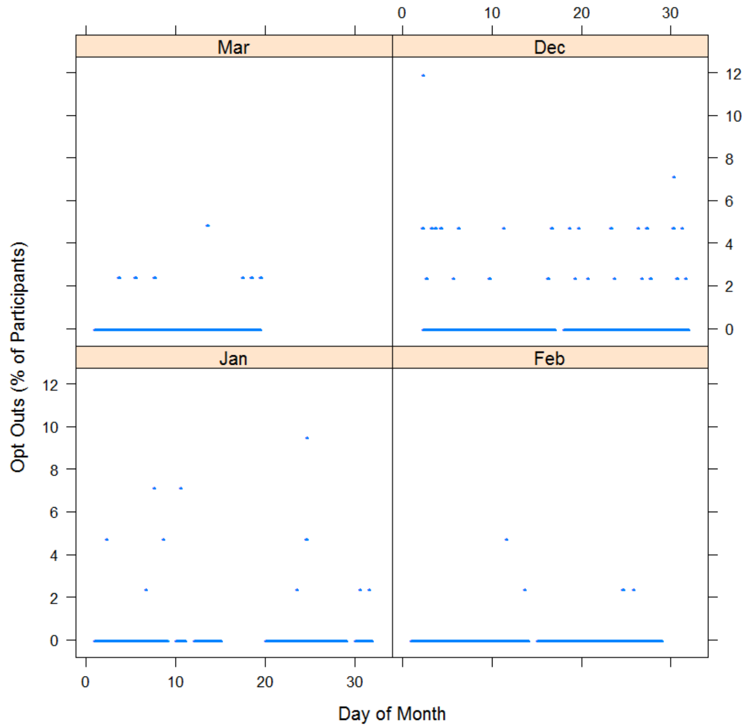


Figure 11.29. Percentage of Residents Opting Out of Thermostat Events in a Given Hour from December 2013 through much of March 2014

Upon surveying the participating residents late in the project, the utility learned that there was very little negative feedback. A few customers had inadvertently locked their thermostat's keypad during the demonstration. Also, some older heating, ventilation, and air-conditioning systems had been found to be difficult to integrate with the new digital equipment. Three-fourths of those surveyed said they would enroll in this program again going forward, but 15% said they would not. Sixty-five percent of the thermostat households indicated they had overridden an event at least once.[1]

11.7 In-Home Displays

Idaho Falls Power installed 860 IHDs, and 431 of these premises were identified in the data supplied by Idaho Falls Power as belonging to an IHD test group. Premises that had received other smart grid equipment in addition to the IHDs were excluded from the test group. The utility expected energy conservation from the installation of these devices due to behavioral changes from customers who were provided feedback on their energy consumption via the IHDs. Customers were able to view the following information when they visited the IHD:

- energy consumed in the current month
- energy consumed in the prior day
- the premises' energy consumption profile during the prior 24 hours

[1] Ibid.

- energy consumption estimated for the major appliance categories
- conservation tips
- utility service status
- weather information and forecasts
- demand-response events

The system was declared installed and tested February 22, 2013.

The annualized costs of the system and its components were estimated as shown in Table 11.16. The greatest costs were those allocated to the system for utility staff labor, for the AMI system, for administration of the project, and for the purchase and installation of the IHD hardware that includes the ZigBee smart energy profile. Smaller costs were estimated for integrating the system with the transactive system, for improving cyber security, and for outreach activities.

Table 11.16. Idaho Falls Power Costs of In-Home Display System

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Idaho Falls Power Staff Labor	25	119.7	29.9
AMI Meter System			23.7
• Equipment	100	9.2	9.2
• Installation and Integration	100	5.7	5.7
• Testing (new and existing meters)	100	0.9	0.9
• Communication Network System	20	3.9	0.8
• Head-End Server	20	1.2	0.2
• System Applications (includes MDM)	20	19.4	3.9
• AMI Four-Year Standard Maintenance Warranty	17	17.9	3.0
Administrative	11	151.5	16.8
In-Home Display Installation (ZigBee smart energy profile)	100	11.0	11.0
Network Engineering for Transactive Control and Cyber Security	13	85.4	10.7
Vulnerability and Penetration Testing for AMI Network	14	48.8	7.0
Outreach and Education	25	24.4	6.1
Total Annualized Asset Cost			**$105.1K**

11.7.1 Data from the In-Home Display System

Idaho Falls Power recruited 431 residents to receive IHDs. The test-group premises were located on many feeders in the distribution circuit. Idaho Falls Power also recruited another 212 premises to act as a baseline for this demonstration. The baseline premises had received AMI, but they did not receive the IHD hardware and the energy information that was available to the test group via their IHDs. The IHDs were installed at nearly the same time as the AMI had been, which created some challenges for analysts to separate the influences of the AMI from those of the IHDs.

The average per-premises power for the test group and its baseline are shown in Figure 11.30. Because the project wished to understand the impact from installing IHDs, the utility provided the project historical data from years before the installation of the IHDs and AMI. Prior to the installation of AMI, utility power data was limited to monthly meter reads. Therefore, the early data from meter reads is shown to be a constant average power throughout each month. It was presumed that the meter reads had occurred precisely at the months' transitions, which, of course, cannot be strictly true. This is a source of error. Energy prior to the installation of AMI might have been shifted between prior and following months.

The consumption by the test and baseline groups rose and fell similarly. Monthly data suggests that the baseline group ("No IHDs") typically consumed more energy than the test group ("IHDs") even before the AMI had been installed. The average of the all of the project's test-group premises power data was 1.55 kW, and that of the baseline group was 1.54 kW.

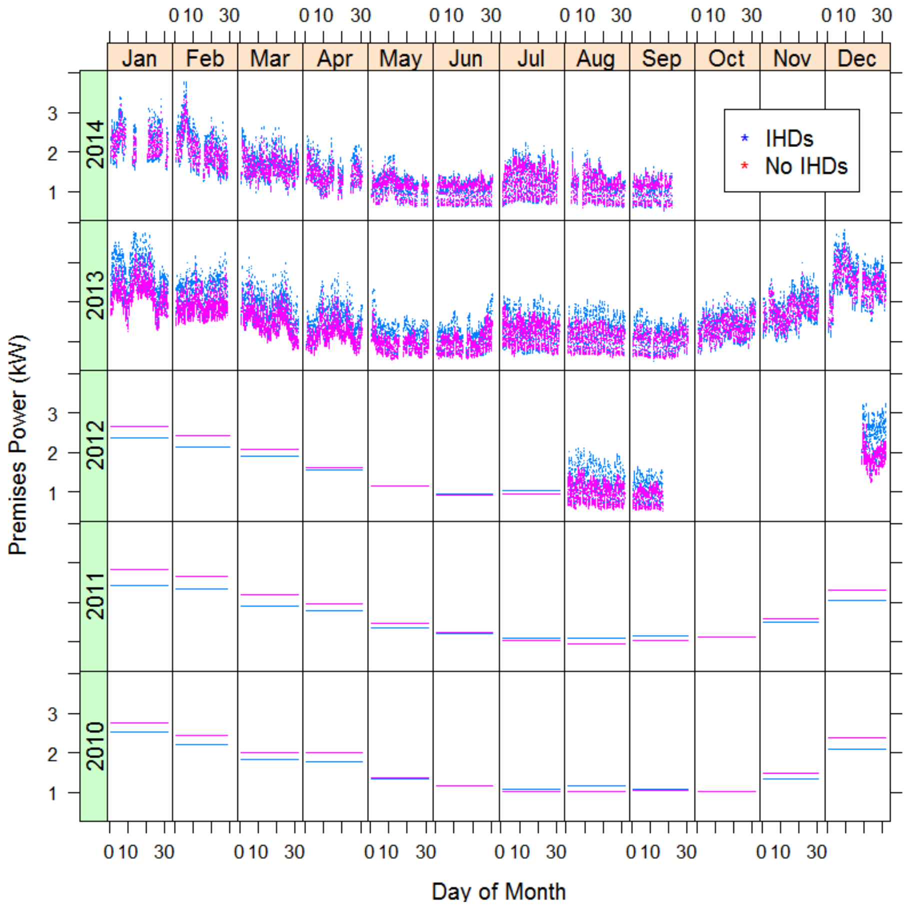


Figure 11.30. Monthly and 5-Minute Data Made Available to the Project by Idaho Falls Power

The project found complete sets of temperature data from the Idaho Falls, Idaho, regional airport and from the weather station IDA (central Idaho Falls on the west side of the Snake River). Nearly five years of these ambient temperatures are shown in Figure 11.31. While the temperature time series were found to be quite complete, temperatures were interpolated across any short data gaps less than 6 hours. It is this temperature time series that was used to generate the temperature-correction regression model and its baseline.

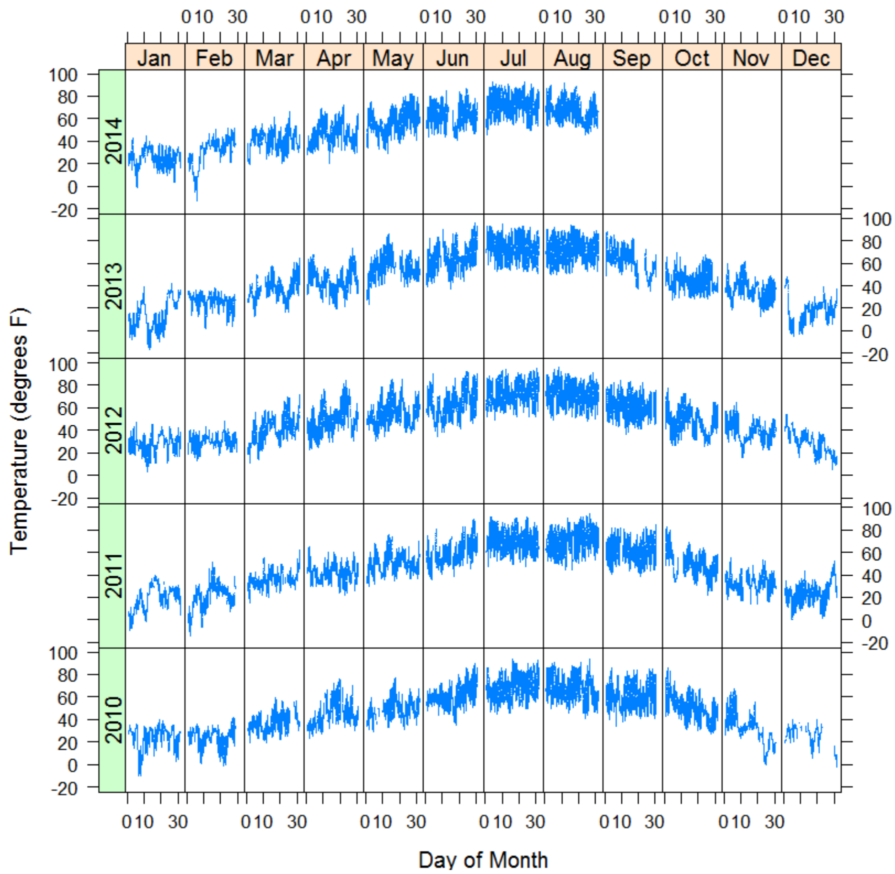


Figure 11.31. Temperature Data Available to the Project at the Idaho Falls Site

11.7.2 Analysis of the In-Home Display System

Historical data intervals were 1 month long, so regression modeling also was based on 1-month intervals. The average premises power data was converted into average monthly premises energy consumption for both the test group and the baseline group. These monthly energy usages are plotted as a function of net degree-days in Figure 11.32, where net degree-days have been defined as the sum of the product of all interval durations and their corresponding Fahrenheit temperatures for the month.

The temperature-based data representation reveals the typical curve that increases to the left—the heating curve—and to the right—the cooling curve. A separation between cooling and heating regimes was determined precisely as 57.5°F. This is the temperature at which the linear regression fits to warm temperatures (cooling regime) and cold temperatures (heating regime) intersect, giving a minimum total residual error for the two linear models.

In Figure 11.32, both the test and baseline (Control) groups are further distinguished by whether the months preceded or followed February 2013, the month when the IHDs are believed by the project to have begun informing their residences about energy consumption. Observe that the points after February 2013 appear to have a much more linear relationship—a stronger temperature correlation—than months before. The earlier months are probably affected by the uncertain dates and times of manual meter reading.

For the test group, if the information from the IHDs was, in fact, effective at reducing electricity consumption, the months after February 2013 should fall below those before February 2013. The impact for the test group includes the effects of both the IHDs and the AMI system that was installed about the same time. The baseline group received AMI, but they did not receive IHDs. If the baseline group after February 2013 falls below the values in the months before then, the difference might be attributed to the AMI alone. The differences between the test and baseline groups might inform us about the impact of IHDs alone.

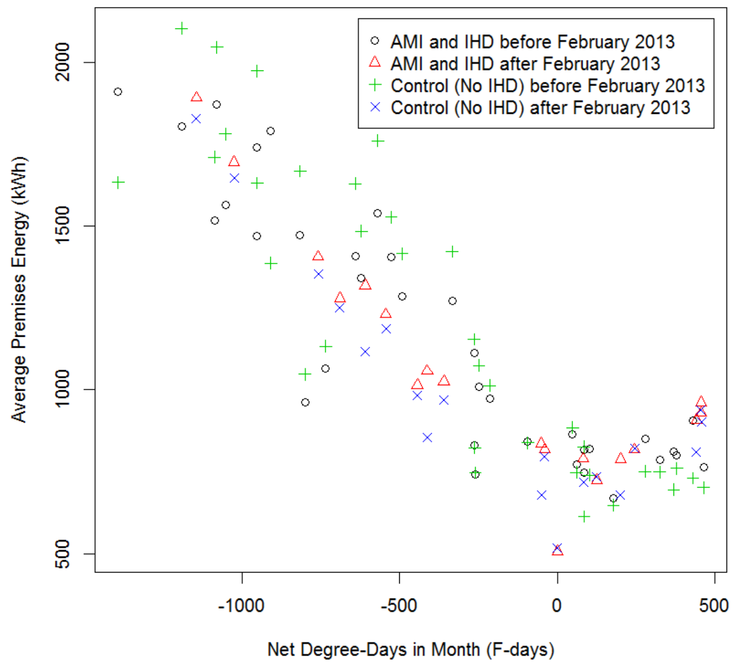


Figure 11.32. Measured Premises Energy Usage from Regression Models of the Test and Comparison Groups from Before and After February 2013 Plotted against the Net Degree-Days that Month

The data of Figure 11.32 were used for linear regression analysis. One variable in the regression fit was whether the month was before or after February 2013. The model was also fit to cooling degree-days and heating degree-days. These two variables are different from the net degree-days used in the plot of Figure 11.32. The net degree-days are the sum of cooling degree-days and heating degree-days.

Temperature data from project months was used in the regression models for the test and baseline groups before and after February 2013; the modeled per-premises energy usages are those shown in Figure 11.33. This is a check that the modeled energy usages resemble the raw data, which they do.

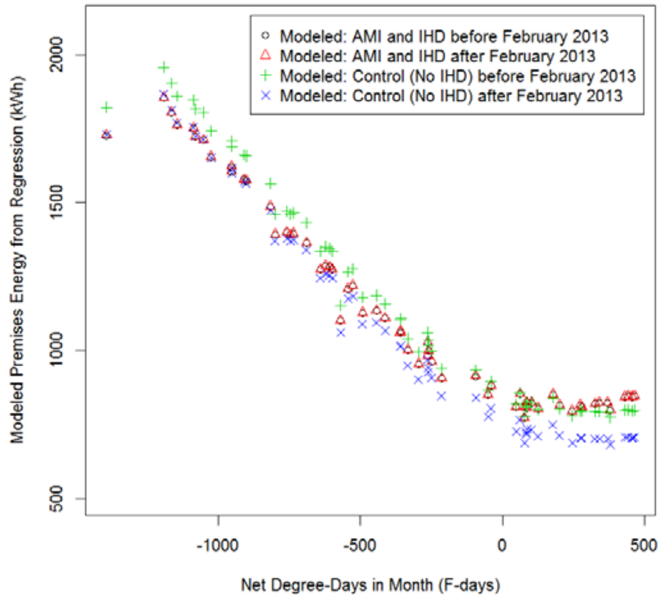


Figure 11.33. Monthly Premises Energy Use from Regression Models of the Test and Comparison Groups from Before and After February 2013 Plotted against the Net Degree-Days that Month

Based on the linear fit conducted in the R software environment (R Core Team 2013), the average monthly energy consumption of the test-group premises that received both AMI and IHDs was *increased* by 2 ± 44 kWh per month after the AMI and IHDs had been installed. The average monthly energy consumption of baseline-group premises that had received AMI and not IHDs was decreased by 92 ± 56 kWh.

The installation of AMI for the baseline group appears to have significantly reduced their metered electricity consumption. The result is not so clear for the premises that received both AMI and IHDs. While the regression fits were similar in respect to cooling and heating degree-days and intercept, the fact that the energy usages of the test and baseline groups behaved differently in warm and cool weather (review Figure 11.33) makes the project reluctant to say much about the impact of IHDs alone.

Looking back at the its experience with IHDs, Idaho Falls Power recounts obstacles including lack of vendor product integration, incomparable capabilities of pricing displays, unexplained meter outliers, and some connectivity issues.[1]

When the municipality polled the test residents after the project, it learned that 39% reported to have looked at the displays daily, 27% weekly, 16% monthly, 10% never and 5% had it unplugged. Sixty percent said their electricity usage remained unchanged throughout the program, while 35% said their usage was slightly lower, and the remaining residents said their usage was significantly lower. Thirty-five percent said they had a positive experience and would like the program to expand; 25% said they would like more information.[2]

[1] Ibid.
[2] Ibid.

11.8 Conclusions and Lessons Learned

Idaho Falls Power tested as many smart grid assets as any other participating utility. Using automated voltage regulation, they demonstrated on one feeder that they could reduce the feeder's consumption by, on average, 137 kW. The way they operated the system during the project demonstrated they could reduce the annual cost of their energy purchases by $2,710 and could possibly reduce these purchased by $5,420 if the practices were more consistently applied through the year. The system might reduce peak demand charges by $3,570–$6,770 per year. The installation of the automated voltage management practically eliminated low- and high-voltage alarms that had occasionally been received from customer AMI concerning their supply voltages.

The utility corrected the power factor on two feeders that supply large industrial breweries. Power factors were clearly improved. By installing switched capacitors, Idaho Falls Power reduced the average distribution current by 12% on one feeder and 4% on the other. While the project was unable to quantify the impact of line losses as an absolute energy magnitude, line losses are inferred to have been reduced by about 22% and 7.5% on the two feeders.

The utility applied fault detection, isolation, and restoration distribution automation on the feeders from their Sugarmill substation. Yearly reliability indices were collected, but the project did not draw a final conclusion as to whether the circuits' reliability had been significantly improved.

Idaho Falls Power installed over 200 water heater controllers. Possibly because these controllers were divided into and controlled in four subgroups, neither the utility nor the project was able to discern any reduction in power at the times the water heaters were reported to have been controlled. In fact, some of the statistical approaches applied by the project suggest the utility's method of water heater control might have even increased overall power. Event periods were uncertain.

The utility installed a 10 kW modular battery energy storage system near it headquarters, which also hosts PHEV charging stations and solar PV power generation. The vendor halted its support of the module before usable data had been procured.

About 42 residents' premises were given controllable thermostats. The project determined that the devices reduced consumption by about 52 W per premises. The total impact on energy supply and energy-supply costs was negligible. However, based on the way the utility operated the thermostats for part of a year, demand charges were reduced by about $473. Had the system been exercised similarly throughout the year the reduction might have been $631 or more.

Finally, the utility and the project installed IHDs at 431 residences that also received AMI and compared them against similar premises that that had received AMI but not IHDs. The project modeled the change in behavior between months before and after the AMI and IHDs had been installed. The homes receiving only AMI reduced their monthly energy consumption by 92 kWh, but it seems that the premises receiving both the AMI and IHD slightly increased their energy consumption.

When asked about the lessons they had learned from the project's experiences, Idaho Falls Power said that interoperability is still very new in the smart grid industry, despite some vendors' claims. Integration of systems was difficult, time consuming and expensive.

Idaho Falls Power polled its residents who had participated in the project. Some of the results from this poll have been inserted elsewhere in this chapter with the technologies being discussed. The entire set of results is not included in this report.

When asked for the principal reasons that participants had participated in the program,

- 44% said helping the community reduce energy use during peak times was very important
- 47% said taking advantage of the latest technologies was very important
- 55% said minimal lifestyle interference was important
- 54% convenience of participation was very important
- 53% said helping the environment by reducing energy use was very important
- 65% said lowering their bill was very important

When asked about their interest in a web portal or mobile app that would enable them to analyze their electric use in near-real time, 17% of respondents gave this the lowest ranking (least interested), while 47% of respondents gave this the top ranking (most interested).[1]

[1] Ibid.

12.0 Lower Valley Energy Site Tests

Additional chapter coauthors: R Knori and W Jones – Lower Valley Energy

Lower Valley Energy is a rural electric cooperative located in Northwest Wyoming and Eastern Idaho. It serves 27,000 electric customers. Their service territory is expansive, featuring towns, very remote rural substations, and even a mountain ski resort. Terrain is mountainous at the feet of the impressive Teton Mountains. The backbone of their distribution electric system is the Teton-Palisades power interconnect—a loop that includes lengths of Lower Valley Energy 115 kV lines and connects to the regional Bonneville Power Administration (BPA) transmission system at the Teton and Palisades stations.

The cooperative offered altogether four demonstration sites where it planned to test its asset systems. The sites are listed here with the types and quantities of newly installed equipment at each of the sites:

- East Jackson Substation, East Jackson, Wyoming
  - 2,665 Aclara and Landis+Gyr advanced premises meters
  - substation Two-Way Automatic Communication System (TWACS) infrastructure, including a modulation transformer unit, a control and receiving unit, and an outbound modulation unit
  - in-home displays (IHDs)
- Afton substation, Afton, Wyoming
  - 1,530 Aclara and Landis+Gyr advanced premises meters
  - substation TWACS infrastructure, including a modulation transformer unit, a control and receiving unit, and an outbound modulation unit
  - IHDs
- Hoback substation, Bondurant, Wyoming
  - 300 kVAr static volt-amperes reactive (VAr) compensator (SVC)
  - 20 kW solar photovoltaic (PV) array
  - four 2.5 kW wind turbines
  - 125 kW, 250 kWh battery bank.[1]

Lower Valley Energy originally had intended to engage distributed generation at the Jackson Hole Mountain Resort as one of their project sites, but these plans fell through. The remaining three sites are shown by blue stars on the Lower Valley Energy service territory map in Figure 12.1.

[1] The demonstrated power and energy capacities of this battery system, as reported to the project by Lower Valley Energy, fell considerably short of these nameplate values, as will be discussed later in this chapter.

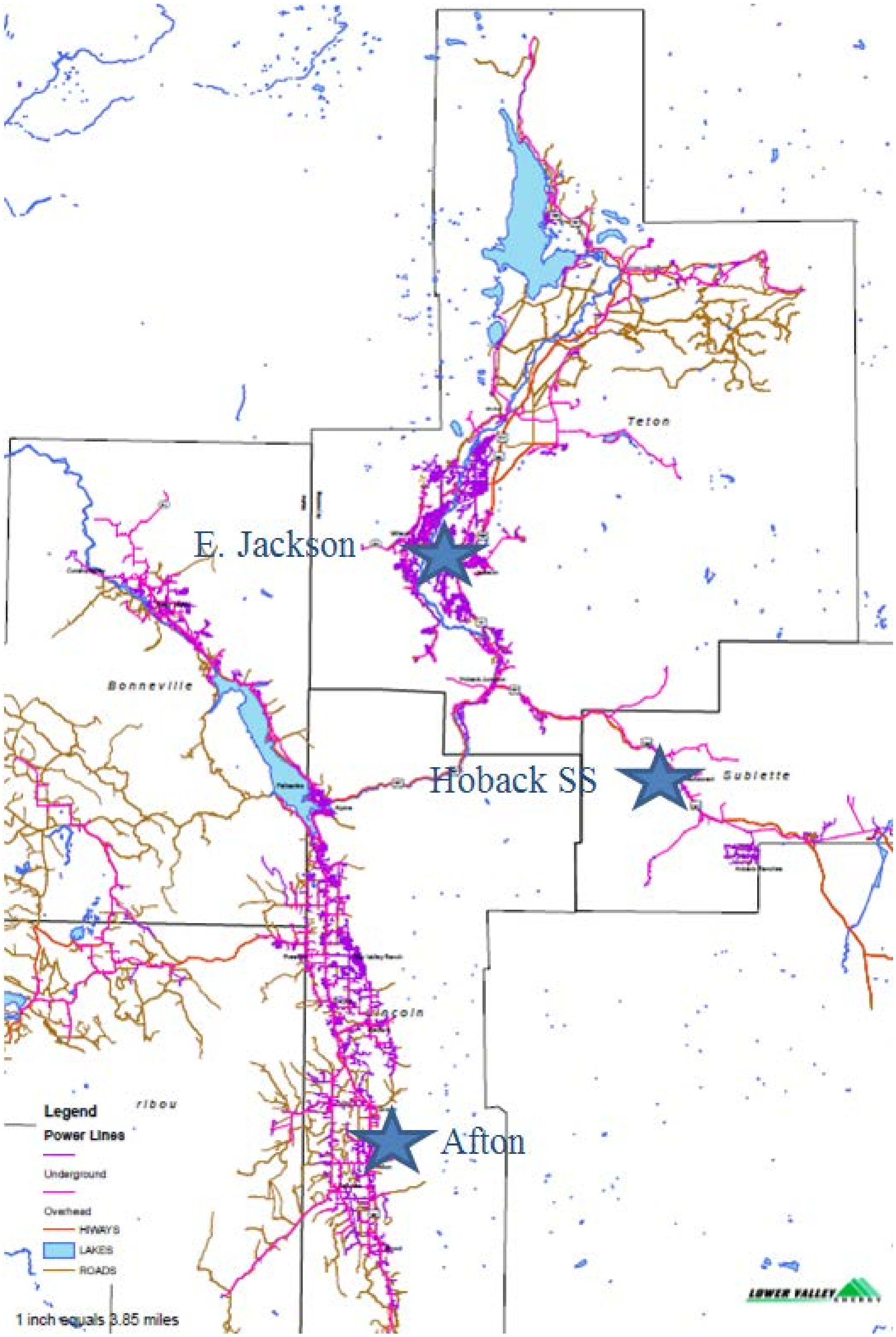


Figure 12.1. Lower Valley Energy Sites. The corridors highlighted in red are important Eastern Idaho transmission lines that supply Lower Valley Electric. (Lower Valley Energy 2015)

The East Jackson and Afton sites are moderately populated. These two sites were primarily used to test member interaction with advanced metering and IHDs. In contrast, the Bondurant, Wyoming site is rural and is at the remote end of a long distribution line. While some premises on this feeder also received advanced metering and IHDs, the cooperative hoped to strengthen the electrical supply to the Hoback substation, which serves Bondurant, and to defer upgrades using a diverse set of SVCs, renewable energy resources, and battery energy storage. The existing C3-ILEX SCADA (supervisory control and data acquisition) system and remote terminal units were used to control and monitor these assets during the project.

The project organized the Lower Valley Energy asset systems into eight tests. These are the eight asset systems that were demonstrated, including their site locations and the chapter sections where each is discussed:

- advanced metering infrastructure (AMI) and IHDs (all sites) (Section 12.2)
- demand-response units (DRUs) (all sites) (Section 12.3)
- DRUs and AMI for reliability (all sites) (Section 12.4)
- adaptive voltage management (East Jackson site) (Section 12.5)
- 300 kVAr static VAr compensator (Hoback site) (Section 12.6)
- 125 kW battery storage system (Hoback site) (Section 12.7)
- 20 kW solar PV system (Hoback site) (Section 12.8)
- four 2.5 kW wind turbines (Hoback site) (Section 12.9).

The layout diagram in Figure 12.2 shows how these asset systems and their test groups lie among the cooperative's distribution feeders.

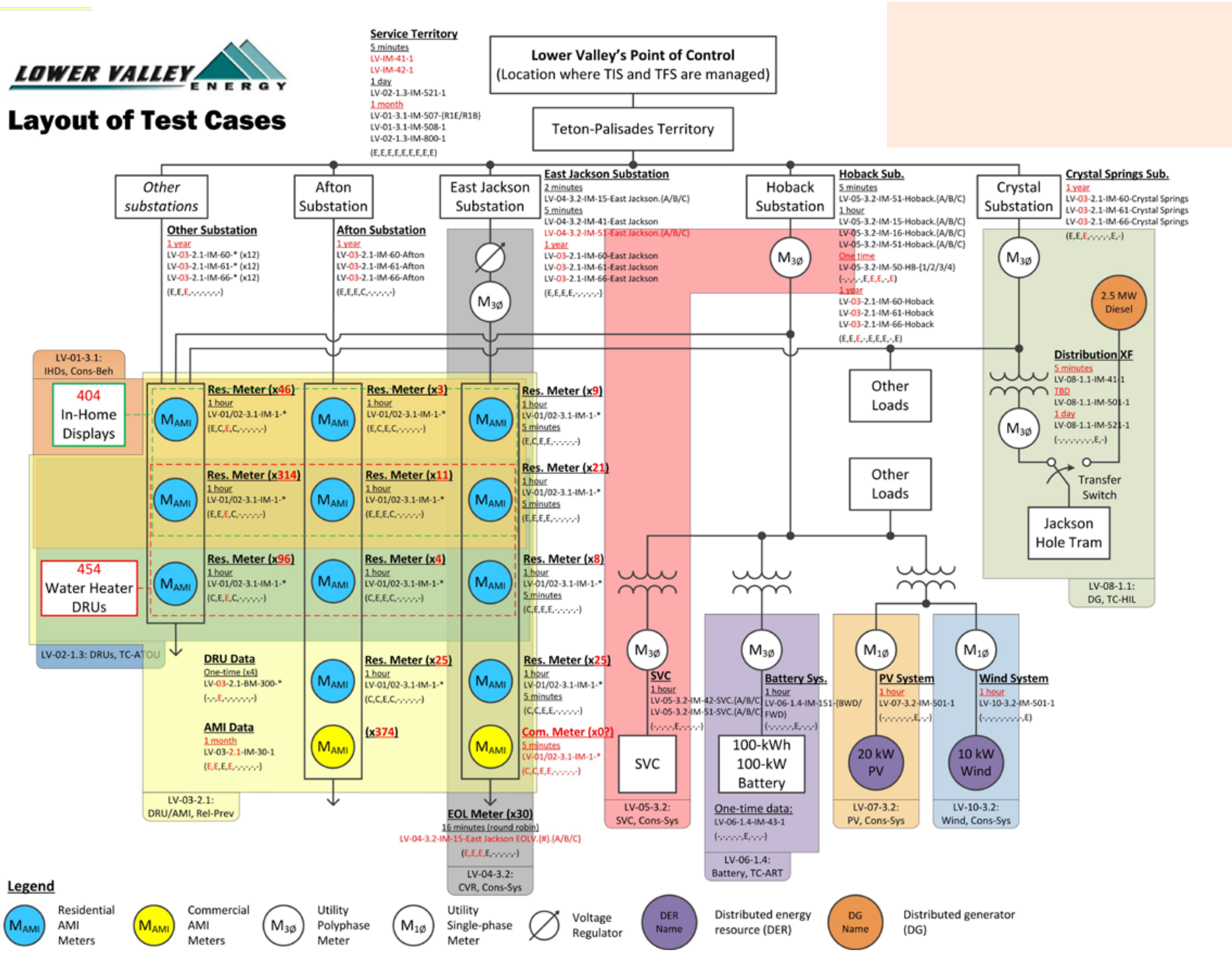


Figure 12.2. Layout of Lower Valley Energy Test Groups and Asset Systems on their Distribution System

Figure 12.3 is a picture of several of the assets that were installed at the Bondurant, Wyoming (Hoback substation) site. The Lower Valley Energy asset systems will be discussed in greater detail in the sections below.

Figure 12.3. Bondurant Site where SVC, Solar PV, Wind, and Battery Systems Resided

The cooperative's service territory is in a relatively cold part of the country and is strongly winter peaking. Figure 12.4 shows the average premises power of the cooperative's members whose data was collected during the project. Strong morning peaks are evident during winter and spring seasons.

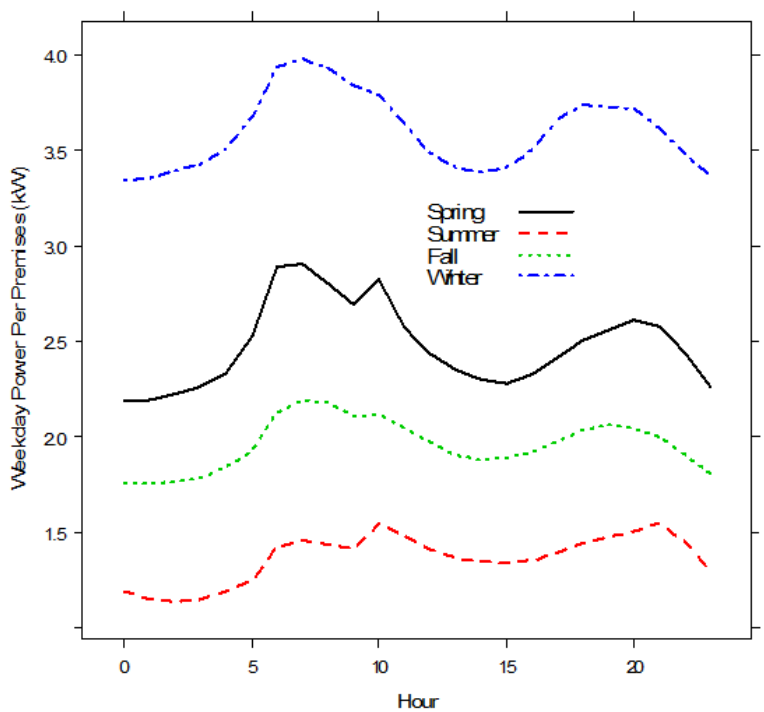


Figure 12.4. Representative Average Per-Premises Power by Season for Lower Valley Energy Cooperative Members. The time scale shows local Mountain Time hour.

12.1 Lower Valley Energy's Transactive Demand-Charges Function

A transactive system function was created to help the cooperative anticipate monthly peak demand and to augment the transactive system's incentive signal such that the battery system and other system assets might help mitigate the cooperative's peak demand. Lower Valley Energy chose to create and operate only one transactive site for the entire Lower Valley Energy service territory, so the demand-charges function attempted to respond to total utility demand. Preferably, if the Hoback site had been defined as another transactive site, the function might have helped the battery system respond to the specific load on the long Hoback distribution lines. As it was, the cooperative already had an application that monitored the distribution line and predicted peak, so they did not especially need the transactive function that attempted to predict and mitigate their demand charges.

The demand-charges function began to successfully identify the timing of new peaks by fall 2013, but its impact on the site's transactive signal was never correctly assessed or calibrated.

12.2 AMI and In-Home Energy Displays

Lower Valley Energy wished to induce energy conservation by providing IHDs and information to its members. They targeted the installation of 500 IHDs, primarily at their Afton, Wyoming site. Landis+Gyr meters equipped with Aclara TWACS modules were also installed, and these meters were used to communicate with and monitor the performance of the system of premises having IHDs. The IHDs were managed from the cooperative's Afton, Wyoming control center.

The cooperative wished to engage its members via the IHDs to reduce its needs for future BPA TIER-2 power, which is the more expensive power that must be used after the utility's allocation of TIER-1 power has been consumed. The IHDs were initially to respond to the project's transactive system, but early during the project the cooperative opted not to use transactive technology at this site. Instead, they asked the project to help them assess the conservation impact. The cooperative originally targeted 8–15% conservation using the IHDs.

Members were able to view their real-time power demand and energy that they had consumed during the current month (for some members) when they visited their IHD.

Participating members were not charged for the IHDs and were not given any monetary incentives by Lower Valley Energy for their participation in the project.

As shown in Table 12.1, the annualized costs of the Lower Valley Electric in-home display system included premises metering, the IHDs, operations and maintenance (O&M) costs, administrative costs, and the costs of educating members concerning how they may interact with their IHDs. The annualized costs were calculated for each component according to that component's estimated useful lifespan.

Table 12.1. Lower Valley Electric Costs of In-Home Display System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Advanced Metering			57.1
• AMI System (backbone)	25	129.8	32.4
• AMI Meters (premises with IHD)	50	26.5	13.3
• AMI Meters (premises with IHD and DRU)	33	29.8	9.9
• AMI Meters (premises with IHD and affected by CVR)	33	2.5	0.8
• AMI Meters (with IHD, DRU, and affected by CVR)	25	2.6	0.7
In-Home Energy Displays	100	8.7	8.7
Ongoing O&M Costs	100	6.1	6.1
Administrative	100	3.7	3.7
Outreach and Education	100	2.9	2.9
Total Annualized Asset Cost			**$78.4K**

CVR = conservation voltage reduction

12.2.1 Characterization of the In-Home Display System

Working with the project, Lower Valley Energy established premises test groups based on the assets that were installed at those premises. The test groups overlap one another, meaning that some of the groups were affected by multiple asset systems. Some of the premises hosted a DRU, (Section 12.3). Some of the premises resided on the East Jackson feeder where voltage regulation (Section 12.5) was being exercised and others did not. The counts of the various test populations are summarized in Table 12.2.

Table 12.2. Counts of Premises in Each Test Population According to Assets at the Premises

Assets at the Premises	No CVR	CVR	**Totals**
AMI only	24	24	**48**
AMI and IHD	15	3	**18**
AMI, IHD, and DRU	324	27	**351**
AMI and DRU	103	5	**108**
Totals	**466**	**59**	**525**

The challenge, then, is to isolate a conservation impact that is attributable to the installation of IHDs. Ideally, the 15 premises having IHDs should be compared against the 24 premises where no assets other than advanced meters were installed. An alternative exists if we can compare the 234 premises that have both a DRU and an IHD against those 103 that receive only the DRU.

Lower Valley Energy informed the project that the IHDs were installed over a three-month period, January through March 2012. They supplied historical data from monthly meter reads for these test sets starting from September 2009. The early historical data let the project establish a baseline prior to the installation of the IHDs.

It was found that data quality changed the same months that the IHDs were being installed. The IHDs were installed near the same time that premises meters were upgraded, which added variability to the data. This data's variability might be attributable to the inexact timing of dates and times that premises meters were read. In the months of early 2012, hourly interval measurements became available to the project as the advanced premises meters were activated. Because the installations of advanced metering and IHDs were concurrent, the impacts from the new metering and assets might not be fully separable.

Figure 12.5 shows a sample of the averaged premises power for the test group that received IHDs (red) and the control group that did not (blue). The figure shows data for all of 2012, during which both IHDs and AMI were actively being installed. The data markers that remain constant for an entire month at a time represent the historical data that was available from monthly manual meter reads prior to the installation of AMI.

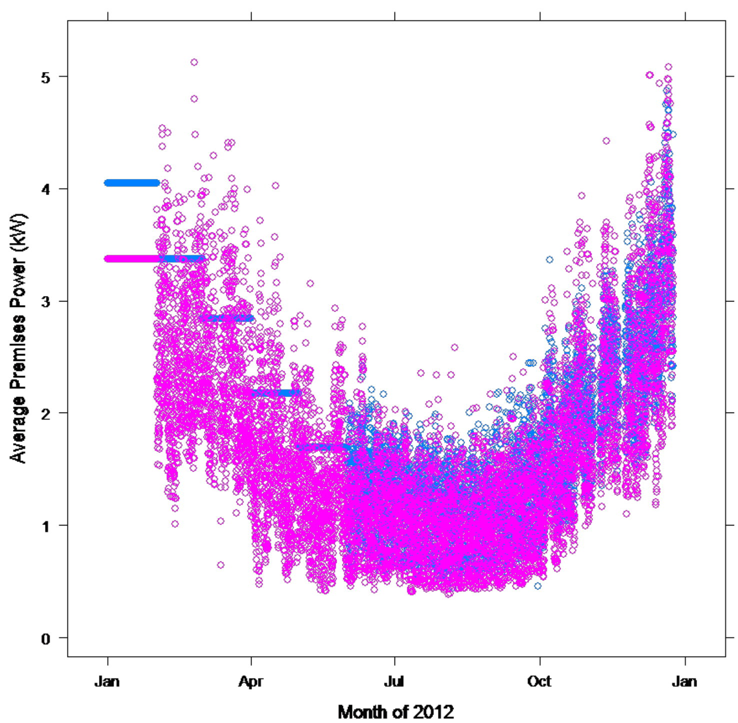


Figure 12.5. Average Premises Power of the Test Group that Received In-Home Displays (red) and the Control Group (blue) during Early 2012, when Both the Advanced Meters and In-Home Displays were Being Installed

The aggregate premises power data was reviewed. If the power for the test groups and/or their baseline groups were found to be uncharacteristic during any time period, then the data from both test groups was removed for that period. If either the test group or baseline was unavailable, then the other was made unavailable. Inexplicable low measurements below about 0.3 kW per premises were removed because these values were remote from other measurements and were not characteristic of normal premises behavior.

As for the historical monthly power data, these were believed to derive from monthly meter reads. Total monthly premises energy was divided by the hours in the month to create an average per-premises power. The project believes the historical data should not have been subject to the same types of errors from missing data as were the recent measurements.

All premises data were averaged across the test groups shown in Table 12.2, stating average power per premises. The data was also averaged by calendar month to make data from the recent and historical periods comparable. Figure 12.6 shows the monthly average premises power for one of the pairs of comparable test and control groups. The arrow on this figure points to the center of the installation period. The data from February 2014 was entirely removed because visual inspection revealed stepwise reductions in one of the time series and not the other that month. Except for the winter of 2012, the yearly profiles appear similar to each other.

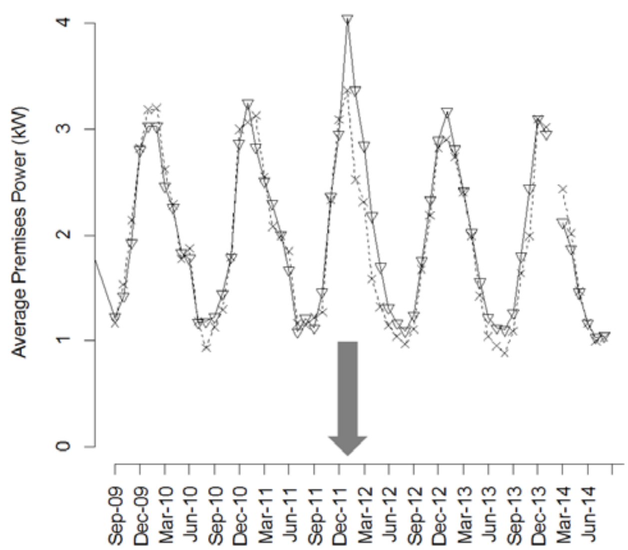


Figure 12.6. Monthly Average Premises Power for Premises that have Both Advanced Meters and In-Home Displays (dashed line with cross markers) and Those Receiving only Advanced Meters but Not IHDs (solid line with triangle markers)

The aggregated monthly data for the alternative pairing of premises that also have DRUs is shown in Figure 12.7. As for the comparison in Figure 12.6, the two data series differ only in that one of each pair had IHDs installed and the other did not. The data sets graphed in Figure 12.7, for premises that also had DRUs, are much larger and might be expected to have better statistical outcomes than for the comparison using premises that did not receive DRUs (Figure 12.6). Some interesting anomalous patterns are observed, however, in the control set that did not receive IHDs. The peak 2013 and 2014 winter average power consumption exhibits uncharacteristic dips or flattening of peaks. Furthermore, a relatively constant reduction in energy consumption appears over the project's duration that was not as evident in Figure 12.6.

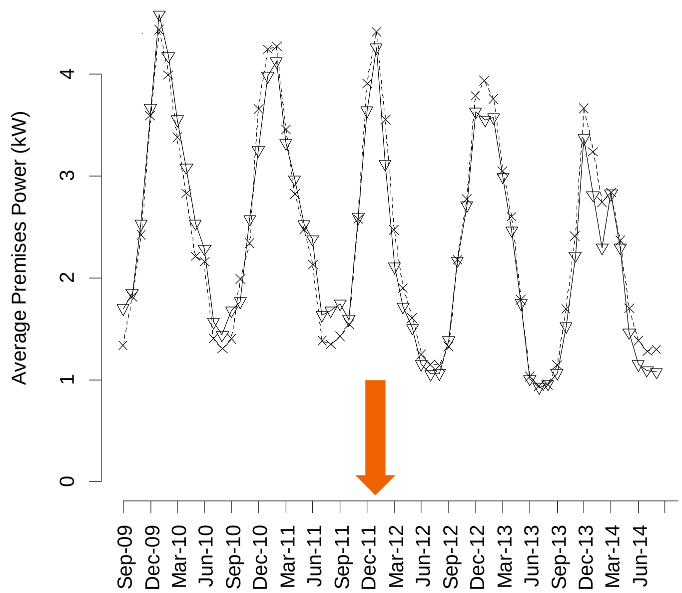


Figure 12.7. Monthly Average Premises Power for Premises that have Advanced Meters, DRUs, and In-Home Displays (dashed line with cross markers) and those receiving only Advanced Meters and DRUs but Not IHDs (solid line with triangle markers)

Analysis also used ambient temperature in the formulation of modeled data sets. Temperatures were accessed primarily from weather station D1489 in Wilson, Wyoming. Wherever these measurements were found to be missing, replacement data was generated from a linear model that was informed additionally from weather station KJAC, Jackson Hole Airport, Jackson Hole, Wyoming.

12.2.2 Performance of the Advanced Metering and In-Home Display System

The project first attempted to directly compare the raw data sets that were shown in Figure 12.6 and Figure 12.7. That is, presuming the test groups are comparable, did the installation of IHDs change the relationship between the two test groups? This method generated results that, at first, seemed compelling, but the results turned out to be contradictory between the datasets in Figure 12.6 and those in Figure 12.7. The effect apparent from the simple comparison also dissolved away after temperature-based modeling approaches were applied.

Because advanced metering had been installed concurrently with the IHDs, the project first tried to isolate any impact from the smart meters alone. Using the average monthly per-premises power of the 24 members who received only advanced metering, the project created a linear parametric model using R software (R Core Team 2014). Because the project wished to estimate and eliminate the impact from any consistent change in affluence for the population over time, the model was fit to an affine fractional year counter. The model also used average ambient temperatures and a Boolean indicator for the months that advanced meters had been activated. The date of advanced meter installation was inferred from when interval measurements changed from monthly to hourly.

Northwestern Wyoming is a cool climate. The highest average monthly temperature was about 65°F (~18°C). Little air conditioning is needed or used by these premises. The load was quite (inversely) linearly proportional to the temperature, so separation of cooling and heating regimes was deemed unnecessary for the month-interval data.

The linear fit suggested that average load is increasing about 93 W per premises per year in this population. The average monthly premises load decreased by about 43 W for every 1°F increase in average ambient temperature. (78 W/°C). Finally, the installation of advanced metering seems to have reduced average premises power consumption by 266 W.

The model was then used to generate predictions of what the average per-premises consumption would be if advanced meters were never installed. This prediction was useful for the project to understand the statistical confidence that should accompany the reduction. Based on a Student's t-test comparison between modeled and actual average monthly premises power, the project reports that the installation of advanced metering reduced average premises power by 270 ± 70 W in this test group. The results were further assessed by month in Figure 12.8, in which the heavy error bars represent standard error and the longer bars estimate a 95% confidence interval.

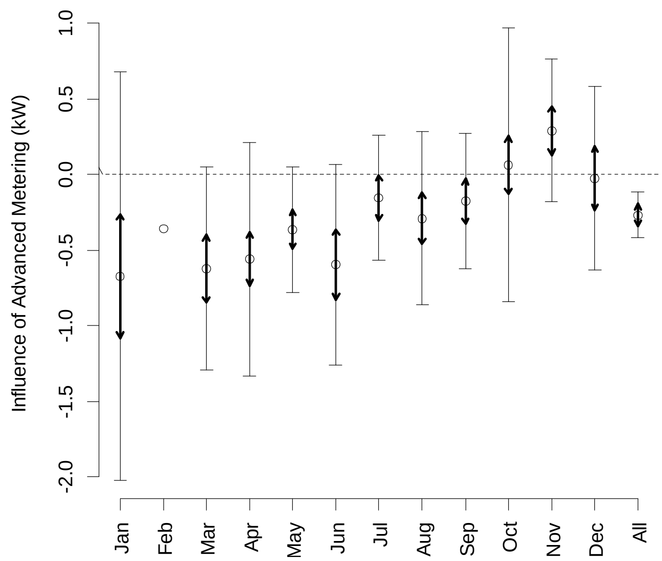


Figure 12.8. Impact of Installing Advanced Premises Metering on Average Premises Power by Calendar Month

For confirmation, the analysis was repeated using the alternative test group that received DRUs but never received IHDs. Formally, this result should be described as the long-term conservation impact from installing both advanced metering and DRUs. The installation of advanced meters and DRUs reduced average premises power consumption by 400 ± 110 W. For this test group, premises power consumption also decreased at a rate of 22 W per year throughout the 5 years.

The project then created similar models for the test group that had received both advanced meters and IHDs to see whether the addition of the IHDs changed the outcome. The same parametric variables were used for the linear fit as for the modeled control group that received only advanced meters. In this case, a reduction of 210 ± 70 W was found. This result is a little less than, but otherwise very similar to, that found for advanced meters alone. It probably confirms that outcome for the impact of advanced metering, but nothing can be said about the incremental impact of the IHDs.

The results from this last analysis are shown broken out by calendar month in Figure 12.9. This figure may be compared against Figure 12.8 that was for premises that received only advanced meters. Again, the results are similar. Even the monthly patterns share similarities.

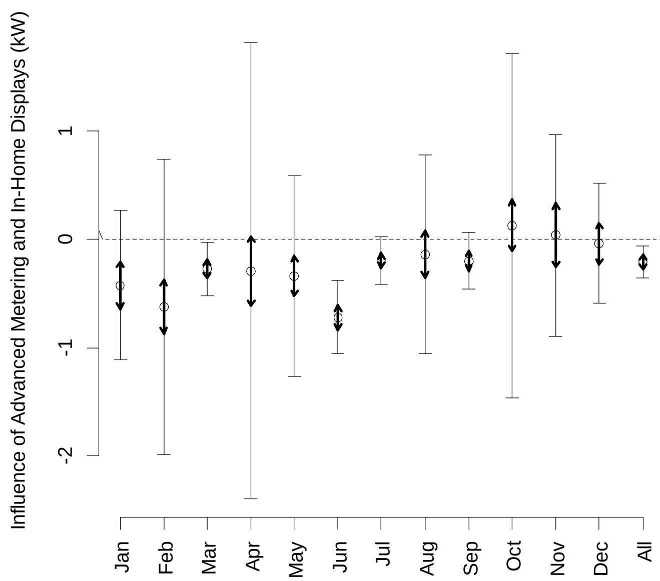


Figure 12.9. Change in Premises Power from Installation of Both Advanced Metering and IHDs by Calendar Month

The project made further attempts to distinguish the impacts of installing IHDs from that evident from installing advanced metering. Any results that were found were small in comparison to the impacts from installing advanced metering, and the project could not confidently state that any effects were significant.

The project was not able to differentiate any diurnal impacts of the conservation with the available data. The impact on peak premises load must be presumed to be identical to the global finding.

In conclusion, the project was not able to confidently attribute any reduction in power consumption to the installation of IHDs, but the project found compelling evidence that the installation of advanced metering reduced premises power consumption. One hypothesis is that an actual power reduction follows the installation of advanced metering because the information and education received by the affected members induces them to truly conserve energy. Another hypothesis is that the newer meters are calibrated differently from the older meters and in the cooperative members’ favor.

12.3 DRUs

Lower Valley Energy reported installing 530 Aclara DRUs on premises controlling 566 water heaters at the Afton, Wyoming site. Electric water heater load was to be curtailed when advised to do so by the project's transactive control system. The system of DRUs was managed from the Afton control center. The cooperative's main purpose for the DRUs was reduction of monthly system peak and reduction of the corresponding demand charges that it pays for peak demand.

The utility had already installed about 50 DRUs prior to their participating in the project. Curtailments of varying durations were being conducted on subgroups of this population to determine members' tolerance for the curtailments.

Lower Valley Energy waived a $15 monthly service facility charge for participating members who allowed the utility to install a DRU to control their electric tank water heater. This monthly credit was later reduced to $10. Briefly stated, the utility justifies this expense based on peak demand charges that will be avoided. The total incentives to be paid for this responsive asset by the utility were predicted by the utility to be about $87 thousand per year.

Lower Valley Energy offered to make the DRUs responsive to the project's transactive system. In fact, only several of the DRUs—those at utility offices and under close utility supervision—were made automatically responsive to the project's transactive system. Lower Valley Energy had a second objective that was automated through their SCADA system to automatically respond at preset demand thresholds.

The vendor provided additional features. The DRUs were configured to automatically respond to under-frequency and under-voltage events that they detected in the distribution system. Furthermore, the DRUs were programmed to delay the reconnection after distribution outages to provide cold-load pickup for the utility. These responses were thought by the utility to be useful, especially when the DRUs were positioned on long, rural distribution feeders.

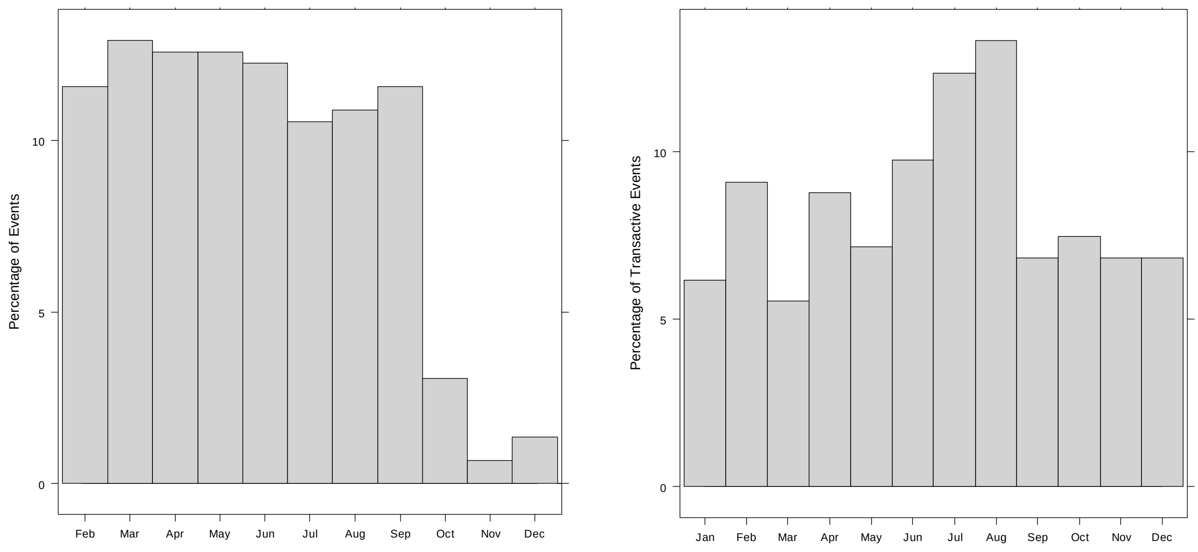
The annualized costs of the Lower Valley Energy DRU system and its components are summarized in Table 12.3. The greatest annual cost is for member incentives. The costs of the members' advanced metering were included because these meters were essential for monitoring and controlling the DRUs. Other costs to the utility include the purchase and installation of the DRUs, system upkeep, connecting control of the DRUs to the transactive system, and administrative costs.

Table 12.3. Lower Valley Electric Costs of DRU System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Member Incentives	100	72.0	72.0
Advanced Metering			57.4
• AMI System (backbone)	25	129.8	32.4
• AMI Meters (premises with DRU)	50	27.1	13.6
• AMI Meters (premises with IHD and DRU)	33	29.8	9.9
• AMI Meters (with DRUs and affected by CVR)	33	2.5	0.8
• AMI Meters (with IHD and DRU and affected CVR)	25	2.6	0.7
Water Heater DRUs	50	17.1	8.5
Ongoing O&M Costs	100	6.1	6.1
Transactive Signal	50	8.4	4.2
Administrative	100	3.7	3.7
Outreach and Education	100	2.9	2.9
Total Annualized Asset Cost			**$154.9K**

12.3.1 Characterization of Asset System Responses

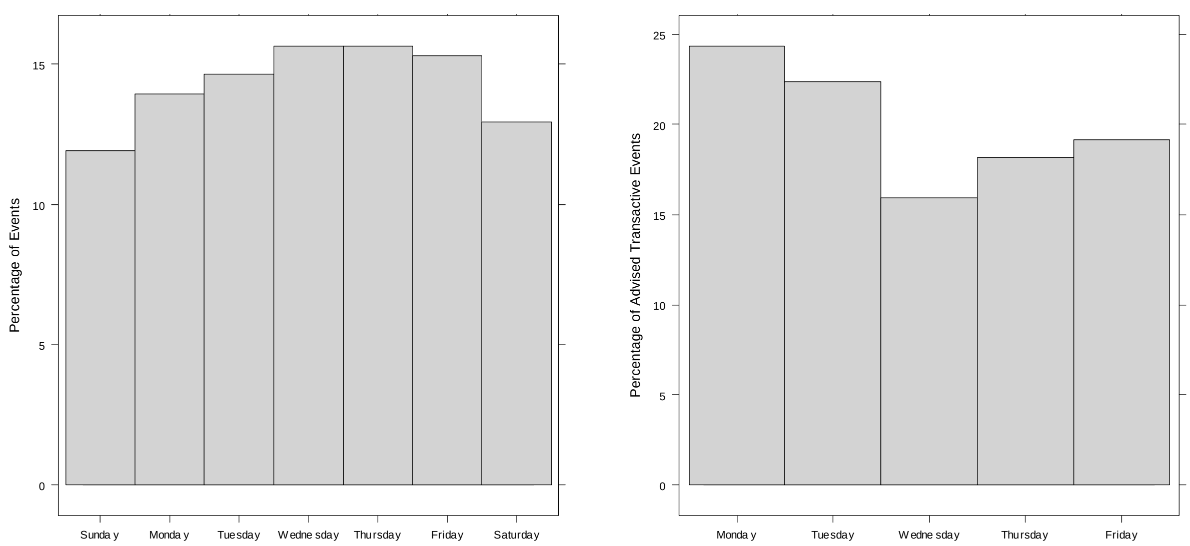
Figure 12.10 shows the relative numbers of times per calendar month that the DRUs were reported to have been engaged (left) and had been advised to respond by the transactive system (right). The utility did not engage the DRUs much during the calendar months October, November, and December.



(a) (b)

Figure 12.10. Distributions of the Months that (a) DRUs were Truly Engaged and (b) Transactive System DRU Engagements were Advised

Histograms of the reported and advised events are shown in Figure 12.11. Analysts were somewhat surprised that the DRUs had been engaged all days of the week, including weekend days. The toolkit function that was established to advise event periods for the system of DRUs was apparently configured to disallow weekend events.



(a) (b)

Figure 12.11. Distributions of Weekdays that (a) the Lower Valley Energy DRUs were Reported to Have Been Engaged and (b) the Transactive System Advised the DRU System to Become Engaged

When analysts reviewed the durations of events that had been initiated by the utility, over 80% of the DRU events had been precisely 3 hours long. Figure 12.12 shows the distribution of the event durations with the most predominant duration being 36 5-minute intervals, which is 3 hours. An extremely long event was omitted from this figure and must have been an outlier.

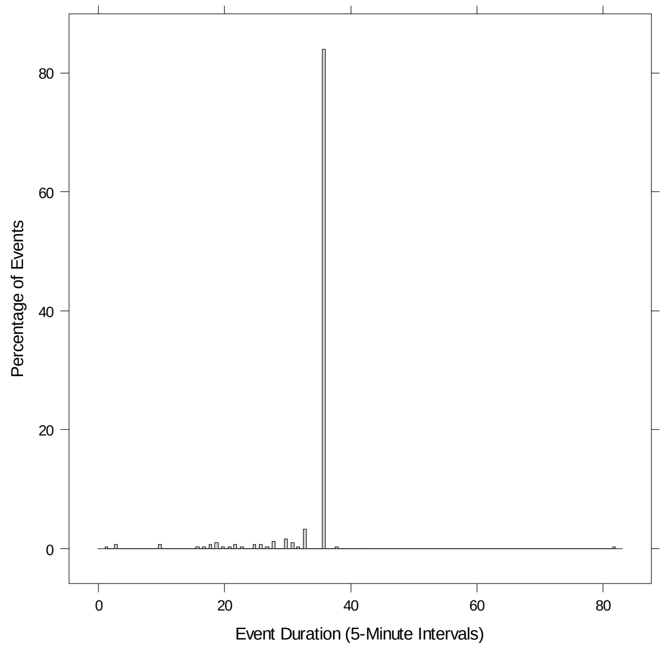
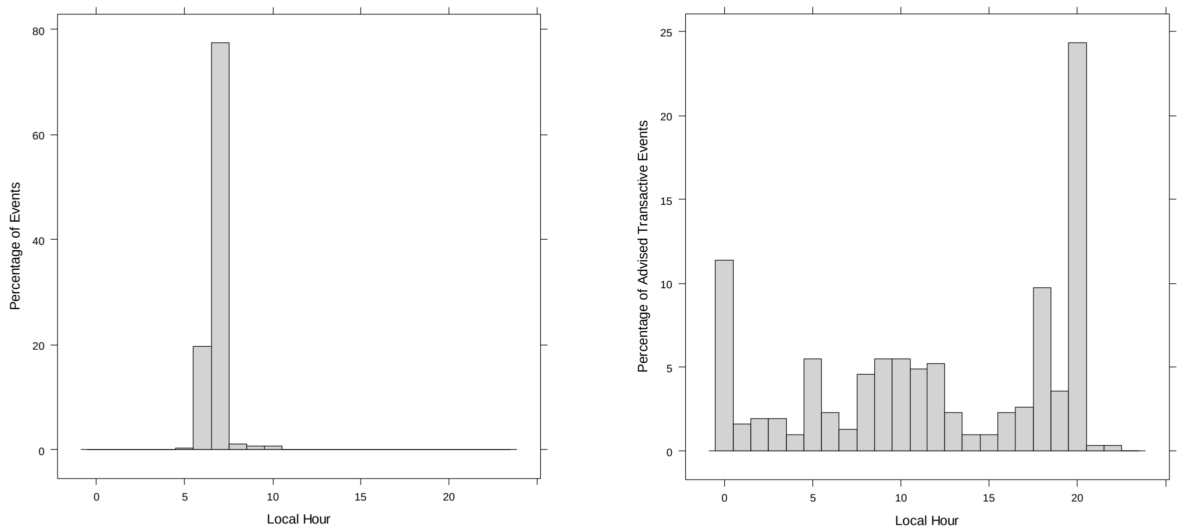


Figure 12.12. Histogram of Event Durations for Lower Valley Energy DRU Engagements. Very long event #253 was deleted prior to this and most other analyses in this section.

Figure 12.13 shows the local hour when the events were engaged by Lower Valley Energy (left) and the starting hours that events were advised by the transactive system (right). The utility engaged the DRUs during a narrow window of morning hours between 05:00 and 10:00. The transactive system advised events all hours of the day, including too many midnight and late evening hours (e.g., 20:00), which might be attributable to the challenges the PNWSGD encountered as it calibrated the transactive signals and the asset's toolkit function.



(a) (b)

Figure 12.13. Local Hours that DRU Engagements (a) Actually Began and (b) Were Advised to Begin by the Transactive System

12.3.2 Performance of the Lower Valley Energy DRUs

The project analyzed the change in power during the times that the loads on the DRUs were reported to have been curtailed. Both comparison and modeled baselines were established for this analysis. The comparison baseline was created from the approximately 24 premises that had neither DRUs nor IHDs (Section 12.2). The average power consumption data series from these comparison premises were normalized to have the same monthly mean and standard deviation as for the approximately 104 premises that had only DRUs. The DRU-event time periods were excluded from the normalization. A further global correction was then performed to make the global means the same each hour of the day. Neither the test nor comparison premises groups resided on the East Jackson feeder to avoid any potentially confounding interactions with the adaptive voltage management being practiced there (Section 12.5).

The averaged premises power consumption of the 104 premises that had DRUs was modeled using R software to create a modeled baseline. The linear model incorporated the parameters month, hour, weekday, temperature, and any permutation of the first three factors with the ambient temperature. The DRU-event time periods were excluded during the training of the linear model.

As stated before, temperatures were accessed primarily from weather station D1489 in Wilson, Wyoming. Wherever these measurements were found to be missing, replacement data was generated from a linear model that was informed additionally from weather station KJAC, Jackson Hole airport, Jackson Hole, Wyoming.

The two baselines (“comparison” and “modeled”) predicted what the premises power time series would have been had there been no DRUs. The comparison baseline was derived from the behaviors of a set of control premises that did not receive DRUs. The modeled baseline was formulated by linear regression using the average power of the test group that had received DRUs. The project compared the differences between the test and baseline time series both during event periods and during non-event periods to help mitigate any biases in the baselines.

The project reports a reduction of 370 ± 80 W per premises during DRU events after combining the results from both baseline approaches. Using the modeled baseline only, the project observed a reduction of 420 ± 20 W per premises. The project observed a reduction of 310 ± 20 W per premises using the comparison baseline approach.

The results are reported for each project month in Figure 12.14. As expected, the monthly results show large confidence intervals. Most of the months' results show power reduction, but there are some months that show increases in power consumption instead. Note the consistent power reduction in early 2012 when the DRUs were being exercised almost daily. The consistent results from those four months heavily influenced the final results being reported by the project. This influence may be clearer below when we look at cumulative results.

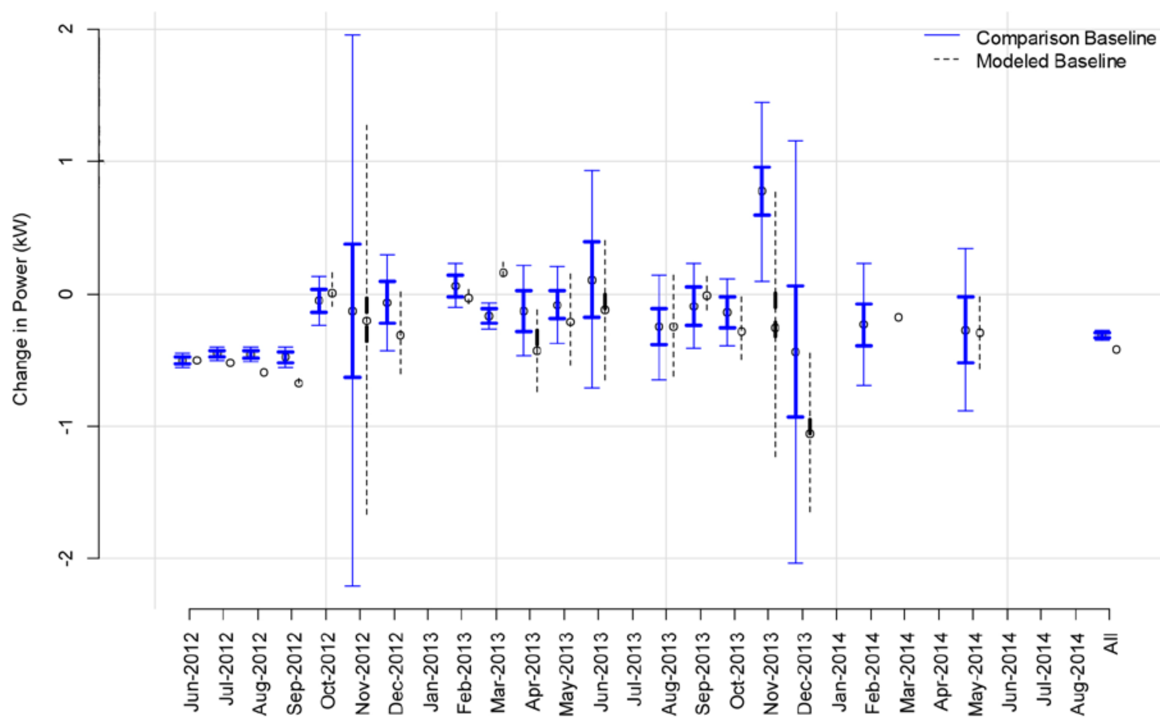


Figure 12.14. Average Impact on Premises Power Observed during DRU Curtailment Events Each Project Month According to the Comparison (blue) and Modeled (black dashed) Baselines

The project next looked at the impact on premises power during the hours immediately following the ends of events. During these hours, the thermostatically controlled devices that had been curtailed by the DRUs attempt to consume the energy that had been denied to them during the event.

The project reports that a 150 ± 150 W increase in power consumption per premises occurred during the rebound hour following DRU events. This result combines both the comparison and modeled baseline approaches. Actually, the comparison baseline itself yielded a convincing increase of 260 ± 70 W per premises by itself, but the results from the modeled baseline were smaller and inconclusive. When the same evaluation was conducted on East Jackson premises, a consistent increase of 440 ± 50 W was found, but this result is potentially confounded by voltage management on the East Jackson feeder. The project elected to use only the results that were not on the East Jackson feeder. The results again appear more consistent during the time the DRUs were being consistently exercised in early 2012.

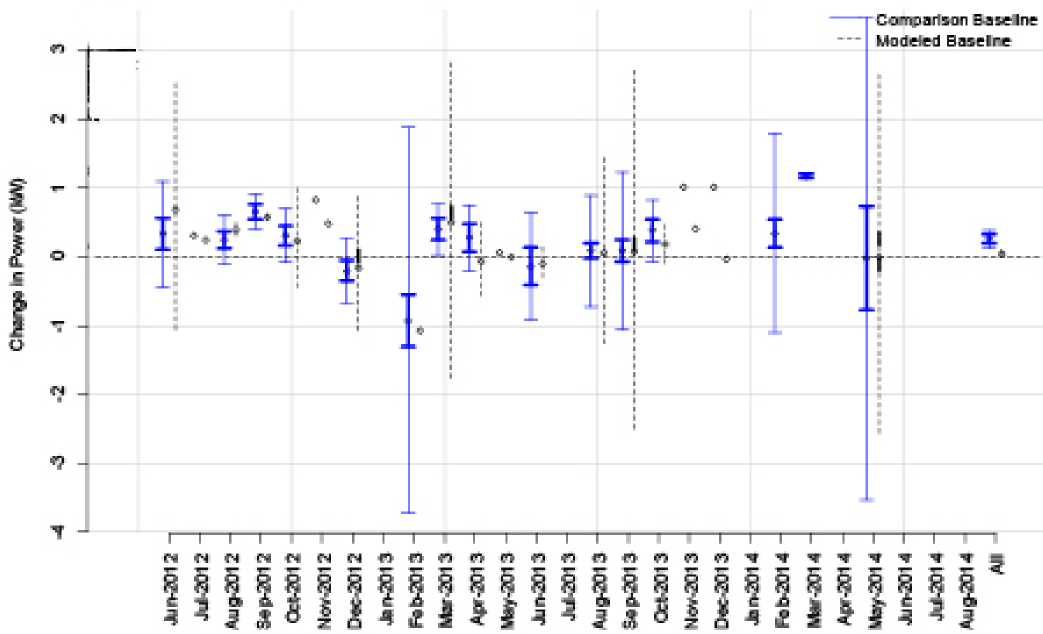


Figure 12.15. Average Impact during Rebound Hours each Project Month using the Comparison (blue) and Modeled (black dashed) Baselines

Throughout event days, the project observed that average premises consumption was reduced by 60 ± 70 W. Both baseline methods indicated that a significant reduction had occurred. However, the results from the two baseline approaches—105 ± 7 W per premises using the modeled baseline and 10 ± 7 W per premises using the comparison baseline—differed. Therefore, the project is reporting the variability as the standard deviation of the two results, which is much greater than the standard errors from either of the two baseline approaches. The broadened uncertainty is further justified by the monthly results in Figure 12.16, from which these final results are not obvious.

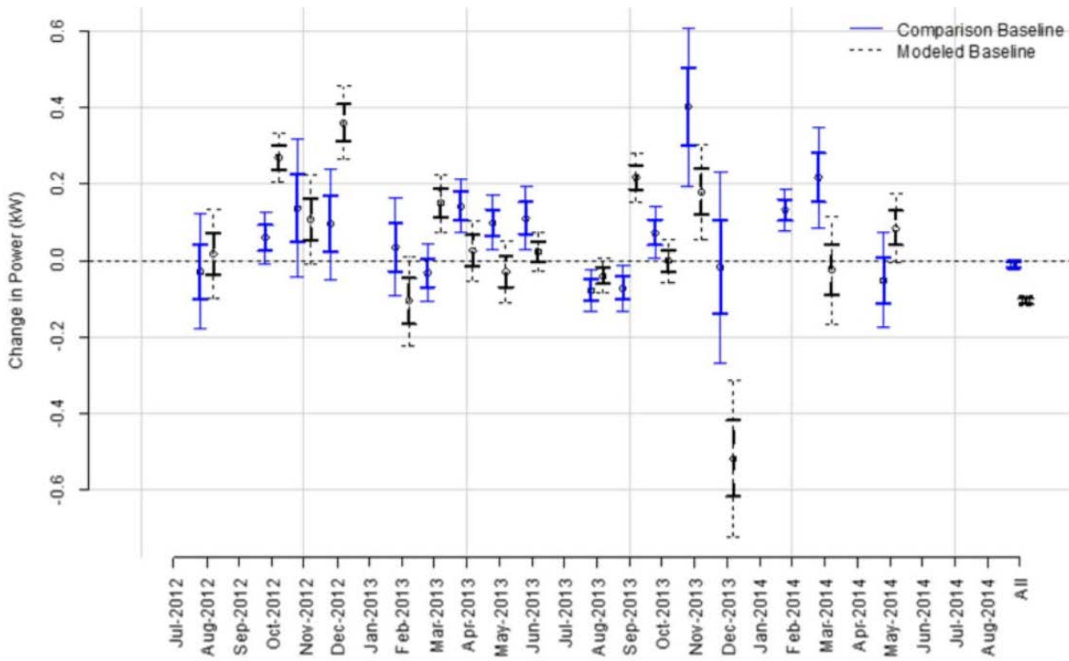


Figure 12.16. Average Impact throughout Days that DRU Events Occurred Using the Comparison (blue) and Modeled (black dashed) Baselines

The DRUs were not exercised in the same fashion throughout the project's duration. Therefore, the monthly representations in the above figures might overstate the variability and understate the potentially verifiable impacts during events, rebound hours, and event days. In the next section, the cumulative results are presented, which better show the consistency with which the system was operated in early 2012.

One of the curtailment events (number 12) has been ignored in this analysis because it lasted 11 days—much longer than the cooperative would actually permit a DRU to remain curtailed.

The following analysis uses only the comparison baseline approach to state cumulative impacts. The modeled approach could have been selected instead. Either baseline approach would support the discussion, but minor differences might be observable in the resulting figures and exemplar values.

Figure 12.17 shows the cumulative system energy impact (black solid line) on its left-hand axis. This is the cumulative sum of the change in energy per premises during curtailment events, multiplied by the numbers of premises that have the DRUs. This test group hosted about 104 of the total 459 controlled water heaters installed by Lower Valley Energy for this project. The figure also shows the cumulative product of the number of impacted premises and the hours that their DRUs were reported to be curtailed over time. The long, almost linear parts of these two lines show that the system was frequently and regularly engaged during early 2012. The energy impact accumulated accordingly.

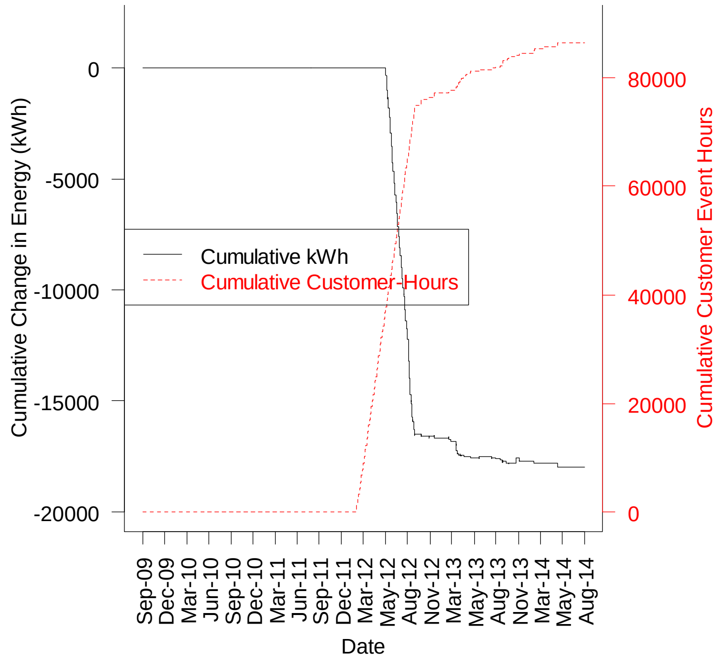


Figure 12.17. Cumulative System Energy Impact and Cumulative Customer Event Hours throughout the Project. Lower Valley Energy exercised the system frequently in the early months of the 2012 calendar year.

When the cumulative energy impact is plotted against the cumulative customer curtailment hours (Figure 12.18), the impact is demonstrated to be consistent throughout the project. The downward slope of the line represents the energy reduction per customer curtailment hour. That is, because this figure was based on the comparison baseline approach, the slope will be −470 Wh per customer-hour. This happens to be precisely the impact observed from June through September 2012 in Figure 12.14. If the modeled baseline approach had been used, the result would be similar, but the slope would be a little steeper.

The slope of the line in Figure 12.18 diminishes during the latest customer hours. This might indicate that the system impact and the quality of system processes diminished late in the project. This might be attributable to the system itself, but it could also be attributable to poorer data collection late in the project.

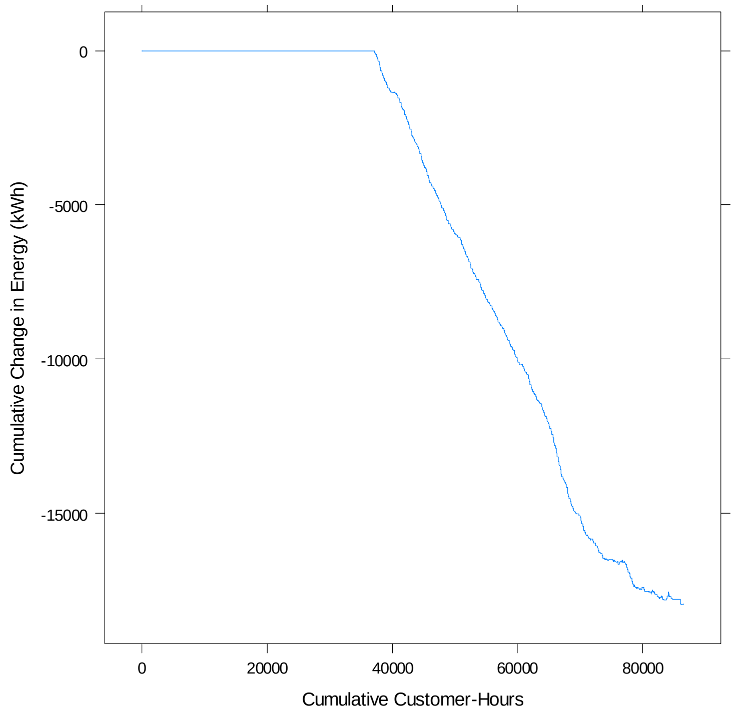


Figure 12.18. Cumulative Impact on System Energy Plotted against Cumulative Customer Hours. The slope of this curve represents the average premises power impact.

12.4 DRUs/AMI for Improved System Reliability

Lower Valley expected to improve the reliability indices at all its feeders by employing advanced metering and other smart grid assets. The improved metering provided them better overall visibility of the Lower Valley Energy distribution system. Additionally, autonomous tripping of water heater DRUs (Section 12.3) during under-frequency and under-voltage events can shed load and perhaps avoid some outages. The water heater DRUs also may be commanded to remain off during cold-load pickups, thus helping the utility recover from outages.

Lower Valley Energy therefore supplied to the project all three major reliability indices— System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and Customer Average Interruption Duration Index (CAIDI)—at yearly intervals for each of its feeders. The project worked with them to determine whether any measureable improvement in these indices accompanied the installations of their smart grid assets.

The installation of new, smart assets is just one of many things that may affect reliability indices. The quality of utility O&M processes is all important. Outages may certainly be caused or mitigated by equipment, but they may also be caused and mitigated by personnel. The analysis conducted in this section is a correlation study. If a correlation can be found, it cannot be definitively attributed to the smart equipment or any other factor.

The annualized costs of the system are listed in Table 12.4. A significant fraction of the costs of advanced meters is allocated to this system and toward the improvement of distribution system reliability. A fraction of the cost of the DRU system is also included because these assets contribute autonomous responses and cold-load pickup capabilities. A fraction of the cost of substation TWACS communication system components was included because such communication is critical to mitigating and preventing outages. The remaining annualized costs include labor, outreach, and data activities and equipment. The total annualized cost of the system was estimated as $156.5 thousand per year.

Table 12.4. Annualized Costs of the DRU and AMI System and its Components

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Advanced Metering			122.4
• AMI System (backbone)	25	129.8	32.4
• AMI Meters (with no devices, unaffected by CVR)	100	28.4	28.4
• AMI Meters (with no devices, but affected by CVR)	50	44.9	22.5
• AMI Meters (premises with DRU)	50	27.1	13.6
• AMI Meters (premises with IHD)	50	26.5	13.3
• AMI Meters (premises with IHD and DRU)	33	29.8	9.9
• AMI Meters (with IHD and affected by CVR)	33	2.5	0.8
• AMI Meters (premises with DRU and affected by CVR)	33	2.5	0.8
• AMI Meters (with IHD and DRU and affected by CVR)	25	2.6	0.7
Water Heater DRUs	50	17.1	8.5
Substation TWACS Components			6.8
• Outbound Modulation Unit	50	6.2	3.1
• Control and Receiving Unit	50	3.8	1.9
• Modulation Transformer Unit	50	3.6	1.8
Ongoing O&M Costs	100	6.1	6.1
Administrative	100	3.7	3.7
Operations Labor[(a)]	50	6.7	3.4
Outreach and Education	100	2.9	2.9
Backroom Data	50	3.2	1.6
Control Network - Power Line Carrier	50	1.3	0.7
Substation Network Multiplexer	50	0.9	0.5
Total Annualized Asset Cost			**$156.5K**

(a) Operations labor was shared between this asset system and adaptive voltage regulation (Section 12.5).

12.4.1 Available Data

Lower Valley Energy reported to the project that this system that was to improve distribution system reliability was installed and useful by early 2011. The meters and other components were used as soon as they became installed. The installation proceeded over months.

As stated earlier, the utility submitted yearly SAIDI, SAIFI, and CAIDI data for each distribution feeder and an overall assessment of the percentage of meters that were read by 02:00. These meter reading assessments were found to be yearly summaries, and the assessments for 2013 and 2014, the only years for which data was received, were identical at 95%.

Table 12.5 lists the calculated SAIFI index for each of 16 Lower Valley Energy distribution feeders for the years 2010 through 2014. The utility calculated and delivered these values to the project. These numbers represent the average number of sustained outages incurred by a cooperative member in the given year. The largest index is about 8.4 and the smallest is 0.03. It is difficult to see a clear trend.

Table 12.5. Calculated SAIFI for 16 Lower Valley Energy Distribution Feeders by Year (Outages per Year)

	2010	2011	2012	2013	2014
Afton	0.67	0.03	0.63	0.43	0.32
Bedford	1.10	1.18	1.15	0.27	1.08
Crystal	0.60	1.01	0.37	0.74	0.13
Drycreek	0.07	0.76	0.82	1.46	0.17
E Jackson	0.10	0.16	0.19	0.56	0.19
Freedom	1.67	0.81	0.82	0.58	3.73
Grover	2.44	0.33	1.28	1.22	5.18
Hoback	1.82	1.03	1.05	9.48	2.10
Jackson	0.09	0.35	0.83	0.37	0.05
Kelly	1.95	0.23	2.25	1.20	1.61
Lanescreek	0.09	2.04	1.73	8.37	0.15
Moran	3.11	1.98	2.72	2.97	4.63
Pinecreek	1.64	2.19	1.06	1.99	1.93
Rafterj	0.22	1.38	0.24	0.80	0.05
Snake	0.55	1.30	1.17	1.50	1.24
Wilson	1.11	0.20	0.74	0.96	1.10

The sets of feeder indices in a given year were grouped in the quartile plots of Figure 12.19. In this plot, each box represents the range from 25–75% of the year's feeder indices, and the extended bars represent the remaining two quartiles. The median appears to be creeping upward gradually throughout the 5-year data period. The range of calculated SAIFI indices in 2012 narrowed compared to those in earlier and later years.

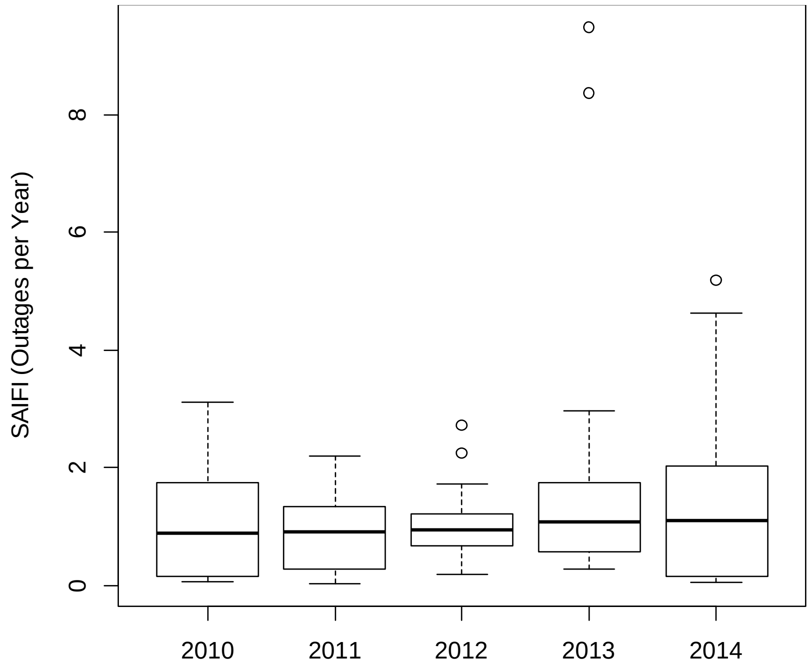


Figure 12.19. Quartile Plots of Calculated SAIFI for 16 Lower Valley Energy Distribution Feeders by Year

A similar set of SAIDI indices were gathered and are reported in Table 12.6 and Figure 12.20. These values represent the average number of total sustained outage minutes experienced by a cooperative member in the given year. These indices were calculated by the cooperative.

Table 12.6. Calculated SAIDI for 16 Lower Valley Energy Distribution Feeders by Year (Minutes per Year)

	2010	2011	2012	2013	2014
Afton	39.6	4.8	31.7	29.7	25.3
Bedford	37.2	96.1	57.5	13.0	69.3
Crystal	82.9	59.4	41.3	29.2	12.1
Drycreek	3.6	46.2	133.5	43.2	9.3
E Jackson	12.6	19.2	28.7	16.9	15.4
Freedom	138.7	72.1	59.9	25.0	261.1
Grover	285.2	18.0	170.7	25.5	150.8
Hoback	284.6	135.1	204.8	155.6	259.5
Jackson	13.2	22.8	58.1	14.6	3.3
Kelly	488.7	27.6	365.3	45.4	726.6
Lanescreek	9.6	559.0	390.4	101.7	10.8
Moran	637.6	684.5	1,195.7	42.4	966.2
Pinecreek	190.9	190.9	219.8	36.8	358.0
Rafterj	15.6	72.1	30.5	25.0	7.0
Snake	85.3	180.1	137.1	39.0	165.7
Wilson	145.9	64.2	43.7	27.7	92.8

No sustained trend is evident in Figure 12.20, but 2013 was a remarkable year. The cooperative members experienced, on average, shorter outage durations, and the index was consistently reduced across almost all the distribution feeders.

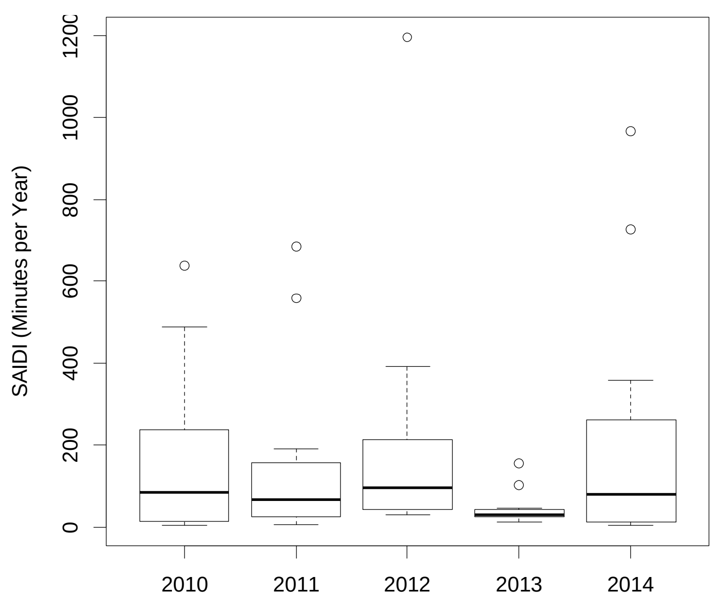


Figure 12.20. Quartile Plots of Calculated SAIDI for 16 Lower Valley Energy Distribution Feeders by Year

CAIDI is not an independent index. It may be calculated from SAIDI and SAIFI. Nonetheless, CAIDI was received by the project from Lower Valley Energy, and the received data is displayed in Table 12.7 and Figure 12.21.

Table 12.7. Calculated CAIDI for 16 Lower Valley Energy Distribution Feeders by Year (Minutes per Outage)

	2010	2011	2012	2013	2014
Afton	59.4	142.2	49.8	52.1	77.6
Bedford	33.6	81.6	49.8	76.0	64.0
Crystal	138.6	59.4	110.4	91.1	90.8
Drycreek	51.0	60.6	169.8	121.8	55.4
E. Jackson	126.6	9.6	147.6	120.5	82.5
Freedom	82.8	48.6	73.2	83.7	70.0
Grover	117.0	19.8	133.8	173.2	29.2
Hoback	156.6	132.0	195.0	219.2	123.8
Jackson	153.0	64.2	70.2	91.8	62.8
Kelly	250.8	123.6	162.6	95.5	451.7
Lanescreek	112.8	273.6	226.2	296.2	69.8
Moran	205.2	345.0	439.2	252.5	208.6
Pinecreek	116.4	87.0	207.0	195.0	185.0
Rafterj	72.0	52.2	125.4	114.7	133.4
Snake	155.4	138.6	117.0	138.8	133.4
Wilson	131.4	316.2	58.8	124.9	84.0

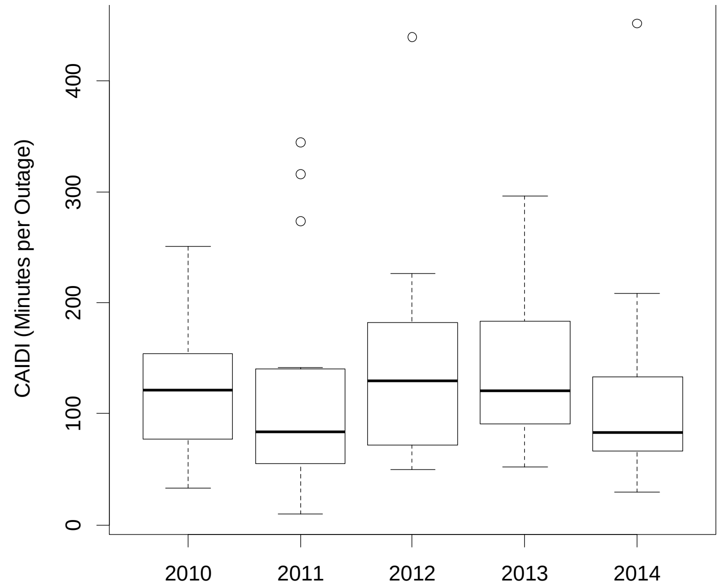


Figure 12.21. Quartile Plots of Calculated CAIDI for 16 Lower Valley Energy Distribution Feeders by Year

12.4.2 Analysis of Trends in the Reliability Indices

Further analysis was conducted to determine whether subtle, significant differences could be detected between the years. The cooperative had reported that the system became useful beginning in 2011. The project looked at this separation, but the separation between other successive years was also tried. The populations of feeder indices before and after the separation were treated as independent populations and were tested using the Student's t-test in the R software environment. The null hypothesis was that the index remained unchanged or had increased across the separation.

The null hypothesis could not be confidently rejected for any of the four possible separations of years or for any of the three tested reliability indices. In fact, the null hypothesis might be accepted when testing SAIFI indices for two of the possible partitions. With better than 95% confidence, SAIFI was found to have *increased* either after year 2011 or 2012. This finding should not be too surprising, given that a consistent increase was observable in Figure 12.19. The increase was about 0.6 outages per year, on average, beginning in 2013.

The project could find no evidence that reliability indices had been reduced during the project term. Of course, it is possible that an impact occurred and was overwhelmed by other natural and induced influences.

12.5 Adaptive Voltage Regulation

With the help of voltage data from its AMI system, Lower Valley used adaptive voltage control and CVR to reduce its peak demand. The voltage was reduced on four feeders and affected about 2,340 premises. The Lower Valley Electric costs of the adaptive voltage regulation system are displayed in Table 12.8.

The annualized costs of the voltage regulation system and its components are listed in Table 12.8. The utility elected to include the costs of the existing load tap changers that are critical to this system and are the system's greatest cost component. The AMI system is next most expensive and is required to verify that end-of-line voltages remain acceptable.

Table 12.8. Lower Valley Electric Costs of Adaptive Voltage Regulation System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Existing Load Tap Changers	100	201.5	201.5
<u>Advanced Metering</u>			<u>91.4</u>
• AMI System (backbone)	25	129.8	32.4
• AMI Meters (with no assets, but affected by CVR)	50	44.9	22.5
• AMI Meters (premises with IHD and affected by CVR)	33	2.5	0.8
• AMI Meters (premises with DRU and affected by CVR)	33	2.5	0.8
• AMI Meters (with IHD and DRU, and affected by CVR)	25	2.6	0.7
Existing SCADA System	100	32.9	32.9
Ongoing O&M Costs	100	30.5	30.5
Integration Between Aclara and Ilex	100	10.4	10.4
Administrative	100	3.7	3.7
Operations Labor[(a)]	50	6.7	3.4
Outbound Modulation Unit	50	6.2	3.1
Outreach and Education	100	2.9	2.9
Control and Receiving Unit	50	3.8	1.9
Modulation Transformer Unit	50	3.6	1.8
Backroom Data	50	3.2	1.6
Control Network – Power Line Carrier	50	1.3	0.7
Digital Channel Bank Network Multiplexer	50	0.9	0.5
Existing Regulators	100	0.0	0.0
Total Annualized Asset Cost			**$351.9K**

(a) The cost of Operations labor was shared between this asset and the DRU/AMI system (Section 12.4).

12.5.1 Characterization of Asset System Responses

The impact of the dynamic voltage management was to be observed on the East Jackson feeder. The diurnal, seasonal, weekday load shapes for this feeder are shown in Figure 12.22. Northwest Wyoming is a relatively cold location. The feeder is winter-peaking, showing two clear peak hours during winters. Only a single afternoon peak is evident on weekdays in summer, the season that has least load. It supplies East Jackson, Wyoming, which is relatively urban for Wyoming. The feeder phase voltage is 7.2 kV, and average load during the project was measured as 8.7 MW.

