Demand Response

Testing the Theoretical Basis for DR

FINAL REPORT | MAY 31, 2014

NRECA
A Touchstone Energy® Cooperative

CRN
Cooperative Research Network

Demand Response

Testing the Theoretical Basis for DR

FINAL REPORT | MAY 31, 2014

Prepared by

Craig Rizzo
Leidos (formerly SAIC)
Director of Microgrid Solutions
Leidos Engineering, LLC

Assisted by

Tom Lovas
Cooperative Research Network
National Rural Electric Cooperative Association
4301 Wilson Boulevard
Arlington, Virginia 22203-1860

for

U.S. DOE/NETL
Morgantown Campus
3610 Collins Ferry Road
PO Box 880
Morgantown WV 26507-0880

PROJECT MANAGER: CRAIG MILLER, PHD

PRINCIPAL INVESTIGATOR: TOM LOVAS

The National Rural Electric Cooperative Association

NRECA is the national service organization for more than 900 not-for-profit rural electric cooperatives and public power districts providing retail electric service to more than 42 million consumers in 47 states and whose retail sales account for approximately 12 percent of total electricity sales in the United States.

NRECA's members include consumer-owned local distribution systems — the vast majority — and 66 generation and transmission (G&T) cooperatives that supply wholesale power to their distribution cooperative owner-members. Distribution and G&T cooperatives share an obligation to serve their members by providing safe, reliable and affordable electric service.

About CRN

NRECA's Cooperative Research Network™ (CRN) manages an extensive network of organizations and partners in order to conduct collaborative research for electric cooperatives. CRN is a catalyst for innovative and practical technology solutions for emerging industry issues by leading and facilitating collaborative research with co-ops, industry, universities, labs, and federal agencies.

CRN fosters and communicates technical advances and business improvements to help electric cooperatives control costs, increase productivity, and enhance service to their consumer-members. CRN products, services and technology surveillance address strategic issues in the areas:

- Cyber Security
- Consumer Energy Solutions
- Generation & Environment
- Grid Analytics
- Next Generation Networks
- Renewables
- Resiliency
- Smart Grid

CRN research is directed by member advisors drawn from the more than 900 private, not-for-profit, consumer-owned cooperatives who are members of NRECA.

Contact Information

National Rural Electric Cooperative Association
Cooperative Research Network ™
4301 Wilson Boulevard
Arlington, VA 22203-1860
703.907.5500

Table of Contents

Page

FOREWORD iv

1.0 Introduction 1

2.0 Overview of NRECA SGDP Demand Response Projects 1

2.1 Description of Co-op Projects 1
2.2 Research Objectives – Economic Value and Consumer Presentment 2
2.3 Role of Demand Response in the 21st Century Co-op 2

3.0 Overview of Demand Response Programs 3

3.1 Applications 3
3.1.1 Peak Demand Reduction 3
3.1.2 System Reliability 3
3.1.3 Other DR Applications 3
3.2 DR Program Benefits 4
3.2.1 Avoided Capital Costs 4
3.2.2 Avoided Energy Costs 4
3.2.3 Other DR Benefits 5
3.3 Enabling Technologies 6
3.3.1 In-home Displays – Types and Information 6
3.3.2 Load Control Devices 7
3.3.3 Ancillary In-Home Devices 7
3.4 Demand Response Program Parameters 7
3.4.1 Financial 7
3.4.2 Temporal 8
3.4.3 Operational Conditions 8
3.4.4 Target Loads and Customer Groups 9
3.5 Success Metrics 9

4.0 Review of Previous Empirical Studies of Demand Response 13

4.1 Study Methodology 13
4.2 Results 14
4.2.1 Dynamic Pricing 14
4.2.2 Direct Load Control 16
4.2.3 Smart Appliances 18

5.0 Overview of Select Co-op DR Programs 18

5.1 Clarke Electric Cooperative 19
5.2 Flint 21
5.3 Corn Belt Cooperatives 22
5.4 Minnesota Valley Electric Cooperative 25
5.5 Delaware County Electric Cooperative 26