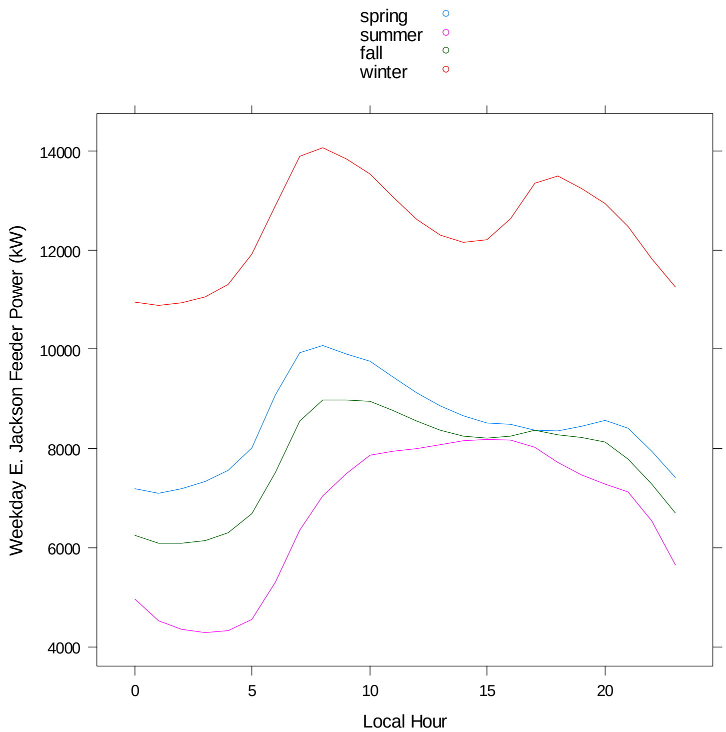


Figure 12.22. East Jackson Diurnal Distribution Feeder Weekday Load by Season

Lower Valley Energy reported the system status to the project, stating when the voltage was being actively reduced on the feeder and when the voltage was normal, unaffected by the voltage-management system. The cooperative told the project the system was in place and active at the end of summer 2012. The status "Early Unknown" was applied to the status of the voltage-management system prior to this date.

Figure 12.23 shows the average per-unit voltage on the East Jackson feeder throughout the data collection period. The base feeder voltage is 7.2 kV. The cooperative separately supplied the three individual phase voltages. The average of the three phases is shown. Values below 0.96 were ignored to better show the intentional voltage reductions.

Lower Valley Energy appears to have practiced voltage reduction for months prior to the date on which the system was declared installed and useful. These events were not analyzed. Thereafter, the voltage was reduced periodically. The correlation between the reported events (blue markers) and reduced average voltage levels is strong, but it is not perfect. There are unreported voltage reductions (red markers at reduced voltages) and reported events while the voltage is in its normal range.

A large range of voltages were measured while the system was active and the voltage reduced. A string of voltage measurements is often observed from about 0.98 to 1.02 pu. Some of this variability might follow from active voltage-management control that is more complex than a simple changing of transformer tap settings. The voltage is managed to carefully move into and out of the reduced-voltage range. Thirty premises meters had been identified at feeder locations that typically had the lowest voltages. These meters were subdivided into eight smaller groups that were sequentially polled at 2-minute intervals. All the meters were polled in 16 minutes.

Data was removed at times that status was undefined and during periods that the feeder power was anomalous. This explains the data gaps in Figure 12.23. The project also eliminated one of the events (event 12) that was reported to the project to have lasted for 11 days but did not coincide with any voltage reduction.

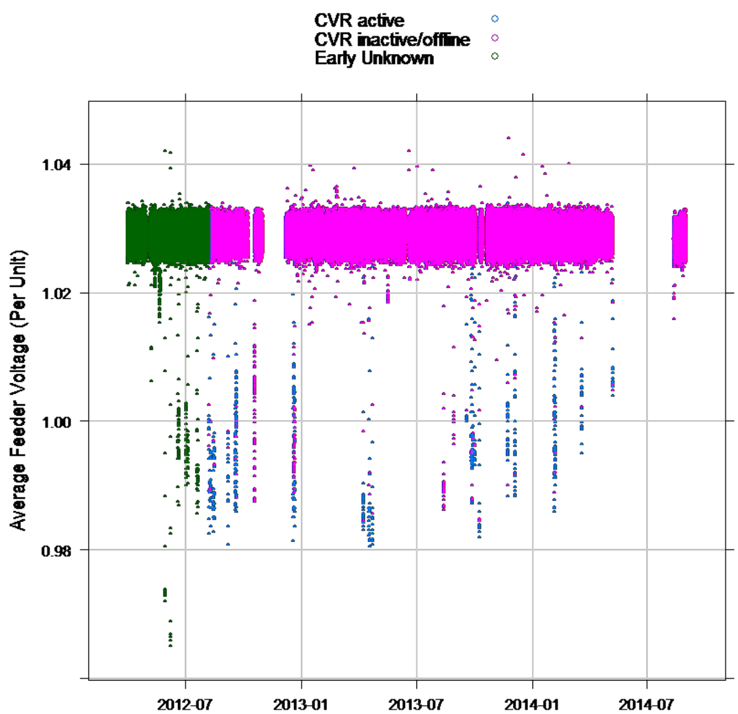


Figure 12.23. Per-Unit Feeder Voltages and their Reported Statuses

Figure 12.24 shows the distribution of per-unit feeder voltages, including a group of reduced voltages centered at about 0.995 per unit. The distribution was necessarily magnified to better show the infrequent reduced voltages. Voltages below about 0.96 were deemed to be predominantly anomalous readings not important to show.

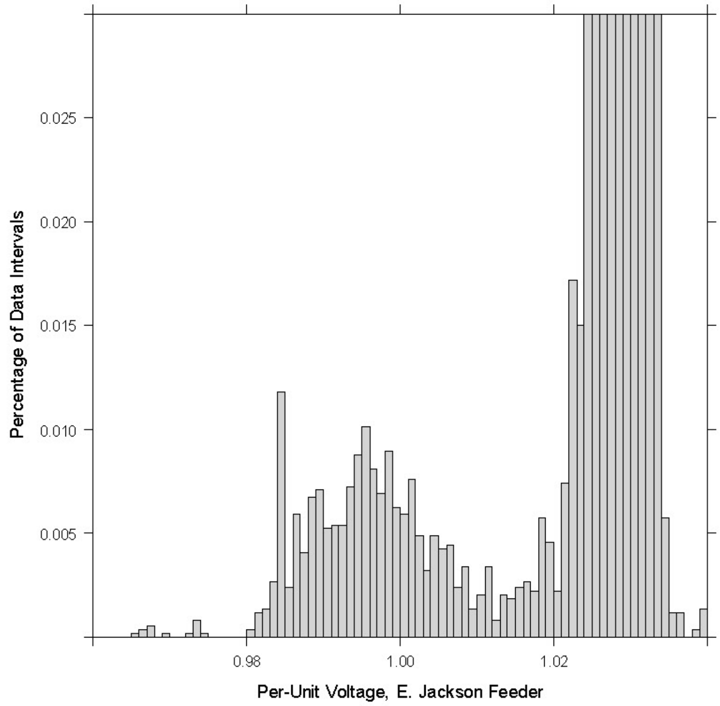


Figure 12.24. Magnified Part of Per-Unit Voltage Distribution that Shows Reduced-Voltage Occurrences

Review Table 12.9 that shows how the reduced voltages were managed over the project months. The reported voltage-management event periods were used to separate monthly voltage measurements into groups—measurements while the voltage was managed, and not. For months when events were reported, this table shows the average percent voltage reduction during the reported events. Voltage was not managed every month. In months that voltage management was exercised, the relative reduction in voltage varied greatly from an insignificant reduction during October 2012 to an average 3.4-% reduction April 2013.

Table 12.9. Average Percent Change in Feeder Voltage for Months in which the Voltage was Modified

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	-	-	-	-	-	-	-	−2.7	−1.4	−0.0	-	−1.8
2013	-	-	-	−3.4	-	-	-	-	−1.7	−2.4	−2.5	−2.4
2014	-	−1.9	−2.2	-	−1.9	-	-	-	-	-	-	-

In aggregate, the difference between managed voltages and unmanaged voltages during the project is summarized by Figure 12.25. In this figure, the narrow range of normal per-unit voltages is shown at the left. The box contains 50% of the measurements, and the bars most of the remaining ones. A string of outlier measurements is also shown. The box to the right similarly shows the reduced-voltage measurements. The groupings are fully determined in this plot by the reported status of the voltage-management system.

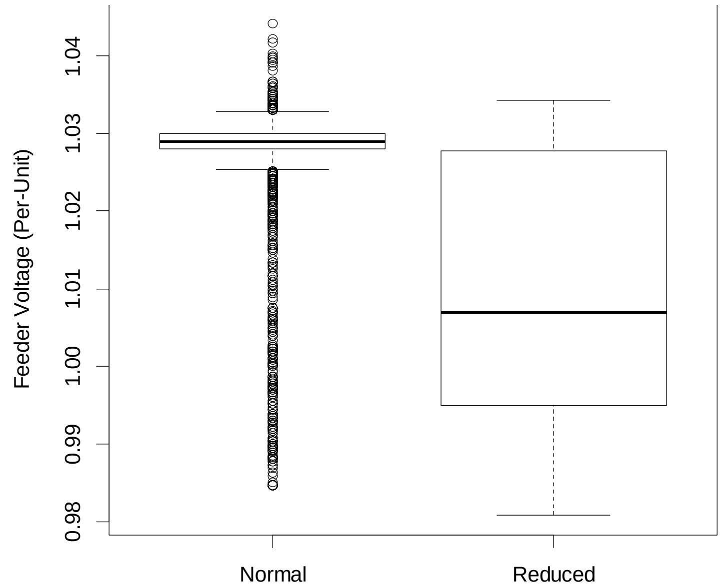


Figure 12.25. Quartile Plots of all the Measured Per-Unit Feeder Voltages at the Normal and Reduced-Voltage Settings

The cooperative reported 38 events from August 2012 through May 2014. The dates, times, and durations of these events are listed in Table 12.10.

Table 12.10. List of Events when Lower Valley Energy Reduced the East Jackson Feeder Voltage

Event	Year	Month	Day	Weekday	Local Hour	Minute	Duration (d h:m)
1	2012	Aug	9	Thursday	9	0	1:00
2	2012	Aug	10	Friday	8	0	2:00
3	2012	Aug	15	Wednesday	8	0	2:00
4	2012	Aug	16	Thursday	8	0	2:00
5	2012	Sep	7	Friday	8	5	1:55
6	2012	Sep	12	Wednesday	7	30	2:30
7	2012	Sep	13	Thursday	7	0	3:00
8	2012	Sep	14	Friday	7	0	3:00
9	2012	Sep	18	Tuesday	7	10	2:50
10	2012	Sep	19	Wednesday	7	0	3:00
11	2012	Sep	20	Thursday	7	15	2:45
12[a]	2012	Oct	8	Monday	8	0	11 1:20
13	2012	Oct	24	Wednesday	7	10	2:20
14	2012	Oct	25	Thursday	7	0	3:00
15	2012	Oct	26	Friday	7	0	3:00
16	2012	Nov	27	Tuesday	7	5	2:35
17	2012	Dec	19	Wednesday	6	0	3:00
18	2012	Dec	20	Thursday	6	0	3:00
19	2012	Dec	21	Friday	6	0	2:35
20	2013	Apr	8	Monday	7	25	2:05
21	2013	Apr	17	Wednesday	6	55	1:20
22	2013	Apr	18	Thursday	6	45	1:35
23	2013	Apr	23	Tuesday	8	0	1:30
24	2013	Sep	19	Thursday	7	0	2:30
25	2013	Sep	26	Thursday	7	15	2:15
26	2013	Sep	27	Friday	7	0	2:30
27	2013	Sep	28	Saturday	7	35	1:55
28	2013	Oct	1	Tuesday	7	50	1:40
29	2013	Oct	9	Wednesday	7	35	1:35
30	2013	Nov	22	Friday	6	45	2:45
31	2013	Dec	4	Wednesday	10	55	3:10
32	2014	Feb	4	Tuesday	7	0	2:30
33	2014	Feb	5	Wednesday	6	45	2:45
34	2014	Feb	6	Thursday	6	45	2:45
35	2014	Feb	27	Thursday	8	15	0:05
36	2014	Mar	19	Wednesday	7	0	2:10
37	2014	May	7	Wednesday	7	5	2:20
38	2014	May	12	Monday	6	45	2:05

(a) Event number 12 was very long, and the voltage did not appear to have been reduced during this event. It was excluded from most analysis.

Lower Valley Energy initiated voltage-management events at times that might reduce their system peak demand. The next figures demonstrate the months, days, and hours that the events were begun.

The reported events were quite evenly distributed among calendar months, as is shown by Figure 12.26. The exception is September, in which the cooperative initiated almost three times as many events as in other calendar months.

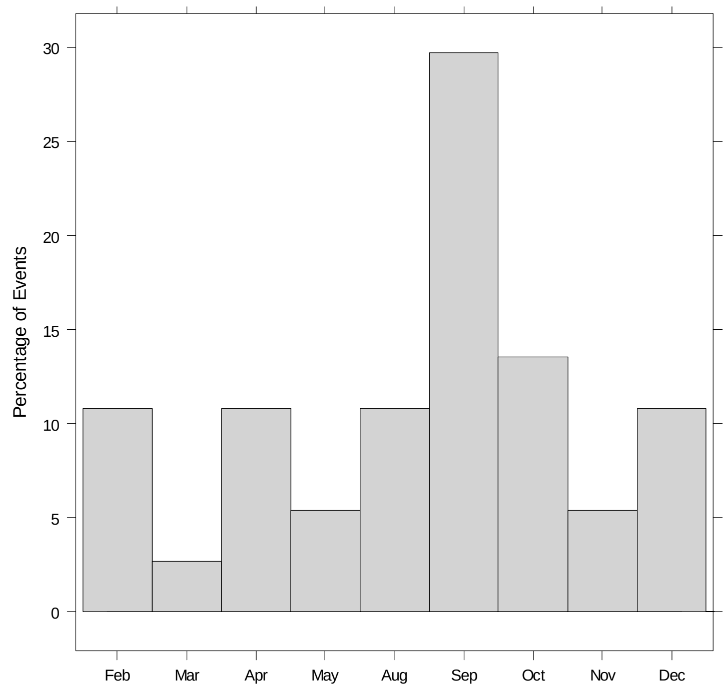


Figure 12.26. Distribution of the 37 Event Months that Lower Valley Energy Reduced the Voltage on the East Jackson Feeder

Lower Valley Energy tended to exercise the voltage-management system in the middle of the work weeks as shown in Figure 12.27. Wednesdays and Thursdays were preferred days for conducting voltage management. The system was activated only once during a weekend day. This distribution ignored 11-day-long event 12.

Because the system was exercised predominantly during weekdays, the results of project analysis can only be stated for weekdays. Results will not necessarily help predict performance of the system on weekends. The shape of the weekday distribution weights the results, but there are typically small differences in load behavior from one weekday to another.

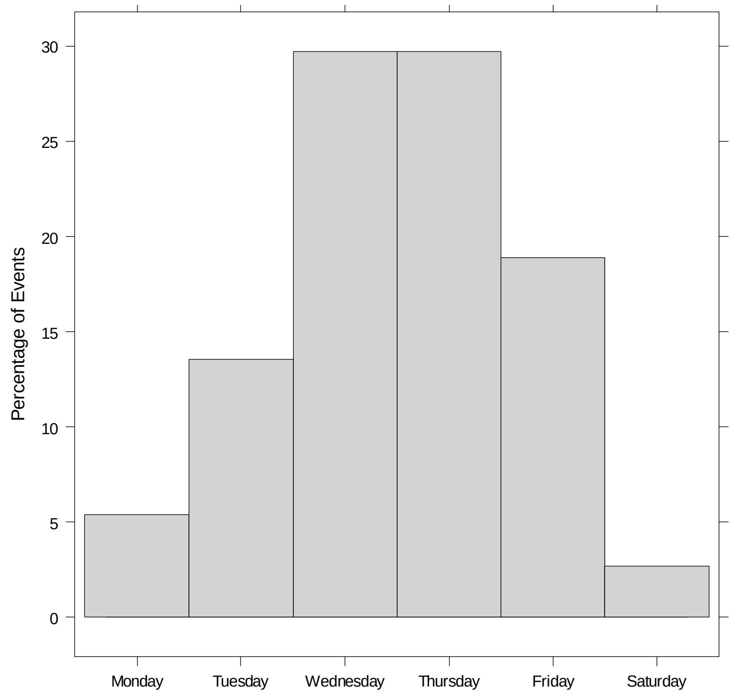


Figure 12.27. Distribution of Weekdays that Lower Valley Energy Reduced East Jackson Feeder Voltage

Lower Valley Energy initiated the events tightly clustered around 07:00 local Mountain Time, as shown in Figure 12.28. All of the events were initiated between 06:00 and 10:00 local Mountain Time. Again, Lower Valley Energy exercised the system only during these limited morning hours. Analysis results do not necessarily extend to afternoon and other times of the day.

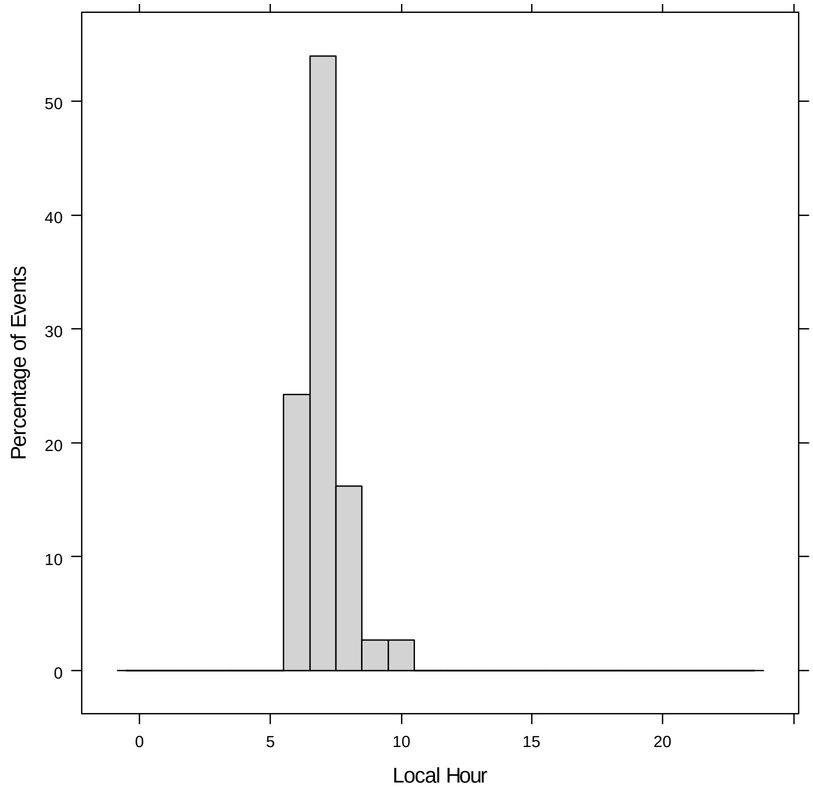


Figure 12.28. Distribution of Hours (Mountain Time) that Voltage-Reduction Events Began

12.5.2 Performance of the Dynamic Voltage-Management System

A parametric linear model of the East Jackson feeder load was created to model power as a function of month, day of week, hour, and ambient temperature. The event periods reported for both DRU engagements (Section 12.3) and voltage reduction were not used during the training of the model. The East Jackson distribution load was then predicted from this parametric model as a comparison baseline. This comparison baseline should have predicted what the load might have been had DRU curtailments and voltage reductions not occurred.

Unless otherwise stated, analysts removed eleven-day-long event number 12 prior to the calculations in this section. Voltage was never actually reduced during that event period. The analysis did not include any impacts from voltage reductions that were evident in Figure 12.23, but had been reported by Lower Valley Energy with the status “Early Unknown.”

The average change in power that may be attributed to the dynamic reduction of voltage on the East Jackson feeder was a reduction of 300 ± 100 kW. This is about 3.4% of the average load on the East Jackson feeder during the project (8.7 MW).

While DRUs (Section 12.3) were colocated on the East Jackson feeder, were engaged at similar event times, and admittedly confounded these results, only about 32 premises on this feeder possessed DRUs. The total impact from the DRUs should therefore be less than about 15 kW during events, presuming that each premises might experience a reduction of about 0.5 kW. The rebound impact might be twice as great, adding perhaps 30 kW where the DRU rebound hour happened to fall within a voltage-reduction event on the East Jackson feeder. These impacts are smaller than the uncertainty of the distribution impact.

No significant rebound impact could be observed in the hours after feeder voltage had been returned to normal levels. None was expected. The analysis might have been polluted by rebound impacts from the 32 DRUs that were colocated on the East Jackson feeder.

An average power reduction was observed at the feeder level throughout the days on which voltage-reduction events had occurred. A reduction of 50 ± 30 kW was observed throughout event days. This is probably evidence that the reduction in power during events was truly conservation and not a shift of energy consumption from event hours to other hours. That is, this magnitude is very close to the 300 kW reduction through a 3-hour event (i.e., 900 kWh), averaged though an entire event day. That calculation would yield an expected reduction of about 38 kW, virtually indistinguishable from the analysis result.

Analysts also looked at the impact at the premises level. The aggregate average hourly load of a set of premises supplied by the East Jackson feeder was compared against that of premises that were supplied by other feeders. The comparison group members were selected to possess neither IHDs (Section 12.2) nor DRUs (Section 12.3). Each test group had about 24 premises. The per-premises power measurements from the comparison group were scaled to have the same averages and standard deviations as the test group each project month. The measurements were further scaled globally to have the same average power on an hour-by-hour basis. This diurnal correction was conducted because the test and comparison populations differed somewhat in their diurnal consumption patterns.

The short-term reductions, however, appeared to have *increased*, not decreased, consumption at premises. Per-premises power consumption was found to have increased 120 ± 60 W during events. Consumption increased even more during the hours following the voltage reductions—200 ± 100 W. This rebound impact might have been confounded somewhat by coincident rebounds among the East Jackson test-group premises that also had DRUs. This method also indicated a strong increase in consumption by premises throughout event days.

The cumulative distribution energy impact and the cumulative event hours are shown in Figure 12.29 for the period from 2012 until the end of data collection in August 2014. A consistent reduction in energy is evident through 2012, but the trend disappeared for the remainder of the project through 2013 and 2014. No seasonal trend can be claimed because the reduction evident in late 2012 became an increase in late 2013 during the same months.

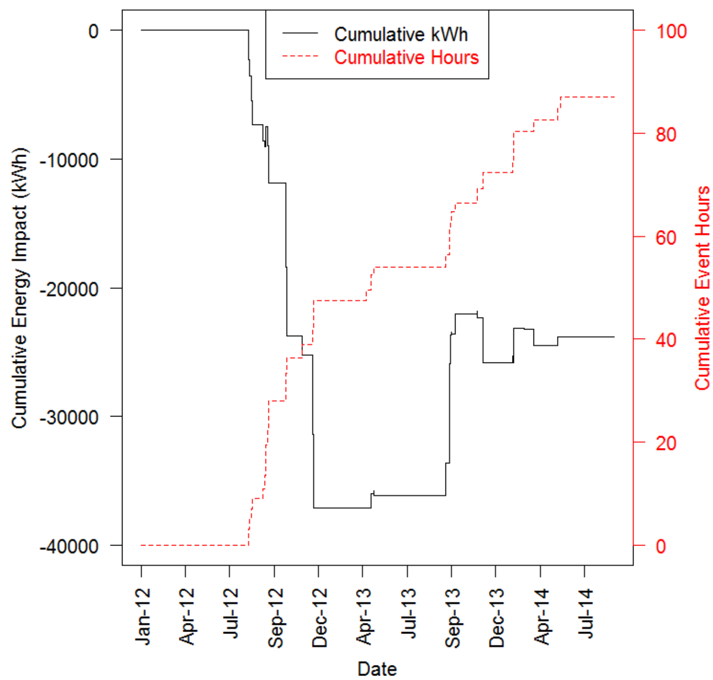


Figure 12.29. Cumulative Energy Impact and Cumulative Event Hours when Distribution Voltage was Reported to have been Reduced

The cumulative distribution energy impact was plotted against cumulative event hours in Figure 12.30. The slope of this curve is the power reduction during voltage-reduction events on the East Jackson feeder. Again, the trend toward power reduction reversed itself and disappeared after about 45 event hours. It is tempting to report the slope of only the downward trend, but the project reports instead the average slope from the top left to the last event hour. A fair demonstration evaluation must report the long-term benefit, which may be affected not only by performance of the system itself, but also by fatigue and by the quality of measurement and validation processes.

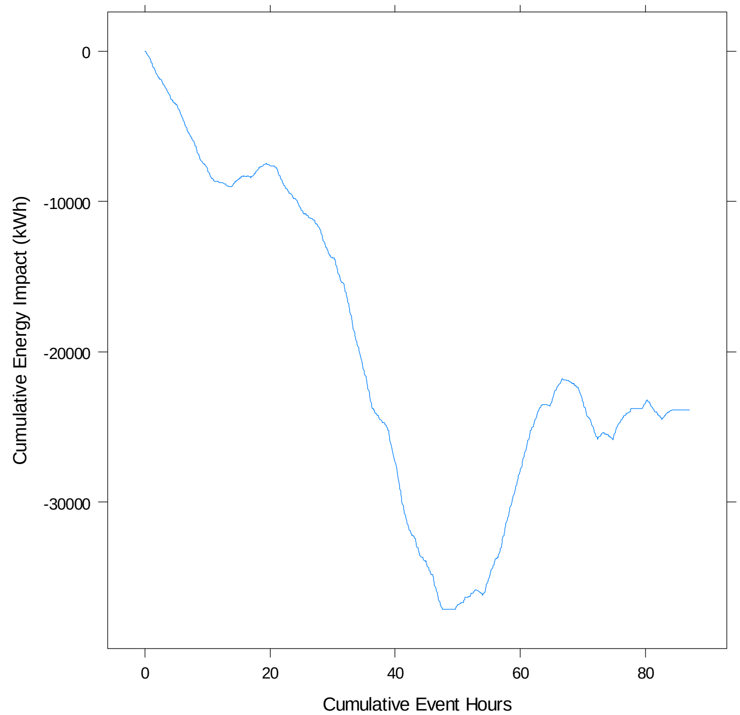


Figure 12.30. Cumulative Energy Impact as a Function of Cumulative Event Hours

The majority of the impacts of CVR are often attributed to end uses and less to distribution efficiency (Schwartz 2010). A contrary result was observed by the project when it evaluated consumption by residential premises. Figure 12.31 shows both a cumulative energy impact per residential premises and a cumulative sum of customer event hours. The cumulative energy curve rarely decreases throughout the project duration as customer event hours are accumulated. This trend may be seen more clearly in Figure 12.32, where the cumulative energy impact per residential premises has been plotted against accumulated customer hours. This cumulative premises impact was based on a set of about 24 premises that were on the affected feeders but did not possess other devices that might confound the results. The average per-premises consumption of this test group was compared against that of a normalized control group, also having 24 premises, that was unaffected by the voltage reductions.

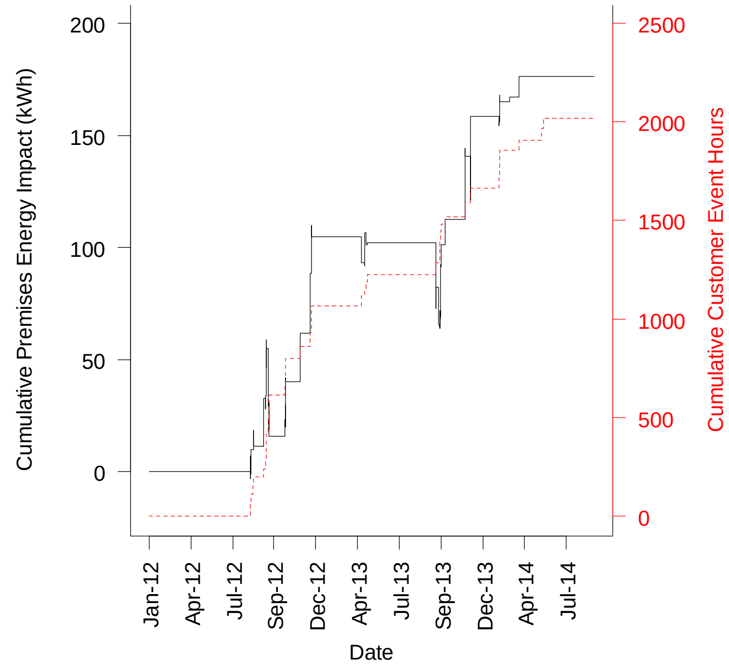


Figure 12.31. Cumulative Energy Impact and Customer Hours at Premises that were Affected by Dynamic Voltage Reductions

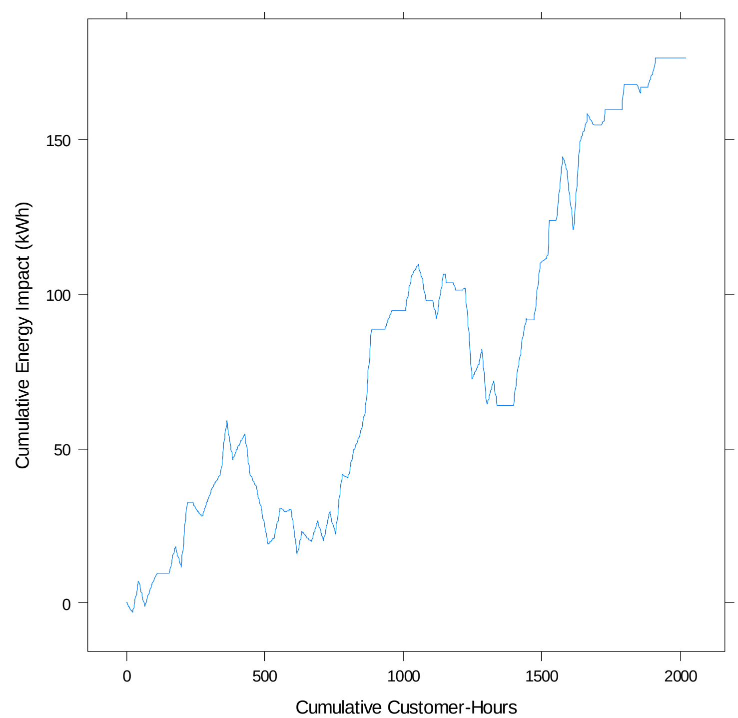


Figure 12.32. Cumulative Premises Energy Impact as a Function of Cumulative Customer Event Hours

The average trend is consistent at premises. A seasonal influence might exist at premises; perhaps consumption increased at premises in late fall and early winter, but was flat or even decreased in other seasons.

The results of Figure 12.31 and Figure 12.32 used a comparison baseline, in which consumption at residential premises on the East Jackson feeder was compared against a normalized comparison group that was composed from consumption at residential premises on other feeders. The project repeated this analysis at the premises level using a linear model baseline having parameters for month, day of week, hour of day, and temperature. Similar results and trends were observed, giving the project additional confidence in this finding.

In conclusion, a strong reduction in feeder distribution power was observed for the typically 3-hour-long voltage-reduction events on the East Jackson feeder, but the impact diminished after a strong showing in 2012. However, the project found evidence that consumption at residential premises actually increased during these events. Test groups would need to be better controlled for the potentially confounding impacts from DRUs (Section 12.3) and repeated to confirm the contrary result at the premises level.

12.6 SVC for Power Factor Improvement

Lower Valley Energy procured and installed a 600 kVAr Asea Brown Boveri SVC, at the Bondurant, Wyoming, site, supplied from the Hoback substation. The device is shown installed in Figure 12.33. When its SVC was engaged, Lower Valley expected to decrease about 300 kVAr for power factor and voltage support. The device was installed to be remotely controllable via a remote terminal unit and existing SCADA at the substation. Automation was installed to make the SVC responsive to reactive-power readings from the distribution lines that supply the substation.

This site is at the remote end of a long, lightly loaded distribution line. The power factor on this line was heavily leading, and the SVC somewhat improved the power factor. The power factor lagged only during cold-load-pickup periods immediately following power outages. By improving power factor, the cooperative hoped to reduce line losses and to improve voltage management on the feeder.

Figure 12.33. 300 kVAr SVC at the Bondurant, Wyoming, Site

The annualized costs of the system and its component parts are listed in Table 12.11. The largest cost is that of the SVC, followed by upgrades to the existing SCADA communications, upgrades to the site, O&M, outreach, and administrative costs. Many component costs were shared between this and other asset systems that Lower Valley Energy installed at the Bondurant site or at the Hoback substation, Wyoming. The total annualized cost is estimated to be $43.8K.

Table 12.11. Lower Valley Electric Costs of Power Factor Improvement System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
SVC	100	34.1	34.1
Existing SCADA System[(a)]	25	25.7	6.4
Operations Labor[(a)]	25	5.5	1.4
Building	25	3.9	1.0
Building Site	25	2.1	0.5
Ongoing O&M Costs[(a)]	25	0.6	0.2
Outreach and Education[(a)]	25	0.6	0.2
Administrative[(a)]	25	0.4	0.1
Quest[(b)]-to-SCADA Comm. Fees	25	0.2	0.1
AMI Meter	100	0.0	0.0
Total Annualized Asset Cost			**$44.0K**

(a) These components were shared among the SVC system (Section 12.6), battery storage system (Section 12.7), PV array (Section 12.8), and wind turbine (Section 12.9).
(b) Quest is a well-known communications provider.

12.6.1 Project Data and Operation of the SVC

The SVC was installed and operational by mid-2012. The cooperative submitted data stating when the SVC system became active and inactive. This list is believed accurate because its transitions were found to coincide well with observed changes in power factor and reactive power near the site and at the Hoback substation. The transitions were infrequent and irregular.

The cooperative supplied the following data for the evaluation of the SVC system performance: They supplied 5-minute reactive-power data from a point on the source side of the SVC site, which is quite remote from the Hoback substation. They also submitted data from the Hoback substation for this feeder, including phase currents, phase voltages, and power factor.

These data were all found to have “stuck” at certain magnitudes many of the project months. These data periods were removed from analysis. Hoback feeder data was not available after March 2014.

The project also observed that the test feeder’s phase-c voltage had been periodically modified several months during the project. The project elected to remove these periods from analysis because the impact of voltage management on the feeder could confound observations of the SVC system’s performance.

In the figures shown in this and following sections, the data has been filtered to remove time periods that had “stuck” values and potentially confounding voltage management.

Other variables were necessarily calculated from the data that was received. For example, the real and reactive-power totals for the Hoback feeder were calculated from the phase voltages, phase currents, and phase power factors. Because the power factors were crudely discretized, the calculated power levels were also discretized and were of limited value for quantitative analysis.

Figure 12.34 shows another interesting observation about voltage management on this feeder. Starting November 2013, Lower Valley Energy raised the voltage on this feeder. This is different from the previously described voltage management that affected only one of the feeder phases. The figure shows the magnitudes of a phase-averaged feeder phase voltage. Because the phases of this feeder are relatively poorly balanced, care was taken in the calculation of the average feeder voltage, weighing the contribution of each phase by its current magnitude. A step is clearly evident in the resulting voltage. Note also the key of this figure that helps demonstrate the infrequent and irregular pattern of SVC system engagement. The change in feeder voltage may confound observation of SVC system performance. The discussion that follows may refer to “early” and “late” voltage-management periods for the data before and after November 1, 2013.

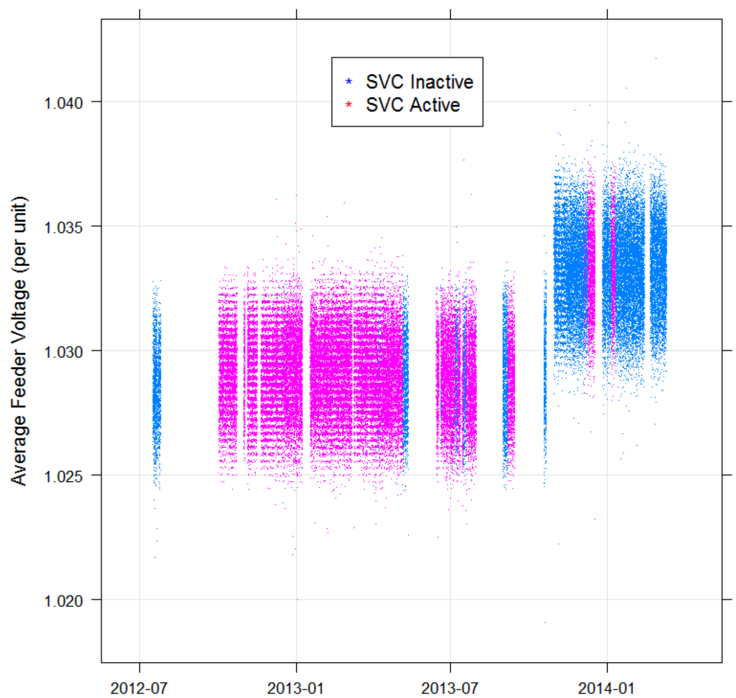


Figure 12.34. Averaged Per-Unit Feeder Voltage for the Hoback Feeder that was Affected by the Project’s SVC

Figure 12.35 shows the reactive-power data series for each of the three feeder phases at the Hoback substation. The phases are not well balanced, as often occurs for long, rural feeders. Jumps may be seen in the reactive power of each phase. These jumps are attributable to changes in the engagement of the SVC system. The jumps are greatest for the phase that has the greatest reactive-power magnitude (the pink markers). The project did not further investigate differences between the performance on each phase, but it seems that the SVC also contributes to balancing the three phases.

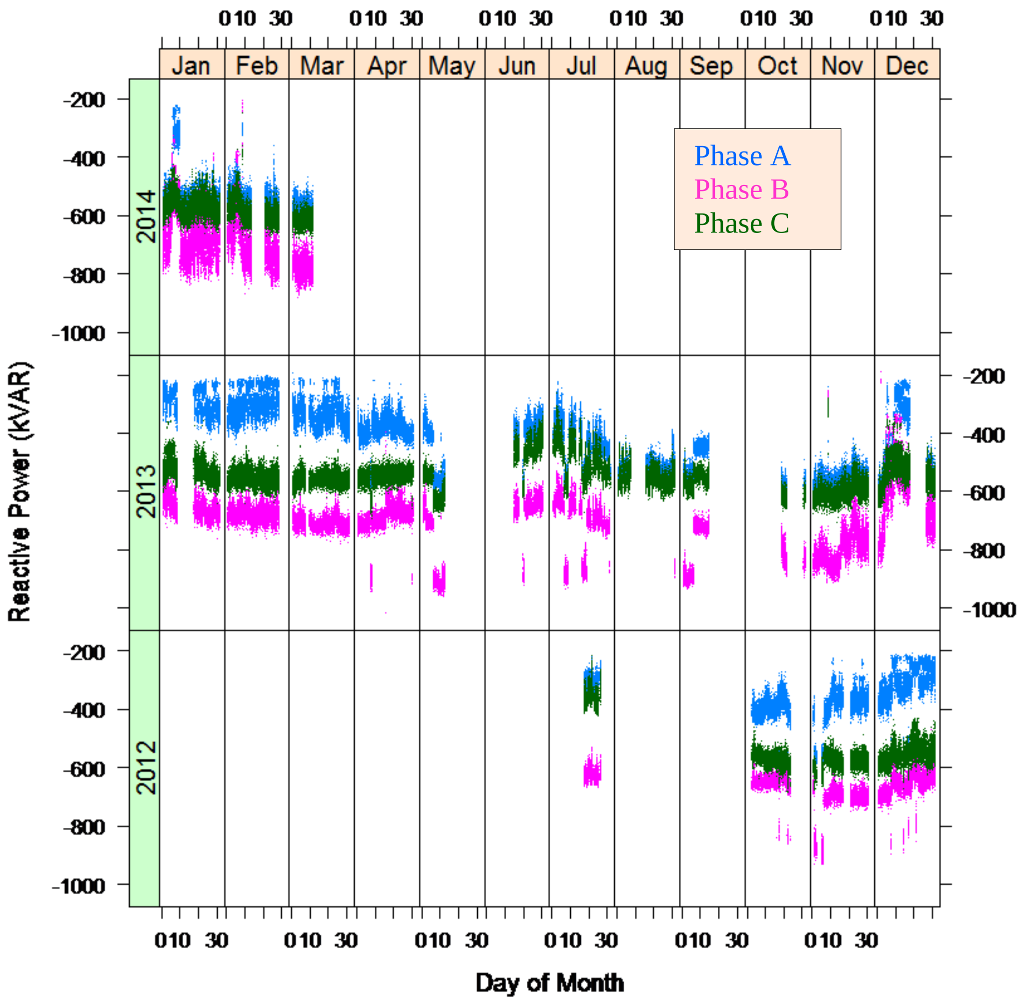


Figure 12.35. Reactive Power Levels of the Three Hoback Feeder Phases that were Affected by the Project's SVC

Figure 12.36 similarly shows the individual power factors for each feeder phase at the Hoback substation. Again, it is evident that the phases are imbalanced and do not possess comparable power factors. The phases' capacitive power factors improve during the cold months when demand is greater. The worst phase consistently has power factors as low as 0.5. Such a low power factor means it is taking approximately twice as much distribution current to serve the load as would be needed if the power factor were unity.

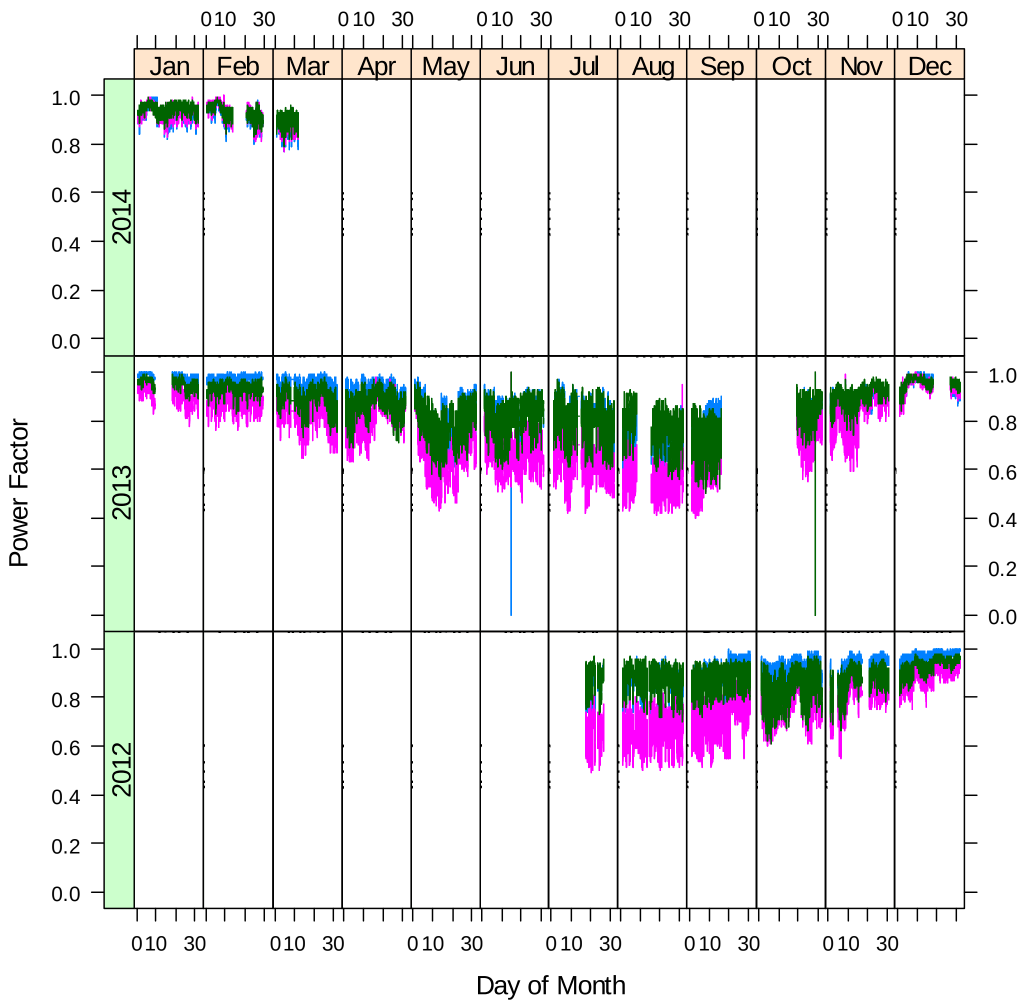


Figure 12.36. Three-Phase Power Factors at Hoback Substation that were Affected by the Project's SVC

12.6.2 Performance of the SVC

The impact of SVC system operation is more clearly seen in Figure 12.37, which displays the calculated total feeder reactance (note that the vertical axis is negative). The circuit is capacitive regardless of the status of the SVC system. The magnitude of reactive power is usually diminished (less negative) when the SVC system is active (pink markers). The exceptions early in the project may have resulted from misstatements of the SVC system engagement periods.

By inspection, the differences in total reactive power when the SVC system is engaged are about 500 kVAr. Analysts presumed that the entire difference was attributable to the SVC system, but it is possible that other non-project assets were also being engaged by the utility on this feeder.

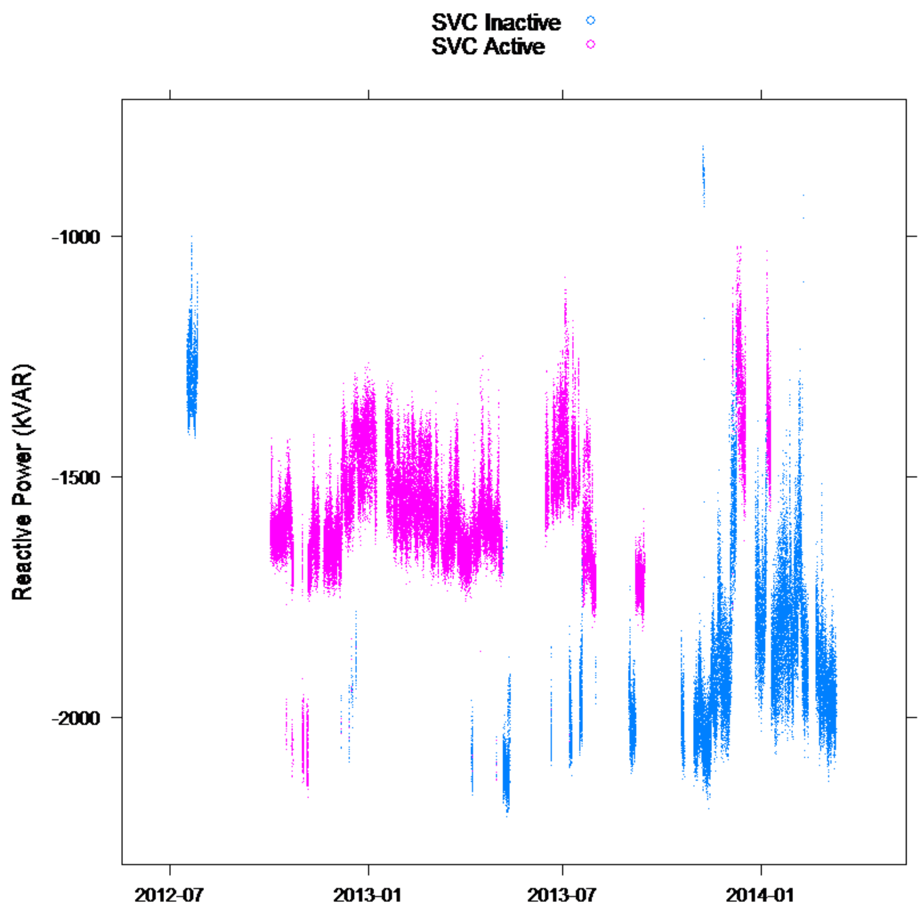


Figure 12.37. Feeder Reactive Power for the Hoback Feeder that was Affected by the Project's SVC

The project also calculated and reviewed feeder real power. See Figure 12.38. If the operation of the SVC system affected real power on the feeder, it is not evident by inspection. Lower Valley Energy activated the SVC system throughout most of the winter peak months of 2012–2013, but they activated the system less frequently during the winter of 2013–2014. The demand was greater during the second winter than it had been during the first. This pattern challenged the project as it attempted to quantify an energy impact from the raw data. Differences in the power demand over time may be caused by weather, affluence, load growth, or other influences.

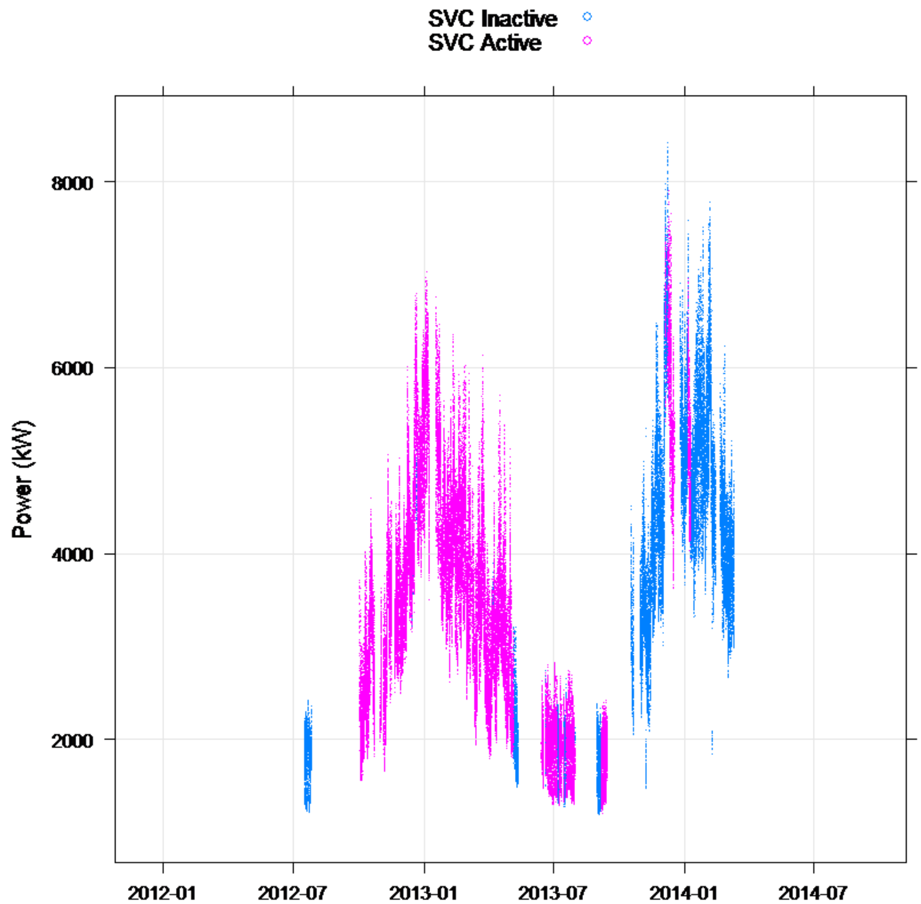


Figure 12.38. Feeder Power for the Hoback Feeder that was Affected by the Project's SVC

The influence of the SVC operation on feeder reactive power at the Hoback substation is more easily observed and quantified than its impact on real power. Figure 12.39 displays the quartile populations of the reactive power that has been calculated for the feeder. The magnitudes of the reactive power are significantly less (i.e., less negative) when the SVC system was active. The left two boxes represent the measurements prior to April 2013 when the feeder was being managed to a lower voltage than thereafter. The right two boxes are from the latter period when feeder voltage was higher. The impact is similar for both feeder voltages.

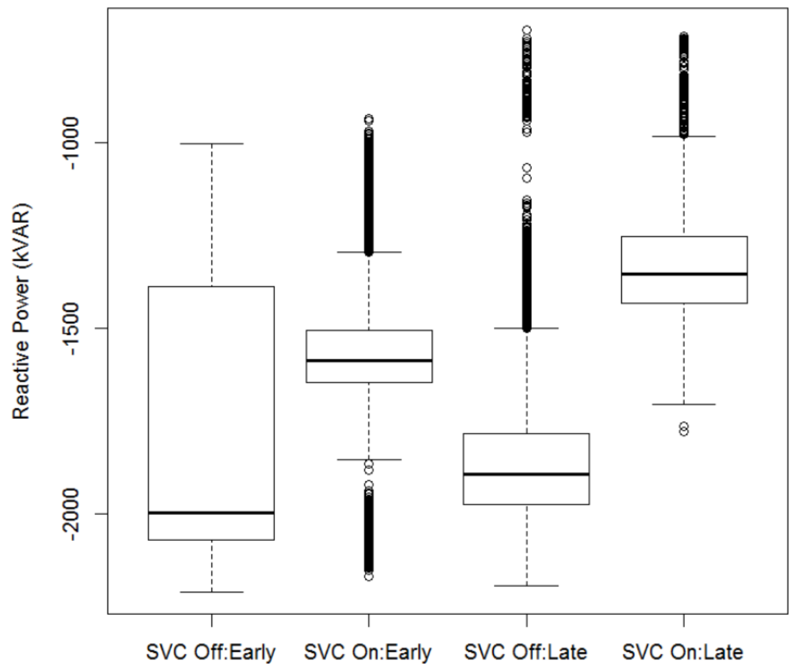


Figure 12.39. Averaged Feeder Reactive Power with the SVC Inactive and Active under the Lower ("Early") and Higher ("Late") Voltage Strategies

A similar quartile representation, this time displaying feeder power factor, is shown in Figure 12.40. The improvement in median power factor when the SVC system becomes engaged prior to April 2013 is remarkable. The power factors were improved after April 2013 when the voltage was managed at a greater magnitude, but the SVC system still appears to further improve the power factor when it becomes activated. Analysts did not discern whether the improvement after April 2013 could be attributed to the change in voltage management. It is possible that other utility circuit improvements also came into play at that time. Upon its review, Lower Valley Energy staff thought this improvement might be attributable to an additional set of reactors that were activated on the circuit on July 8, 2013.

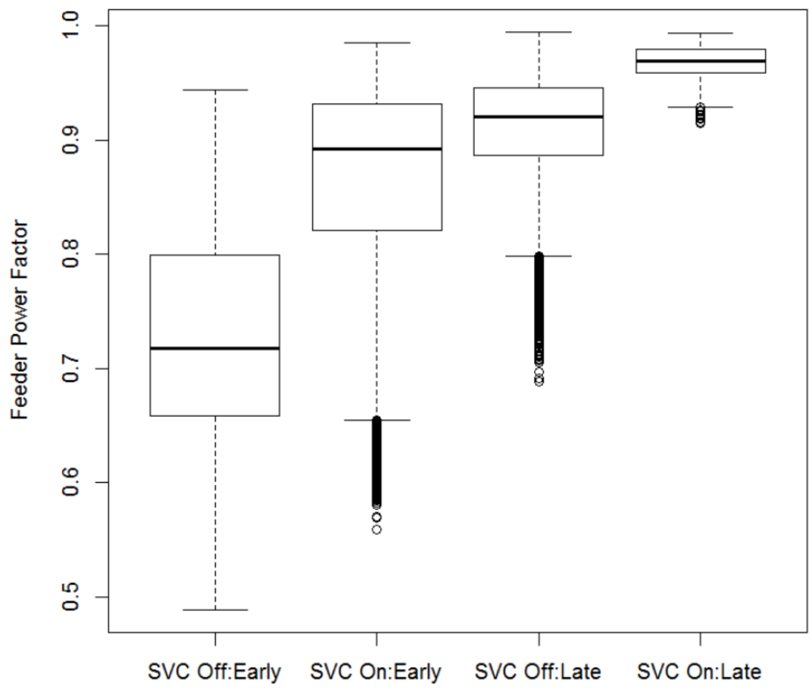


Figure 12.40. Feeder Power Factor with the SVC Inactive and Active Under the Lower (“Early”) and Higher (“Late”) Voltage Strategies

The project attempted to quantify power savings directly from feeder power calculations and a modeled baseline, but this effort was not successful. No significant real-power difference could be determined. A carefully designed experimental procedure would need to be devised and followed to observe the change in power, which might be estimated to be on the order of 1.3% of the supplied feeder load.[1] Perhaps the SVC system should be engaged and disengaged alternating days during the trial to mitigate the many other influences that potentially confounded the project’s efforts to measure this small change in feeder load.

A relative impact may be stated. The averaged feeder power factors are summarized in Table 12.12 according to the reported status of the SVC system and whether the measurements were taken at the new, higher feeder voltage level after April 2013, or not. Based on these ratios of power factor, the project concludes that distribution currents were reduced 11% prior to April 2013 and 6.2% after that date. The reduction of distribution line losses when the SVC was active was therefore approximately 30% prior to April 2013 and 13% thereafter.

[1] This estimate presumes 5% of feeder load is lost in the distribution feeder and that the SVC operation reduces those losses by 25%.

Table 12.12. Feeder Power Factors as affected by SVC Status and Voltage-Management Status

	Before April 2013	After April 2013
SVC Inactive	0.753	0.912
SVC Active	0.861	0.968

The project has reservations claiming these impacts on power factor. As was described earlier in this section, the SVC was engaged dissimilarly in the two project years. Power factor is a function of total real power, and load is greatest in winter for the Lower Valley Energy service territory. Because the asset was not applied similarly by year and by season, seasonal variations might well confound the project's measurements of impacts of the SVC.

12.7 Battery Storage System

Lower Valley Energy installed a 125 kW, 250 kWh battery storage system. Ideally, for the demonstration, this battery storage system was to be controlled automatically according to advice received from the project's transactive system. Except for a week in January 2014, Lower Valley Energy primarily controlled this system by direct demand-response commands and restricted the engagements to limited time periods.

The battery system was controlled and monitored via a remote terminal unit and the existing SCADA system at the Hoback substation. When a control signal was received by the asset system, it either supplied energy to or stored energy from the feeder line. Lower Valley Energy sought to reduce its peak demand, reduce distribution line losses, and defer distribution capacity investments on the distribution supply to the Hoback substation.

A transactive system function was created by the project to advise the battery system when to generate or store energy. This function advised the battery system when to charge and discharge at optimal times using the predicted transactive incentive signals (TISs). The function could be configured with the system's energy storage capacity, charge and discharge power ratings, minimum and maximum states of battery charge, and a parameter with which the system's owner could modify the aggressiveness of their battery management strategy. An aggressive strategy permits many rapid changes between charging and discharging, whereas a conservative strategy might limit the system to few charge cycles per month. It will be shown in this section that Lower Valley Energy was unable to capitalize on this function and automate the control of the battery system. The function remained configured more aggressively than the utility could allow based on the very limited number of lifetime duty cycles promised by the battery system.

The annualized costs of the system and its components are listed in Table 12.13. The largest cost was the battery system itself with the requisite power inverter. Other costs included upgrades to SCADA communications at the substation, working with the project to implement an instantiation of the transactive system at the site, labor, site upgrades, outreach, and O&M costs. The total annualized cost was estimated to be about $55.8K.

Table 12.13. Lower Valley Electric Costs of Battery Storage System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
100 kW Battery/Inverter Package	100	41.8	41.8
Existing SCADA System[(a)]	25	25.7	6.4
Transactive Signal	50	8.4	4.2
Operations Labor[(a)]	25	5.5	1.4
Building	25	3.9	1.0
Building Site	25	2.1	0.5
Outreach and Education[(a)]	25	0.6	0.2
Ongoing O&M Costs[(a)]	25	0.6	0.2
Administrative[(a)]	25	0.4	0.1
Quest-to-SCADA Communication Fees	25	0.2	0.1
AMI Meter	100	0.0	0.0
Total Annualized Asset Cost			**$55.8K**

(a) These components were shared among the SVC system (Section 12.6), battery storage system (Section 12.7), PV array (Section 12.8), and wind turbine (Section 12.9).

12.7.1 Characterization of the Battery System and Data

The function that generated advice for the battery system concerning when it should charge or discharge its stored energy operated continuously from November 2013 through the end of data collection at the end of August 2014. The function's outputs are shown in Figure 12.41. The outputs are intentionally scaled from −127 to 127 (i.e., 1 signed byte) so that a designed function, once designed, could be applied to other similar asset systems. Ideally, only configuration changes are needed to move the function from one battery system to another. The full range of advisory signal outputs represents the entire range from fully charge (negative advisory signal) to fully discharge (positive advisory signal).

The function scheduled the battery's state of charge based on the transactive incentive signal at the Lower Valley Energy site. The advice would induce the battery system owners to discharge energy at relatively high incentive costs and to recharge at low ones. If properly configured, the function takes into account the battery system's capabilities and the owners' preferences for the frequency of charge and discharge cycles. The function did not optimize the value of the battery system as had been hoped for these reasons:

- The TIS was not used for billing. The region's and Lower Valley Energy's benefits were not correctly represented in the transactive signals at this site.
- Lower Valley Energy did not configure the function and heed the advice the function gave. The system offered far fewer lifetime charge and discharge cycles than had been anticipated.
- Persistent issues with the forecast within the transactive signals caused the function to advise nonsensical outcomes. Lower Valley Energy lost confidence as these issues remained unresolved.

Figure 12.41 also shows the statuses that were reported to the project by Lower Valley Energy concerning whether the system was charging (blue markers), discharging (red), or idle (green). These indicators changed character in late March 2014 when the transactive function became updated and improved and was reinstalled at the utility site. The system was exercised regularly after March 2014, so the project limited its analysis to the months March through July 2014.

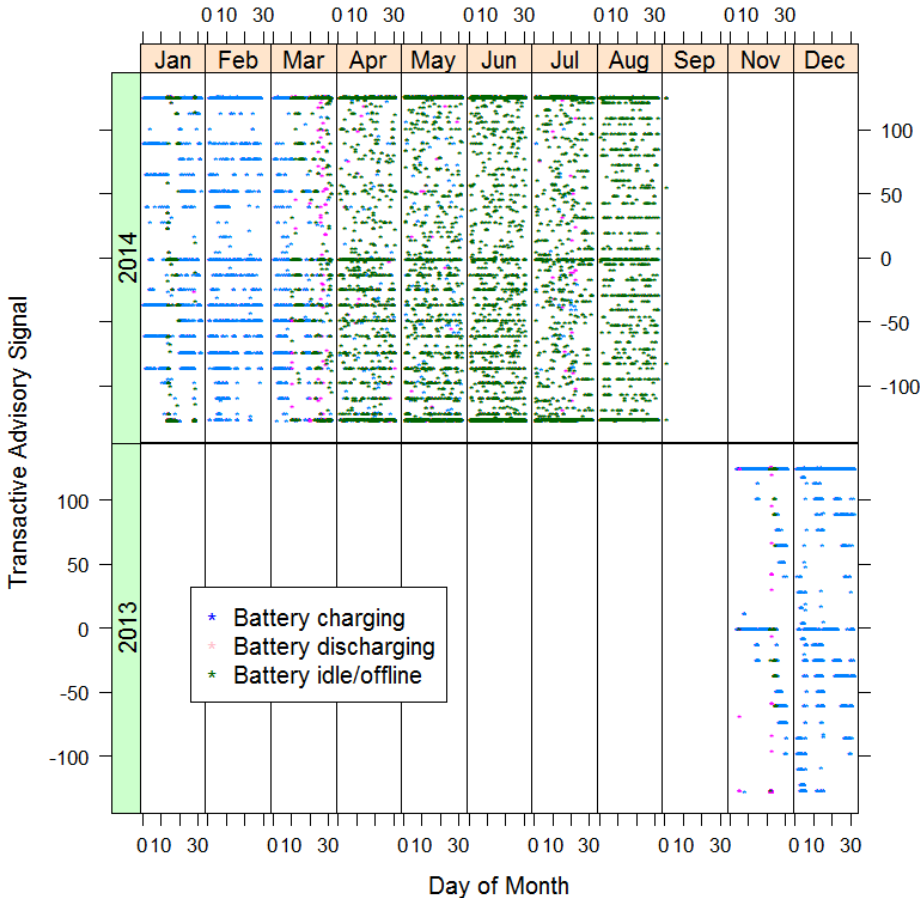


Figure 12.41. Output of the Transactive Function that advised the Battery System when to Charge (negative) and Discharge (positive)

The actual battery power data from this period is in shown in Figure 12.42. Again, this figure includes color coding for the data according to the system status reported by the utility to the project. The reported statuses are meaningful. The periods of maximum charging and discharging are pretty accurately assigned to the data near positive and negative 20 kW, respectively. The status "idle/offline" was applied over a large range of intermediate charging and discharging rates.

Analysts were not able to resolve with Lower Valley Energy staff the discrepancy between the power levels that were received in the utility's data and the claim that this was a 125 kW, 250 kWh storage system. The project's power data seems to be about one-fifth the magnitudes that should be expected from this battery system. Utility staff reported that metering was poor, and utility staff had even regenerated electronic data manually from paper results at one time. This question remains unresolved. The impacts may be up to 5 times greater than those reported in this section.

The project has low confidence in the data prior to March 20, 2014. No useful data was received after July 2014. Data from June 2014 was unavailable.

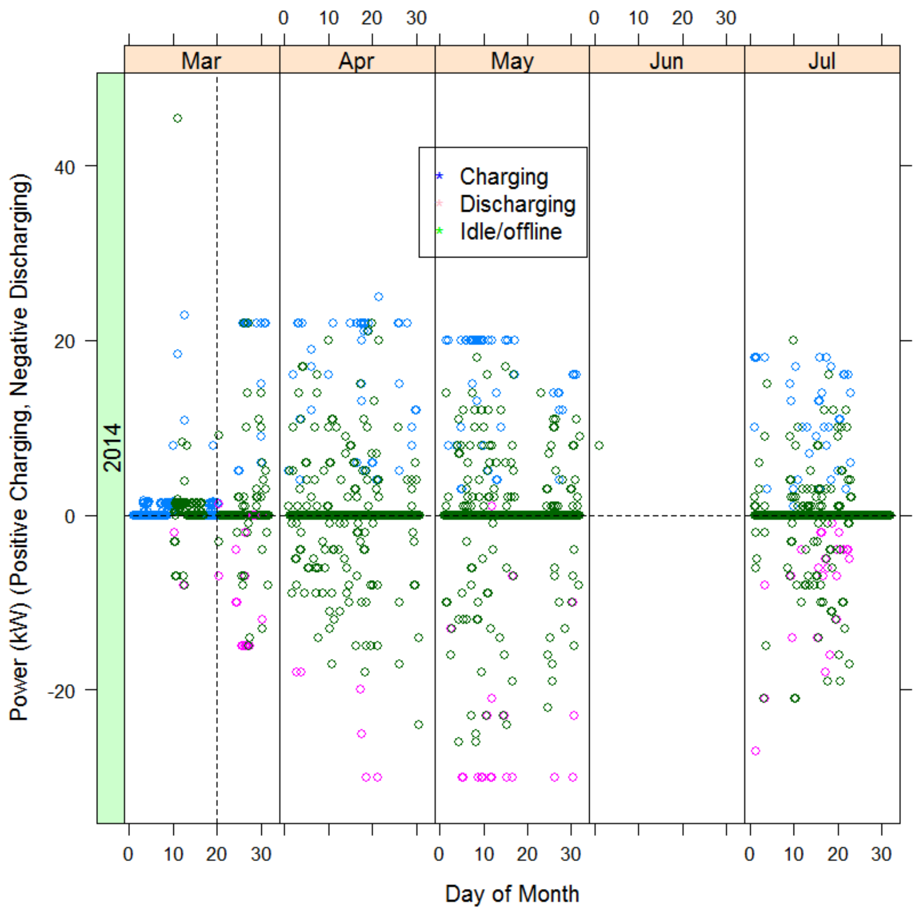


Figure 12.42. Power Data as the Battery System is Charged (Positive) and Discharged (Negative) During Spring and Early Summer 2014

The next figure, Figure 12.43, drives home the point that battery system operations and the advice from the transactive system were not well correlated. This figure uses data from March–May and July 2014. The quartiles of battery power are plotted for each transactive advisory level. If the advice from transactive function were followed, there would be a strong negative correlation. The battery was requested to discharge its stored energy (negative power) when the advisory signal was positive.

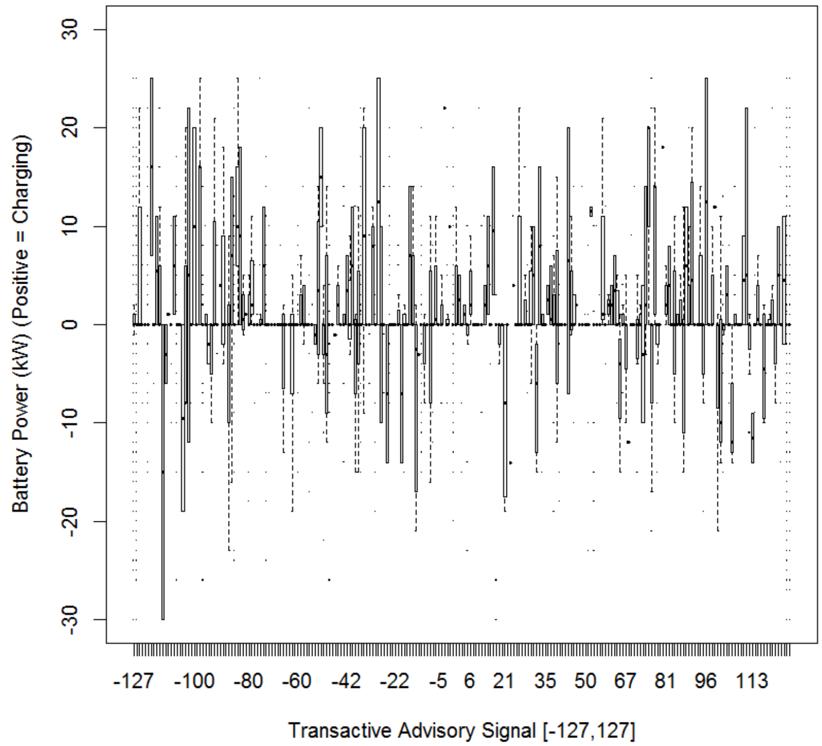


Figure 12.43. Correlation of Battery System Charging and Discharging to the Output of the Transactive System Function that Advised the System when to Charge (transactive signal is negative) and Discharge (transactive signal is positive)

12.7.2 Performance of the Battery System

Lower Valley Energy conducted tests January 13–17, 2014 in which they cautiously had the battery system track advice from the transactive system. According to Lower Valley Energy's test report,[1] only 700–800 discharge and charge cycles are anticipated for the life span of the battery system. This would allow perhaps eight cycles per month. The transactive function was configured to allow multiple daily cycles at the time of this testing.

To ease the potential stress on the battery system during this testing, the utility narrowly limited its operating hours and the system status. Discharging was permitted 07:15–09:30 and 16:30–19:00 Mountain Time when it coincided with a load-shedding level calculated by the utility's engineers. Similarly, charging was permitted from 22:00–03:00 Mountain Time. The system was commanded to charge if it had not reached 118 kWh by 03:00.[2]

[1] Dory, H. January 20, 2014. *Lower Valley Energy Battery Controller Test*. Lower Valley Energy report concerning battery system tests that were conducted January 13–17, 2014. Lower Valley Energy, Jackson, Wyoming 83001. (unpublished).
[2] The transactive function preferably receives updates from the system concerning its state of charge. This feedback was not implemented in this instantiation.

The utility observed unacceptable fast changes in the advisory signal. For example, the signal was observed to have changed from advising full charging (−126) to idle (0) in five minutes. This behavior might have been mitigated by eventual improvements in the function that allowed the system to perform fewer charge and discharge cycles. The utility also observed a pronounced dip in the TIS each day at 07:00. They hypothesized that this dip might have corresponded to regional operations in the Pacific Time Zone that were conveyed to the site through the transactive system. Peak incentive signals rarely occurred during the utility's peak during the testing.

The capabilities of the battery system were observed to change during testing. The testing was halted after less than a week.

Thereafter, Lower Valley Energy controlled the system to more directly address system peak. The daily pattern is evident in the quartile graph of Figure 12.44. Battery power levels are displayed for each local Mountain Time hour. The median battery power each hour is usually zero, as is indicated by the diamond-shaped markers in this figure. The battery system is frequently idle. This figure includes data from March 20 through July 2014 when data quality was good and the system was being routinely exercised. While there is much diversity in day-to-day operations, the system primarily discharges (negative power) near the daily peak hours and recharges elsewhere during the day. The power capacity of the system is being cautiously employed.

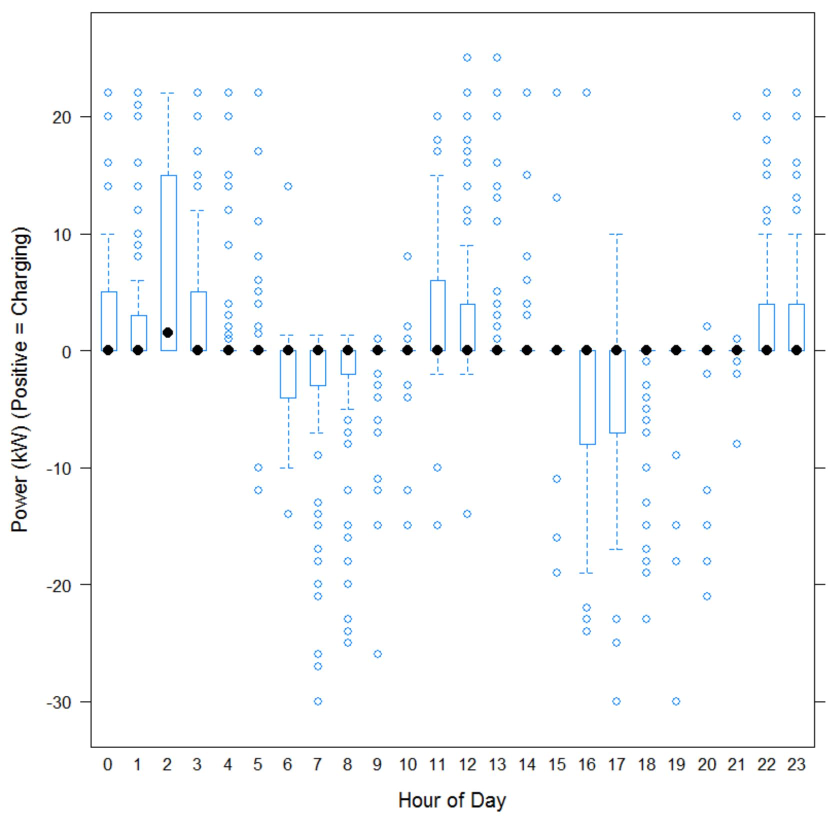


Figure 12.44. Quartile Battery Power each Hour of the Day (Mountain Time) from March 20 through July 2014. The diamond markers are median values for each hour. The boxes and whiskers represent approximately one-fourth of the data each hour.

The observance of this daily charging and discharging pattern is clearer in Figure 12.45 that shows the hourly average charge and discharge rates during the same time period. On average, the utility displaced a little more than 4 kW during peak morning and afternoon hours. The system was charged at almost 7 kW in the hour between 02:00 and 03:00.

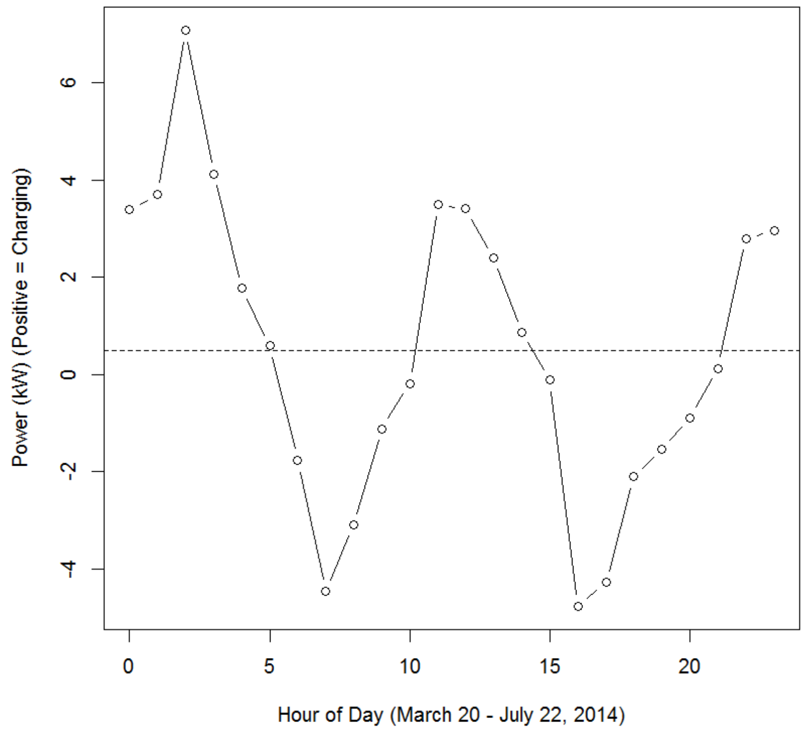


Figure 12.45. Average Battery Charge or Discharge Rates each Hour for the Period from March 20 through July 2014

It had appeared in Figure 12.44 that the battery system might charge more than discharge. This conjecture was tested by summing cumulative energy exchange during the period from March 20–May 31, 2014 (see Figure 12.46). This figure shows cumulative energy—both charging and discharging—plotted against the hours that the system was available or active. The cumulative energy rises steadily over the hours. The system consumes energy over time. This might be an indicator of the inefficiency of the system. Not all the energy stored by the system is available to be reinjected back into the distribution system later. A line was fit to the data. The slope of the line is 0.64 kWh/h. While small, these losses reduce the monetary benefits available to the system, regardless of how cleverly the battery system is operated.

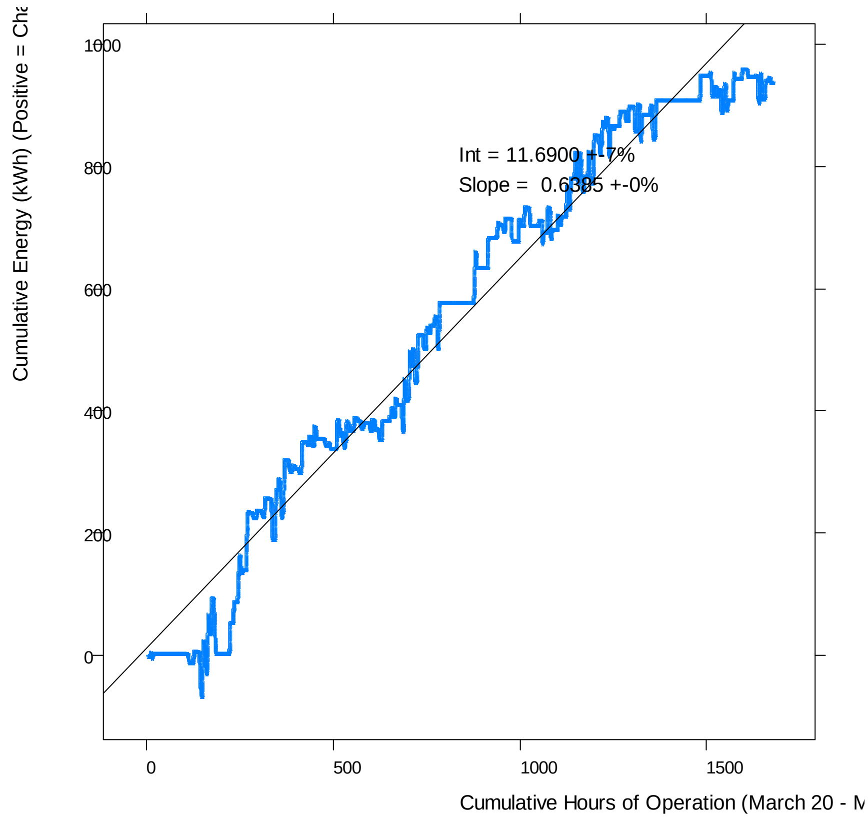


Figure 12.46. Battery System Cumulative Energy Intake over its Operating Hours. The graph shows that the system lost 640 W, on average, from March 20 through May 31, 2014.

The project has summarized the monthly and total energy and demand impacts based on the way that Lower Valley Energy operated its battery system during four months of 2014. This performance is summarized in Table 12.14. The average monthly charging and discharging rates were determined for heavy-load hours (HLHs) and light-load hours (LLHs), as defined for BPA customers (Appendix C), and these power levels were then used to extrapolate the total energy that would have been generated or consumed that month during those hour types. The standard deviations of the months' measurements were determined and used to estimate the standard error range of the monthly energy consumption values. Using BPA's most recent load-shaping rates (Appendix C), these monthly energy totals were then used to estimate the value of the net BPA energy supply that was consumed or generated during the BPA HLH and LLH hours.

A strong pattern was evident. For each month that was evaluated, the batteries performed net discharge of energy during HLH hours and net charging of energy during LLH hours. However, there was more net charging energy consumed each month during LLH hours than net discharged energy during the HLHs. Even though LLH energy supply is less expensive than HLH supply, there was a small net loss in the supply energy that was consumed and later displaced each month.

In order to predict the total yearly energy cost impact, analysts had to presume that the system would be operated for the unavailable eight months as it had been operated for the four months that good data was available. If the system were to be similarly operated through a year, the project predicts that the utility would *lose* about $69 ± 19 through the arbitrage of energy supply.

The project also evaluated the impact of operations on demand charges. Lower Valley Energy incurs demand charges most months from its energy supplier BPA. They supplied the project a list of the peak HLH hours that triggered these charges, and these example hours are listed in Table 12.14. Observe the same peak hour might be listed multiple times for any given calendar month. The project evaluated the battery power produced and consumed each HLH each month. Data was available from four months of early 2014. Presuming that battery operation during these four months was representative of the way that Lower Valley Energy would continue to exercise the system, the project estimated the monthly demand impacts. The monthly demand charges are primarily impacted by the month's BPA demand rate (Appendix C) and the difference between the peak-hour demand and the average HLH demand. This approach allows for a statistical treatment, including an estimation of the corresponding variability for the demand impacts and costs.

The monthly monetary impacts on the utility's demand charges are shown in Table 12.14. The system was operated in ways that reduced the monthly demand charges three of the four months for which data were available. The pattern of charging and discharging did not work well in July, when the exemplary peak hour was in the evening.

Presuming that the costs from the four months with data are similar to those of the remaining eight, the project estimated the yearly impact of battery operations on demand charges. The system would net charge 4.56 ± 0.73 MWh throughout the year if it were to be operated all year in the same way it had been demonstrated. The cost of the supplied energy would be a net loss of $72 ± 18 per year for the utility, based on the costs that it pays its wholesale supplier for this lost energy. The system would reduce lower Valley's demand charges by about $120 ± 40 per year.

Table 12.14. Summary of Monthly Energy and Demand Impacts from the Demonstrated Operation of the Battery System

		Energy[a] (MWh)	Energy Cost ($)	Historical Peak Hours[c]	Demand Cost[d] ($)
Jan		-	-	08:00, 07:00	-
Feb		-	-	07:00, 07:00	-
Mar	HLH	−0.37 ± 0.20	−11 ± 6	07:00, 07:00	−12 ± 14
	LLH	0.95 ± 0.21	24 ± 5		
Apr	HLH	−0.40 ± 0.12	−10 ± 3	07:00, 07:00	−24 ± 12
	LLH	0.91 ± 0.12	18 ± 2		
May	HLH	−0.36 ± 0.14	−7 ± 3	07:00, 08:00	−21 ± 9
	LLH	0.66 ± 0.13	9 ± 2		
Jun		-	-	09:00, 08:00	-
Jul	HLH	−0.29 ± 0.14	−9 ± 4	21:00	17 ± 11
	LLH	0.42 ± 0.09	10 ± 2		
Aug		-	-	21:00	-
Sep		-	-	08:00	-
Oct		-	-	07:00	-
Nov		-	-	07:00, 07:00	-
Dec		-	-	07:00, 07:00	-
Year		**4.56 ± 0.73**[f]	**72 ± 18**[b]		**−120 ± 40**[e]

(a) The total month's energy impact is extrapolated using available power measurements and the numbers of HLH and LLH each month. Numbers are rounded to the nearest 0.01 MWh.

(b) The total year energy supply cost impact is estimated by presuming the values for the eight unmeasured months are similar to the four that were available. Numbers are rounded to the nearest whole dollar. Positive values represent increased supply cost for the utility. Positive values are utility supply costs and negative values are displaced supply costs.

(c) These are the starting hours (Mountain Time) of peak demand hours reported to the project for these months. If more than one hour is listed, the multiple hours were from multiple historical years for the given calendar month.

(d) The monthly impact on BPA demand charges uses the average impact on HLHs and the average impact on the listed exemplary peak hours. Other secondary billing impacts may come into play and were not considered here.

(e) The total yearly demand-charges impact is estimated by presuming that the eight unavailable months are similar to the four that had data available. The negative value indicates that supply costs have been displaced by the asset.

(f) This sum has been projected as if the battery system were used as it was demonstrated, but throughout the year.

12.8 20 kW Solar PV System

Lower Valley Energy installed a 20 kW solar PV generator system at its Hoback substation, Bondurant, Wyoming. The cooperative hoped to displace energy supply and learn the cost-benefit of investing in PV systems. The panels are shown during their assembly in Figure 12.47.

Figure 12.47. Lower Valley Electric Cooperative Solar and Wind Site near their Bondurant Substation

The cooperative worked with the project to estimate the PV system's annualized costs, which are listed in Table 12.15. The greatest annualized cost is that of the PV system hardware, but the utility also elected to include significant costs incurred for upgrading the substation's SCADA system to monitor the PV system. Other smaller cost components include the costs of operations, the building and building site, maintenance, outreach, administrative costs, and a cellular wireless connection to the SCADA system. The overall annualized costs are $18.8K.

Table 12.15. Lower Valley Electric Costs of 20 kW Solar Photovoltaic System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
20 kW Solar PV System	100	9.0	9.0
Existing SCADA System[a]	25	25.7	6.4
Operations Labor[a]	25	5.5	1.4
Building	25	3.9	1.0
Building Site	25	2.1	0.5
Ongoing O&M Costs[a]	25	0.6	0.2
Outreach and Education[a]	25	0.6	0.2
Administrative[a]	25	0.4	0.1
Quest-to-SCADA Communication Fees	25	0.2	0.1
AMI Meter	100	0.0	0.0
Total Annualized Asset Cost			**$18.8K**

(a) These components were shared among the SVC system (Section 12.6), battery storage system (Section 12.7), PV array (Section 12.8), and wind turbine (Section 12.9).

12.8.1 Characterization of the Data

The PV system was reported to be installed and useful by the end of October 2012. Lower Valley Energy submitted hourly power generation data to the project from that time through August 2014. The entire data set is shown in Figure 12.48. The data quality faltered and did not recover after mid-April 2014. The project elected to ignore the data after March 2014 and prior to November 2012. The project determined that there were 17 meaningful months having usable power data.

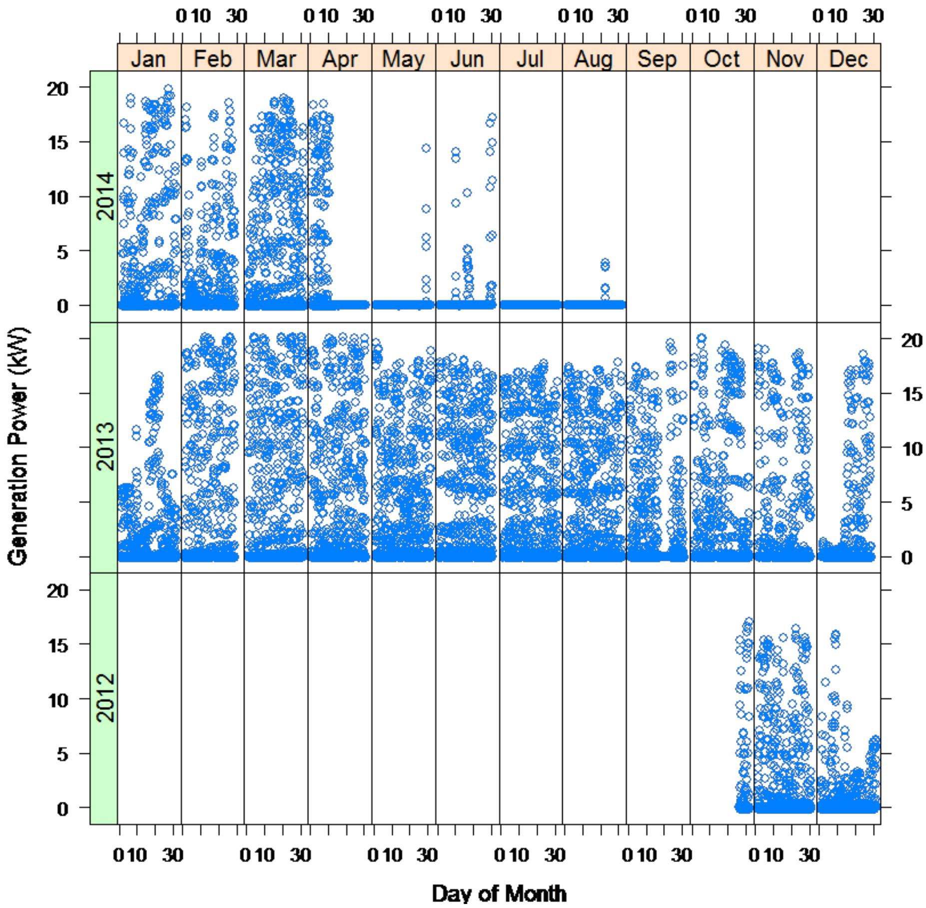


Figure 12.48. Complete Series of Solar Generation Power Data Received by the Project from Lower Valley Energy

Analysts then plotted the hourly generation pattern for each project month (Figure 12.49). The patterns are acceptable and rule out data time shifts that have plagued the project. Months that demonstrated many zero values throughout days invited further review. Closer inspection of these months showed that the system was offline the week September 16–23, 2013. Occassional system outages for maintenance or other purposes are probably characteristic of this system's operation. The project therefore chose not to remove this or any other apparent outages from analysis.

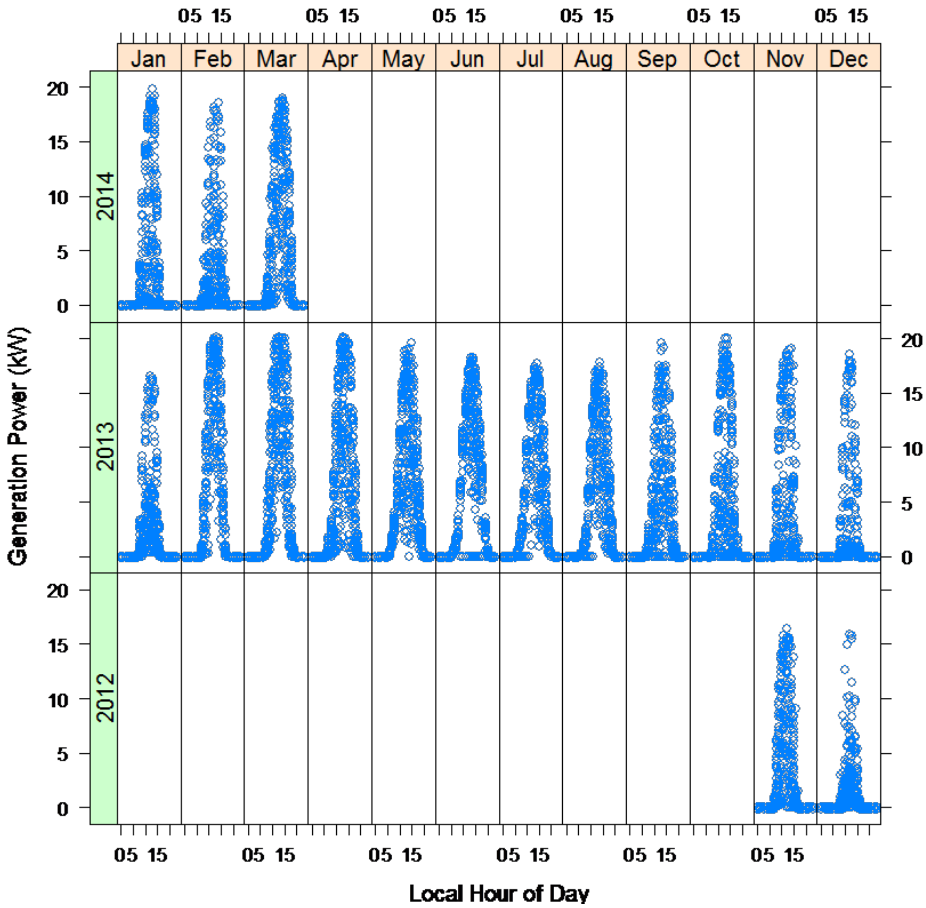


Figure 12.49. Solar Power by Local Hour and by Project Month after Filtering Out Early 2012 and Later 2014 Data

The project located two weather stations that reported solar insolation, but these data were not close enough to the site being analyzed to yield strong correlation.

12.8.2 Performance of the PV System

The project characterized the solar power generation by season and according to the beginning of the given hour. These results are summarized in Figure 12.50. The markers are the average power generation for these hours, local Mountain Time. The error bars represent the standard deviations of the measurements received for the hour. More precisely, the error bars span from the bottom of the 16th percentile to the top of the 84th percentile and are not necessarily symmetrical about the average values.

Average generation in the winter is 8.4 kW and the array generates power from about 07:00 until 18:00 local time. The maximum average summer and spring generation is almost identical at 13.3 kW, but the spring peak hour begins at 13:00 rather than noon. Generation lasts from 05:00 until 21:00 during the summer months.

The tops of the 84th percentile bars are remarkably similar each month—17.9 kW in winter, 18.7 kW in spring, 16.9 kW in summer, and 17.3 kW in fall. However, the generation is more variable in the fall and winter than in the spring and summer. The variability is also greater in the afternoon than in the morning hours.

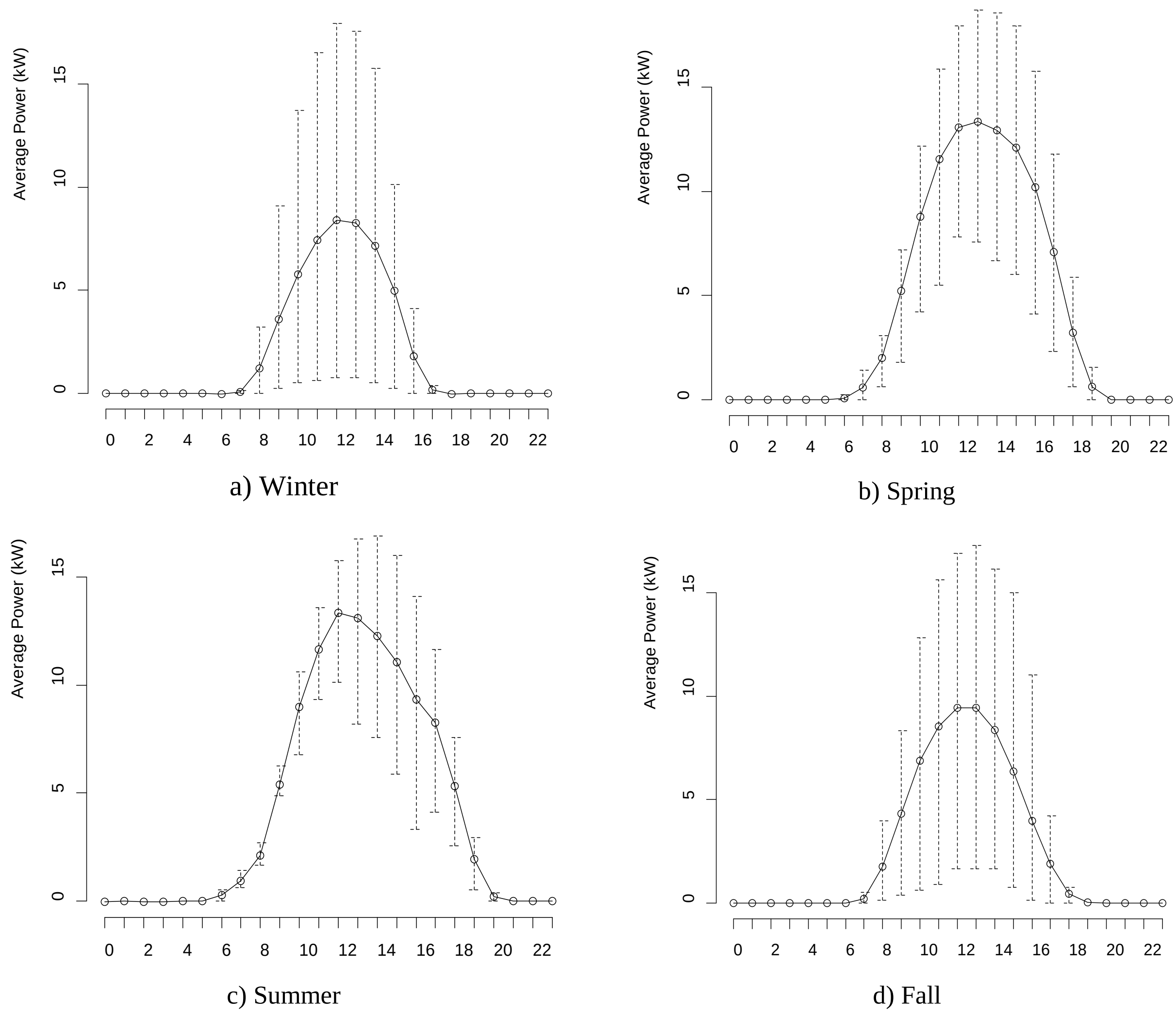


Figure 12.50. Hourly Solar Power Generation by Seasons (a) Winter, (b) Spring, (c) Summer, and (d) Fall. The vertical dashed lines represent standard deviations of the hourly measurements.

The project estimated the annual generation from the solar generation system by calendar month and by BPA hour type, which is critical for the way that displaced energy supply must be valued. These results are summarized in Table 12.16. The average generation during HLH and LLH hours was determined using all available data for the given months. The variability was estimated by separating the population of 2013 measurements from those of other years. Comparison months were available for five of the 12 months. A Student's t-test was used to estimate the variability of the calculated averages. The magnitudes of the uncertainties justified reporting no more than about two significant digits for most of the analysis results.

Table 12.16. Summary of Generation and the Value of Its Displaced Supply

		Average Generation[b] (kW)	Energy[b] (MWh)	Displaced Supply Value[b,c] ($)	Historical Peak Hours[d]	Change in Demand Charge[e] ($)
Jan	HLH	3.0 ± 0.3	1.30 ± 0.14	48 ± 5	8:00, 7:00	27 ± 4
	LLH	0.8 ± 0.2	0.26 ± 0.08	8 ± 2		
Feb	HLH	4.5 ± 0.4	1.70 ± 0.16	63 ± 6	7:00, 7:00	46 ± 3
	LLH	1.0 ± 0.3	0.28 ± 0.08	9 ± 3		
Mar	HLH	6.2 ± 0.5	2.60 ± 0.19	78 ± 6	7:00, 7:00	53 ± 4
	LLH	1.5 ± 0.3	0.50 ± 0.11	13 ± 3		
Apr[a]	HLH	6.5	2.70	70	7:00, 7:00	47
	LLH	1.2	0.36	7		
May[a]	HLH	6.3	2.60	55	7:00, 8:00	26
	LLH	1.6	0.52	7		
Jun[a]	HLH	6.8	2.70	62	9:00, 8:00	19
	LLH	1.9	0.60	9		
Jul[a]	HLH	6.6	2.80	84	21:00	60
	LLH	1.5	0.50	12		
Aug[a]	HLH	5.9	2.60	87	21:00	59
	LLH	1.4	0.43	12		
Sep[a]	HLH	3.9	1.50	65	8:00	29
	LLH	0.8	0.27	9		
Oct[a]	HLH	4.5	1.90	61	7:00	41
	LLH	1.1	0.36	10		
Nov	HLH	3.5 ± 0.37	1.40 ± 0.15	50 ± 5	7:00, 7:00	34 ± 4
	LLH	0.9 ± 0.25	0.28 ± 0.08	9 ± 3		
Dec	HLH	1.6 ± 0.26	0.66 ± 0.11	25 ± 4	7:00, 7:00	19 ± 3
	LLH	0.5 ± 0.17	0.16 ± 0.06	5 ± 2		
Year			**28.98 ± 0.60[f]**	**858 ± 20[f]**		**460 ± 12[f]**

(a) The variability could not be stated this month because only one calendar month of this type was demonstrated during the project.
(b) The uncertainty in these columns is estimated by comparing 2013 hours against hours from other years using a Student's t-test on the populations.
(c) This is the value of the energy that need not be purchased by the utility from BPA in the given month.
(d) These are the starting hours (Mountain Time) of monthly peak demand reported to the project for these months. There are two hours listed for calendar months for which two historical years' peak hours were available.
(e) The impact on BPA demand charges is estimated as the average generation during HLHs, minus the average generation during peak demand hours in the given month. The sign reversal results from the fact that generated power is displacing power that would otherwise be purchased from BPA. Positive results in this column mean that demand charges are being increased in the given month by the diurnal pattern of solar generation.
(f) The standard error of this yearly estimate has been projected from the five months for which standard error could be estimated.
(g) The variability in the other months is presumed to be similar in magnitude.

The average power was used to estimate the total monthly and annual energy generation. The total energy values are listed in Table 12.16 by calendar month and are grouped according to HLH and LLH hours. The project reports that based on this systems' installation, location, and the way it was operated by Lower Valley Energy, its annual generation should be expected to be 28.98 ± 0.60 MWh. Of this generated energy, 24.4 ± 0.52 MWh occurs during HLH hours, and 4.5 ± 0.29 MWh occurs during LLH hours.

One of the benefits of this system is its ability to displace energy that would otherwise need to be supplied from BPA. These results were tabulated for the asset based on the most recent set of BPA load-shaping rates (Appendix C). Again, these are shown in Table 12.16 by calendar month and are grouped according to HLH and LLH hours. The project reports that the value of annual displaced supply energy for Lower Valley Energy is $858 ± 20. Of this, about $748 ± 18 is during HLH hours, and $108 ± 8 is during LLH hours.

The project also estimated the monthly and annual impacts from BPA demand charges and the load-shaping rate determinant that is used to calculate the utility's monthly demand charges. The cooperative reported their monthly peak hours to the project. These are listed in Table 12.16. The BPA determinant for demand charges is based primarily on the difference between demand during the peak hour each month and the average heavy-load hour demand. Lower Valley Energy typically exceeds its determinant every month. The solar generation changes the determinant according to its average generation during HLH hours and the generation that occurs during the single peak hour each month. The impact on the peak hour is estimated from typical generation during the exemplary peak hours. Refer to Figure 12.50 to see the approximate magnitudes at the given exemplary peak hours.

An ideal resource would displace supply energy during the peak HLH hours more than during other HLHs. That is not the case for solar energy in the Northwest. The peak HLH hours lie predominantly in early morning and late afternoon hours when solar power is weak. However, much of the solar energy is generated during off-peak HLHs, further decreasing the billing determinant.[1] The resource appears to *increase* the annual demand charges by $460 ± 12.

For the five months that Lower Valley Energy supplied more than one month's data, the variability in the demand charges was calculated. This was done by comparing 2013 hours against other hours using a Student's t-test to estimate the natural variability from cloud cover and other environmental variables that affect the generation from one year to the next. The uncertainty in the average HLH component was already discussed. The variability of the peak-hour impacts was derived from the hourly statistics of the hours that match those in the historic peak hours column each month. Monthly results were rounded to the nearest whole dollar.

[1] The BPA supply bill includes some secondary effects and corrections that could come into play, but these were not considered here.

12.9 Four 2.5 kW WindTronics Wind Turbines

Lower Valley intended to displace energy supply and better understand the costs and benefits of investing in wind turbines. Lower Valley installed 10 kW WindTronics wind generators at the Hoback substation, Bondurant, Wyoming. These turbines had an innovative design with the generator surrounding the turbine blades (Popular Science 2014). Regrettably, Lower Valley Energy was not able to achieve acceptable performance from these turbines. They reported to the project that the company is no longer in business, which is supported by a statement from the company (WindTronics 2013).

The project assessed the annualized costs of the system and its components as shown in Table 12.17. Components include upgrades to the existing SCADA system, the wind generators, building site improvements, outreach, operations costs, administrative overhead, and fees for cellular communication with the SCADA at this remote site. The annualized cost of the system was estimated as $15 thousand.

Table 12.17. Lower Valley Electric Costs of a 10 kW Wind Turbine System

	Shared Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Existing SCADA System[a]	25	25.7	6.4
10 kW WindTronics Generators (four)	100	5.2	5.2
Operations Labor[a]	25	5.5	1.4
Building	25	3.9	1.0
Building Site	25	2.1	0.5
Outreach and Education[a]	25	0.6	0.2
O&M[a]	25	0.6	0.2
Administrative[a]	25	0.4	0.1
Quest-to-SCADA Communication Fees	25	0.2	0.1
AMI Meter	100	0.0	0.0
Total Annualized Asset Cost			**$15.0K**

(a) These components were shared among the SVC system (Section 12.6), battery storage system (Section 12.7), PV array (Section 12.8), and wind turbine (Section 12.9).

According to Lower Valley Energy staff, the wind turbine at times consumed more energy than it generated, resulting in energy consumption instead of generation. Data were collected from late October 2012 through August 2014. All of the generation supplied to the project is shown in Figure 12.51. The reported generation is less than 1 kW, and the generation is negative as often as it is positive. Furthermore, the data is badly discretized.

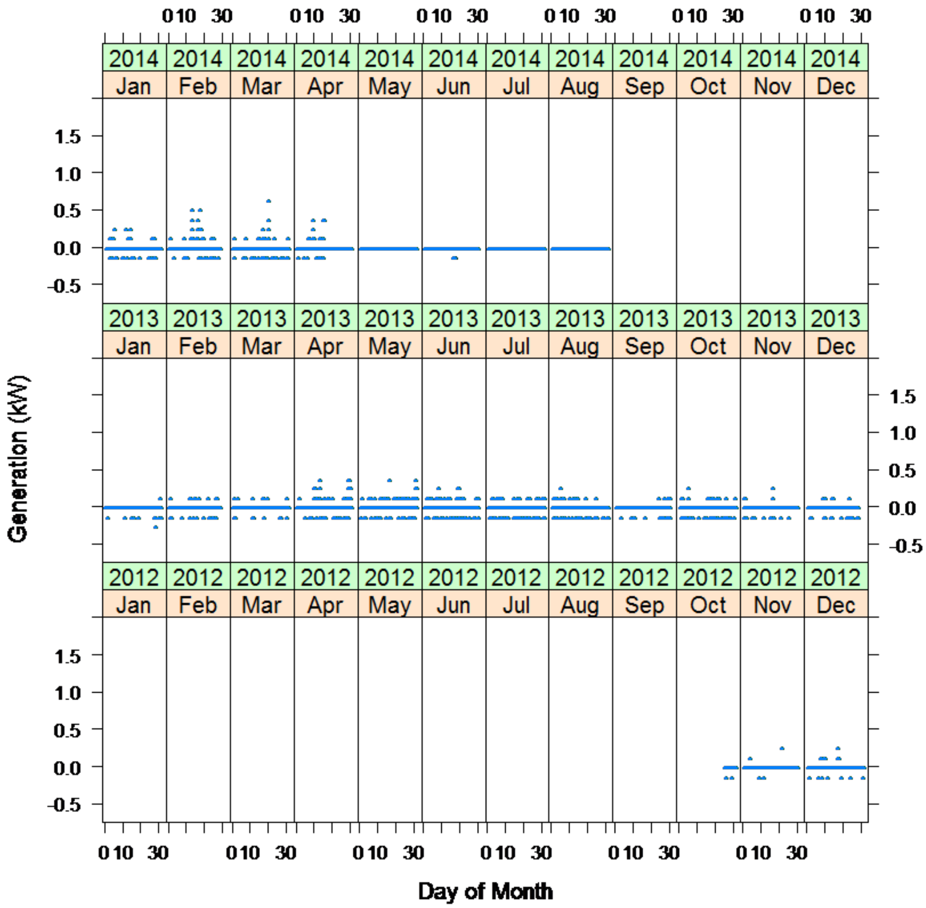


Figure 12.51. Wind Generation Reported to the Project by Lower Valley Energy

The project, of course, mistrusts this data, but the cooperative, when asked, insisted that this data is correct and is all that is available from the monitoring of this asset. The project cannot proceed any further with analysis using this data. No significant generation can be reported. No meaningful correlation to wind speed could be determined. The utility appears to have achieved no monetary benefits from this asset system.

12.10 Conclusions and Lessons Learned

Lower Valley Energy tested eight technologies during the PNWSGD. The project looked at historical and recent energy usage at premises that received various smart grid devices, including AMI, IHDs, and DRUs. A gradual, long-term reduction in average premises energy consumption appeared for many of the groups that were tested. The installation of AMI appears to have reduced energy consumption by about 0.2 kW at premises, but the impact from additional IHDs was probably negligible. Premises that had received both AMI and DRUs reduced their consumption a little more than those that received only the AMI.

The cooperative installed DRUs and controlled about 566 electric water heaters. The performance of this system was inconsistent over the PNWSGD, according to the project's analysis. Based on all the curtailment events that the cooperative had reported that they controlled these DRUs, the project concluded that, on average, each DRU had conserved just over 0.1 kW during the events. Upon looking at the cumulative impacts over time, the project identified several months of peak performance, when each DRU curtailed about 0.47 kW. The reason for the inconsistent performance was not fully determined.

The cooperative compiled yearly reliability indices for each of 16 feeders and submitted these to the project. Analysis was conducted by the project to determine whether the features of the recently installed AMI and DRU systems helped the cooperative improve its service reliability. Advanced meters quickly alert the cooperative to outages. And the DRUs included under-frequency responses and cold load pickup capabilities that were hypothesized to help the cooperative avoid and recover from outages. The project could not determine a global improvement in system reliability had occurred. In fact, the last two project years may have exhibited elevated SAIFI metrics. The project recommends that the metrics should be calculated and compared monthly with prior months' performance.

Lower Valley Electric periodically reduced the voltage on its East Jackson feeders by what was measured to be about 2%. This was normally done for up to three hours during the morning peak hours. By analyzing distribution power data, the project calculated that the events had reduced the distribution load by about 300 kW, or about 3.4% of the feeder's average load. When the project analyzed the impact of the short voltage reductions at a sample of 24 premises, an *increase* in premises load was found. A similar result was found by the project at Milton-Freewater (Chapter 13) that had also conducted short-term voltage reductions on its feeders. Researchers hope to revisit this analysis to determine if the counterintuitive result is real and meaningful.

The cooperative installed a 600 kVAr SVC at its remote Hoback substation to mitigate power factor issues on this long, rural feeder line. Power factors were improved over time, and the installation is estimated by the project to have reduced feeder line losses by 13 to 30%.

The cooperative installed a 125 kW, 250 kWh battery energy storage system at its remote Bondurant, Wyoming site. A discrepancy was found between the system's reported capacity and the power data received from the utility by the project. The utility successfully moved electric load from HLH hours to LLH hours. However, the battery system is a net consumer of energy, and the monetary value of system energy losses overcame any benefit the utility might have gleaned from arbitrage of HLH and LLH energies.

Lower Valley Energy also installed and demonstrated a 20 kW PV solar generation system. The system performed well and would be expected to generate about 29 MWh each year. However, solar generation at this location was found to impact average heavy-load hour while infrequently coinciding with the utility's actual monthly peak demand hour. The system helps the utility reduce its purchases of wholesale energy, but it does not help toward reducing its demand charges.

The cooperative installed four 2.5 kW WindTronics wind turbines, but these failed to ever generate significant amounts of energy. The product's vendor experienced financial difficulties during the PNWSGD and their assistance was discontinued.

Among its lessons learned, Lower Valley Energy reported that they should have budgeted more money for integration and project reporting expenses. Generally, their vendors had had difficulty meeting production time deliveries. Some equipment had been damaged during shipment, resulting in unexpected delays. Device integration was particularly challenging between existing systems that used MultiSpeak® (MultiSpeak 2015) and new devices that did not. While the new technologies had made compelling business cases to the utility, one of the vendors had gone into bankruptcy before the product warranty could be exercised.

13.0 City of Milton-Freewater Site Tests

Additional chapter coauthor: T Kain − City of Milton-Freewater

The City of Milton-Freewater is a municipality in northeast Oregon that serves about 7,000 residents. It is proud to be one of the oldest municipal electric utilities in Oregon and has power rates among the lowest in the Pacific Northwest. The city's electric utility is a pioneer in energy conservation and demand-response (DR) programs. For example, its Radio Energy Management System direct DR program began in 1986 and has helped the city keep its electric rates low (City of Milton-Freewater 2014).

The City of Milton-Freewater offered its entire municipality to be used as a Pacific Northwest Smart Grid Demonstration (PNWSGD) project site. The site's electric circuit consists of three substations—Freewater #1, Freewater #2, and Milton—and altogether 13 feeders that are supplied by these three substations. The distribution circuit is radial during normal operations, but the city can move electrical load from any feeder to be supplied by an alternative feeder during maintenance outages and after unplanned outages. The city helped the project track the times when their distribution circuit was in an alternative configuration so that analysis could focus on normal operation. The city gets its electricity from the Bonneville Power Administration (BPA).

Within PNWSGD transactive coordination system, the City of Milton-Freewater is Site 9, which was included within Transmission Zone 11 (NE Oregon). Refer to the transactive coordination system topology (Appendix B). The transactive signals represented the cost and quantity of electricity at the BPA transformer that supplies the entire city. (Some background information about the PNWSGD transactive system was given in Chapter 2.) The site's transactive feedback signal predicted the electric power received at this BPA transformer, and the transactive incentive signal (TIS) predicted the unit cost of the electric energy received from BPA at this point. This virtual point of interconnection is at the top of the Milton-Freewater layout diagram, Figure 13.1.

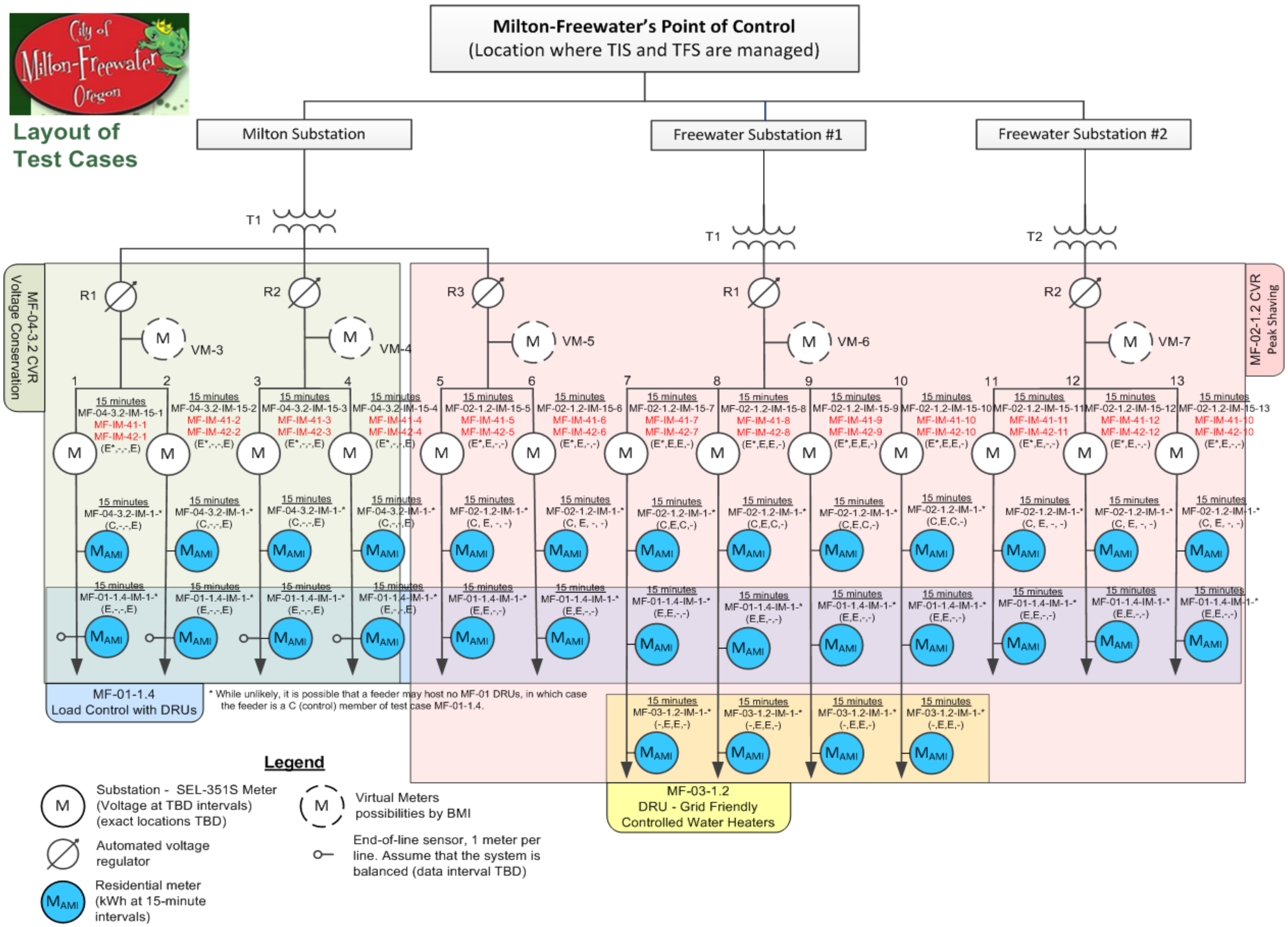


Figure 13.1. Layout of Milton-Freewater Test Populations in Relation to One Another and the City's Distribution Feeders. Premises groups are positioned to show which feeders they are supplied by, not their positions on the feeders.

The city accepted an instantiation of the IBM iCS (Internet-scale Control System) software that initialized basic system functionality and communication within the PNWSGD transactive system. The acceptance of an IBM iCS reference implementation somewhat hastened the establishment of their transactive system site. Additionally, QualtityLogic used a test harness that it had developed to enforce the conformance of the site to the project's reference implementation and its documentation. CVO Electrical Systems, LLC, helped the city establish and configure site functionality and communication.

The magnitude of the site's incentive signal was usually identical to the modeled cost of energy supplied by Transmission Zone 11 in the transactive system. However, the site also implemented the project's BPA demand-charge toolkit function, which (1) monitored and predicted peak load, (2) estimated the cost impact that was to be incurred by a newly predicted system peak, and (3) added this cost impact to the site's TIS during periods of peak demand. The revised incentive signal then caused site assets to curtail load when the incentive signal reflected the additional costs that were being incurred to supply peak demand. The site thereby could reduce its peak-demand costs for the month. At this site, the formula for monetizing peak-demand impacts was based on BPA customer demand rates (Appendix C).

Advanced metering was a component of several of the city's asset systems. The city procured and installed 3600 Landis+Gyr single-phase electric meters, 610 Elster three-phase electric meters, and 2,400 Badger Orion water meter transmitters within its Milton-Freewater service area boundary. All these meters use Aclara's Two-Way Automatic Communication Systems (TWACS®) over power-line carrier and were therefore compatible with the existing systems that the city had previously installed. Some new substation TWACS communication equipment had to be purchased and installed to support the new premises metering.

The 2,400 Badger Orion water meter transmitters were installed at locations where the city was upgrading premises metering. Because the city supplies its residents both electricity and water, the same advanced meter infrastructure could be used to read both electricity and water usage. Efficiency was gained because these transmitters communicate to the premises' electrical meters.

The city installed Aclara disconnect-switch interbase collars (Aclara 2011) on a sample of its single-phase premises meters. The collars provide a convenient means to remotely disconnect and reconnect customers, which may be useful for rental properties, vicious dogs, inaccessible meters, habitually delinquent customers, and in prepaid utility programs. Two hundred eighty-six of these were initially purchased by the city for the project. Because of their success, even more were purchased and installed during the project, and the city plans to install still more of these disconnect collars in the future.

The city installed the following four asset systems in the PNWSGD. The first three were responsive to the PNWSGD transactive coordination system.

- Demand-response units (DRUs) on water heaters and space conditioning equipment (Section 13.2)
- Dynamic distribution voltage management (Section 13.3)
- Voltage-responsive, grid-friendly DRU (Section 13.4)
- (Static) conservation voltage reduction (CVR) (Section 13.5).

The primary purpose of the first three asset systems was to respond to infrequent events. From the NorthWest power system's perspective, asset's system responses mitigate regional issues of those entities that have generated and supplied the power that was used by the city. From the city's perspective, response of system assets reduces the high costs of serving monthly peak demand. As shown in Figure 13.2, the City of Milton-Freewater residential demand peaks in the morning during winters, has similar morning and afternoon peaks during spring and fall, and has a single afternoon peak during summer. This figure represents average weekday power per premises for members of the DRU test group at Milton-Freewater (Section 13.2). Premises consume much more power during winter than during the other seasons.

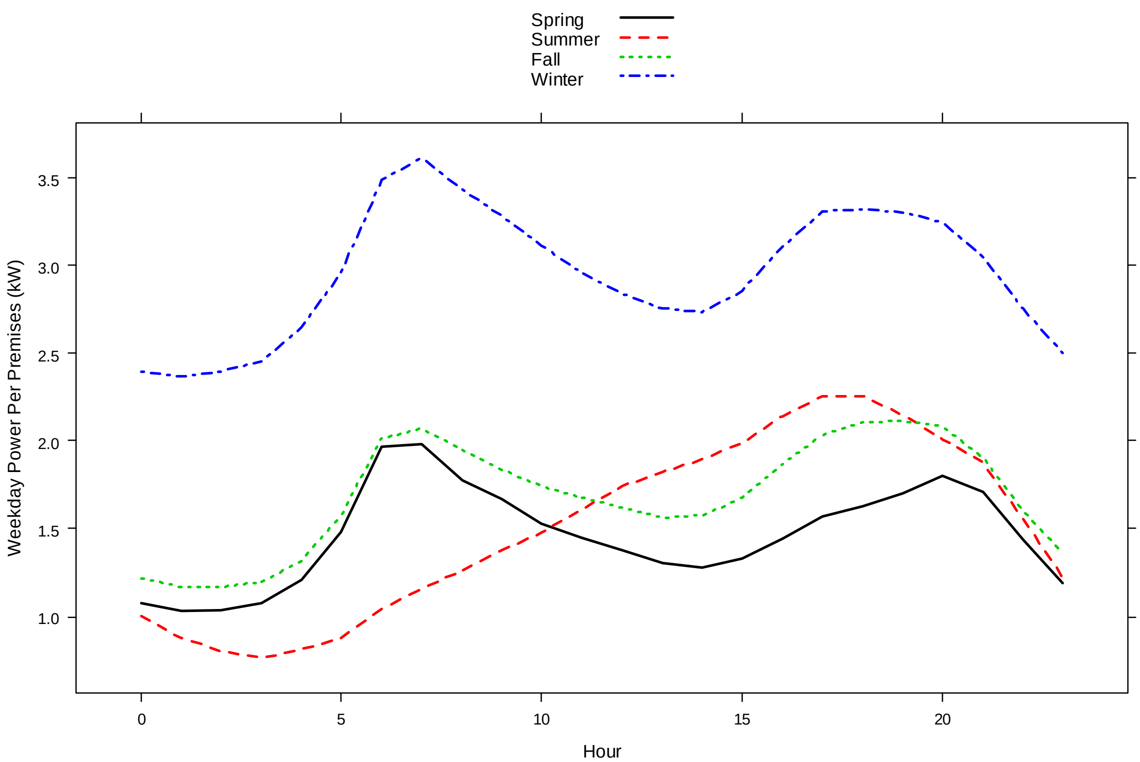


Figure 13.2. Seasonal, Per-Premises Load Shapes for the Homes among the Milton-Freewater DRU Test Groups

The data collection layer of the iCS reference model automatically submitted data to the transactive system, including system management commands, system state, predicted weather variables, predicted total site electric load, the site's versions of the TIS and transactive feedback signal, and the advisory control signals and predicted impacts (changes in load) that were exchanged with each of the three responsive asset systems.

Other data (i.e., non-transactive data) were submitted by the city to the PNWSGD secure file transfer protocol site. These data included 15-minute-interval distribution meter data, premises data, and the actual engagement statuses of the asset systems. Sparse data was sometimes submitted directly from the city to data collection team members at Battelle.

The analysis of the two asset systems that managed distribution voltage anticipated an impact at the level of the distribution feeders. Figure 13.3 summarizes the three groupings of summed feeder power that were useful in analyzing distribution-level impacts. The groupings of feeders correspond to the groupings that are shown in the layout diagram, Figure 13.1. Feeders 1–4 are where the static version of CVR was exercised (see Section 13.5), and the dynamic version of voltage management (see Section 13.3) affected Feeders 5–13. The sum power on Feeders 7–10 was useful as the project attempted to isolate the impacts of voltage-responsive water heaters on these feeders (see Section 13.4) from the more passive impacts of voltage management on the larger set of Feeders 5–13.

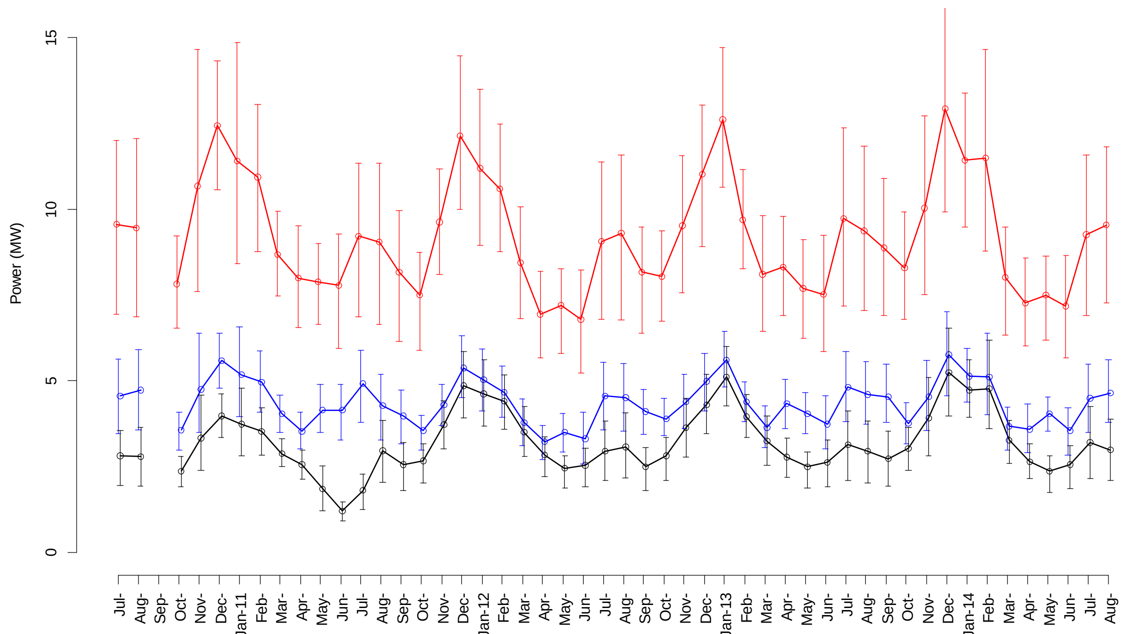


Figure 13.3. Averaged Monthly Power for Summed Feeders 1–4 (black), 5–13 (red), and 7–10 (blue). The bars represent standard deviations of the monthly data sets.

Groupings of residential meters were used to analyze impacts of the various Milton-Freewater asset systems at the premises level. The premises power was averaged for the members of each of these groups at a data interval of 15 minutes. The most important premises groupings are shown in Figure 13.1. More detail about the test and baseline groupings will be provided in the detailed discussion of each asset system.

13.1 Transactive Demand-Charges Function

The City of Milton-Freewater has long used DR programs to reduce its exposure to demand charges. Should the demand exceed a threshold value, BPA charges the city an elevated demand rate that is based on the difference between its total demand during its peak, heavy-load hour each month and its average load during all the month's heavy-load hours. So the challenge is to observe demand, anticipate peak hours, and curtail load during these hours. During 2013, the city exceeded its demand threshold at least once during nine of the 12 calendar months.

The city's staff, after years of experience, possesses keen abilities to accurately predict these peak days and hours without automation. An automated system must do at least as well as these experienced people if it is to be adopted.

Working with the PNWSGD, the city allowed its incentive signal to be affected by an automated BPA demand-charges function. This function monitored the predicted total demand at Milton-Freewater and increased the incentive signal magnitude as new monthly peak demands occurred. Had this function worked as intended, the DRUs and other of the city's asset systems would have become automatically engaged by the elevated incentive signal. Unfortunately, the demand-charges function did not accurately predict the actual system demand magnitude and the timing of peak hours. The load that was predicted by the transactive system and actual SCADA (supervisory control and data acquisition) measurements were not tightly coupled during the project, which coupling is necessary if predicted load is to be corrected and improved over time. Therefore, while the project's approach to automation of responses during utility peak hours may be valid, the project's automation was not especially effective at engaging the DRUs at the correct times.

The transactive demand-charges function initially tried to reproduce the entire calculation used by BPA to determine peak-demand charges for its customers (BPA 2011, Section 5.3). The BPA charges are presently determined after the fact at the end of each calendar month. Some, but not all, the calculation's inputs can be known at the beginning of each month. This method proved too cumbersome to apply well, and there was resistance from utility sites to provide all the inputs that were needed to predict a reasonable demand threshold power level. In Milton-Freewater's case, the demand-charges function never achieved a workable configuration. The function output predicted that demand charges were being incurred only for a few minutes in May 2013. What proved more useful was for knowledgeable utility staff to predict a reasonable demand threshold based on their intuition and experience. The alternative approach was simple and more successful.

The demand-charges function also failed to reasonably predict a useful time interval around the times at which new demand thresholds were likely to become established. Therefore, the function made the incentive signal spiky, and it was not interpreted well by the assets that could have responded to the incentive signal. Perhaps statistical likelihood would be useful to meaningfully disincentivize load during peak hours.

Fortunately, the city retained the ability to manually engage or disengage this system, as needed, even if doing so was contrary to the advice from the transactive system.

13.2 Load Control with DRUs

The City of Milton-Freewater purchased 800 Aclara DRUs (Aclara 2012) and installed them at residences and a few commercial buildings throughout their distribution circuits. These devices control either conventional 240 volts alternating current electric tank water heaters or space conditioning units. When they receive a command to curtail load via the TWACS power-line carrier communication system, they open a switch to their electrical load and curtail or defer its energy consumption. While advanced premises metering might not be required at locations that host these DR units, premises metering is useful to confirm the impacts of load curtailments.

The main purpose for which the city installed the DRUs was to reduce demand charges that it incurs in its monthly bill from the BPA. The Aclara DRU system provides some software assistance and automation based on the city's demand metering, and this system engages subpopulations of the entire DRU population to keep system load under a desired threshold. The events initiated independently by Milton-Freewater staff (i.e., ones that were not advised by the transactive system) were found to include the control of subpopulations and feedback—features provided by vendor software. Automated responses to the project's TISs, however, did not include these features and simply controlled the entire block of DRUs. Regrettably, a vendor software error was found to have prevented many of the project's transactive system events from having been acted upon prior to about July 2014.

The city allowed customers who possessed DRUs to be subjected to no more than five curtailment events in any calendar month. The city prefers that the curtailment events not persist more than four hours, beyond which duration its customers become inconvenienced.

The estimated annualized DRU system costs are shown in Table 13.1. These cost estimates are for the entire system that would be needed to operate the DRUs. The city provided input to the project concerning how it perceives these costs. A major cost component is the 800 DRUs. The system also includes a fraction of the advanced premises meters that are colocated with the DRUs and a fraction of the cost of automating the system and connecting it to the transactive system. Lesser component costs included installation labor, operations and maintenance, and requisite software. These lesser costs were included with the costs of the listed major equipment. These costs have been annualized in the sense that we assume all equipment will be perpetually maintained and replaced after its expected lifetime.

Table 13.1. Annualized Costs of the Milton-Freewater System of 800 DRUs

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
AMI Meter System			154.7
• Residential and Commercial	33	270.3	90.0
• Water	100	64.7	64.7
DRUs	100	100.5	100.5
Transactive Node	33	9.8	3.2
Programming to Link SCADA	100	1.9	1.9
Total Annualized Asset Cost			**$260.4K**

AMI = advanced meter infrastructure

13.2.1 Characterization of DRU System Responses

The DRUs were curtailed 200 times from August 2012 through August 2014, and these event periods have been summarized in Figure 13.4. In this figure, the vertical bars represent the durations of the events (vertical distance) on the days that the events occurred (horizontal axis).

The DR vendor provided a feature that engaged and released the DRU curtailments based on feedback of total city demand. Series of multiple, short-lived events were combined by the project during analysis and were treated like a single event if they were separated by less than 1 hour of disengagement.

The multiple short events might pose a problem for analysis. First, unless the transition times are very accurate, the impacts may be applied to the wrong periods. Even if the event times are accurate, the transition times did not always align with the 15-minute measurement intervals that were employed by Milton-Freewater. Therefore, the impacts will tend to be understated.

Additionally, the project confirmed that the remaining curtailment events that did not employ the vendor feature described above were often ignored prior to summer 2014, when a software error was found and corrected by the DR vendor. This is unfortunate and will cause the project to further understate the impacts from the DRU curtailments.

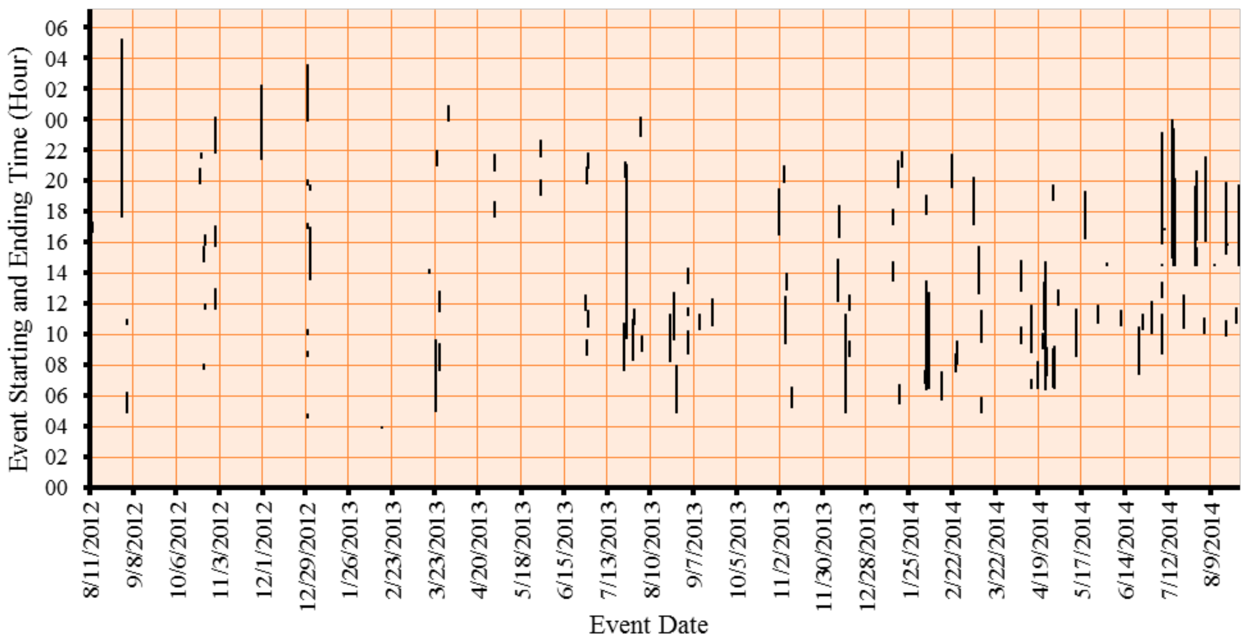


Figure 13.4. Days and Durations of Milton-Freewater DRU System Events during the Term of the PNWSGD Project

DRU curtailment periods happened to occur during the utility's actual monthly peak hours only one month during the project. The DRU curtailment times were found to have occurred 84% of the time during BPA heavy-load hours. The DRU curtailment times were found to have occurred 84% of the time during BPA heavy-load hours.

The project had requested but not insisted that DRU events be conducted at the times advised by the project's transactive system. In fact, the DRUs were found to have been curtailed for 71% of the time periods that had been advised by the transactive system. Sixty-eight percent of the time that DRU events were conducted, the events were also being advised by the transactive system. None of the advised transactive event periods were determined to have actually coincided with one of the city's monthly peak hours.

Figure 13.5 summarizes the months when the DRU curtailment events that were shown in Figure 13.4 occurred. Events were not counted if they followed the preceding curtailment by less than 1 hour. The fraction of August curtailments is overstated because there were three Augusts during the project, while there were only two instances of the other 11 months. The curtailments were fairly evenly distributed by month, but the system might be employed more frequently during winter and summer peaks.

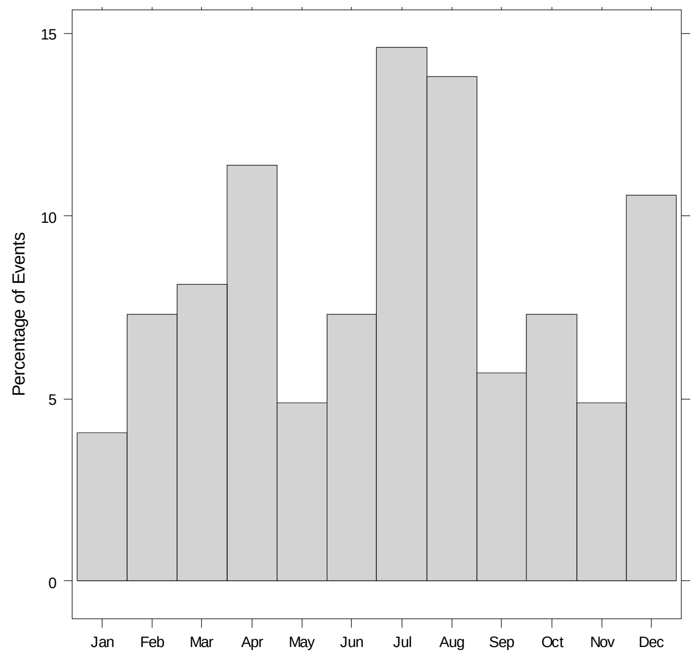


Figure 13.5. Months in which DRU Events were Called by Milton-Freewater. This histogram excludes multiple consecutive events that were separated by less than 1 hour.

Figure 13.6 summarizes the hours (local Pacific Time) that the DRU events started. The transactive system might have advised curtailment of the DRUs during any hour based on regional transmission and generation conditions, but the city benefited most directly from curtailments that coincide with the city's morning and afternoon heavy-load and peak hours.

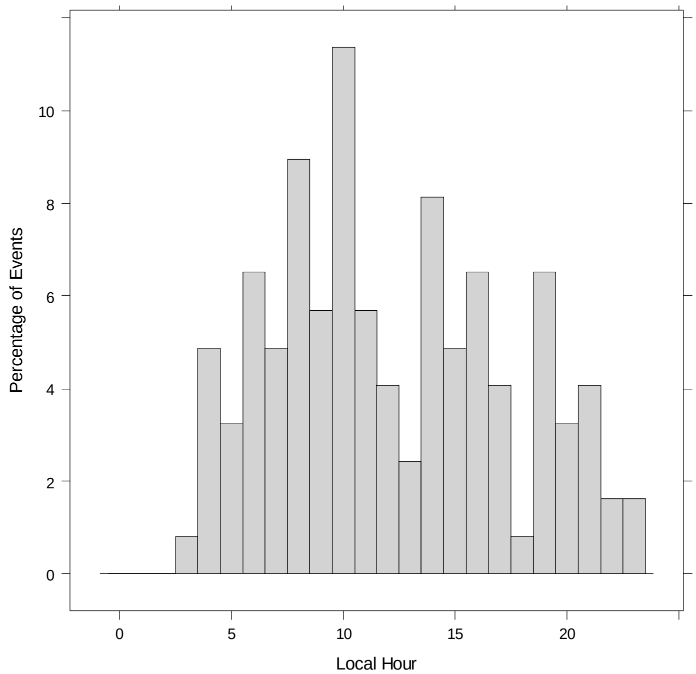


Figure 13.6. Local Starting Hours (Pacific Time) when DRU Events were Called by Milton-Freewater. This histogram excludes consecutive events that were separated by less than 1 hour.

Review of premises power data from during the curtailment events indicates that many events from late in the project exhibit the expected power reduction during events and the even-more-evident rebound afterward. The effect of the rebound is often more pronounced than the reduction and should be a reliable marker in time. However, the data from some curtailments appear to be shifted with respect to the event indicators that were given to the project by Milton-Freewater. Figure 13.7 is one such instance when it appears, based on the rebound impact marker, that the event markers are shifted 1 hour earlier than the actual event. Figure 13.8 suggests that the event might have been terminated earlier than was indicated. If the event indicators are in error, then the event and rebound impacts will be somewhat miscalculated.

It has already been stated that, because of a vendor software error, many curtailments from early in the project period might have never been acted upon. Neither curtailment reductions nor rebound increases were evident by inspection in early (i.e., prior to July 2014) DRU event data.

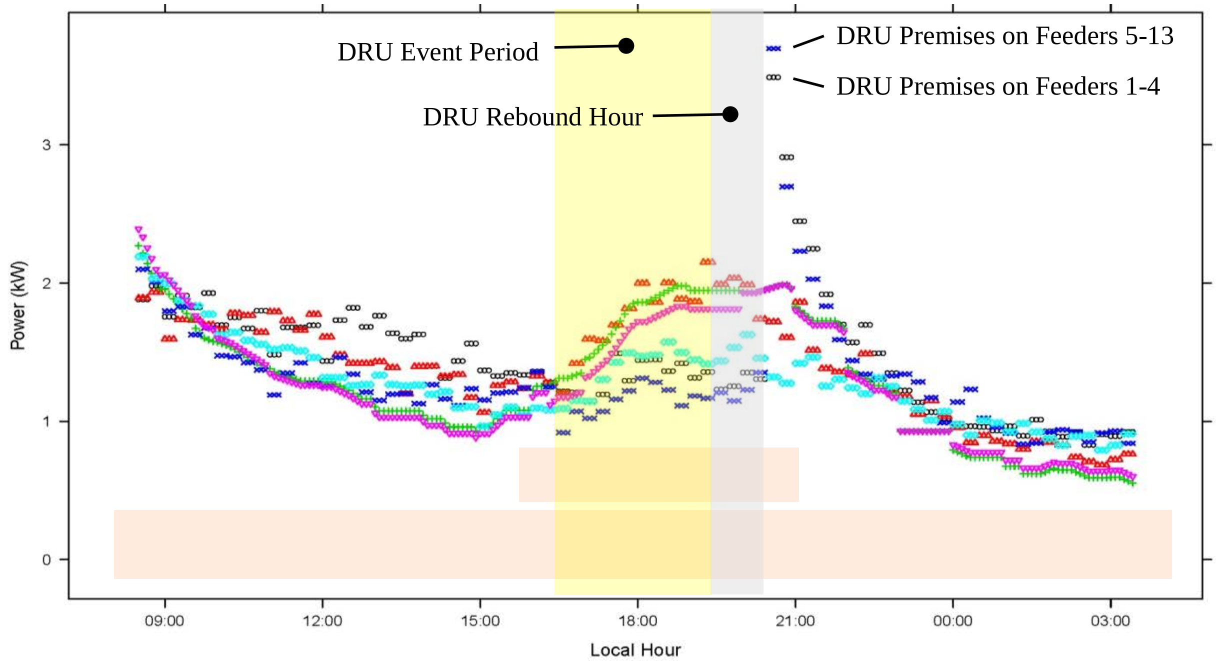


Figure 13.7. DRU Curtailment Event from November 1, 2013. The average DRU premises powers on Feeders 5–13 (blue "x"s) and on Feeders 1–4 (black circles) exhibit rebound effects, but they occur more than 1 hour after the event period (yellow shading) was reported to have ended and after the rebound hour (gray shading). The other time series are from various Milton-Freewater premises that did not have DRUs.

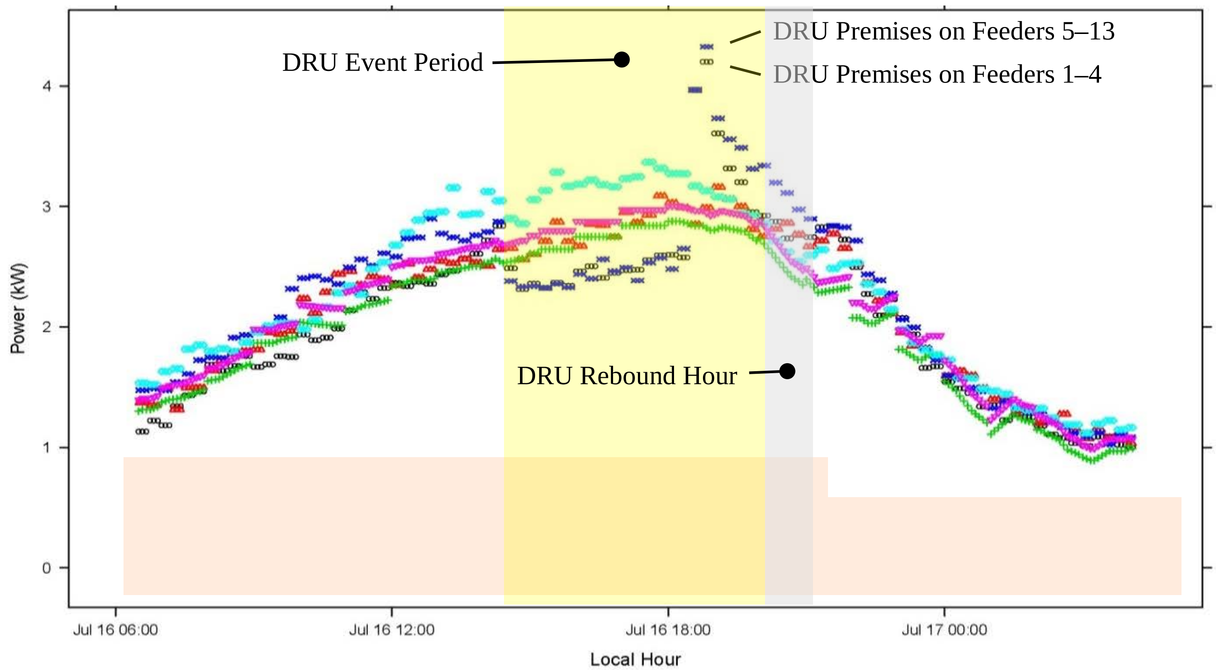


Figure 13.8. DRU Curtailment Event from July 16, 2014. In this example, the rebound effect on average premises powers from premises on Feeders 5–13 (blue "x"s) and Feeders 1–4 (black circles) occurred prior to the reported conclusion of the event period (yellow shading) and rebound hour (gray shading). The other time series are from various Milton-Freewater premises that did not have DRUs.

Figure 13.9 shows a DRU curtailment event from July 15, 2014 that was managed by vendor software using feedback from the city's entire electric power load. The event period is shown by yellow shading and the rebound hour is shown by gray shading. The vendor's software engaged and disengaged the DRUs multiple times during the event period, but the project reported and analyzed this period as a single event. Some degree of reduction and increase seems to accompany the curtailment and rebound periods. The rebound peaks for these events are not as great as for events that were simply turned on and then off. The project has some concerns whether the data and event indicators will accurately align for such active management with rapid transitions from the DRUs being engaged and not. If the alignment of DRU actions and event indicators is inaccurate, the impacts from curtailment and rebound will be miscalculated once again.

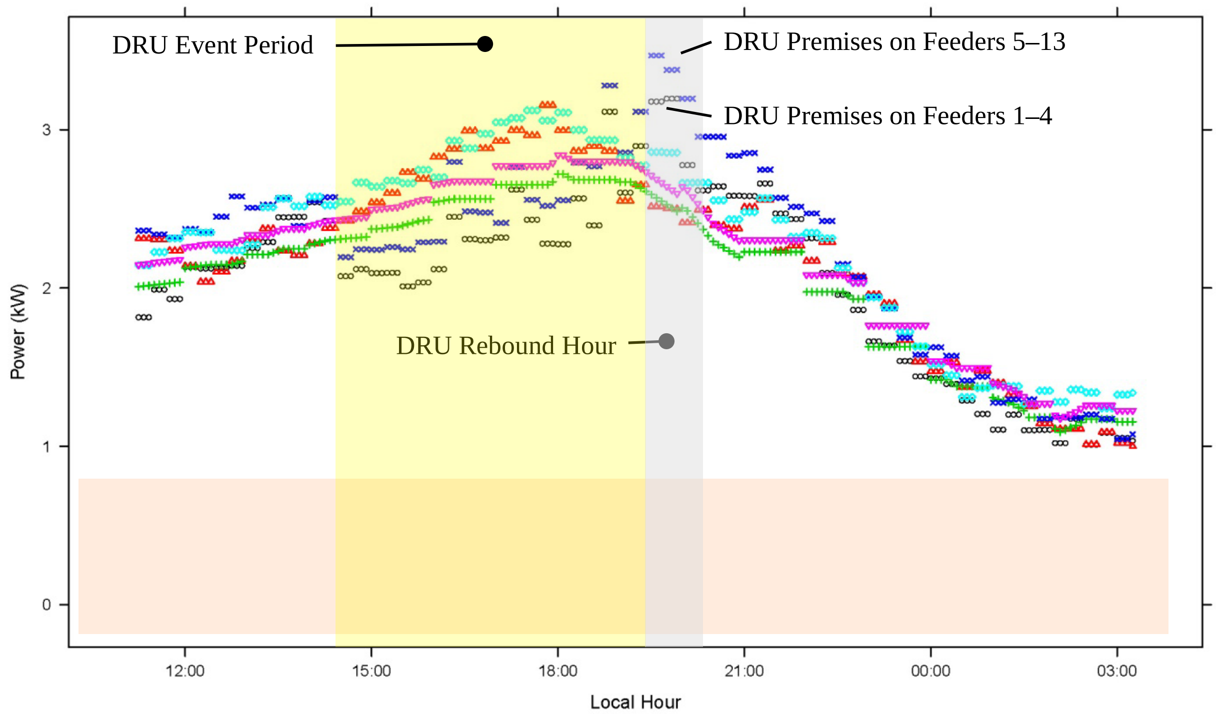


Figure 13.9. DRU Curtailment Event from July 15, 2014. This is an example of multiple events separated by less than one hour using a software control feature provided by the vendor. The averaged DRU premises loads supplied by Feeders 5–13 (blue "x"s) and Feeders 1–4 (black circles) were affected by the curtailment period (yellow shading) and rebound hour (gray shading), but the rebound effect was less pronounced. The other time series are from various Milton-Freewater premises that did not have DRUs.

The Milton-Freewater site configured a transactive function to advise the city when the DRUs should be curtailed. Predicted events further modeled and predicted the total change in city load if the DRUs were to become curtailed by the transactive system. The predicted curtailment impact from 800 water heaters should be 160–640 kW, depending on the time of day the event occurred. The transactive function used by the project to model water heaters was not yet sophisticated enough to predict the magnitude and duration of the rebound effect after the curtailment event is halted.

Altogether 95 transactive events were requested by the transactive system from the Milton-Freewater DRU system from December 2012 through August 2014. Figure 13.10 shows the distribution of these events by day of week, and Figure 13.11 shows how the events' starting times were distributed by local (Pacific Time) hour. Most of the events occurred in midmorning when electricity demand is often great at Milton-Freewater. The average advised transactive event was 1 hour 43 minutes long. The median was 1 hour 5 minutes. The durations ranged from 5 minutes to over 11 hours, but the extremes probably occurred while the project struggled to correctly configure the automation to respond to the utilities' preferences.

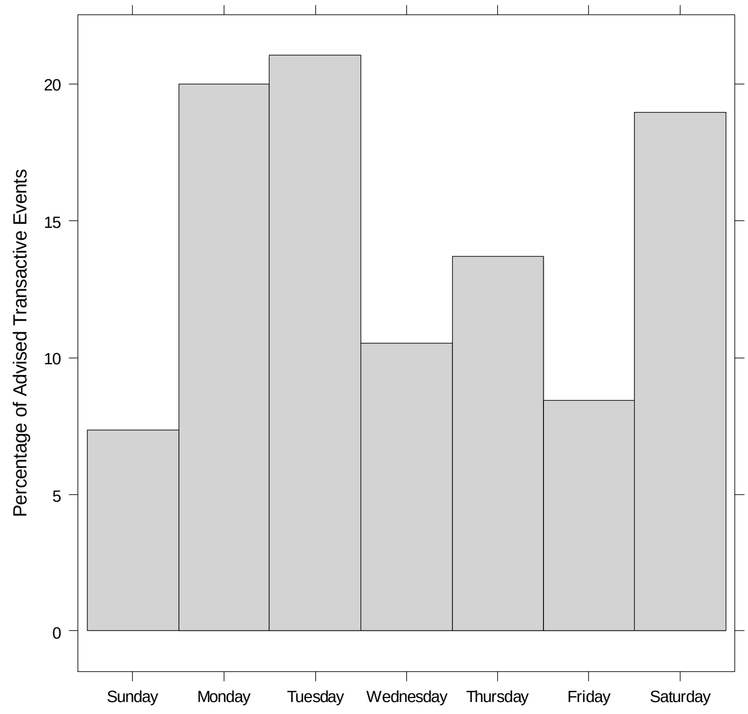


Figure 13.10. Advised Transactive DRU Events by Day of Week

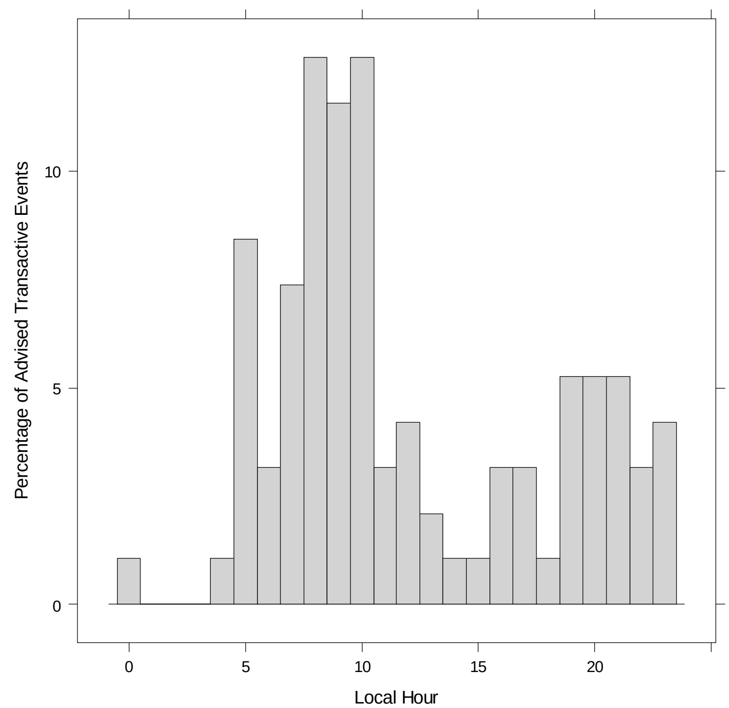


Figure 13.11. Advised Transactive DRU Events by Hour

13.2.2 DRU System Performance

Analysts attempted to verify the impacts from the DRUs by comparing a set of residential premises equipped with DRUs against a similar set of residential premises that did not have DRUs and had been normalized to have similar monthly average power and standard deviation as the experimental group. The resulting baseline emulates average premises power for premises that have no DRU. This chapter will refer to this baseline as the *control baseline*. It will be compared against average DRU premises power to infer the impacts of DRU curtailments.

See the City of Milton-Freewater Layout Diagram, Figure 13.1. Comparisons were conducted separately for Feeders 1–4, which were potentially affected by the city's CVR tests (Section 13.5), and Feeders 5–13, which were potentially affected by the city's dynamic voltage management (Section 13.3). These two sets of feeders experienced different experimental voltage management strategies that could potentially confound observations of DRU performance.

Another pair of baselines was constructed, based on linear regression models of premises having DRUs. The resulting baseline again emulates what the average premises power would have been if the premises had not had DRUs. These baselines will be called *modeled baselines*. Separate modeled baselines were created for premises on Feeders 1–4 and Feeders 5–13 because voltage was being managed differently in those two sets of feeders. Analysts used R software (R Core Team 2014) to conduct the linear regression and to create the modeled baselines. Average premises power was modeled as a function of ambient temperature, separately assessed by month, day of week, and hour of day. The event statuses concerning voltage management in Feeders 1–4 and 5–13 were also used by the regression to help avoid the potentially confounding impacts of the voltage management in those two feeder sets.

Curtailment of an electric water heater in the Pacific Northwest could defer consumption of up to 0.8 kW, on average, during peak hours. Much of the curtailed energy is expected to be consumed after the water heaters are returned to normal operation as the water heaters heat cold water that entered the bottom of the tank during the curtailment period. The maximum benefit for this system of 800 DRUs would therefore be about $54,000 per year, presuming the city could correctly predict and respond to every monthly peak hour for which it will incur demand charges.[1]

The demonstration could confirm only a fraction of the theoretically achievable benefit using its analysis methods and the data that it collected. Actual curtailment events and advised transactive events largely failed to identify the monthly hours on which demand charges were, in fact, incurred. This means that one of the major available monetary benefits was not, in fact, earned by the city. The demonstrated impacts were also reduced by asset installation and implementation, in that many of the curtailments were not acted upon early in the demonstration period due to a software error. Finally, the demonstrated impacts were reduced because the analysis results were affected by both the actual asset performance and the performance of premises metering and data collection processes.

[1] This maximum benefit assumes the following: (1) demand charges are presently incurred during nine project months each year, (2) there are 800 active water heaters, (3) each water heater defers 0.8 kW, on average, while it is being curtailed, (4) the average demand rate is $9.32 / kW, and (5) the change in peak demand from the DRU system is not large enough to completely avoid demand charges.

Residential premises metering allowed the project to compile 15-minute aggregated customer power data. The city marked these data according to the test assets that they possessed and the feeder on which the premises resided. The project aggregated the premises data according to asset ownership and separate groups for Feeders 1–4 and 5–13. The city also provided the project an event indicator when the DRUs were, according to their records, curtailed and released.

The project first reviewed the performance of the DRU's performance during the curtailment periods. The analysis was separately conducted for the two feeder groups and by baseline type. Monthly results from both the controlled and modeled baseline approaches suggest that the system performance improved and became more consistent over time during the project. This can be seen explicitly in the following plots of *cumulative* energy change and customer hours. Results for Feeders 5−13 are shown below. Similar analysis could be done for circuits 1–4.

To understand these plots, first consider Table 13.2, which shows a few representative rows out of the 185 event records contributing to this analysis.

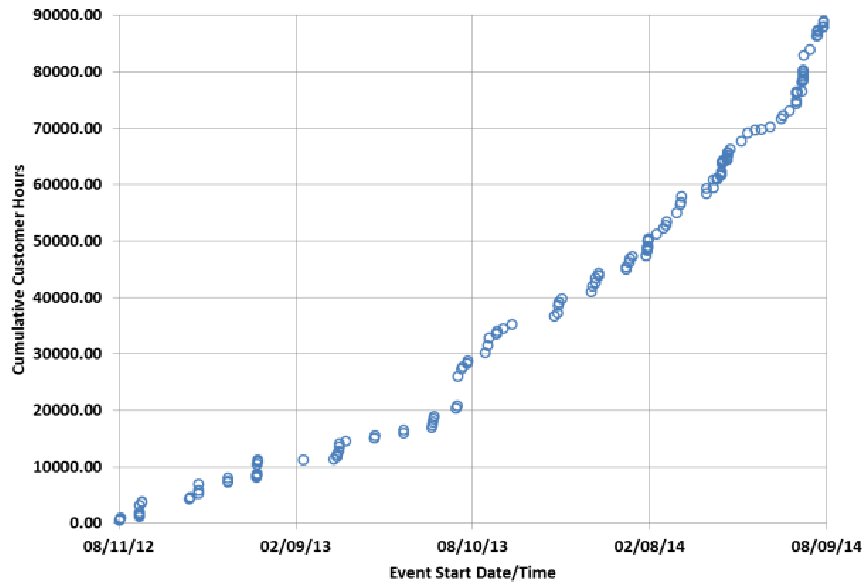
Table 13.2. Representative Rows from a Table for Accumulating Customer Hours and Total Energy Impact by Event and Cumulatively

Event Index	Event Start Date and Time	Event Duration (Hours)	Average Number of Premises	Customer Hours[(a)] (Hours)	Cumulative Customer Hours (Hours)	Event Energy[(b)] (kWh)	Total Cumulative Energy[(b)] (kWh)
1	8/11/2012 4:55	1.33	403.8	538.4	538.4	58.0	58.0
2	8/11/2012 22:40	0.67	404.0	269.3	807.8	21.6	79.6
3	8/12/2012 16:40	0.67	388.0	258.7	1066.4	40.1	119.7
4	8/31/2012 17:40	0.33	403.3	134.4	1200.8	29.7	149.4
…	…	…	…	…	…	…	…
185	8/11/2014 14:30	0.08	468.0	39.0	89055.9	−4.6	−5486.9

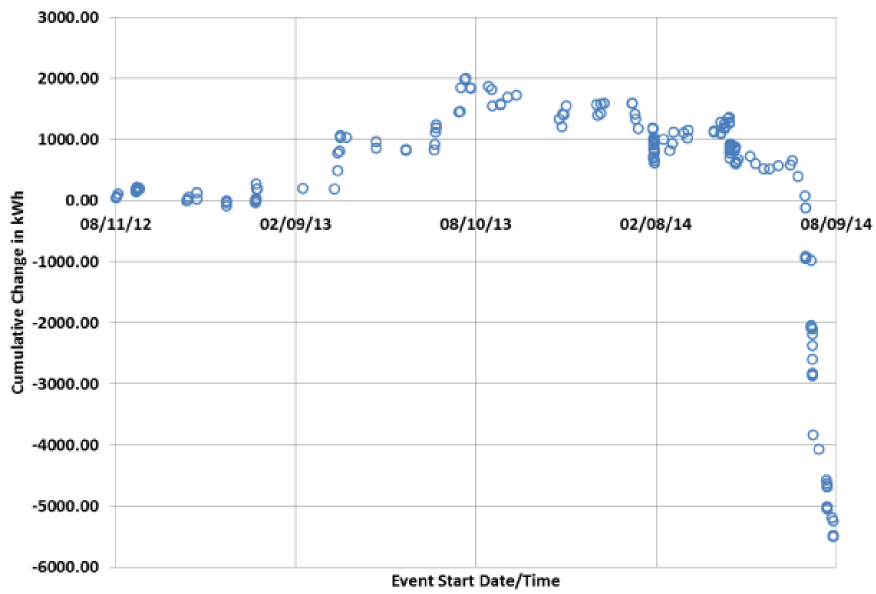
(a) Customer hours were calculated as the product of event duration and average number of premises.

(b) Positive energy values in these columns mean that the DRUs were analyzed to have *increased* energy consumption, as was the case for the first events that are shown here.

The next figure shows two of the columns from the above table. Plots of cumulative customer hours and total cumulative change in energy versus the events' starting times are shown in Figure 13.12a and Figure 13.12b, respectively. The cumulative customer hours show a steady increase as the DRUs were exercised during the project term. The accumulation of customer hours accelerated some over time. However, the cumulative energy benefit was random, even harmful, until late in the project, according to the project's analysis methods and data. A consistent energy benefit was illusive until late summer 2014.



(a) Cumulative Customer Hours



(b) Total Cumulative Change in Energy

Figure 13.12. Cumulative Sums over Time of (a) Customer Hours and (b) Total Analyzed Change in Energy during Event for the 185 Events in this Analysis

Figure 13.13 is a very instructive that combines the cumulative customer hours and cumulative energy impacts that were shown in Figure 13.12. The plot shows DRUs providing little or no reduction in energy in the beginning periods of the project, with gradual improvement, presumably as problems are resolved, and finally steady performance. The slope of the red line toward the end of the project is about 0.27 kW per customer, meaning that each DRU was reducing its owner's electric load by about 0.27 kW during the project's last events.

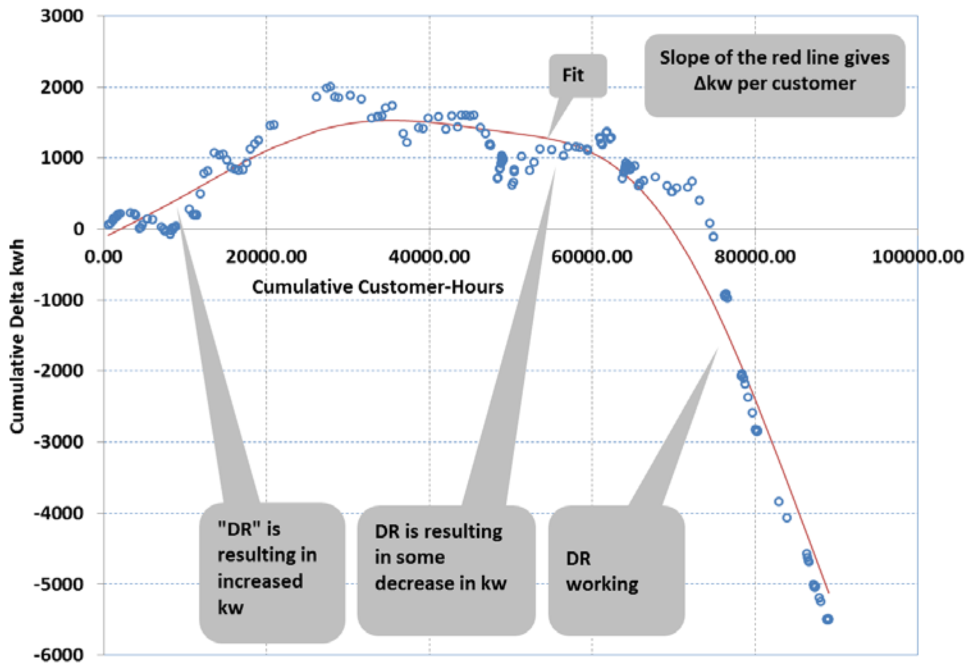


Figure 13.13. Cumulative Energy Impact versus. Cumulative Customer Hours for the Milton-Freewater DRUs during the Term of the PNWSGD

Figure 13.14 shows many of the same observations, but a statistical impact on average premises power during DRU events is shown for each project month. The monthly results were predominantly reductions in power after the first half or so of the project term. The entire figure represents averaged changes in power per premises during events upon comparing with modeled baselines. The impact is defined as the average DRU premises power consumption during the months' events minus the averages from the corresponding baselines. The blue markers are results for Feeders 1–4, and the dashed black markers are for Feeders 5–13. The heavier vertical bars approximate standard error and the longer bars approximate 95% confidence intervals for results from the given months.

The confidence intervals correspond to statistical confidence in the calculated average impact, based on a Student's t-test. The intervals are a little too optimistically stated because they presume independent samples, which is not fully true. The standard deviations of the differences are much larger than the intervals shown for the averaged results. The project was unable to determine why results in November 2012 and June 2013 showed large *increases* in power, which appear to have been outliers among the other results.

The results at the far right-hand side of Figure 13.14 are for *all* curtailment periods during the project, as calculated using the modeled baselines. The overall averaged results are reductions per DRU premises of 110 ± 10 W for Feeders 1–4 and 100 ± 10 W for Feeders 5–13 during the curtailment periods. The agreement between the results for the two feeder sets is strong.

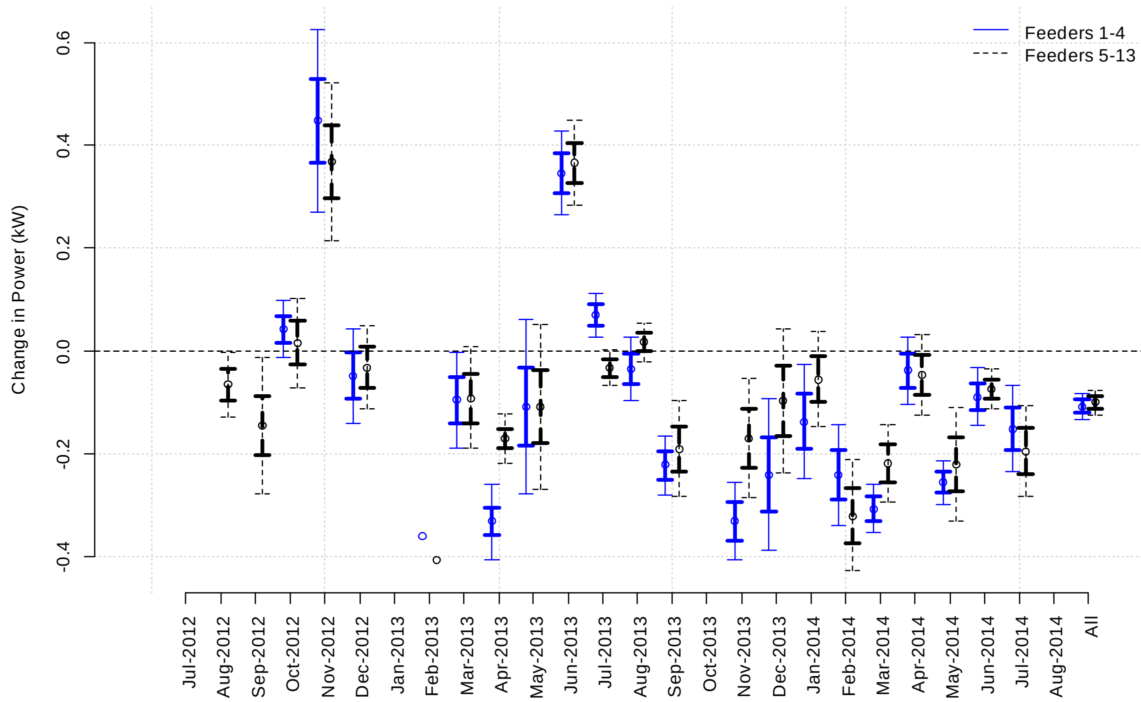


Figure 13.14. Event Statistics by Project Month Based on the Modeled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

A similar analysis was conducted concerning impacts during DRU curtailments using the controlled baselines. The monthly summaries are shown in Figure 13.15; however, the reader should refer back to the discussion from Figure 13.14 concerning the interpretation of the diagram, which will not be repeated.

Again, there appears to be a trend toward improvement (i.e., more power reduction) and consistency over the period of the demonstration. The comparison of the populations was affected by the variability in both the test and normalized control populations. The method proved resilient against pervasive data issues that sometimes fooled the modeled-baseline approach.

The largest *positive* results occurred in the Feeder 5–13 test population for months March 2013 and June 2013. The results in the last two demonstration months, July and August 2014, showed convincing reduction in premises power during the DRU curtailments. Overall, the comparison-baseline approach estimates the per-premises reductions to be 110 ± 10 W for Feeders 1–4 and 60 ± 10 W for Feeders 5–13.

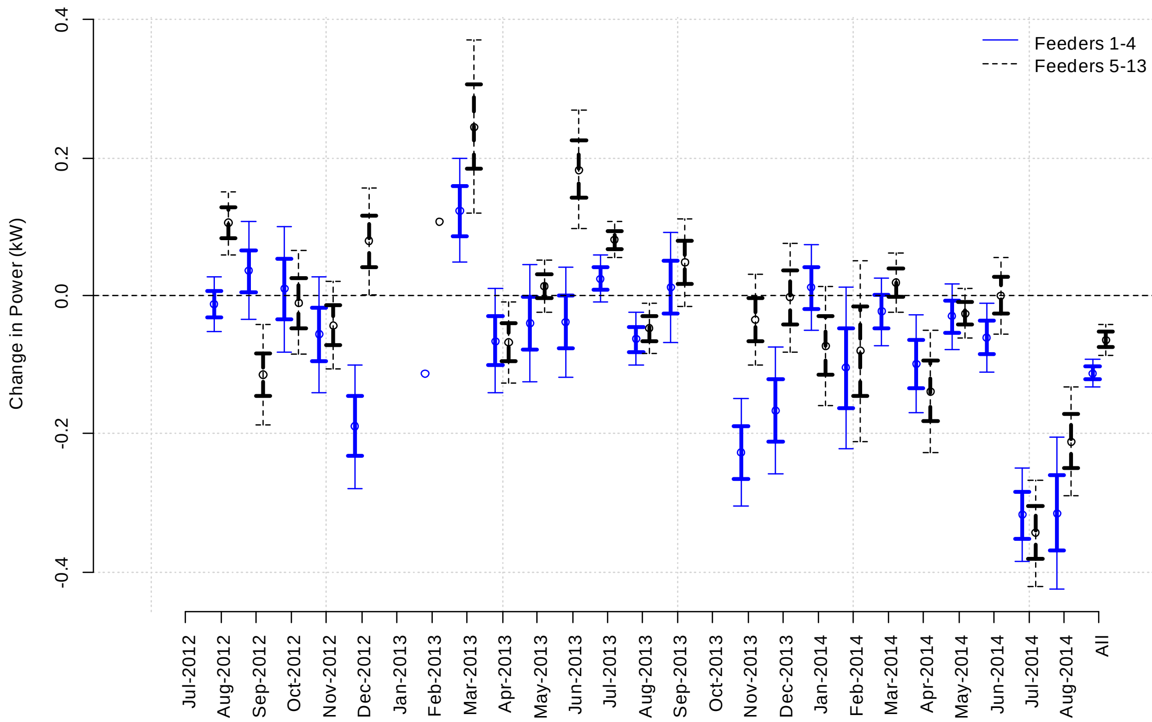


Figure 13.15. Event Statistics by Project Month Based on the Controlled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

The best single estimate of the confirmed per-premises reduction in power during DRU curtailments initiated by the project is therefore a reduction of 100 ± 10 W. Here the variability has been stated as the standard deviation of the results from the two methods. This is less than one-half of the reduction that should be expected according to typical diurnal power consumption by tank electric water heaters. This estimate would have been greater had the demonstrated system performance early in the project matched that at the end.

The project next looked at the rebound impact, which will be defined as the average change in premises power during the hour that immediately followed the conclusion of any DRU curtailment. The month-by-month variability of the impact from the modeled-baseline approach is large, as shown in Figure 13.16. A reason for the increased uncertainty is that data is limited to a single hour per event. No clear pattern in time may be discerned in this figure as the project term progresses. However, based on all project data and using the modeled baselines, the average power increased 40 ± 20 W and 60 ± 20 W, on average, during the rebound hours for Feeders 1–4 and Feeders 5–13, respectively.

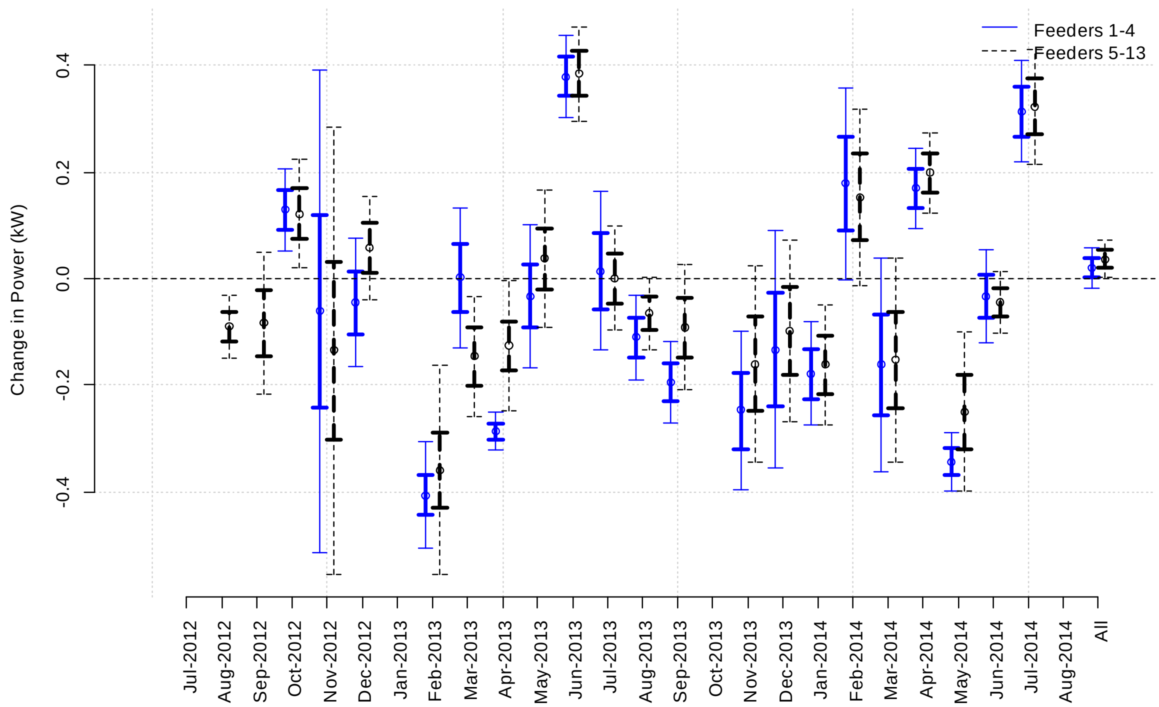


Figure 13.16. Rebound-Hour Statistics by Project Month Based on the Modeled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

Using the controlled baselines, the rebound-hour impact may be estimated as an increase per premises of 70 ± 10 W and 110 ± 10 W for Feeders 1–4 and Feeders 5–13 during the hours following DRU curtailments (Figure 13.17). Using this controlled baseline, we observe a trend toward greater and more consistent rebound impacts toward the end of the project.

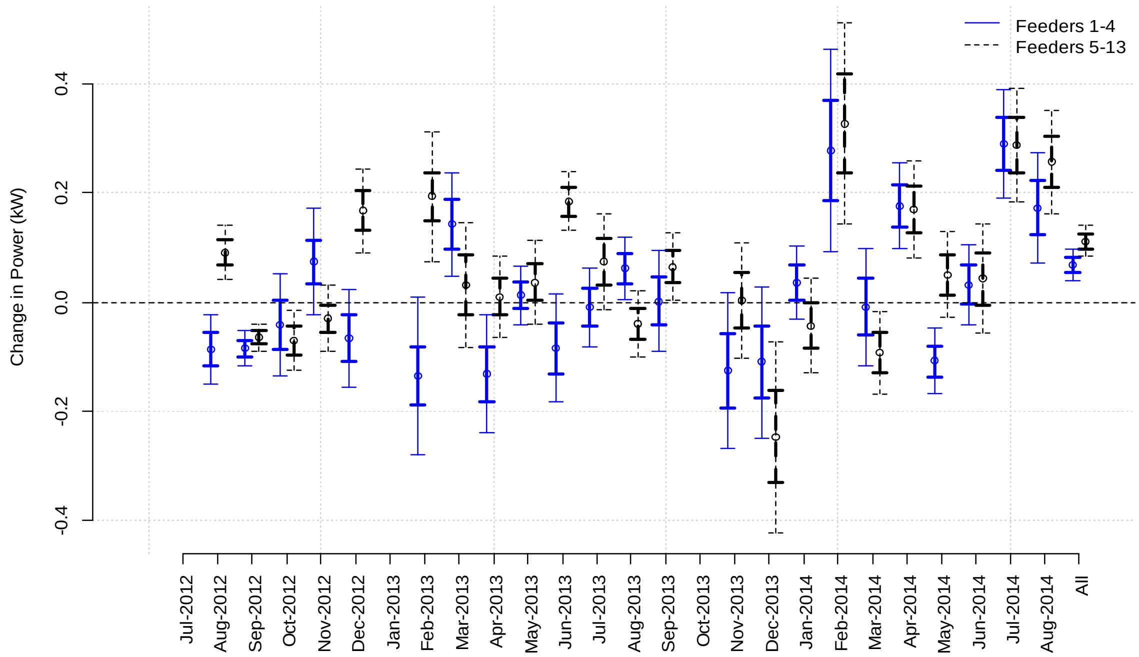


Figure 13.17. Rebound-Hour Statistics by Project Month Based on the Controlled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

The modeled baselines yielded smaller, more conservative estimates of the rebound impact than did the controlled baselines. Upon averaging the results from both baselines and for both sets of feeders, the project reports an average increase of power per premises of 70 ± 30 W during rebound hours. Again, the variability used here is the standard deviation from the results of using the two baseline types. This result is probably conservative. The deferred energy demands from the curtailment of water heaters may result in short-term peaks like those evident in Figure 13.7 and Figure 13.8 when the water heaters are released from curtailment. The spike may be even greater than the averaged magnitude that is being reported here for an entire hour following DRU curtailments.

Next, the project evaluated the entire days on which DRU curtailments had occurred. Upon reviewing results from using the modeled baselines (Figure 13.18), a small average reduction might be reportable for Feeders 1–4 (7 ± 4 W), but neither a reduction nor an increase can be confidently reported for Feeders 5–13.

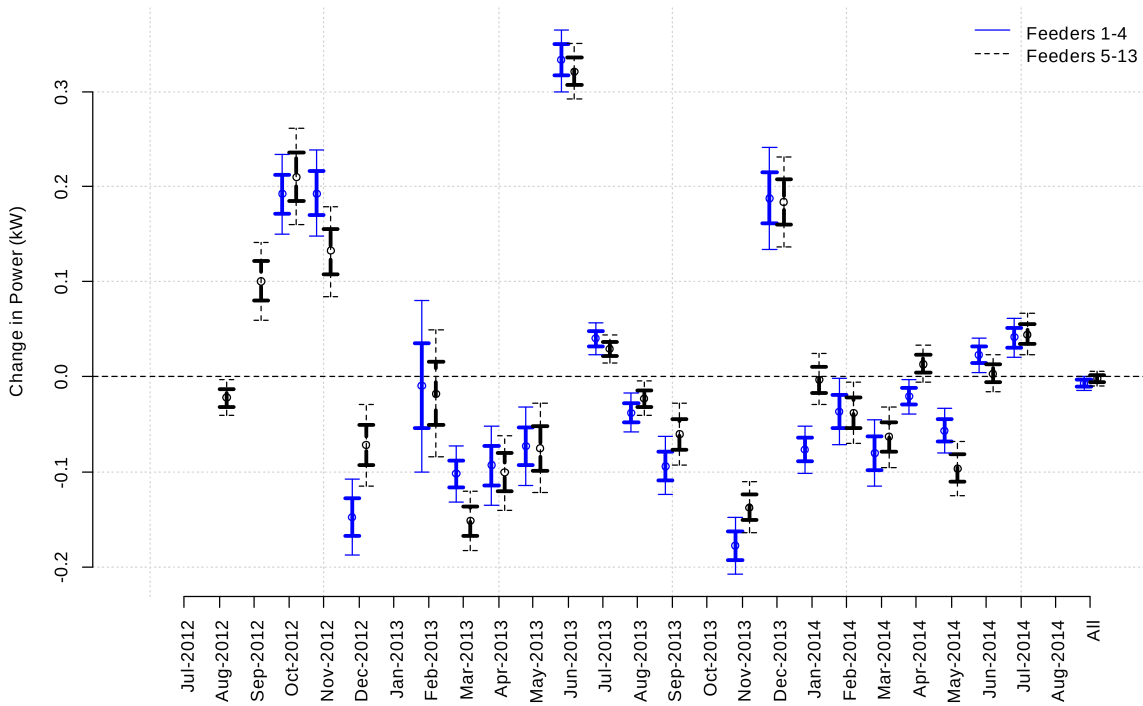


Figure 13.18. Event-Day Statistics by Project Month Based on the Modeled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

The impact of DRU events throughout event days was inconclusive using the comparison-baseline approach (Figure 13.19). Contradictory results were obtained for the two feeder sets. A moderate decrease seemed to occur for Feeders 1–4 (10 ± 2 W), but an increase of similar magnitude occurred for Feeders 5−13 (8 ± 3 W).

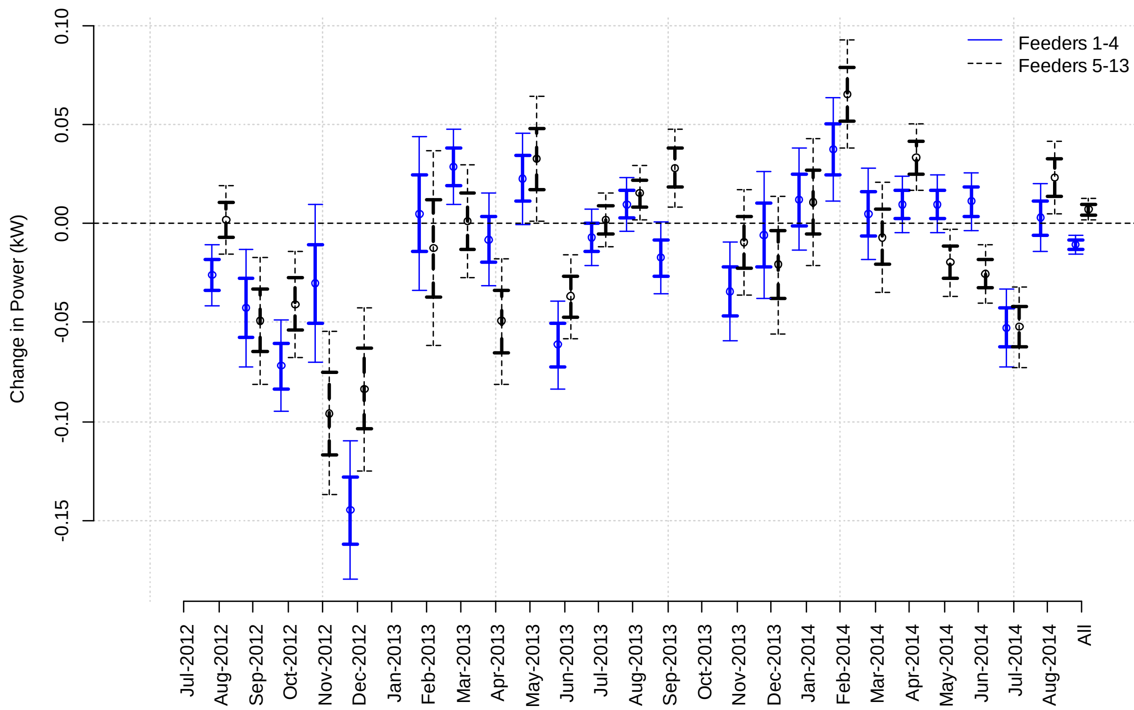


Figure 13.19. Event-Day Statistics by Project Month Based on the Controlled Baselines for Feeders 1–4 (blue) and Feeders 5–13 (black dashes)

The project therefore reports that there was virtually no impact confirmed concerning any change in the energy that was consumed on days that DRU curtailments had occurred (a reduction of 2 ± 2 W). This result is probably sensible. It means that the energy that was curtailed during DRU events is most likely simply deferred to another time that same day. Little or no actual conservation occurred.

Table 13.3 summarizes the value of the supply energy that is curtailed while the DRU events are active. The sum energy during the HLH and LLH may be used to estimate the value of this energy using BPA's load-shaping rates (Appendix C). Only a small amount of energy, about 7 MWh per year is avoided during the year's events, and the wholesale value of this energy to the city is about \$232 ± 23. This impact would likely have been greater had the performance of the DRUs early in the project matched their performance at the end.

Table 13.3. Estimated Supply Energy and the Value of Supply Energy Displaced each Calendar Month by Milton-Freewater's DRU Events

	HLH		LLH		Total	
	(kWh)[(a)]	($)[(b)]	(kWh)[(a)]	($)[(b)]	(kWh)[(a)]	($)[(b)]
Jan	−378 ± 83	−14 ± 3	−64 ± 11	−2 ± 0	−442 ± 84	−16 ± 3
Feb	−890 ± 280	−33 ± 10	−27 ± 1	−1 ± 0	−920 ± 280	−34 ± 10
Mar	−520 ± 110	−16 ± 3	145 ± 71	4 ± 2	−380 ± 130	−12 ± 4
Apr	−880 ± 250	−23 ± 6	−47 ± 8	−1 ± 0	−930 ± 250	−24 ± 6
May	−461 ± 62	−10 ± 11	23 ± 5	0 ± 0	−438 ± 62	−9 ± 1
Jun	240 ± 140	5 ± 3	263 ± 22	4 ± 0	500 ± 140	9 ± 3
Jul	−2,400 ± 490	−73 ± 15	0	0	−2,400 ± 490	−73 ± 15
Aug	−1,010 ± 190	−34 ± 6	44 ± 24	1 ± 1	−970± 190	−33 ± 6
Sep	−190 ± 80	−6 ± 3	0	0	−190 ± 80	−6 ± 3
Oct	141 ± 42	4 ± 1	−29 ± 25	−1 ± 1	112 ± 49	4 ± 1
Nov	−610 ± 120	−22 ± 4	126 ± 72	4 ± 2	−480 ± 140	−18 ± 5
Dec	−290 ± 180	−11 ± 7	−237 ± 66	−8 ± 2	−530 ± 190	−19 ± 7
Totals	**−7,250 ± 720**	**−232 ± 23**	**200± 130**	**0 ± 4**	**−7,050 ± 730**	**−232 ± 23**

(a) The energy is negative in these columns if the net energy consumption was reduced according to the project's analysis methods and project data.
(b) The dollar amounts in these columns are negative if the utility has reduced its purchase of wholesale supply energy according to the project's analysis.

Table 13.4 was created to help estimate the impacts of the DRUs on Milton-Freewater's demand charges. A preliminary table (not shown) was created to compile the average impact that DRU events had during the HLH hours of every calendar month. The city provided the project a list of historical hourly peak hours that could then be compared with the preliminary table. The peak hours were used to weight the hourly impacts each calendar month. If no events had been exercised on any of the peak hours in a given calendar month, the DRUs were given no credit that month for reducing demand charges. Also, no credit was given toward reduction of demand charges any month that the city had not, in fact, incurred demand charges. The estimate of peak-demand impact is probably still generous or optimistic because it presumes that the utility will accurately apply the DRUs during not only the correct hours, but also during the right day of each month.

The impact of the DRUs on average HLH hours (aHLH) were calculated simply by summing the energy impacts during all of a month's HLH hours and dividing by the number of HLH hours in that month.

Finally, the effect on monthly demand charges was calculated by multiplying the differences between the demand and aHLH components by the BPA demand rate (Appendix C). If the system of DRUs were operated as it was during the PNWSGD, and if the events were accurately placed coincident with the monthly peak hours, the city might reduce its BPA demand charges by \$4,400 ± 1,300 per year. This impact, again, would likely have been greater had the performance of the DRUs early in the project matched the quality of their performance at the end.