6.0 Review of Available Program Data 28

6.1 Study Data and Asset Tracking System (SDATS) 28
6.2 SDATS Data 28

6.2.1 Customer Systems Build Metric Data ... 28
6.2.2 AMI and Customer Systems Impact Metric Data ... 29
6.2.3 Meter Location Data ... 29
6.2.4 Meter Interval Data ... 29
6.2.5 DR Event Data ... 29
6.3 Data Quality Issues ... 30
6.3.1 Meter Location Data ... 30
6.3.2 Customer Load Data ... 30
6.3.3 Conclusions ... 31
7.0 Statistical and Econometric Analyses of Cooperative DR Program Data – Testing the Theoretical Basis for Demand Response ... 31
7.1 Testing the Theoretical Basis for Demand Response—Overview of Analysis Objectives ... 31
7.2 Analytical Approach and Data Sources ... 32
8.0 Statistical and Econometric Analysis Results ... 34
8.1 Summary of Findings ... 34
8.1.1 Clarke Electric Cooperative ... 36
8.1.2 Flint ... 37
8.1.3 Iowa Lakes ... 37
8.1.4 Prairie ... 38
8.1.5 Minnesota Valley Electric Cooperative ... 38
8.1.6 Delaware County Electric Cooperative ... 39
8.1.7 Overall Findings – Insights on the Theoretical Basis for DR ... 39
9.0 Observed Data Challenges and Issues—Econometric Analysis ... 41
10.0 Nexus between Analysis Results and DR Screening Tool ... 42
11.0 Lessons Learned ... 43
Appendix A: Demand Response Planning Model ... A-1
A.1 Purpose ... A-1
A.2 Model Overview ... A-2
A.3 Approach to Gathering Endogenous Model Inputs ... A-5
A.4 Model Architecture ... A-8
A.5 Approach to Gathering Endogenous Model Inputs ... A-15
A.6 Summary ... A-19

List of Figures

Page

Figure 1. Peak Reduction by Rate Type and Technology for Dynamic Pricing Pilots 14
Figure 2. Peak Reduction by Rate Type and Technology for Dynamic Pricing Pilots 15
Figure 3. Peak Reduction, by Rate Type and Technology for Dynamic Pricing Pilots 16
Figure 4. Comparison of Control vs. Non-Control Days with Similar Weather Conditions........ 36
Figure 5. Top-Level Demand Response Planning Model Architecture....................................... 42

List of Tables

Page

Table 1. Summary of Co-op DR Equipment Acquired..2
Table 2. Summary of Estimated Savings and Snapback − Residential...17
Table 3. Statistics of Meter Location and Interval Data Extraction from SDATS.........................29
Table 4. Summary of Research Objectives...32
Table 5. DLC Event Estimated kW Impacts—Water Heater Programs.......................................34
Table 6. DLC Event Estimated kW Impacts—AC Programs...34
Table 7. DLC Event Estimated kW Impacts—Combined AC & Water Heater Programs...........34

FOREWORD

The National Rural Electric Cooperative Association (NRECA) has organized the NRECA-U.S. Department of Energy (DOE) Smart Grid Demonstration Project (DE-OE0000222) to install and study a broad range of advanced Smart Grid technologies in a demonstration that involved 23 electric cooperatives in 12 states. For purposes of evaluation, the technologies deployed have been classified into three major sub-classes, each consisting of four technology types.

Enabling Technologies:	Advanced Metering Infrastructure Meter Data Management Systems Telecommunications Supervisory Control and Data Acquisition
Demand Response:	In-Home Displays & Web Portals Demand Response Over AMI Prepaid Metering Interactive Thermal Storage
Distribution Automation:	Renewables Integration Smart Feeder Switching Advanced Volt/VAR Control Conservation Voltage Reduction

To demonstrate the value of implementing the Smart Grid, NRECA has prepared a series of single-topic studies to evaluate the merits of project activities. The study designs have been developed jointly by NRECA and DOE. This document is the final report on one of those topics.

1.0 Introduction

The National Rural Electric Cooperative Association (NRECA), through its research arm, the Cooperative Research Network (CRN), supports co-ops in the adoption of new technology and technology applications meant to control costs and improve reliability and service levels. The NRECA Smart Grid Demonstration Project (SGDP), as awarded by DOE, has directly benefited co-op utilities by furthering their understanding of the impacts and risks associated with smart grid technology deployments. It has further benefited utility customers through education on the potential benefits of modern technologies.

This Final Report includes information on several of the demand response (DR) programs deployed under NRECA's SGDP. It provides an overview of DR study objectives, co-ops participating in the DR study, and the programs implemented. It also provides a general overview of relevant DR technologies, program benefits, and solution costs. Data collected and reviewed to date are summarized, along with a discussion of data issues and anomalies specific to each co-op. Finally, the research objectives, approach, and results of our detailed econometric analysis—which was focused on testing the theoretical basis for DR—are presented, along with a discussion of the nexus of our study boundaries and the proposed Demand Response Screening Tool, which is detailed in Appendix A. Lessons learned from the entire research and analysis effort also are provided to inform future analyses.