Table 13.4. Estimated Impact of Milton-Freewater's DRUs on the Utility's Demand Charges

	Δ Demand[a] (kW)	Δ aHLH[a] (kWh/h)	Δ Demand Charges[b] (\$)
Jan	0	0	0
Feb	−292 ± 93	−2 ± 0	−3,161 ± 1,014
Mar	124 ± 46	−1 ± 1	1,116 ± 411
Apr	−257 ± 66	−2 ± 0	−1,941 ± 502
May	0	0	0
Jun	0	0	0
Jul	−145 ± 34	−6 ± 0	−1,252 ± 306
Aug	−47 ± 38	−2 ± 1	−451 ± 381
Sep	0	0	0
Oct	217 ± 8	0	2,025 ± 75
Nov	−65 ± 12	−2 ± 1	−662 ± 126
Dec	−10 ± 18	0	−115 ± 206
Total			**−4,400 ± 1,300**

(a) A negative demand value in this column means that the demand determinant was reduced, according to the project's analysis and data.

(b) Negative dollar amounts in this column mean that the utility's demand charges were decreased, according to the project's analysis.

13.3 Conservation-Voltage-Regulation Peak Shaving

The City of Milton-Freewater configured nine of its distribution feeders (Feeders 5–13) to reduce their voltages by 4.5% (3 transformer tap settings) during events when curtailment was advised. These events typically lasted several hours. The voltage was returned to normal at the conclusion of each event.

The main impetus for short-term power reduction for the city was avoidance of BPA demand-charge increases. The city's cost impact from demand charges was represented and predicted by a transactive function, so this objective should have been met to the degree that monthly peaks were accurately predicted by the function.

Energy consumption might also have been moved out of heavily loaded hours, when energy is more expensive, to lightly loaded hours. However, the project failed to represent the different costs of heavily and lightly loaded hours at this site through its transactive system, so this objective was not achieved by the transactive system.

If voltage-responsive DRUs (Section 13.4) had not been collocated on these distribution feeders, the city would have perhaps allowed more frequent voltage reductions, and for longer durations. However, the city did not want customers who had voltage-responsive DRUs to be inconvenienced. So, the transactive system at this site was configured to allow few, short voltage-reduction events. The voltage-responsive DRUs necessarily responded to the voltage reduction on Feeders 7–10. Great care was needed by analysts to isolate independent impacts from the voltage reduction itself and the consequent curtailment of the voltage-responsive DRUs.

The city's distribution system is relatively urban. Conductor lengths are short. Based on prior analysis, the city asserted that there was no significant risk that reducing supply voltage by 4.5% would degrade customer power quality. Their system, in their assessment, did not require persistent end-of-line feedback monitoring of end-of-line voltage to be built into their control system.

The annualized costs of system modifications have been summarized in Table 13.5. The city already had installed the tap-changing transformers that were needed for this voltage management system. A fraction of the additional software and engineering costs to automate the tap changers and to make them respond to the project's transactive system was shared among this and other site asset systems. The city also elected to apply one-third of the costs of updated premises metering to this asset system.

Table 13.5. Costs of the Milton-Freewater Voltage Management on Feeders 5–13

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Residential and Commercial Advanced Meters	33	270.3	90.0
Programming for Automatic Control of Voltage SCADA	50	11.0	5.5
Transactive Node	33	9.8	3.2
Total Annualized Asset Cost			**$98.7K**

13.3.1 Characterization of the CVR Peak-Shaving System Responses

The City of Milton-Freewater reported to the project the times during which it had reduced voltage on Feeders 5–13 by three tap settings, or 4.5%. This list of events was found to be somewhat inaccurate when the project compared the list against distribution voltages measurements that had been reported by Milton-Freewater to the project. Figure 13.20 demonstrates this inaccuracy. The times that voltage had been intentionally reduced are evident, and these voltage fall well below 1.0 per unit. The data during reported event times are shown in red. Some voltage reductions were accurately reported, but there are also many unreported voltage reductions and reported events that had evidently not been responded to. The cause of these inaccuracies is not known.

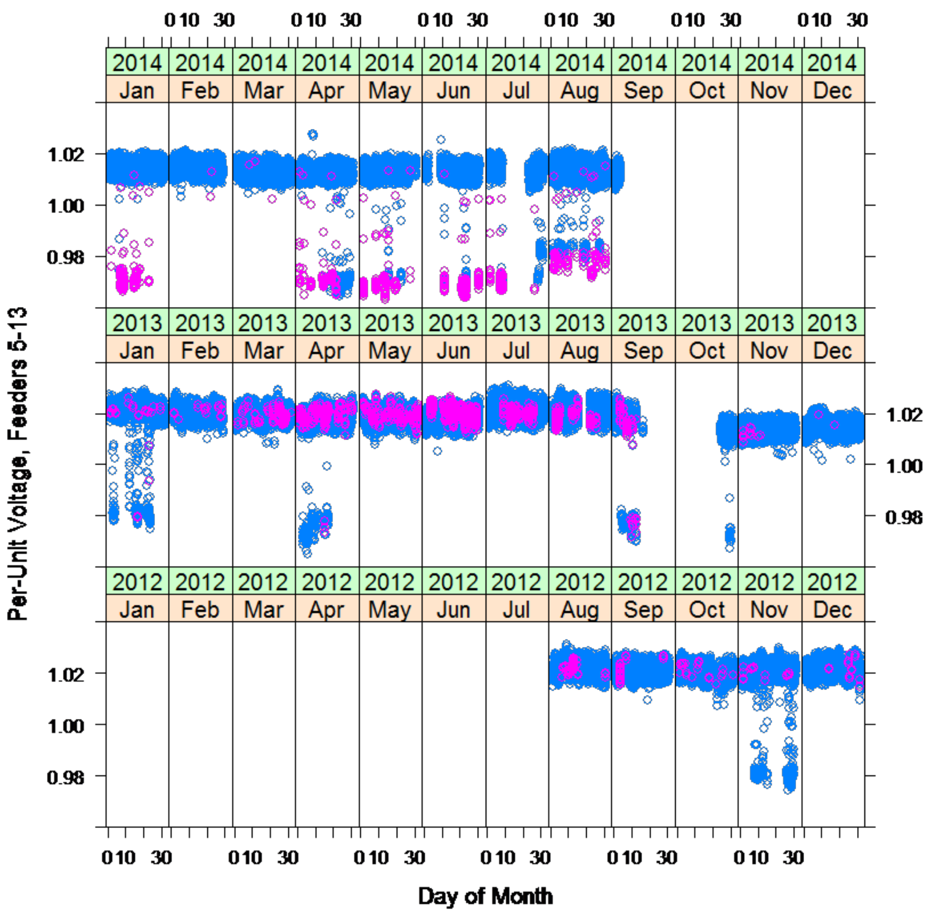


Figure 13.20. Correlation between Periods when the Average Distribution Voltage on Feeders 5–13 is Reduced (blue) Versus the Periods when it is Reported to have been Reduced (red)

Fortunately, a histogram of averaged per-unit voltage on these feeders showed a fairly clear distinction between the feeders' normal and reduced voltages. The voltage was found to have been controlled to an intermediate level, perhaps one transformer tap reduction, during September 12–16, 2013 and again July 18–21, 2014. These two periods were discarded from the analysis so that a clean comparison could be made between only two settings. The resulting histogram of per-unit voltages is shown in Figure 13.21.

Project analysts elected to infer the true events from the magnitude of the distribution voltage. After the data was scrubbed, those voltages less than or equal to 1.005 per unit were inferred to have been intentional reductions. It is the inferred events, not the reported ones, that were used for analysis and in the discussion that follows. Overall, 217 events were inferred to have been initiated from August 2012 through August 2014. The voltage was found to have been truly reduced 40% of the hours that the voltage had been reported to have been reduced. Events were reported for only 33% of the hours that the voltage had, in fact, been reduced, according to the project's data.

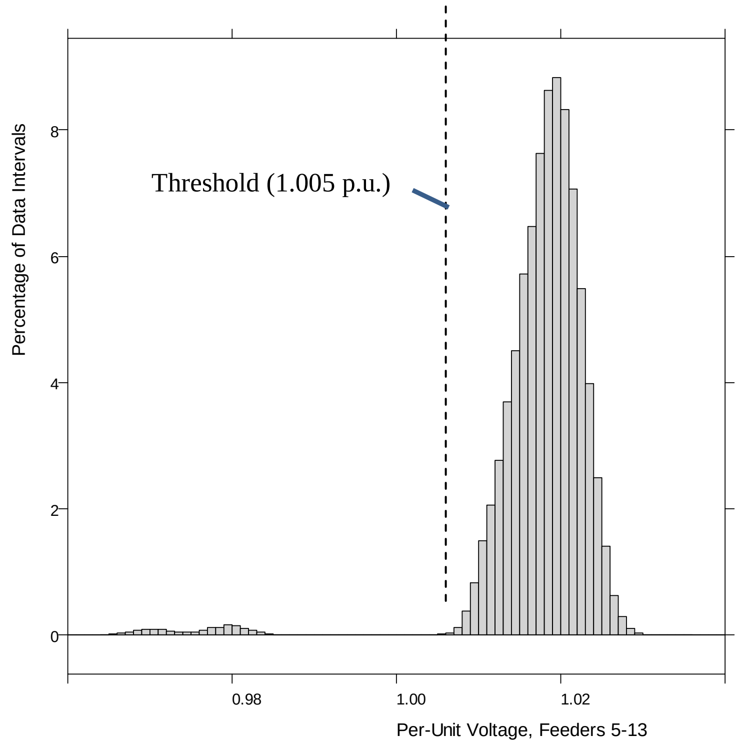


Figure 13.21. Per-Unit Distribution Voltages on Feeders 5–13 after Two Periods having an Intermediate Voltage were Removed

Because the events were necessarily inferred, it is plausible that some of the inferred events are spurious. Figure 13.22 shows that just over 14% of the events were only 15 minutes in duration, the shortest measured interval. However, 5% of the events were only two 15-minute intervals in duration. The project applied no further filtering to determine whether the inferred events might have been intentional or not. The longest inferred interval was 16 hours and 45 minutes long.

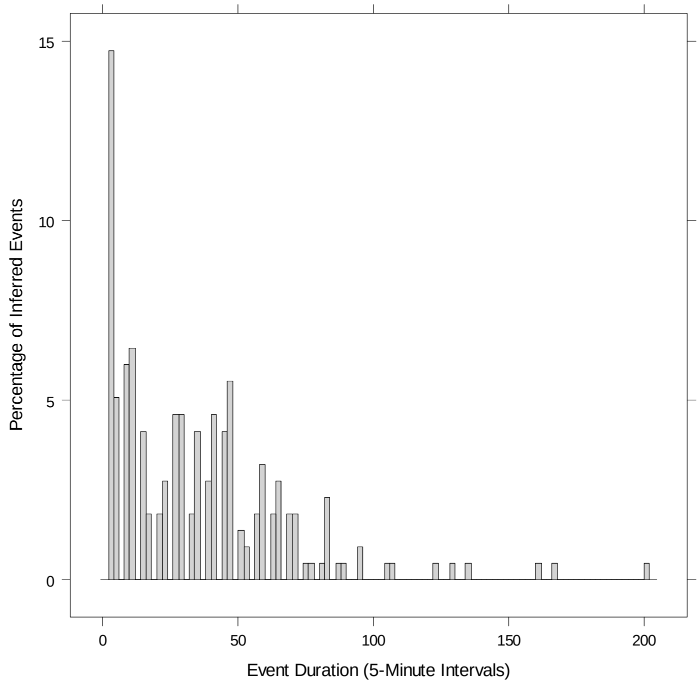
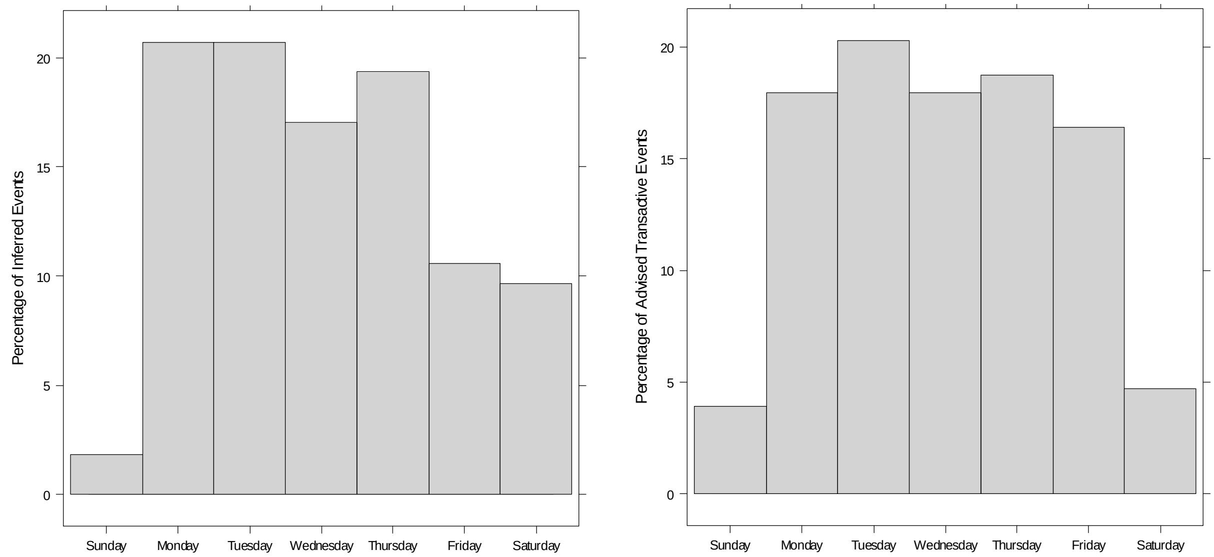


Figure 13.22. Durations of the Inferred Events when Voltage had been Reduced on Feeders 5–13

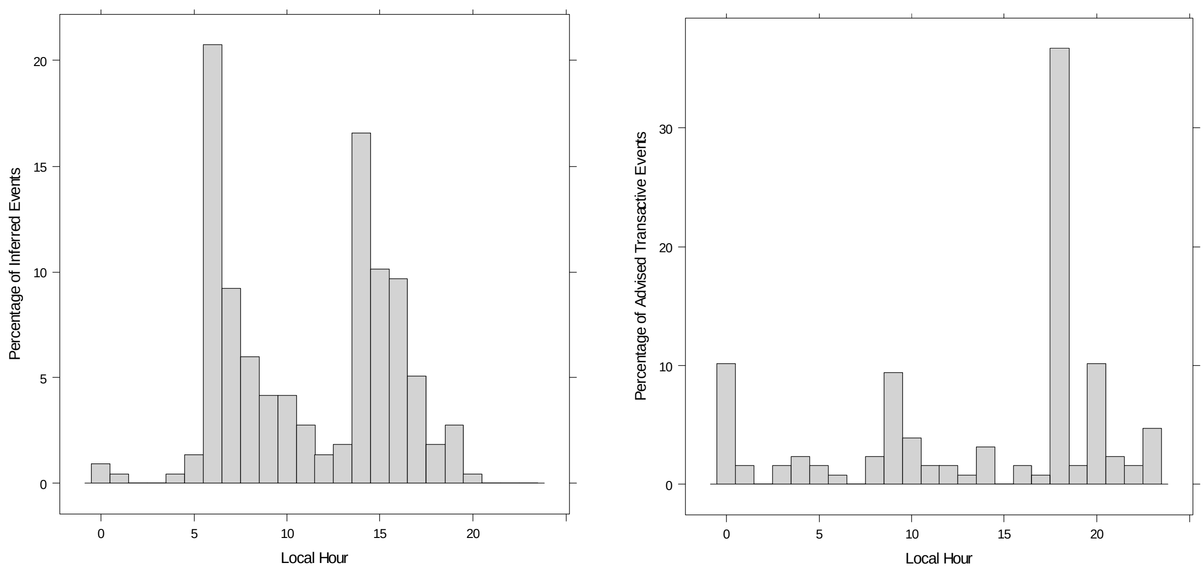
Because this asset system is primarily installed to avoid increased peak demand and its charges, events should mostly occur during heavily loaded hours, which are the only hours that demand charges may be incurred from supplier BPA. This expectation is somewhat confirmed for both inferred events (Figure 13.23a) and advised transactive events (Figure 13.23b). Some of the Sunday events (by definition, BPA heavy-load hours cannot occur on Sundays) may have occurred while Milton-Freewater was working to tune its system. The likelihood that a transactive event will be advised to occur on given weekdays is configured by the code that generates the advice to the asset system. As for other of the project's asset systems, such configuration was often delayed or never finalized.



(a) Inferred Events (b) Advised Transactive Events

Figure 13.23. Days of Week that (a) Inferred and (b) Advised Transactive (right) Voltage Reductions were Initiated

According to Figure 13.24a, the actual voltage reductions were initiated near the hours that Milton-Freewater load reaches its peak load (see Figure 13.2). The hours that the transactive system advised voltage reduction (Figure 13.24b) were not so structured. The transactive system never matured to identify useful response periods for this asset system, and it was not properly configured for this asset system to enact the responsiveness that Milton-Freewater desired.



(a) Inferred Events (b) Advised Transactive Events

Figure 13.24. Hours that (a) Inferred and (b) Advised Transactive Voltage Reductions were Initiated

13.3.2 Conservation-Voltage-Regulation Peak-Shaving System Performance

The theoretical total power reduction during voltage-reduction events should have been from 0.3 to 0.7 MW.[1] Very little, if any, rebound effect should be expected when the voltage is returned to nominal at the conclusion of an event. A transactive function at this site predicted the effect during reduced-voltage events. The function was very simple; it was based on a presumed CVR factor, the designed change in voltage (i.e., three tap settings), and the predicted total load on these feeders at their nominal, unreduced voltage.

While voltage reductions were applied to all the Feeders 5–13, a population of voltage-responsive water heaters was installed on a subset of these feeders (Feeders 7–10) and responded to the same stimulus (see Section 13.4). The project chose to evaluate only Feeders 5, 6, 11, 12 and 13, which were unaffected by the voltage-responsive water heaters, to separate the passive response to the voltage reduction from those of the more responsive water heaters.

Two baseline-comparison methods were used. These baselines parallel those that were developed for analysis of the other asset systems. First, the total power consumption on Feeders 5, 6, 11, 12 and 13 was modeled using linear regression to predict what the power would have been if voltage had not been reduced during events. The regression incorporated the influences of outdoor temperature, separately assessed by month, day of week, and hour of day in this model. The resulting baseline will be called the *modeled baseline*.

Second, the total power consumption on Feeders 1–4, which were not subjected to the same 4.5% voltage reduction, was normalized to have the same monthly average and standard deviation as the total power on the subset of affected feeders, where the short-term voltage reduction was being practiced. Care was taken in this comparison to mitigate potentially confounding impacts from the different voltage levels used for CVR experimentation on Feeders 1–4. The resulting baseline will be called the *controlled baseline*.

The load on both the Feeders 1–4 and the subset of Feeders 5, 6, 11, 12 and 13 may be affected by the status of the system of 800 DRUs on those feeders (see Section 13.2). Those DRUs were collocated among all Milton-Freewater feeders and might confound the evaluation of the effects of short-term voltage reduction. In fact, the DRUs were found to be active 14% of the time the voltage had been reduced. The voltage was reduced 44% of the time that the DRUs were active. Because the DRU events and voltage reduction were often coincident, it was challenging to completely isolate the effects of voltage reduction from the effects of the DRUs. In continuing with the comparison of Feeders 5, 6, 11, 12 and 13 against Feeders 1–4, an implicit assumption must be made that the two sets of feeders are similarly affected by the DRUs.

Analysis yielded a rather surprising result at the distribution level. Figure 13.25 shows the statistical changes in average distribution power each month on the five feeders when voltage was reduced, according to comparisons with the modeled and controlled baselines. Analyses using the controlled and

[1] This prediction assumes a typical CVR factor of 0.8, 4.5% voltage reduction, median total load of 8.9 MW, and peak load of 20.5 MW for these nine feeders.

modeled baselines agreed that there had been an *increase* in electric load while the voltage was reduced on the subset of feeders. Using the modeled baseline, 190 ± 10 kW more power was consumed during events and 40 ± 10 kW more was consumed on the five feeders according to the controlled baseline. The project reports an average 100 ± 100 kW increase for the five feeders while voltage was reduced.

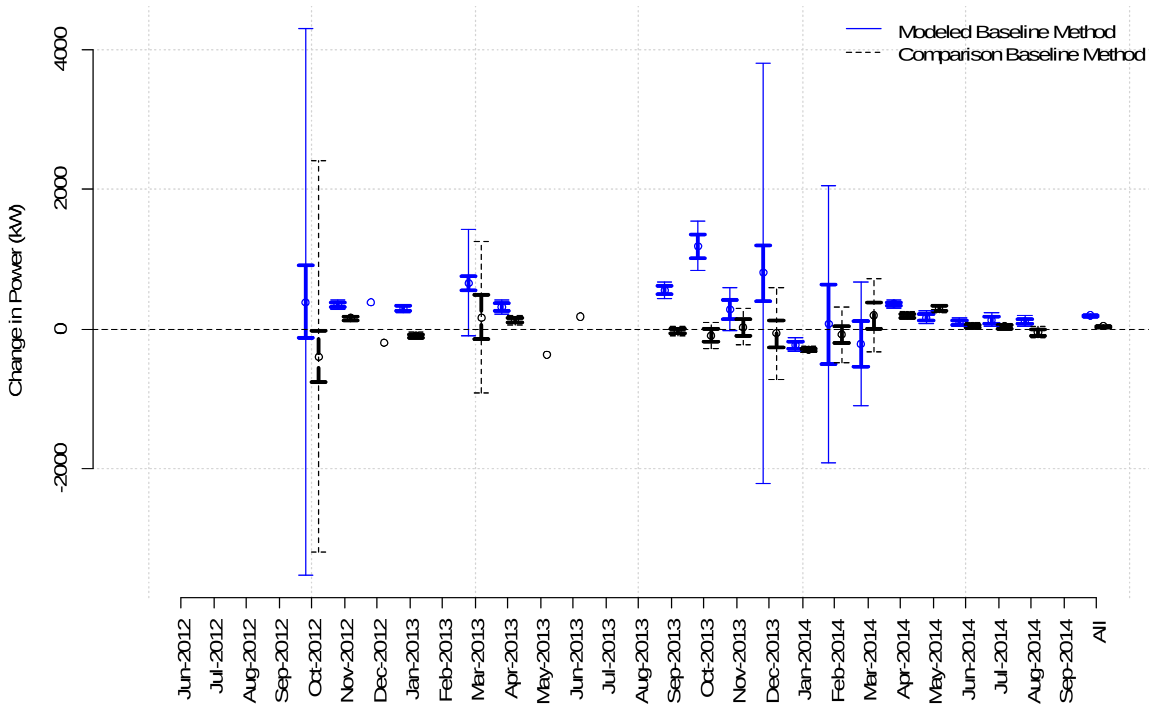


Figure 13.25. Monthly and Project Power Impact on Feeders 5, 6, 11, 12 and 13 while Voltage was Reduced and Using the Modeled (blue) and Controlled (black dashes) Baselines

The project then analyzed the distribution power data on these five feeders to see whether a rebound effect could be detected the hour after voltage had been restored. The statistical average monthly rebound impacts are shown in Figure 13.26 for the project months and using the two baselines. Comparison using the modeled baseline yielded an increase, but no reportable effect can be reported from using the controlled baseline by itself. Upon combining the results of the two methods, the project reports that, on average, 70 ± 80 kW more power was used during rebound hours than at other times. This result is not especially convincing, and it is similar in magnitude to, but less than, the result that was determined during the events.

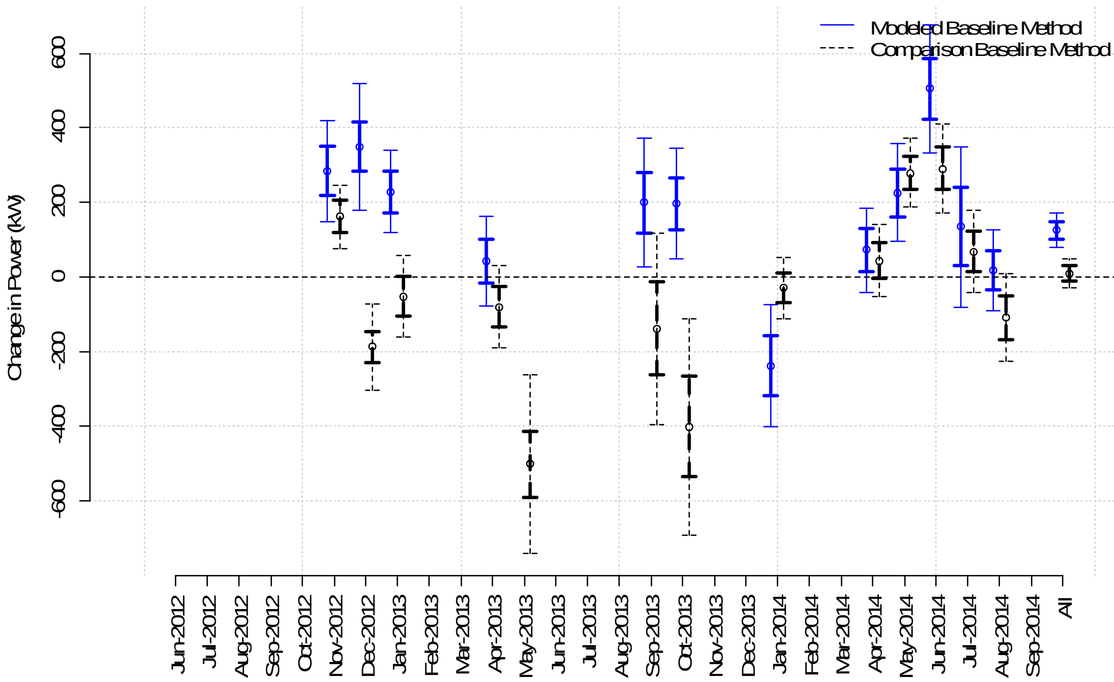


Figure 13.26. Monthly and Project Rebound-Hour Power Impact on Feeders 5, 6, 11, 12 and 13 Using the Modeled (blue) and Controlled (black dashes) Baselines

Finally, the project considered the average impacts throughout event days for days on which the voltage had been inferred to have been reduced. As shown in Figure 13.27, analysis using both baseline types agreed that there was a modest increase in feeder load on the days that voltage had been reduced. The project reports the averaged increase in load as 60 ± 30 kW averaged throughout event days.

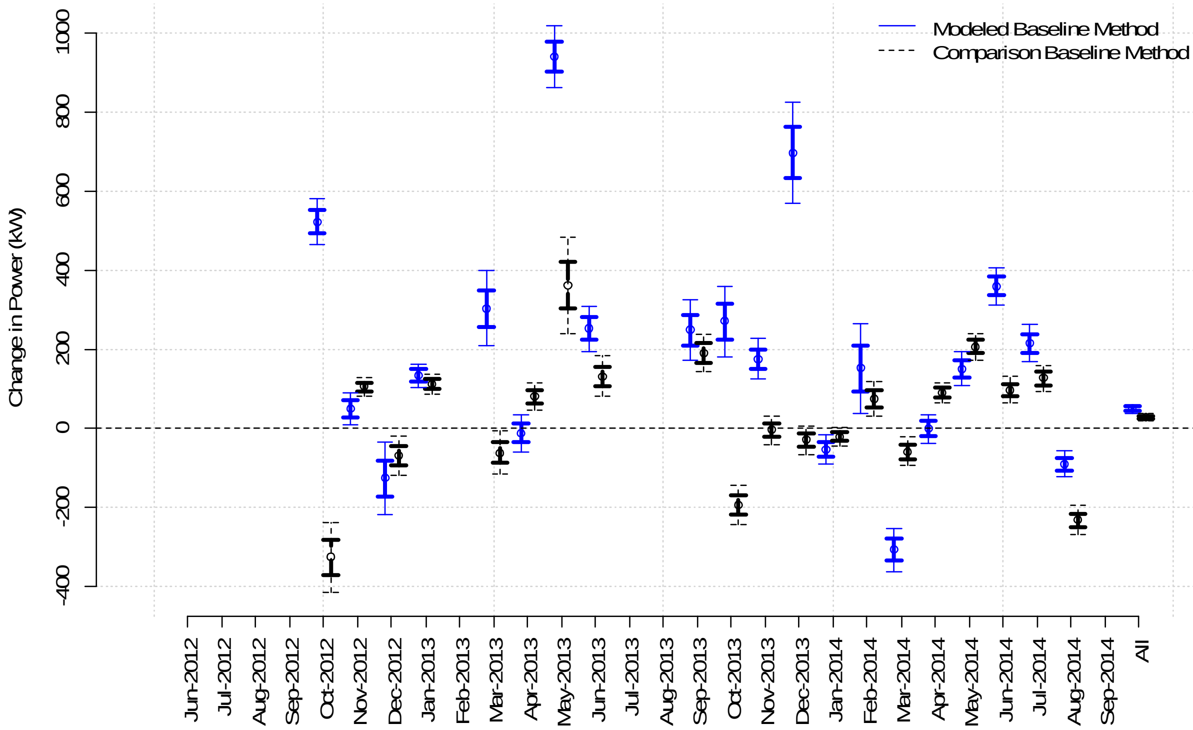


Figure 13.27. Monthly Averaged Event-Day Power Impacts on Feeders 5, 6, 11, 12 and 13 Using the Modeled (blue) and Comparison (black dashes) Baselines

The project also analyzed the impact at a sample of residential premises that are on these affected feeders to determine whether a premises-level effect could be observed. Another regression model was created to model residential power consumption. The model emulated consumption at premises on Feeders 5–13 that received the affected voltage magnitude but possessed neither conventional demand-responsive DRUs (Section 13.2) nor the voltage-responsive ones (Section 13.4). Therefore, any impact on these premises might be attributable solely to the passive impact from short-term voltage reduction on premises electric loads. The regression model fit average premises power to ambient temperature (according to weather station D3057 in Milton-Freewater) by month, hour of day, and day of week.

The comparison-baseline approach was not used to evaluate the performance of these premises.

Increases in premises consumption were identified while the voltage was reduced, for the hour after the voltage was restored, and through the days on which event had occurred, just as had been found when using feeder load data. According to analysis using the modeled baseline, each premises consumed 73 ± 8 W *more* while the voltage remained reduced. The additional consumption remained similar at 70 ± 20 W during the hour after voltage had been restored to normal. The premises consumed 31 ± 3 W more throughout event days than they did on days that the voltage had not been reduced.

Project analysts had expected to observe a reduction in consumption for distribution feeders and at premises, as is normally the case for static CVR that is applied over long time periods. This expectation could not be confirmed. Quite the opposite appeared to be the case for short, dynamic voltage reductions on these Milton-Freewater feeders.

A short-term reduction in voltage could conceivably increase overall electric load through the interplay of load types and distribution line inefficiencies. The project has reservations confirming this result, however, because of the potentially confounding impacts that were encountered and that could be only partially mitigated. But the impacts of the coincident DRU curtailments, for example, would be predicted to have reduced, not increased, the apparent change in load.

The increase being reported is on the order of 2% of the average load on the five feeders, and a little less than 4% of an average premises load. These percentages are of a reasonable magnitude, but their sign is wrong. Upon inspecting the power data near in time to where voltage had been reduced, no “notch” could be observed among the noisy distribution and premises data. Milton-Freewater disputes this finding, saying that they often observe their load to decrease immediately as feeder voltages are reduced. The discrepancies between the findings in this section that are based on the project’s data analysis and this feedback from the utility based on their real-time observations remain unresolved.

Project analysis was halted at this point. It did not make sense to further compile benefits after the project’s analysis could find no net reduction in load during the system’s events. We will try to revisit this analysis later to determine the sources of the contradictory findings.

13.4 Voltage-Responsive, Grid-Friendly DRUs

The City of Milton-Freewater allowed about 100 of their new water heater DRUs to be made responsive to voltage reduction rather than otherwise communicated to via demand-response signals. This is a technology that had been described in (Hammerstrom 2010) as “augmented” CVR. The principle is that devices like water heaters may autonomously sense voltage-reduction events and interpret these events as requests for DR curtailment. In this case, the City of Milton-Freewater worked with vendor Aclara to configure their DRUs to recognize and respond to the 4.5% voltage reductions that already were occurring on Feeders 7–10 as part of the city’s dynamic voltage-reduction system (Section 13.3). The Aclara DRUs already featured an under-voltage response capability that could be modified for this purpose (Aclara 2012).

As for the previous two transactive asset systems at the City of Milton-Freewater that were discussed in Sections 13.2 and 13.3, curtailment of the voltage-responsive water heaters could help the city avoid demand charges from BPA if the curtailments were made to reliably coincide with peak utility hours each month. The city limited the number of curtailments and their durations on DRU water heaters so that its customers would not be inconvenienced. City staff said that they probably would have conducted more and longer reduced-voltage events on Feeders 5-13 had the voltage-responsive water heaters not been responsive to the voltage reduction. This is a lesson learned for this technology.

The stimulus for these voltage-responsive water heater DRUs is the same as that for the dynamic voltage management asset system (Section 13.3). Voltage-responsive water heaters might be simpler and more cost effective to deploy than those that require explicit DR communications, because they need no external communication infrastructure or its constantly evolving communication protocols. The water heater controllers sense when voltage has been reduced and curtail their loads. The water heater is returned to its normal operation after voltage has been returned to its normal level. Additional features can be added to the autonomous controllers to tailor their responses.

The annualized cost of this asset system was estimated from the actual cost of the DRUs and their installation, plus one-third of the costs incurred while establishing the local transactive system at the site and automating the city's responses to the transactive system. See Table 13.6, which summarizes the annualized system costs.

Table 13.6. Costs of the Milton-Freewater Voltage-Responsive DRU Water Heaters

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Water Heater DRUs	100	9.9	9.9
Transactive Node	33	9.8	3.2
Administrative (management and record keeping labor)	50	6.3	3.1
Outreach and Education	33	2.2	0.7
Total Annualized Asset Cost			**$17.0K**

13.4.1 Characterization of the Voltage-Responsive Water Heater System

The discussion of voltage-responsive water heater events is necessarily the same as that above concerning the voltage management system on Feeders 5–13 (i.e., Section 13.2.1). Recall that the times of reported events were found to be inaccurate. The project elected to infer the events from reductions of distribution voltage that were observed in the data supplied by Milton-Freewater.

Milton-Freewater informed the project that they might have conducted longer voltage-reduction events on Feeders 7–10 if the voltage-responsive water heaters had not been installed there. They feared inconveniencing the water heater owners if the voltage remained reduced for more than a few hours.

Milton-Freewater began to define a population of premises having voltage-responsive water heaters in June 2012. From then until the end of August 2014, the city maintained about 152 premises, on average, in this test group. There were briefly as many as 158 participating premises. Raw meter data was collected by the city's Aclara TWACS system from these premises at 15-minute intervals. The project calculated average per-premises power consumption of this test group and compared the consumption time series against two baselines.

The city worked with the project to establish a control population of premises that also were supplied by Feeders 7–10, but which did not have voltage-responsive water heaters or any of the city's other premises asset systems installed. The control group experiences the same voltage reductions as does the test group. The control group peaked at 310 participating premises and averaged 245 throughout the project's data collection period.

13.4.2 Voltage-Responsive Water Heater System Performance

The project analyzed premises data to see whether it could confirm an effect from the curtailment of the voltage-responsive water heaters. The test group was compared with a normalized baseline that was based on the control group (Section 13.4.1) and with another baseline, based on linear regression. As before, the corresponding baselines will be referred to as the *controlled* and *modeled* baselines.

Like the test premises, the control premises were supplied by Milton-Freewater Feeders 7–10, but they did not have voltage-responsive water heaters. The average per-premises power of this control group was scaled each month to have the same average and standard deviation as the test group. Small variations in hourly load profile were still observed between the two populations, so the control group's time series was further globally corrected for any differences from the test group's hourly consumption.

Another baseline time series was generated using linear regression to emulate the average power consumption of test premises had they not had voltage-responsive water heaters. Analysts used R software to generate this regression model. The test group data was fit to ambient temperature (weather station D3057 in Milton-Freewater) by month, day of week, and hour of day to create the modeled baseline.

Project analysts compared the test-group premises' power with the two baselines using an independent Student's t-test. The reported statistical results are the monthly and project averages during inferred curtailment events, during the rebound hour following the events, and during entire event days. The error bars that will be shown in these figures represent standard error (heavy bars) and 95% confidence intervals (lighter, dashed bars).

Theoretically, each water heater that becomes curtailed should reduce the utility's total load by 0.2−0.8 kW, depending on the time of day. Therefore, the set of 100 water heaters should reduce city electric load by 20–80 kW while they remained curtailed. The impact from these water heaters on the transactive system should have been estimated by a transactive function that predicted the impact of dynamic voltage management (Section 13.3) along with the other impacts that would accompany voltage reduction on Feeders 5–13. This special case of the CVR toolkit function (i.e., the one that included the predicted impact from these voltage-responsive water heaters) was never implemented during the project, so the predicted change in load was not incorporated into the site's transactive power feedback prediction.

While the voltage was in its reduced state, the test group premises consumed 144 ± 6 W less power or 200 ± 5 W less power, according to the modeled and controlled baselines, respectively. The calculated results using the two baselines are shown in Figure 13.28 to be tightly clustered around these values except for several months that exhibited greater variability. The averaged result from using the two baselines is a reduction of 170 W. Because the two methods generated somewhat different results, the project will report the standard deviation of the results from the two methods, ± 40 W, as the variability of this result. The voltage-responsive water heaters were reliably and consistently curtailed by the reduction in distribution voltage.

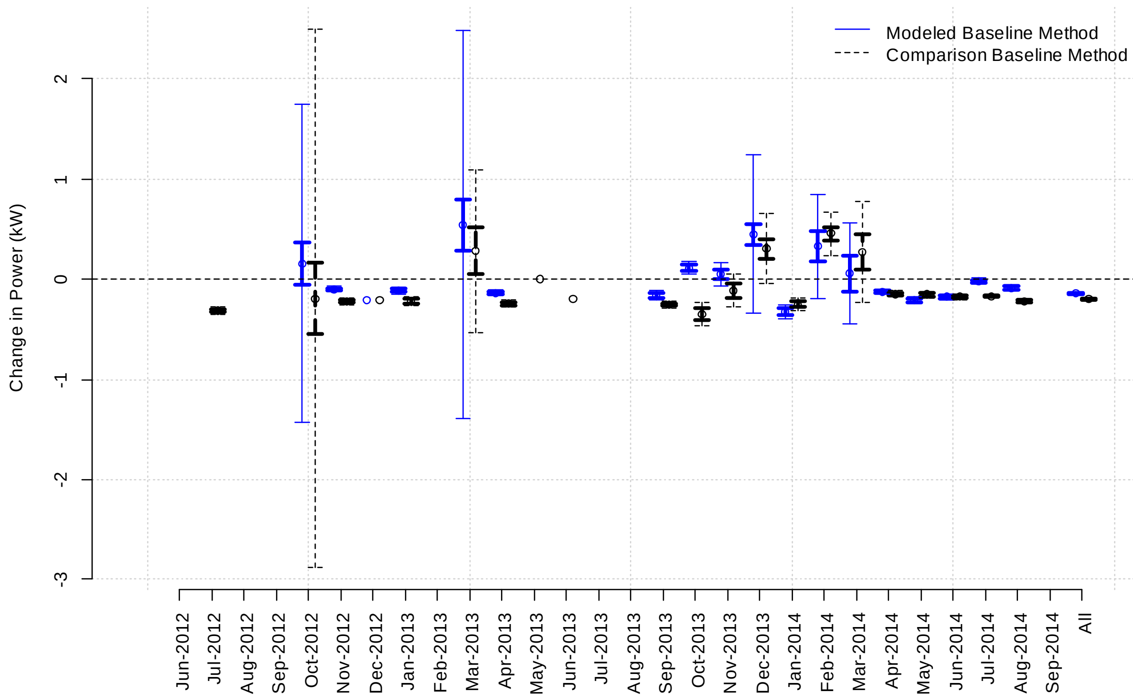


Figure 13.28. Power Curtailed per Voltage-Responsive DRU Premises by Month and for the Entire Project using the Modeled (blue) and Controlled (black dashes) Baseline

A strong rebound effect occurred at these test premises in the hours immediately following the reductions in feeder voltage. The spike in average premises power consumption was almost always evident by inspection of the time series. Comparison with the modeled baseline indicated an increase of 330 ± 20 W per premises during rebound hours. The controlled baseline suggested a similar increase of 290 ± 20 W. If the results of these two methods are averaged, the project should report a rebound of 310 ± 30 W, where the variability is the standard deviation of the two results from the two methods.

The month-by-month measurements were quite consistent, as is shown in Figure 13.29. It is clear that the rebound effect is strong for water heaters controlled in bulk by this method. Control logic could be added to mitigate the strong rebound at the device level.

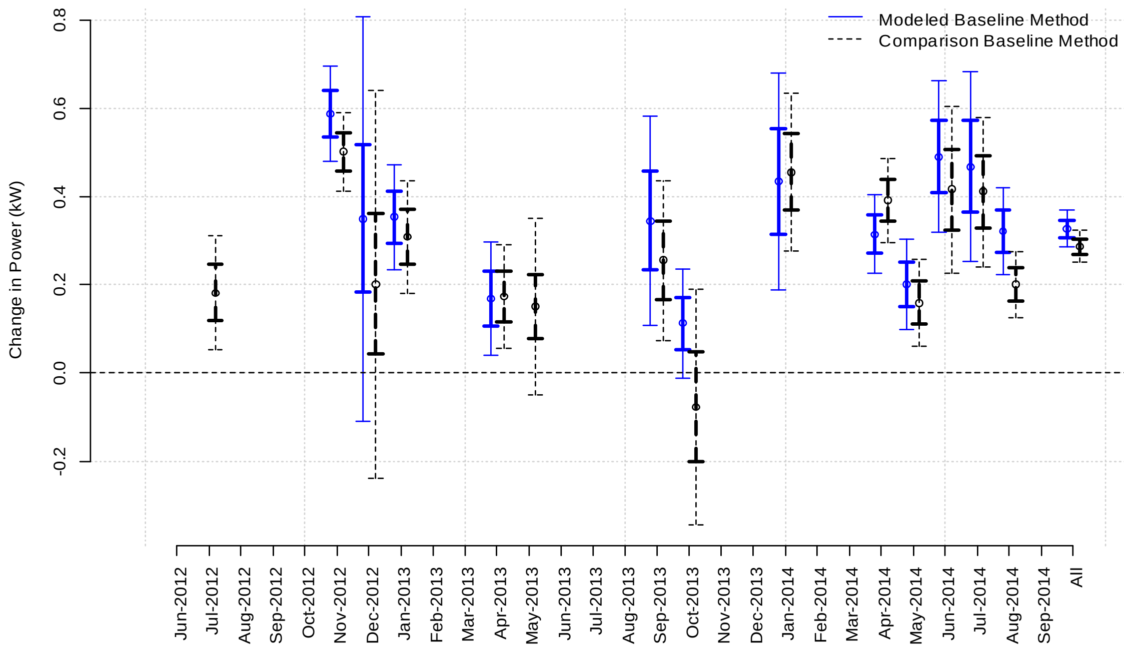


Figure 13.29. Average Rebound Power of the Premises that Had Voltage-Responsive Water Heaters in the Hours following Events using the Modeled (blue) and Controlled (black dashes) Baselines

The rebound spike is often a strong time marker location in the time series as is evident in Figure 13.30, which shows the average test group per-premises power time series (blue) and its controlled (green) and modeled (pink) baselines for an extended time period before and after an August 27, 2014 event. The event period has been shaded yellow, and the rebound hour has been shaded gray. A rebound spike is clearly evident during the rebound hour.

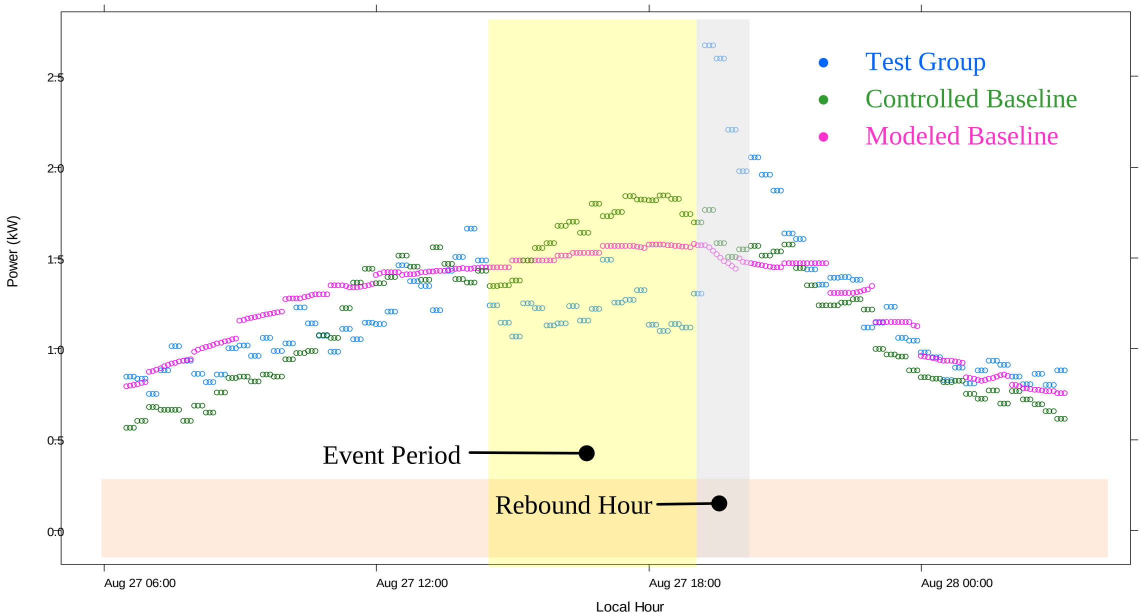


Figure 13.30. Test Group Per-Premises Power (blue) and its Controlled (green) and Modeled (pink) Baselines on August 27, 2014. The event period (shaded yellow) and rebound hour following the event (shaded gray) are also shown.

For some undetermined reason, the rebound spike in the time series was observed sometimes to occur after the rebound hour (not shown). That is, the rebound spike occurred more than an hour after the voltage had been returned to its normal level. Consequently, the rebound impact might be even larger than what is being reported by the project. There might have occurred additional logic in the autonomous responses of the water heaters that is unknown to the project. Alternatively, a one-hour timing shift might have occurred occasionally in data collection processes between the reported distribution voltage and premises power time series. The project has not been able to determine the precise cause.

Regardless, large rebound impacts are potentially problematic for this and other curtailment programs that engage, then disengage, large electric load populations. As the utility strives to reduce a load peak, it might inadvertently create another as the curtailments are halted. The magnitude of the rebound may be reduced or eliminated with additional logic at the controllers that spreads the release of the event over time for the population.

The two baseline approaches yielded small, contradictory results concerning the average change in power consumption of the test group over days that voltage had been reduced. See Figure 13.31. The result from the comparison-baseline approach might be more trusted because it explicitly excluded entire event days during its normalization, while the model excluded only event and rebound periods. Regardless, the project reports that virtually no net impact was measured throughout event days for the voltage-responsive water heater system.

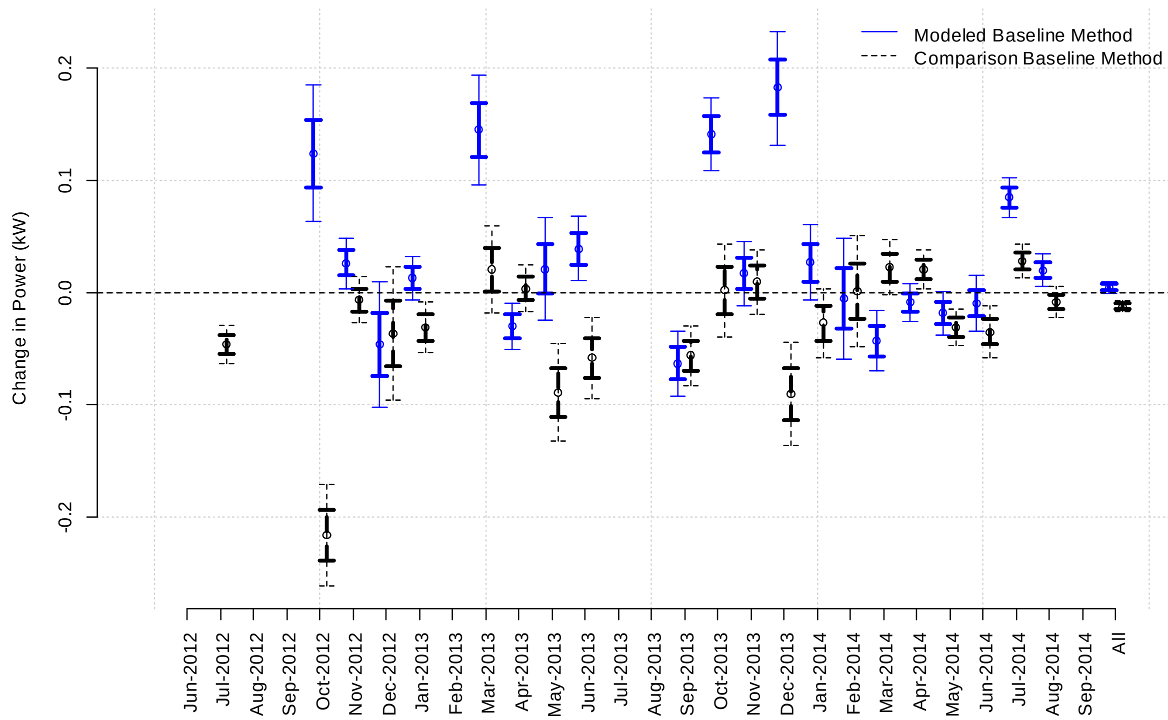


Figure 13.31. Change in Average Per-Premises Power Consumption on Days that Voltage had been Reduced Using the Modeled (blue) and Controlled (black dashes) Baselines

Based on the analyzed effect of voltage-responsive water heater events on system load, Table 13.7 estimates the total impact on the city's load by calendar month. The impact is separately assessed for HLH and LLH hours so that BPA's load-shaping rates (Appendix C) may be used to estimate the value of the unneeded energy. If the city were to continue engaging this set of voltage-responsive water heaters as it did during the PNWSGD, it would purchase about 5.5 MWh less energy from BPA each year worth about $162.

Much of the water heaters' curtailment energy is simply deferred to be used later after the event has concluded. As was discussed in the previous section, the project was not able to determine with confidence how much of the energy was deferred and how much was truly conserved.

Table 13.7. Estimated Supply Energy and the Value of Supply Energy Displaced each Calendar Month by Voltage Responsive Water Heater Events

	HLH		LLH		Total	
	(kWh)[(a)]	($)[(b)]	(kWh)[(a)]	($)[(b)]	(kWh)[(a)]	($)[(b)]
Jan	−943 ± 87	−35.6 ± 3.3	−15 ± 9	−0.5 ± 0.3	−958 ± 87	−36.1 ± 3.3
Feb	−400 ± 36	−14.8 ± 1.3	−21 ± 7	−0.6 ± 0.2	−421 ± 37	−15.4 ± 1.3
Mar	−570 ± 39	−17.2 ± 1.2	−137 ± 22	−3.4 ± 0.6	−707 ± 45	−20.7 ± 1.3
Apr	−449 ± 56	−11.6 ± 1.4	−25 ± 23	−0.5 ± 0.5	−474 ± 61	−12.1 ± 1.5
May	−626 ± 67	−13.1 ± 1.4	−24 ± 11	−0.3 ± 0.1	−650 ± 68	−13.5 ± 1.4
Jun	−1,000 ± 110	−22.7 ± 2.5	−206 ± 50	−3.0 ± 0.7	−1,210 ± 121	−25.7 ± 2.6
Jul	−72 ± 66	−2.2 ± 2.0	−12 ± 6	−0.3 ± 0.1	−84 ± 66	−2.5 ± 2.0
Aug	−231 ± 33	−7.8 ± 1.1	−9 ± 14	−0.2 ± 0.4	−240 ± 36	−8.1 ± 1.2
Sep	−9 ± 26	−0.3 ± 0.9	−16 ± 17	−0.4 ± 0.5	−25 ± 31	−0.7 ± 1.0
Oct	−4 ± 9	−0.1 ± 0.3	11 ± 10	0.3 ± 0.3	7 ± 13	0.2 ± 0.4
Nov	−355 ± 32	−12.6 ± 1.1	−41 ± 13	−1.3 ± 0.4	−396 ± 35	−13.9 ± 1.2
Dec	−284 ± 43	−11.0 ± 1.7	−75 ± 17	−2.5 ± 0.6	−359 ± 46	−13.5± 1.8
Totals	**−4,940 ± 200**	**−149.2 ± 5.9**	**−570 ± 70**	**−12.8 ± 1.5**	**−5,520 ± 210**	**−162.0 ± 6.1**

(a) Negative energy values in these columns mean that load was reduced during events, according to the project's analysis methods and data.

(b) Negative dollar amounts in these columns mean that the utility's net cost of wholesale energy decreased during events, according to the project's analysis. Dollar amounts have been rounded to the nearest dime.

Table 13.8 shows the calculated impacts that the voltage responsive water heaters each calendar month and for an entire year. A preliminary table was first generated from the devices' performance to compile the average change in load during events by calendar month and individual HLH hours. Because there were often multiple event periods in each calendar month and HLH hour, an average change in power and standard error could be calculated for each hour and month. Next, a list of the city's historical peak hours was compared with this table. The set of peak hours each calendar month determined the weighting the hours and their impacts would have in the statistical analysis. The second column of Table 13.8 is the result of that assessment. It predicts the change in peak-hour energy each month based on the system's demonstrated performance. The values are somewhat optimistic because the method presumes that the city will accurately engage the system during the peak hours.

The average impact on the demand during HLH hours was calculated by summing the energy during the HLH hours in a month and dividing that energy by the number of HLH hours in the month.

Finally, the differences between the peak-hour demand impacts and the aHLH impacts were multiplied by the corresponding monthly BPA demand rates (Appendix C). Milton-Freewater would reduce its demand charges by about $1,620 ± 260 each year if it were to continue operating the voltage-responsive water heaters as demonstrated and if it were to accurately engage the system during peak hours each month.

Table 13.8. Estimated Impact of Milton-Freewater's Voltage-Responsive Water Heaters on the Utility's Demand Charges

	Δ Demand (kW)	Δ aHLH (kWh/h)	Δ Demand Charges ($)
Jan	−56 ± 7	−2.3 ± 1.4	−600 ± 80
Feb	−28 ± 9	−1.04 ± 0.33	−294 ± 98
Mar	1 ± 5	−1.32 ± 0.21	13 ± 45
Apr	−6 ± 9	−1.1 ± 1.0	−37 ± 69
May	−4 ± 23	−1.56 ± 0.68	−15 ± 143
Jun	−26 ± 8	−2.41 ± 0.58	−159 ± 54
Jul	−6 ± 6	−0.18 ± 0.08	−52 ± 54
Aug	−4 ± 6	−0.54 ± 0.82	−35 ± 61
Sep	5 ± 4	−0.02 ± 0.02	50 ± 40
Oct	9 ± 2	−0.01 ± 0.01	84 ± 19
Nov	−5 ± 2	−0.89 ± 0.28	−43 ± 21
Dec	−47 ± 10	−0.71 ± 0.16	−531 ± 115
Total			**−1,620 ± 260**

(a) Negative demand amounts in these columns mean that the impact during events reduced the determinant component during events, according to the project's methods and data.

(b) A negative dollar amount in this column means that the utility's demand charges were analyzed to have decreased by the given dollar amount.

13.5 Conservation from CVR on Feeders 1–4

The voltage management system on site Feeders 1–4 is similar to that on Feeders 5–13 (Section 13.3), except that more traditional, static CVR was used on Feeders 1–4. The system on Feeders 1–4 was not made responsive to the project's transactive system and its incentives. Every other week, the City of Milton-Freewater staff reduced the distribution feeder voltages for Feeders 1–4 by one transformer tap—about 1.5%. The change in voltage was performed at the same time each Wednesday during the term of the project. The project observed total feeder power on distribution Feeders 1–4 and compared the power between periods when the voltage was reduced and when it was normal.

The city wished to investigate CVR as a means to conserve electricity. However, based on discussions with city staff, the benefit of this energy conservation to the city is unclear. The city's electricity customers consume less while voltage is reduced, meaning that its revenues are reduced and the city purchases less energy from its supplier. The benefit to the city is unclear.

The City of Milton-Freewater and the project jointly estimated the annualized system costs. These costs included the costs of four Metrum model L+G 25 tap-changing transformers, labor and software to install the system and make it remotely responsive by the city, and approximately one-third of the costs of premises meters and meter systems. Refer to Table 13.9 for the summarized annual system costs.

Table 13.9. Costs of the Milton-Freewater CVR System on Feeders 1–4

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Residential and Commercial Premises Meter System	33	270.3	90.0
Programming for Automatic Control of Voltage SCADA	50	11.0	5.5
End-of-Line Voltage Sensing	33	7.3	2.4
Total Annualized Asset Cost			**$97.9K**

Refer back to the layout of the City of Milton-Freewater asset systems in Figure 13.1 to comprehend the relationships between this asset system and the city's circuits and its other asset systems that were being tested during the PNWSGD.

13.5.1 Characterization of the CVR System Responses

The project received distribution voltage readings every 15 minutes and averaged these reading for Feeders 1–4. Figure 13.32 demonstrates the control of averaged per-unit distribution voltage on CVR Feeders 1–4 during the project duration. The voltage clearly changes on a weekly basis. Additionally, the voltage changes correspond accurately with the CVR conditions that the City of Milton-Freewater reported to the project. The colors refer to periods when the city had reported normal operation (red) and reduced-voltage operation while CVR was engaged (blue).

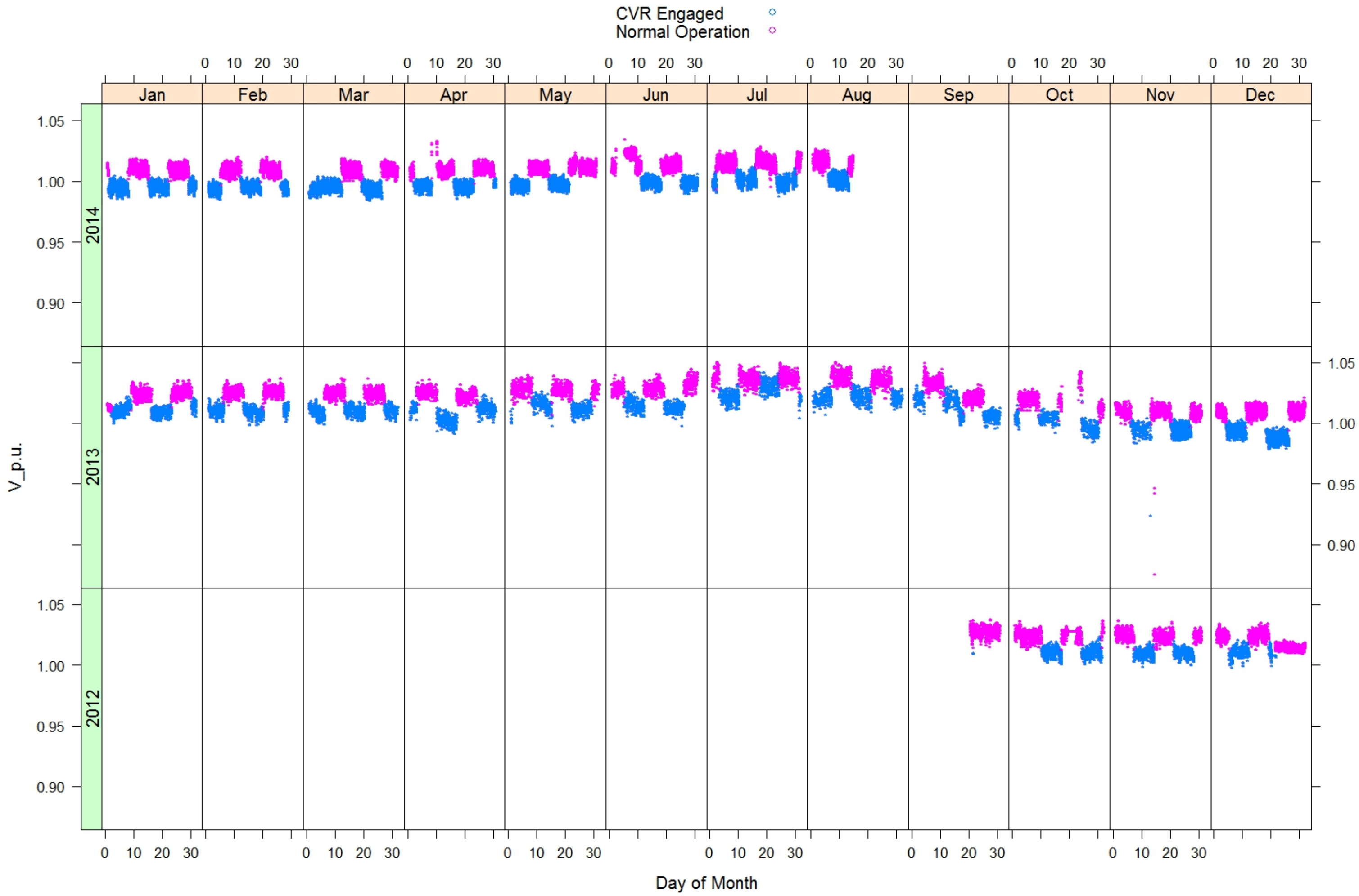


Figure 13.32. Average Per-Unit Voltage on CVR Feeders 1–4 by Project Year, Month, and CVR Status

The nominal voltage was unusually large during parts of October 2013, May 2014, and June 2014. A nominal voltage that is too large might result in an overstatement of the impact of CVR during these months. In contrast, the nominal voltage might be too low the last week of December 2012 and into January 2013, which would have the opposite effect on the analysis.

The CVR voltage reduction appears to have been too small during the third week of July 2013. The effect of this small voltage reduction would be an understatement of the CVR impact that month. While data collection began late in September 2012, CVR was not truly active, and analysis is probably not meaningful for that September.

Figure 13.33 shows the observed distribution voltage on Feeders 1–4 for each project month. As predicted, a voltage reduction averaging 1.52% accompanies a single tap-setting change. The months December 2012, July 2013, October 2013, and December 2013 exhibited voltage changes that were somewhat smaller or larger than anticipated. Long-term changes in the target voltage setting are evident in Figure 13.33 that were not easily seen in Figure 13.32. Perhaps the distribution system was operated one tap setting higher during the summer of 2013 and was reduced two full tap settings in October 2013. These management strategies affected both the “normal” and reduced-voltage settings each month. In fact, the “reduced” voltage setting from the first half of the demonstration became the “normal” setting during the second half.

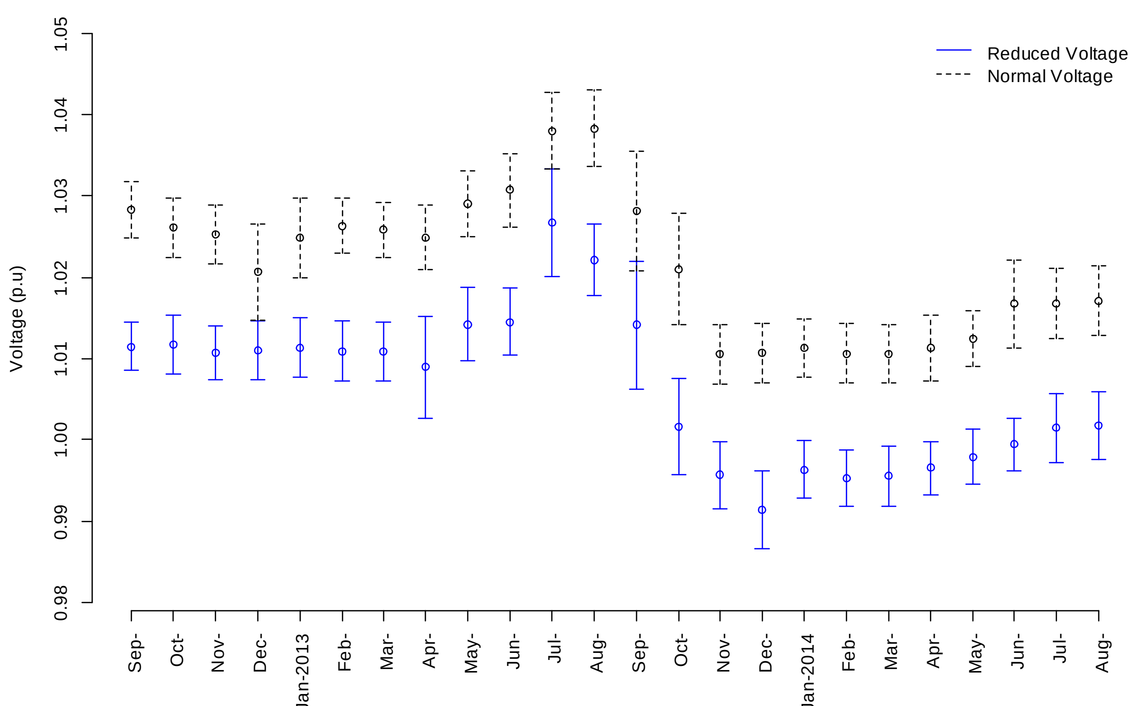


Figure 13.33. Observed CVR Change in Per-Unit Voltage by Project Month when Voltage is Reduced (blue) and Normal (black dashes). The bars represent standard deviations during the months.

13.5.2 Conservation-Voltage-Regulation System Performance

The project analyzed the data provided from the City of Milton-Freewater to determine the impact on distribution power consumption of reducing the distribution voltage by 1.5%.

The project received distribution feeder power data with 15-minute data intervals. There were two important sets of aggregated feeder power data used to analyze the CVR impact. The sum of the power on Feeders 5–13, which were not subjected to the same voltage management, was normalized and compared against total power on Feeders 1–4, where CVR was being practiced. These are two of the aggregated power time series that were shown in Figure 13.3.

A simple normalization approach was used to scale the sum power from Feeders 5–13 to have the same mean and standard deviation month by month as that of the sum power of Feeders 1–4 when the voltage on Feeders 1–4 was normal. The scaled time series was used to infer what the CVR feeders' power might have been if the feeders had remained at their nominal voltage levels.

This method should be compared and contrasted with other methods discussed in the literature. In RTF CVR Subcommittee (2012), an alternate day protocol involving CVR being on or off on alternate days is proposed along with a temperature normalization regression method. The protocol used in this project is alternate week protocol. A regression is performed to relate average hourly kW to hourly heating and cooling degree days and average hourly voltage. In this project, the dependence of the Feeders 1−4 power on non-measured variables is implicitly accounted for through its relationship with Feeders 5−13. The resulting *change* in power (rather than absolute power) can now be related to *change* in voltage and temperature. Such a detailed analysis is left for future work. In this project an overall voltage reduction and power reduction during analysis period is used in determining CVR factor.

Another baseline-comparison time series was created similarly to predict what the CVR feeders' power would have been if they had remained at their *reduced*-voltage levels. The advantage of using this baseline was that a comparison could then be made throughout each month, not limited to times that the voltage had been reduced. This reduces biases between the test and control feeders because any biases between the compared feeders are added one week, then subtracted the next. Furthermore, this baseline approach is unlikely to have been adversely affected by the changing target voltages that were evident from Figure 13.33. The two baselines serve as checks on one another.

Because transactive DRUs (see Section 13.2) resided in similar relative numbers on the experimental and control feeders (Feeders 1–4 and 5–13, respectively) and the DRU curtailment events were short and infrequent, the DRU events were mostly ignored. However, care was taken during analysis to avoid potentially confounding effects from the dynamic transactive voltage management on Feeders 5–13 (Section 13.3) because these events were more frequent and directly impacted the comparison baseline. Both control and experimental data were removed any time the dynamic transactive voltage management (Section 13.3) events were active.

The city occasionally reconfigures its distribution switches, and one or more feeders' demand may be then supplied from different feeders' transformers. If any of the electric load on Feeders 1–4 becomes supplied from Feeder 5–13 transformers, or vice versa, then the aggregated power measurements from these aggregate groups become tainted. The city listed for the project time periods when their 13 feeders were abnormally configured. These abnormal circuit conditions were found to occur infrequently, so the project elected to simply not use data when the circuit conditions were abnormal.

Figure 13.34 exemplifies the aggregated Feeder 1–4 power (blue) and the two baseline time series that represent normal voltage (red) and reduced-voltage (green) conditions for several project months in 2014. The baseline powers are similar to the experimental feeders' power. However, close comparison of the series revealed some residuals for differences by time of day.

Data is missing where the circuit configuration was abnormal and where potentially confounding voltage management events occurred on Feeders 5–13. Differences between the experimental and baseline time series are difficult to see amidst normal noise in feeder power.

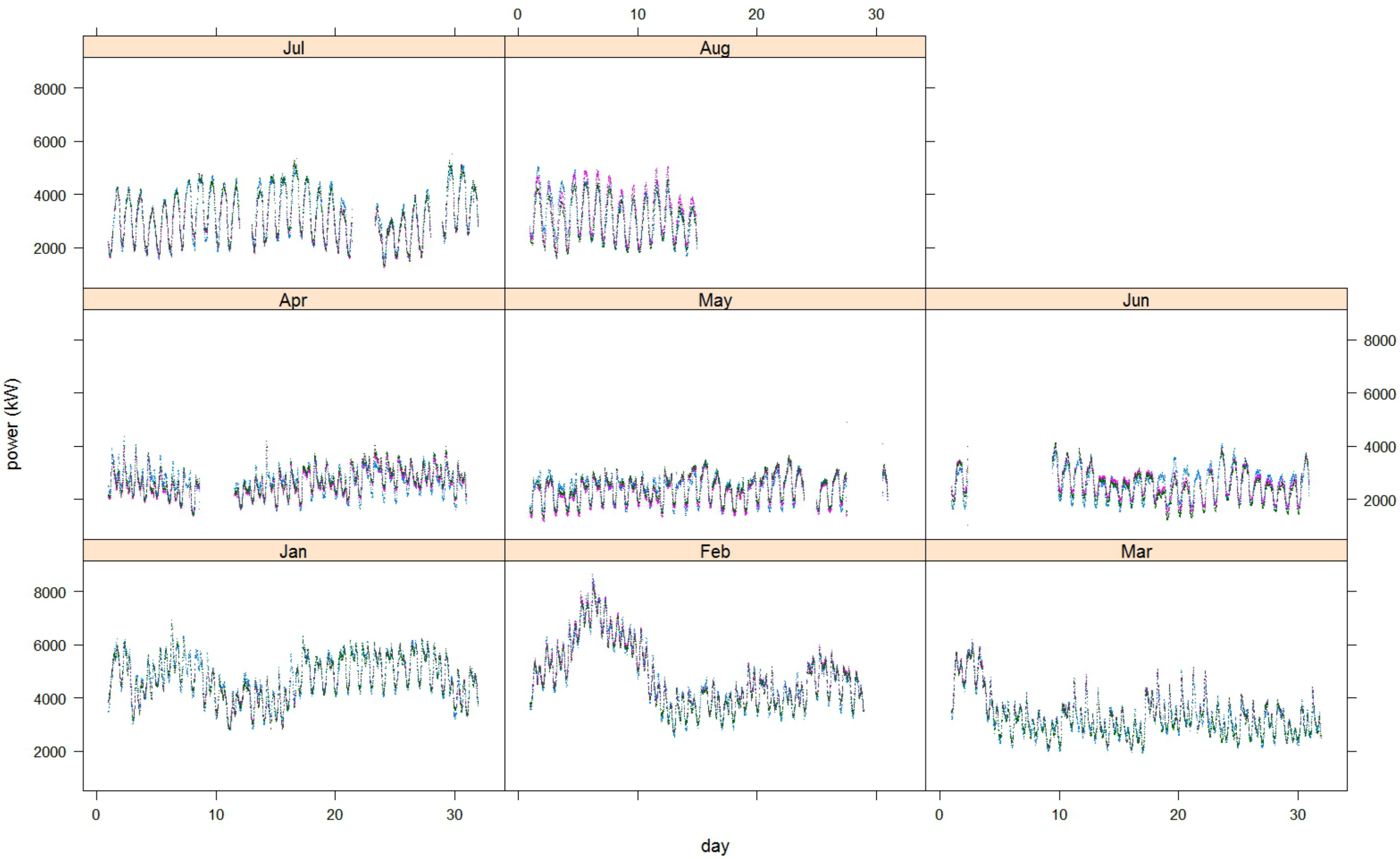


Figure 13.34. Example Aggregated Experimental and Baseline Feeder Power Data from 2014 that was Used to Analyze the Impact of CVR at Milton-Freewater

The change in power attributable to the practice of CVR each month on Feeders 1–4 is shown in Figure 13.35. The x-axis is the set of months in which data was collected. On the far right is an aggregate result for all project months. Each marker is an average difference in power between reduced-voltage operation and a baseline that represents operation under the normal voltage. Two methods of comparison were employed. The blue markers are the difference between the Feeders 1–4 measurements under reduced voltage and the baseline that represents normal operation. The dashed black markers are the difference between the Feeders 1–4 measurements while voltage is normal and the baseline that represents reduced-voltage operation. The two normalization approaches are found to yield consistent results each month regardless of which baseline was used for the normalization. The arrow lengths estimate a standard-error bound on the monthly averaged differences. The extended bars indicate estimated 95% confidence intervals based on each month's data.

Most, but not all, the monthly results show a reduction in power consumption. The project reports an overall power reduction of 26 ± 2 kW, using both of the controlled baselines and all available project data. Note that the magnitude of power reduction during CVR is a function of the voltage change. Based on the average load on Feeders 1–4 (3.25 MW), this is a 0.80% average power reduction on these feeders when CVR is engaged. The CVR factor is 0.53. This calculation has used a constant voltage change even though the voltage change was shown during analysis to have differed somewhat throughout the project.

The City of Milton-Freewater had expected a substantially greater impact from this asset system.

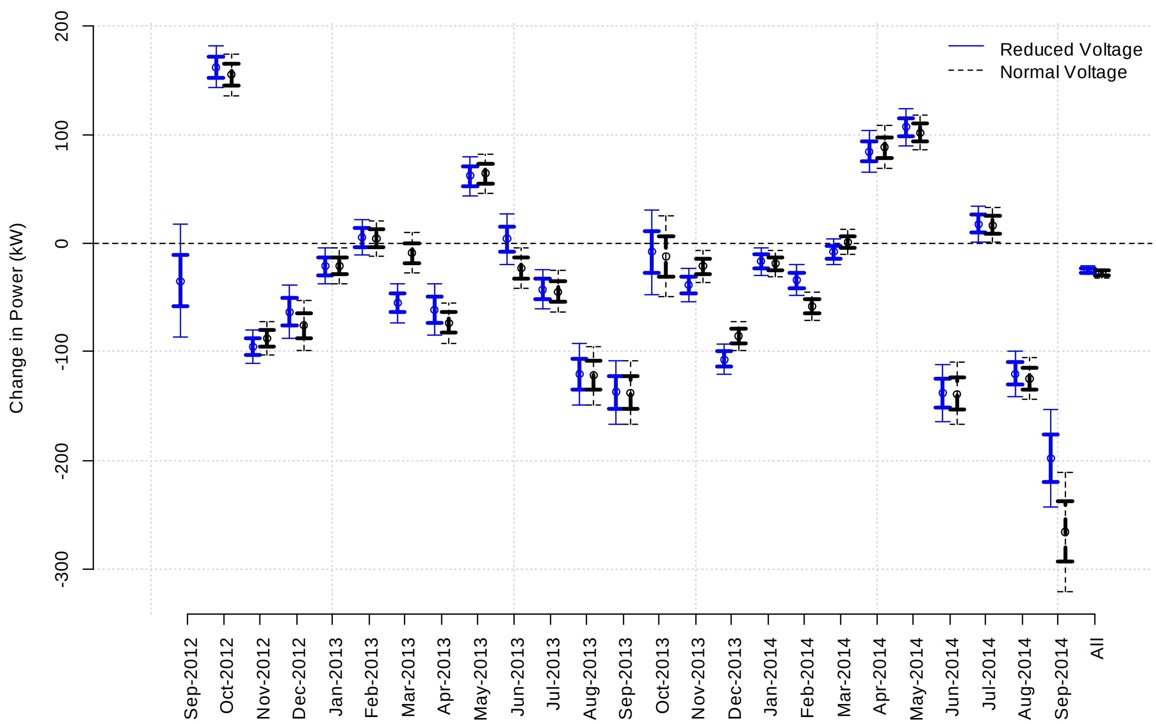


Figure 13.35. Change in Total Power on Feeders 1–4 Attributable to CVR each Project Month Using Two Baselines Suited for Comparisons while Voltage is Reduced (blue) and Normal (black dashed).

In Figure 13.36, the same data has been parsed by local hour of day and by whether the hour occurs on a weekday (blue) or weekend (dashed black). The impacts for weekday hours are shown to vary less than for the weekend ones. Weekend Hours 8, 9 and 10 show an interesting *increase* in power consumption while voltage is reduced. Otherwise, consumption is reduced by CVR more on weekend hours than on weekday hours. This is plausible given that the city's electric loads during weekdays and weekend days may be quite different.

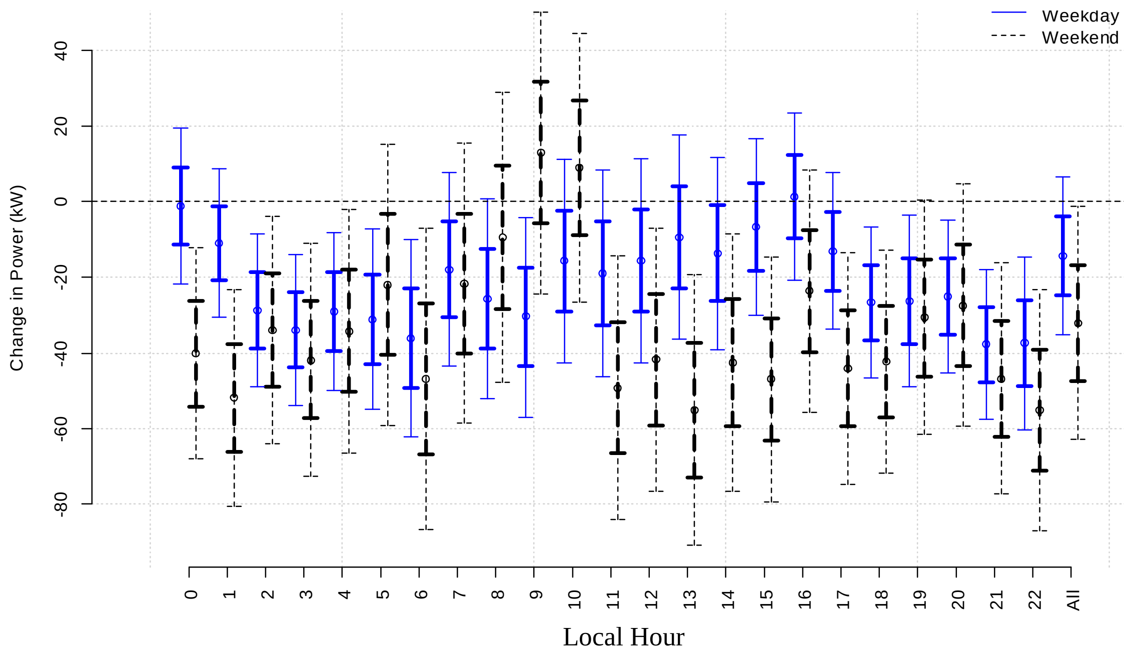


Figure 13.36. Total Change in Power Attributable to CVR on Feeders 1–4 By Hour (Pacific Time) and Weekday (blue) and Weekend (black dashes)

Table 13.10 summarizes the cumulative impact that the practice of CVR would have on Feeders 1–4 if the voltage were to remain reduced by 1.5%, the voltage reduction that was used during the demonstration. The results are calculated for each calendar month and for an entire year. The calculations were separately performed for HLH and LLH hours so that BPA's load-shaping rates (Appendix C) could be used to estimate the monetary value of the avoided wholesale energy purchases. Based on the project's analysis methods and data, Milton-Freewater would avoid buying 99.3 MWh each year, which is presently worth about $3,520 ± 240 to Milton-Freewater according to BPA load-shaping rates.

The utility, however, also loses the opportunity to sell sale much of this energy to its customers, which would be worth about $4,970 to Milton-Freewater at $0.05 per kWh.

Table 13.10. Projected Supply Energy and the Value of Supply Energy that Would be Displaced by CVR on Feeders 1–4. Calculated impacts presume that voltage remained reduced on Feeders 1–4, not just on alternating weeks.

	HLH		LLH		Total	
	(MWh)	($)	(MWh)	($)	(MWh)	($)
Jan	−2.2 ± 1.6	−83 ± 60	−5.7 ± 1.2	−175 ± 37	−7.9 ± 2.0	−258 ± 70
Feb	−1.0 ± 1.5	−37 ± 55	−3.9 ± 1.0	−119 ± 31	−4.9 ± 1.8	−156 ± 63
Mar	−5.3 ± 1.7	−160 ± 51	−7.0 ± 1.5	−176 ± 38	−12.3 ± 2.3	−336 ± 64
Apr	5.8 ± 2.1	149 ± 54	−2.8 ± 2.0	−56 ± 40	3.0 ± 2.9	93 ± 67
May	14.8 ± 1.7	311 ± 36	14.9 ± 1.5	195 ± 20	29.7 ± 2.3	506 ± 41
Jun	−19.3 ± 2.7	−439 ± 61	−5.5 ± 1.8	−80 ± 26	−24.8 ± 3.2	−519 ± 66
Jul	−1.4 ± 1.7	−43 ± 52	−2.7 ± 1.3	-66 ± 32	−4.1 ± 2.1	−109 ± 61
Aug	−26.9 ± 2.3	−914 ± 78	−11.5 ± 1.3	−312 ± 35	−38.4 ± 2.6	−1,226 ± 85
Sep	−22.2 ± 2.3	−747 ± 77	−13.1 ± 1.2	−365 ± 33	−35.3 ± 2.6	−1,112 ± 84
Oct	15.7 ± 2.5	496 ± 79	28.4 ± 2.4	779 ± 66	44.1 ± 3.5	1,280 ± 100
Nov	−14.8 ± 1.5	−526 ± 53	−7.9 ± 1.1	−247 ± 34	−22.7 ± 1.9	−773 ± 63
Dec	−9.7 ± 1.4	−377 ± 54	−16.0 ± 0.9	−532 ± 30	−25.7 ± 1.7	−909 ± 62
Totals	**−66.5 ± 6.8**	**−2,370 ± 210**	**−32.8 ± 5.2**	**−1,150 ± 130**	**−99.3 ± 8.6**	**−3,520 ± 240**

(a) Negative energy values in these columns mean that net load was decreased by the CVR according to the project's methods and data.

(b) Negative dollar values in these columns mean that CVR decreased the wholesale energy that the utility would have otherwise purchased according to the project's analysis.

The impact of the CVR system on the utility's demand charges has been estimated in Table 13.11. These estimates are "projected" in that they presume CVR was practiced on Feeders 1–4 throughout the year, not on alternate weeks. The second column projects the impact of CVR on the utility's demand during each calendar month's peak hour. This column was calculated by first preparing a preliminary table (not shown) of statistical impacts for each calendar month and its HLH hours. This preliminary table is much like the data that was plotted in Figure 13.36, except it is separately created for each calendar month and uses only HLH hours. Because there were multiple instances of each hour and month, both the average and standard error of the potential impact on the utility's demand could be calculated for each calendar month and HLH hour. Next, the utility's historical peak hours for each calendar month were used to determine an average impact for that month for coincident HLH hours. Each historical peak hour was presumed to have equal likelihood, and these sample hours were then used to weight the impacts from the individual coincident HLH hours.

The impact on average heavy load hour (aHLH) demand was estimated by averaging the impacts from all the aHLH hours in each calendar month.

Finally, the estimated impact on demand charges was estimated by multiplying the differences between the peak hour impacts and aHLH impacts by the corresponding months' BPA demand rates (Appendix C). The continuous practice of CVR on Feeders 1–4 would reduce the utility's demand charges by about $4,400 ± 1,500 per year.

Table 13.11. Projected Impact of CVR on the Utility's Demand Charges. Calculations presume the voltage is always reduced on Feeders 1–4.

	Δ Demand[a] (kW)	Δ aHLH[a] (kWh/h)	Δ Demand Charges[b] ($)
Jan	−62 +/- 31	−5 ± 1	−640 ± 350
Feb	−101 ± 37	−3 ± 1	−1,070 ± 400
Mar	−49 ± 38	−12 ± 3	−330 ± 340
Apr	1 ± 50	14 ± 10	−100 ± 390
May	89 ± 30	37 ± 4	322 ± 190
Jun	−81 ± 47	−46 ± 15	−240 ± 332
Jul	23 ± 28	−3 ± 2	230 ± 250
Aug	−129 ± 45	−62 ± 7	−670 ± 460
Sep	−271 ± 92	−56 ± 5	−2,140 ± 920
Oct	181 ± 45	36 ± 3	1,350 ± 420
Nov	−109 ± 27	−37 ± 5	−760 ± 290
Dec	−55 ± 30	−24 ± 1	−360 ± 340
Total			**−4,400 ± 1,500**

(a) Negative demand and average demand values in these columns mean that the demand was reduced by CVR according to the project's methods and data.

(b) Negative dollar values in this column mean that CVR is projected to reduce the utility's demand charges by this amount according to the project's analysis.

13.6 Conclusions and Lessons Learned

The City of Milton-Freewater tested four asset systems during the PNWSGD. An objective of the city was to control the responses of three of these systems to reduce its monthly demand charges. Toward this end, the city participated in the project's transactive system and established a demand-charges function that was to help engage the city's responsive assets whenever the city might be experiencing its monthly peak demand. The demand-charges function was established and was connected to the regional transactive system, but it never became fully configured and functional and therefore did not much help the city automate its efforts to reduce its demand charges.

One of the responsive systems was a set of about 800 DRUs attached to various 240-Volt premises loads like water heaters and air conditioners throughout the city. The switchable devices interacted with and could be communicated with via the existing TWACS system in Milton-Freewater. Two different classes of responses were established by the city. Some events were called at the times suggested by the project's transactive system; however, the city independently initiated additional events using features of its vendor's software, which conducted sequential engagements and disengagements of multiple DRU subgroups while automatically observing the magnitude of the city's demand. At one point, vendor software was found to have been preventing the DRUs from responding to the events that had been initiated by the transactive system. For this and other reasons the early performance of the system was poor, but the performance of the DRUs improved toward the end of the project period. The project calculated that, on average, each DRU had reduced its premises' load by about 100 W during all the project's DRU curtailment events. Toward the end of the project, the DRUs were consistently curtailing 270 W at each DRU location.

Milton-Freewater tested a dynamic voltage reduction that might be controlled to shape load and avoid demand charges. On nine of its 13 feeders, the city reduced the feeders' voltage by up to 4.5% (three taps) for hours at a time. The project looked for the system's impacts in the summed power from the five of affected feeders that had no voltage-responsive water heaters, another asset system tested by the city during the PNWSGD. The city's list of times when it was to have reduced the voltage in this way was found to be inaccurate when it was compared with feeder voltage data. Therefore, the project inferred event periods from its observations of feeder data. While the city contends that they can easily observe reductions in feeder load soon after the feeders' voltages have been reduced, the project could not consistently observe such a reduction from the data that the city had submitted. In fact, an *increase* in load was calculated by the project for the periods that the voltage had been reduced. Furthermore, the increase was found in both feeder-level and premises data. Researchers hope to revisit this analysis and learn why the analysis results were contradictory.

About 100 voltage-responsive water heaters were installed at premises on four of the city's feeders. These four feeders were among the nine city feeders that were affected by the aforementioned 4.5% voltage reductions. These water heaters recognized the voltage reduction as their signal to fully curtail the water heater load without requiring the complexity of wired or wireless communications to the devices. The project found the voltage-responsive water heaters to have reliably curtailed about 170 W each, on average, during the voltage-reduction events. City staff was concerned that the water heaters' owners might be inconvenienced if the water heaters were curtailed for multiple hours. Had these voltage-responsive water heaters not been collocated on the feeders where the city practiced dynamic voltage reduction, the city says it probably would have conducted more and longer voltage-reduction events.

The city tested convention CVR on four of its distribution feeders. For almost two years, city staff toggled the system to reduce the feeders' voltages by about 1.5% every other week. The project calculated that the power had been reduced about 26 kW, on average, during the times that voltage was reduced. This is about 0.8% of the typical load on these feeders. The city had anticipated a more beneficial impact from its CVR, and researchers hope to revisit this analysis and its methods in the future to see if those impacts were understated.

Among the lessons that it learned during the PNWSGD, Milton-Freewater, a small municipality, said that it had badly underestimated the staff time it would take to participate in the PNWSGD. They underestimated the time it would take to implement the project and to complete necessary accounting and reporting. The city has no information technology department and must rely on consultants to help with its computer and computer security issues. The city says it has a much clearer understanding of cyber security now than it did prior to the project.

While the city continues to have strong relationships with its vendors who helped it during the PNWSGD, some of the vendors' claims were found to have been optimistic. Milton-Freewater is still working toward a more automated system that will help it shave its monthly peak demand. Its present system lacks functionality, and it required a difficult integration between the city's SCADA and meter data management systems. The DRUs cannot yet be addressed and controlled differently according to the classes of devices that they control (e.g., water heaters vs. air conditioners). And the city received some calls from its residents because of confusing indicator lights on its vendors' devices.

All four asset systems that were installed by the city during the PNWSGD remain installed and useful.

14.0 NorthWestern Energy Site Tests

Additional chapter coauthors:
K Subbarao − Battelle Memorial Institute;
J Pusich-Lester, G Horvath, and B Thomas − NorthWestern Energy

NorthWestern Energy serves over 400,000 electric customers in a service territory that covers much of Montana, South Dakota, and Nebraska. The service territory covers approximately 123,000 square miles and manages 27,600 miles of electric transmission and distribution lines. In the Pacific Northwest Smart Grid Demonstration (PNWSGD), they think of their participation as having two distinct sets of activities that address utility and customer activities.

The utility-side activities included

- a form of distribution automation (DA) known as fault detection, isolation, and restoration (FDIR) (Section 14.2)
- integrated volt/VAr control (IVVC) , also known as volt/VAr integration and optimization (VVO) (Section 14.1 and Section 14.4).

On the customer side, the utility provided a set of residential and commercial customers the means to control their electricity usage, respond to time-of-use pricing, and participate in demand-response (DR) load control (Section 14.3).

The utility offered the PNWSGD two field sites. The first involved eight distribution circuits from three of the seven utility substations in Helena, Montana. This site is relatively urban for Montana and engaged approximately 200 residential customer homes and two Montana State government buildings. The second site was a much more rural region and electric circuit near Philipsburg, Montana. This site included only one substation and circuit; the circuit extends 40 miles from the substation and consists of approximately 240 line miles.

Figure 14.1 is Northwestern Energy’s layout diagram that shows the relative placement of the utility’s test equipment and test groups among the distribution circuits that it operates in Helena and Philipsburg, Montana.

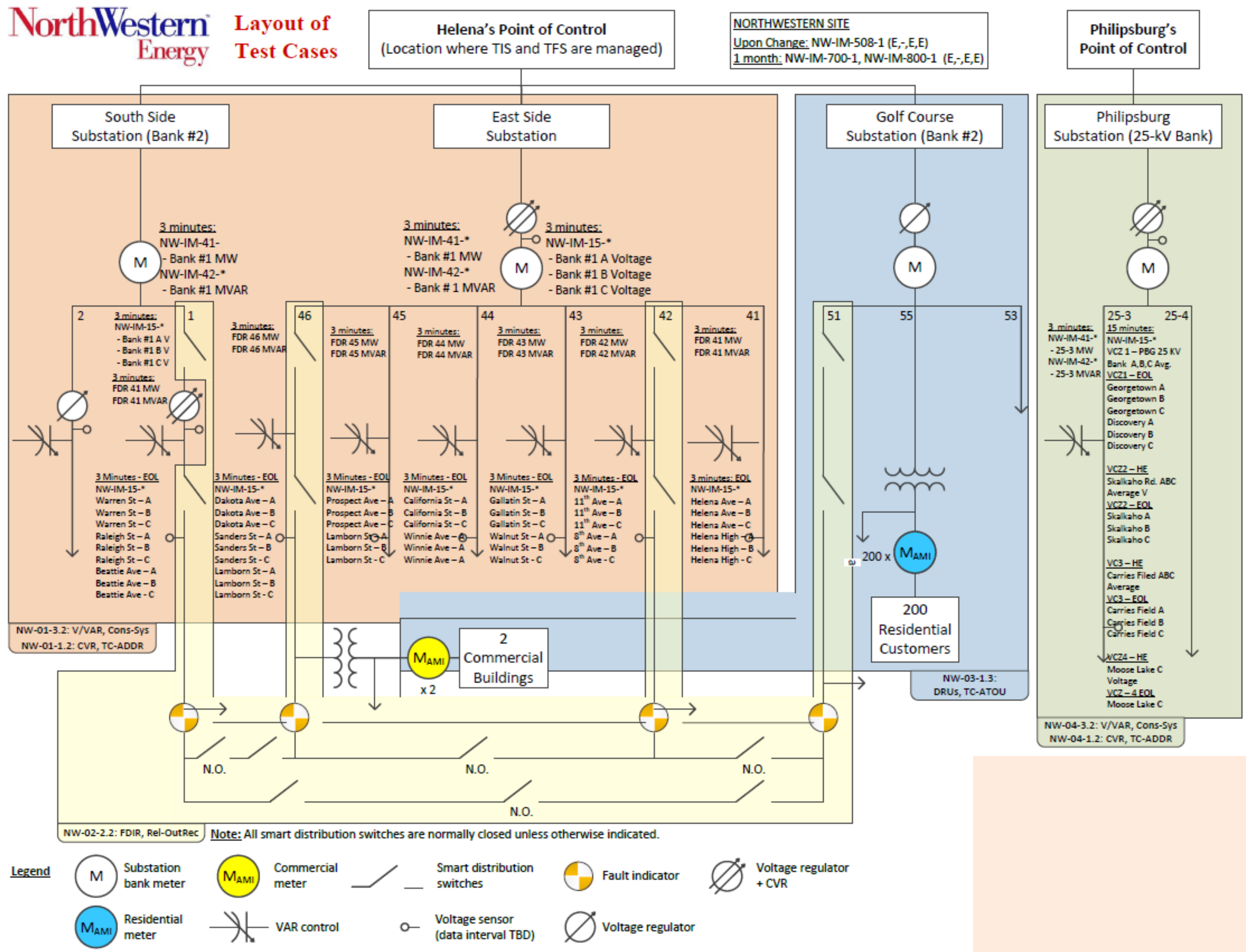


Figure 14.1. NorthWestern Energy Tests Overlaid on the Helena, Montana and Philipsburg, Montana Distribution Circuits

14.1 Automated Voltage and Reactive Power Control – Helena

Automated voltage regulator controls, automated capacitor banks, distribution voltage sensors, and distribution system software were used to automate voltage and reactive power control (IVVC) on several feeders in NorthWestern Energy's Helena, Montana service territory. In Helena, voltage and reactive power control affected 6,100 customers on seven circuits supplied by two substations. The Helena IVVC system was deployed on South Side Feeders 1 and 2 and East Side Feeders 41 through 46.

The utility also installed an IVVC system on a more rural feeder at Philipsburg, Montana, and that system is described later in Section 14.4.

The utility's objective with this system is to demonstrate that voltage and reactive power control automation produces benefits without customer complaints, and to measure its benefits. The system regulates reactive power (VArs) by switching strategically placed capacitors controlled via an algorithm from S&C Electric Company. The algorithm flattens the feeder voltage profile and reduces line losses by increasing power factors in the distribution system.

Helena devices included two Beckwith load tap changer (LTC) controllers, seven Beckwith capacitor controllers, and 48 distribution voltage sensors for end-of-line voltage sensing. The annualized costs of the Helena IVVC system and its components are shown in Table 14.1 and sum to about $181.5 thousand per year.

Table 14.1. Annualized Costs of the Helena IVVC System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
CVR/Volt-VAr and DA System Software	50	154.9	77.5
Helena Capacitor Bank (new banks with controller)	100	33.7	33.7
Helena Communications (radio and tower)	33	72.1	24.0
Helena Distribution Voltage Sensors	100	17.2	17.2
Helena Substation Communications	50	29.7	14.9
Helena Substation RTUs and Relaying	50	21.4	10.7
Helena Substation Regulator/LTC Controls	100	3.6	3.6
Total Annualized Cost			**$181.5K**

CVR = conservation voltage reduction
RTU = remote terminal unit
VAr = volt-amperes reactive

14.1.1 Data and System Operation Concerning the Helena IVVC System

The IVVC voltage status of the South Side and East Side circuits were reported to the PNWSGD by NorthWestern Energy using the many enumerations listed here. The same enumerations were used for both the voltage control and reactive power control components of their IVVC systems:

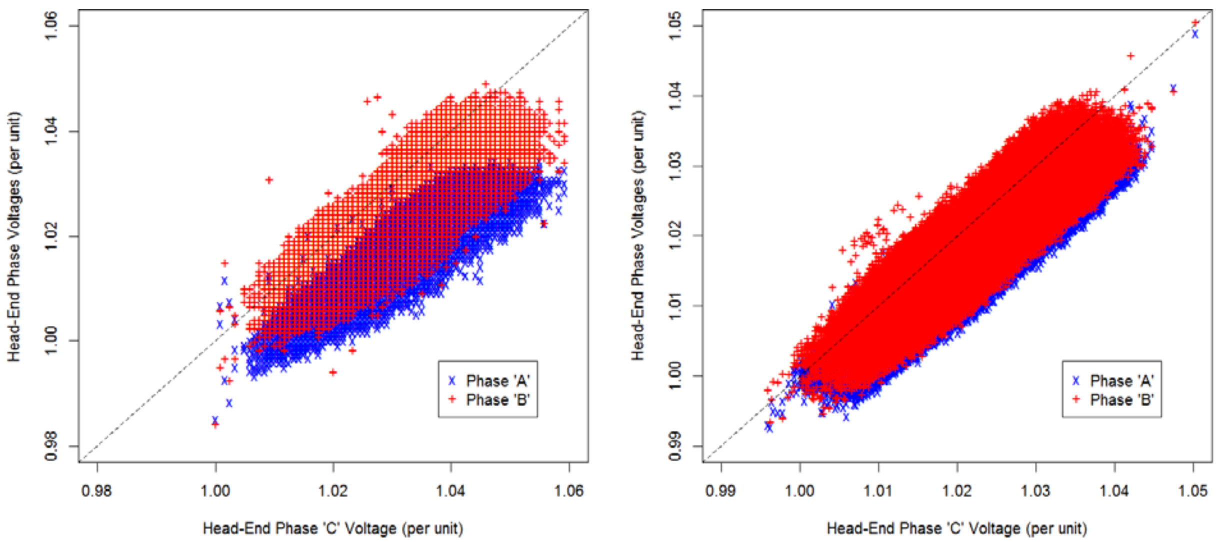
- "Engaged"
- "Engaged – Comm Restored" (East Side only)
- "Engaged – Scada Restored"
- "Engaged – Via Schedule" (East Side only)

- "Not Engaged"
- "Not Engaged – By Scada (YFA[1])"
- "Not Engaged – Comm Loss"
- "Not Engaged – Comm Restored"
- "Not Engaged – Missing Data" (South Side only)
- "Disabled" (South Side only)
- "Early Unknown"

This is an example of an enumeration that attempts to capture multiple statuses. This set not only states whether the IVVC system is engaged, it also tries to address the status of communications, the source of the control directive, the status of the supervisory control and data acquisition (SCADA) system, and whether the system has been disabled. From the project analysts' perspectives, only the engagement status verification is needed, which should be indicated by the distinction between the enumerations listed in the left-hand column and those listed in the right-hand one.

[1] YFA = Yukon Feeder Automation

NorthWestern Energy provided the PNWSGD with head-end distribution phase voltages for the South Side and East Side circuits. The data for both circuits began in mid-March 2013 and continued to the end of the PNWSGD data collection period at the end of August 2014. The phase voltages for both circuits were observed to be similar and to track one another closely, as shown in Figure 14.2. There exists an offset between the voltages of Phase “a” and Phase “b” in the South Side circuit, as shown in Figure 14.2a, but the sets have similar slopes, meaning that changes in one phase’s voltage are also seen similarly in the other phases. The dashed line represents perfect correlation. If the circuit were perfectly balanced and had similar loads on all phases, the correlation between phase voltages would be close to this line. Because the phases are seen to track one another well, analysts had confidence that they might calculate and use the average of each circuit’s phase voltages to simplify analysis.



(a) South Side Circuit (b) East Side Circuit

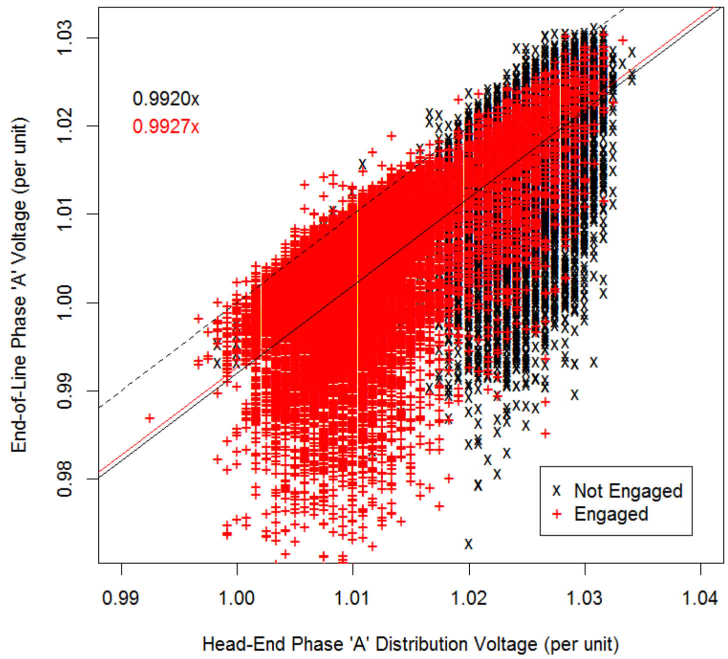
Figure 14.2. Head-End Phase “A” and Phase “B” Voltages Plotted Against the Phase “C” Voltage for the (a) South Side and (b) East Side Circuits. The argument is made that the phase voltages are similar and change together, so analysis may proceed using an averaged phase voltage.

It is also worthwhile to check the relationship between the end-of-line service voltages and the head-end distribution voltages on a phase-by-phase basis. The impact of voltage reduction is often reported in terms of end-of-line voltages and changes in end-of-line voltages. Additionally, IVVC systems monitor the end-of-line service voltage to make sure that electricity is always delivered at or above an accepted minimum voltage level. This comparison is done in Figure 14.3, using the phases of the South Side circuit to demonstrate the comparison.

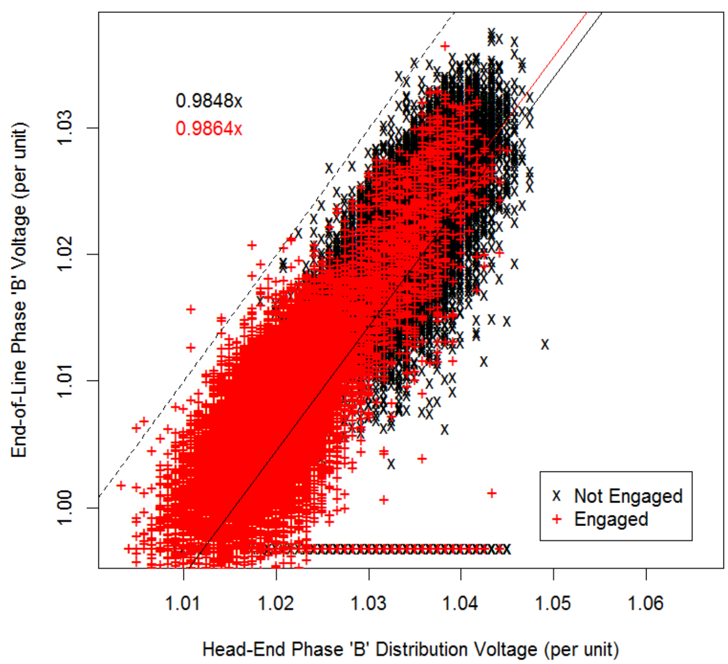
The vertical axis is the per-unit end-of-line service voltage. The utility will strive to keep the customer delivery voltage at or above 114 V. This is 0.95 p.u., based on a 120 V service voltage (which is the case here). The reduction in voltage indeed reduces the average service voltages, but there remains a safety cushion above the 0.95 p.u. criterion.

The horizontal axis is the head-end per-unit phase voltage. This is the voltage at or near the substation transformer. If there were no voltage drop (or increase) during distribution of electricity on this circuit, the data points would lie along the dashed black line, which would mean that the head-end and end-of-line voltages are the same. Both the “Engaged” and “Not Engaged” data sets lie below the dashed black line, meaning that all phases experience voltage drops during distribution. For some reason, the voltage drop is greater on Phase “c” than on Phases “a” and “b.” Since the LTCs control all three phases together, it is Phase “c” that will ultimately limit the magnitude of the reduction that may be achieved. Best-fit lines and their slopes have been provided in Figure 14.3. These presume the line must go through the origin. The x-coefficients (slopes) inform us of the characteristic line drop on the corresponding phase. These coefficients may be used to depreciate the change in voltage that is observed in the head-end voltages, to thereby estimate the corresponding changes in end-of-line phase voltages. However, it is the worst-case data points, those that potentially fall below acceptable service voltages, that determine the acceptability of the IVVC algorithms.

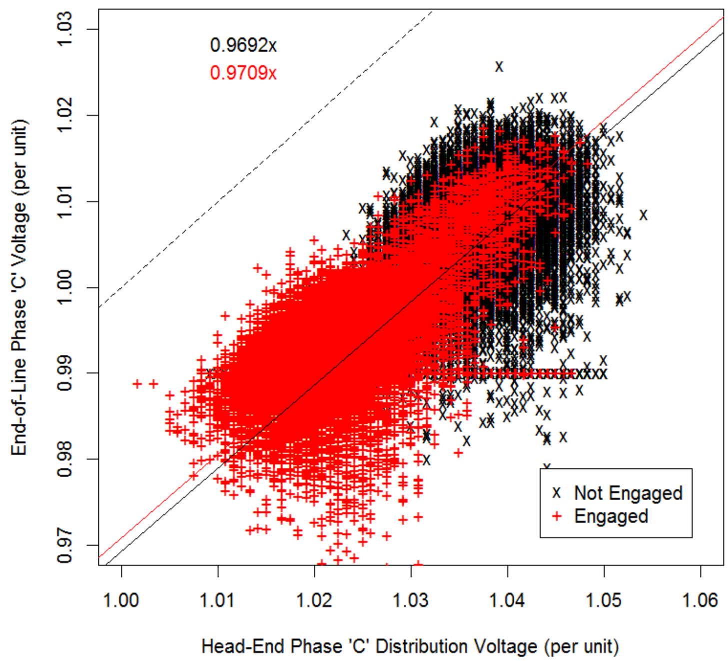
The relationship between end-of-line and head-end voltage on the East Side circuit is acceptable but will not be shown here.



(a) South Side Phase "A"



(b) South Side Phase "B"



(c) South Side Phase "C"

Figure 14.3. End-of-Line Per-Unit Phase Voltages as a Function of the Corresponding Head-End Per-Unit Phase Voltages on the South Side Circuit. The dashed black line represents perfect correlation. The solid red and black lines are the linear best fits for the "Not Engaged" (black) and "Engaged" (red) data sets.

All the distribution voltage data received from NorthWestern Energy is represented in Figure 14.4. This figure shows the results of some of the simplifications that were justified in the discussion leading up to this point. First, the per-unit voltage being plotted is the average of the head-end phase voltages reported for the South Side circuit. Second, the color coding has used a simplification of the IVVC voltage status indicator, where all the enumerations of type "Engaged" were combined, and all the enumerations of type "Not Engaged" were also combined. The status "Disabled" was assigned to the "Not Engaged" group and "Early Unknown" status was treated as unavailable.

A fairly complete time series exists for the South Side head-end voltages. The first data became available in mid-March 2013 and data collection ended at the end of August 2014. The data "stuck" on a constant value through parts of June 2013 and February 2014.

There exists evidence of day-on, day-off voltage reduction experimentation in Figure 14.4. This experimentation appears at this scale to be the simultaneous assignment of "Engaged" and "Not Engaged" statuses, but is, in fact, successive alternate assignments being made on short (daily) intervals. Candidate evaluation time periods like those shown with yellow shading on the figure should both show evidence of alternating voltage treatment and have been assigned meaningful, accurate status indicators during the period. The second criterion helps make sure that the changes in voltage are intentional and being applied for the purposes being studied.

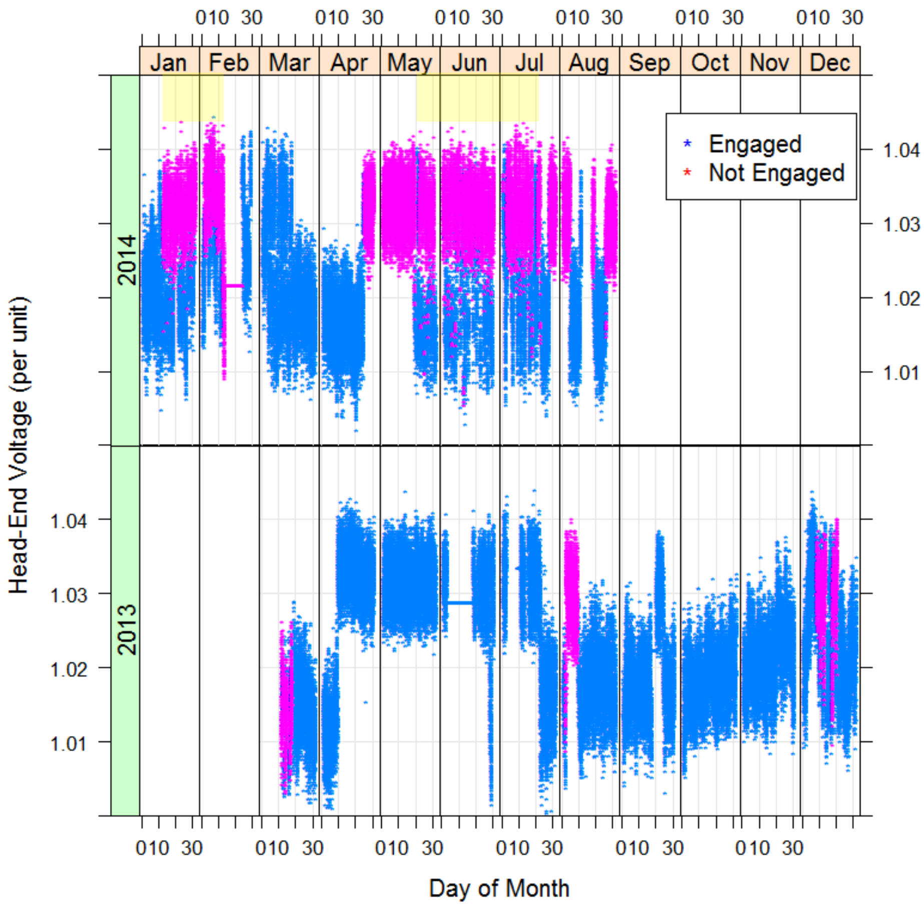


Figure 14.4. Average Head-End Phase Voltages for the South Side Circuit, Including the Simplified IVVC Status for that Circuit. Candidate evaluation periods have been marked by yellow shading.

Similar data and similar data treatments are shown in Figure 14.5 for the East Side circuit. Head-end phase data became available from the last weeks of July 2014, and this data was collected until the end of the PNWSGD data collection period at the end of August 2014. As in the South Side figure, candidate evaluation periods have been marked with yellow shading.

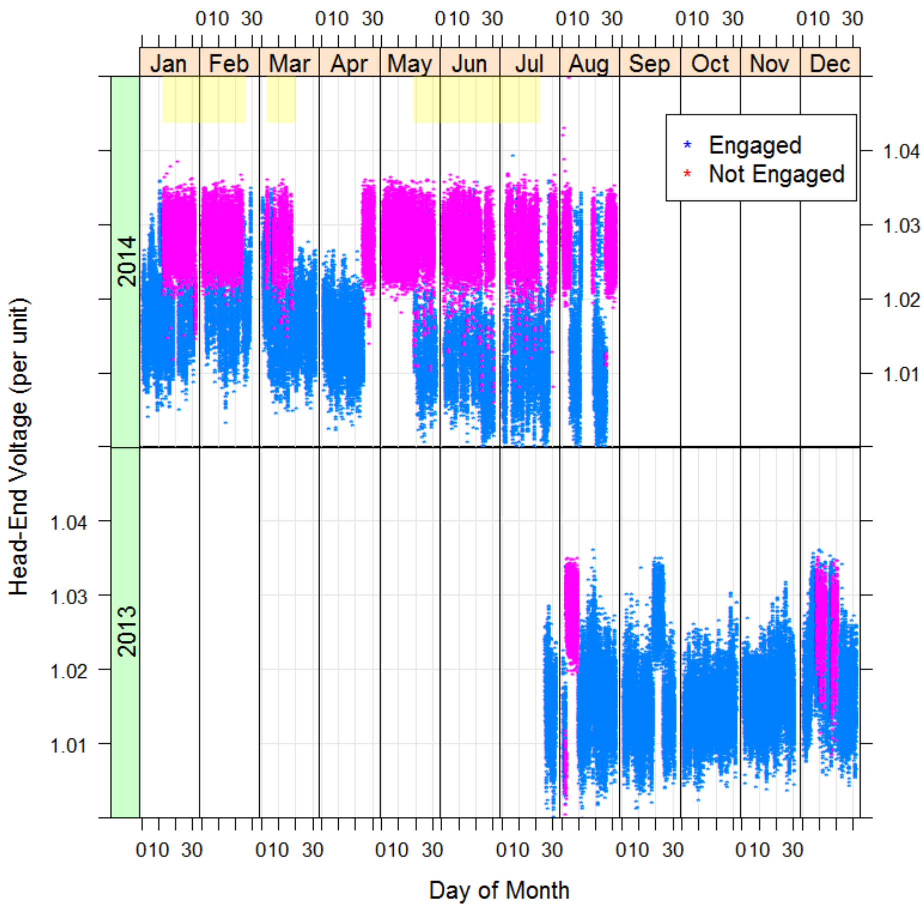


Figure 14.5. Average Head-End Phase Voltages for the East Side Circuit, Including the Simplified IVVC Status for that Circuit. Candidate evaluation periods have been marked by yellow shading.

The corresponding real and reactive power loads on the South Side and East Side circuits are now shown in Figure 14.6 and Figure 14.7, respectively. These data have fine resolution at 5-minute intervals. The South Side circuit is winter peaking, but the East Side circuit exhibits an unusual peak during July and August each year. Some step changes occur in the reactive power of both plots, but these do not appear to be correlated with the patterns of or times that day-on, day-off voltage experimentation had occurred. This power data should support analysis.

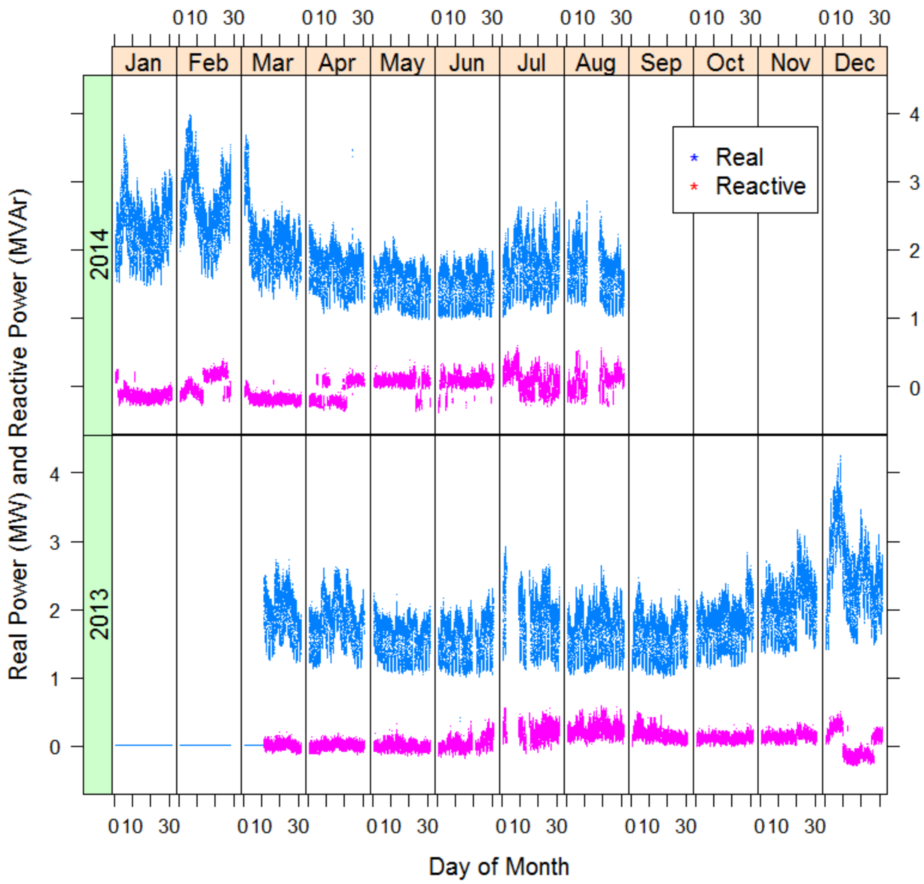


Figure 14.6. Total Real and Reactive Loads on the South Side Circuit

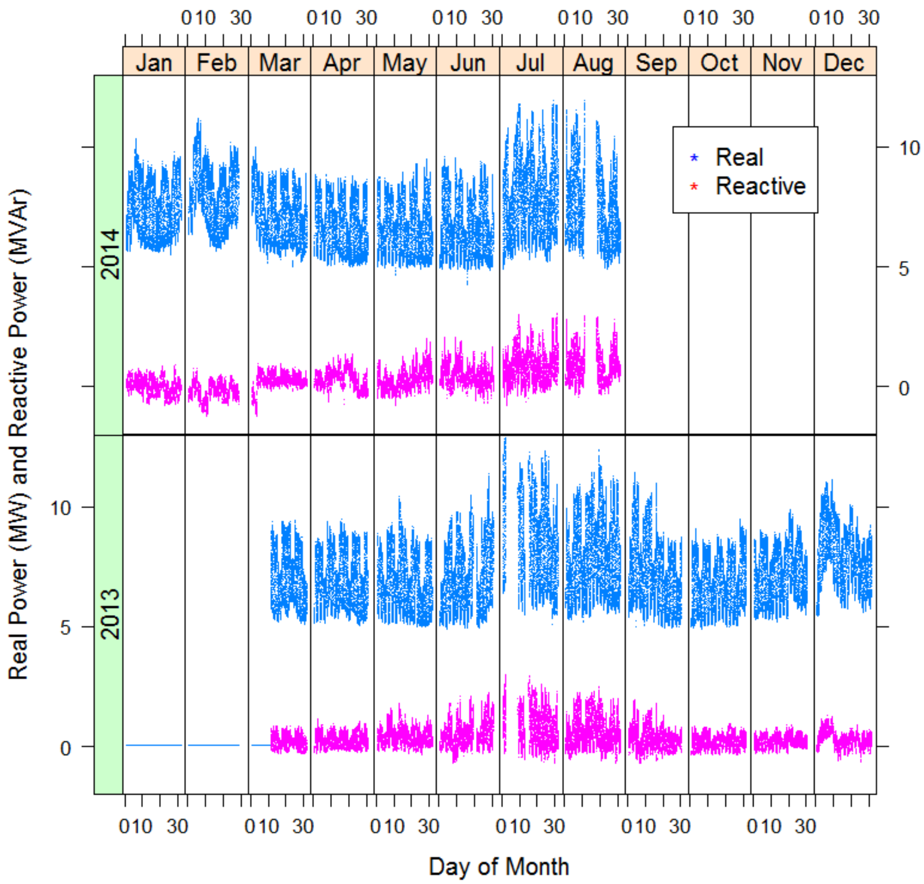


Figure 14.7. Total Real and Reactive Loads on the East Side Circuit

14.1.2 Analysis of the Helena IVVC Systems

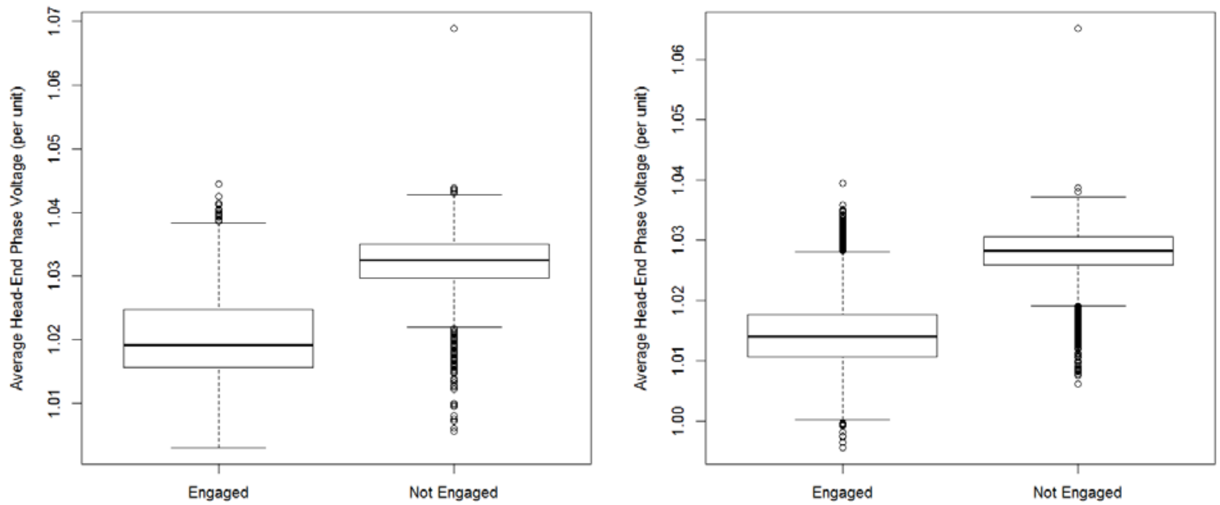
Analysts reviewed and refined the evaluation periods to make sure that they included only times that voltage changes occurred and had been accurately marked. This was done by inspection on a month-by-month basis.

South Side IVVC voltage evaluation periods were January 12–February 12 and May 19–July 22, 2014, excluding July 1, 2014.

East Side IVVC voltage evaluation periods were January 12–February 23, March 6–March 19, and May 19–July 20, 2014.

Figure 14.8 shows the quartile distributions of the head-end distribution voltages according to the engagement statuses at the South Side (Figure 14.8a) and East Side (Figure 14.8b) circuits. These are being reported for the narrowed evaluation periods that were defined for each of the circuits. The South Side voltage is seen to be reduced by 0.013 p.u., based on the calculated difference between the medians of the head-end voltages under the two control statuses. This is a reduction of 1.3%. The East Side head-end voltage was reduced by 0.014 p.u., or 1.4%, based on the change in the median voltages between the two voltage levels. Given that the end-of-line voltages were determined to be 97–99% of the head-end voltages (on a per-unit basis) the changes in voltage would be the same if it were measured at an end of the line (within a couple of significant digits).

NorthWestern Energy had reported that when they first exercised their Helena IVVC system in December of 2013, they observed an average change of 1.21% in the voltage.



(a) South Side Circuit (b) East Side Circuit

Figure 14.8. Quartile Plots of the Average Per-Unit Head-End Phase Voltages at the (a) South Side and (b) East Side Circuits during their Respective Evaluation Periods

Analysts created linear regressions of the circuits' real power as functions of ambient temperature and separately calculated by month, weekday type, and hour of day. The temperature from station HVMT in Helena, Montana was used. The records of temperature were found to be quite complete, but the data was further interpolated to fill in all the missing 5-minute intervals and thereby use more power measurements in the regression models. Only data in the evaluation periods was used. R software (R Core Team 2012) was used to facilitate the linear regression modeling.

The linear model at the South Side site had an impressive R^2 value of 0.9599. Based on this regression model, the circuit consumed 16.6 ± 1.5 kW less power when the IVVC system was "Engaged" than it did while it was "Not Engaged." That is about 0.9% of the average power on the circuit during 2014 and about 0.4% of the peak power during 2014. In a 24-hour period that would be almost 400 kWh energy savings, on average.

For the East Side circuit, the R^2 of the fit was 0.944. Unfortunately, the change in power determined by the approach using the East Side circuit was inconclusive.

14.2 Fault Detection, Isolation, and Restoration

NorthWestern Energy installed FDIR technology at their Helena and Philipsburg Montana sites. This is a form of DA that automatically reconfigures circuits after outages to restore service to as many customers as possible. They wanted to quantify the benefits they would realize from its use, including the improvement of service and reliability.

Circuits in Helena with FDIR affected 4,800 customers on four circuits that are served by three substations—Eastside (42 and 46), Golf Course (51), and Southside (1). The four circuits are tied together by reclosers that are programmed as sectionalizing switches. The feeder can be further sectionalized by its in-line reclosers that are also programed as sectionalizing switches. A communication system between all the smart devices allows Cooper Power Systems' Yukon Feeder Automation (YFA) software to isolate the fault, sectionalize the fault, and restore as many customers as possible without overloading any field devices or conductor line segments. The YFA software also communicates with Schweitzer Electric Laboratory relays to retrieve loading information.

Table 14.2. Annualized Costs of the FDIR System and its Components over the Four-Year Term

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Smart Distribution Switches	100	123.7	123.7
CVR/Volt-VAr and DA System Software	50	154.9	77.45
Helena Communications (radio and tower)	33	72.1	24.0
Helena Substation Communications	50	29.1	14.55
Fault Indicators	100	11.5	11.5
Helena Substation RTUs and Relaying	50	21.4	10.7
Total Annualized Cost			**$261.9K**

14.2.1 Reliability Metrics for the FDIR Circuits

The PNWSGD collected several metrics from NorthWestern Energy, hoping that these metrics might confirm reliability improvements that would be possibly attributable to the FDIR systems. These metrics include the utility's yearly distribution restoration costs, Customer Average Interruption Duration Index (CAIDI), and System Average Interruption Duration Index (SAIDI).

NorthWestern Energy submitted their yearly distribution restoration costs to the PNWSGD for the years from 2010 into 2014. The logic was that these restoration costs might have been reduced if the utility were able to recover from its outages more efficiently. These costs were rounded to the nearest $100 and are listed in Table 14.3. The costs for year 2014 are incomplete because PNWSGD data collection stopped at the end of August that year. The costs for the complete years 2010 through 2013 appear to have remained fairly constant. We cannot conclude that distribution restoration costs were reduced from this reporting.

Table 14.3. Yearly Distribution Restoration Costs that were Reported to the PNWSGD by NorthWestern Energy ($K)[(a)]

2010	2011	2012	2013	2014
28.7	25.2	20.3	25.4	8.5[(b)]

(a) Yearly restoration costs have been rounded to the nearest $100.
(b) This is the sum of 2014 costs through September that year.

The yearly calculated CAIDI values for 2010 through 2013 and part of 2014 are listed in Table 14.4 for each of the four circuits on which FDIR was exercised in Helena, Montana. These are the average number of minutes that a customer experiences an outage on each of these circuits. These minutes should become reduced if outages can be responded to and mitigated more quickly. No clear trends are evident from the yearly CAIDI values.

Table 14.4. Yearly CAIDI Values Reported to the PNWSGD by NorthWestern Energy for the Four Helena Circuits in which FDIR was Used (minutes per customer outage)[(a)]

Circuit	2010	2011	2012	2013	2014[(b)]
South Side #1	102	50	62	180	118[(b)]
East Side #42	82	207	89	120	0[(b)]
East Side #46	26	41	136	61	63[(b)]
Golf Course #51	43	110	65	128	51[(b)]

(a) CAIDI values have been rounded to the nearest minute.
(b) 2014 CAIDI was calculated for the period January – September 2014, not the entire year.

The calculated yearly SAIDI values for these same four feeders are listed in Table 14.5. These are the average total outage durations that each customer experienced on the given feeder in the given year. As with CAIDI, total duration outages might be reduced and reflected in SAIDI if outage durations have been reduced. Again, the 2014 data is incomplete, but it appears that the circuits were having a remarkably reliable year from the beginning of 2014 to the time that data collection ceased at the end of August 2014. None of the recent years has exceeded the 2010 SAIDI values on three of the four circuits.

Table 14.5. Yearly SAIDI Values Reported to the PNWSGD by NorthWestern Energy for the Four Helena Circuits in which FDIR was Used (outage minutes per customer)[a]

Circuit	2010	2011	2012	2013	2014[b]
South Side #1	278	57	90	46	10[b]
East Side #42	4	31	3	2	0[b]
East Side #46	94	50	18	23	11[b]
Golf Course #51	91	78	3	30	~0[b]

(a) SAIDI values have been rounded to the nearest minute.
(b) 2014 SAIDI was calculated for the period January – September 2014, not the entire year.

FDIR may not be effective on all types of outages. We will consider some anecdotal observations in the next section that might point to improved responses to outages.

14.2.2 Anecdotal Results

NorthWestern Energy reported two outage events to the PNWSGD in great detail because these two point to advantageous use of the new FDIR system.

Event #1, June 12, 2013. This was a tree fall incident on one of the Helena South Side feeders. The Cooper YFA system operated as programmed. The circuit breaker locked out, and the majority of the circuit load was transferred to a Helena Golf Course feeder by the FDIR system within 51 seconds. Because of its actions, 1,250 of the circuit's 1,506 customers experienced the 51-second outage instead of the 119-minute outage that was experienced by the remainder of customers for whom power could not be as quickly restored. NorthWestern attributes the avoidance of 148,000 customer outage minutes to the FDIR system during this event. The consensus of the utility investigators was that, for this event, the FDIR system did not necessarily change the expenditure in lineperson and response efforts because the experienced staff believed they would have similarly found and remedied the source of the outage. A similar outage had occurred near that same circuit location not long before then.

Event #2, September 5, 2013. At about 07:50, a squirrel caused Helena Eastside Feeders 44 and 46 to lock out. Circuit 46, which is under FDIR control, was able to automatically restore power to 780 of the circuit's 1,007 customers within 30 seconds by activating one of its recloser switches. Feeder 44 is not equipped with FDIR. Its 492 customers, and about 220 customers on Feeder 46, whose power could not so quickly be restored experienced 30 minutes without electricity. These two feeders also serve many businesses, and even a hospital.

NorthWestern Energy reports that it has seen its new FDIR system operate three times in Helena so far, all successfully. They also had one event in Philipsburg, although a communications issue prevented one of the Philipsburg reclosers from performing correctly for that event. By the utility's calculations, the two Helena events described above represent a savings of approximately 0.2 SAIDI minutes within its Montana system calculations. Approximately 20 man-hours were also avoided (6–8 man-hours per event) restoring the power after those events.

14.3 Residential and Commercial Building Demand Response

NorthWestern Energy supplied groups of its residential- and commercial-scale customers sets of tools with which they could learn about and better manage their electricity consumption. The suite of tools included demand-responsive, controllable loads that the utility could engage to reduce its peak energy consumption.

About 208 residential customers received these devices:

- smart meter—serves as the basis for 15-minute interval premise energy measurements and facilitates remote reading of meters
- energy portal, or home area network (HAN)—facilitates communication of energy information and energy price information with which the customers may modify their electricity consumption
- plug-load switch—load controller that may be configured by the customer to respond at different energy price levels
- in-home display—source of energy information in the home, including price signals
- Web-based services—source of energy use profiles and metrics that may be displayed via in-home displays or the internet
- programmable thermostat—about 22.6% of the 208 residential customers received controllable thermostats that could respond to pricing levels

The utility hopes to evaluate the performance of the types of tools and the ways they were used by their customers. The utility took a small step toward exploring variable pricing and was able to observe and learn from its customers' responses to the price signals. The utility surveyed the residential customers at the conclusion of the PNWSGD to learn from their experiences.

On the commercial side, Helena is the capitol of Montana and hosts Montana State buildings. The utility outfitted the Lee Metcalf building with lighting control, installed automated dimming on overhead lights that were near outside windows, and installed dimming control in other building areas.

At the Lee Metcalf building, the heating, ventilating, and air conditioning system was upgraded with additional air conditioning controls and improved ventilation. The utility planned to also make state buildings demand responsive by integrating controllable loads using the Lockheed Martin SEELoad™ DR application, but this plan did not come to completion due to the Lockheed Martin software's inability to interface with the building's automation management system. At the Walt Sullivan building, HVAC systems were not incorporated into the control network due to the building automation system's legacy software.

All the residential customers who accepted the suite of tools were also placed on a time-of-use pricing schedule. They could reduce their energy bills if they modified the times that they consumed electricity according to this schedule of prices. For example, they could schedule their controllable plug loads to respond to any of the three price levels in the time-of-use schedule. However, there were no losers; any customer whose time-of-use-calculated bill was greater than it would have been under the normal flat rates paid the lower amount.

Critical peak pricing, or DR, responses were also facilitated through residential pricing. This is how the project understands the DR to have worked: First, a pricing signal was sent to the building automation control system. The buildings respond according to predetermined load curtailment schedules to reduce load based on price. Building energy measurements were then fed back to the Lockheed Martin SEELoad DR application. In near-real time, communications were then sent to building occupants through graphical displays on computer screens. The occupants, having been informed of the changes being made to temperature or lighting levels, recognize the changes as intentional efforts to modify the building's energy consumption.

The annualized costs of the commercial and residential DR system are summarized in Table 14.6. The total annualized cost of the system was estimated to be about $668.0 thousand per year.

Table 14.6. Annualized Costs of the Helena Residential and Commercial DR System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
DR - Energy Management Software (Lockheed Martin)	100	248.9	248.9
HAN Management Software and Services (Tendril®)	100	211.5	211.5
Helena DR Devices - Lighting Control Modules[(a)]	100	69.0	69.0
Helena DR Devices - Smart Plug-Load Outlet	100	33.2	33.2
Helena Meter Data Collectors	100	27.3	27.3
Helena Communications (radio and tower)	33	72.1	24.0
Advanced Metering Software and Services	100	12.8	12.8
Helena DR Devices - Home Energy Displays	100	10.3	10.3
Helena Advanced Residential Electric Meters	100	10.0	10.0
Helena DR Devices - Programmable Thermostats	100	8.7	8.7
Helena HAN (bridge/communication)	33	23.2	7.7
Helena DR Devices - Load Control Switches	100	3.8	3.8
Helena Advanced Commercial Electric Meters	100	0.8	0.8
Total Annualized Cost			**$668.0K**

(a) For two commercial buildings

To boost interest in their time-of-use pilot, NorthWestern Energy conducted quarterly contests and rewarded those participating customers who had conserved the most energy in the quarter compared with their consumption in that quarter the prior year. The results from the first quarter's competition (April–June 2013) and its prize awards are listed in Table 14.7.

Table 14.7. Outcome of the First Quarterly (April–June 2013) Customer Conservation Contest and its Top Three Customer Awards

Place	Energy Conserved (kWh)	Customer Cost Savings ($)	Prize ($)
1st	2,176	132	100
2nd	1,459	136	50
3rd	1,440	193	25

14.3.1 Characterization of Asset System Responses

Of the 208 premises that were reported to participate in the DR program, all received automatic meter reading, a plug-load control switch, an energy portal, and an in-home display. Of these participants, 22.6% also received programmable thermostats.

Three DR events occurred and are listed in Table 14.8 as they were reported to the project by NorthWestern Energy.

Table 14.8. DR Events Reported to the Project by NorthWestern Energy. All events were reported to have occurred August 28, 2014.

Event Number	Reported Hour	Scheduled Participants	Scheduled Devices	Program Scale (%)	Predicted Load Reduction (kW)	Actual Load Reduction (kW)
1	14	26	102	100	306	5
	15	26	102	100	357	4
2	13	26	102	100	408	6
3	14	41	120	70	770	3
	15	41	120	70	855	2

Figure 14.9 shows the available sets of averaged premises power data for the approximately 101 residential test premises that are supplied from the Golf Course substation, and another approximately 87 that are supplied from the West Side substation. The horizontal axis in each of the panels depicts the time of day. The change in consumption patterns by month should be evident. However, the plots also reveal discrepancies from year to year that are likely attributable to persistent time-shift problems that the project was unable to trace down and fix as it worked with the utility.

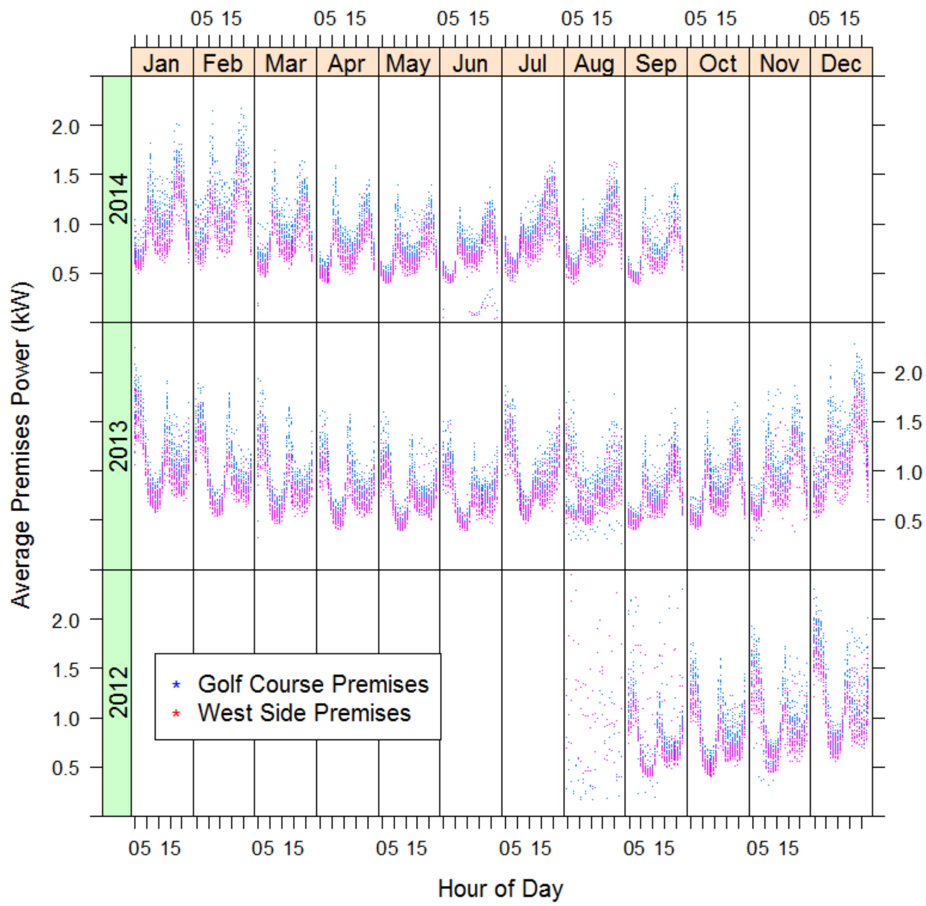


Figure 14.9. Average Premises Power of the DR Golf Course and West Side Test Groups as Functions of Hour of Day. We believe the data still exhibits time-shift issues based on the differences seen in the data from year to year.

The utility's time-of-use pricing program was initiated at all the DR test premises soon after the suite of DR devices had been installed in September 2012. There is no interval metering available from these premises from before the time-of-use program began. These were the only residences whose energy was monitored by the project using premises interval metering.

NorthWestern Energy designated three price levels—off-peak, mid-peak, and on-peak—to influence when plug loads at participating residential locations would be switched on and off. The designations of this schedule and its assigned unit price levels are shown in Table 14.9. The light-load hours have been consistently assigned the off-peak price level, regardless of the season. The position of the on-peak period is seen to vary some through the year as the utility's load shifts from peaking in the mornings during cold weather months to peaking in the afternoon during the hottest months.

Customers had the option of assigning each of their plug loads to one of the price levels. Customers were able to view their energy consumption via the web portals and could view how they compared to other customers. They could adjust the assignments of their plug loads under the different price levels to modify their energy consumption.

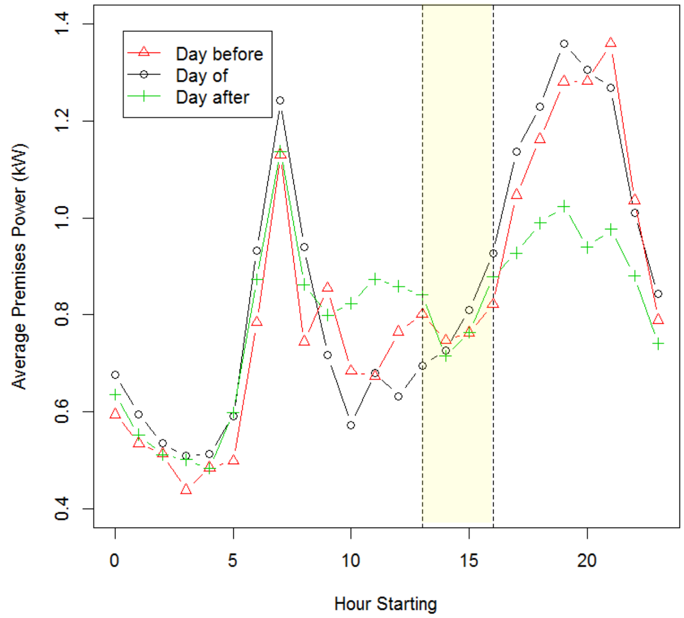
Table 14.9. Time-of-Use Pricing for Selected Participants Showing On-Peak (red, $0.08/kWh), Mid-Peak (yellow, $0.05/kWh), and Off-Peak (green, $0.03/kWh) Price Levels

	Mountain Time - Hour Ending																							
	1 AM	2 AM	3 AM	4 AM	5 AM	6 AM	7 AM	8 AM	9 AM	10 AM	11 AM	NOON	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM	9 PM	10 PM	11 PM	12 AM
Jan	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03
Feb	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03
Mar	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03
Apr	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
May	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
Jun	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
Jul	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
Aug	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
Sep	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.03
Oct	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03
Nov	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03
Dec	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08	0.08	0.08	0.08	0.08	0.05	0.03

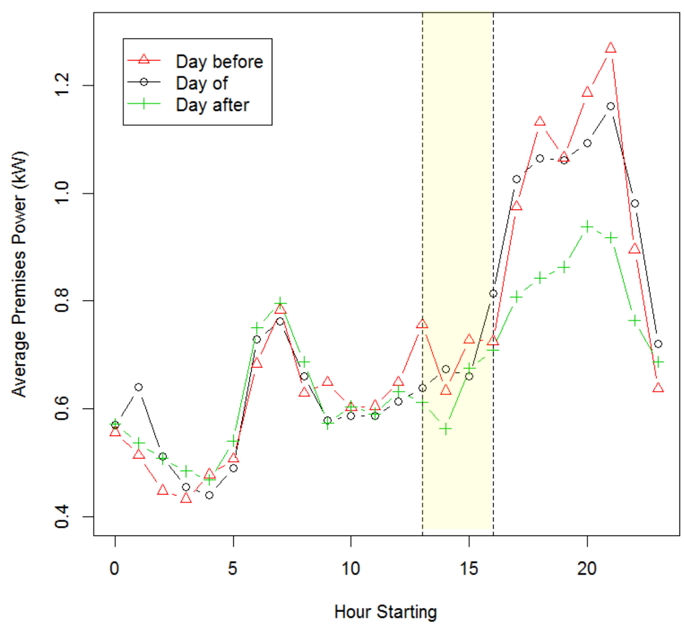
14.3.2 Analysis of NorthWestern Energy's DR Experience

Project analysts attempted to observe a reduction in average premises loads for those premises on the West Side and Golf Course circuits that had received the suite of DR equipment. The project was not provided comparable power consumption for premises that did not receive the suite of DR equipment, so there is no control population available for comparison.

There are only three relevant hours to review according to Table 14.8—hours 13:00–16:00 Mountain Time, August 28, 2014. Figure 14.10 plots the average premises consumption for the test premises on the (a) Golf Course and (b) West Side circuits during August 28, 2014, a Thursday, when the DR tests were reported to have happened. The hours of the tests have been bordered by dashed vertical lines at 13:00 and 16:00. The plots also include the average premises data for these test groups on the days before and after the test events.



(a) Golf Course DR Premises



(b) West Side DR Premises

Figure 14.10. Average Premises Power Consumption of (a) Golf Couse DR Premises and (b) West Side DR Premises for the Days before, on, and after August 28, 2014, when NorthWestern Conducted DR Tests. The tests were reported by the utility to have occurred between 13:00 and 16:00, which are shown in the figure by dashed vertical lines.

No characteristic curtailment notches are evident in the power data during the hours that testing was reported to have occurred. The data from the day before, a Wednesday, is similar to that from the test day, a Thursday. The Friday power consumption patterns are somewhat different from those of the test day. Regardless, the average power consumption during the event hours does not appear to differ significantly among the days.

Next the project reviewed the data to see whether any impacts might be attributable to the time-of-use price differences that were applied to premises in the DR group. This was deemed impossible with the present data. No historical premises-power data was available from prior to the initiation of time-of-use pricing. No control group data was collected from similar control premises that were not subjected to time-of-use pricing. No meaningful data analysis was possible with the existing data sets for this asset system.

The utility reported that its residential participants had, in fact, lowered their electricity bills in the program by shifting electric load to times having lower electricity prices. The program began with 195 participants and ended with 190. There was some flux with customers entering and leaving the program over its duration. The maximum bill credit earned by a customer was $31.15, in January 2013. The highest average savings occurred that month, too, when the average customer earned $8.88. The lowest average savings were earned in October 2013, when the average participant earned $1.33.

There was no penalty if the bill according to the price levels exceeded the bill that would have been incurred under the flat rate. In that case, the customer simply paid the lower of the two calculated bills. Therefore, some customers had no bill savings.

14.4 Philipsburg/Georgetown IVVC

Automated voltage regulator controls, automated capacitor banks, distribution voltage sensors, and distribution system software were used for voltage and reactive power control on Feeder 25-3 in NorthWestern Energy's Philipsburg/Georgetown service territory. The community is rural. It includes approximately 240 line miles of distribution service and stretches 40 miles to the most extreme line end. This region is in mountainous terrain that presented challenges for the wireless communications. Its power supply includes the 2 MW Flint Creek hydroelectric generation site.

NorthWestern Energy also installed an IVVC system in Helena, and that system was described in Section 14.1.

The Philipsburg/Georgetown IVVC system includes five voltage control zones, four of which were controlled by IVVC. Equipment includes seven Beckwith voltage regulator controllers, three Cooper voltage regulator controllers, one Beckwith capacitor bank controller, and 13 distribution voltage sensors for sensing end-of-line voltages.

The annualized costs of the Philipsburg IVVC system and its components are shown in Table 14.10. The total annualized cost of the system over the four-year term was estimated at about $202.7 thousand per year.

Table 14.10. Annualized Costs of the Philipsburg IVVC System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
CVR/Volt-VAr and DA System Software	50	154.9	77.5
Philipsburg Line Regulator Controls	100	51.6	51.6
Philipsburg Substation Communications	100	25.2	25.2
Philipsburg Substation Regulator / LTC Controls	100	19.9	19.9
Philipsburg Distribution Voltage Sensors	100	8.7	8.7
Philipsburg Communications (radio and cell phone)	100	7.3	7.3
Philipsburg Substation RTUs and Relaying	100	6.8	6.8
Philipsburg Capacitor Banks (new banks with controller)	100	5.7	5.7
Total Annualized Cost			**$202.7K**

14.4.1 Data and Operations Concerning the Philipsburg IVVC System

NorthWestern Energy reported to the project that the Philipsburg IVVC system was installed and active by February 2014. The reactive power control IVVC component was reported never to have become engaged due to technical challenges, but the voltage control component was reported to have been engaged on an on/off testing basis from late February through the remainder of the PNWSGD. The combination of long distribution line lengths, multiple voltage control zones (multiple sets of voltage regulators controlling their downstream area), and excessive voltage drop in certain line segments limited the ability to achieve voltage reductions in two of the four voltage control zones.

The utility provided head-end phase voltages for this feeder covering a period from the end of April 2013 until the end of the PNWSGD data collection period at the conclusion of August 2014. Analysts confirmed that the individual head-end phase voltages tracked one another well and behaved similarly during at least the months March through July 2014, when the feeder's voltage will be shown to have been actively managed. This fact is demonstrated by Figure 14.11, in which two of the head-end phase voltages have been plotted against the third. This similarity gave analysts confidence that the individual phase voltages could be averaged for the remainder of analysis.

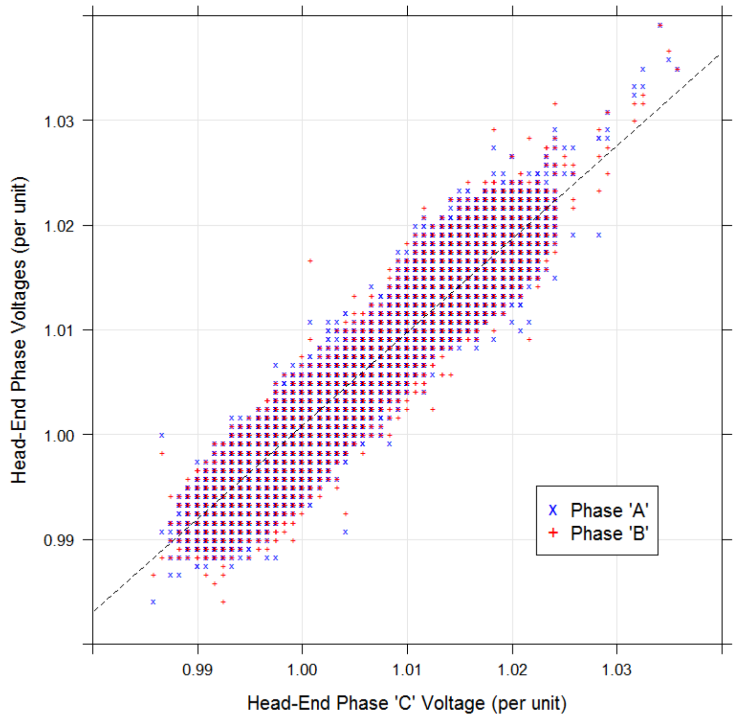


Figure 14.11. Head-End Distribution Voltages from Phases "A" and "B" Plotted against the Corresponding Voltage of Phase "C". Upon this confirmation that phase voltages behave similarly, the average phase voltage was calculated and used for further analysis.

Figure 14.12 shows the resulting average per-unit phase voltage at the Philipsburg feeder. The months from March through much of July 2014 exhibit evidence of active control. A pattern of approximately daily changes between reduced and normal voltage levels is evident these months, even though the system had been reported to be continuously under reactive power control throughout the period.

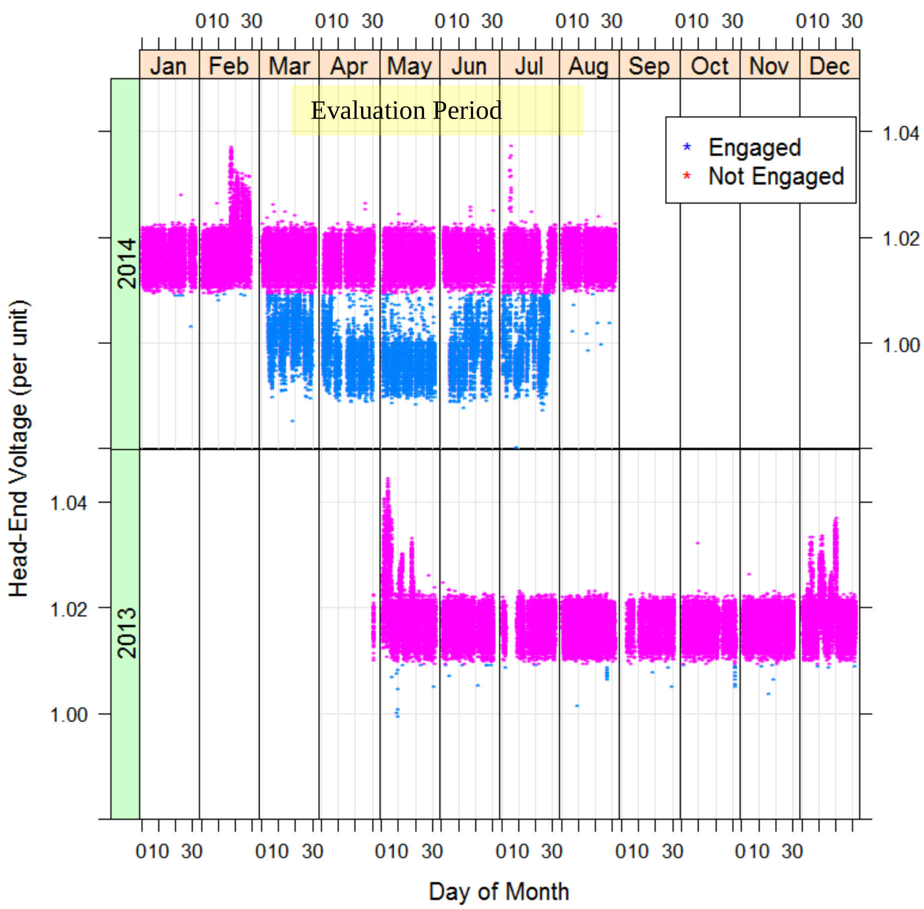


Figure 14.12. Average Head-End Per-Unit Phase Voltage for the Philipsburg Feeder that was Under IVVC Control. The shaded yellow box represents the period that analysts inferred IVVC control had been active.

The project selected the months March through July 2014 as its evaluation period based on Figure 14.12, and the analysis period is shown in the figure by yellow shading. The figure's legend also distinguishes the color of voltage measurements that are normal, when the IVVC system was inferred to not be engaged (blue). The reduced voltages, when the IVVC system was inferred to have been engaged, are shown by red data markers.

Figure 14.13 provides the basis for the inferred distinction between normal and reduced voltages during the analysis period. This is a distribution of the average head-end phase voltages during that evaluation period. It is clear from this distribution that the system was operated under two distinct modes—one having normal voltages and the other having reduced voltages. By inspection, the separation between the populations was determined to be about 1.0095 p.u. The two populations are shown to overlap some, so the inference cannot perfectly recreate the precise timing of the controls that are being inferred. Since voltage is managed fairly smoothly over time, minor incorrect assignments of voltages near the separation are unlikely to greatly change the analysis results. Based on Figure 14.12, the inferred assignments of the data values between the groups "Engaged" and "Not Engaged" seem to be reasonable.

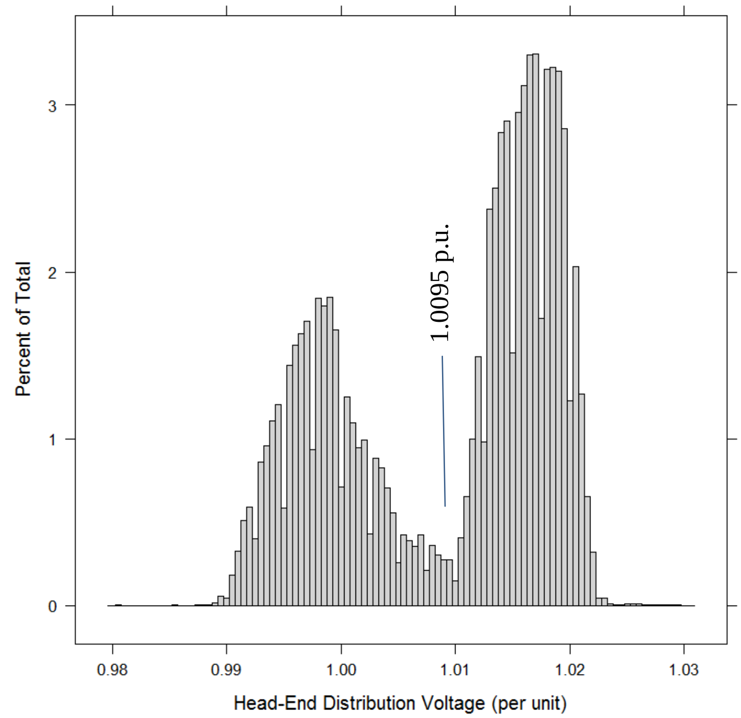


Figure 14.13. Distribution of the Average Head-End Per-Unit Voltages on the Philipsburg Feeder from March through July 2014 while Voltage Appeared to Have Been Managed. Based on this distribution, the separation between normal and reduced voltages was assigned the value 1.0095 p.u.

Figure 14.14 shows the real and reactive powers of the Philipsburg feeder where IVVC was being exercised. This is all the Philipsburg distribution power data that was delivered to the PNWSGD by NorthWestern Energy. The power is observed to become negative at times in the months March through September each year, which is presumed to be caused by power generation from Flint Creek hydroelectric generation on this circuit. The circuit becomes a net exporter of power those months. The intermittent periods when the net power again became strongly positive these months are probably attributable to periodic maintenance on the hydroelectric generators.

No clear changes in real or reactive power are evident in the period March–July 2014, when the IVVC is inferred to have changed status approximately daily. Interestingly, periodic changes in reactive power are observed late September through mid-December 2013. Distribution voltages had been steady that period. The utility reports that the system is capacitive (reactive power is negative) due to the significant amount of underground 25 kV primary conductor near the ends of that circuit.

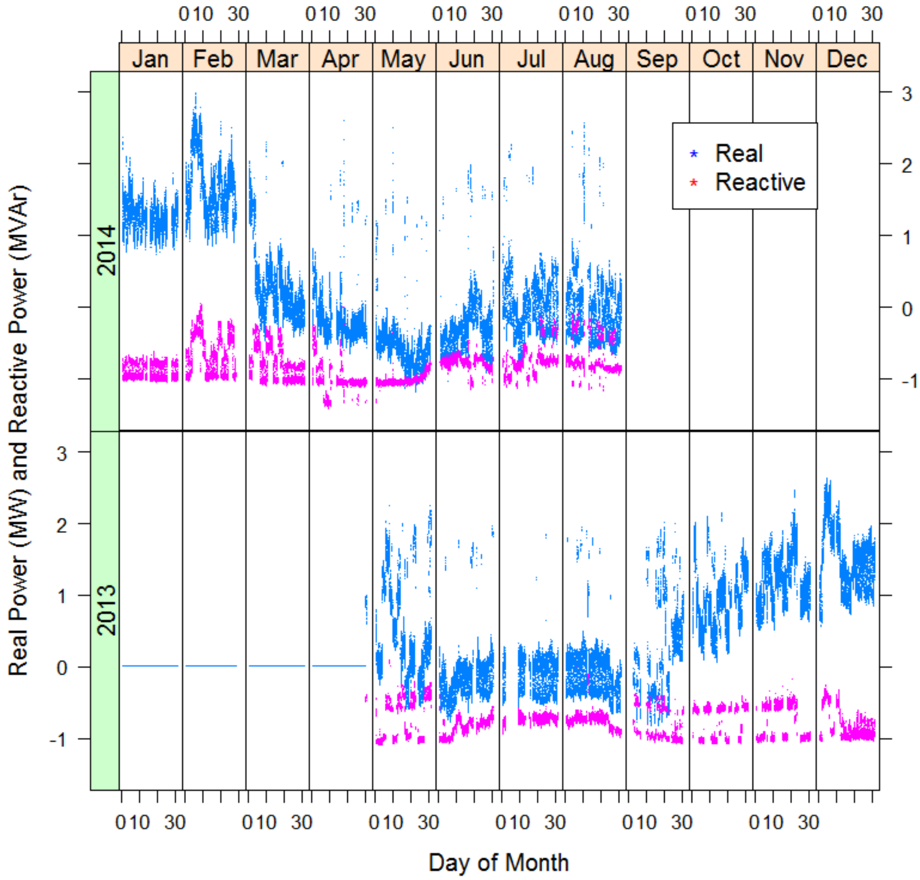


Figure 14.14. Real and Reactive Power on the Philipsburg Feeder

14.4.2 Analysis of the Philipsburg IVVC System

Based on the inference of IVVC status, the project compared the head-end distribution voltages at the times that system was inferred to be engaged and not. A quartile plot is presented in Figure 14.15 to compare the voltages during the two inferred statuses during the evaluation period. During the evaluation period, the median of the voltages was reduced by 0.018 p.u., or 1.8%, on average, during voltage reduction periods.

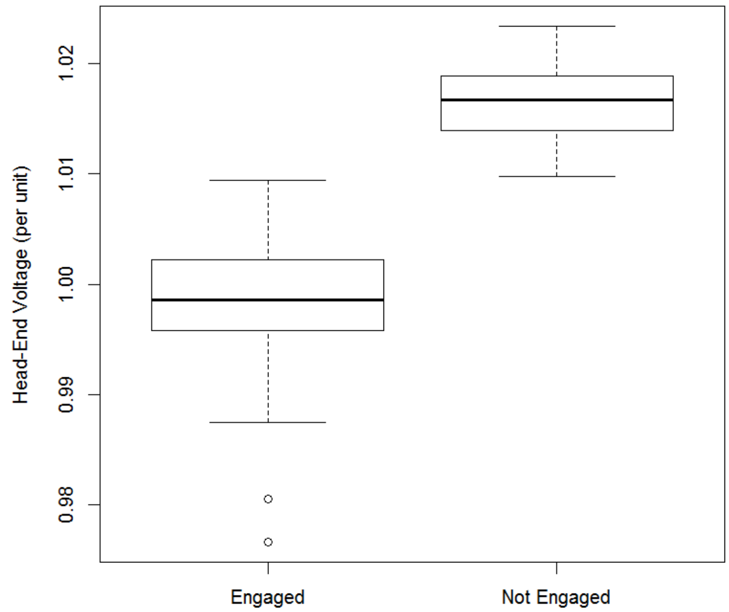


Figure 14.15. Quartile Plot of the Philipsburg Average Head-End Phase Voltages when the IVVC System was Inferred to be Engaged and Not Engaged

Analysis of the Philipsburg IVVC system was confounded by the generated power levels and the intermittent starting and stopping of generation at the Flint Creek hydroelectric plant. The resulting step discontinuities prevent the meaningful application of regression methods on the days that the discontinuities occurred. Ideally, the generated power would be removed from the load power before completing the analysis.

In the absence of power generation data from the Flint Creek generator, the project attempted to mitigate its influences. A filtered data set was prepared to include only the evaluation period from March 2014 through July 2014, inclusive. Any day on which the load power jumped to an elevated power consumption level was eliminated from the filtered data set. These jumps were assumed to be short periods when generation at the Flint Creek generator had been halted. The thresholds above which the day was eliminated from analysis varied by month, as were determined by inspection of the months' data. The specific thresholds were 1.0, 1.0, 0.0, 0.5, and 1.0 MW for the five contiguous months in the evaluation period. The resulting filtered load is shown in Figure 14.16.

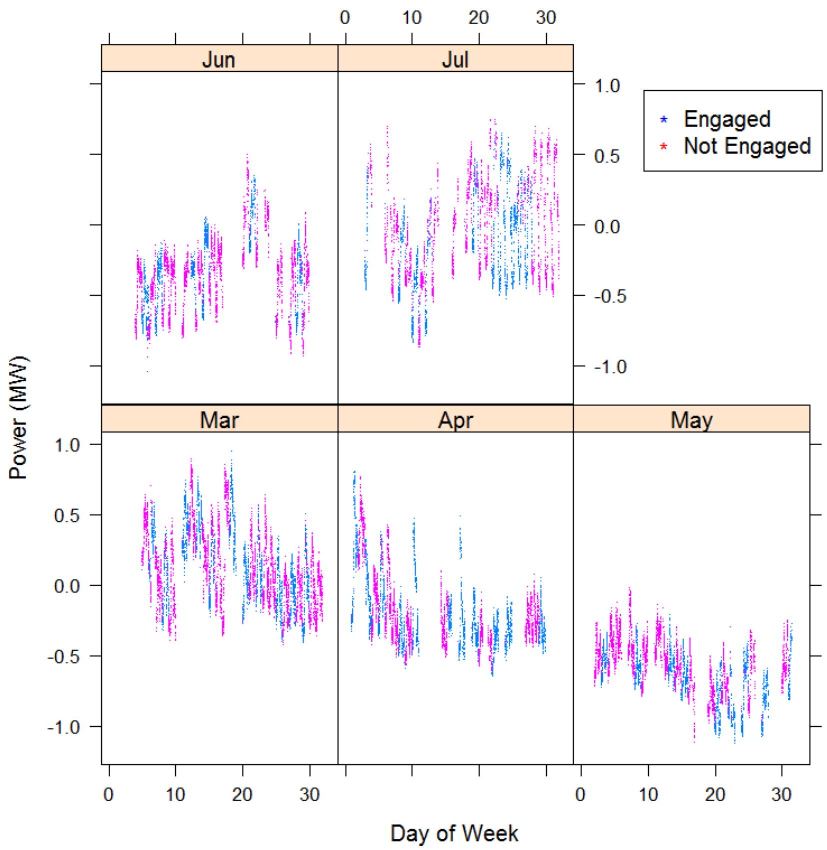


Figure 14.16. Filtered Load Power for the Philipsburg Circuit during the Evaluation Period. Days have been removed from analysis if positive spikes were observed in the load, which are assumed to be periods when Flint Creek generator stopped generating. The circuit is a net exporter of power at times during these months.

Linear regression analysis was then conducted using the software tool R (R Core Team 2013). Implicit assumptions are that the generation at Flint Creek (a) is slowly varying from day to day, (b) is random over time (which seems unlikely based on the consistent magnitudes of the spikes in Figure 14.14), or (c) that generation conforms to a consistent diurnal pattern for months at a time. Any of these conditions could allow a meaningful analysis; however, these assumptions have not been fully tested or confirmed.

The regression was fit to ambient temperature in Philipsburg, Montana (weather station PHGM8), separately calculated by month, weekday type, and hour of day. The temperature data was found to be very complete, but it was further interpolated across short missing data periods (spans less than 6 hours) so that more data points would be used in the regression analysis. The final fit had an R^2 value of 0.733. A single coefficient was determined for the inferred voltage status for all included months, weekday types, and hours. It was determined that the circuit used 27.6 ± 2.5 kW more power, on average, when the voltage was at its normal level than it did when the voltage was reduced. This magnitude is approximately 1% of the peak Philipsburg load on this circuit during times of the year that the generator is not operating. This corresponds to about 660 kWh reduction in energy consumption for any 24-hour period that the voltage is reduced.

14.5 Conclusions and Lessons Learned

NorthWestern Energy implemented IVVC at two locations to optimize real and reactive power control. The implementations were successful both in the somewhat urban Helena circuits and at the more rural Philipsburg circuit. Analysts were able to detect carefully conducted day-on, day-off voltage control at both sites. The voltages had been reduced by approximately 1.5%. Using regression analysis, project analysts were able to confirm that power levels of the Philipsburg circuit and one of the Helena circuits are reduced by about 1% of average load while the voltage is reduced. The analysis on the other Helena circuit was inconclusive. Also, the presence of the Flint Creek hydroelectric generator in Philipsburg created new challenges for the analysis and somewhat reduces our confidence in the findings from regression there.

The utility also implemented FDIR to improve service reliability on four Helena circuits. No improvements could be detected from the yearly reliability indices that had been calculated by the utility, including annual restoration costs, CAIDI, and SAIDI. However, the utility had three outage events in Helena and another in Philipsburg that had tested the FDIR systems at these two sites. Two of the Helena outages in particular convinced the utility that the FDIR system had significantly reduced customer outage minutes and had, to a lesser degree, reduced its response man hours. A communication problem at the Philipsburg site prevented the FDIR system from fully responding to the one outage that was encountered there.

NorthWestern Energy gave a suite of DR equipment to about 200 of its residential customers. Further, the customers were placed under a time-of-use pricing plan for the remainder of the PNWSGD to see how they would respond and configure their equipment to automatically respond to the various pricing levels. Customer acceptance in the pricing program was strong. DR requests could also be initiated by the utility through the price levels, but this option was rarely exercised, and its results are uncertain. The project’s efforts to quantify the changes in customer behavior were unsuccessful. No prior baseline 15-minute interval meter data exists for these customers, and no control population was defined. Regardless, the utility believes that conservation was achieved. Many, but not all, customers lowered their electricity bills. Some even won a clever quarterly completion award and monetary prize for lowering their consumption more than the other participants had.

Looking to the future, NorthWestern Energy continues its work to determine the actual costs and cost savings to the smart grid activities that it conducted. As a company, it must keep its focus on cost recovery. The influences to watch include load growth, both in Montana and through the larger region, peak demand, renewable energy integration, and the evolving state of smart grid technologies. The utility intends to implement smart grid technology as the values of such technologies become proven, and is moving ahead with the wireless communication deployment across its Montana service territory to prepare its systems for future smart grid deployments as these begin to make business sense to perform.

The following sections contain responses that were received from NorthWestern Energy when they were asked to list their lessons learned from the PNWSGD.

14.5.1 Lesson Learned #1: Vendors (Good Experiences and Challenges)

NorthWestern Energy used many vendors and their products to implement the various technologies used to set up the smart grid transactive systems. These vendors included Lockheed Martin, Spirae, Inc., S&C Electric, Cooper Power Systems, Tendril, and Itron. The technologies ranged from software and hardware for FDIR, for volt-VAr control, for residential home area management, and for commercial building automation.

Since the inception of this PNWSGD, we have observed that many vendors have left the smart grid business and are no longer involved in smart grid technology. It is important to choose a vendor that has a solid financial history and has a proven track record with their technology. For example, NorthWestern Energy faced increased pressure on schedule and cost due to one manufacturer having been bought out by another prior to producing an agreed-upon FDIR software package. Additionally, another vendor downsized staff numbers in order to stay in business, which meant decreased technical support time and constant changes in project management and sales. When implementing a new product for our customers, it is imperative that they see a consistent brand and also have consistent and timely technical support when required.

At the beginning of a project, it is important to develop a backup plan that includes both estimated costs and schedule changes in the event that one of your primary vendors exits the field.

Keep in mind that some of your vendors are in competition with other vendors, and they will attempt to slow or derail another vendor’s product. This can be as subtle as not approving design documents in a timely manner or not responding to software code updates.

First-time integration of systems and products from various manufacturers and vendors will generally never go as planned. Budget a large contingency in time and funds at the beginning of the project to make sure that integration issues can be overcome. NorthWestern Energy found that setting up a demonstration lab prior to customer installation helped to alleviate some integration issues and helped to keep this aspect of the project on schedule and budget.

On a positive note, we have had several vendors stay very committed to the project even though other factors outside of their, and our, control caused delays. These were vendors with a proven track records and solid financial bases. They seemed to recognize that they were part of a demonstration project, their name and their technology were on the line to a degree, and hence they became committed to the success of the project.

14.5.2 Lesson Learned #2: Experimental Nature of the Project

The concept of smart grid and transactive control is relatively new to the utility industry and to NorthWestern Energy as well. Therefore, NorthWestern was pleased to be able to investigate and test a pilot-scale smart grid project prior to undertaking a larger-scale deployment. Additionally, having multiple project participants from many types of energy users, producers, and distributors was a bonus, since we are all able to learn from each other as we apply different smart grid technologies.

The smart grid pilot project touched almost every department of the utility. This included distribution engineering, distribution operations, business technology, regulatory affairs, legal, contracting, customer care, billing, corporate communications, safety, health, environmental, and construction. Many personnel, from all of these disciplines, worked to complete the design, installation, and testing of the project.

We found that most of our customers were not familiar with smart grid technology; hence recruitment of participants in our target area was difficult. We deemed it important to hire a third-party installation company that knew the customer base and was willing to take extra time with each customer installation, in order to teach the customers about the equipment and explain the benefits of a smart electrical system. The installer explained what smart grid is about from a customer perspective, a utility perspective, and a regional perspective. This installer had performed many home visits while conducting energy audits for NorthWestern Energy customers over the last 20 years and had a good sense of how much time and effort would be required for each installation. An allowance for this time was added to the budget at the start of the project and proved to be money well spent.

System maintenance was also added to all vendor contracts associated with customers prior to the contracts being issued. This forethought helped in many situations where the customer had issues and new equipment was required.

It proved difficult to recruit the small number of test customers for the HAN portion of the project. The footprint of this part of the project was enlarged so that the required number of participants could be secured. Enlarging the geographic area caused an increase in project cost and schedule. Additionally, up to 10% of these customers moved or dropped out of the project during the testing period. This required additional recruitment of new participants, thereby increasing costs and lengthening the schedule. Anticipate at least a 10% dropout rate from the beginning of a project and budget both time and resources for new participants.

NorthWestern Energy found that involving all departments in our organization, from the beginning of the project, helped to alleviate concerns and motivate each to help make the project a success. All areas within the organization worked to solve problems that developed and helped to integrate this unique project into NorthWestern Energy's distribution system. Many managers in different functional areas identified leads and backup personnel so that a smooth flow of information and work could be completed regardless of the problems encountered.

Over the course of integrating hardware, software, and systems from various vendors, the utility found that, as a general rule, it takes much more effort and time to integrate devices into a smart grid system than originally anticipated. Interoperability is an item that needs to be addressed in this industry. In the world of personal computers and home electronics, for example, the computer system components of today do generally "plug and play," even though that was not the case many years ago. The smart grid systems of today are like the early stages of the personal computer industry, where standards were in their infancy or did not exist at all. Similar standards work needs to be done in the smart grid industry today.

One of the software vendors sold the utility their product at the beginning of the project. Software was installed and parts of its functions were not used until the last year of the project. By this time, other software superseded the hardware and software in the field and could no longer communicate with the existing software. The cost and time to upgrade the existing software was never considered in the original design. This meant these functions were never used, because the project did not have the additional time or budget.

14.5.3 Lesson Learned #3: System Integration (FDIR System)

NorthWestern Energy completed DA by using Cooper Power YFA software, automated reclosers and radio communications. The DA was completed in rural and urban settings. Data was collected at a central server in another location that was running Open Platform Communications-compliant software. S&C Electric IntelliTeam® volt/VAr control software was used to automatically modify LTC settings at the substations and end-of-line voltage sensors for feedback values. Additionally, automated capacitor controllers were used in locations along the feeders and were also controlled by S&C Electric IntelliTeam software. Communication in the urban setting was done using Redline radios, and in the rural setting using both SpeedNet™ and FullMAX™ radios.

NorthWestern Energy found that these types of equipment deployments and systems do not "plug and play out of the box." They require several iterations of fine tuning to get all of the components to work together efficiently. Additional equipment may be required for different systems to interface. For example, an Open Platform Communications server was added to the server node to translate data to a protocol that was common between systems.

For NorthWestern Energy, YFA factory testing was exceptional to prove interoperability. Cooper Power simulated integration for the utility in their lab prior to field deployment, proving interoperability. As a result, the utility had minimal issues during field commissioning. S&C Electric (originally Current Group) had verified the interoperability of their system with certain Beckwith LTC and capacitor controllers. The utility purchased these controllers and had minimal interoperability issues.

A robust communication network is paramount for the system to operate properly. In the rural location, testing and deployment was delayed on several occasions because of communication failure issues. Devices consistently went into communication loss; however, a firmware upgrade to the FullMAX radios in late December 2013 appears to have improved their spotty connections. Several radio failures occurred with extreme temperatures (below −20F) and high winds.

SpeedNet radios deployed in Philipsburg did not allow Dynamic Host Configuration Protocol, so the utility had to manually set Internet Protocol addresses at each site.

E-mail notifications are being used to notify personnel when an event occurs on the system. It is difficult to use auto-generated e-mails; the event must be described well enough that it can be understood by the recipient without viewing the on-line system in real time.

In summary, allow additional time, resources and funds for integration of systems, especially communications. Verify interoperability with devices, communications, software, etc., on the bench before deploying devices in the field. Allow event notification recipients access to on-line systems in real time so that they can respond to events.

14.5.4 Lesson Learned #4: IVVC System Observations

NorthWestern Energy enabled IVVC on both the urban and rural locations. S&C Electric IntelliTeam volt/VAr control software was used to automatically modify LTC settings at the substations and end-of-line voltage sensors for feedback values. Additionally, automated capacitor controllers were used in locations along the feeders, and were also controlled by S&C Electric IntelliTeam software.

The utility saw that IVVC has enabled a more efficient operation of the distribution system; however, additional testing needs to be completed to determine the predictability of the CVR control strategy to achieve the calculated savings. For example, the utility found that a limited number of end-of-line sensors had lower than normal voltage; therefore, these low end-of-line voltage points controlled the savings for the entire circuit. Also, the low voltage points may occur in the middle of the feeder due to other factors such as overloaded secondary transformers, low secondary power factor, and long secondary feeders. Going forward, the utility believes the secondary circuit should be more closely analyzed to determine sensor placement. It may be advantageous to perform secondary upgrades to achieve a greater overall voltage reduction.

Furthermore, the utility found that operating in the lower portion of the American National Standards Institute standard caused an increase in tap changes. This was especially true in the five voltage control zones in the rural area. When the software adjusted the voltage in the first voltage zone, it caused all downstream voltages regulators to readjust to maintain their current voltages based on their end-of-line sensors. In the future, the utility hopes to implement a control logic that would attempt to keep the number of tap changes the same or reduce them.

In the rural area, two of the five voltage control zones were unable to achieve any savings. The utility saw a large voltage drop along these, which limited their ability to further reduce the circuit's voltage. Therefore, circuit improvements should be more closely investigated before implementing VVO.

Two urban substations used LTCs to adjust the bus voltage, and software capabilities limited individual control of single-phase regulators located in the rural substation. The utility believes additional savings could be achieved if single-phase voltage regulators could be individually controlled. This would not only help balance the voltages on all phases, it would allow all phases to be lowered to the minimum allowed voltages for the greatest savings.

Without standardized measurement and verification processes, the utility found verifying actual savings difficult. Going forward, they hope to outline a second measurement and verification process, such as sister feeder comparison with base-case testing or CVR Protocol Number 1 alongside S&C's power flow model. This would allow more confidence in the results they observed.

In summary, IVVC has enabled a more efficient operation of the distribution system, but additional testing needs to be completed to determine the predictability of the CVR control strategy to achieve calculated savings. Circuit improvements should be more closely investigated before VVO is implemented to achieve the greatest savings.

15.0 Peninsula Light Company Site Tests

Additional chapter coauthors: M Simpson and R Grinberg − Peninsula Light Company

Peninsula Light Company is the second-largest rural electric cooperative in Washington, serving over 65 thousand people with over 31 thousand electric meters. Roughly 88% of its members are residential—73% of the electric load. Their service territory includes peninsulas and islands that surround Gig Harbor. The temperatures on the island are moderate, meaning that the island's residents require some energy for winter heating but little energy for summer cooling.

The cooperative chose to focus its project resources on Fox Island (lower left in Figure 15.1). The island was served from the Gig Harbor Peninsula by only two distribution circuits. With load growth preceding the project start, either of these circuits' capacity limits could be exceeded if the other circuit were to fail. The Fox Island feeders were among their 10 least reliable feeders. Load factor was poor because virtually all the island load was residential. As an island with rugged terrain, capacity improvements were anticipated to be expensive.[1]

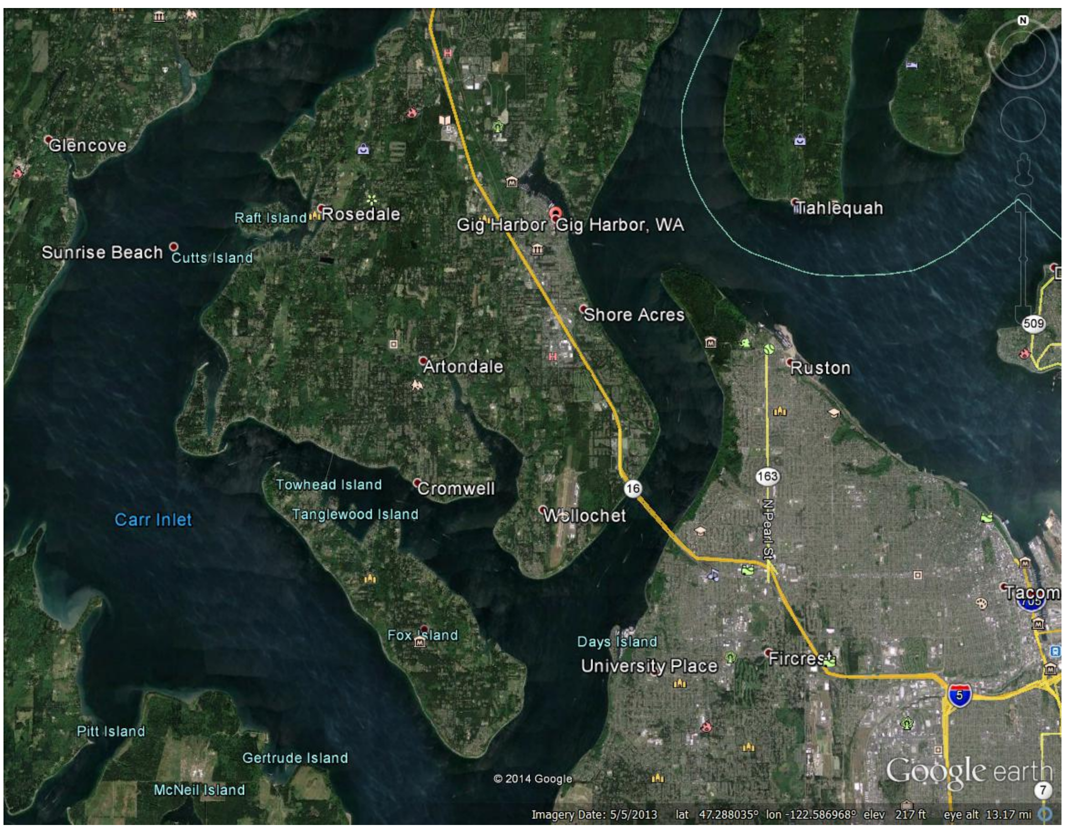


Figure 15.1. Aerial View of Fox Island, Gig Harbor, and Vicinity

[1] The facts in these introductory paragraphs were gleaned primarily from unpublished project presentation slides titled "Peninsula Light's Smart Grid Project." These presentation slides were found among July 15, 2010 Pacific Northwest Smart Grid Demonstration weekly project participant meeting slides.

Peninsula Light Company resolved to work with the project to

- install and evaluate demand-side management on the island using load-control modules (LCMs) (Section 15.1)
- apply distribution management on the island, including model-based dynamic conservation voltage reduction (CVR) that monitored end-of-line voltages (Section 15.2)
- improve member service quality on the island using dynamic distribution automation, including fault detection, isolation, and restoration (FDIR) (Section 15.3).

These three efforts were divided into three asset systems by the project. Details about the three asset systems will be discussed in subsections of this chapter. Figure 15.2 depicts the three asset systems and their components overlaid on the Fox Island distribution circuit. In Figure 15.2, text that begins "PL-IM-" represents data collection points defined in Table 15.1.

Table 15.1. Definitions of Data Collection Points that Were Shown in Figure 15.2

Data Label	Description
PL-IM-1-*	Daily Electricity Usage from One of 2,650 Customers
PL-IM-15-2	Hourly Feeder Voltage at Head-End of Feeder 2
PL-IM-15-6	Hourly Feeder Voltage at Head-End of Feeder 6
PL-IM-41-2	Hourly Distribution Feeder (Average) Power Loading on Feeder 2
PL-IM-41-6	Hourly Distribution Feeder (Average) Power Loading on Feeder 6
PL-IM-42-2	Hourly Distribution Feeder (Average) Reactive Power Loading on Feeder 2
PL-IM-42-6	Hourly Distribution Feeder (Average) Reactive Power Loading on Feeder 6

In Figure 15.2, text such as "(C, E, E)" is a nominal description of whether the data is a member of the Control or Experimental set for each of the three assets.

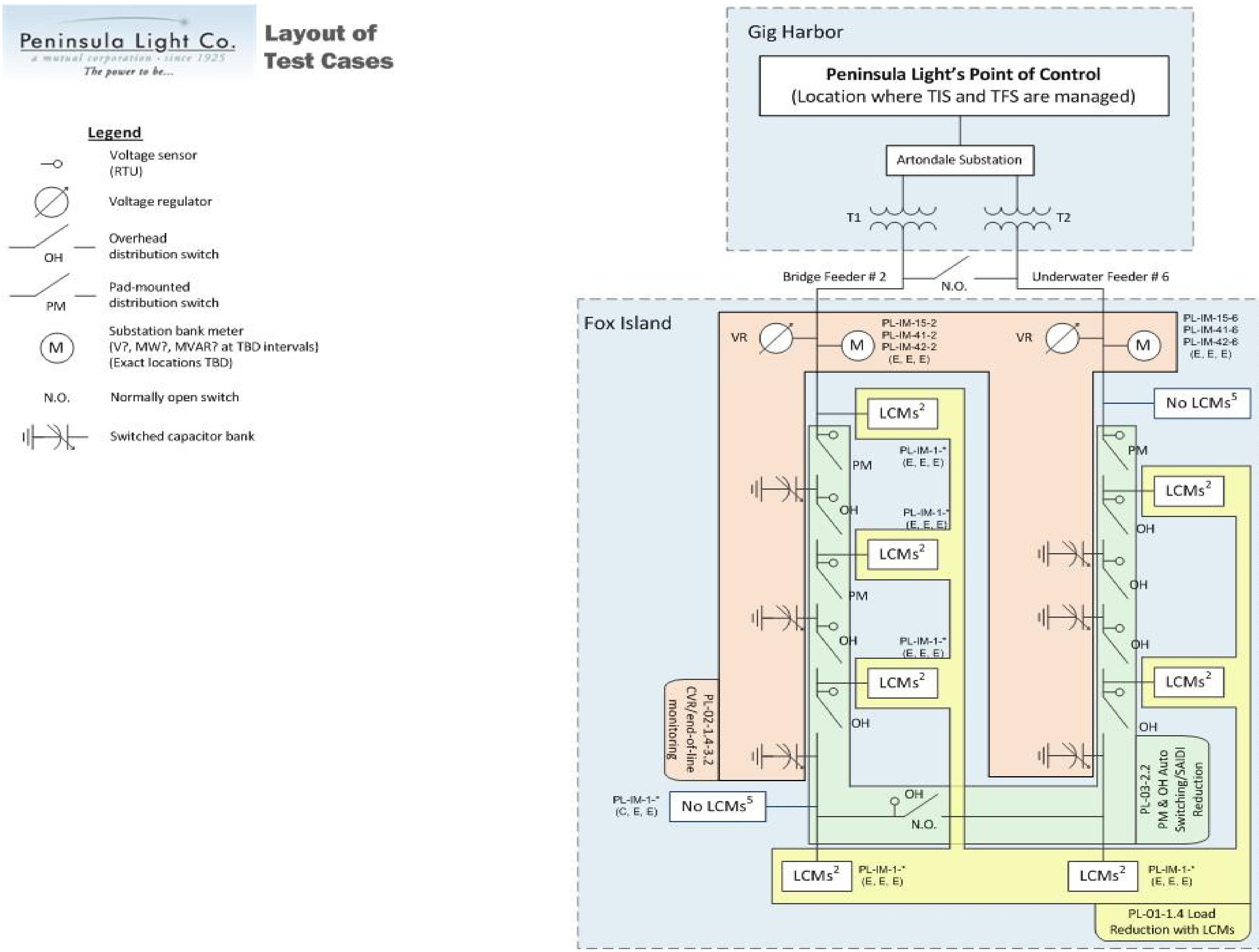


Figure 15.2. Layout of the Test Groups and Assets on the Fox Island, Washington, Distribution Circuit

15.1 Load Reduction with Load-Control Modules

Peninsula Light Company installed and engaged approximately 500 Landis+Gyr residential LCMs during the project. These devices were to disconnect hot water heaters and other household resistive loads in order to achieve demand reduction. They were controlled using the utility’s existing power line carrier (PLC) network.

Members who allowed the LCMs to be installed were given a $5 monthly bill credit.

The original plan had been to fully automate the curtailments of the LCMs according to advice that was being received from the project’s transactive system. This transactive system implementation proved challenging for the cooperative, but it eventually aligned control of the system of LCMs with the transactive system. In the end, the system of LCMs was engaged about 61% of the time that advice was received from the transactive system, and 87% of the time periods that load was curtailed had been advised by the transactive.

The capabilities of the PLC premises metering system limited the observations available to the cooperative and project. Installed PLC equipment was unable to carry the bandwidth that was needed for hourly or finer premises data intervals. Therefore, the project had to do its best with daily premises energy consumption measurements. The utility’s efforts to resolve this lack of resolution during the project were unsuccessful. The lack of resolution especially limited the project’s ability to observe the behaviors of premises equipment, such as the system of LCMs, that was typically engaged for hours, not days, at a time.

The annualized costs of the LCM system and its components are listed in Table 15.2. As a reminder, each component’s cost was annualized over the expected useful lifetime of that component. The only subsystem component that was shared with other asset systems by this one was the implementation and integration of the transactive node—the local software that interacted with the larger transactive system. Most of the annualized cost is for the LCMs. Other smaller costs were for member incentives, transactive system integration, outreach, upgrades to the PLC system, and training. The total system’s annualized cost was estimated at $450.1K.

Table 15.2. Annualized Cost of the Load-Control Module System and Its Components

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
LCMs	100	410.7	410.7
Incentives	100	30.0	30.0
Transactive Node (integration)	50	8.9	4.4
Outreach and Education	100	3.4	3.4
PLC Communication Infrastructure	100	1.0	1.0
Training	100	0.6	0.6
Total Annualized Asset Cost			**$450.1K**

15.1.1 Characterization of Asset System Responses and Data

Peninsula Light Company submitted premises power data from August 2012 through August 2014, when the project data collection ceased. The project aggregated this data into various test and baseline comparison groups. As already stated, averaged premises power data was available only for one-day intervals. All of the daily average premises power measurements for the test group of premises that eventually possessed project LCMs are shown in Figure 15.3. Peninsula Light Company began allowing the LCMs to be curtailed gradually beginning in June 2013.