Our desired analysis approach was to test various dimensions of the diverse co-op programs and validate the theoretical basis of these programs across a wide spectrum of variables. Gaining an understanding about demand response performance versus pricing program mechanisms and varying customer attributes enables co-ops to make educated decisions on the type of program that would serve their needs effectively, not only from a program structure design approach but also considering the customer type that would be ideal to recruit. Based on the limited number of co-ops that had valid and useful data and their current DR programs, our initial objectives were tailored to align with this less diverse field of analysis. Given that each of the co-ops had implemented demand response only with direct load control (water heating and air conditioning), the findings presented in this report are reflective of these types of programs only.

2.0 Overview of NRECA SGDP Demand Response Projects

2.1 Description of Co-op Projects

The SGDP included installation and demonstration of equipment designed to affect consumer behavior and alter the time pattern of electric energy usage by certain installed appliances. Systems deployed included in-home displays (IHDs) and load control switchgear. The technology of an IHD provides an avenue for the presentment of pertinent electric energy information, such as the current or cumulative level of consumption, the current effective price for time of use (TOU) and other dynamic pricing programs, and notice of incipient demand charges to the consumer. This enables consumers to make appliance use choices based on economic criteria. Load control devices on appliances provide an avenue for cooperatives to manage load by direct action. AMI systems with two-way communications are considered enabling technologies for direct load control (DLC). The SGDP included advanced metering infrastructure (AMI) as an enabling technology for the DR programs, along with previous or newly installed communications networks. **Table 1** depicts the equipment deployed by the participating cooperatives that considered demand response programs.

Table 1. Summary of Co-op DR Equipment Acquired

Participants	Demand Response			
	IHD/Web Portal Pilots	DR over AMI	Prepaid Metering	Interactive Thermal Storage
Adams Electric Co-op, IL	X	X		
Calhoun Co. ECA, IA		X		
Clarke Electric Co-op, Inc., IA		X		
Delaware County Electric Co-op, NY	X	X		
Delta Montrose EA, CO	X		X	
EnergyUnited, NC			X	
Flint EMC, GA	X			
Great River Energy, MN				X
Humboldt REC (Midland), IA		X		
Iowa Lakes EC, IA	X	X		
Kaua'i Island Utility Co-op, HI	X	X		
Kotzebue Electric Assn., AK	X		X	
Lake Region Electric Co-op., MN	X			
Menard Electric Co-op, IL	X			
Minnesota Valley EC, MN	X	X		
Owen Electric Co-op, Inc., KY	X	X		
Prairie Energy Co-op, IA		X		

These methods of managing consumer demand are intended to operate in such a way as to minimize environmental discomfort and increase consumer satisfaction. The benefits that accrue over time are expected to include reduced costs of power supply to the utility and related electric energy cost savings for retail consumers.

2.2 Research Objectives – Economic Value and Consumer Presentment

Consumer- or cooperative-initiated actions to affect end-use activity can provide several benefits to the electric system. NRECA/CRN's primary research objective was to examine the validity of previously hypothesized and tested demand response models, thus enabling revisions of and enhancements to these models. The models would then be available to be included in the Open Modeling Framework (OMF) to provide a means to more thoroughly estimate such factors as distribution system losses and the interrelationship of distribution automation with demand response. The OMF thus could be used to evaluate the economic impacts of both utility and end-user actions, such as response through in-home displays, within a single computational framework.

2.3 Role of Demand Response in the 21st Century Co-op

Co-ops increasingly are looking to demand response as a means of shifting and reducing peak demand, deferring capital upgrades to distribution infrastructure, and minimizing wholesale energy demand charges. As co-ops and the utility industry evolve into the 21st century, the utility will continue to be the primary beneficiary of most direct benefits; however, these cost savings in theory should be reflected as future energy and demand charge reductions for co-op customers.

Demand response likely will continue to grow in its influence on customer energy awareness and usage. IHDs and smart thermostats can help customers manage their load profiles and total consumption, leading to further dollar savings.

Another form of demand response is likely to continue growing in popularity and grid impact—the use of distributed generation (DG) and energy storage to shift and reduce peaks. Among many other grid, environmental, and financial benefits, the benefits of DG and storage to peak load management will be significant to co-ops and associated G&Ts, given the dispatch flexibility and ramp times characteristic of some of these assets.