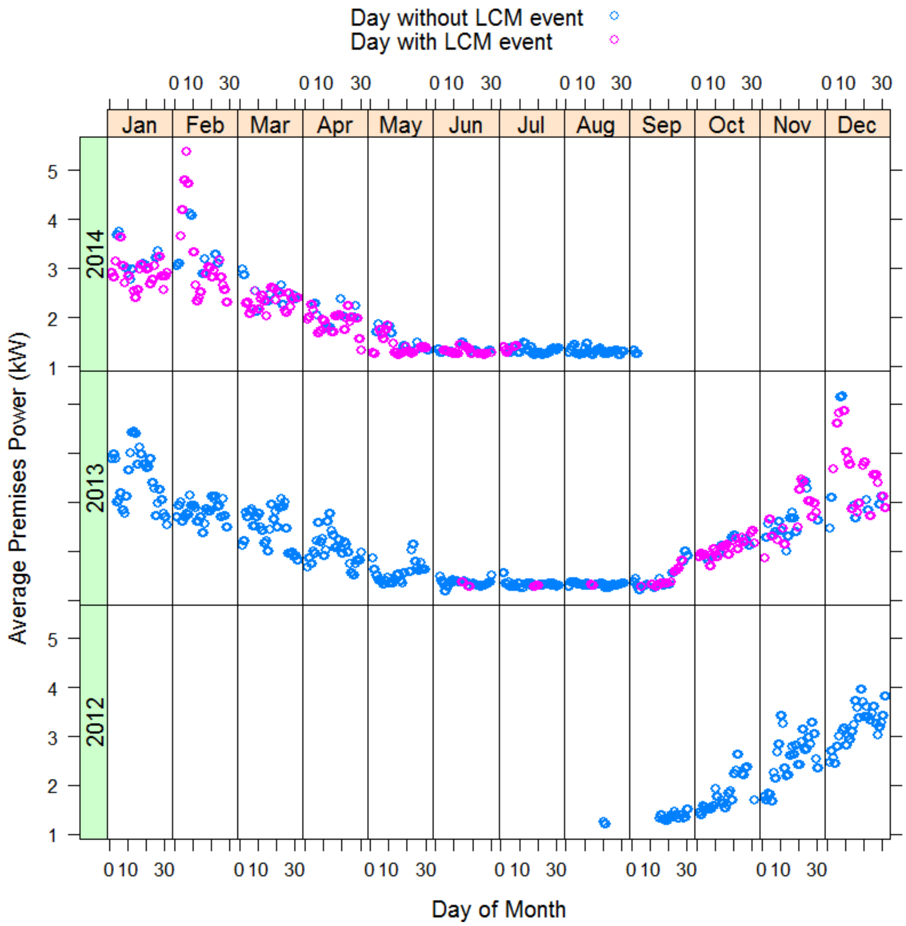


Figure 15.3. Time Series of Daily Mean Power for Premises Test Group that Received Load-Control Modules

The sum distribution power for Fox Island, Washington, was available to the project at hourly data intervals (Figure 15.4). This data was collected at the Artondale substation, which supplies all of Fox Island as well as additional mainland loads. The distribution data was available from August 2012 forward, but the LCM system was not declared installed and operational until summer 2013. Once operational, the system was engaged routinely until August of 2014. The quality of the distribution data appears good. A strong diurnal pattern was evident (not shown in Figure 15.4). There were only infrequent zero values—possibly low outliers—observed.

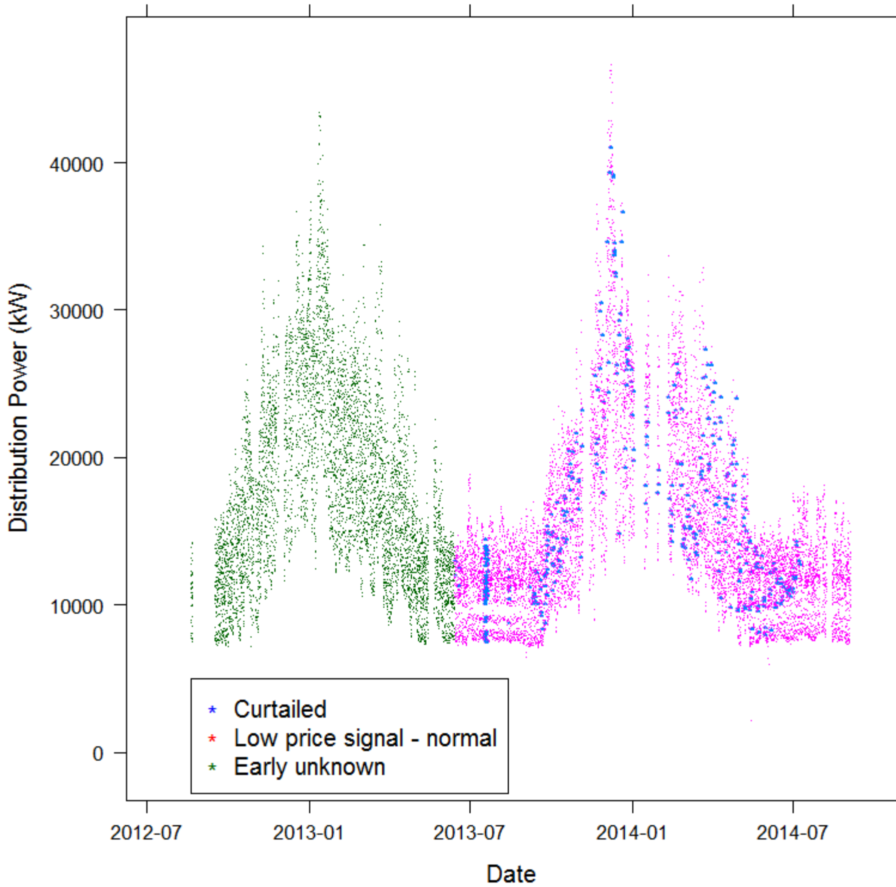


Figure 15.4. Total Hourly Distribution Power Measurements and Reported LCM System Status

Ambient temperature data was collected from weather station KTIW at the Tacoma Narrows Airport. The data intervals of weather data vary over time. Available measurements were treated as instantaneous measurements and were mapped to the corresponding 5-minute interval. These temperature measurements were averaged within the corresponding hours and days, according to the shortest data intervals that were available for premises and distribution circuit data.

There were altogether 217 curtailments called for by the LCMs during the project. The third event, in July 2013, was reported to have remained engaged for over 65 hours. That is unlikely, and Event 3 was therefore excluded from the analyses that the project conducted, except as noted. Figure 15.5 shows the percentage of curtailment events by calendar month.

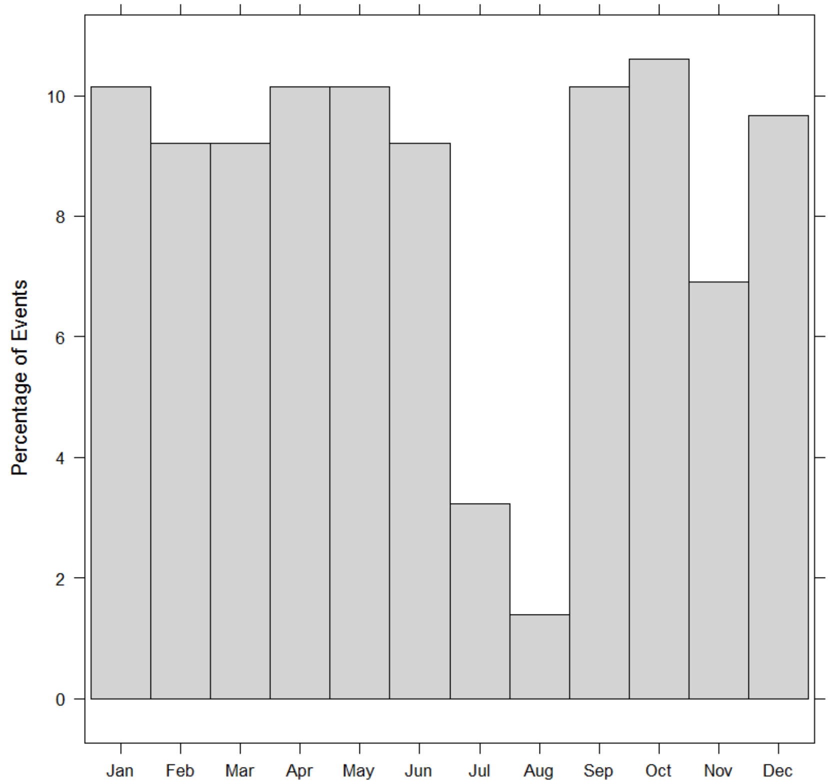


Figure 15.5. Percentage of Calendar Months that LCM Events were Conducted

As shown in Figure 15.6, most of the events were called on weekdays. For this reason, analysis carefully excluded or separately handled weekday and weekend days to avoid confounding impacts from differences between weekday and weekend loads and load patterns. The events were fairly equally distributed across the five week days.

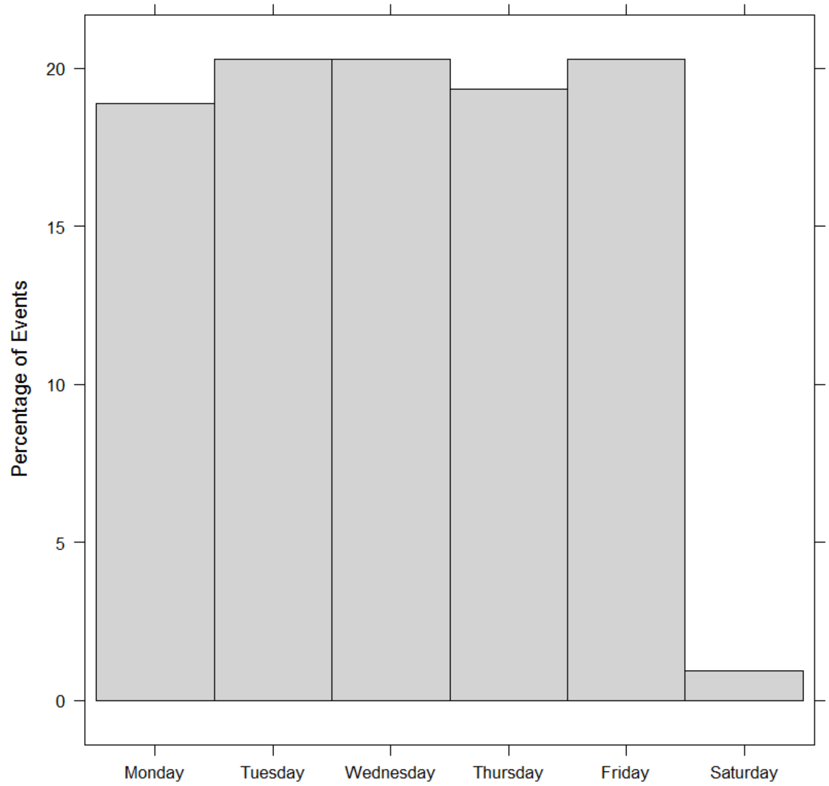


Figure 15.6. Days of the Week that LCM Events were Conducted

The project next looked at the hours during which these events began; see Figure 15.7. The events were most often initiated between 11:00 and noon local Pacific Time. The starting hours are less likely to be before or after those times. The midnight and very late evening events were probably attributable to a startup period while the project was teaching the transactive system how to select and configure meaningful event periods.

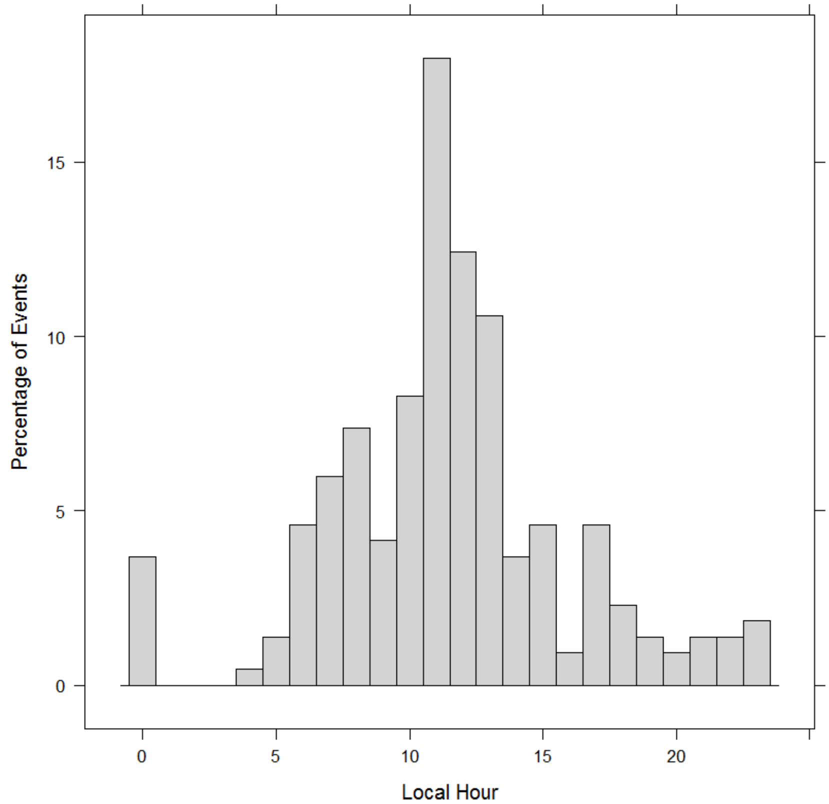


Figure 15.7. Local Pacific Time Hour that LCM Events Started

15.1.2 Performance of the Load-Control Module System

Having observed that the system of LCMs had been exercised only during the second year of data collection, analysts compared data from the two years to make sure that load growth and changes in customer affluence over the years would not confound the results. The 2013 and 2014 data sets' temperature dependence is compared in Figure 15.8. The data from the two years appears to be similar, although there might be small differences in the data at and above 60°F.

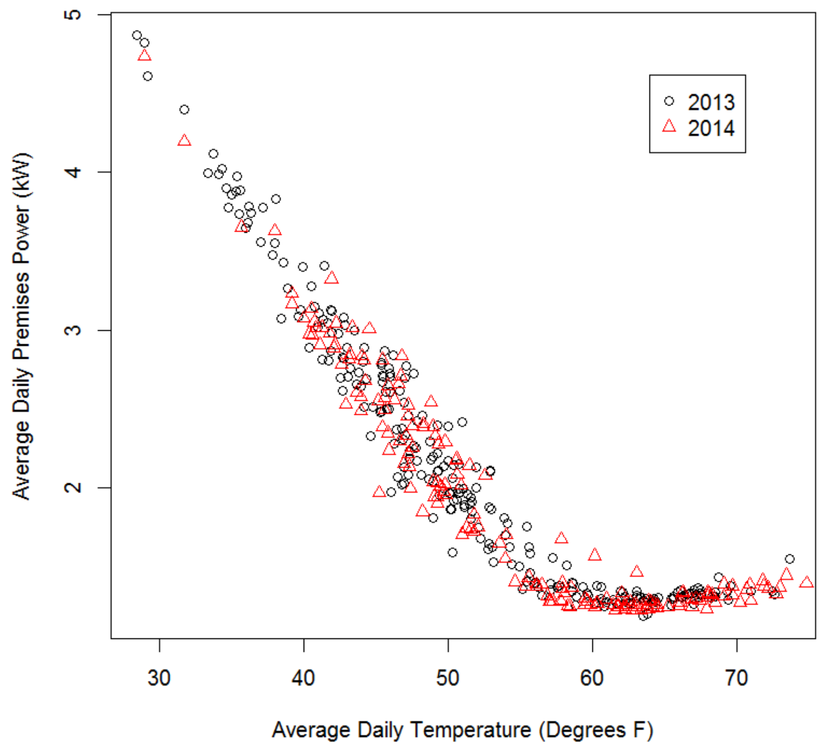


Figure 15.8. 2013 and 2014 Test-Group Average Daily Premises Power as a Function of the Average Daily Outdoor Temperature. The LCM system operated from summer 2013 to summer 2014.

Peninsula Light Company supplied daily premises power data from a group of Fox Island premises that did not participate in the LCM system. Figure 15.9 compares the power data from the LCM test group and this baseline group as functions of temperature. By inspection, these groups are dissimilar. The LCM test-group premises, on average, consume more power than the baseline group during cold days. They may also consume more during hot days, but the warm weather trend is not so evident. The project chose to not use this control group. The two groups might have different size homes or homes that were built using different insulation practices, for example.

Both Figure 15.8 and Figure 15.9 include the long Event 3 from July 2013, but its inclusion does not appreciably influence the conclusions that will be based on the observations. Each point in these figures represents the average premises power over an entire day from local Pacific midnight until the following midnight.

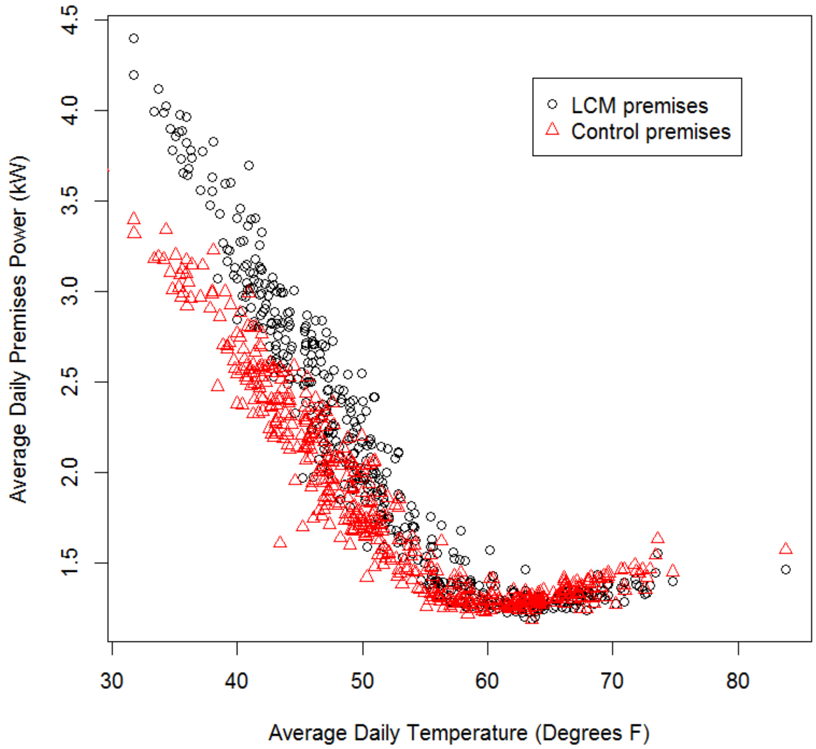


Figure 15.9. Average Daily Power of Test-Group Premises, which Received LCMs, and a Candidate Control Group, both as Functions of Outdoor Temperature

Figure 15.10 addresses only the test group that had LCMs installed, comparing days when LCMs were engaged to days when they were not. Only measurements from weekdays were used. Using the data from days that the LCMs were not engaged, linear regression was conducted to determine a line for a heating regime and another for a cooling regime. Similar regression lines are shown for event days. The analysis is based on average daily temperature to correspond to the daily average premises power interval. The dashed vertical line is the temperature that minimizes the modeling errors for the linear fits to the temperatures above (cooling regime) and below (heating regime) this temperature—about 56.7 degrees Fahrenheit in this case.

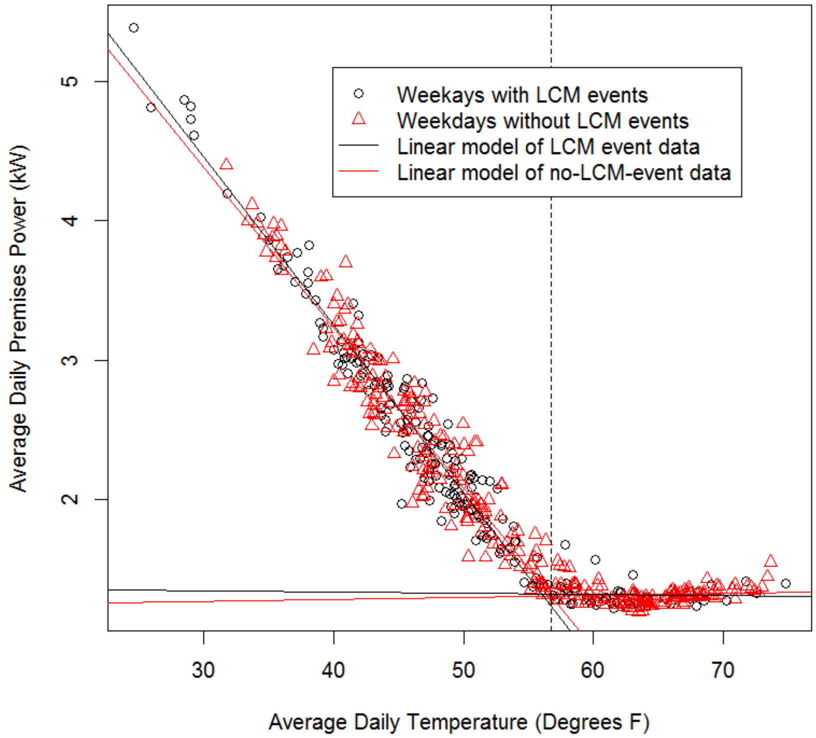


Figure 15.10. Average Premises Power on LCM Event and Non-Event Days as Function of Temperature. The lines show regression fits of cooling and non-cooling regimes based on days that no events occurred.

The equations for the linear models are listed in Table 15.3, but they have been referenced not to 0°F but to the temperature T_{cp} that separates the heating and cooling regimes. The intercepts are the average daily premises power consumptions that would be expected on days that the average temperature is 56.7°F. Upon taking the difference between the linear models during event days and non-event days, the impact of events is represented as an offset and temperature coefficient for the heating and cooling regimes. On average, premises consumed 67 W less power during event days than during days that had no events, but the impact was reduced by about 5 watts for every average Fahrenheit degree below T_{cp}. The two lines cross in the heating regime. The lines in the cooling regime also cross one another.

Table 15.3. Linear Models of the Average Daily Premises Power Consumption for Cooling and Heating Regimes during Event Days and Non-Event Days. The temperatures have been referenced to temperature T_{cp}=56.7°F that separates the cooling and heating regimes.

	Heating Regime (average kW)	Cooling Regime (average kW)
Event Days	$1.244 - 0.120\ (T - T_{cp})$	$1.325 - 0.000931\ (T - T_{cp})$
Nonevent Days	$1.311 - 0.115\ (T - T_{cp})$	$1.311 + 0.00137\ (T - T_{cp})$
Difference	$\mathbf{-0.067 + 0.005\ (T - T_{cp})}$	$\mathbf{0.014 - 0.00230\ (T - T_{cp})}$

The residual differences between the event-day data and the linear model baseline for nonevent days are plotted in Figure 15.11 as a function of outdoor temperature. In this figure, the negative differences represent reductions in average premises power for the daylong intervals.

There is a very small reduction in average premises power on the days that events occur, based on the simple temperature model that has been described in this section. The magnitude is about 7 W. However, the project's confidence is low (~72%) that any reduction occurred for premises on event days. The project cannot state with satisfactory confidence that any reduction occurred with the actuation of the LCMs. This was as good as analysts could do with daily premises data.

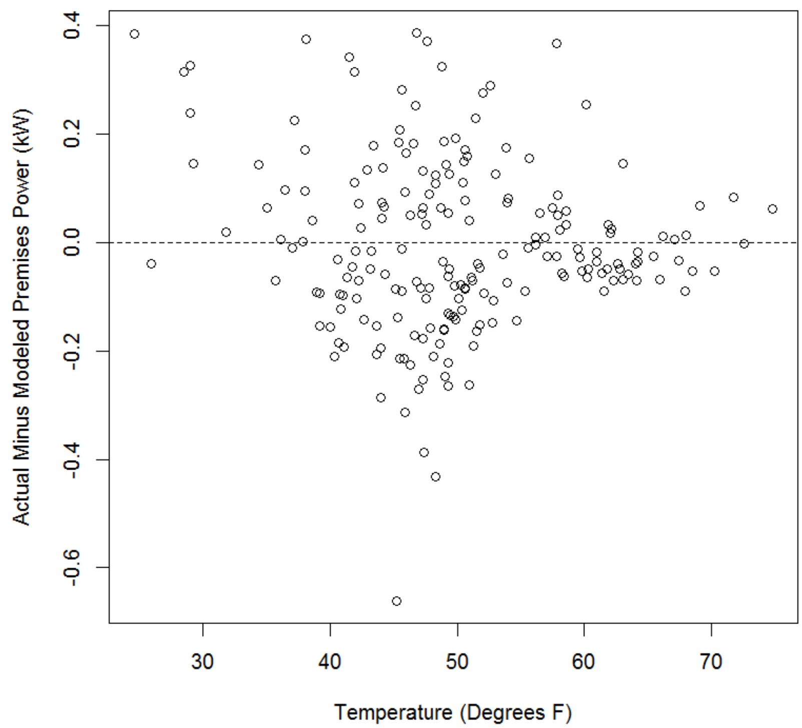


Figure 15.11. Power Difference: Premises Power During Event Days Less the Temperature-Modeled Power from Non-Event Days

Because analysis at the premises level was inconclusive, the project proceeded to analyze distribution power data from the Artondale substation. This data is available at hourly intervals, but it includes a larger distribution circuit, not all of which participated in the LCM system tests. Figure 15.12 shows distribution system power data as a function of temperature. Different markers were used for the hours that the LCMs were engaged and not. It appears that the data points from hours that the LCMs were engaged are toward the top of the cluster of measurements, meaning that the power load is higher when the LCMs are engaged. That observation simply means that the cooperative wisely engaged the asset when load was high.

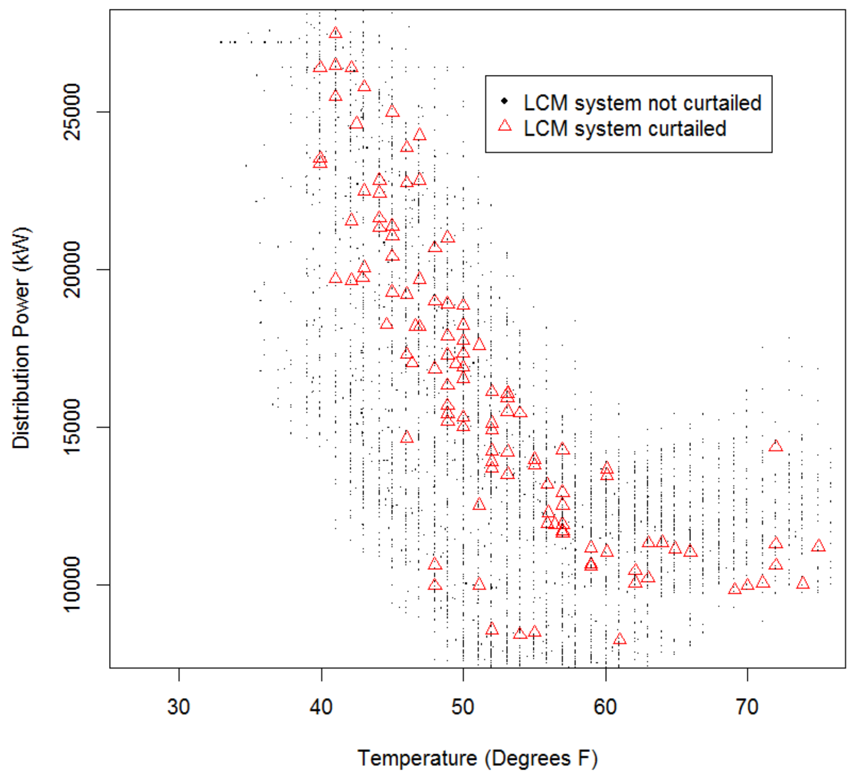


Figure 15.12. Average Hourly Distribution Power from Artondale Substation as a Function of Temperature and LCM System Status. This plot excludes the prolonged Event 3.

A regression model was created to better analyze whether any reduction may be observed from the distribution data. The model was fit to the status of the LCM system, calendar month, whether the days were weekdays or weekend days, hour, temperature, and the permutations of temperature with the hour. The analysis excluded all data from the time period that prolonged Event 3 had been reported to have been engaged. A baseline was generated from the regression model to emulate what the distribution power might have been had the LCMs never been engaged.

When a Student's t-test was run on the difference between distribution power levels during LCM event periods and otherwise, a small reduction was calculated. However, the result was reported with very low confidence. The project can report no impact evident from the distribution data.

15.2 Conservation Voltage Reduction with End-of-Line Monitoring

Peninsula Light Company procured and installed two voltage regulator banks and controlled six existing capacitor banks to facilitate CVR on Fox Island, Washington. The system was intended to reduce electricity demand, especially at times that the system was heavily loaded.

The cooperative offered to have the CVR system become dynamically responsive to advice from the project's transactive system. A function was established to determine when the CVR system should be engaged and for how long it should remain engaged based on the predicted magnitudes of the transactive incentive signal. The cooperative was unable to fully automate the responses, but some coincidence was achieved through a combination of automation and manual responses. The CVR system was reported to have been engaged about 24% of the hours that it had been advised to engage by the transactive system. The transactive system advised the system to respond about 59% of the total hours that the system was reported to have, in fact, responded.

The asset's transactive function modeled the expected change in system load that should have accompanied each event and its controlled change in system voltage. However, the predicted change in load remained poorly configured throughout the project, and the model failed to predict reasonable power magnitudes for the CVR system.

It will be shown in this section that the project could not detect that any change in voltage, in fact, took place when the CVR system was reported to have been activated. Given this lack of evidence, the project elected not to compile and present detailed information about the actual and advised transactive system events in this subsection.

The annualized cost of the CVR system and its components are listed in Table 15.4. The cost of implementing and integrating the transactive system was shared with that of the system of Fox Island LCMs (Section 15.1). The costs of all the other listed system components were fully borne by the CVR system. The greatest costs were for six capacitor banks, supervisory control and data acquisition (SCADA) upgrades, and utility engineering staff. Other less costly components included radio equipment, integration of the transactive system, two voltage regulators, and maintenance and administrative costs. The total annualized cost of the CVR system was estimated to be $226.9K.

Table 15.4. Annualized Cost of the CVR System and its Components

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
Distribution – Six Capacitor Banks	100	101.1	101.1
SCADA Control Module	100	52.9	52.9
Peninsula Light Line and Engineering Personnel to Design and Install Equipment	100	31.5	31.5
SCADA Software Module	100	21.9	21.9
Communication (radio) Equipment	100	8.4	8.4
Transactive Node (integration)	50	8.9	4.4
Distribution – Two Voltage Regulator Banks	100	4.1	4.1
Administrative	100	2.2	2.2
Hardware SCADA Maintenance	100	0.4	0.4
Total Annualized Asset Cost			**$226.9K**

15.2.1 Conservation Voltage Reduction Data

Two feeders (Numbers 2 and 6) supply electricity to Fox Island from the Artondale substation. Peninsula Light Company supplied averaged hourly phase voltage for each of these feeders, normalized to 120 V. The project averaged the data from the two feeders and restated them as per-unit quantities. The average per-unit voltage data is shown in Figure 15.13. The voltage appears to have been managed within a very narrow range throughout the project. The first data was made available from late July 2010 through the remainder of the project. Data was unavailable for July and much of August and September 2012.

The figure's markers have been colored to represent the status of the CVR system. Prior to 2014, the system was not yet installed and was inactive. In January 2014, the utility declared the system installed and useful. They reported that the system became engaged periodically throughout the remainder of the project for several hours at a time. It is not evident in Figure 15.13 that the voltage, in fact, changed at all during these reported events. Even during June and July 2014 the "on" voltages, which might have been reduced, are not abnormally low compared with normal ("off") operations.

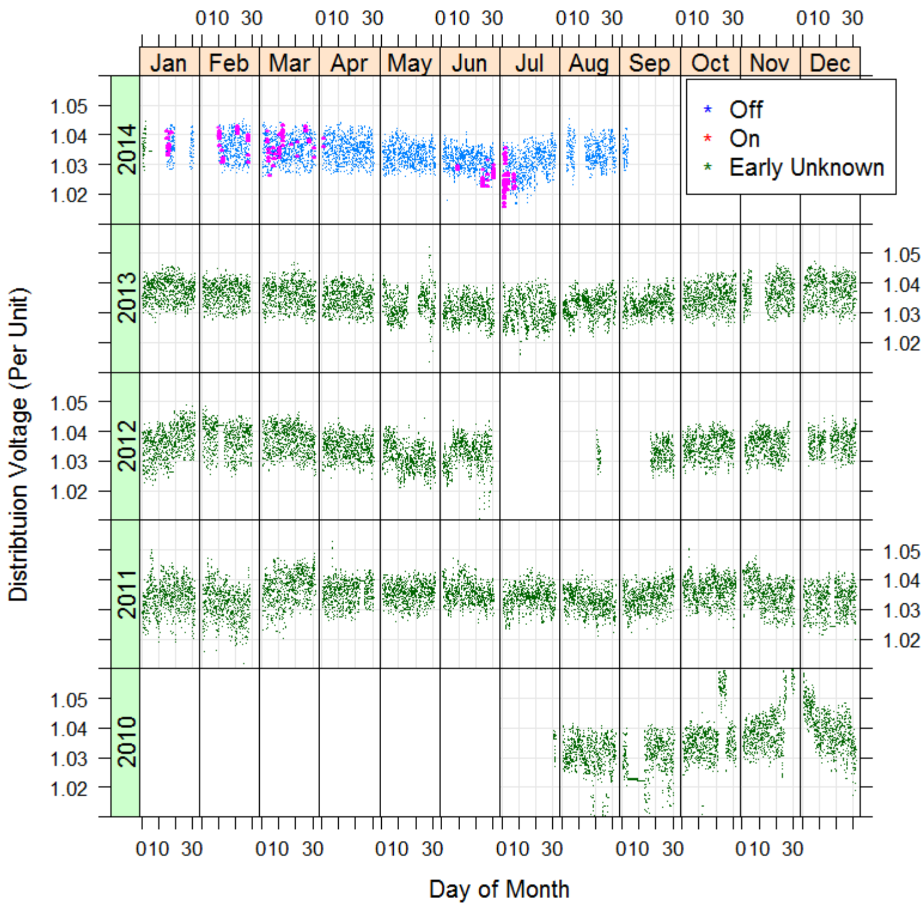


Figure 15.13. Average Distribution Feeder Per-Unit Phase Voltage. Marker colors indicate the status of the CVR system.

The project also collected total power for the two Artondale substation feeders over the same period. The availability of this data was similar to that of the voltage data; see Figure 15.14. The median total power over all project data for these two feeders was 14.6 MW. The average was 16.4 MW. The maximum approached 47 MW.

No reduction in the feeders' power during reported event periods was evident by inspection at this or any other scale.

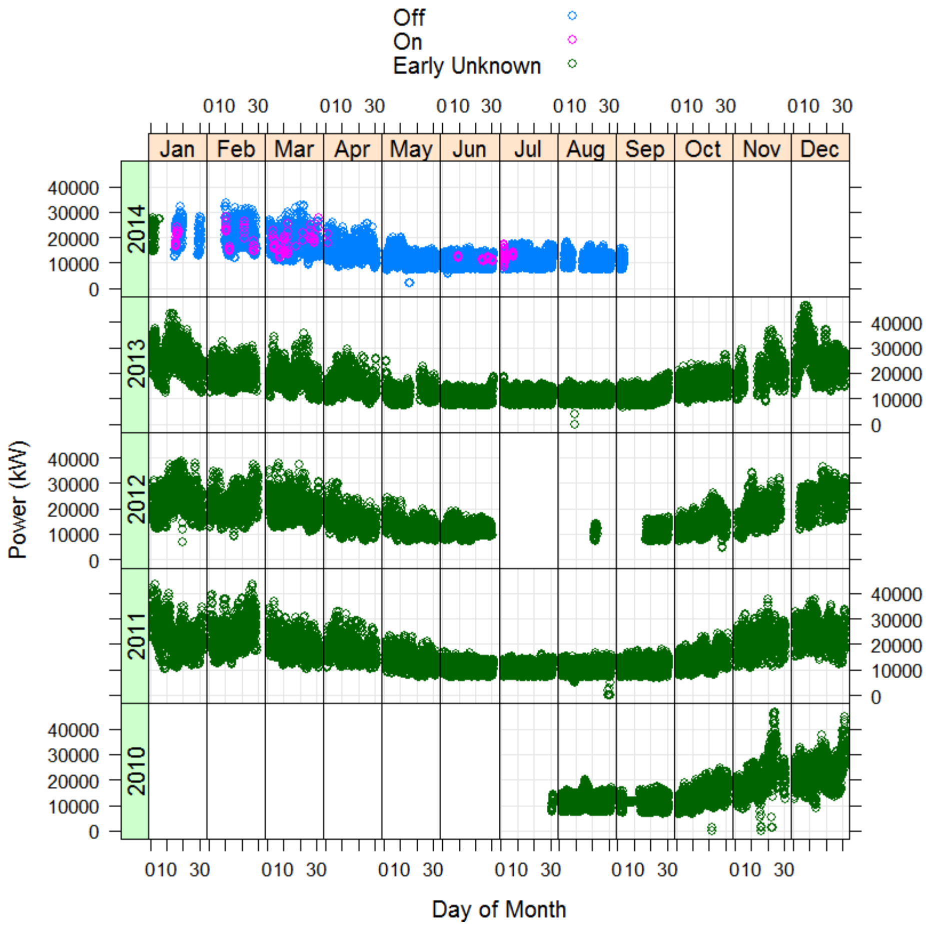


Figure 15.14. Average Hourly Distribution Feeder Power. Marker colors indicate status of the CVR system.

The feeders' sum reactive power was similarly plotted in Figure 15.15. Either the reactive power or the quality of the reactive power data changed March 5, 2013. Prior to that date, the reactive power data was dynamic. The load was inductive, but it occasionally changed sign to become slightly capacitive. After that date, the system data is less dynamically variable. The system load appears to have become strongly capacitive.

Neither the project's data staff nor Peninsula Light Company personnel have yet been able to confirm this change in behavior or to confirm and correct any data problems. Candidate causes include the activation of a new submarine cable from the mainland to Fox Island, activation of a new bank of distribution capacitors, or simply miscommunication of data.

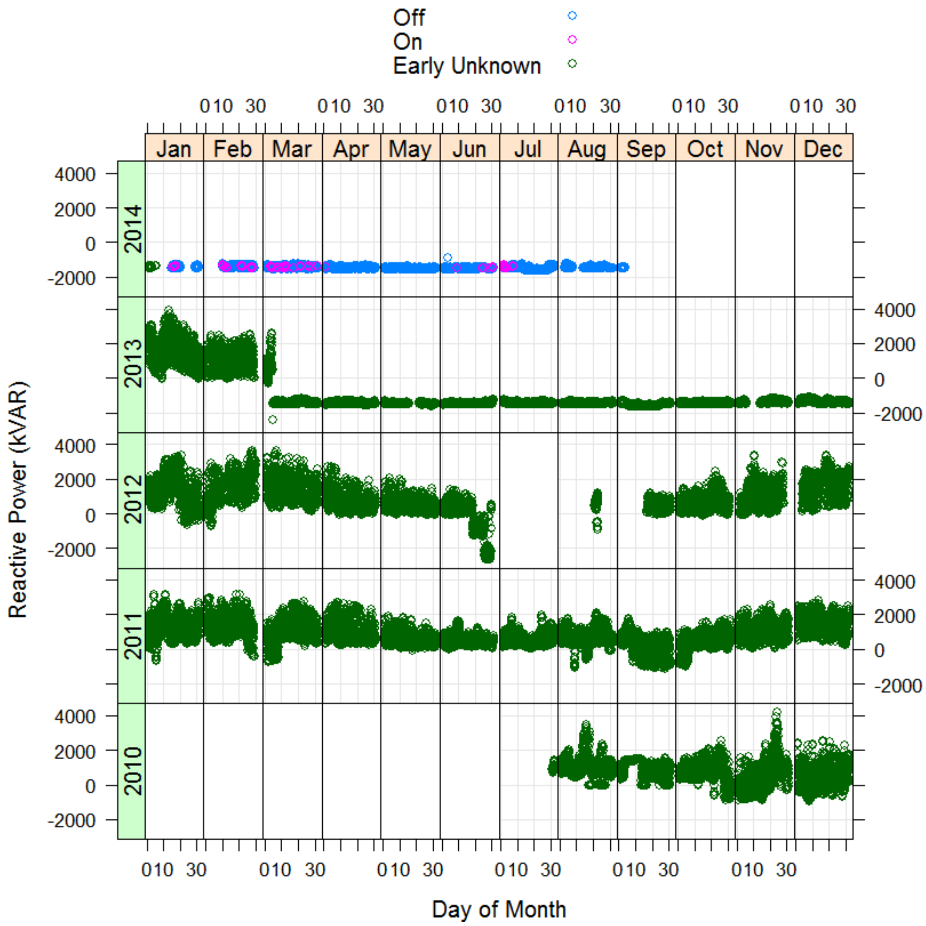


Figure 15.15. Average Hourly Distribution Feeder Reactive Power. Marker colors indicate the status of the CVR system.

15.2.2 Performance of the Conservation Voltage Reduction System

Quartile plots of distribution voltage as a function of CVR system status are shown in Figure 15.16. The CVR system is active when the status is “On.” The median and many of the values are somewhat smaller when the CVR system is engaged than when it is not. A Student’s t-test was run on the “on” and “off” populations. The difference is significant, but the average difference in voltage is a reduction of only about 0.12%. No measureable impact should be expected for such a small voltage difference. No further analysis was conducted.

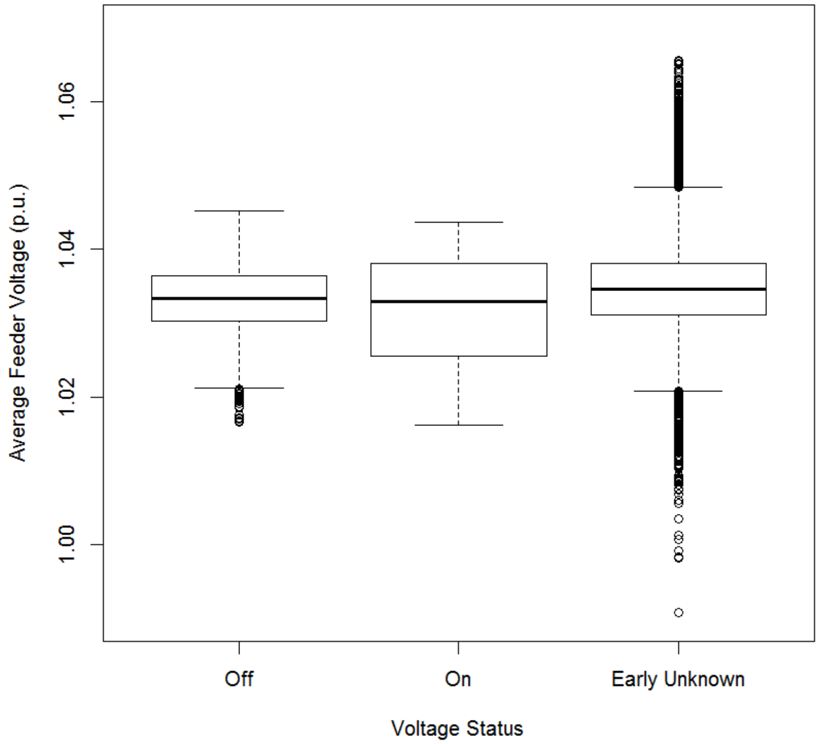


Figure 15.16. Quartile Plots of Average Per-Unit Distribution Feeder Voltage According to the CVR System Status

In summary, the project has found no evidence that the system behaviors were significantly changed at the times that the system was reported to have differently managed distribution voltages. The actions taken by the utility on event days were similar to actions that were taken on nonevent days anyway.

15.3 Pad-Mounted and Overhead Automated Switching

Peninsula Light Company applied FDIR with SCADA-controlled distribution switches to monitor and more quickly recover from distribution system faults on Fox Island. The SCADA system maintained a real-time state of the connected network with load flow and circuit ratings, and calculated an optimal network configuration in the event of a faulted section of network. The objective was to reduce the System Average Interruption Duration Index (SAIDI) and perform cold-load pickup by quickly restoring as much healthy network as practical, without exceeding circuit capacity. Peninsula Light Company declared the FDIR system installed and useful beginning September 2012.

The annualized costs of this system and its components are listed in Table 15.5. The greatest costs were for the FDIR module, SCADA system upgrades, and the pad-mounted and overhead distribution switches. Smaller costs were for administration, upgrades to radio communication, and utility staff labor. Total annualized cost of the system was estimated to be $187.4K.

Table 15.5. Annualized Costs of the Automated Switching System and its Components

	Shared Usage of Component (%)	Annualized Component Cost ($K)	Allocated Annual Component Cost ($K)
FDIR Module	100	47.7	47.7
SCADA Hardware Resources	100	46.5	46.5
Backroom Server	100	36.5	36.5
Distribution Pad-Mounted Switchgear	100	28.8	28.8
Distribution Overhead Switches, 600 A	100	13.8	13.8
Administrative	100	6.2	6.2
Communication (radio) Equipment (remote)	100	3.8	3.8
SCADA Components and Software Integration	100	3.5	3.5
Staff	100	0.5	0.5
SCADA-Mate® Switching System Overhead	100	0.0	0.0
Total Annualized Asset Cost			**$187.4K**

15.3.1 Switching System Data

Peninsula Light Company submitted monthly SAIDI values for the project footprint that was affected by this FDIR system on Fox Island. These calculations were performed by the utility, and the project performed no review of their calculation. The values were made available for the months from June 2012 through August 2014. The SAIDI values are listed by month and year in Table 15.6 to two significant digits.

Table 15.6. SAIDI Values[(a)] by Month (Average Minutes per Member

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	-	-	-	-	-	0.0	4.3	90	3	2.9	24	0.0
2013	0.00093	0.62	0.0	13	6.7	2.8	0.0	0.0	430	0.0	260	58
2014	79	660	0.27	0.0	4.6	0.28	0.93	2.2	-	-	-	-

(a) Reported values have been rounded to two significant digits.

It was the project’s practice to normalize duration indices like this based on the data time interval. Therefore these are stored in the project database as the typical outage minutes each 5 minutes—a very small number. The advantage of this practice is that the index may be restated for longer intervals—a month, for example—by simply summing the individual records from the included data intervals. The practice allowed the project to address data with diverse measurement intervals in the same database. The practice is not normally needed when utilities calculate SAIDI at monthly, or longer, intervals.

The SAIDI values have been plotted by project month in Figure 15.17. It is clear from this figure that members experienced relatively long outages during the months of fall 2013 and the winter that followed. The dashed horizontal line is the average of the SAIDI value for all project months—60.4 minutes per member per month.

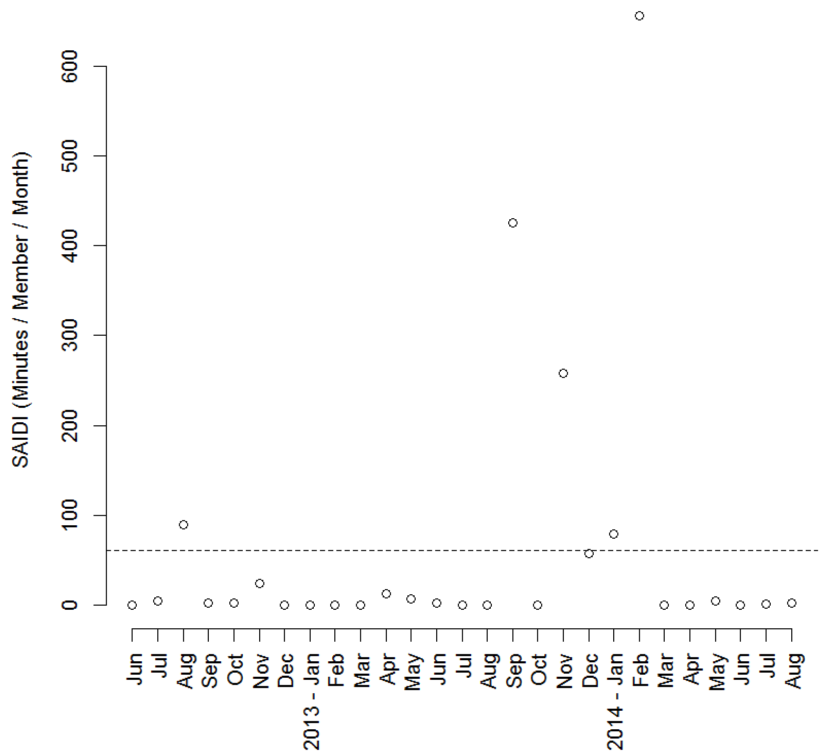


Figure 15.17. Monthly SAIDI Values

Peninsula Light Company also tracked outage response minutes, another indicator of the speed with which the utility recognized and responded to outages. The cooperative calculated these durations and submitted their calculations to the project for months from June 2012 through August 2014. The index is listed in Table 15.7.

Table 15.7. Average Outage Response Times[(a)] (Minutes per Outage)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	-	-	-	-	-	0.00	97.2	356	305	182	191	0.00
2013	0.00	318	0.00	265	136	256	0.00	0.00	148	0.00	148	76.2
2014	274	144	69	0.00	296	145	239	278	-	-	-	-

(a) Reported outage response times have been rounded to three significant digits.

Because the outage response times are normalized by outages, the monthly calculations were simply duplicated in the project's database throughout the project month to which the index referred.

The outage response times from Table 15.7 are plotted in Figure 15.18. No clear pattern is evident in this figure. The dashed horizontal line is the average of all the monthly outage response times collected by the project and displayed in this figure—145 minutes per outage per month.

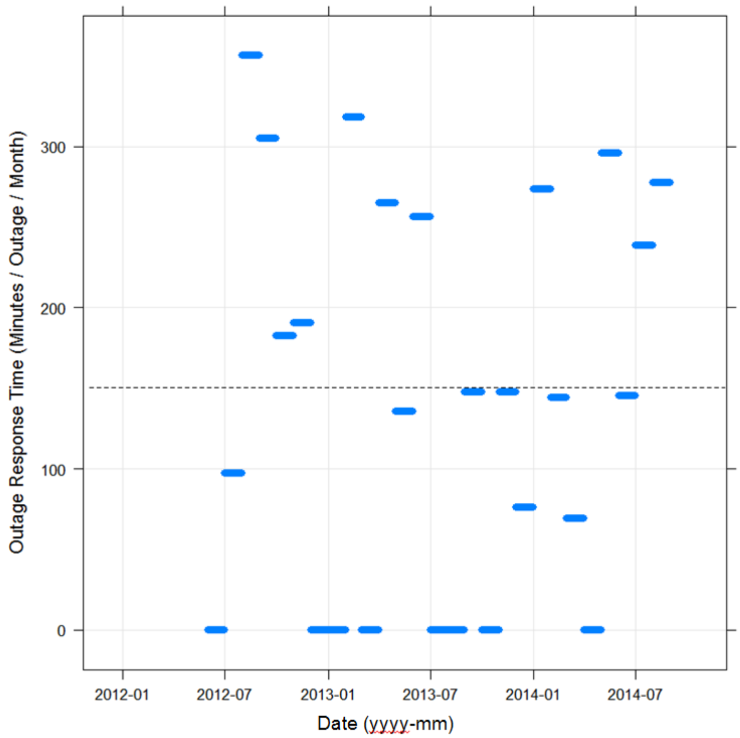


Figure 15.18. Outage Response Times by Month

The utility submitted its monthly service restoration costs for Fox Island, which have been plotted in Figure 15.19. Some of their worst restoration costs were incurred during the last project months of 2014.

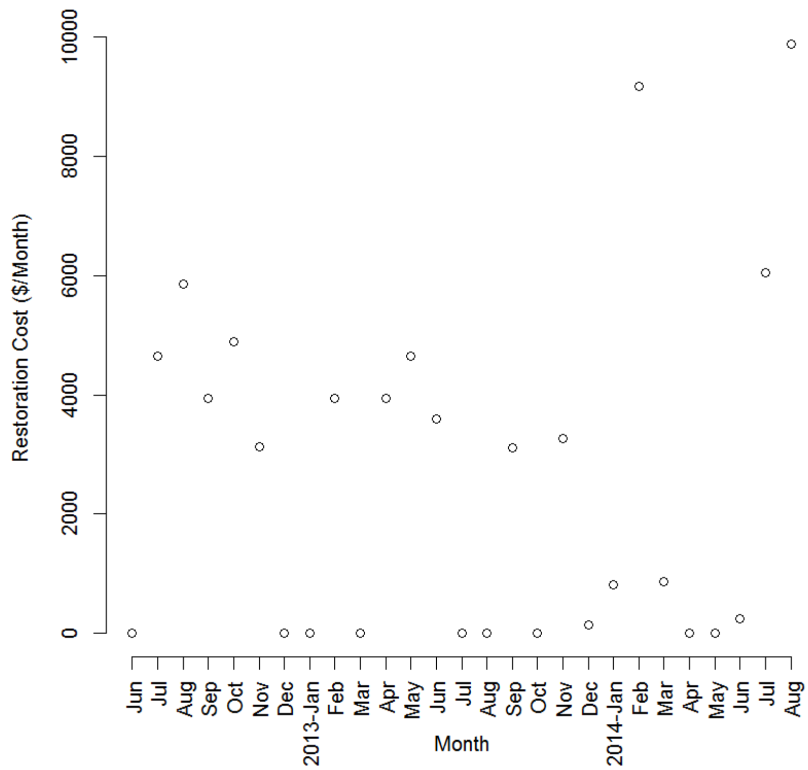


Figure 15.19. Peninsula Light Company's Monthly Restoration Costs during the Project

15.3.2 Switching System Performance

The utility supplied the project very little historical data concerning reliability indices before about September 2012 when the system was reported to be installed and useful. Regardless, the project conducted analysis on the series of monthly reliability indices to determine whether any significant change in the distribution system's reliability could be identified. This approach might be novel.

The approach was as follows. The indices from the successive months were separated according to whether they occurred before or after the beginning of a given project month. The resulting two groups of monthly indices were treated as independent populations of indices. A Student's t-test was run to determine whether the two groups differed significantly. The resulting probability value from the test states the probability with which the null hypothesis should be rejected. Both of the reliability indices in this section should have decreased if the utility's efforts to improve system reliability had been successful. Therefore, the null hypothesis was that the indices instead *increased* after the start of the given month. Analysts would normally reject the null hypothesis if the probability exceeded 95%.

The described analysis was duplicated for each project month. That is, the beginning of each project month was used to separate the reliability indices into two sets for comparison. The first months' and last months' results must be used cautiously. The Student's t-test naturally accounts for variability and the size of data sets, but the results should be questioned if either comparison set has only one or a small number of samples.

Because the project conducted an observational study, any improvement detected by this method can only be said to be correlated to the asset system's engagement or another utility practice. It was hoped that the installation of the FDIR system would correspond to the timing of a significant improvement in one or both reliability indices.

Figure 15.20 shows the result of this analysis for the reliability index SAIDI. Recall that the worst indices occurred in late fall 2013 and into the following winter. The indices were very favorable from March 2014 until the end of data collection. This pattern might indicate that a change in members' electric reliability indeed occurred beginning March 2014. The difference between SAIDI values before and after March 2014 is significant according to the Student's t-test method that has been described. The null hypothesis should be discarded with better than 95% certainty (the upper dashed horizontal line).

Then again, the result might be caused by chance and favorable weather patterns.

Regardless, the project cannot state that SAIDI improved with the installation of the FDIR system in September 2012.

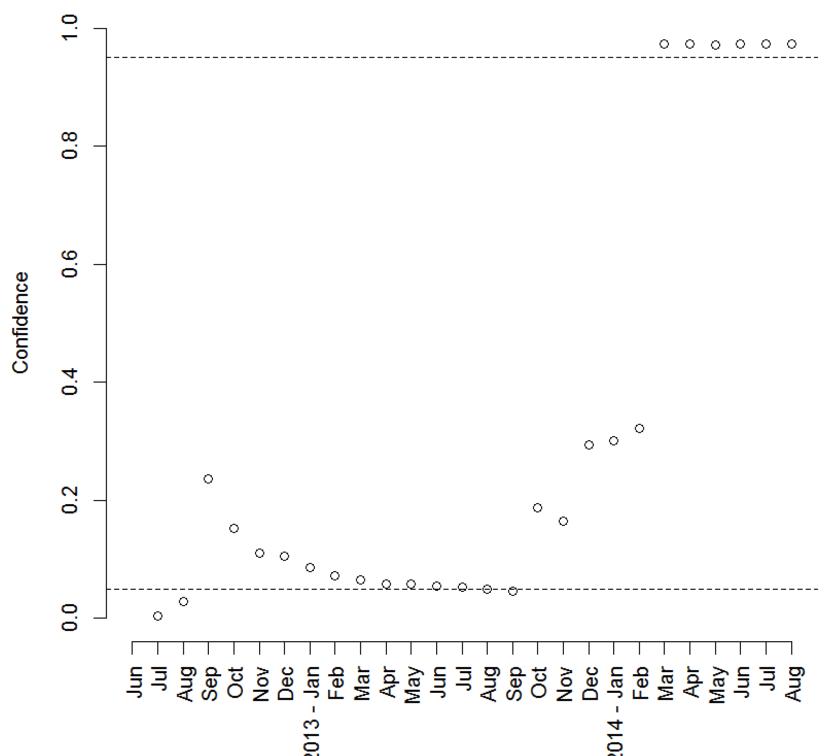


Figure 15.20. Student's T-Test Confidence that SAIDI in the Following Months is Smaller than in Prior Months

A similar analysis was conducted on outage response time; see Figure 15.21. While no clear trend was evident in the raw data, the method used in this section seems to show a long-term worsening of outage response time. In fact, the last months' values might be interpreted to indicate we should be confident in declaring this worsening. However, the last months might have simply exhibited higher indices within the normal variability of the index over time.

Regardless, the project cannot state that the utility's outage response times improved significantly with the installation of the FDIR system in September 2012.

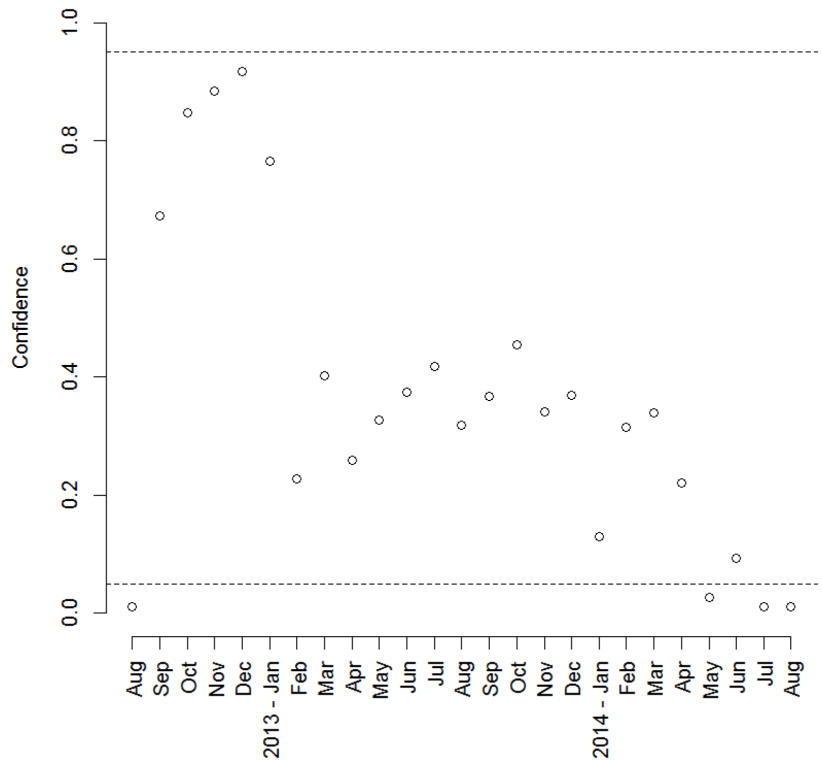


Figure 15.21. Student's T-Test Confidence over Time that the Following Month's Response Times Were Shorter than in Prior Months

The analysis was repeated using the monthly restoration costs that had been reported to the project by Peninsula Light Company. The confidence that restoration costs had decreased after a given month when compared with prior months is shown in Figure 15.22. Because the last project months had incurred some of the greatest restoration costs, the trend shown in this figure is generally downward, meaning that restoration costs appear to be getting worse, not better.

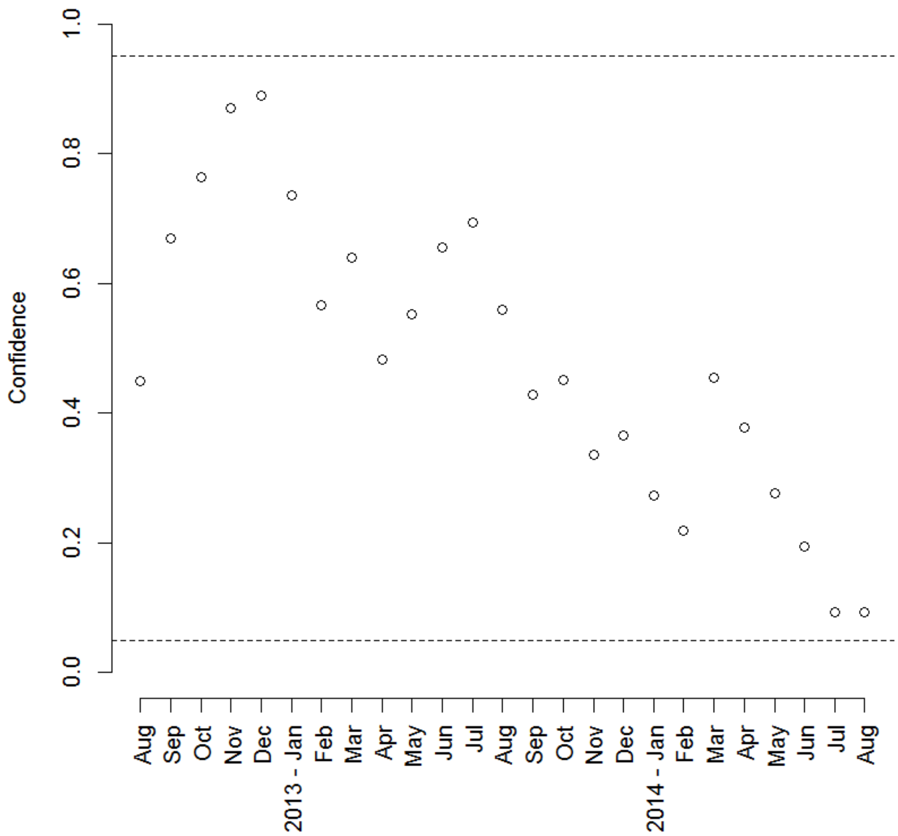


Figure 15.22. Confidence Levels when Comparing Restoration Costs before and After Each Project Month. Confidence should approach unity if following months have a significantly reduced restoration cost compared to preceding months.

15.4 Conclusions and Lessons Learned

Fox Island proved to be a challenging test site because of its natural isolation, the growing demand, and the predominantly residential member population. Peninsula Light Company tested three technologies during the Pacific Northwest Smart Grid Demonstration.

The utility engaged about 500 LCMs for the curtailment of electric tank water heater load on the island. These modules were engaged soon after they became deployed to help the Peninsula Light Company manage the failure of one of the lines that supplied the island from the mainland. The project analyzed data from the premises of members that had received the LCMs. The utility's existing PLC meter technology was found to not support premises metering for intervals shorter than 24 hours. The project was not able to confidently confirm that any power reduction had occurred at the premises from the 1-day interval data. The project also reviewed feeder data. Again, no power reduction could be confirmed from this data that had much shorter hourly intervals. The curtailment impact was perhaps too small a fraction of the overall feeder power for its signal to be identified.

The second technology to be demonstrated was active voltage management with end-of-line voltage monitoring. Peninsula Light Company encountered delays in the implementation of this asset because the existing infrastructure could not provide rapid, accurate voltage measurements that were necessary.

Transformer monitors were eventually installed to satisfy this requirement. Regardless, the project was unable to confirm significant changes in feeder voltage at the times that the system was reported to have been engaged. No change in system power could be determined during the engagements.

The utility also installed overhead and pad-mount switches throughout Fox Island to practice FDIR and improve its member's service reliability there. Two of the biggest challenges in implementing this system were the improvement and management of the site's circuit model and obtaining accurate voltage measurements back from circuit locations. A more detailed discussion of these challenges by the cooperative is included later in this section. The project analyzed reliability indices to determine whether an improvement could be confirmed. While the project cannot definitively attribute improvements to the FDIR system, the values of SAIDI at the site have been small since spring 2014. An outage response time metric did not mirror this improvement. The method applied by the project in this analysis might be generally useful to utilities as they monitor monthly changes in their reliability indices.

The following lessons were authored by Peninsula Light Company staff for the project.

There have been many challenges in the implementation of the Peninsula Light Company demonstration tests. The challenges primarily fell into two camps: technology and integration. An additional factor that added to the challenge was changes to the cooperative's engineering staff after the tests had been defined and equipment and software had been selected and purchased. The collective shortcomings of the hardware, software and existing system capabilities that emerged as the project progressed would have been a challenge even without changes in utility personnel.

Following is a summary of the lessons learned by Peninsula Light Company while implementing its demonstration component in the Pacific Northwest Smart Grid Demonstration project.

15.4.1 Accuracy of the System Model is Critical

The utility is currently using an Environmental Systems Research Institute geospatial database (Esri 2015) model. The Environmental Systems Research Institute model was built from a very difficult import of a legacy called 4th Dimension Database Log File (4DL) system. Many compromises had to be made to get the model to import and display correctly. The need for integration with a new design tool further exacerbated the problems.

The system model is the underpinning of the FDIR and integrated volt/VAr control (IVVC) functionality. The model is used by a prediction engine to determine the most likely location of a fault, calculate the impact of switching loads, or estimate voltage drop. Depending on the vendor and how the modules are configured, any errors in the mapping system may cause the system to crash (to varying degrees) or if addressed, can be processed through rules or manually overcome.

If a map-dependent application is being considered and an existing mapping system is in place, extract at least a portion of the system for vendors to evaluate before a vendor product selection is made.

15.4.2 Know Integration Dependencies of Software

When vendors were being considered for the IVVC and FDIR systems, there were two viable choices: select the vendor of the utility's current SCADA system or select a vendor whose solution could bolt on to the utility's existing SCADA system.

Although the utility's existing SCADA vendor had not deployed either module elsewhere, a decision was made to select them because of the inherent integration that would result from using the existing vendor. The same model and analysis tools used by the utility's existing outage management system (OMS) would be shared. Ultimately, this turned out to be a liability because problems in one area would affect other areas.

Furthermore, the chosen system relied on a single instance of a database runtime engine. This engine was also shared between the test system and the production system. An additional instance could have been added, but at very high cost.

The alternative vendor that was considered had several systems deployed and operational. They offered a stand-alone product that was configured with a simplified version of the system model, and obtained status and sent controls via industry standard master/slave protocols. The strength of this solution was that if a problem emerged in the OMS module, the OMS could have been down, but the SCADA system would then likely remain functional and could continue to interface with the bolt-on solution.

Accurately assess the system model and fully understand the impact of any errors on the software that is being considered. Some programs are written to effectively work around connectivity errors. Do not purchase software that does not allow direct editing of any database that supports that software. Regardless how attractive a single vendor solution looks, seriously consider a best-of-breed approach if the players are well established in their fields and have a track record of successful deployments.

15.4.3 Automated Meter Reading Power Line Carrier Technology is Slow but Reliable

The asset systems chosen by Peninsula Light required voltage measurements (IVVC) and energy measurements (load control). The existing automated meter reading (AMR) system was purported to be able to provide both. When the asset systems were being considered, discussions with Landis+Gyr indicated that the AMR system was capable of measuring voltage, and the voltage measurements would be returned with data packets. Furthermore, the energy measurements needed for measurement of the efficacy of the load-control tests could be returned on an hourly basis.

In order to get hourly data measurements (with a two-hour lag), the units needed to be configured to use 11 carrier channels per meter over the power line versus one channel for its normal one-read-per-day configuration. Equipment currently installed in the site's substations did not have the channel capacity to provide for all of the meters on the test circuits. Upgrades necessary to support this would have been

$100,000–$200,000 for the system, and would have used all of the channels that were available for the whole system on a single substation. This could have been repeated at all of the substations; however, it would have precluded switching feeders between substations because the channel numbers would not be unique to each substation.

The accuracy of the voltage measurements turned out to be inadequate for the IVVC application. In addition, the IVVC vendor required voltage measurements every five minutes, at a minimum.

Understand the capabilities and limits of any supporting system or infrastructure, regardless of the technology used. Each has its own peculiarities. Get vendor commitments on data accuracy and data flow rates to make sure all performance needs are met.

15.4.4 Secondary Data Sources are Expensive (Additional Transformers / Sensors)

The IVVC system required highly accurate voltage measurements and the ability to collect those data measurements at five-minute intervals. The need for accuracy was known early on, but the requirement for the short intervals was not revealed by the vendor until we were close to software deployment.

As Peninsula Light Company explored other ways to collect accurate voltage measurements, it found that pole-mounted transformers and other sensors were expensive and came in a difficult form factor. As the need for five-minute intervals emerged, the issues were compounded by the location of the sensors and the additional equipment that would need to be installed for communication.

Ultimately, cellular-based private network communications proved to be the most effective way to provide the necessary polling rates and in the locations that were needed. The project was delayed somewhat while the utility waited for vendors to get their equipment certified on Verizon’s 4G LTE network. Interestingly, vendors/devices certified in one area of the country do not necessary get immediate certification in other parts.

To obviate the need for additional equipment at each location, use equipment that could be used elsewhere in the system and keep the costs in check. Seek solutions that provide other functionality in addition to supporting cellular communications. For example, switches were augmented or replaced with reclosers and controllers capable of using Distributed Network Protocol. Transformer monitors allowed precise energy measurements, 0.05%-accuracy voltage, and expandability with daughter cards and power quality measurements. Both solutions were widely deployed and had proven track records.

To every degree possible, develop taxonomy for every functionality being considered and evaluate all vendors/solutions against it.

15.4.5 Load Controllers Leveraged the Existing AMR System but with Limited Performance

To support the load-control demonstration, switches controlled by the Landis+Gyr PLC system were installed in member homes. There was no real-time feedback on whether an “open” or “close” command had been executed. The use of the PLC load controllers seemed ideal for the load-control tests, but in retrospect, a more robust system would have been preferable. Wireless/modem technologies or ping-capable PLC products would have enabled immediate feedback. Regardless of the organic capabilities of any existing systems, consideration should be given to all solutions.

15.4.6 Involve Operations Personnel in the Selection of Field Devices

Switching devices were necessary to support the FDIR demonstration. The overhead switches were selected based on lowest cost, and the pad-mount switch controllers were chosen for the same reason. Siemens switches were selected for the overhead switching functionality, and when delivered, the switch configuration and provisions for manual operation were contrary to preferences of the utility’s operations department. The switches contained a remote terminal unit that, though adequate for the basic functionality of the switch, was inadequate for additional functionality that was necessary. The voltage and current measuring capability of the switches did not meet expectations or requirements of the operations staff.

For the pad-mounted switches, the lack of voltage and current sensors on different switch configurations detracted from the functionality. The sensors were not selected because the cost of the controller that supported the sensors was higher. Retrofitting the switches was impractical.

All equipment selections should be carefully reviewed from every aspect of use. The short-term and long-term needs of the system should be considered. If possible, arrange for the vendor to bring units on site for evaluation. Talk to other customers who have purchased the product. Purchase based on value.

15.4.7 Reclosers are the New Overhead Switch

Switching devices were necessary to support the FDIR demonstration. The overhead switches were selected based on lowest cost. The shortcomings of the overhead switches discussed above were further highlighted when the utility was looking for voltage sources for the IVVC functionality. The remote terminal units in the switches were inadequate for the task and the sensors were incomplete.

Reclosers were chosen to augment the system because they served the needs of more than one asset system and were deemed to add high value to the systems. Reclosers have built-in high accuracy sensors and a microprocessor-based controller that can be polled via industry standard protocols for voltage and current data. In addition, the inclusion of reclosers at key locations in the system yielded additional protective functions to circuits when reconfigured on the fly.

Recloser costs are about the same as those for switches when all aspects are considered, i.e., speed, sensors, control, status, etc., and they are inherently more flexible in their applications.

15.4.8 When a Historian is not a Historian

Reporting requirements for Peninsula Light Company's demonstration components required SCADA data to be sent to the project. The SCADA system stores data in flat files, so a tool was necessary to convert and present the data in a friendlier format. The software package sold by the vendor was represented as a historian.

For speed and efficiency, event status, control action and analog points are stored by the SCADA system in binary, flat files for speed and efficiency. These files are generally not reader friendly and are sometimes written in manner similar to encryption. To review the data, present it in a usable format, or otherwise manipulate it, another software package was required. The package our vendor offered was their "historian." Peninsula Light Company's existing SCADA system did not have one, so it was purchased.

The tool was an extraction and reporting tool, not a true historian. Furthermore, the configuration of the software was incomplete, and status and control points were not included. Only the analog data necessary for the demonstrations was included. For reasons outside the scope of the demonstration, this was a fatal flaw and for all intents and purposes, the utility still does not have a historian. Although a true historian was not necessary for the project, it would have been of great value to the rest of the enterprise.

Carefully review software functionality before making a purchase decision. Make sure that the capabilities of the packages are evaluated by personnel with the experience necessary to note the subtle differences that may exist. When software is purchased and deployed, make sure that the personnel with the right experience are driving the configuration and participate in any evaluations concerning the performance of the delivered product. If the knowledge and experience does not exist in-house, consider hiring a third party to provide the oversight and deployment management.

15.4.9 Manage Change

Technology deployment and integration inherently heralds change, and all aspects of the change must be addressed. The changes associated with the newly deployed technologies included new hardware, software, processes, operational ownership, etc. It is common knowledge that change must be managed, but when the changes are subtle, occur in unexpected areas, or emerge too quickly, silos form and progress is slowed. Ownership of a function or area of responsibility may need to change in the midst of the change. The end user is the true measure of how well the change is being managed.

Carefully assess the impacts of the technologies and integration, including a comparison between the landscape at the start and what it might look like at the end. Discuss the changes openly so everyone has a good idea of what to expect going forward. Define terms and concepts so everyone is clear on expected roles and responsibilities. Ask very specific questions.

16.0 Portland General Electric Site Tests

Additional chapter coauthors:
K Whitener, S Chandler, M Phan, L Beckett, C Mills, D Garcia, R Bass, W Sanders, M Osborn and W Lei − Portland General Electric

Portland General Electric is a vertically integrated, investor-owned utility that serves much of Portland, Oregon, and areas south, including its project site in Salem, Oregon. It is Oregon's largest utility, serving 843 thousand customers, of which 100 thousand are commercial customers. The utility owns a diverse mix of generation resources including thermal, natural gas, hydropower, and renewables (Portland General Electric 2015).

The utility focused its Pacific Northwest Smart Grid Demonstration (PNWSGD) project participation in Salem, Oregon, and referred to these demonstration activities collectively as their Salem Smart Power Project (SSPP). Portland General Electric was interested in testing and demonstrating many smart grid technologies, but the most ambitious is the large battery energy storage system at its Salem Smart Power Center. The utility had planned to demonstrate the following five asset systems, which are discussed in much greater detail later in this chapter:

- residential demand response (DR) (Section 16.2)
- commercial DR (Section 16.3)
- commercial distributed standby generation (DSG) (Section 16.4)
- battery storage in a high-reliability zone (Section 16.5)
- distribution switching and residential/commercial microgrid (Section 16.6).

The relationships between these components of the SSPP and the Salem distribution grid are shown in Figure 16.1. The PNWSGD used this layout diagram to suggest how the various assets could affect the site's distribution system and how system impacts might be metered for verification. Table 16.1 provides a key to the naming convention that was used for the data in Figure 16.1. Text in Figure 16.1 such as "(-,C,C,C,C)" and "(-,E,E,E,E)" is a nominal description of whether the data is a member of the control (i.e., "C") or experimental ("E") groups in the ordered list of asset systems. Asset PG-01, concerning residential DR, was removed from the layout diagram. Few willing residential customers were recruited, and the effort was abandoned when its risks exceeded the value of continuing.

Table 16.1. Key to Data Stream Names Used in Figure 16.1

Data Stream Name	Description
PG-IM-1-*	Customer meter power
PG-IM-41-*	Feeder real power
PG-IM-42-*	Feeder reactive power
PG-IM-60-1	System Average Interruption Frequency Index
PG-IM-62-1	Momentary Average Interruption Frequency Index
PG-IM-64-1	Distribution reliability incidents
PG-IM-68-1	Momentary Average Interruption Frequency Index time threshold
PG-IM-151-1	Energy stored in the battery

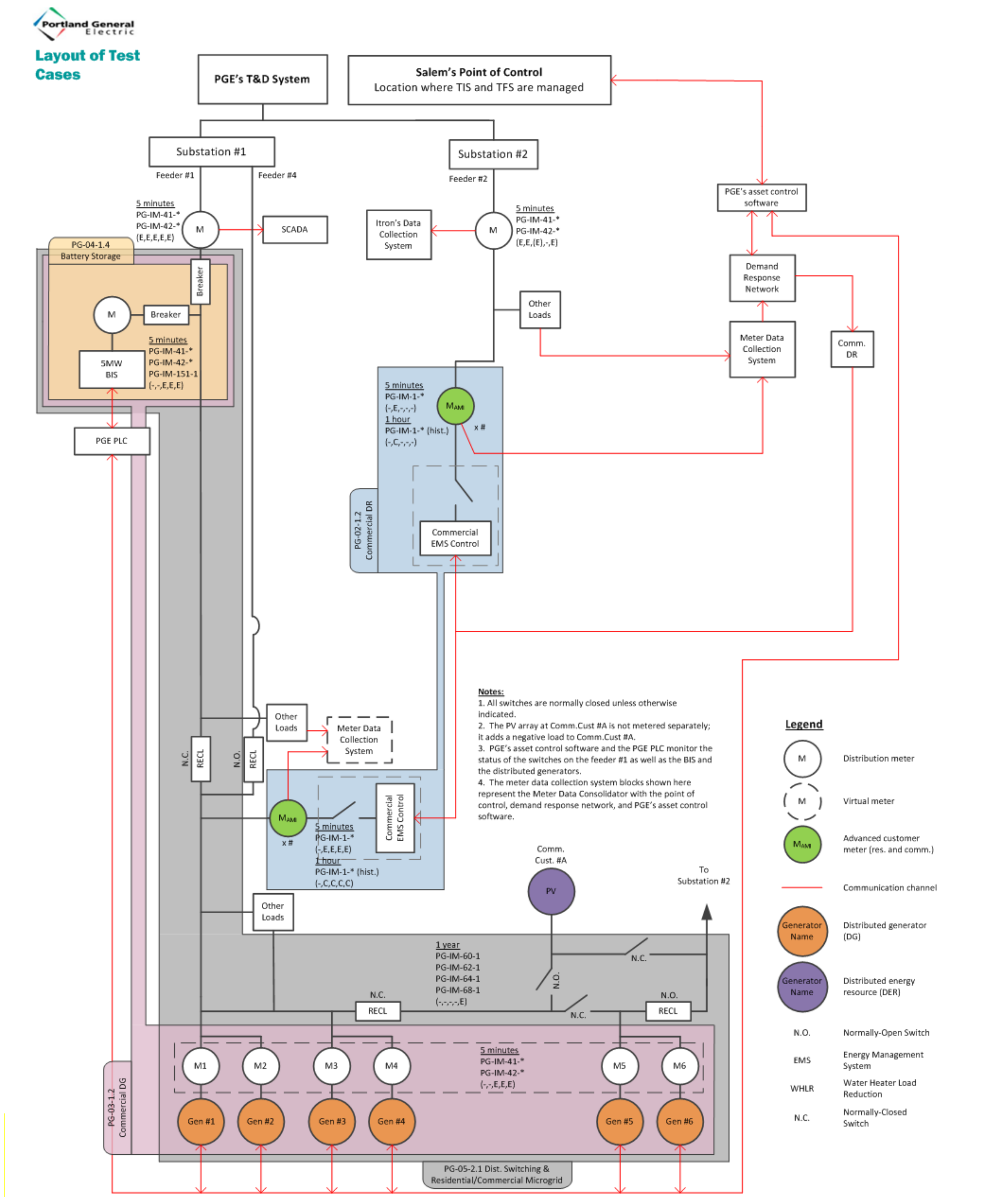


Figure 16.1. Layout of the Portland General Electric Asset Systems on Their South Salem, Oregon, Distribution Circuit

16.1 Portland General Electric's Utility Economic Dispatch Function

The PNWSGD project featured a transactive system (Chapter 2). Portland General Electric reported that its transactive system received and used the transactive incentive signal (TIS) that it received from the Western Oregon transmission zone (TZ05) of the transmission system as it made decisions as to when and how long to dispatch its asset systems, including its battery system.

Portland General Electric developed and implemented its own toolkit functions to dispatch its project resources and DR assets using the TIS that it received from the transactive system and other available information. Portland General Electric's toolkit functions were enacted by a neural network that was trained to recognize opportunity for dispatch based upon a comparison of the incoming TIS and a threshold cost that was tailored uniquely for each of its transactive assets, while constrained by battery- or feeder-specific operational parameters and other asset parameters.[1]

The economic dispatch function seeks to optimize cost over time while, in the case of the battery, also seeking to increase the value of discharge cycles. This function should generally charge the battery in off-peak times and discharge it at peak times, presuming price maxima correlate well with load maxima.[2]

Portland General Electric set operational constraints on the system and enforced these through the automated dispatch function. The battery may not be charged or discharged for less than one full cycle, between 20% and 80% state of charge. This range corresponds to approximately two hours of use per 24-hour calendar period, including one charge and one discharge. This behavior notably corresponds to the battery toolkit function designed by the project[3] that was generally enacted in an IBM Internet-scale Control System-configured node.[4]

The project received no information from the utility about the other conditions that might have affected the dispatch decisions made by Portland General Electric's transactive system and its artificial intelligence (Figure 16.2). Project analysts desired more insights into system control at this site, but it is an intentional design feature of a transactive system that the abundance and availability of power may be communicated without revealing proprietary information throughout the system.

Further conceptual and technical details about this artificial intelligence system and its implementation may be found in (Chandler and Hughes 2013a) and (Chandler and Hughes 2013b).

---

[1] K Whitener, C Mills, A Ross, B Barney, C Steeprow, D Brown, D Garcia, J Ross, W Lei, B Campbell, V Bhavaraju, A Wick, B Stoick, C Hartzog, T Hans, J Istre, and B Watts (Whitener et al.). April 8, 2014. Salem Smart Power Project Microgrid Aspects. Joint report by Portland General Electric, Eaton, and EnerDel. Portland General Electric, Portland, Oregon, April 8, 2014 (unpublished).
[2] Ibid.
[3] In the project's naming practice, this was "TKLD_4.1."
[4] Whitener et al. 2014 (unpublished).

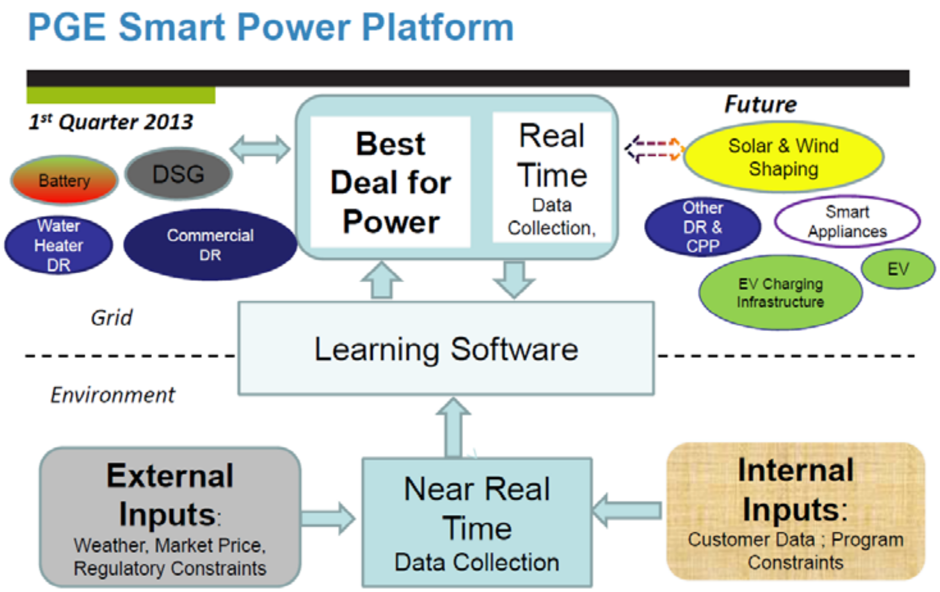


Figure 16.2. Artificial Intelligence was Incorporated into the Smart Power Platform that Engaged the Project's Transactive Assets (from Portland General Electric March 2014, p. 20)[1]

16.2 Residential DR

Portland General Electric had intended to offer residential DR technologies, including water heater timers, air conditioner controls, home energy management systems and/or energy management displays, to qualifying residential households within the site boundary. The objective of the utility's residential DR technology demonstration was to test customer acceptance of energy management devices and to measure the degree to which load might be reduced or shifted. This system was to be responsive to advice from the transactive system.

This activity had already begun by the beginning of the PNWSGD. The utility did not request any project funding for the residential DR devices, but they used demonstration funding to engage the vendor Utility Integration Solutions, Inc. for data management services and for the development of software that would be used to monitor or control the DR measures.

After considerable recruitment efforts, Portland General Electric was able to identify 20 suitable customers for this program. Only two of these premises became observable to the project through data collection. The Rural test feeder definition necessarily changed in 2013 to safely accommodate testing of the utility's battery system, which redefinition limited the observability of the premises data. The program was terminated in October 2013 after an installed load-control device malfunctioned at a residential customer's house.[2] No useful data were received by the project concerning the performance of the residential DR devices.

[1] "EV" is an abbreviation for "electric vehicle," and "CPP" is "critical peak pricing."
[2] Reported by the utility to Battelle in an e-mail dated September 24, 2014.

16.3 Commercial DR

The utility offered DR technologies including building management systems, control relays, and space conditioners to qualifying businesses such as retail and service outlets within the site boundary. The DR assets were made automatically responsive to the utility's transactive system.

Portland General Electric used their commercial DR system to engage commercial loads with customers within the demonstration feeder, thus reducing load when an event was called. Commercial DR control was voluntary, meaning customers could opt not to participate in an event. Based on its historical data and research, the utility accrued a maximum of approximately 25 kW power curtailment from the eight commercial customers on the demonstration feeder. Approximately 1.2 kW of load reduction was expected by the utility during a called event, a curtailment of 5% of the peak load.[1]

Portland General Electric's toolkit function for the control of this asset engaged a neural network that had been trained to recognize opportunity for dispatch based on a comparison of the incoming TIS and the cost-to-go function for the transactive asset. The *cost-to-go* function may be generally described as a function that seeks to optimize cost impacts over time while conforming to all the asset system's constraints. This goal-seeking behavior of the neural network generally implements curtailment events at peak times, providing that price maxima correlate well with load maxima. Responses by the system are constrained by time of year (seasonality), allowed duration of dispatch, time of day, time remaining before the next dispatch, and other parameters. For example, the behavior of the commercial DR system was limited by season and time of day as is shown in Table 16.2.[2]

Table 16.2. Portland General Electric Commercial DR Temporal System Limitations[3]

Constraint Name	Season	Times	Limitation
Seasonal -1	Winter (Dec 1 - Feb 29)	06:00–09:59	Usage approved
		05:00–20:59	Usage approved
		10:00–16:59	Usage restricted
		21:00–05:59	Usage restricted
Seasonal -2	Summer (July 1 - Sep 30)	15:00–19:59	Usage approved
		19:00–14:59	Usage restricted

None of the DR equipment that was placed at commercial sites to provide these DR measures was provided by the project or counted as project cost share. The utility offered the project an opportunity to observe and analyze data from the technology with them and to report about the technology among its final reporting. No demonstration funding was requested from the project for the purchase, installation, or provision of this DR equipment. However, the utility used demonstration funding (or cost share) to engage the vendor Utility Integration Solutions, Inc. for data management services and the development

[1] Whitener et al. 2014 (unpublished).
[2] Ibid.
[3] Ibid.

of software that was used to monitor or control the DR devices. The objective was to test commercial customer acceptance of energy management devices and to measure available load reduction and shifting from the responses.

The annualized costs of the system and its components are listed in Table 16.3. The total system's annualized cost was estimated by the sum of each component's annualized cost, based on the anticipated useful lifetime of the component. Observe that the load-control devices themselves were not included among system costs in this table. The greatest costs were for upgrades to the DR tracking system and the costs of connecting the asset to the Portland General Electric transactive system. Smaller annualized costs were estimated for materials, technical labor, and outreach.

Table 16.3. Annualized Costs of the Commercial DR System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Utility DR Tracking System	50	375.0	187.5
Transactive Node Development and Equipment	25	109.0	27.2
Materials and Supplies	20	104.4	20.9
Engineering/IT Support	25	7.8	2.0
Outreach and Education	20	6.1	1.2
Total Annualized Asset Cost			**$238.8K**

IT = Information Technology

16.3.1 Characterization of Asset System and Data

Portland General Electric provided the project with premises power data for the eight commercial locations on their demonstration feeder. The project aggregated the data as an average for the eight locations. The data set extends from late September 2012 to early September 2014 and is shown in Figure 16.3. The averaged power magnitude appears similar to that of residences. Upon its review, the utility agreed that the reported average power appeared too small, given the types of commercial sites they believed to have been included. The project reviewed the data it had received and could not find any error that would have caused the power to have been underreported.

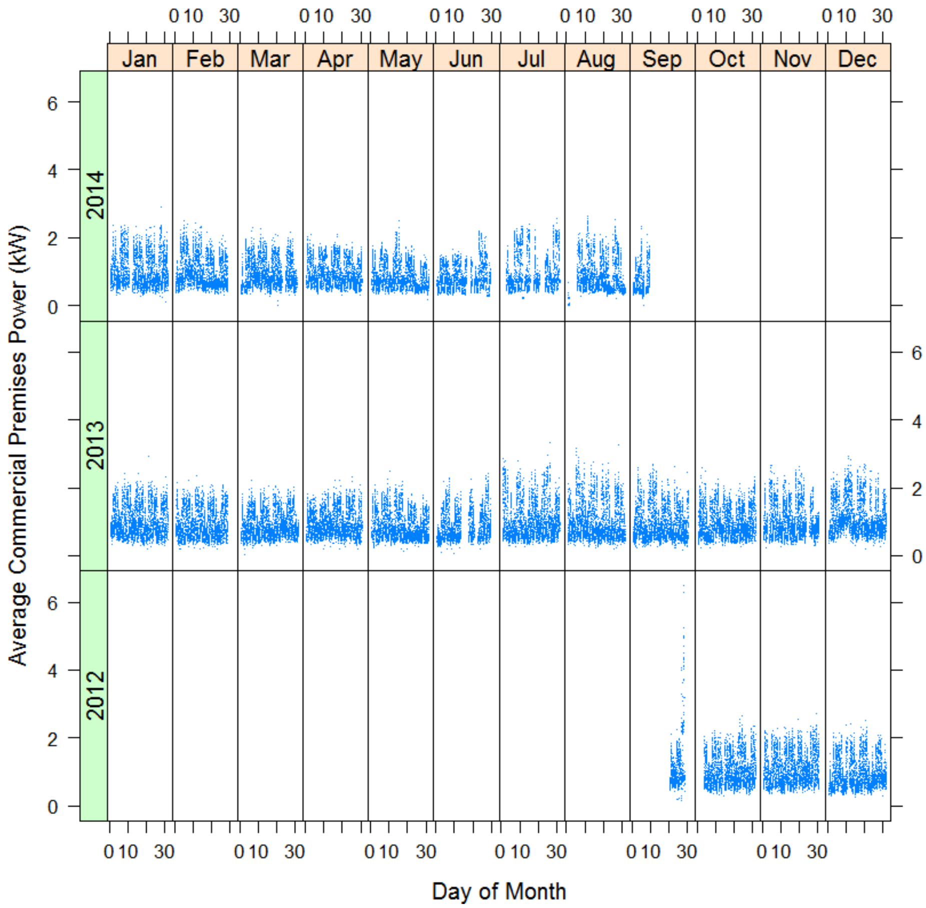


Figure 16.3. Average Power of Commercial Premises

Figure 16.4 shows the average diurnal demand of these eight commercial locations for the four seasons. Unlike residential load, the commercial sites do not exhibit pronounced morning and afternoon peaks. The load is almost symmetrically allocated around noon. There is relatively little difference in the hourly power patterns or magnitudes between the four seasons.

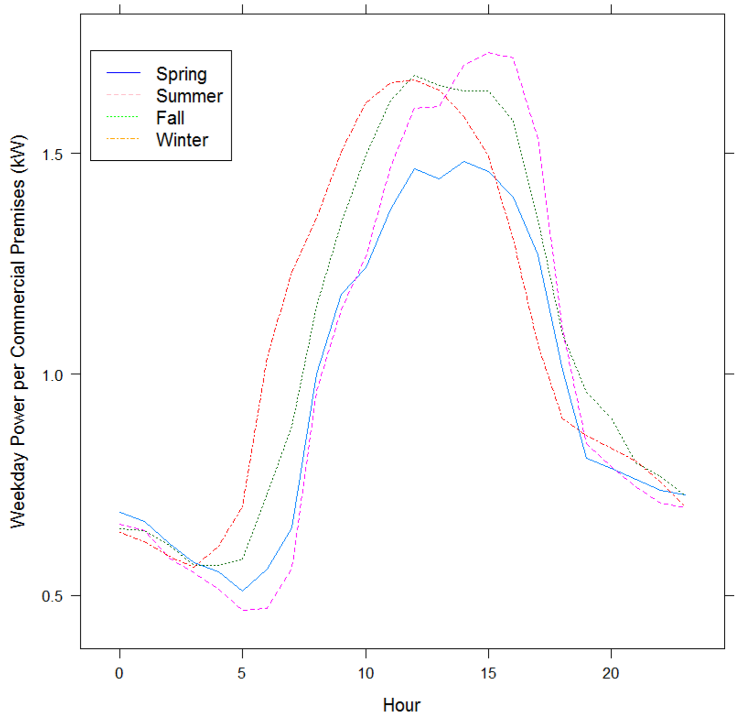


Figure 16.4. Averaged Weekday Diurnal Load Pattern for the Monitored Commercial Premises

The system was declared installed and operational by the end of January 2013. Only three curtailment events were reported by Portland General Electric for the commercial DR system. All three occurred during 2013. The starting times and durations of these events are listed in Table 16.4.

Table 16.4. Three Commercial DR Events that Occurred in 2013

Month	Day	Day of Week	Local Start Time (hh:mm)	Duration (h:mm)
January	31	Thursday	16:00	1:00
July	2	Tuesday	16:00	1:00
December	10	Tuesday	00:00	3:00

16.3.2 Performance of the Commercial DR System

The project generated a regression model of the average commercial premises load. The model was fit to the variables month, weekday, hour, and temperature. The resulting baseline should predict the average power of the commercial premises without DR. Portland General Electric had expected a total reduction of 1.2 kW from the commercial DR system. Based on the three reported events and this regression model baseline, an *increase* in premises power (~200 W) might have occurred during the events. The result was not statistically relevant.

The curtailment was not validated by regression analysis, and it was not evident as a notch by inspection. The system would perhaps need to be engaged more frequently to observe and confidently claim any curtailment benefit.

16.4 Commercial Distributed Standby Generation

Portland General Electric offered to engage 5.7 MW of their DSG system at commercial customer sites within the demonstration feeder, effectively reducing circuit load when an event was called. The utility pioneered engagement of such distributed generation resources via its GenOnSys control system in Portland, Oregon. When called upon via DSG controls, the system was to initiate generation from distributed stationary diesel reciprocating engines at Oregon Military Department, Armed Forces Reserve Center, and Oregon Data Center customer sites.

The DSG system is automated, meaning customers may not opt to cancel an event when called upon by the system; however, the DSG controls group may cancel an event for operational purposes or to meet the requirements of U.S. Environmental Protection Agency regulations governing emergency generation response characteristics. Maximum generation available to the program was approximately 5.7 MW for the three commercial customer DSG sites on the demonstration feeder. Based on the utility's experience with these generators, the response may be fully ramped up within 10 minutes to achieve 100% of the nameplate output.