3.0 Overview of Demand Response Programs

Cooperatives and other utilities have used demand response since the mid-1900s to ensure that demand does not exceed supply and to manage the cost of supply. Early programs employed utility direct load control of customer-owned loads in the residential sector and interruptible programs in the commercial and industrial (C&I) sectors. Particularly prominent for cooperatives, management of irrigation pumps has been a productive demand resource for many years. As technology has enabled greater customer participation, some DR programs have migrated from direct utility control to customer control in response to a signal from the utility. This section summarizes the major parameters, applications, and technologies of demand response for cooperative utilities.

3.1 Applications

3.1.1 Peak Demand Reduction

The principal focus of demand response is generally to reduce peak demand. Other goals—such as energy conservation—typically are secondary and/or separately addressed. Depending on the cost structure of a co-op's power supply, reducing peak demand reduces generation, transmission demand charges, or operating costs, thus reducing overall cost of service for all members.

Reducing peak demand also can delay the need to expand transmission and distribution (T&D) capacity. Over the life of a distribution system, using demand response routinely to delay capacity upgrades by, for example, one year, can save a significant sum, roughly equal to the interest charge at prevailing rates on the utility's annual capacity expansion budget.

In addition, though often not financially quantifiable, reducing demand may reduce the co-op members' carbon footprint if peaking supplies are more carbon intensive than base load supplies. This will be the case, for example, if base load is supplied by nuclear or hydro sources and peak is served by fossil-fueled generation.

3.1.2 System Reliability

In the form of direct load control, demand response has always served an important role in system reliability by mitigating peak demand during challenging operating periods. These periods may arise due to unexpectedly high demand (e.g., due to unseasonably hot weather) or diminished supply (e.g., due to unscheduled supply shutdown or maintenance).

In some electric markets, demand response is now treated on a par with conventional generation as a non-spinning reserve that the system operator can invoke to balance supply and demand.

3.1.3 Other DR Applications

In the same way that local demand response can defer the need for distribution capacity expansion, coordinated regional DR programs can mitigate transmission congestion and delay the cost of transmission expansions. The value of this extends well past its financial impacts into environmental and social domains, where transmission expansion often encounters major obstacles.

Perhaps the most important role of demand response, just now emerging, is to dynamically manage demand to follow the variation in intermittent renewable supplies, such as wind and solar energy. While the technology for this appears to be available now, policy and practice are just beginning to apply it as renewable sources become economically attractive. Over time, by enabling reliable and renewable electric supply, success in this effort will very substantially mitigate greenhouse gas emissions, supporting regional economies that are concurrently robust and environmentally more benign.

3.2 DR Program Benefits

3.2.1 Avoided Capital Costs

As mentioned in the previous section, judicious use of demand response can delay the need to expand T&D capacity. Similarly, it can defer the need to acquire new generation resources. In both cases, the direct financial value to the co-op is equal to the interest on capital that would have been applied to secure the new T&D or generation. For example, deferring a $100,000 distribution upgrade for 3 years garners a $15,000 benefit if the utility's cost of capital is 5% ($5,000 per year on $100,000).

Some may debate whether the result is an avoided capital cost, or simply a delayed one. As demand response becomes integral to electric infrastructure operation, we may reasonably expect that (for example) deferring that $100,000 upgrade for 3 years will, for the same reasons, defer all subsequent upgrades for that system segment for generations to come. In effect, it achieves a permanent reduction in the capital cost of the electric assets needed to serve that load—an avoided capital cost.

Secondary benefits are more uncertain but may be much larger because things that change during the delay period can significantly alter the investment results. For example: the price of natural gas (or another major factor) may change a generation decision substantially; demand response or generation investments by others in the region may reduce some of the local need for new capacity; changes in DR technology or public participation/response may further delay the investment.

3.2.2 Avoided Energy Costs

Energy cost per kWh during peak periods is typically higher—sometimes much higher—than during off-peak periods. Therefore, demand response can reduce energy cost to the co-op, even though it does not always reduce total energy consumption. For example, shifting water heating load from peak to off-peak periods will have no direct effect on members' use of hot water. Thus, the kWh consumed to heat the water will not change materially. If the water heaters are controlled off for a long period, making the water less hot, members are likely to use more of it, with the result that the energy use will be about the same. In all cases, the "rebound" or "catch-up" consumption that occurs after the control to bring the water heaters back up to full temperature will offset the kWh reduction during the peak period.

Controlling air conditioners often results in some kWh reduction because members receive less space cooling. Therefore, the co-op and its members benefit from the reduced kWh incurred at peak period prices and from a small reduction in overall kWh consumption for the day. By the time the control program ends in early evening, the day is cooler and the catch-up consumption is less than the kWh avoided during the peak period.