As for the other responsive assets in this chapter, the responses of the DSG system to the transactive system are enacted by a neural network that has been trained to recognize opportunity for dispatch of the assets based on a comparison of the incoming TIS and the corresponding threshold for the transactive system asset. The algorithm that determines the dynamic threshold seeks to optimize the cost of serving load over time while avoiding asset constraints. This goal-seeking behavior is expected to initiate DSG power generation at peak times, especially when price maxima correlate well with load maxima. The system is constrained by asset parameters including seasonality, permitted minimum and maximum dispatch durations, customer-specific time-of-day limitations, time remaining before the next anticipated dispatch, replacement diesel fuel costs, and other parameters. The DSG assets were prohibited, for example, from operating for less than 1 hour after generation had begun, and the generators must remain inactive for at least an hour before they may be restarted.[1]

Portland General Electric worked with the project to estimate an annualized cost for engaging the distributed generators automatically via the transactive system. The annualized costs of the system and its components are listed in Table 16.5. Observe that the costs of the generators themselves are not included among the system's costs. The starting point of this cost estimate presumes that generators, such as those that exist as backup generators at many commercial and industrial facilities, exist and can be remotely energized. The greatest cost was predicted to be for integration of the generators' controls with the transactive system. Other costs were for materials, backroom communications, and outreach.

[1] Ibid.

Table 16.5. Annualized Costs of the Commercial Distributed Generation System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Transactive Node Development and Equipment	25	109.0	27.2
Materials and Supplies	20	104.4	20.9
Backroom Server	100	5.0	5.0
Outreach and Education	20	6.1	1.2
Total Annualized Asset Cost			**$54.4K**

On January 30, 2013, the U.S. Environmental Protection Agency finalized amendments to the National Emission Standards for Hazardous Air Pollutants for stationary reciprocating internal combustion engines and the standards of performance for stationary internal combustion engines (78 FR 6674-6724 2013). The ruling allows that for a combined total of 100 hours per year, emergency engines can be used for the following purposes:

- maintenance and testing
- emergency DR for Energy Emergency Alert Level 2 situations
- responding to situations when there is at least a 5% change in voltage
- operating for up to 50 hours to head off potential voltage collapse, or line overloads, that could result in local or regional power disruption.

The net effect of these amendments was that, in the utility's opinion, the contracted generators, which are all diesel fired reciprocating engines, could no longer routinely respond (i.e., be grid-tied) to a pure signal like that from the transactive system that is based on an economic value proposition. After this, the utility investigated ways that generators could demonstrate responsiveness to the transactive system, but without success.

16.4.1 Characterization of Asset System Responses and Data

The project received data from Portland General Electric concerning the power generation from this set of distributed standby generators for a period from June 2011 through early September 2014. The data that was received changed in quality several times during the project, as is shown in Figure 16.5. The utility's definition of the data was uncertain. Some of the uncertainty was caused by the occasional redefinition of the utility's demonstration test circuit. The circuit was occasionally altered to accommodate the development and testing of the utility's 5 MW battery system (Section 16.5). Starting June 2012, the utility decided to submit data only during project transactive events for this asset. The generators are typically required to be tested monthly, but the project received data at a frequency considerably less than monthly.

Based on all the nonzero 2013 and 2014 power data that is shown in Figure 16.5, there have been seven distinct generation levels: 5.4, 3.8, 1.6, 0.82, 0.50, 0.44, and 0.16 MW. Reactive power was also reported during these periods of generation, but the reactive power was more variable and might have been actively managed. The power factor was always 0.94 or better.

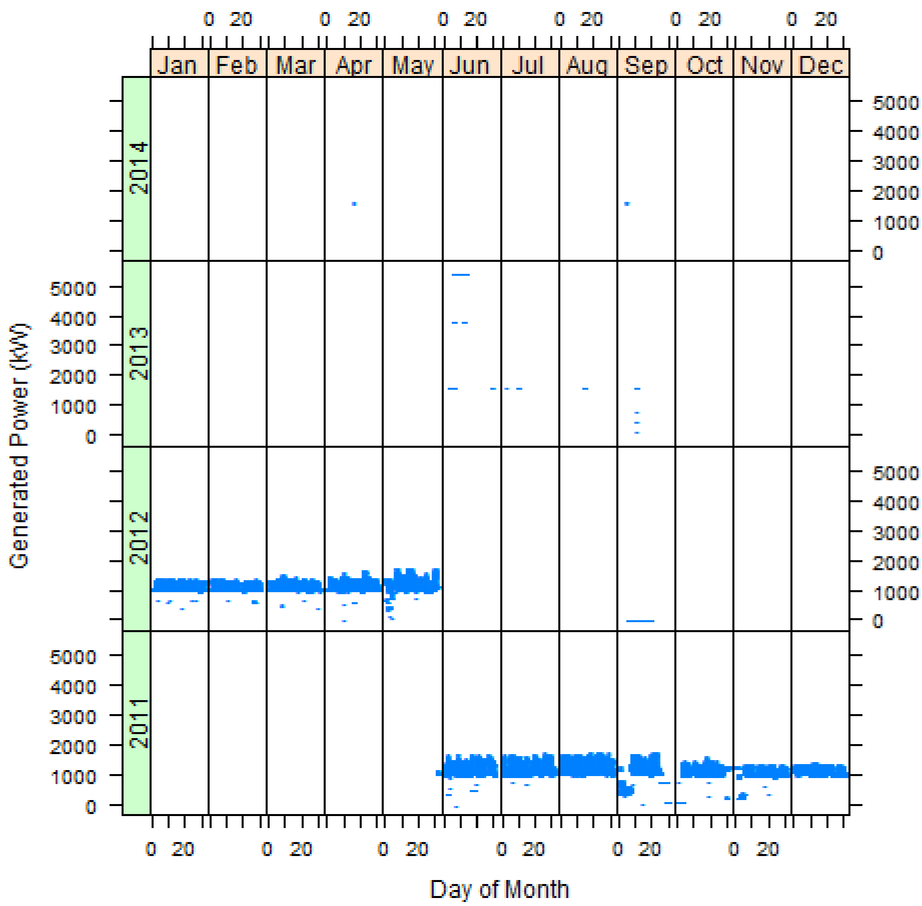


Figure 16.5. Distributed Power Generation Reported to the Project by Portland General Electric

The system was reported to have been installed and useful beginning early April 2013, based on the moment that its reported system status changed from “early unknown” to “off.” Figure 16.5 shows power generation during the summer of 2013, but these were not reported by the utility to have been events. The utility reported only one test event to the project for a short 10-minute period, 14:55–15:05 April 16, 2014, when the generators were reported to generate 1.6 MW.

16.4.2 Performance of the Distributed Generator System

From the project’s perspective, the received data demonstrates perhaps a discrete set of power generation magnitudes that might be engaged by the DSG system, but the project cannot independently conclude anything about the demonstrated benefits from the operation of the asset. The system was reported to have responded to the transactive system only one time during the project. Nothing can be said about the actual alignment of the asset’s operation with any of Portland General Electric’s objectives or those of the larger project region. Regardless, this section appends the following hypothetical monetary benefits that were projected for this asset system by Portland General Electric staff.[1]

The differences between the threshold price for engaging DSG assets ($0.288/kWh) and the TIS (~$0.075/kWh) were not sufficient to cause the Portland General Electric transactive system to engage the DSG resources. In the present system, the delivered cost of electricity would need to be artificially elevated above $0.288/kWh to have engaged the generators. That was not done.[2]

Using the approximate frequency of the most expensive wholesale hours each year at the interconnect between the utility and the Western Electricity Coordinating Council (WECC) region as projected by Portland General Electric staff and reproduced in Table 16.6, the WECC energy cost would exceed the threshold price ($0.288/kWh) and would cause the DSG system to generate nine hours in a typical year. If all the generators were to generate during these hours, the benefit each hour would be the product of the generated energy (5.7 MWh) and the price differential between the wholesale price and the threshold target price that hour. The tenth hour wholesale cost would be less than the threshold target, and the generators would not be operated. The differential and cumulative monetary benefits have been calculated in Table 16.6 for each wholesale price. The total annual value of the energy generated these nine hours would be $3,200.[3]

Table 16.6 is hypothetical. It presumes a WECC price cap of $0.45/kWh and further presumes that the hourly price distribution declines exponentially.

Table 16.6. Approximate Distribution of the Highest Hourly WECC Interconnect Prices per Year and Value of Energy Generated these Hours[4]

Wholesale Energy Price this Hour($/kWh)	Number of Hours at this Price	Differential Value of Generated Energy ($K)	Cumulative Value of Generated Energy ($K)
0.45	1	0.9	0.9
0.40	2	1.3	2.2
0.35	2	0.7	2.9
0.30	4	0.3	3.2
0.25	8	−1.7	-

Based on Table 4-4, “Small Commercial and Industrial Customers US 2008$ Summary of the Cost of a 1-Hour Interruption,” in Sullivan et al. (2009), the cost of a 1-hour electricity service interruption to small commercial customer in the Western United States is $886. Portland General Electric hypothesizes that its 110 commercial and industrial customers might avoid one such outage each year through the coordinated responses of its DSG and battery systems. Consequently, the value of these systems toward reduction of commercial customer outages is over $97,500. The battery system responds quickly so that

[1] Ibid.
[2] Ibid.
[3] Ibid.
[4] Ibid.

the DSG system generators can pick up their load after about 10 minutes. The utility therefore suggests that $81,200 of this benefit (about five-sixths, or 84%) should be allocated to the DSG system.[1]

Using similar logic, Table 5-4 of Sullivan et al. (2009) states that the cost of a 1-hour outage for a residential customer in the Western United States is $3.70 (2008 dollars). Forty residential customers are served by the demonstration feeder and might avoid one outage per year due to the DSG system. Therefore, the sum monetary benefit to residential customers due to reduced outages might be $150 per year.[2]

According to Portland General Electric's assessments, the DSG system benefits might be on the order of $85,250 for improved customer reliability and avoided energy costs.[3]

16.5 Battery Storage in High-Reliability Zone

A 5 MW, 1.25 MWh lithium-ion battery energy storage system with custom grid-tied inverters was constructed by Portland General Electric in Salem, Oregon. The system is housed at the utility's new 8,000-square-foot Salem Smart Power Center. The battery system supplier was EnerDel™, and the converter manufacturer was Eaton Corporation. One of the 40 battery racks is shown in Figure 16.6, and the inverter system is shown installed at the Salem Smart Power Center in Figure 16.7.

Figure 16.6. One of 20 Modular Battery System Racks at the Salem Smart Power Center[4]

[1] Ibid.
[2] Ibid.
[3] Ibid.
[4] Ibid, p. 25.

Figure 16.7. Eaton Inverters and Isolation Transformer at the Salem Smart Power Center[1]

The battery and inverter system is useful for both this asset system and the high-reliability-zone microgrid that will be described in Section 16.6. This section addresses the dispatch of the battery system for economic purposes using the utility's economic dispatch function, and the next section addresses distribution automation and the application of battery storage to a microgrid.

Vendor specifications limited the operating region of the battery storage to between 20 and 80% of its full energy capacity. However, system testing by the utility and its team suggested the battery capacity had been significantly overdesigned. Therefore, a smaller fraction of the battery energy capacity, perhaps 35–65%, might be used to further increase battery life while still adhering to the vendor's specifications. Based on the projected number of full lifetime charge cycles, the utility foresees cycling the system no more than about 300 times per year.[2]

The battery's control objectives were to reduce peak demand, avoid or reduce durations of service outages for the commercial customers on the demonstration feeder, to move system load away from the costliest WECC supply hours, to mitigate intermittent renewable energy generation, and to otherwise conduct arbitrage using the costs that were revealed by the utility's transactive system.

While 500 kWh of the energy was reserved for maintaining exceptional service reliability in a high-reliability zone that includes their Oxford substation and Rural feeder in south Salem, Oregon, the remaining storage capacity was available for other operational objectives. Portland General Electric carefully evaluated 20 distinct grid services that are available from battery systems according to a California Public Utilities Commission report (CPUC 2012, p. 13). This evaluation and its findings were documented by Osborn et al. (2013). The conclusions were that

- No regulatory barriers prevent the utility from immediately implementing services that have to do with support and dispatchability of renewable energy resources.

[1] Ibid, p. 25.
[2] Ibid.

- The battery system cannot be said to have deferred upgrades or alleviated transmission constraints at its location on the grid, but it might be used to arbitrage the super-peak periods that occur no more than several times per year. Daily arbitrage would not likely be economical because it could reduce system lifetime.
- The battery was not applicable to demand-side management scenarios because it is not located behind a retail meter.
- The battery may economically serve as spinning reserve and supply other ancillary services, but some of the foreseen ancillary services await new markets and regulatory changes.

Portland General Electric developed its own transactive node to economically dispatch its project resources, including this battery system. The dispatch of these systems was automated using a neural network software tool—the *utility economic dispatch function.*

The annualized costs of the battery system and its components are listed in Table 16.7. Of course, the greatest expense went toward purchase and installation of the battery and inverter hardware. Half the cost of the battery and inverter system was allocated to this asset system, which focuses on dispatching the battery for financial purposes, and the other half was allocated to the battery system's facilitation of improved reliability using a microgrid (Section 16.6). The battery and inverter systems required extensive unit and system testing as documented in the development team's test reports.[1] Other significant costs were for the development of the automated transactive system and for materials and supplies.

Table 16.7. Annualized Costs of the Battery Storage System and Its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Battery and Inverter System	50	2,138.9	1,069.5
Transactive Node Development and Equipment	25	109.0	27.2
Materials and Supplies	20	104.4	20.9
Engineering/IT Support	25	7.8	2.0
Outreach and Education	20	6.1	1.2
Total Annualized Asset Cost			**$1,120.8K**

16.5.1 Battery Storage Data

Portland General Electric submitted power data for the battery system from July 2013 until the end of data collection after August 2014. Data from earlier than October 2013 were found to have much greater magnitudes than later and were discarded after the project was unsuccessful interpreting or confirming the units of that early data. The remaining power data are shown in Figure 16.8. The utility submitted status

[1] Ibid.

information that described the system as either available or unavailable. In this figure, positive power represents the discharge of energy from the battery system and negative power is charging it.

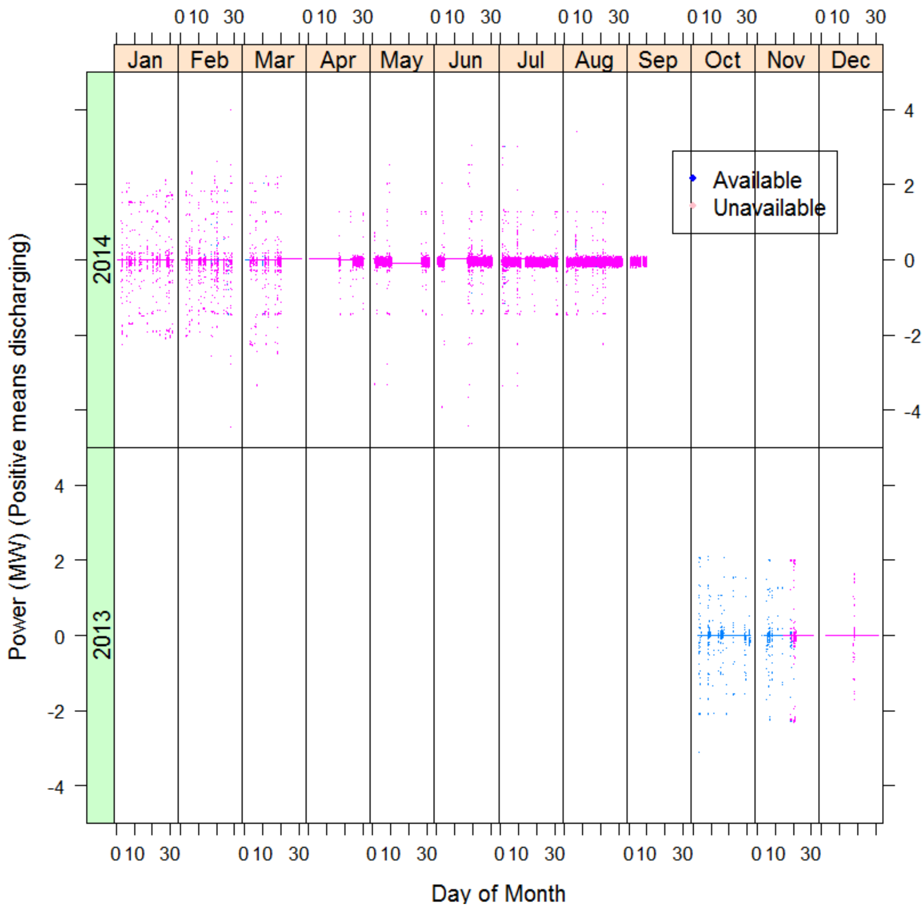


Figure 16.8. Power Discharged from or Charged into the Battery System

It took until spring 2014 before meaningful energy data that reveals the system's state of charge was reported to the project by the utility. The power and energy data are shown in Figure 16.9 for a period between March and August 2014, when both power and energy data were available. The energy data represents the reported total energy state of the battery system that could have theoretically (based on designed system capacity) been 1.25 MWh. The utility asserts that the battery was never discharged to the point that its state of charge was zero. The zero values in Figure 16.9 must therefore be artifacts reported by the system when it became deactivated. The vertical axes ranges in this figure extend to the entire design power and energy capacities of this battery system.

The period of system inactivity in late March 2014 was caused by the failure of the 15 kV pad mount switch that connects the Salem Smart Power Center with the Oxford Rural feeder. It was repaired and the system reactivated in April. The utility and its collaborators do not believe that the failure was caused by operation of the battery system.[1]

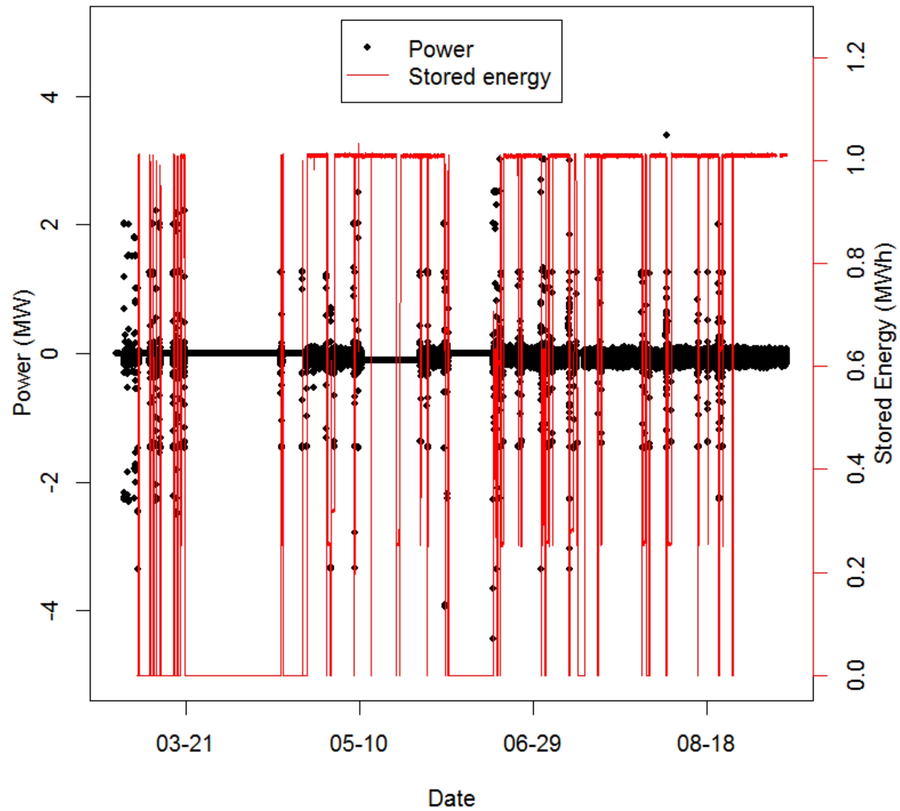


Figure 16.9. Stored Energy and the Charge (negative) or Discharge (positive) Battery Power from Spring and Summer 2014

16.5.2 Performance of the Battery System

The next two figures show narrower time periods for the observation of the battery systems power and energy data. Figure 16.10 shows the energy content and power conversion by the system throughout July 2014. The first day of this month was a Tuesday, so the columns proceed from Tuesday to Monday from left to right. The fifth and sixth columns (i.e., days 5 and 6, etc.) were weekend days. Virtually no testing occurred on weekend days or Mondays. The state of charge increases during charging of the system and decreases during discharging.

[1] Reported in an e-mail from J. Ross of Portland General Electric to S. Kanyid of Battelle dated March 25, 2014.

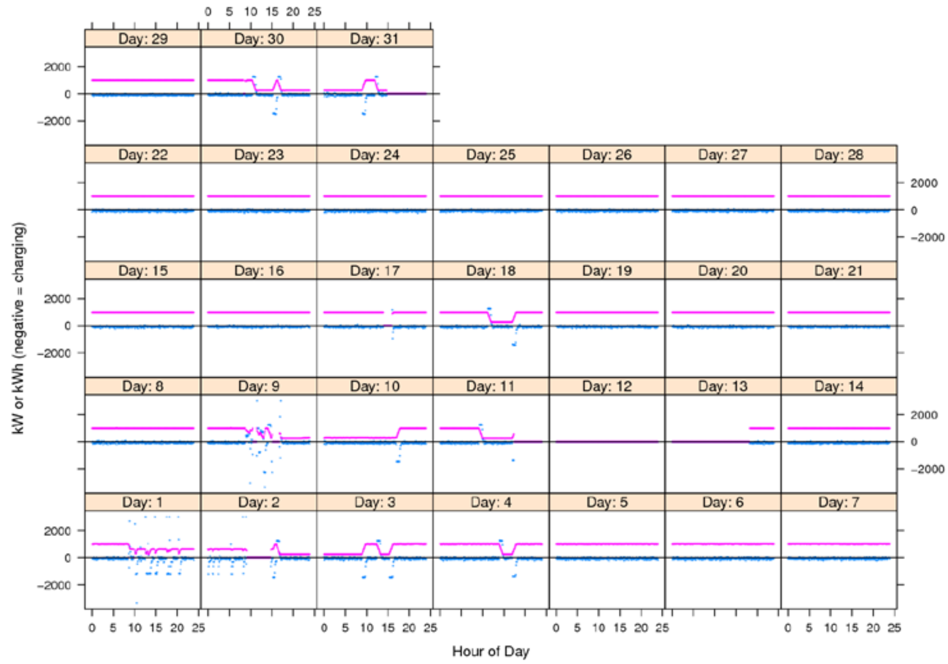


Figure 16.10. Battery Power (blue) and Stored Energy (pink) for Days of July 2014

Figure 16.11 focuses more narrowly on the system's behavior during only three of these days—July 9–11, 2014. The 9th shows much charging and discharging activity. Perhaps a test was being conducted that day to respond to a dynamic signal. The system was recharged the afternoon of the 10th, and cycled again the 11th.

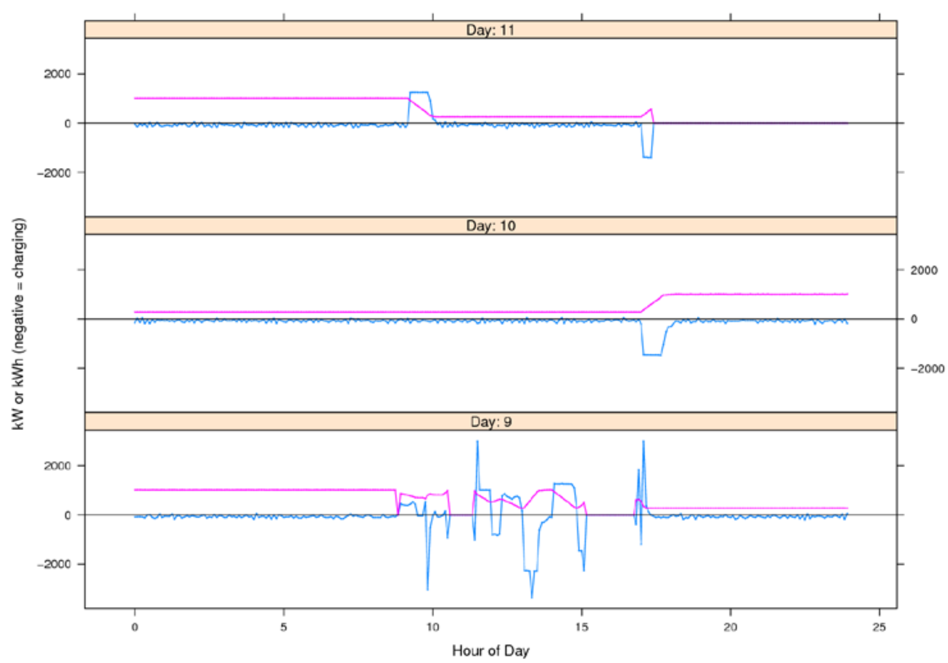


Figure 16.11. Battery Power (blue) and Stored Energy (pink) July 9–11, 2014

In Figure 16.12, the influence of the project's transactive signals on the battery system's charging and discharging is tested. The vertical axis reports the charging (negative) and discharging (positive) battery power. The horizontal axis lists the TISs at these times as received by Portland General Electric from the Western Oregon transmission zone (TZ05) of the project's transactive system. The magnitudes of the transactive signals appear to have had little or no influence on its charging behaviors, regardless of whether the battery system was reported to be available or unavailable to the transactive system. Had the battery system been consistently responsive to the magnitude of the signal that it was receiving from the project's transactive system, power would have been discharged by the battery system at high TIS magnitudes and recharged at relatively lower signal values.

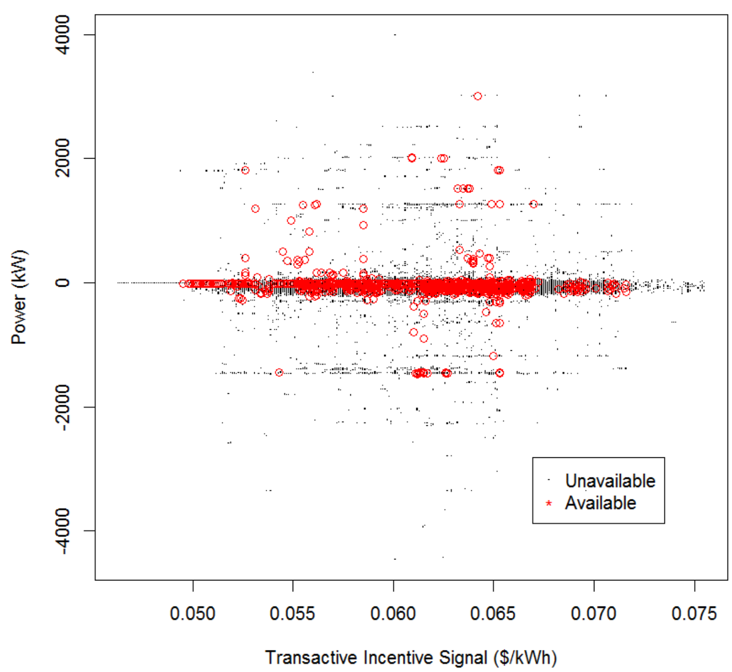


Figure 16.12. Discharge (positive) and Charge (negative) Power as Functions of Transactive Incentive Signal Magnitude and Reported System Availability. Only 2014 data are shown.

Figure 16.13 perhaps reveals an operational strategy used by the utility to charge and discharge the battery system. The height and width of the figure represent the nameplate capabilities of the system. Many of the operating points are located randomly about the center of the power and energy ranges. The state of charge was allowed to vary within a range from about 20 to 80% of the total energy capacity. That is, no operating points were observed below about 0.25 MWh or above about 1.0 MWh. During relatively prolonged charging and discharging, the system was either charged or discharged at the power level 1.25 MW, one-fourth of the system's nameplate capacity. Because this strategy was repeated, we observe a pronounced charge and discharge cycle in the figure. As the target state of charge was approached—often at 20 and 80% of the system's total energy capacity—the charging or discharging rate slowed. The power magnitude decreased until the desired state of charge was achieved.

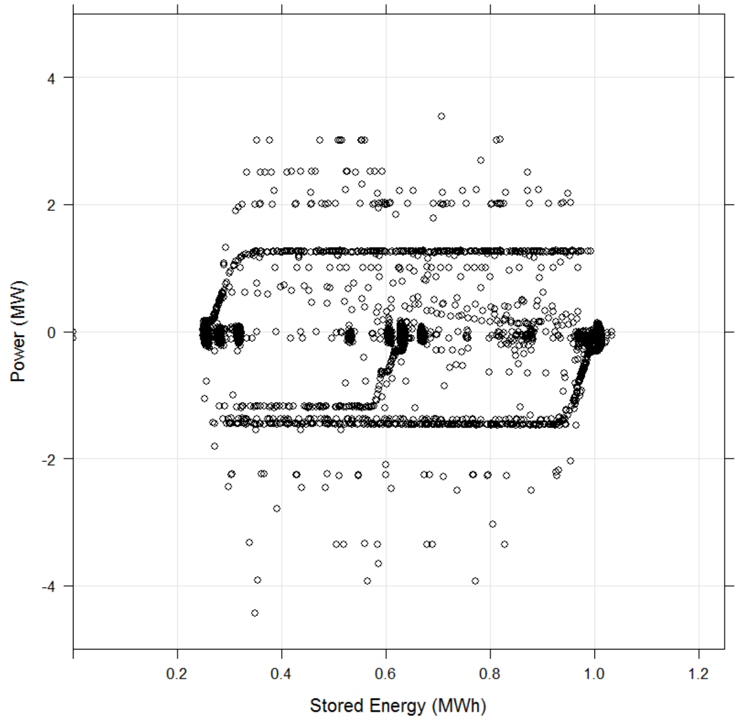


Figure 16.13. Plot of Battery Power versus its State of Charge that Reveals an Operational Strategy

The project investigated the cumulative energy that was reported to have been imported into and generated from the battery system over time in 2014. The resulting Figure 16.14 shows the energy that is lost over this time. The slope of the line changes over time as the operational practices change. If the entire time period is used, altogether 271 MWh were lost over 7,513 hours. The average power loss over this period is 36 kW. This means it takes about 36 kW to keep the battery system operational the way it was used by the utility. This calculation also includes any impacts of conversion inefficiencies during the system's charge and discharge cycles.

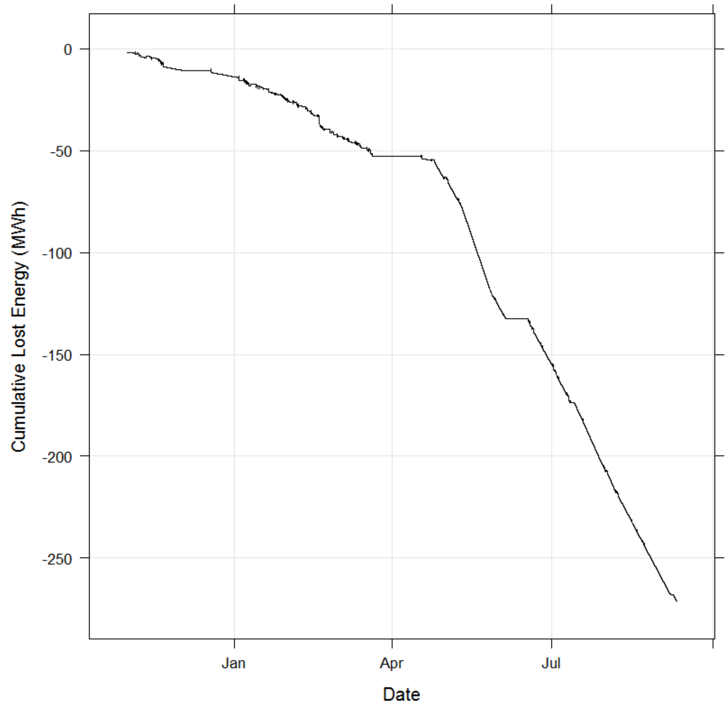


Figure 16.14. Cumulative Energy Exchanged by the Battery System from Late 2013 to the End of the Project

Working with its design team, Portland General Electric monitored the energy that was exchanged during sets of complete charge and discharge cycles. These test results are summarized in Table 16.8. The first row refers to a test in which the system was charged from its 50% state of charge up to its 75% state of charge and back at 25°C and at the target rate 1,250 kW. Because the energy states of charge are returned to their starting levels in each of the four tests, the differences between the amounts of charged and discharged energy may be used to estimate full-cycle efficiency—sometimes called *round trip efficiency*—for these test conditions. The calculated cycle efficiencies ranged from 88.2% to 90.7%.

Table 16.8. Calculated Charge/Discharge Cycle Efficiencies at 25°C and 1,250 kW Charge Rate[1]

Charge/Discharge Cycle (% States of Charge)	Charged Energy (kWh)	Discharged Energy (kWh)	Calculated Charge Cycle Efficiency (%)
50–75–50	536	486	90.7
40–60–40	440	393	89.3
25–5–25	510	450	88.2
25–75–25	1,017	902	88.7

[1] Table PGE-04-4.9-PGE1 in Whitener et al. 2014 (unpublished).

Another interesting finding from the utility's acceptance testing[1] was that the energy storage capacity of the system had been somewhat understated by the battery vendor. The stored energy may be as great as 1.8 MWh, not 1.25 MWh. Consequently, Portland General Electric may be able to narrow its cycle depths and extend the useful life of the system.

Figure 16.15 summarizes the average charging or discharging of the system as a function of time of day local Pacific Time. At least in these, its early days of operation, the battery system was predominantly operated only during daytime. Both the charging and discharging were occurring in daylight hours. Otherwise, there is no clear diurnal pattern yet in the way that Portland General Electric managed the charging and discharging of the battery system.

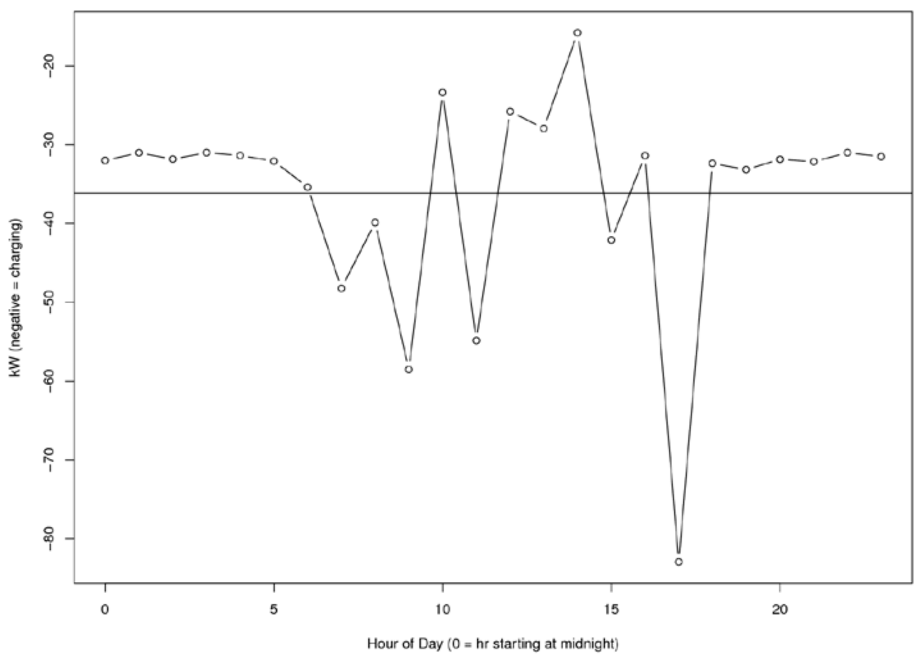


Figure 16.15. Average Charging (negative) and Discharging (positive) Power as a Function of Hour of Day

The following text was paraphrased from unpublished documentation supplied by the utility and could not be confirmed by the project based on data that was delivered to the project by Portland General Electric:

Using the theoretical distribution of daily price differentials in the wholesale price for electricity in the WECC Interconnect, Portland General Electric estimated the monetary benefit available from arbitrage. This distribution and the resulting benefit are presented in Table 16.9. The frequencies of occurrences are presumed to increase exponentially as the price differential diminishes. A presumption is that the system correctly identifies the 300 greatest price differentials each year and fully charges and discharges its nameplate capacity, 1.25 MWh, across this price differential. The system is limited to no

[1] Ibid.

more than these 300 cycles according to vendor specifications. The cumulative yearly benefit estimated for arbitrage is thereby estimated as $9,530 per year.

Table 16.9. Hypothetical Distribution of Differential Wholesale Energy Prices and the Calculated Arbitrage Value that May be Earned using this Differential. This analysis presumes that the full 1.25 MWh is exchanged each charge/discharge cycle.[1]

Energy Price Differential ($/kWh)	Occurrences Per Year	Cumulative Battery System Cycles	Differential Energy Value ($K)	Cumulative Energy Value ($K)
0.09	1	1	0.11	0.11
0.08	2	3	0.20	0.31
0.07	4	7	0.35	0.66
0.06	8	15	0.60	1.26
0.05	16	31	1.00	2.26
0.04	32	63	1.60	3.86
0.03	64	127	2.40	6.26
0.02	128	255	3.20	9.46
0.01	5[(a)]	300[(a)]	0.063	9.53

(a) The cycles have been limited in this row because the battery's vendor specifies only 300 cycles per year for the system.

Based on Table 4-4 in Sullivan et al. (2009), "Small Commercial and Industrial Customers U.S. 2008$ Summary of the Cost of a 1-Hour Interruption," the cost of a 1-hour electricity service interruption to a small commercial customer in the Western United States is $886. If one such outage is avoided by each of 110 commercial customers on the demonstration feeder each year, the cumulative yearly benefit would be about $97,500. The utility projects that this benefit will result from the coordination of the battery system and distributed generators (Section 16.4). The battery, in principle, responds rapidly to the outage until the distributed generators ramp up within 10 minutes. Therefore, only about one-sixth, or $15,600, of this yearly benefit can be allocated to the battery system.

Voltage sag events are valued at $273 per event per commercial customer in the same citation. If each of the 110 commercial customers on the distribution feeder avoids four voltage sag events, the cumulative benefits of the battery system would be about $120 thousand per year.

According to Sullivan et al. (2009), the impact of a 1-hour residential customer outage in the West is $3.70 (2008 dollars) per customer per outage. Averaging over time, with one expected interruption avoided per year (based on historical feeder data for Portland General Electric's demonstration system), and theoretical 40 residential customers, the cumulative benefit of the battery system to residential customers will be about $150 per year.

[1] In an appendix attributed to S Chandler in Whitener et al. 2014 (unpublished).

The same citation valued the cost of voltage sags to residential customers at $2.20 per customer per event. If the theoretical 40 residential customers on the demonstration feeder avoid four voltage sag events per year, the cumulative benefit is about $350 per year. Notably, the time of day strongly influences the results; these results have been averaged for any period.

The sum of all these hypothetical benefits is about $146 thousand per year.

16.6 Distribution Switching and Residential/Commercial Microgrid

Increased reliability and self-healing networks are prominent characteristics of a smart grid. Portland General Electric installed two automated switches and three automated reclosers to allow separation of a microgrid upon a loss of power from their Oxford feeder. During the transient loss of power, the 5 MW battery and inverter system was to provide power until backup generators could be brought on line.

The microgrid assets and interrupter locations have been identified geographically in Figure 16.16 and in block diagram form in Figure 16.17.

Subject to approval from the customers in the area, Portland General Electric was to demonstrate the ability of the microgrid to operate independently from the main grid and also the ability to re-synchronize the microgrid and restore power from the main grid without a power outage. Fiber-based communications were to connect all of the fast-acting devices. Each device was to be programmed with logic to implement a controlled switching sequence based on the extensive modeling and testing conducted prior to implementation on the Salem feeder.

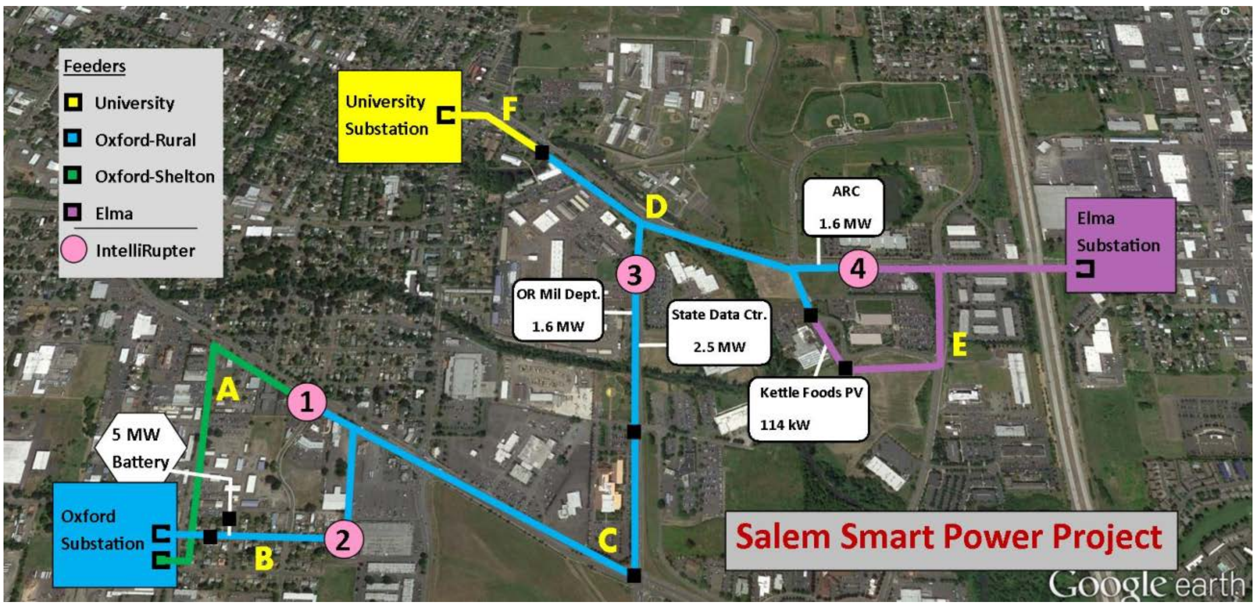


Figure 16.16. Footprint of the Salem Smart Power Project, Salem, Oregon, including its Potential Microgrid Resources and Switches (p.8, Osborn et al., 2013)

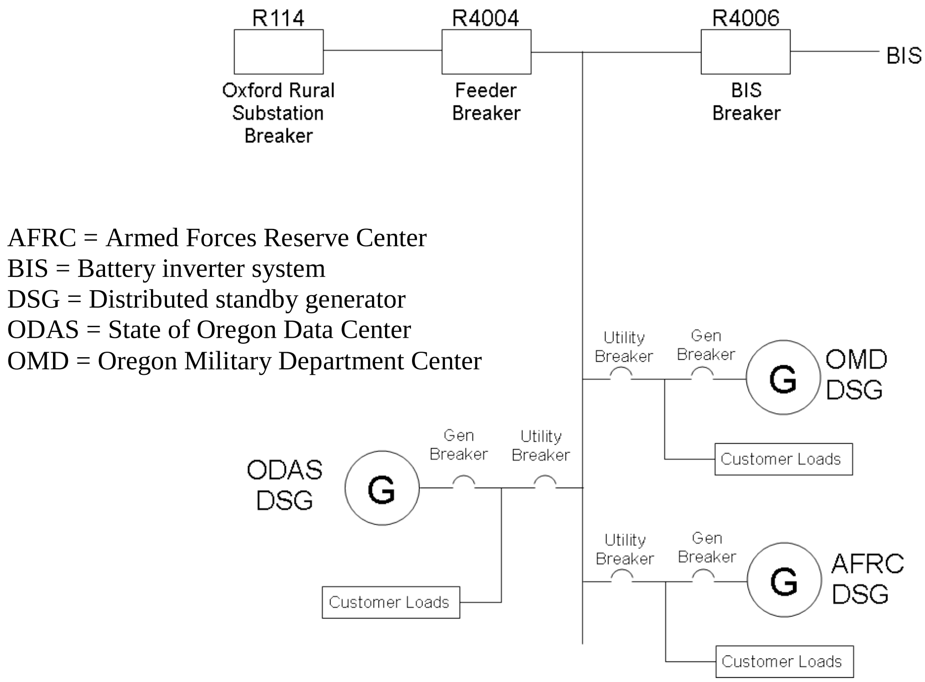


Figure 16.17. Oxford Rural Feeder High-Reliability–Zone Block Diagram[1]

The annualized costs of the system and its components are listed in Table 16.10. The greatest cost component is that of the battery and inverter system. Half of the cost of this system was allocated to this objective (i.e., improved reliability from the definition of a microgrid), and half was allocated to the dispatch of the battery system for economic reasons (Section 16.5). Other significant costs were for automated distribution switches and other materials and supplies.

Table 16.10. Annualized Costs of the Distribution Switching and Microgrid System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Battery and Inverter System	50	2,138.9	1,069.5
Automated Switch/Recloser	100	45.9	45.9
Materials and Supplies	20	104.4	20.9
Engineering/IT Support	25	7.8	2.0
Outreach and Education	20	6.1	1.2
Total Annualized Asset Cost			**$1,139.4K**

[1] In Whitener et al. 2014 (unpublished).

16.6.1 Performance of the Distribution Automation System

Portland General Electric submitted status information concerning the topological status of the demonstration circuit. The four statuses were “Early Unknown,” “Short,” “Residential,” and “Long.” System activity occurred in late February and March 2014 when the circuit was reported to have transitioned through all the four configurations. Thereafter, the circuit remained in its “Residential” configuration. The utility reported that no events occurred during the project on this feeder. System Average Interruption Duration Index, Momentary Average Interruption Frequency Index, and the count of significant events were all reported to be zero. No change in the reliability of the demonstration circuit was demonstrated.

The utility reported that a series of offline tests had been conducted in preparation for microgrid operation. These tests included individual vaults or racks from the battery system as well as generator and laboratory loads. The high-reliability zone has not yet been operated as a microgrid as of the drafting of this report.

16.7 Lessons Learned and Conclusions

Portland General Electric integrated four smart grid technologies during the PNWSGD—commercial DR, commercial DSG, battery, and distribution switching in a high-reliability zone.

Despite strong efforts, the utility was able to recruit only 20 suitable residential customers on its demonstration feeder to participate in residential water heater DR. Most of these premises were unobservable while the Oxford Rural demonstration feeder remained in a safe, alternative configuration through much of 2013. Furthermore, the water heater load-control devices were removed early when the utility became concerned about potential malfunction due to the safety of these devices.

Demand-response equipment was installed at eight commercial customer locations, but the utility’s economic dispatch function engaged these devices only three times during the project. The annualized cost of this system was estimated at about $239 thousand per year. The project was not able to verify the anticipated change in load at these commercial sites. The project was unable to confirm the power magnitudes at the commercial sites.

The utility invited voluntary engagement of 5.7 MW of distributed standby generator capacity. The annualized cost to set up this system and engage these generators was estimated at $54 thousand. Regulatory hurdles were encountered. The project received data that showed sporadic operation of generators, but the utility’s economic dispatch function never called upon the generators to operate during the project. These generators are unlikely to become engaged for economic purposes. However, the utility allocates value to the system of generators because of its potential to prevent or shorten outages on the demonstration feeder—a high-reliability zone. Thus, no benefit could be directly calculated and monetized by the project, but Portland General Electric projects hypothetical benefits of about $85 thousand per year, most of this attributed to avoidance of outages for its commercial and industrial customers.

A 1.25 MWh battery and inverter system was constructed through a collaboration of the utility with EnerDel and Eaton. The project estimated the annualized costs of this system at $1.12 million. Delays were encountered due to the complexity of the system. The project received data that confirmed operation of the system, but the system's operation could not be correlated with the magnitude of transactive signals or any other input by the project. The utility foresees value of the battery system toward firming renewable energy, arbitrage avoidance of super-peak costs, and reduction of outages in the high-reliability zone. While monetary benefits could not be directly confirmed by the project, Portland General Electric projects hypothetical benefits at about $146 thousand per year, most of this attributable to reduced outages and improved voltage quality for its commercial and industrial customers.

At project conclusion, Portland General Electric's project manager offered the following observations about the lessons the company had learned during the project[1]:

Portland General Electric's SSPP deployed and integrated a substantial battery and inverter system from two separate vendors. This proved a challenge inasmuch as both vendors made concessions and design changes to enable the final outcome of grid integration. The inverter is a "smart inverter" capable of four-quadrant performance. As this was a substantial advance in the use of a large capacity battery and inverter systems, utility staff needed to be educated concerning its capabilities and possibilities.

Frequent changes were made by the project to the integration requirements for the proxy node and data gathering schema for site transactive nodes. As is true of many software projects, the requirements continued to change well past the published "build-to" date of the specifications, which caused significant redesign and redeployment issues. Data gathering was addressed during deployment of Phase 2 of the project, creating significant architecture hurdles for utility site participants. For example, several of the utility's project data streams were initially configured with too-low precision, which caused the data to become erroneously rounded to zero. Testing and integration of assets with longer timelines for completion (the battery-inverter system in particular) caused subsequent delay of control algorithm development and testing.

Vendors were slow to provide proper documentation concerning application programming interface systems integration. Vendors lacked processes to protect utility information. As relatively new players with utility software development, vendors lacked necessary processes and controls. Vendor issues for first-ever systems had long timelines, which delayed progress for transactive node development and integration.

The utility needed to engage the public openly and transparently with clear, concise messages on the SSPP assets, purpose, location, and operations. Support from corporate communications, community affairs and government affairs staff was helpful and critical to success on this front.

System security requirements were well established at the beginning of the project, allowing for completion of the required security tasks without issues or redesign. Proxy-node communication support[2] was weak at the beginning of the project, but the proxy-node implementation was finally recognized as a

[1] Edited from C Mills. 2014. Portland General Electric PNWSGD Lessons Learned. Unpublished report, Portland General Electric, Portland, Oregon, September 18, 2014.

[2] "Proxy-node support" refers to one of two classes of specified point-to-point communication used by the project between the utility sites and the more centralized model of the transmission system. Utilities that did not use IBM's software implementation used a proxy server implementation instead.

separate control domain where reporting for transactive control and other mechanisms were necessary with a separate approach supported by project-level participants. This issue could have been thought through earlier by the project, as was eventually done during deployment.

The utility had to conduct the equivalent of profit and loss accounting at the project level.[1] Historically, utilities mostly just track cost to budget. As the SSPP was innovative and the first of its kind, being an innovator had both advantages and disadvantages. Financially, the utility had to anticipate contingencies:

- When in doubt, overestimate costs.
- Make sure corporate overheads are known by year.
- Confirm property ownership at project beginning and end.

For investor-owned utilities, Table 16.11 summarizes at a high level the opportunities and challenges from the utility's project financial accounting perspective.

Table 16.11. Financial Opportunities and Challenges Faced by Portland General Electric during the Salem Smart Power Project

Opportunity	Challenge
Reimbursable expenses	Unfamiliar accounting needs
Several departments are engaged	Not obvious to rest of company
Excellent funding leverage	Accountable to third party

[1] The U.S. DOE required earned value financial reporting. Some of the complexities of this approach necessarily passed through to utility subcontracts.

17.0 University of Washington Facilities Services Site Tests

Additional chapter coauthor: ZT Taylor − Battelle Memorial Institute

The University of Washington (UW) at the Seattle campus is a subproject participating in the Pacific Northwest Smart Grid Demonstration (PNWSGD) project, a project that spans 5 years and includes five Pacific Northwest States (Idaho, Montana, Oregon, Washington and Wyoming). The UW's goals in the project is to monitor and manage more than fifteen million square feet of space, serve over 40,000 students daily, and provide the university with the expectation of saving over $350,000 annually in energy consumption costs.

The following asset systems were demonstrated at the UW site:

- enabling assets, consisting primarily of data collection infrastructure
- power generation assets, including one steam turbine (Section 17.1), two diesel standby generators (Section 17.2), and two small-scale solar photovoltaic (PV) facilities (Section 17.3)
- building heating, ventilation, and air-conditioning (HVAC) controls and lighting controls (Section 17.4)
- student residence and university facilities pilot sub-metering (Section 17.5)
- a facility energy management system (FEMS) (Section 17.6).

Those asset systems were exploited to conduct six experiments that are the focus of this report, each test case comprising one major subsection of this chapter. Figure 17.1 summarizes the layout of the UW asset systems and the organization of test cases.

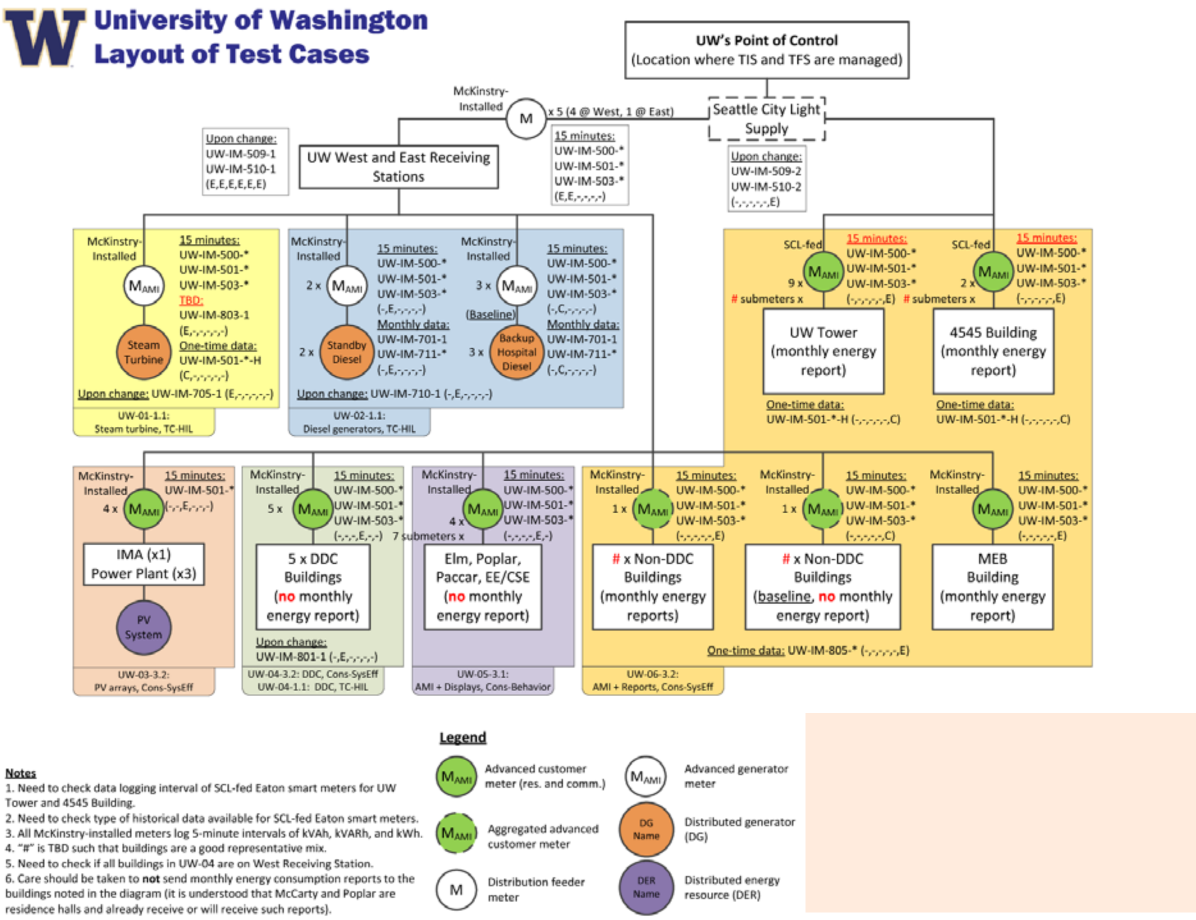


Figure 17.1. Layout of UW Test Cases

17.1 Steam Turbine

The UW deployed an existing 5 MW steam turbine generator with provision to respond to transactive control signals from the PNWSGD project. Availability of the turbine generator was expected to be mostly limited to the fall/winter/spring seasons, as capacity is limited by the exhaust/extraction steam demand from the campus heating systems, which have low demand during the summer season. As with all the UW generation assets, the objective for the steam generator was to test the demand-response (DR) operation and identify opportunities for sustained generation increases in response to pricing incentives or regional renewable energy integration strategies.

Table 17.1 lists the system's components and their annualized costs. To estimate the system's yearly costs, the cost of each individual system component has been annualized according to its expected useful lifespan.

Table 17.1. Annualized Costs of the UW Steam Turbine System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Transactive Node System	33	155.6	51.8
5 MW Steam Turbine Generator (existing)	100	617.4	617.4
Secure, Virtual Private Campus Network (VPN)	17	257.6	43.0
Advanced Meters (at generator)			38.7
• Software and Systems (774 hours)	100	18.9	18.9
• Installation and Integration (1,415 hours)	100	13.4	13.4
• Operations and Maintenance (1 year)	100	6.0	6.0
• Equipment - One Industrial Meter	100	0.2	0.2
• Engineering	50	0.3	0.2
• Equipment - Branch Circuit Monitor	50	0.2	0.1
FEMS			37.2
• Software and Systems (800 hours)	100	19.5	19.5
• Installation and Integration (400 hours)	100	10.0	10.0
• Operations and Maintenance (200 hours)	100	4.9	4.9
• Equipment – VPN Interface Servers	33	6.2	2.1
• Energy Data Collection and Processing Servers	33	2.4	0.8
• Engineering (6 hours)	100	0.0	0.1
Administrative	100	0.4	0.4
Total Annualized Asset Cost			**$788.1K**

17.1.1 System Operation and Data Concerning the 5 MW Steam Turbine Generator

In the earlier stages of the project, the UW planned to manually engage its 5 MW steam turbine generator based on the transactive incentive signal, with the option to automate the control in a direct-DR fashion at some point. The project received from UW a status signal indicating time periods when generator output was engaged. The reported engagement status differentiated whether the turbine was operating normally, with increased output (as would be expected when the transactive signal requested it), with decreased output (a condition the project team does not believe ever occurred), or unavailable. The periods of increased output represent the test “events” during which generator output can be compared against the remaining normal generation periods.

The reported engagement status is shown in Figure 17.2. Note that only the increased-generation event periods and the unavailable periods are plotted; during all other time periods the generator was operated normally. Engagement of the asset occurred only during the winter of 2013–2014 and briefly in the summer of 2014. The limited engagement during the summer was expected since turbine capacity is limited by the exhaust/extraction steam demand by the campus heating systems, which have very low demand in the summer. In all, there were 136 engagement events totaling about 450 hours of operation.

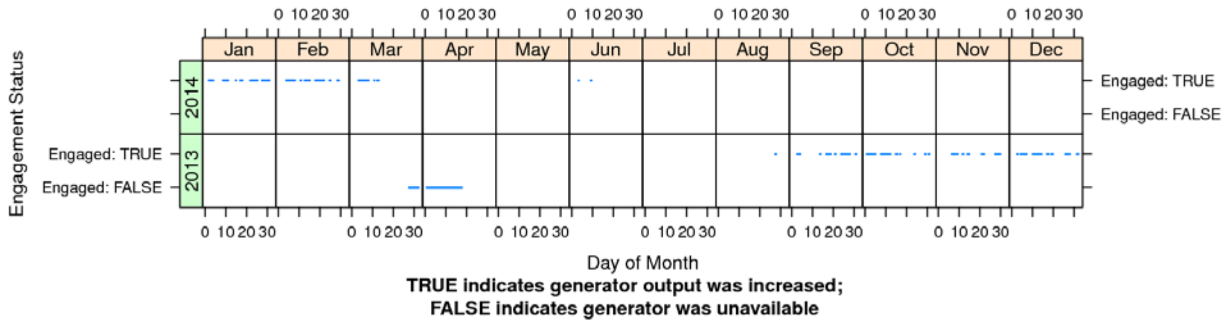


Figure 17.2. Reported Engagement Status of the UW Steam Turbine Generator. Engagement status "true" indicates that the generator output was increased; engagement status "false" indicates that the generator was reported to be unavailable.

Steam turbine generator output for 2013 and 2014 is shown in Figure 17.3. It is clear that the generator was operated differently in winter than in summer months. Winter operation appears to have been continuous and largely unvarying at about one-half rated capacity, while summer operation was more variable, but again topping out at about half of capacity. There was some operation at levels approaching the turbine's 5 MW capacity in the prior (2013) summer, but the project had generated no transactive engagement signals during that time.

The increased output of the turbine during engagement events is evident during the winter period in Figure 17.3, but the few summer engagements are not distinguishable, being "buried" in the cloud of normal operation points.

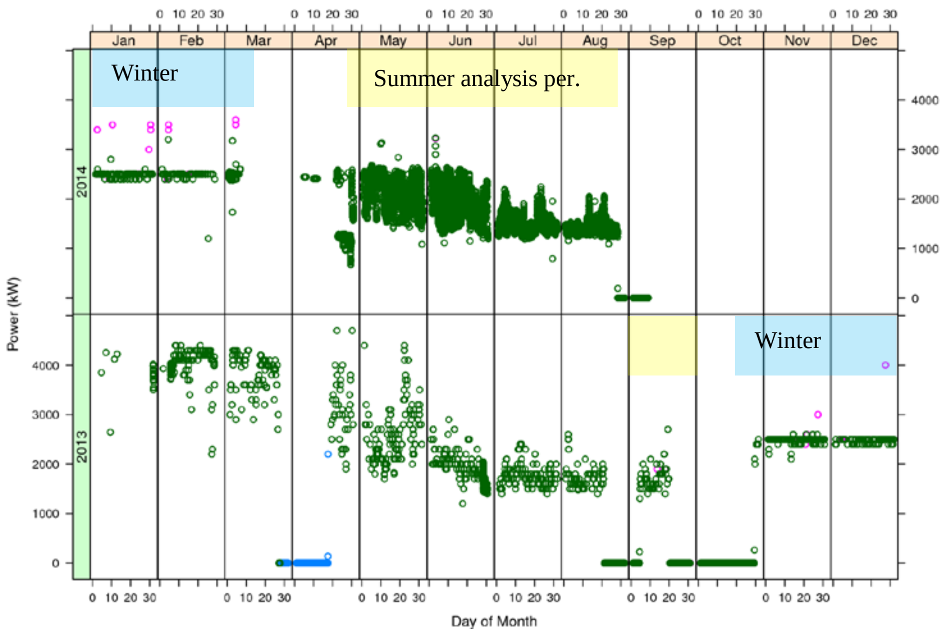


Figure 17.3. Output of the 5 MW UW Steam Turbine Generator. The summer (yellow) and winter (blue) analysis periods have been indicated by shading in the corresponding project months.

17.1.2 Analysis of the 5 MW Steam Turbine Generator

Because of the very different winter and summer operational modes, the project team developed separate models to characterize baseline operation for the two seasons. Both models were implemented as linear regressions that relate the turbine's output to relevant predictive variables. The winter model, built from data between November 1, 2013 and March 10, 2014, inclusive, was trivially represented by the mean non-engagement turbine output over the 2013–2014 winter period. The summer model, built with data from September, 2013 and between April 27, 2014 and August 20, 2014, inclusive, included terms correlating turbine output to the outdoor temperature, partitioned by month, day type (weekend vs. weekday), and hour of day. The vast majority of engagement events occurred on weekdays (131 of 136 events), and events were roughly evenly distributed across the five weekdays.

The winter regression fit characterized turbine output as a constant 2,474 kW during non-engagement periods and, as can be seen in Figure 17.3, the constant value is a reasonably good representation of the turbine's wintertime operation. Although the output data show two consistent levels very close to one another in magnitude, the project team was unable to correlate the slight difference with any pattern of time or weather. The summer regression provided a fairly clean characterization of summer generation output with an R-squared value of 0.75.

Applying the summer and winter regressions gives predicted values for the turbine's output had there been no call for engagement; these values can be compared against the actual output during the periods of engagement. The differences represent the impact estimates of engaging the turbine.

Upon applying this technique to the generated power time series, it appeared that the generation was increased by 253 ± 29 kW at the times the generation had been reported to have been increased during the winter analysis period. The standard deviation of the increase in power generation was about 420 kW. The generation had been reported to have been increased 326 hours during the winter analysis period. We saw some visibly increased data points in Figure 17.3 where the generation was increased by up to 1 MW, but there were many more events that exhibited little or no response.

Analysts then compared the steam turbine's output during times it had been reported to operate with increased and normal generation levels within the summer analysis period. The regression model for the summer analysis period was more complex than that used for the winter one, as was described above. Multiple event periods were found in September 2013 while there was no generation being reported, and these "events" are believed to have occurred while the generator was, in fact, unavailable to respond. UW confirmed that the steam turbine had been removed from service September 20, 2013. These values were removed from the analysis. The consequent analysis using the regression baseline indicated that generation had increased by 468 ± 91 kW during summer events.

17.2 Diesel Generators

The UW included two 2 MW diesel standby generators in the project. These existing generators located at the UW central Power Plant were made available for added generator output as a DR asset. Their availability for providing additional generator capacity to the grid was limited in time and duration to accommodate periodic generator testing requirements and to remain within constraints of UW's existing environmental permit requirements. These generators are normally in standby mode, in which they generate no power.

As with all generator assets included in the project, the objective for the diesel generators was to test DR operation and identify opportunities for responses to pricing incentives or regional renewable energy integration strategies. A pair of generators that does not respond to DR signals was also metered to provide a control signal for comparison with the two experimental diesel generators.

Table 17.2 lists the system's components and their annualized costs.

Table 17.2. Annualized Costs of the UW Diesel Generator System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)	
Transactive Node System	33	155.5	51.8	
Secure, Virtual Private Campus Network (VPN)	17	257.6	43.0	
Advanced Meters (at generator)			39.6	
• Software and Systems (774 hours)	100	18.9		18.9
• Installation and Integration (1,415 hours)	100	13.4		13.4
• Equipment - Industrial Meters (5 meters)	100	1.1		1.1
• Operations and Maintenance (1 year)	100	6.0		6.0
• Engineering	50	0.3		0.2
• Equipment - Branch Circuit Monitor	50	0.2		0.1
FEMS			37.2	
• Software and Systems (800 hours)	100	19.5		19.5
• Installation and Integration (400 hours)	100	10.0		10.0
• Operations and Maintenance (200 hours)	100	4.9		4.9
• Equipment - Mediator	33	6.2		2.1
• Energy Data Collection and Processing Servers	33	2.4		0.8
• Engineering (6 hours)	100	0.1		0.1
2 MW Diesel Standby Generators (two, existing)	100	15.4	15.4	
Administrative	100	0.4	0.4	
Total Annualized Asset Cost			**$187.3K**	

17.2.1 System Operation and Data Concerning the Diesel Generators

Figure 17.4 shows the engagement status signal provided to the project by UW for the two diesel test generators, plotted by project month. There were 32 individual DR events reported to the project, occurring predominantly between August 2013 and March 2014, and typically lasting from one to two hours (though several events had durations less than an hour).

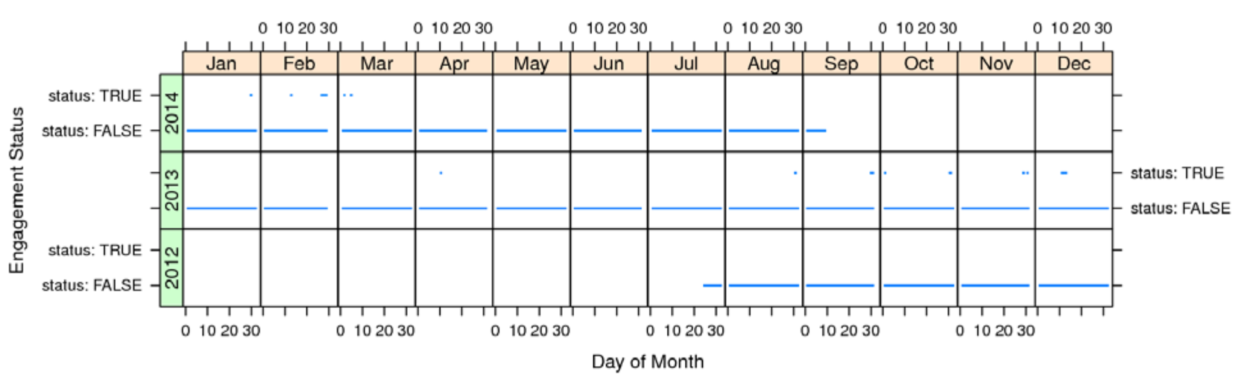


Figure 17.4. Reported Engagement Status for Two Diesel Generators

Analysts compared the times that the PNWSGD transactive system advised transactive events and the times that the UW campus had, in fact, reported to have engaged the diesel generators. Throughout the entire project, the two types of events coincided for 2 hours 10 minutes. That was about 7% of the total duration of UW-initiated events and 3% of the total duration of advised transactive events.

Figure 17.5 shows the reported total power output of the two test generators by project month. It also shows the power that was generated by a baseline, or control, set of three diesel backup generators that were not eligible to be controlled by DR. These backup generators are still subjected to periodic monthly tests to make sure they will respond when they are needed. The backup generators remain idle and produce no energy most of the time.

The behaviors of the two generator sets are similar, as would be expected, but the baseline generators appear to have been active in fewer months. There are very few DR events from Figure 17.4 that are coincident with nonzero power generation. In fact, only one such event exists in the project data. On April 10, the test generators were run for 15 minutes while a 1-hour DR event was active. The generators' output during this event was only about 120 kW.

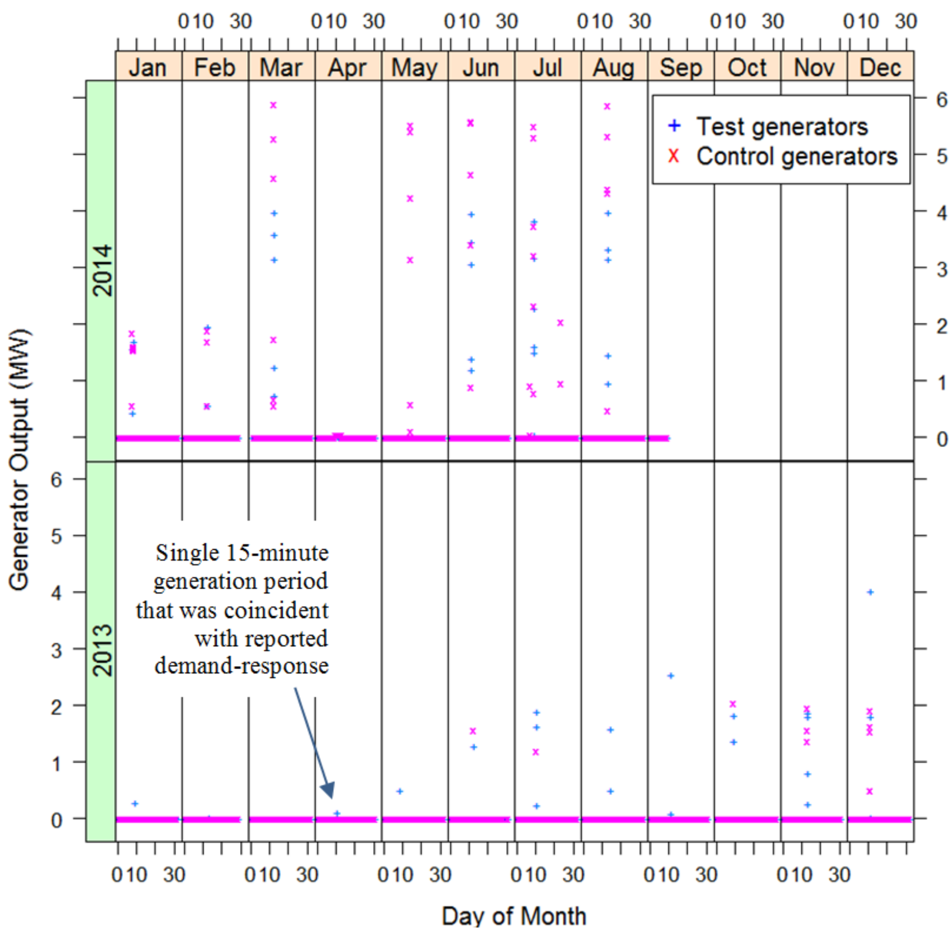
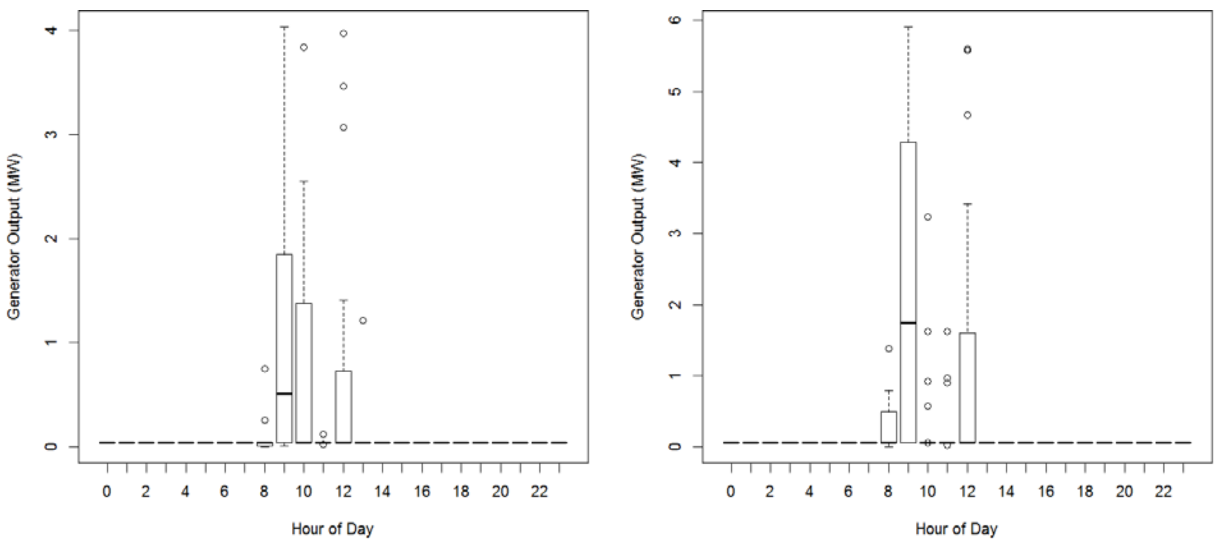


Figure 17.5. Diesel Generator (Test and Baseline Control) Power Output during 2013 and 2014. There was only one 15-minute period when the test generators produced energy coincident with a reported event.

Further characterization of the experimental and baseline control generators' operation is given by Figure 17.6, which shows box-and-whisker plots of the nonzero power generation from the test generators (left) and baseline control generators (right) during 2013 and 2014 as functions of the hours that the nonzero generation occurred. Again, the experimental and baseline control generator sets seem to have been operated similarly throughout the project period, though the baseline control generators may have been operated slightly earlier in the day.



(a) Test Generators

(b) Baseline Control Generators

Figure 17.6. Quartile Plots of the Nonzero Power that was Generated by the (a) Test and (b) Control Generators during 2013 and 2014 by Hour of Day

17.2.2 Analysis of the Diesel Generators

The project has little evidence that the UW campus changed the way it engaged its diesel generators in light of either the events that were advised by the PNWSGD transactive system or the events that were reported by UW to have affected the diesel generators. The project can, however, confirm that the two 2 MW generators achieved their total nameplate ratings, more than 4 MW, during the PNWSGD.

17.3 Solar Renewable Generation

The university provisioned two small-scale solar PV panel facilities (existing), at Merrill Hall and the Mechanical Engineering Building, for inclusion in the PNWSGD. The solar PV facilities were installed to inform the UW regarding costs and benefits of future deployment of larger-scale solar PV facilities. The total capacity of the two PV facilities was 73.4 kW, though at times the larger of the two facilities was found to be offline.

Table 17.3 lists the system's components and their annualized costs.

Table 17.3. Annualized Costs of the UW PV System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
FacNet	17	257.6	43.0
Advanced Meters (at PV arrays)	100	38.9	38.9
FEMS			35.7
• Software and Systems (800 hours)	100	19.5	19.5
• Installation and Integration (400 hours)	100	10.0	10.0
• Operations and Maintenance (140 hours)	100	3.4	3.4
• Equipment - Mediator	33	6.2	2.1
• Energy Data Collection and Processing Servers	33	2.4	0.8
• Engineering (6 hours)	100	0.1	0.1
Administrative	100	0.4	0.4
Small-Scale PV Arrays (existing)	100	0.0	0.0
Total Annualized Asset Cost			**$118.0K**

17.3.1 System Operation and Data Concerning the Solar Renewable Generation

Solar PV energy production is primarily governed by solar availability. The coincidence of PV generation and Seattle City Light (SCL) heavy-load hours (HLHs) and light-load hours (LLHs) determined the value of the energy supply that was displaced by the PV generation.[1] Figure 17.7 shows the power-output time series of the PV panels during the project. Two operating modes are evident: one in which the bulk of the total 73.4 kW capacity is online and operating, and another in which a large portion of the capacity is apparently not online. Full capacity was available from June 29, 2013 through March 7, 2014. This time period will be used for much of the project's analysis and is shown in Figure 17.7 by yellow shading. The blue and red colors in Figure 17.7 represent SCL HLHs and LLHs, respectively. The regular pattern of LLHs on Sundays and overnight is apparent.

[1] The SCL HLH rate applies to energy used between 06:00 and 22:00 Pacific Time, Monday through Saturday, excluding major holidays. All other hours are LLH.

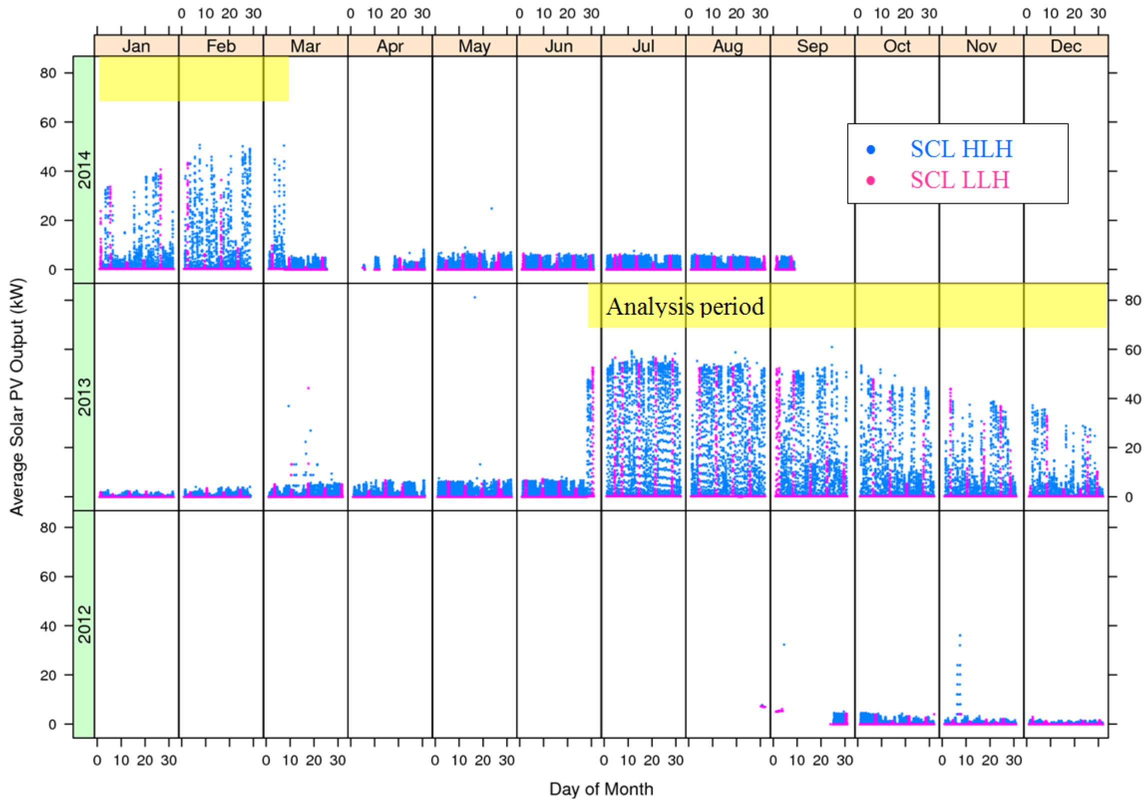


Figure 17.7. Total Power Produced by the UW PV Panels. The color coding refers to power that was produced during the SCL HLL (blue) and LLH (red) periods. An analysis period, when all the PV assets appear to be online and active, is indicated by yellow shading.

The HLH/LLH pattern, as well as the nature of the diurnal solar output by month, is more clearly shown in Figure 17.8, which presents the months of the defined analysis period by hour of day for every day in the period. The regular Sunday/nighttime LLH pattern is clearly visible, and the inclusion of holidays such as Labor Day on September 2 is clear, as are the lower available peak solar irradiation and more frequent cloudy days in the winter months.

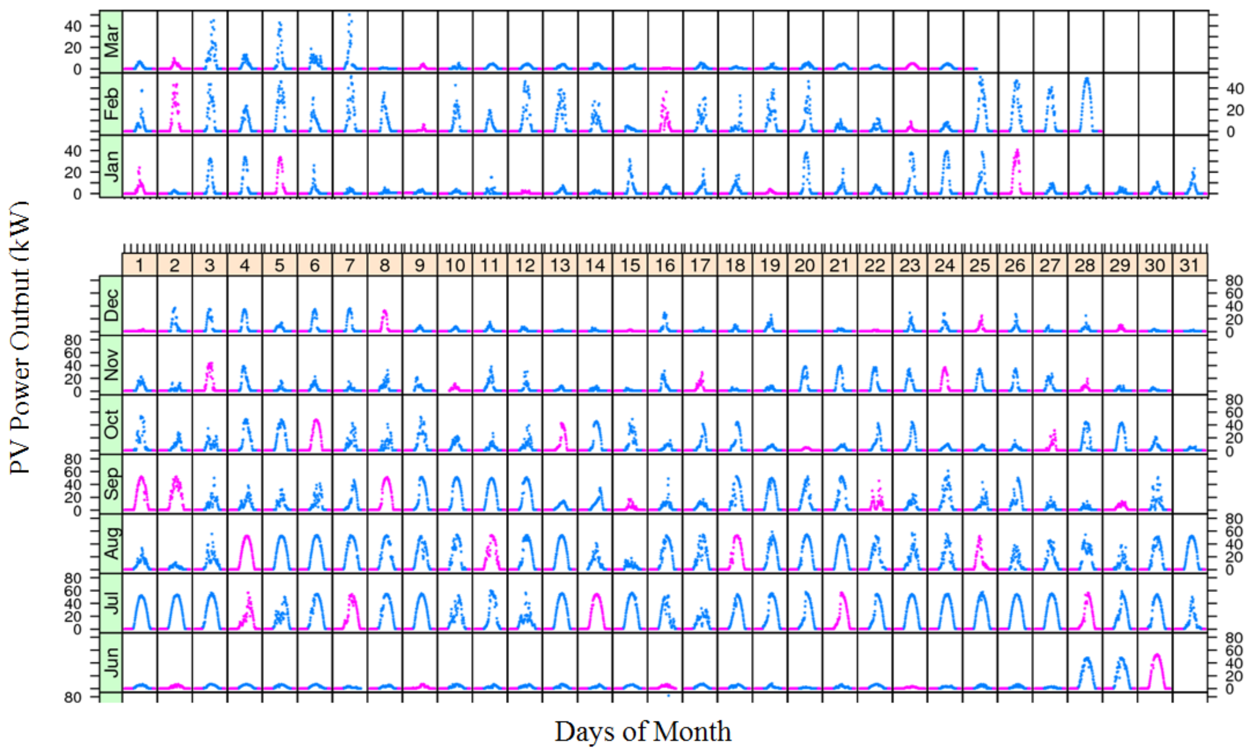


Figure 17.8. Real Power Output of Photovoltaic Panels during the Narrowed Analysis Period of 2013 and 2014. The color coding refers to power produced during the SCL HLH (blue) and LLH (red) periods.

One phenomenon not apparent from Figure 17.8 is an anomalous nighttime generation during the time periods when the bulk of the PV capacity was online and reporting. There is unexpected energy generation during the nighttime hours, amounting to a not-quite-constant reading of about 120 W. Figure 17.9 illustrates this with data from a single day, July 26, 2013. The apparent nighttime output is slightly higher before midnight (about 141 W) than after midnight (about 108 W). The project team was not able to discern the source of this anomaly, which results in an apparent overstatement of total project energy produced by 39 to 51 kWh each of the night hours, and possibly all hours (if the anomaly represents an overall offset). Beyond noting the anomaly, we have not attempted to correct the data.

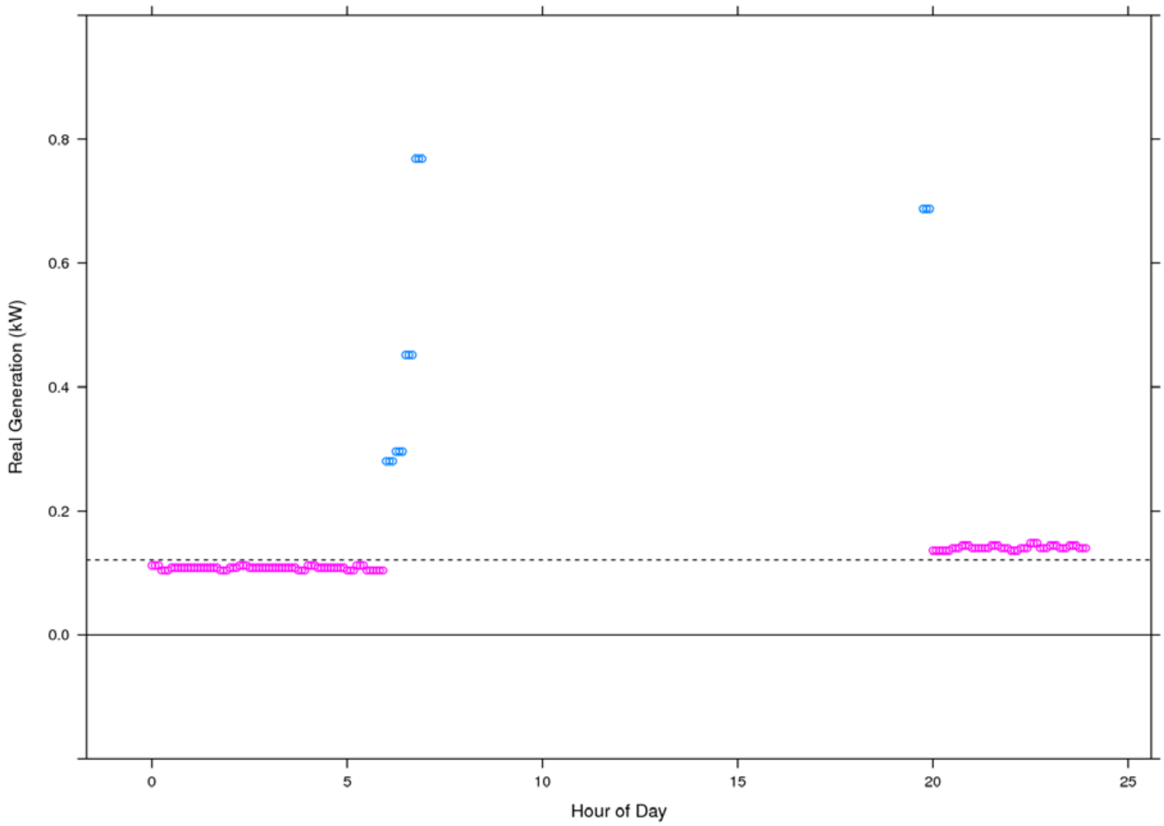
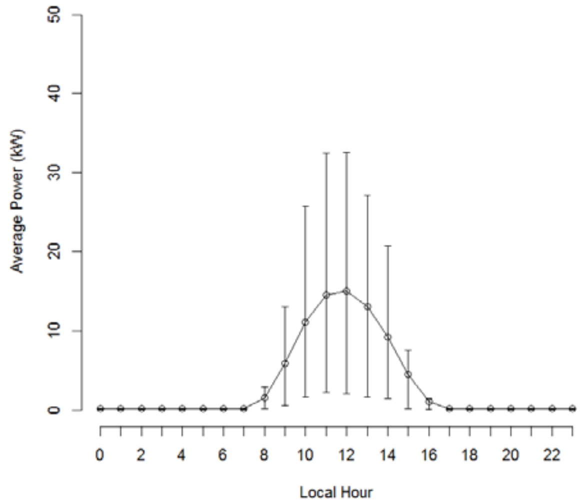


Figure 17.9. Example Plot from July 26, 2013 Showing Anomalous Nighttime PV Generation. The color coding refers to power produced during the SCL HLL (blue) and LLH (red) periods. The dotted line shows a power level of 120 W.

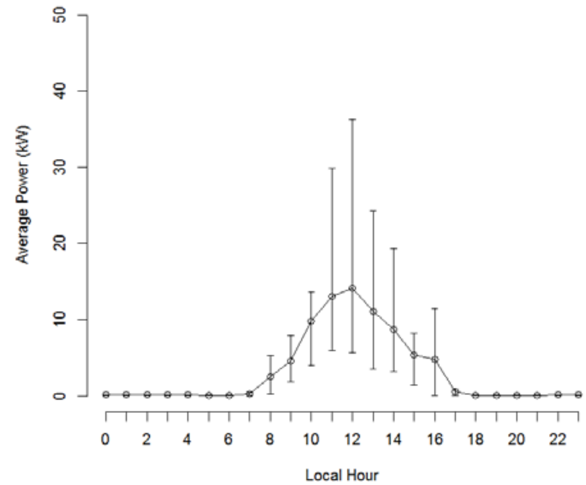
17.3.2 Analysis of the Potential Power Output from the UW PV Arrays

Figure 17.10 shows the average hourly PV power generation by season. The project defined its seasons by three-month periods. Winter, for example, includes the months December through February. The plots include only the data from June 29, 2013 through March 7, 2014, when all the UW PV systems were presumed to be active. The whiskers extend from the 16th to 84th percentiles of the data in the corresponding hour and season. Percentiles were used instead of standard deviation because the data sets do not have Gaussian distributions. The plots were all completed with the same vertical axis ranges to facilitate comparisons. About 44 kW of power generation should be expected during midday hours in summers. Less than 15 kW should be expected those hours in the spring. Generation is quite variable due to the frequent cloud cover in Seattle, Washington.

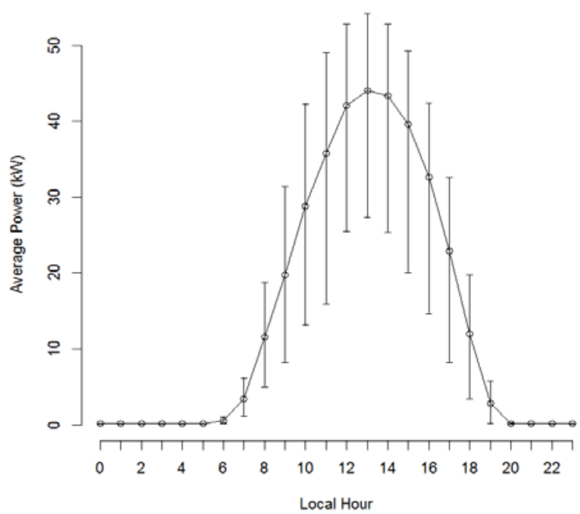
The spring season was represented by only one week, at the beginning of March 2014. The average power that is reported for spring is probably conservative. Furthermore, the short data period might have caused the small anomaly at Hour 16 in Figure 17.10b.



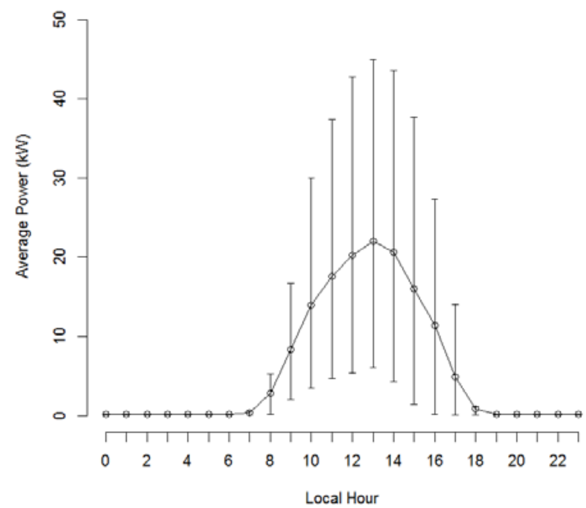
(a) Winter



(b) Spring



(c) Summer



(d) Fall

Figure 17.10. Average Hourly Solar Power Generation during (a) Winter, (b) Spring, (c) Summer, and (d) Fall Seasons. These results are based on the time period from June 29, 2013 through March 7, 2014, when all the UW PV systems appeared to be active. The spring season is poorly represented by only one week of early spring data.

Table 17.4 lists the total energy that might be produced each month, based on the observed power generation from June 29, 2013 through March 7, 2014, when all the UW PV systems appeared to have been active. The entire months of April and May were not represented in this set, and only the first week of March 2014 was used. To reduce the influences of missing data, the average power generation each month and for the two hour types were calculated first. Then these average power values were multiplied by the number of HLH or LLH hours in those months of 2013. This method allowed the project to estimate a value for March, although the value is likely conservative because the data were from early in the month.

The values of the HLH and LLH hours were calculated from the published SCL rates from 2012 (SCL 2012). In that schedule, the HLH rate was $0.0681/kWh, and the LLH rate was $0.0454/kWh.

Because the full contingency of PV generation resources was not active for a full year, there was no good method for estimating the variability that should be expected in these energies and values from year to year. The totals at the bottom of Table 17.4 have been extrapolated to estimate the total yearly energies and dollar values. The values from the months having missing data have been assigned the average value from the ten months for which data is available. The project estimates that the current PV generation resources on the UW campus (~72.4 kW) could generate about 68 MW per year that would displace about $4,300 worth of energy that the campus must presently purchase from SCL. To do this, all the PV resources would need to be online throughout the year, which did not appear to have been the case during the PNWSGD.

Table 17.4. Energy Generated by the UW PV Generators Summed by Month and SCL Hour Type. These calculations used only the power data from June 29, 2013 through March 7, 2014, when all the UW PV systems appeared to have been active.

	HLH		LLH		**Totals**	
Month	(kWh)[a]	($)[b]	(kWh)[a]	($)[b]	**(kWh)[a]**	**($)[b]**
Jan	1,470	100	423	19	**1,890**	**119**
Feb	3,170	216	331	15	**3,500**	**231**
Mar[c]	2,180	149	194	9	**2,380**	**157**
Apr	-	-	-	-	**-**	**-**
May	-	-	-	-	**-**	**-**
Jun	8,950	610	4,360	198	**13,300**	**808**
Jul	9,800	667	1,790	81	**11,600**	**748**
Aug	8,030	547	1,430	65	**9,460**	**612**
Sep	4,670	318	1,340	61	**6,010**	**379**
Oct	3,640	248	620	28	**4,260**	**276**
Nov	1,990	135	554	25	**2,540**	**161**
Dec	1,320	90	273	12	**1,600**	**103**
Totals[d]	**54,300**	**3,697**	**13,600**	**616**	**67,800**	**4,313**

(a) Energy column entries have been rounded to three significant digits. The monthly energy sum was estimated by multiplying the average power generation that month and hour type by the number of hours of that type in the month of 2013.

(b) Dollar amounts have been rounded to the nearest dollar. Recent SCL HLH and LLH rates were found to be $0.0681/kWh and $0.0454/kWh, respectively.

(c) March was represented by only a week's worth of data.

(d) These totals have been projected to represent an entire your by presuming that the data from unavailable months April and May are the average of data from the ten months that data were available.

The project might have adequate data to estimate the impacts that the PV generators have on demand charges that UW incurs from SCL, but that calculation could not be completed during the project.

17.4 Direct Digital Controls in UW Buildings

Five buildings on the UW campus (Conibear Shellhouse, Intramural Activities, Architecture, Fisheries Science, and Gates Law) received direct digital controls (DDCs) that allow HVAC and lighting to be controlled using a “human-in-loop” transactive control strategy. These buildings were made available for operation at reduced load during low occupancy periods, as a DR asset. These buildings have no energy displays (Section 17.5), and no monthly energy reports (Section 17.6) are delivered to their building managers.

Table 17.5 lists the system’s components and their annualized costs.

Table 17.5. Annualized Costs of the UW DDC System and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Transactive Node System	33	155.5	51.8
Secure, Virtual Private Campus Network (VPN)	17	257.6	43.0
Advanced (smart) Meters			21.3
• Equipment - Commercial Meters (17 meters)	100	8.7	8.7
• Operations and Maintenance (60 hours)	100	6.6	6.6
• Integration (480 hours)	100	4.5	4.5
• Software and Systems (60 hours)	100	1.5	1.5
• Engineering (4 hours)	100	0.0	0.0
FEMS			16.2
• Installation and Integration (480 hours)	100	11.7	11.7
• Software and Systems (60 hours)	100	1.5	1.5
• Operations and Maintenance (60 hours)	100	1.5	1.5
• Energy Data Collection and Processing Servers	33	2.4	0.8
• Equipment - VPN Interface Servers	33	2.1	0.7
• Engineering (4 hours)	100	0.1	0.1
Administrative	100	0.4	0.4
Outreach and Education	33	1.2	0.4
HVAC Systems (existing)	100	0.0	0.0
Total Annualized Asset Cost			**$133.1K**

17.4.1 System Operation and Data Concerning DDC in UW Buildings

Figure 17.11 shows the DDC engagement signals that were reported by the UW for the duration of the project. There were 26 individual events during which the buildings responded to calls for load reduction. The events typically lasted between a half hour and 3.25 hours, with the shorter events being more common. The events were fairly widely spaced in time, spanning roughly a one-year period, though DDC events were not initiated during either of the monitored summers.

The university defined multiple engagement levels as follows:

- Not curtailed. The system is installed, but no dispatch signal is being issued to request responses from any buildings. This idle status corresponded to the transactive advisory signal level 0.
- Tier 1. Digital HVAC controls have been dispatched at three campus buildings—Architecture Hall, Conibear Shellhouse, and Fisheries Sciences. This status corresponded to the transactive advisory signal level 42.
- Tier 2. Digital HVAC controls have been dispatched at the three Tier-1 campus buildings, plus the Intramural Activities building. This status corresponded to the transactive advisory signal level 84.
- Tier 3. Digital HVAC controls have been dispatched at the four Tier-2 campus buildings, plus the Gates Law building. This status corresponded to the transactive advisory signal level 127.

The campus's engagement procedure defined override and termination capabilities, but these features were not exercised according to the status information that was received by the project. Tier 1, Tier 2, and Tier 3 statuses may be overridden or terminated by UW Engineering staff.

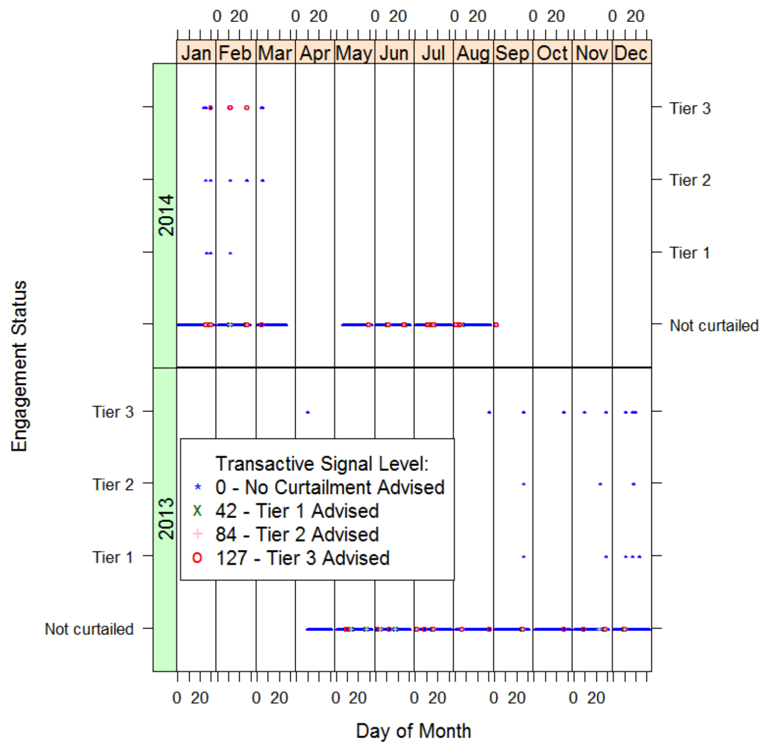


Figure 17.11. Reported Engagement Status of the Buildings with DDCs

When the reported engagement levels were compared with the PNWSGD transactive system advice for this asset system, the system was found to have remained idle during most of the events that the transactive system had advised at the various levels. Tier 3 was engaged for 45 minutes coincident with the transactive advisory signal level "84" and 5 hours 15 minutes coincident with the signal level "127." The advised status from the transactive system was also included in Figure 17.11.

Figure 17.12 shows the total power consumed by the five buildings with DDCs during the PNWSGD data collection period. Although two years of power data were available to the project, responses to the project's transactive signals did not begin until early April 2013. Incomplete power data was received for late March and early April 2014.

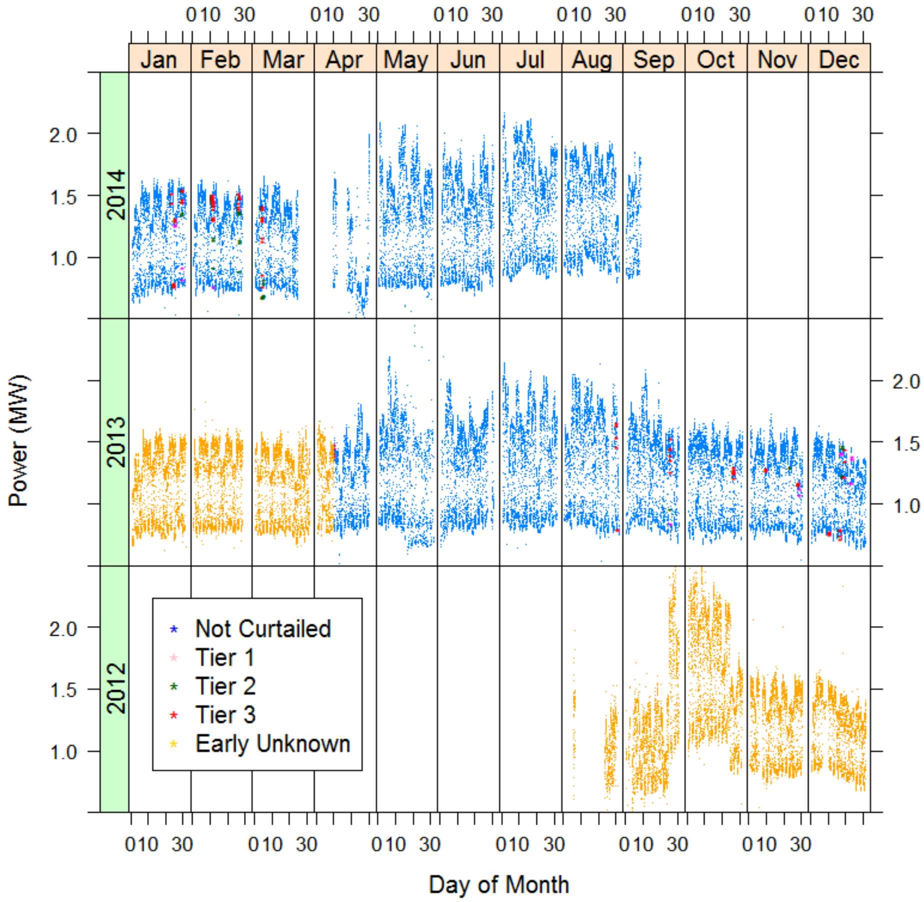


Figure 17.12. Total Power Consumed by the UW Buildings with DDCs during the PNWSGD. The legend includes colors that indicate the reported status of the system as the data was being collected.

Any of the tier levels of engagement is a candidate for analysis, but Tier 3 was chosen because it was said to have affected all the buildings and should therefore create the easiest impact to verify. A histogram of the hours in which these Tier 3 events occurred is shown in Figure 17.13. The high frequency of late and early hour occurrences was unexpected.

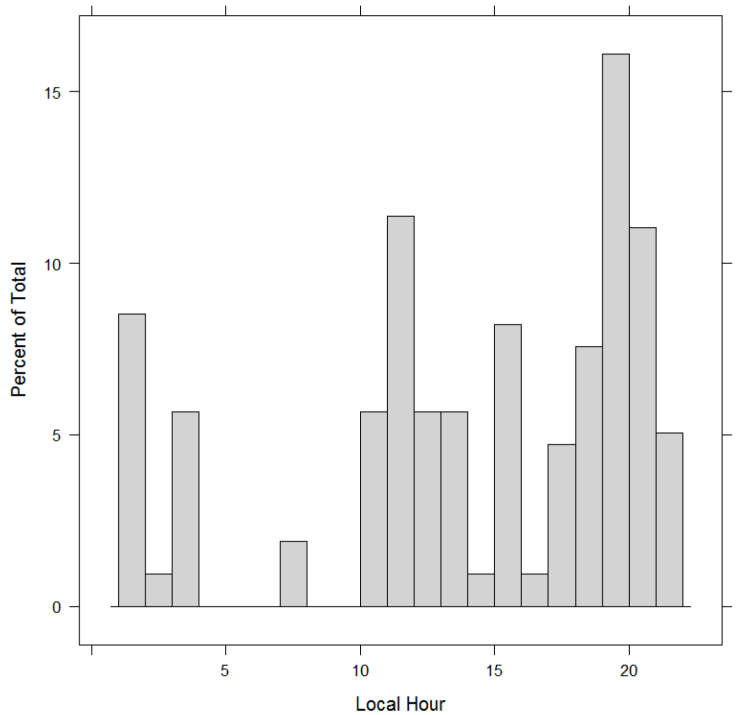


Figure 17.13. Histogram of Local Pacific Time Zone Hours in which Tier 3 Event Periods Occurred during the PNWSGD

17.4.2 Analysis of the DDC Building Controls

Analysts first plotted and observed the buildings' aggregate power data in the time periods that surround and include the Tier 3 events. No impact (e.g., a notch) was evident by inspection.

The project conducted linear regression as a function of ambient temperature for the months, days of week, and local hours that the Tier 3 events had been reported. The regression model was used to construct a baseline. No significant impact could be found.

17.5 Building Advanced Metering Displays and EnergyHub© Devices

The UW provisioned and installed electrical sub-metering and EnergyHub switch controls (EnergyHub 2015) for two residential dormitories and two academic facilities that have a combined mix of laboratories, classrooms, and offices. The sub-meters collected data, sent data to the central data warehouse, and provided the ability to retrieve the data by the residents and authorized researchers. It was postulated that demand reduction would occur by providing near-real-time consumption data to the end users, which in turn would encourage behavioral conservation.

This asset consists of several distinct scopes. First, a newly constructed dormitory was to implement floor-by-floor energy monitoring of the lighting and plug loads to each of the four individual floors. Total near-real-time power consumption for each floor would then be made available for viewing by residents on each floor on a common-area display screen, and by individual resident login to a Website display.

Second, 240 select rooms in McCarty Hall "Engineering House" were to be outfitted with room-by-room electrical power monitoring and dashboard display kits. These kits would consist of one portable room monitor (dashboard), two plug-in style smart outlets, and one power strip containing six smart outlets. These smart kits were to be distributed by the dormitory management to the current residents of the select dorm rooms. Third, floor-by-floor monitoring of receptacle plug-load energy usage was to be provisioned in the newly constructed PACCAR Hall. Fourth, branch circuit monitoring for plug loads was to be provisioned in select laboratories in the existing Electrical Engineering/Computer Science Building. All of the described sub-meters were to collect and send consumption data to the data warehouse. This sub-metering was also expected to facilitate follow-on research to be conducted outside the scope of the PNWSGD.

Table 17.6 lists the system's components and their annualized costs.

Table 17.6. Annualized Costs of the UW System of Displays and EnergyHub Devices and its Component Costs

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Advanced (smart) Meters			65.9
• Operations and Maintenance (320 hours)	100	35.0	35.0
• Integration (2,400 hours)	100	22.7	22.7
• Software and Systems (300 hours)	100	7.3	7.3
• Equipment - Residential (four meters)	100	0.9	0.9
FacNet	17	257.6	43.0
FEMS			36.6
• Software and Systems (800 hours)	100	19.5	19.5
• Installation and Integration (400 hours)	100	10.0	10.0
• Operations and Maintenance (200 hours)	100	4.9	4.9
• Engineering (40 hours)	100	1.0	1.0
• Energy Data Collection and Processing Servers	33	2.4	0.8
• Equipment - Mediator	33	2.1	0.7
Dormitory Individual Room Plug Loads (McCarty)	100	32.8	32.8
Outreach and Education	33	1.2	0.4
Administrative	100	0.4	0.4
Electrical Sub-Meters within Select Building (Poplar)	100	0.0	0.0
Dormitory Floor-by-Floor Energy Monitoring (Poplar)	100	0.0	0.0
Total Annualized Asset Cost			**$179.1K**

17.5.1 System Operation and Data Concerning Building Advanced Metering Displays and EnergyHub Devices

Building power data was submitted by UW for the period from mid-November 2012 through August 2014, when the PNWSGD data collection was ended. According to the installation status that was reported to the project by the university, the system of displays and EnergyHub devices was installed and active by January 21, 2013.

Figure 17.14 shows the total power consumption of the set of four campus buildings—Elm, Poplar, PACCAR, and the Electrical Engineering and Computer Science building—where the advanced metering displays and EnergyHub devices were installed. The figure also shows the total power from another set of six “control” buildings—Odegaard, Kincaid, Gould, Lewis, Roberts, and Wilcox—that did not receive the displays and EnergyHub devices but were otherwise similar to the treatment group. The treatment and control-group member buildings were selected to minimize interactions with other asset systems installed on the UW campus (Figure 17.1).

The control buildings exhibited large step discontinuities in their total power. The reported power nearly doubled during a period from December 2012 into March 2013. The largest reported values were larger than the apparent power values that were also reported to the project by the campus (not shown). This, of course, is physically impossible. The treatment buildings exhibited some discontinuities, too, in March and April 2014. The project elected to focus on the power measurements at a single treatment building—Poplar—that had fairly complete power data and exhibited few discontinuities in its power consumption. The power at the Poplar building is also shown in Figure 17.14. The data from the control buildings was not used.

According to the UW Residence Hall Energy Conservation Study (Black et al. 2014), students on two of Poplar Hall’s floors were given weekly energy tips displayed on a monitor in one of its common areas and were later surveyed. That is the extent of the students’ involvement.

The seasonal influences appear to be weak in the power consumption data from these campus buildings, but the plots reveal some strong weekday and weekend patterns. The limited variability by season is probably attributable to the use of steam heating on the campus, making electrical consumption less temperature dependent.

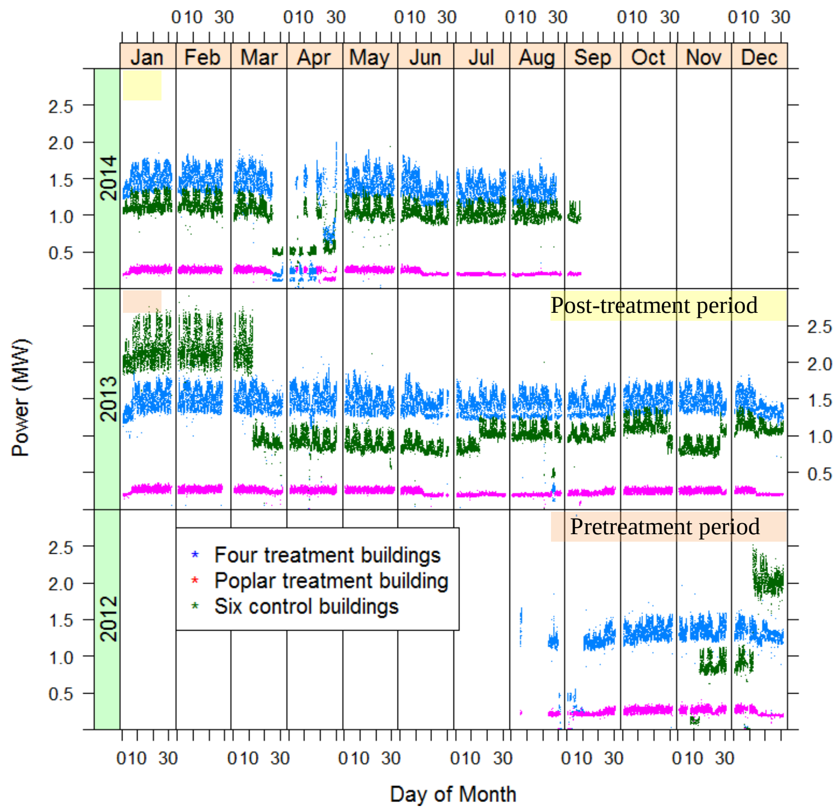


Figure 17.14. Power Consumption of Buildings with Advanced Metering Displays and EnergyHub Devices and of a Set of Six Control Buildings that Have No Advanced Metering Displays or EnergyHub Devices. Pre- and post-treatment analysis periods are shown by shaded boxes.

17.5.2 Analysis of Building Advanced Metering Displays and EnergyHub Devices

Approximately 5-½ months' historical data was available from the *pretreatment* period for comparison with the *post-treatment* period, when building occupants had access to their energy information. Given that the load on a university campus may be strongly affected by student occupancy and class schedules, the project selected a post-treatment analysis period that was precisely one year after the pretreatment analysis period and of the same duration. Therefore, the impacts of seasons and school schedules should be similar between the two groups, but the post-treatment period was well after the devices had been installed.

Even though the buildings' temperature dependence was expected to be weak, analysts corrected for the impact of temperature by calculating degree-days for each day of the pre- and post-treatment periods. The calculated degree-days are equivalent to the average daily temperature. The total energy consumption by the Poplar building from each day in the pre- and post-treatment periods is plotted against the day's corresponding average temperature in Figure 17.15.

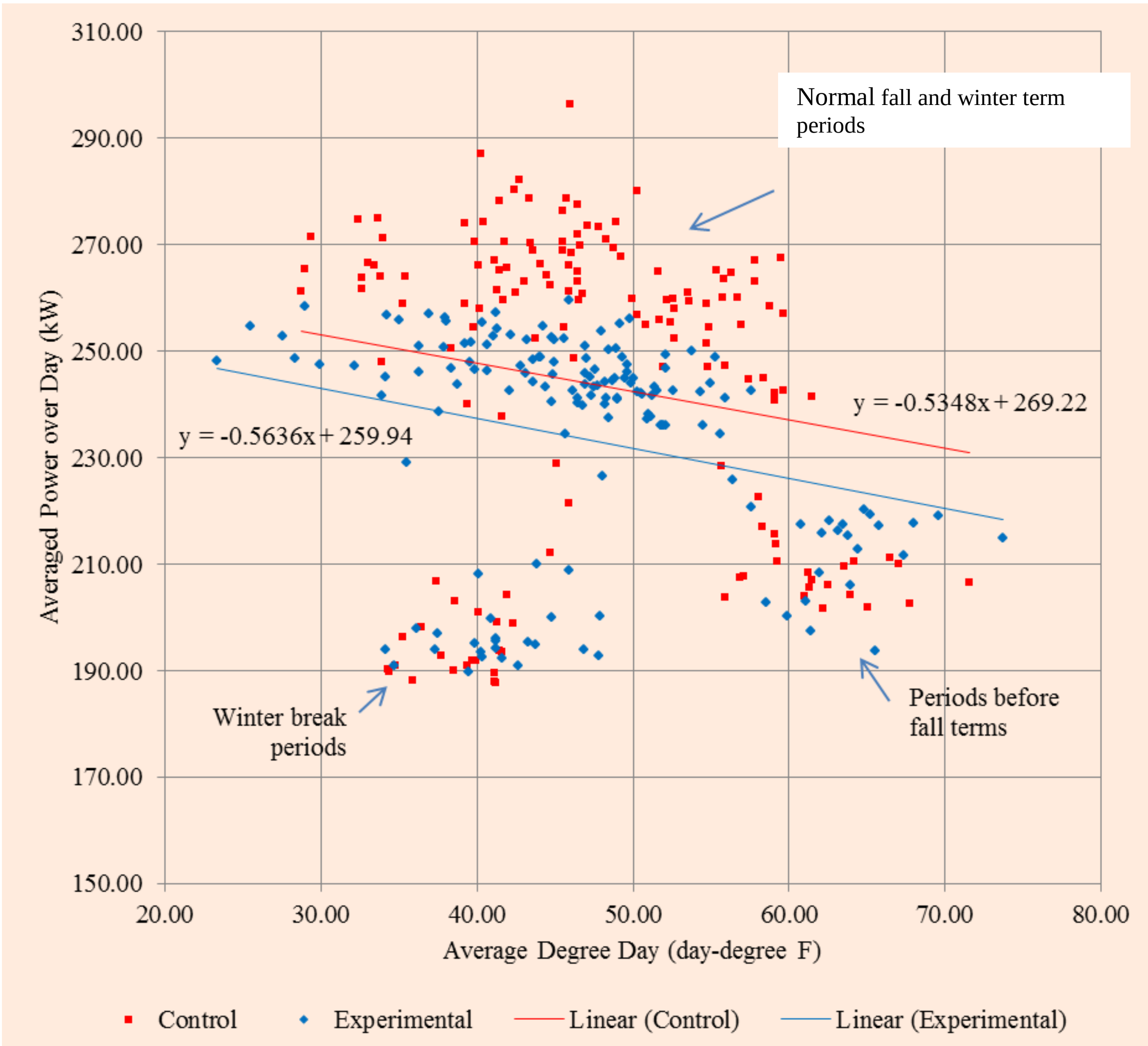


Figure 17.15. Regression Analysis of the Poplar Building with its Advanced Metering Displays and EnergyHub Devices during Pretreatment (blue) and Post-Treatment (red) Periods. The lines show linear regression trends for all the corresponding pre- (blue) and post-treatment (red) days.

Additionally, the linear fit from all the pretreatment days is shown in Figure 17.15 and compared with a corresponding line for the post-treatment days. The differences between the two periods are remarkable, and are evident by visual inspection of the two data sets. The regression lines are parallel to one another, but they are separated by about 9 kW. Most of the impact appears (by inspection) to have occurred during the normal fall and winter school term periods at the center, top of the figure. The campus took steps each year during winter breaks in the school schedule to reduce the building's energy consumption, as is shown at the bottom, left of the figure. A similar reduction is evident from periods prior to fall terms on the bottom right. The reduction in power consumption that was evident during school terms was not evident during the break periods.

So, the application of energy displays and EnergyHub devices at this building might have caused about 9.25 kW power reduction on average, or 222 kWh per day, for the Poplar building. The campus was actively pursuing energy conservation during these years, so it is possible that the observed impact might have been caused instead by other of the campus's conservation efforts that were unknown to the project analysts. If a similar impact were observable at the other three campus buildings where these devices were installed, the impact might be about four times as great.

A group of UW graduate students conducted a more detailed analysis of the impacts from providing energy information and EnergyHub switch devices to student dormitory residents of Poplar Hall and Elm Hall (Black et al. 2014). Their analysis of energy impacts was inconclusive. Survey results suggested that students had not been motivated to change their energy consumption through education or the automation that had been provided them. The study advises that the EnergyHub devices are not currently cost effective for use on the campus. The study contains much rich information and discussion. Based on the more complete description of the participation of Poplar Hall in this study, the project should conclude that the impacts observed in Figure 17.15 were from other facilities energy management and not the system of displays and EnergyHub devices.

17.6 Facilities Energy Management System Data for Campus Building Managers

The UW designed, procured, and installed a FEMS to facilitate system efficiency and conservation. The FEMS is an enterprise platform interface and information system. It was designed to receive sub-metering information from all of the enabling and responsive assets associated with the subproject. Using information stored by the sub-meters in the database warehouse, the FEMS provided access to reports and data, and now provides dashboard visualizations and energy comparison graphics for Web-based displays. The FEMS was listed as a subsystem component of all the five asset systems that have already been discussed in this chapter. The purpose of this section is to assess whether the FEMS as a real-time display system creates a more educated set of building managers and achieves some degree of energy conservation for the campus.

Table 17.7 lists the system's components and their annualized costs.

Table 17.7. Annualized Costs of the UW FEMS and its Components

	Component Allocation (%)	Annualized Component Cost ($K)	Allocated Component Cost ($K)
Advanced (smart) Meters			134.3
• Equipment - Commercial Meters (200 meters)	100	101.9	101.9
• Software and Systems (774 hours)	100	18.9	18.9
• Integration (1,415 hours)	100	13.4	13.4
• Operations and Maintenance (1 hour)	100	0.1	0.1
• Engineering (4 hours)	100	0.0	0.0
FEMS			55.3
• Installation and Integration (1,450 hours)	100	35.6	35.6
• Software and Systems (557 hours)	100	13.6	13.6
• Engineering (200 hours)	100	4.9	4.9
• Energy Data Collection and Processing Servers	33	2.4	0.8
• Equipment - Mediator	33	2.1	0.7
FacNet	17	257.6	43.0
Server and Data Warehouse	100	13.5	13.5
Administrative	100	0.4	0.4
Outreach and Education	33	1.2	0.4
Total Annualized Asset Cost			**$247.0K**

17.6.1 System Operation and Data Concerning the Facilities Energy Management System Data for Campus Building Managers

Figure 17.16 is a snapshot of the UW Energy Dashboard[1] that it constructed during the PNWSGD. This Webpage report includes information about building consumption or campus solar energy generation currently, in the current day, the past week, and past years. The figure shows, for example, 12 hours of energy consumption by the Gates Law building on the UW campus.

[1] The Dashboard is openly viewable to all at http://dashboard.mckinstry.com/uw/.

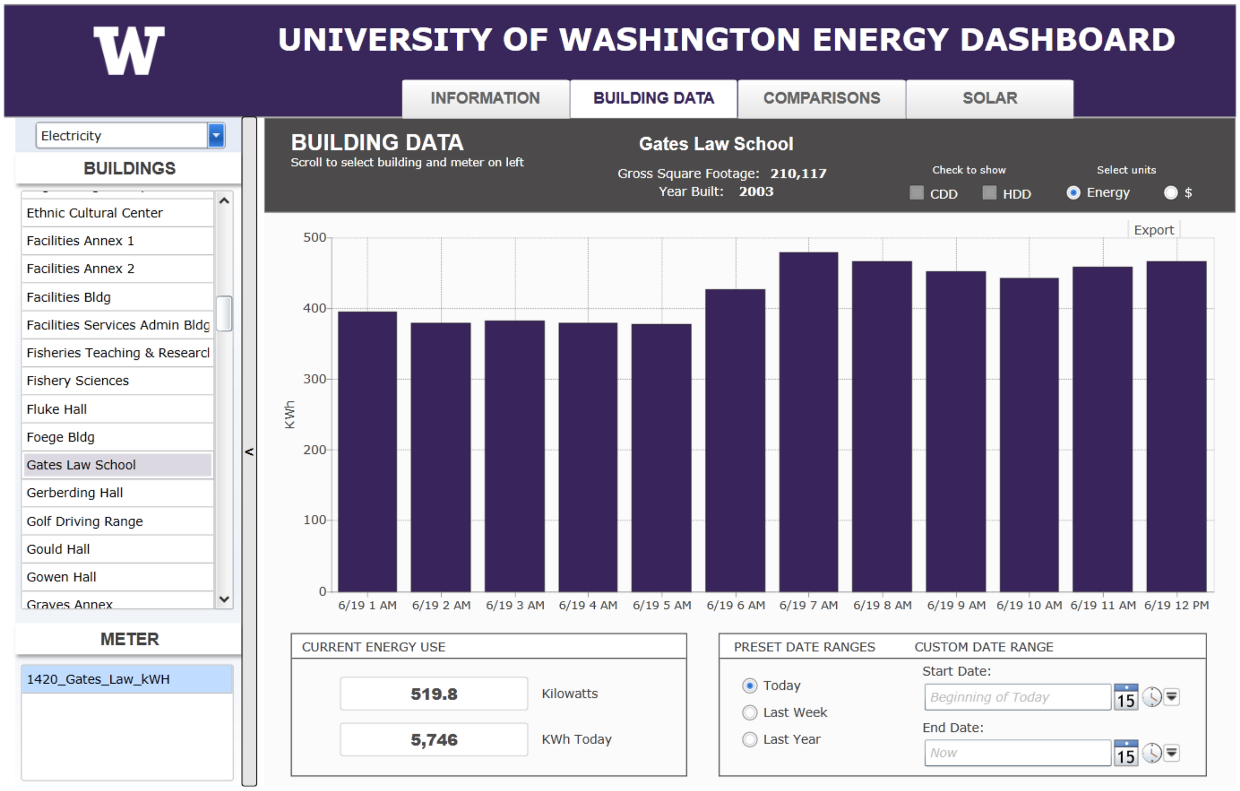


Figure 17.16. Snapshot of the UW Energy Dashboard

17.6.2 Analysis of the Facilities Energy Management System Data for Campus Building Managers

The project was not able to devise a way to separately determine the impact from real-time energy information using the data supplied by UW. The university researched the impact that its energy dashboards had on its building coordinators.[1] The respondents had a wide range of building management experience, from none to over 25 years, and managed a range of buildings aged new to over 120 years. Six respondents eventually were interviewed, and only one of them reported that he had viewed the dashboard as had been requested. The researcher concluded that the UW Energy Dashboard did not appear to have affected the energy behavior of the building coordinators.

[1] M Ostergren. 2013. UW Energy Dashboard Study Final Report. University of Washington technical report dated December 2013, unpublished.

18.0 References

78 FR 6674-6724. January 30, 2013. "National Emission Standards for Hazardous Air Pollutants for Reciprocating Internal Combustion Engines; New Source Performance Standards for Stationary Internal Combustion Engines." *Federal Register*, Environmental Protection Agency (No. 20). Accessed January 27, 2015 at http://www.gpo.gov/fdsys/pkg/FR-2013-01-30/pdf/2013-01288.pdf.

ABB, Inc. 2015. Wireless Networks. Accessed April 14, 2015 at http://new.abb.com/network-management/communication-networks/wireless-networks.

Aclara - Aclara Technologies, LLC. 2011. *Aclara DSI Disconnect Switch Interbase*. Accessed August 8, 2014 at http://www.aclara.com/wp-content/uploads/2014/11/305-R3.LOW_.pdfAclara. 2012. *Aclara*

Aclara - Aclara Technologies, LLC. 2014. TWACS® & eTWACS®: TWACS Technology – Communications for AMI, Networking and Distribution Management. Accessed May 20, 2015 at http://www.aclara.com/solutions/electric/ami-etwacs/.

ACS - Advanced Control Systems. 2015. Accessed March 18, 2015 at http://www.acspower.com/.

Avista Corporation. 2013. Inside Avista. Avista Utilities website, Spokane, Washington. Accessed October 31, 2013 at http://www.avistautilities.com/inside/pages/default.aspx.

Avista Corporation. 2015. Accessed March 17, 2015 at https://www.avistautilities.com.

Battelle Memorial Institute (Battelle). 2011. *Pacific Northwest Smart Grid Demonstration Project: Interoperability and Cyber Security Plan, Revision 3*. PNW-SGDP-TP-001, Battelle Memorial Institute, Columbus, Ohio.

Battelle Memorial Institute. 2013. *Transactive Coordination Signals, Revision X*, PNWSD-4402, prepared for the U.S. Department of Energy by Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington.

Benton PUD - Benton Public Utility District. 2011. Accessed August 15, 2014 at http://www.bentonpud.org/.

Benton PUD - Benton Public Utility District. 2014. Benton PUD Fast Facts – 2013. Accessed March 6, 2015, at http://www.bentonpud.org/images/site/2013%20Fast%20Facts%20Website.pdf.

Benton PUD. 2011. Benton PUD. Kennewick, Washington. Accessed November 4, 2013 at http://www.bentonpud.org.

Bergey WindPower. 2012. *The Excel 10kW Wind Turbine: Bergey is the Right Choice for Your Small Wind Needs*. Bergey WindPower Company. Norman, Oklahoma. Accessed September 20, 2013 at http://bergey.com/products/wind-turbines/10kw-bergey-excel.

BPA - Bonneville Power Administration. 2011. *2012 Wholesale Power and Transmission Rate Adjustment Proceeding (BP-12): Tiered Rate Methodology*. BP-12-A-03. The Bonneville Power Administration, Portland, Oregon, July 2011. Accessed June 4, 2015 at https://www.bpa.gov/Finance/RateCases/InactiveRateCases/BP12/Final%20Proposal/BP-12-A-03.pdf.

BPA - Bonneville Power Administration. 2014. Current BPA Power Rates. Accessed April 14, 2014 at https://www.bpa.gov/power/psp/rates/current.shtml.

BPA - Bonneville Power Administration. 2015. Pacific Northwest Smart Grid Demonstration Project: A Compilation of Success Stories. Accessed at https://www.bpa.gov/Pages/home.aspx.

BPA - Bonneville Power Administration. 2015. Wind Generation & Total Load in the BPA Balancing Authority. Accessed April 30, 2015 at http://transmission.bpa.gov/Business/Operations/Wind/default.aspx.

Chandler S and J Hughes. 2013a. "Smart Grid Distribution Prediction and Control Using Computational Intelligence." Slide presentation at the *1st IEEE Conference on Technologies for Sustainability (SusTech)*. August 1, 2013. Accessed January 26, 2014 at http://sites.ieee.org/sustech/files/2013/12/SG1_Chandler-SGCompIntelligence.pdf.

Chandler S and J Hughes. 2013b. "Smart Grid Distribution Prediction and Control Using Computational Intelligence." In *1st IEEE Conference on Technologies for Sustainability (SusTech)*. August 1-2, 2013, pp. 86-89.

City of Ellensburg. 2013a. *Ellensburg's Renewable Energy Park*. Slide presentation given at the CommRE webinar on renewable energy parks. March 19, 2013. Accessed December 30, 2014 at http://energy.gov/eere/about-us/march-19-2013-webinar-renewable-energy-parks.

City of Ellensburg. 2013b. *Ellensburg Smart Grid Demonstration Project Completion Report*. City of Ellensburg city council report dated October 21, 2013. Accessed December 30, 2013 at http://www.ci.ellensburg.wa.us/DocumentCenter/View/3030.

City of Ellensburg. 2013c. Smart Grid Demonstration Project Completion Report: Wind Turbine Case Studies. Report to the City of Ellensburg City Council dated November 1, 2013. Accessed December 31, 2013 at http://www.ci.ellensburg.wa.us/DocumentCenter/View/3096.

City of Milton-Freewater and Battelle Memorial Institute. 2010. *Subproject Technical Summary and Statement of Work*. Accessed at https://share.pnwsmartgrid.org/subprojects/milton_freewater/Shared%20Documents/Milton-Freewater%20Subproject%20Description.docm (unpublished).

City of Milton-Freewater. 2013. The Official Web Site for Milton-Freewater, Oregon. Accessed November 4, 2013 at http://www.milton-freewater-or.gov/electric.

City of Milton-Freewater. 2014. The Official Web Site for Milton-Freewater, Oregon. Accessed July 31, 2014 at http://www.mfcity.com/.

Cooper Power Systems. 2013. Voltage Regulators. Accessed March 18, 2015 at http://www.cooperindustries.com/content/public/en/power_systems/products/voltage_regulators.html.

CPUC - California Public Utilities Commission. 2012. *Energy Storage Framework Staff Proposal*. CPUC Energy Storage Proceeding R.10-12-007, April 3, 2012.

Demand Energy Networks, Inc. 2014. Demand Energy. Accessed August 15, 2014 at http://demandenergynetworks.com/.

Demand Energy Networks, Inc. 2015. Accessed February 6, 2015 at http://www.demandenergynetworks.com/.

DOE – U.S. Department of Energy. 2013. *Smartgrid.gov Recovery Act Smart Grid Programs: Smart Grid Demonstration Program*. Accessed November 28, 2013 at http://www.smartgrid.gov/recovery_act/overview/smart_grid_demonstration_program.

DOE-OE – U.S. Department of Energy Office of Electricity Delivery and Energy Reliability. 2015. PNWSGD Build Metrics. Accessed June 9, 2015 at https://www.smartgrid.gov/project/battelle_memorial_institute_pacific_northwest_division_smart_grid_demonstration_project/latest_data.html (data cumulative through June 21, 2013).

DRU Demand Response Unit. Accessed August 8, 2014 at http://www.aclara.com/wp-content/uploads/2014/11/Aclara_DRU.pdf.

Ecobee. 2015. Ecobee$_3$: The Smarter Wi-Fi Thermostat with Remote Sensors. Accesses April 27, 2015 at https://www.ecobee.com/?gclid=CNOL3YzPl8UCFSVo7AodLUwAtA.

Ellensburg – City of Ellensburg. 2013. City of Ellensburg Washington. Accessed November 4, 2013 at http://www.ci.ellensburg.wa.us.

Esri - Environmental Systems Research Institute. 2015. Smart Mapping: Mapping Made Easy. Accessed June 3, 2015 at http://www.esri.com/landing-pages/arcgis-online/smart-mapping.

FEC – Flathead Electric Cooperative, Inc. 2014a. "Your Coop: Flathead Electric—Community … Integrity … Reliability." Accessed August 19, 2014 at http://www.flatheadelectric.com/.

FEC – Flathead Electric Cooperative, Inc. 2014b. Email attachment "FEC design.pdf" from Teri Rayome-Kelly to DJ Hammerstrom September 17, 2014. Unpublished.

Flathead Electric. 2013. Flathead Electric. Flathead Electric Cooperative, Kalispell, Montana. Accessed November 4, 2013 at http://flatheadelectric.com.

GE – GE Appliances. 2014. GE Brillion™ Connected Appliances. Accessed August 19, 2014 at http://www.geappliances.com/connected-home-smart-appliances/.

Gridwise Architecture Council. 2015. Transactive Energy. Accessed January 16, 2015 at http://www.gridwiseac.org/about/transactive_energy.aspx.

Hammerstrom DJ, R Ambrosio, TA Carlon, DP Chassin, JG DeSteese, RT Guttromson, OM Jarvegren, R Kajfasz, S Katipamula, P Michie, T Oliver, and RG Pratt. 2007. *Pacific Northwest GridWise Testbed Projects: Part 1. Olympic Peninsula Project, Technical Report*. PNNL-17167, Pacific Northwest National Laboratory, Richland, Washington.

Hammerstrom DJ, RB Melton, TV Oliver, and R Ambrosio. 2009. “Standardization of a Hierarchical Transactive Control System.” Presented by Don Hammerstrom (Invited Speaker) at Grid-Interop Forum 2009, Denver, Colorado on November 17, 2009. PNNL-SA-69636. Accessed January 16, 2015 at http://www.gridwiseac.org/pdfs/forum_papers09/don-business.pdf.

Hammerstrom DJ. 2010. *Pacific Northwest Smart Grid Demonstration Project: Conceptual Design, Revision 1*. PNWD-4440, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington.

Hammerstrom DJ. 2010. *The Pacific Northwest GridWise® Testbed Demonstrations*. Conference presentation at Harvesting Clean Energy—Northwest Pioneers of the Smart Grid, Kennewick, Washington.

Harvey A and SJ Koopman. 1993. “Forecasting Hourly Electricity Demand using Time-Varying Splines.” *Journal of the American Statistical Association* 88:1228–1236.

Home Energy International. 2013. *Energy Ball V200®* (Grid connected). Accessed January 13, 2015 at http://home-energy.com/int/ebv200.htm.

Howard Industries. 2015. Accessed March 18, 2015 at http://howard-ind.com/DefaultPage.asp.

Idaho Falls Power. 2013. The City of Idaho Falls Idaho. Idaho Falls, Idaho. Accessed November 4, 2013 at http://www.idahofallsidaho.gov/city/city-departments/idaho-falls-power.html (updated 2015).

Idaho Falls. 2014. “The City of Idaho Falls, ID.” About Us. Accessed August 28, 2014 at http://www.idahofallsidaho.gov/city/city-departments/idaho-falls-power/about-us.html.

IEEE - Institute of Electrical and Electronics Engineers. 2004. *IEEE Guide for Electric Power Distribution Reliability Indices*. IEEE Std. 1366-2003 (Revision of IEEE Std. 1366-1998), New York City, New York.

IEEE - Institute of Electrical and Electronics Engineers. 2014. *IEEE Guide for Collecting, Categorizing, and Utilizing Information Related to Electric Power Distribution Interruption Events*. IEEE Std. 1782-2014, New York City, New York.

Itron. 2015. Accessed March 18, 2015 at https://www.itron.com/na/pages/default.aspx.

Lower Valley Energy. 2013. Lower Valley Energy. Jackson, Wyoming. City of Milton-Freewater, Milton-Freewater, Oregon. Accessed November 4, 2013 at http://www.lvenergy.com.

Lower Valley Energy. 2015. Lower Valley Energy Service Territory. Accessed June 12, 2015 at http://www.lvenergy.com/wp-content/uploads/LVE_Service_Territory2-2.pdf.

Melton RB and DJ Hammerstrom. 2011. *Transactive Control of Distributed Energy Resources*. PNNL-SA-84354, Battelle Memorial Institute, Richland, Washington, at Grid-Interop 2011, Phoenix, Arizona, December 5-9, 2011. Accessed January 16, 2015 at http://www.pointview.com/data/2011/12/53/pdf/Ron-Melton-OVBTIPYV-13819.pdf.

Melton RB and DJ Hammerstrom. 2012. *Pacific Northwest Smart Grid Demonstration Project: Technical Status Update for GWAC Transactive Energy Workshop*. PNWD-SA-9681, Battelle Memorial Institute, Richland, Washington. Accessed January 16, 2015 at http://www.gridwiseac.org/pdfs/tew_2012/presentations/meltonpres_tew12.pdf.

Melton RB and DJ Hammerstrom. 2014. "Distributed Resource Integration with Transactive Control." *IEEE Smart Grid Newsletter*. June 2014. Accessed January 16, 2015 at http://smartgrid.ieee.org/june-2014/1112-distributed-resource-integration-with-transactive-control.

Melton RB. 2013. "Transactive Control in the Pacific Northwest Smart Grid Demonstration." Presentation, *Trustworthy Cyber Infrastructure for the Power Grid (TCIPG), Information Trust Institute*. Urbana, Illinois, May 3, 2013. Accessed January 16, 2015 at http://tcipg.org/events/seminars/transactive-control-pacific-northwest-smart-grid-demonstration.

Miller J. 2008. "Smart Grid Metrics: Monitoring Our Progress." Presented at the *Smart Grid Implementation Workshop*, June 19, 2008 suggested metric fraction of time transmission loaded >90% capacity.

MultiSpeak. 2015. *MultiSpeak®: Software Interoperability Made Easier*. Accessed June 12, 2015 at http://www.multispeak.org/Pages/default.aspx.

NERC - North American Electric Reliability Council. 2014. Additional Off-Peak Days (aka "Holidays"). Accessed April 14, 2014 at http://www.nerc.com/comm/OC/RS%20Agendas%20Highlights%20and%20Minutes%20DL/Additional_Off-peak_Days.pdf.

NorthWestern Energy. 2013. Northwestern Energy. Sioux Falls, South Dakota. Accessed November 4, 2013 at http://www.northwesternenergy.com/home.

Osborn M, J Heimensen, K Kaufmann, J Lovinger, E Lovro, and C von Reis. 2013. *Executive Summary: Opportunities and Challenges for Portland General Electric's Salem Smart Power Project (SSPP): An Evaluation of the SSPP's Potential System Benefits, Cost-Effectiveness, and Market Participation*. White paper, Portland General Electric, Portland, Oregon. Accessed January 27, 2015 at http://lklaw.com/opportunities-and-challenges-for-portland-general-electrics-salem-smart-power-project-sspp/.

Peninsula Light Company. 2013. Peninsula Light Co. Peninsula Light Company, Gig Harbor, Washington. Accessed November 4, 2013 at http://www.penlight.org/power-resources/.

PNWSGD – Pacific Northwest Smart Grid Demonstration. 2011. *Pacific Northwest Smart Grid Demonstration: Interoperability and Cyber Security Plan, Revision 3*. PNWD-4238, Battelle Memorial Institute, Richland, Washington.

PNWSGD – Pacific Northwest Smart Grid Demonstration. 2013a. *Pacific Northwest Smart Grid Demonstration: Metrics and Benefits Reporting Plan, Revision 3.2*. PNNL-22261 Rev. 3.0, Battelle Memorial Institute, Richland, Washington.

PNWSGD – Pacific Northwest Smart Grid Demonstration. 2013b. *Pacific Northwest Smart Grid Demonstration: Transactive Coordination Signals, Revision X*. PNWD-4402, Battelle Memorial Institute, Richland, Washington.

PNWSGD – Pacific Northwest Smart Grid Demonstration. 2015. *Pacific Northwest Smart Grid Demonstration: Conceptual Design, Revision 1.1*. PNWD-4440, Battelle Memorial Institute, Richland, Washington.

Popular Science. 2014. *Best of What's New 2011: Windtronics Honeywell Wind Turbine*. Accessed November 14, 2014 at http://www.popsci.com/bown/2011/product/windtronics-honeywell-wind-turbine.

Port of Whitman. 2014. Accessed March 20, 2015 at http://portwhitman.com/.

Portland General Electric. 2013. Portland General Electric. Portland, Oregon. Accessed November 4, 2013 at http://www.portlandgeneral.com/default.aspx.

Portland General Electric. 2015. Accessed at https://www.portlandgeneral.com/residential/default.aspx.

Portland General Electric. March 2014. *Salem Smart Power*[SM] *Project—OPUC, ODOE Workshop*. Slide presentation March 2014. Accessed January 13, 2015 at http://www.oregon.gov/energy/docs/Energy%20Storage/WayneLei_Salem%20Smart%20Power_PGE.pdf

R Core Team. 2013. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria. Accessed at http://www.R-project.org/.

Regional Technical Forum. 2015. "Automated Conservation Voltage Regulation (CVR) and Voltage Optimization." *Northwest Power and Conservation Council Regional Technical Forum*. Accessed April 27, 2015 at http://rtf.nwcouncil.org/subcommittees/cvr/.

RTF CVR Subcommittee. 2012. CVR Standard M&V Protocol #1 (Draft – May 15, 2012, revised January 24, 2012) Accessed February 22, 2015 http://rtf.nwcouncil.org/subcommittees/cvr/Draft_CVR%20Protocol%20wEfficiency.docx.

Schwartz L. 2010. *Is It Smart If It's Not Clean? Strategies for Utility Distribution Systems, Part 1*. Publication of the Regulatory Assistance Project (RAP). Accessed December 4, 2014 at http://www.raponline.org/document/download/id/656.

SEL - Schweitzer Engineering Laboratories. 2015. Accessed March 18, 2015 at https://www.selinc.com/.

Sensus. 2015. FlexNet™ Advanced Metering Infrastructure System (AMI). Accessed March 4, 2015 at http://sensus.com/web/usca/product?division_id=electric&product_line_id=smart-grid-communications-network&product_id=flexnet-ami-system.

Southwest Windpower. 2012. Skystream 3.7: The Original Skystream Personal Wind Turbine. Southwest Windpower, Inc. Broomfield, Colorado. Accessed September 20, 2013 at http://skystreamenergy.com/products/skystream/skystream-3.7.

Spirae, Inc. 2015. Accessed April 7, 2015 at http://www.spirae.com/.

Sullivan MJ, M Mercurio, and J Schellenberg. 2009. *Estimated Value of Service Reliability for Electric Utility Customers in the United States*. LBNL-2132E. Ernest Orlando Lawrence Berkeley National Laboratory. Berkeley, California. Accessed January 15, 2015 at http://emp.lbl.gov/sites/all/files/REPORT%20lbnl-2132e.pdf.

Survalent Technology. 2015. SmartSCADA. Accessed March 3, 2015 at http://survalent.com/solutions/adms/scada.

Tangarie Alternative Power. 2013. *Gale Vertical Axis Wind Turbine*. Tangarie Alternative Power, LLC. Vernon, Texas. Accessed September 20, 2013 at http://www.tangarie.com/products/gale_vertical_axis_wind_turbine.php.

Tendril. 2014. Tendril. Boulder, Colorado. Accessed September 10, 2014 at http://www.tendrilinc.com/.

University of Washington Facilities Services. 2011. *University of Washington Facilities Services*. Campus Engineering and Operations. Seattle, Washington. Accessed November 4, 2013 at http://www.washington.edu/facilities/ops.

Urban Green Energy. 2015. Accessed January 8, 2015 at http://www.urbangreenenergy.com/.

Ventera Wind. 2015. Product Specs: Ventera VT10—240 Specifications. Accessed January 8, 2015 at http://www.venterawind.com/product/product-specs/.

Whitener K, S Chandler, M Phan, L Beckett, C Mills, D Garcia, R Bass, W Sanders, and W Lei. 2014. *Salem Smart Power Project Acceptance Test Documentation and Results: Pacific Northwest Smart Grid Demonstration Project*. Acceptance testing report, Portland General Electric, Portland, Oregon.

Windspire Energy, Inc. 2010. The Windspire. Windspire Energy, Inc. Reedsburg, Wisconsin. Accessed September 20, 2013 at http://www.windspireenergy.com/windspire/.

WindTronics Energy Solutions, Inc. 2013. WindTronics Wind Turbine – Model WT6500. WindTronics, Inc., Windsor, Ontario, Canada. Accessed September 20, 2013 at http://windtronics.com.tr/en/urunler/windtronics-ruzgar-turbini-model-wt6500/.

WindTronics Energy Solutions, LLC. 2013. WindTronics Europe. Accessed November 14, 2014 at http://www.windtronics.eu.com/.

Wing Power Energy. 2012. Wind: The most efficient energy producer. Wing Power Energy, Burlington, Massachusetts. Accessed September 26, 2013 at http://www.wingpowerenergy.com/products/wind/.

WISDM Corporation. 2003. *Developing Your Project's Mission Statement*. Volume 3, Spring 2003, Renton, Washington. Accessed January 16, 2015 at http://www.wisdm.com/spring2003.pdf.

WU - Wirtschaftsuniversitat Wien Institute for Statistics and Mathematics. 2014. The R Project for Statistical Computing. Accessed October 8, 2014 at http://www.r-project.org/.

ZigBee Alliance. 2014a. Zigbee® Alliance: Control your world™. Accessed August 16, 2014 at http://www.zigbee.org/.

ZigBee Alliance. 2014b. Smart Energy Profile 2: Greener homes, businesses and utilities. Accessed August 16, 2014 at http://www.zigbee.org/Standards/ZigBeeSmartEnergy/SmartEnergyProfile2.aspx.

Appendix A

Technical Documents Generated by the Pacific Northwest Smart Grid Demonstration

Appendix A

Technical Documents Generated by the Pacific Northwest Smart Grid Demonstration

The following annotated list presents technical design documentation of the Pacific Northwest Smart Grid Demonstration (PNWSGD) transactive system that was developed during the project. Documents that are unpublished have a footnote with author information. Battelle Memorial Institute or the listed authoring organization must be contacted if the reader requires access to unpublished documentation.

Transactive Node Framework and Toolkit Library Functions[1] − functional specification of a transactive node's computational framework. Includes a most general functional specification of toolkit functions and how they are integrated into this framework.

ALSTOM Toolkit Functional Description, Version 0.3[2] − as-built description of inputs requirements, available inputs, data assumptions, schedule formulation, operating limits, and modeling of the DC intertie by Alstom Grid's informed simulation that emulated the behaviors (transmission power flow, monetization of energy resources, and incentives) in the PNWSGD transmission region.

Transactive Coordination Signals (Battelle Memorial Institute 2013) − PNWSGD report and deliverable to the U.S. Department of Energy that explains important features of the project's transactive system. Two classes of transactive signals, the two types of system node sites in the project, signal timing, toolkit functions, and the nature of the system's predictive time domain are all explained. Skeleton models of the transactive node object are presented and explained.

Smart Grid Project-Level Infrastructure: Functional Requirements Specification, Level 1, Version 1.0[3] (unpublished) − specification of the transactive system that was produced through the project participants' collaboration and using the system requirements and process modeling methodology (WISDM) process that was developed by H Blair Burner (WISDM Corporation 2003). This document includes the project's justification for its mapping of transmission zones, an early interconnectivity map showing the initial connections between system nodes, and the functional requirement specifications for many system objects.

---

[1] DJ Hammerstrom. 2011. *Pacific Northwest Smart Grid Demonstration: Transactive Node Framework and Toolkit Library Functions, Version 1.0*. Unpublished specification, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington, March 3, 2012.

[2] Alstom Grid. 2014. *PNWSGD ALSTOM Toolkit Functional Description, Version 0.3*. Alstom Grid, 10865 Willows Road NE, Redmond, Washington 98033, September 9, 2014, unpublished.

[3] Battelle Memorial Institute. 2014. *Smart Grid Project-Level Infrastructure: Functional Requirements Specification, Level 1, Version 1.0*. Unpublished specification, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, March 26, 2014.

Regional and Subproject Transactive Control Nodes and Network Topology, Version 1.2[1] − definitive map of transactive system nodes and their interconnectivity.

3TIER As-Built Documentation[2] − documents 3TIER wind data and data feeds that were made available to the project concerning predicted and actual wind generation in the region.

Design/As-Built Documentation BPA Data Feed for the Transactive Coordination System (TCS) of the Pacific Northwest Smart Grid Demonstration (PNWSGD) Project, Version 1.0[3] − detailed descriptions of data that were made available to the project by Bonneville Power Administration (BPA). The data includes exemplary NETMOM (Alstom data set) files, up to 10 other files in csv format, and the data processes by which the data was securely made available to Alstom Grid for the purposes of the operating the transmission zones of the project's transactive system. These files facilitated the project's tracking of system load and resource scheduling.

PNW Certification Authority Design Document, Version 1.2[4] − provides the design for the setup and operation of a common X509 Certification Authority for the trial period of the PNWSGD project.

Pacific Northwest Smart Grid Demonstration Project: Conceptual Design, Revision 1 (Hammerstrom 2010) − early conceptual design that guided development of the transactive system.

Pacific Northwest Smart Grid Demonstration Project: Interoperability and Cyber Security Plan, Revision 3 (Battelle 2011) − presents the interoperability and cyber security plan for the PNWSGD project. The interoperability and cyber security aspects of the demonstration are addressed in three areas: interoperability and cyber security of the project-level infrastructure, interoperability and cyber security of the utility subproject participants, and cyber security of the project collaboration environment and documents.

PNWSGD Project: Implementation Design of Transactive Node, Version 2.3[1] − includes system definitions at a level needed for runtime system design.

[1] M Yao. 2014. *Regional and Subproject Transactive Control Nodes and Network Topology, Version 1.2*. Unpublished design document, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, 2014.

[2] A Vandervoort. 2013. *Design/As-Built Documentation, 3TIER System, Version 1.0*. Unpublished document, 3TIER, Inc., 2001 6th Avenue, Suite 2100, Seattle, Washington 98121, June 14, 2013.

[3] Bonneville Power Administration (BPA). 2014. *Design/As-Built Documentation BPA Data Feed for the Transactive Coordination System (TCS) of the Pacific Northwest Smart Grid Demonstration (PNWSGD) Project, Version 1.0*. Unpublished document, Bonneville Power Administration, Portland, Oregon, 97218, 2015.

[4] M Steiner. 2011. *PNW Certification Authority Design Document, Version 1.2*. Unpublished specification, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, September 8, 2011.

Pacific Northwest Smart Grid Demonstration: Transactive Control System Data Collection, Version 1.1[2] − identifies five data buffers that should be maintained at system nodes and defines their contents that must be collected to conduct the analysis of the PNSGD.

PNW Smart Grid Demonstration Project: Conformance Test Specification, Version 2.7[3] − documented conformance tests for project node software implementations.

PNW Smart Grid Demonstration Project: Interoperability Test Specification, Version 1.1[4] − describes the methodology used for interoperability testing of nodes within the PNSGD project.

Pacific Northwest Smart Grid Demonstration: InfoSphere Streams Subsystem Integration Design Specification, Version 3.0[5] − covers the usage of IBM's product InfoSphere Streams within Release Cycle 1 of the PNWSGD. In particular, the current plan is for the use of Streams version 1.2.0.1.

Pacific Northwest Smart Grid Demonstration: InfoSphere Streams System Test Plan, Version 2.0[6] − plan for system testing what will be the implementation of the design described in the PNWSGD InfoSphere Streams Subsystem Integration Design Specification. This document is a system test plan for the usage of IBM's InfoSphere Streams version 1.2.0.1 product within Release Cycle 1 of the PNWSGD project.

Pacific Northwest Smart Grid Demonstration: InfoSphere Streams Unit Test Plan[7] − plan for unit testing what was the implementation of the design described in the Pacific Northwest Smart Grid

---

[1] M Yao. 2012. *PNWSG Project: Implementation Design of Transactive Node, Version 2.3*. Unpublished design document, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, May 2, 2012.

[2] DJ Hammerstrom. 2011. *Pacific Northwest Smart Grid Demonstration: Transactive Control System Data Collection, Version 1.1*. Unpublished specification, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, December 20, 2011.

[3] L Rankin and G Cooper. 2011. *PNW Smart Grid Demonstration Project: Conformance Test Specification, Version 2.7*. Unpublished specification, QualityLogic, Inc., 5401 Tech Circle, Moorpark, California 93021.

[4] G Cooper, S Kang, L Rankin. 2011. *PNW Smart Grid Demonstration Project: Interoperability Test Specification, Version 1.1*. Unpublished specification, QualityLogic, Inc., 5401 Tech Circle, Moorpark, California 93021.

[5] MA Cohen. 2011. *Pacific Northwest Smart Grid Demonstration: InfoSphere Streams Subsystem Integration Design Specification, Version 3.0*. Unpublished design specification, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, April 28, 2011.

[6] MA Cohen. 2011. *Pacific Northwest Smart Grid Demonstration: InfoSphere Streams System Test Plan, Version 2.0*. Unpublished test plan, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, April 28, 2011.

[7] MA Cohen. 2011. *Pacific Northwest Smart Grid Demonstration: InfoSphere Streams Unit Test Plan*. Unpublished test plan, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, October 11, 2011.

Demonstration Release Cycle 2 Real-Time Data Collection Management Design Specification. This document is a unit test plan for the usage of the data mediation from the Data Collection System to the Netezza data warehouse via IBM's InfoSphere Streams version 2.0 product within Release Cycle 2 of the PNWSGD project.

PNW Smart Grid Project Name Spaces, Revision 2[1] − sub-document of the subsystem specification that was maintained separately to better facilitate any change in software object name spaces.

Pacific Northwest Demonstration Project: Test Plan and Requirements, Version 1.0[2] − describes the plan, strategy and methods used for functional conformance and interoperability testing of transactive nodes that are the fundamental building blocks used in a hierarchical transactive control system. Based on this strategy, requirements such as software or system management capabilities are described.

Pacific Northwest Smart Grid Demonstration Project: Subproject Implementation User's Guide, Version 0.9[3] − user's guide for project sites intending to implement an instantiation of one of the project's transactive nodes. Includes pointers to a reference node implementation, signal schema, system state model, and toolkit functions. Describes required conformance testing.

Toolkit Function Implementation User Guide, Version 0.11[4] − provides major updates to three groups of toolkit functions for system implementers.

Resource or Incentive Toolkit Function 2.1: Wind Energy[5] − as-built specification of how wind energy and its monetization were included in the PNWSGD transactive system.

Resource or Incentive Toolkit Function 2.3: Hydropower[1] − as-built specification of how hydropower energy and its monetization were included in the PNWSGD transactive system.

---

[1] A Webb. 2010. *PNW Smart Grid Project Name Spaces, Revision 2*. Unpublished specification, International Business Machines Corporation, TJ Watson Research Center, Yorktown Heights, New York 10598, December 2, 2010.

[2] G Cooper, S Kang, and L Rankin. 2011. *Pacific Northwest Demonstration Project: Test Plan and Requirements, Version 1.0*. Unpublished test plan, QualityLogic, Inc., 5401 Tech Circle, Moorpark, California 93021.

[3] L Connell. 2012. *Pacific Northwest Smart Grid Demonstration Project: Subproject Implementation User's Guide, Version 0.9*. Unpublished user guide, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, November 11, 2012.

[4] Battelle Memorial Institute (Battelle). 2013. *Toolkit Function Implementation User Guide, Version 0.11*. Unpublished user guide, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, October 20, 2013.

[5] Battelle Memorial Institute (Battelle). 2014. *Resource or Incentive Toolkit Function 2.1: Wind Energy, Version 0.7*. Unpublished design specification of the Pacific Northwest Smart Grid Demonstration, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, April 9, 2014.

Resource or Incentive Toolkit Function 3.0: Fossil Generation[2] − as-built specification of how thermal energy and its monetization were included in the PNWSGD transactive system.

Resource or Incentive Toolkit Function 4.0: General Infrastructure Cost[3] – as-built specification of how the costs of infrastructure were included in the PNWSGD transactive system.

Resource or Incentive Toolkit Function 5.1: Transmission Flowgate[4] − specification of how the cost impacts of transmission load at flowgates were formulated for the PNWSGD transactive system. This toolkit function was never successfully deployed due to its unstable behaviors.

---

[1] Battelle Memorial Institute (Battelle). 2014. *Resource or Incentive Toolkit Function 2.3: Hydropower, Version 0.7*. Unpublished design specification of the Pacific Northwest Smart Grid Demonstration, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, April 1, 2014.

[2] Battelle Memorial Institute (Battelle). 2014. *Resource or Incentive Toolkit Function 3.0: Fossil Generation*, *Version 0.4*. Unpublished design specification of the Pacific Northwest Smart Grid Demonstration, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, April 3, 2014.

[3] Battelle Memorial Institute (Battelle). 2014. *Resource or Incentive Toolkit Function 4.0: General Infrastructure Cost*, *Version 1.4*. Unpublished design specification of the Pacific Northwest Smart Grid Demonstration, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, April 2014.

[4] Battelle Memorial Institute (Battelle). 2014. *Resource or Incentive Toolkit Function 5.1: Transmission Flowgate*, *Version 0.3*. Unpublished design specification of the Pacific Northwest Smart Grid Demonstration, Battelle Memorial Institute, Pacific Northwest Division, Richland, Washington 99352, April 4, 2014.

Appendix B

Regional and Subproject Transactive Nodes and Network Topology

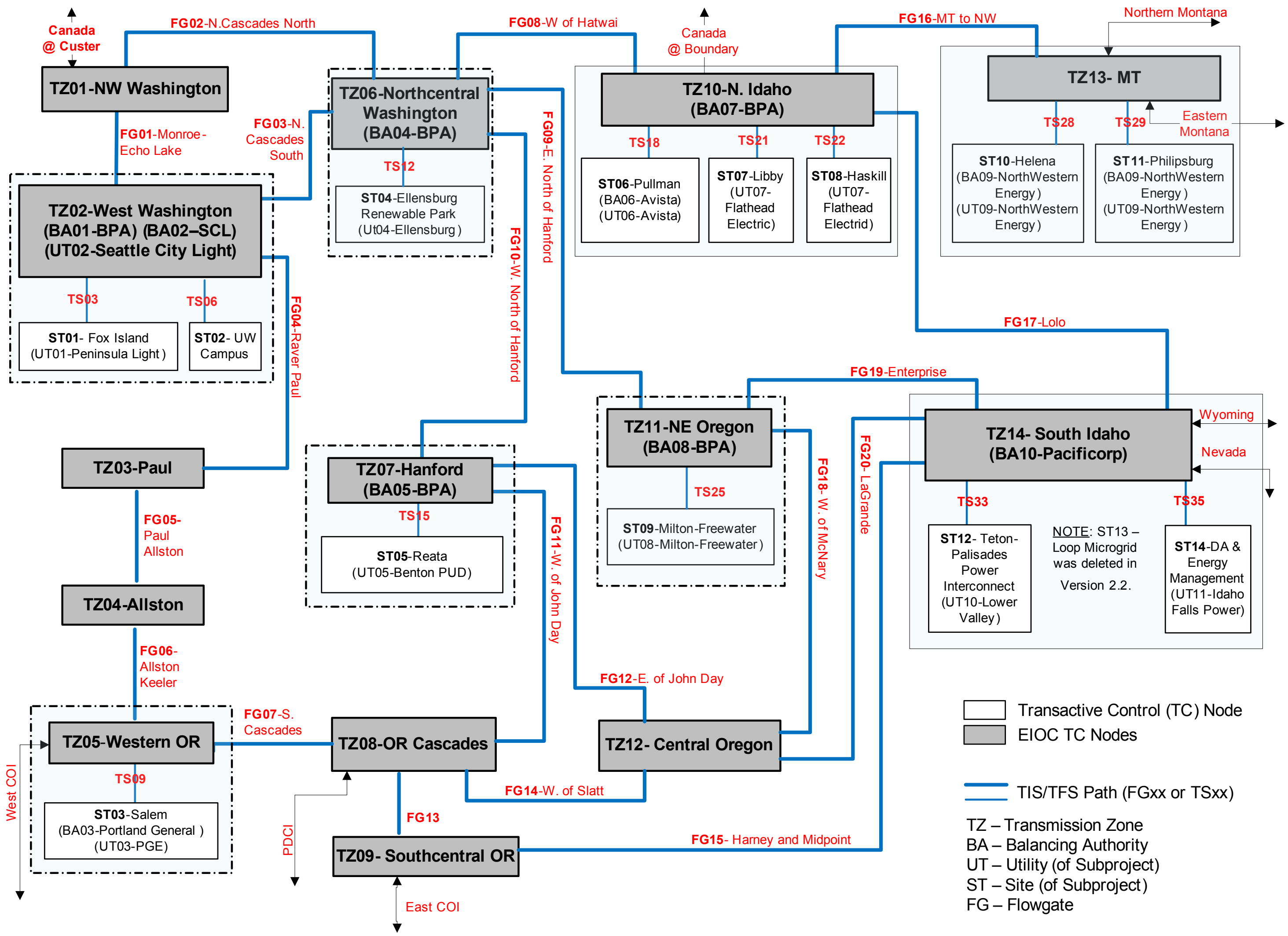


Figure B.1. Regional and Subproject Transactive Nodes and Network Topology

Appendix C

Bonneville Power Administration Tiered Rate Methodology

Appendix C

Bonneville Power Administration Tiered Rate Methodology

The value of energy and peak capacity at utilities that are Bonneville Power Administration (BPA) customers may be evaluated based on BPA Tiered Rates Methodology (BPA TRM BP-12-A-03). While the entire methodology is very complex and includes many rate categories, the differential monetized values of energy and capacity at these utilities is estimated well from BPA load-shaping rates and demand rates.

Heavy-Load Hours and Light-Load Hours

A time-of-use type of price signal is sent to BPA customers by the differentiation of heavy-load hours (HLHs) and light-load hours (LLHs). Heavy-load hours are hours from 06:00 until 22:00 Pacific Time, excluding Sundays and six North American Electric Reliability Council holidays: New Year's Day, Christmas Day, Labor Day, Thanksgiving Day, Memorial Day, and Independence Day (NERC 2014). All other hours are LLHs.

Load-Shaping Rates

The energy rates shown in Table C.1 and Table C.2 apply to Tier 1 electricity supply at many BPA customer utilities in the Northwest.

Table C.1. BPA Load-Shaping Rates from October 1, 2011 through September 2013 (BPA 2012 Power Rates Schedules and General Rate Schedule Provisions)

	Load-Shaping Rate	
Month	HLH ($/kWh)	LLH ($/kWh)
Oct	0.03786	0.03120
Nov	0.03837	0.03140
Dec	0.04110	0.03339
Jan	0.04003	0.03170
Feb	0.04093	0.03317
Mar	0.03957	0.03233
Apr	0.03753	0.03041
May	0.03506	0.02440
Jun	0.03597	0.02302
Jul	0.04207	0.02991
Aug	0.04435	0.03215
Sep	0.04345	0.03359

Table C.2. BPA Load-Shaping Rates from October 1, 2013 through September 2015 (BPA 2014 Power Rates Schedules and General Rate Schedule Provisions)

	Load-Shaping Rate	
Month	HLH ($/kWh)	LLH ($/kWh)
Oct	0.03159	0.02743
Nov	0.03556	0.03127
Dec	0.03884	0.03327
Jan	0.03780	0.03067
Feb	0.03689	0.03060
Mar	0.03023	0.02510
Apr	0.02576	0.02012
May	0.02100	0.01308
Jun	0.02273	0.01457
Jul	0.03049	0.02450
Aug	0.03396	0.02709
Sep	0.03365	0.02790

Demand Rates

For most utilities that are BPA customers, the demand rates shown in Table C.3 and Table C.4 apply. The demand billing determinant is calculated as the highest hourly power purchase amount during the HLH in a calendar month, less the average power purchased during all HLHs in the month, less a grandfathered amount that has been determined from the particular utility's performance in prior years. Demand charges apply in any month in which the calculated billing determinant is a positive value.

The first two terms may be known from a utility's hourly distribution power data for the month. These first two terms are most important for assessing a differential impact from demand charges. The third term is important for calculating a month's demand charges, but it may often be ignored when comparing alternative scenarios.[1]

[1] More detailed analysis is necessary if the determinant is often near to and less than zero.

Table C.3. BPA Demand Rates from October 1, 2011 through September 2013 (BPA 2012 Power Rates Schedules and General Rate Schedule Provisions)

Month	Demand Rate ($/kW/month)
Oct	9.18
Nov	9.31
Dec	9.97
Jan	9.70
Feb	9.92
Mar	9.60
Apr	9.10
May	8.50
Jun	8.72
Jul	10.20
Aug	10.75
Sep	10.53

Table C.4. BPA Demand Rates from October 1, 2013 through September 2015 (BPA 2014 Power Rates Schedules and General Rate Schedule Provisions)

Month	Demand Rate ($/kW/month)
Oct	9.33
Nov	10.50
Dec	11.47
Jan	11.17
Feb	10.90
Mar	8.93
Apr	7.61
May	6.20
Jun	6.72
Jul	9.01
Aug	10.03
Sep	9.94

Appendix D

Flathead Electric Company 2014 Peak Time Demonstration Project Member Survey Results

Appendix D: Flathead Electric Company 2014 Peak Time Demonstration Project Member Survey Results

Teri Rayome Kelly, Demand Response Coordinator
Flathead Electric Cooperative, Inc.
121 W 4th ST, Libby MT 59923

September 24, 2014

In 2009 Flathead Electric Cooperative had the opportunity to join with Bonneville Power Administration and eleven other utilities in the Pacific Northwest Smart Grid Demonstration Project to investigate the cost effectiveness of smart grid technology. The project was dubbed the Peak Time Demonstration Project and included 341 participants from Flathead's Libby, Marion and Kila service areas in the height of the project. Flathead's objectives included completing installation of the advanced metering infrastructure in Northwest Montana, determining member preferences and comparing the cost effectiveness of three program options offered to members who volunteered.

The current pilot project will end September 1, 2014 and Flathead chose to conduct a survey of participants of the project. In May of 2014 Flathead Electric mailed the survey to the remaining 302 participating members of its Peak Program. Of those surveys, 191 or 63% were completed and returned. The survey itself was designed to gather basic information on the dwelling such as square footage, heat source, energy saving structural updates completed during the project, type of home, etc., as well as potential changes in behavior the member could identify.

Flathead also felt it was important to offer the opportunity for feedback from the participating members so comment sections were included and encouraged. Some of the comments are relevant to the questions while others include additional or non-relevant information. All comments were included in the results and follow up calls were done with members as needed to address questions or concerns noted in the comments.

D.1 Method of Evaluation

In order to record and compile results of the survey, Flathead used a simple spreadsheet. The responses to each survey were entered on an individual sheet and then a basic formula was used on a summary sheet that calculated and compiled all responses. Each response was given a "1" in the correlating answer section and then added into the main sheet. In responses for water heater size and thermostat settings, each response was entered on an individual's sheet and then averaged on the main sheet.

The data was also broken into which equipment group the participant was in as well as what geographical location they were located in. While participants had the opportunity to identify themselves in the survey, this was not required in order to participate. Not all participants chose to answer all of the questions, which is reflected in the results in the Cumulative Survey Results. Although directed to choose only one answer on many of the questions, some participants chose more than one answer. For instance, when asked to choose one type of secondary heat source that was used in the home, the member listed two types of secondary heat source because the member uses multiple heat sources in different parts of the home.

The data in the following table, Table D.1: Method Example, is populated using the individual answers listed on each survey response. Each response asked for one answer, and if the member identified themselves in the survey then the geographical location was also entered. Members were also given the choice to identify which equipment group they were in. The individual sheet was populated in this method. If the member identified themselves as living in Libby, participating in the IHD group, and using electric baseboard heat as their main source of heat, then a number "1" was placed in the corresponding column.

Table D.1. Method Example

My home's main heating system is: (Check one)	IHD	DRU	Appliance	Unknown	Libby	Haskill	Unknown
Electric, central forced air							
Electric baseboard	1				1		
Electric heat pump, central forced air							
Electric radiant heating							
Portable electric heater(s)							
Oil, or propane central forced air							
Woodstove, fireplace or pellet							
Other (describe)							

D.2 Calculated Percentages

In addition to the findings in the Cumulative Survey Results, Flathead was interested in individual response results, shown below in Table D.2: Results by Percentage. This data gives us a more general picture of various aspects of the members' home and life, and what kinds of changes they potentially made that were unrelated to location or group.

For example, the percentage of members using some type of electric heat source as their main source of heat was calculated. One hundred seventeen of the 200 responses received, or 58%, indicated that they used electric heat as their main source of heat. Electric heat on the survey included electric central forced air, baseboard, heat pump, radiant heating and portable electric heaters. The remaining 42% heated their homes by means other than electric heat.

Table D.2. Results by Percentage

Main source of heating:	
Electric - electric central forced air, baseboard, heat pump, radiant heating and portable electric heater	58%
Other - oil or propane forced air, woodstove, fireplace or pellet stove and other non-electric heat	42%
Programmable thermostat in the home:	
YES	50%
NO	44%
No thermostats available	6%
Has the home heating system had changed during the course of the program:	
YES	19%
NO	71%
Unsure	6%
I have changed the way they manage their heat since participating in the Peak Program:	
rarely/never	38%
sometimes/occasionally	26%
most of the time	23%
definitely all the time	13%
Household temperature in winter:	
average daytime temperature	60°F
average nighttime temperature	57°F
Do not have a thermostat	9%
Have a source of electric cooling: including heat pump, central forced air, wall or window unit(s) or other	53%
No source of electric cooling using other methods: such as opening windows at night for air circulation	47%
Household temperature in summer:	
average daytime temperature	64°F
average nighttime temperature	65°F
I have changed the way they manage their cooling since participating in the Peak Program:	
rarely/never	64%
sometimes/occasionally	13%
most of the time	14%
definitely all the time	9%
Type of home:	
House	88%
Duplex/townhouse or apartment	11%
Manufactured or mobile home	4%
Have you made structural upgrades to your home including:	
YES	58%
NO	42%
If YES, type of improvement:	
Attic insulation upgrades	67%
Crawl space insulation upgrades	27%
Window replacement	68%
Manufactured home duct sealing	5%
Other improvements	15%
How many of the following appliances do you own:	
Refrigerator	250
# of units per household	1.3
Freezer	215
# of units per household	1.13

Main source of heating:	
Clothes washer	184
# of units per household	.96
Clothes dryer	182
# of units per household	.95
Dishwasher	154
# of units per household	.80
Stove/range	189
# of units per household	.99
Microwave oven	189
# of units per household	.99
Hot tub/spa	31
# of units per household	.16
Made changes in my schedule when using this appliance as a result of participating in the Peak Program for the following appliances	
Dishwasher	48%
Stove/range	12%
Laundry washer/dryer	54%
Remaining appliance including microwave ovens, TVs and hot tubs	7%
Total Number of electric water heaters reported	203
# of units per household	1.07
Average size for first water heater	45 gallons
Average size for second water heater	50 gallons
Total Number of propane water heaters reported	3
Members that have at least one electric water heater were asked if they would participate in an on-going program to decrease demand at critical peak periods in an effort to reduce costs to Flathead Electric.	
Would participate	88%
Would not participate	9%
Did not answer	5%
Household has made changes in the times we shower (or bathe) as a result of participating in the Peak Program	
YES	25%
NO	75%
Has the household had the Free Home Energy Audit offered by Flathead	
YES	30%
NO	70%
Would participants choose to participate in a similar pilot program again	
YES	97%
NO	3%
Would participants recommend the pilot to a friend or neighbor	
YES	97%
NO	3%
Geographical location of responding participants:	
Libby	63%
Marion/Kila	14%
Unknown	23%
Study group of responding participants:	
Appliance group	38%
Water heater group	33%
In Home Display group	27%
Unknown	2%

D.3 Member Comments and Feedback

Numerous comments were submitted by members and were much appreciated by Flathead as it gave us the opportunity get a general sense of how our members felt about the project. Some of the comments received pertained to other areas of Flathead such as energy audits, usage or rebate questions. In such cases, if the member identified themselves, the information was made available to the appropriate department to enable staff to address those questions or comments.

The following comments are selected examples of feedback received from members:

"I liked the program but we constantly had problems with the in home display not working correctly. Changed the way we wash clothes, use the dryer and run the dishwasher. We tried to use non-peak times as much as we can." Appliance Group
"Didn't affect us at all! Nice program!" Water Heater Group
"This program is exceptional in getting people to adjust their behavior. I didn't think I would be able to run my household with hot water available only at certain times and cooking mostly at night. I learned how to use the timers on my dishwasher, oven and washing machine and used those off-hours. We set our hot water heater for 5hrs/day during the off-peak hours and got along just fine. And we were very surprised at the check in December for what we saved!" IHD Group
"The in-home display didn't do much, unfortunately. But it was good to know when there was a peak time." IHD Group
"We never noticed that the hot water heater was off. It is well worth participating in the program." Water Heater Group
"I didn't like when my washer/dryer or dishwasher wouldn't work at peak times" Appliance Group
"We have not received much information from our in home display. Being retired we have no problem working around peak time. As I understood using portable heaters we are not able to get home energy audit why?" IHD Group
"We never really even noticed the difference in the hot water from before the control switch was put in to after. I liked the fact that I was helping to conserve energy. I would be more interested in knowing when the peak times are so that we could be more proactive in conserving our energy." Water Heater Group

D.4 Cumulative Survey Results

Flathead used the simple spreadsheet in Cumulative Survey Results as a tool to record and compile survey responses. The spreadsheet used basic formulas and functions as discussed in the Method of Evaluation section to populate the Cumulative Survey Results, shown below.

My home's main heating system is: (Check one)	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**		**Total**	**% Libby**	**% Haskill**	**% Unknown**
Electric, central forced air	6	9	9	0	15	2	7	24	24	**Electric heat**	117	69%	10%	21%
Electric baseboard	10	5	6	1	14	2	6	22	22					
Electric heat pump, central forced air	13	24	23	2	45	7	10	62	62					
Electric radiant heating	2	1	1	0	2	1	1	4	4					
Portable electric heater(s)	3	2	0	0	5	0	0	5	5		**Total**	**% Libby**	**% Haskill**	**% Unknown**
Oil, or propane central forced air	8	11	11	0	20	3	7	30	30	**Other heat - not electric**	83	60%	19%	20%
Woodstove, fireplace or pellet	11	16	8	0	22	6	7	35	35					
Other (describe)	5	4	9	0	8	7	3	18	18					

My home's second heating system is: (Check all that apply)	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**		**Total 2nd electric heat**	**% Libby**	**% Haskill**	**% Unknown**
Electric, central forced air	3	5	3	1	6	2	4	12	12	**Second heat system electric heat**	90	59%	16%	26%
Electric baseboard	8	15	8	1	21	5	6	32	32					
Electric heat pump, forced air	1	5	4	0	7	1	2	10	10					
Electric radiant heating	2	4	1	0	4	0	3	7	7					
Portable electric heater(s)	6	14	8	1	15	6	8	29	29		**Total**	**% Libby**	**% Haskill**	**% Unknown**
Oil, or propane central forced air	10	9	10	0	24	2	3	29	29	**Second heat system - not electric**	116	66%	16%	17%
Woodstove or fireplace	18	17	28	0	38	12	13	63	63					
Other (describe)	10	7	7	0	15	5	4	24	24					

My home has a programmable thermostat: (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Program-mable Thermostat	Total	% Libby	% Haskill	% Unknown
Yes	25	32	36	1	65	12	17	94	94	**Yes**	94	69%	13%	18%
No	27	30	23	2	47	13	22	82	82	**No**	82	57%	16%	27%
Do not have a thermostat	3	3	5	0	8	2	1	11	11	**Do not have a thermostat**	11	73%	18%	9%

My home's heating system has changed during my participation in the Peak Program: (Check one).	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home's heating system has changed during my participation in the Peak Program	Total	% Libby	% Haskill	% Unknown
Yes	9	10	14	2	20	4	10	35	34	**Yes**	35	57%	11%	29%
No	41	48	48	1	89	22	26	138	137	**No**	138	64%	16%	19%
Unsure	4	4	3	0	8	0	3	11	11	**Unsure**	11	73%	0%	27%

I have changed the way I manage my heat since participation in the Peak Program: (Check one).	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	I have changed the way I manage my heat since participation in the Peak Program	Total	% Libby	% Haskill	% Unknown
Definitely all of the time	5	7	12	1	17	5	3	25	25	**Definitely all of the time**	25	68%	20%	12%
Most of the time	12	9	22	1	31	3	10	44	44	**Most of the time**	44	70%	7%	23%
Sometimes/ Occasionally	15	15	16	1	29	7	11	47	47	**Sometimes/ Occasionally**	47	62%	15%	23%
Rarely/Never	23	30	16	0	43	10	15	69	68	**Rarely/ Never**	69	62%	14%	22%

If you've changed how you manage your heat, please provide details:	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Provided details or comments for change in heating usage	Total	% Libby	% Haskill	% Unknown
	16	16	32	2	47	8	11	66	66	**Detailed provided**	66	71%	12%	17%

During the Summer (Jul-Aug) my thermostat setting during the: (Please fill in the box)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Average Summer Thermostat Setting	AVG TEMP	% Libby	% Haskill	% Unknown
Daytime is usually set at	65	64	64	68	58	7	22	88	87	**Daytime** is usually set at	65	32%	4%	12%
Night time heat is usually set at	63	62	63	68	54	6	19	79	79	**Night time** heat is usually set at	64	29%	3%	10%
Do not have a thermostat	3	9	5	0	11	4	2	17	17	Do not have a thermostat		6%	2%	1%

During the winter (Dec-Feb) my thermostat setting during the: (Please fill in the box)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Average Winter Thermostat Setting	AVG TEMP	% Libby	% Haskill	% Unknown
Daytime is usually set at	68	69	67	34	106	22	35	168	163	**Daytime** is usually set at	60	31%	6%	10%
Night time heat is usually set at	65	65	65	34	104	22	34	165	160	**Night time** heat is usually set at	57	30%	6%	10%
Do not have a thermostat	3	6	4	0	7	4	2	13	13	Do not have a thermostat		2%	1%	1%

My home has ____ thermostat(s) (Check one).	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home has ____ thermostat(s) (Check one).	Total	% Libby	% Haskill	% Unknown
1	30	39	33	1	64	14	25	103	103	1	103	62%	14%	24%
2	7	9	5	0	17	1	3	21	21	2	21	81%	5%	14%
more than 2	12	11	22	1	31	8	7	46	46	more than 2	46	67%	17%	15%

My home's air conditioning system is a: (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home's air conditioning system is a:)	Total	% Libby	% Haskill	% Unknown
None	26	26	26	1	47	15	17	79	79	None	79	59%	19%	22%
Heat pump	16	24	27	2	48	8	13	69	69	Heat pump	69	70%	12%	19%
Central forced air	2	3	1	0	3	1	2	6	6	Central forced air	6	50%	17%	33%
Wall or window unit(s)	10	8	7	0	21	0	4	25	25	Wall or window unit(s)	25	84%	0%	16%
Other	2	4	3	0	5	3	1	9	9	Other	9	56%	33%	11%

I have changed the way I manage my home cooling since participation in the Peak Program (Check one).	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	I have changed the way I manage my home cooling since participation in the Peak Program	Total	% Libby	% Haskill	% Unknown
Definitely all of the time	2	5	6	2	13	0	2	15	15	Definitely all of the time	15	87%	0%	13%
Most of the time	6	5	11	0	15	3	4	22	22	Most of the time	22	68%	14%	18%
Sometimes/Occasionally	5	6	8	0	15	2	2	19	19	Sometimes/ Occasionally	19	79%	11%	11%
Rarely/Never	29	40	27	0	58	16	22	96	96	Rarely/ Never	96	60%	17%	23%

If you've changed how you manage your cooling, please provide details:	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	I have changed the way I manage my home cooling since participation in the Peak Program	Total	% Libby	% Haskill	% Unknown
	6	9	12	0	23	2	2	27	27	Responded	27	85%	7%	7%

My home is a: (Check one).	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home is a:	Total	% Libby	% Haskill	% Unknown
Trailer/Mobile Home	3	3	6	1	9	2	2	13	13	Trailer/Mobile Home	13	69%	15%	15%
Manufactured Home	4	3	0	0	5	0	2	7	7	Manufactured Home	7	71%	0%	29%
Apartment/ Condominium	1	0	0	0	0	0	1	1	1	Apartment/ Condominium	1	0%	0%	100%
Duplex/ Town-home	0	1	0	0	0	0	1	1	1	Duplex/ Townhome	1	0%	0%	100%
House	46	55	57	1	105	24	30	159	159	House	159	66%	15%	19%

My home's square footage is approximately (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home's square footage is approximate-ly	Total	% Libby	% Haskill	% Unknown
Less than 1,000 sq. ft.	5	7	1	0	7	2	4	13	13	Less than 1,000 sq. ft.	13	54%	15%	31%
1,000 – 1,499 sq. ft.	16	17	8	1	26	5	11	42	42	1,000 – 1,499 sq. ft.	42	62%	12%	26%
1,500 – 1,999 sq. ft.	11	19	23	1	40	5	9	54	54	1,500 – 1,999 sq. ft.	54	74%	9%	17%
2,000 – 2,499 sq. ft.	11	11	18	1	28	6	7	41	41	2,000 – 2,499 sq. ft.	41	68%	15%	17%
2,500 – 2,999 sq. ft.	5	4	6	0	9	2	4	15	15	2,500 – 2,999 sq. ft.	15	60%	13%	27%
3,000 – 3,499 sq. ft.	2	3	7	0	6	5	1	12	12	3,000 – 3,499 sq. ft.	12	50%	42%	8%
More than 3,500 sq. ft.	2	1	1	0	1	2	1	4	4	More than 3,500 sq. ft.	4	25%	50%	25%

My home has had the following structural energy upgrades (Check all that apply)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home has had the following structural energy upgrades	Total	% Libby	% Haskill	% Unknown
Insulation upgrade - attic	24	26	22	2	46	10	18	74	74	Insulation upgrade - attic	74	62%	14%	24%
Insulation upgrade – crawl space	11	12	6	1	22	3	5	30	30	Insulation upgrade – crawl space	30	73%	10%	17%
Window replacement	24	26	23	2	51	5	19	75	75	Window replacement	75	68%	7%	25%

Manufactured home duct sealing	3	2	1	0	2	2	2	6	6	Manufactured home duct sealing	6	33%	33%	33%
Other	6	4	7	0	12	1	4	17	17	Other	17	71%	6%	24%
Unsure	3	12	5	1	14	1	6	21	21	Unsure	21	67%	5%	29%

How many of the following appliances are in your home? (If non please list "0")	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**	**How many of the following appliances are in your home?**	**Total**	**% Libby**	**% Haskill**	**% Unknown**
Refrigerators	71	81	93	5	162	38	50	250	250	Refrigerators	250	65%	15%	20%
Freezers	59	69	84	3	144	29	40	215	213	Freezers	215	67%	13%	19%
Clothes washers	54	62	65	3	122	26	36	184	184	Clothes washers	184	66%	14%	20%
Clothes dryers	53	61	65	3	122	26	34	182	182	Clothes dryers	182	67%	14%	19%
Dishwashers	46	41	64	3	99	25	30	154	154	Dishwashers	154	64%	16%	19%
Stoves/ranges	54	64	68	3	125	27	37	189	189	Stoves/ranges	189	66%	14%	20%
Microwave ovens	55	63	67	4	124	27	38	189	189	Microwave ovens	189	66%	14%	20%
Hot tubs/spas	9	9	13	0	18	8	5	31	31	Hot tubs/spas	31	58%	26%	16%

I have made changes in my schedule when using this appliance as a result of participating in the Peak Program. (Check one for each appliance)	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**	**I have made changes in my schedule when using this appliance as a result of participating in the Peak Program.**	**Total**	**% Libby**	**% Haskill**	**% Unknown**
Dishwasher										Dishwasher				
Yes	21	15	48	1	59	11	16	85	86	Yes	85	69%	13%	19%
No	18	33	15	1	38	13	16	67	67	No	67	57%	19%	24%
Unsure	2	1	0	1	2	0	2	4	4	Unsure	4	50%	0%	50%

Stove/range										Stove/range				
Yes	8	6	6	1	13	3	5	21	21	Yes	21	62%	14%	24%
No	37	54	50	2	93	19	31	143	143	No	143	65%	13%	22%
Unsure	2	1	2	0	4	0	1	5	5	Unsure	5	80%	0%	20%
Laundry washer/dryer										Laundry washer/dryer				
Yes	28	15	50	2	63	10	22	95	95	Yes	95	66%	11%	23%
No	21	44	12	1	50	14	14	78	78	No	78	64%	18%	18%
Unsure	2	1	0	0	2	0	1	3	3	Unsure	3	67%	0%	33%
Microwave oven										Microwave oven				
Yes	4	2	4	1	5	2	4	11	11	Yes	11	45%	18%	36%
No	39	56	51	2	101	19	28	148	148	No	148	68%	13%	19%
Unsure	1	1	0	0	1	0	1	2	2	Unsure	2	50%	0%	50%

Personal computer										Personal computer				
Yes	3	2	5	0	5	1	4	10	10	Yes	10	50%	10%	40%
No	40	53	51	3	97	20	30	147	147	No	147	66%	14%	20%
Unsure	1	1	1	0	2	0	1	3	3	Unsure	3	67%	0%	33%

Large screen TV										Large screen TV				
Yes	3	2	3	0	5	1	2	8	8	Yes	8	63%	13%	25%
No	28	46	42	2	78	19	21	118	118	No	118	66%	16%	18%
Unsure	1	1	2	0	3	0	1	4	4	Unsure	4	75%	0%	25%
Regular TV										Regular TV				
Yes	5	1	4	1	6	1	4	11	11	Yes	11	55%	9%	36%
No	29	50	42	2	80	17	26	123	123	No	123	65%	14%	21%
Unsure	2	1	0	0	1	0	2	3	3	Unsure	3	33%	0%	67%

Hot tub/spa										Hot tub/spa				
Yes	1	2	1	1	1	2	2	5	5	Yes	5	20%	40%	40%
No	6	9	10	0	16	5	4	25	25	No	25	64%	20%	16%
Unsure	0	1	0	0	0	0	1	1	1	Unsure	1	0%	0%	100%

My home has ____ water heaters. (List how many waters heaters of each type)	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**	**My home has ____ water heaters. (List how many waters heaters of each type)**	**Total & AVG Cap-acity**	**% Libby**	**% Haskill**	**% Unknown**
Propane	2	0	1	0	3	0	0	3	3	Propane	3	100%	0%	0%
Electric	58	68	74	3	131	31	40	203	202	Electric	203	65%	15%	20%
Water heater capacity (gallons):	48	50	52	30	49	52	50	179	151	Water heater capacity (gallons):	45	110%	116%	111%
If you have more than one water heater please list additional capacity for each water heater below								**Group Total Answered**	**Location Total Answered**	If you have more than one water heater please list ad capacity below	**Total**	**% Libby**	**% Haskill**	**% Unknown**
Water heater capacity (gallons):	49	53	48	0	49	42	80	149	171	Water heater capacity (gallons):	50	99%	84%	161%
2nd Water heater count	8	4	9	0	15	5	1	21	21	2nd Water heater count	21	0%	0%	0%

My household has made changes in the times we shower (or bathe) as a result of participating in the Peak Program (Check one).	**IHD**	**DRU**	**Appli-ance**	**Unknown**	**Libby**	**Haskill**	**Unknown**	**Group Total Answered**	**Location Total Answered**	**My household has made changes in the times we shower (or bathe) as a result of participating in the Peak Program**	**Total**	**% Libby**	**% Haskill**	**% Unknown**
Yes	14	18	14	1	35	3	9	47	47	Yes	47	74%	6%	19%
No	41	47	51	4	82	24	31	143	137	No	143	57%	17%	22%

What other If you have at least one electric water heater in your home are you interested in participating in an ongoing program to decrease demand at critical peak periods in an effort to reduce costs to Flathead electric? (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	If you have at least one electric water heater in your home are you interested in participating in an ongoing program?	Total	% Libby	% Haskill	% Unknown
Yes	42	58	61	3	103	24	35	164	162	Yes	164	63%	15%	21%
No	9	6	2	1	10	2	6	18	18	No	18	56%	11%	33%

My home has had a Free Home Energy Audit thru Flathead Electric	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	My home has had a Free Home Energy Audit thru Flathead Electric	Total	% Libby	% Haskill	% Unknown
Yes	13	17	20	2	26	12	14	52	52	Yes	52	50%	23%	27%
No	39	43	36	2	83	14	20	120	117	No	120	69%	12%	17%

Which option did you participate in: (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Which option did you participate in:	Total	% Libby	% Haskill	% Unknown
In Home Display	56	0	3	2	35	6	18	61	59	In Home Display	61	57%	10%	30%
Water Heater Control Switch	0	67	1	1	41	10	18	69	69	Water Heater Control Switch	69	59%	14%	26%
Smart Grid Enabled Appliances	1	0	60	1	44	11	7	62	62	Smart Grid Enabled Appliances	62	71%	18%	11%

Would you choose to participate in a similar pilot program again? (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Would you choose to participate again?	Total	% Libby	% Haskill	% Unknown
Yes	53	62	61	4	110	26	42	180	178	Yes	180	61%	14%	23%
No	3	3	0	0	4	0	1	6	5	No	6	67%	0%	17%

If you chose “yes” and the program were offered again which option would you choose? (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	If you chose “yes” and the program were offered again which option would you choose?	Total	% Libby	% Haskill	% Unknown
In Home Display	37	12	22	2	44	8	21	73	73	In Home Display	73	60%	11%	29%
Water Heater Control Switch	14	43	18	2	45	10	19	77	74	Water Heater Control Switch	77	58%	13%	25%
Smart Grid Enabled Appliance	6	8	46	1	43	12	6	61	61	Smart Grid Enabled Appliance	61	70%	20%	10%

Would you recommend this program to a friend or neighbor? (Check one)	IHD	DRU	Appli-ance	Unknown	Libby	Haskill	Unknown	Group Total Answered	Location Total Answered	Would you recommend this program to a friend or neighbor?	Total	% Libby	% Haskill	% Unknown
Yes	51	62	63	4	110	26	42	180	178	Yes	180	61%	14%	23%
No	2	4	0	0	4	1	1	6	6	No	6	67%	17%	17%