Energy avoided can be significant in a DR program in which the utility sends a signal (a price signal or simply an event signal) to members and allows them to control the loads. In such cases, members will often do things the utility cannot do to reduce their consumption. They may turn off lights, decide to cook on a gas grill instead of an electric range, go to the movies and limit air conditioning (AC) of the house, reduce ventilation power to the barn if the day is windy, etc. DR programs that let the consumers decide what loads to shed consistently produce greater kWh reductions than utility direct control programs because the consumers have greater access to more of their loads and are commonly willing to respond to the financial incentives of the program.

3.2.3 Other DR Benefits

DR produces many other benefits that, though not large individually, are important in aggregate.

Electric line losses are proportional to the square of the current in the line. Therefore, when line current is high, losses are disproportionately higher. Demand response reduces the current when it is highest. For example, a 17-amp current in a distribution line may be reduced to 15 amps—a 12% reduction.[1] The losses in that line will be reduced by 22%, however.[2] Therefore, demand response reduces line losses at the time when they are the highest, reducing the co-op's operating costs by improving the overall efficiency of distribution.

The life of current-carrying assets in electric distribution is a function of time, temperature, and electric load. Partly because load affects asset temperature, high loads disproportionately shorten asset life. DR programs that reduce peak distribution loads extend the life of the distribution assets by reducing the time incurred at high load and high temperature. Expressed as a percentage, the potential for life extension is small, less than 10%. Because the total capital cost of the assets is large, however, this benefit is significant in the long run.

In parallel with the longer equipment life, demand response reduces maintenance costs for that equipment. Transformer overloads are reduced in frequency and severity, stress on connections is reduced, and switches last longer. The saving is small but cumulatively important over time.

Demand response lowers co-op members' electric bills directly in two ways, as mentioned above. It reduces the cost of energy by avoiding kWh during peak periods (or by minimizing demand charges to the co-op), and it reduces members' kWh consumption, especially if they have responded individually to DR events by shedding significant loads. The "other DR benefits" mentioned in this section also translate into bill savings for members. That is, reduced losses, extended asset life, and reduced maintenance costs all contribute to better service at lower cost. This enduring member benefit is the "bottom line" of demand response and is where the overall value of demand response shows the most.

[1] $100\% \times [1 - (15 \div 17)]$.

[2] $100\% \times [1 - (15^2 \div 17^2)]$.

3.3 Enabling Technologies

Demand response and load management (LM) systems are composed of the following:

- Devices at customer sites to communicate with customers and display information to them (optional in pure “direct” load control programs);
- Devices at customer sites to control customer loads; and
- IT resources at the utility to manage the program and data, and conduct communication with customer equipment.

It is productive, and therefore usual, to guide and enhance the load management process by using Supervisory Control and Data Acquisition (SCADA) resources. This section describes these elements individually. Communication equipment and networks interconnect the system elements to transfer messages and data. These networks are diverse and may be public (e.g., a cellular phone network, broadcast FM radio, or the Internet) or private (e.g., a utility-owned meter communication network).

3.3.1 In-home Displays – Types and Information

IHDs make available real-time cost, usage, and related information to the customer. They range from simple to full featured and, correspondingly, from lower to higher cost. Some displays are able to receive signals from ZigBee-equipped smart meters, while others that do not are suitable for homes that have more traditional or advanced meters without ZigBee.

Simple devices only receive and display energy information. More capable versions allow the user to tailor the way the information is displayed, such as altering units (e.g., Fahrenheit or Celsius) or time dependence (e.g., hourly average kWh, daily average kWh, etc.). Even more capable devices can control the home’s energy consumption in response to user programming. Some combine energy information and management with other convenience features.

The information residents receive from an IHD principally comprises energy (kWh) consumption and demand (kW) from any of a wide range of intervals the resident chooses. For example:

- Current kW demand
- kWh consumed so far today
- Maximum demand today
- kWh consumed and maximum demand to date this month
- kWh consumed and demand yesterday (or last week or month) or any individual day (or week or month)

Most devices also display the current time, day, and date. Those that can receive utility signals display DR event alerts. More capable (and expensive) devices provide more information, including inside and outside temperature, electricity price, graphs of any of these parameters over various periods, and projections of total kWh (and sometimes even the cost in dollars) at the end of the current month. Some also display environmental impact information, such as the estimated carbon footprint associated with the recorded kWh consumption.

Appendix A lists additional examples and their features. Note that the devices shown in Appendix A rely on a ZigBee-equipped smart meter to send meter data to the IHD or thermostat. However, DR programs can still be practical when the utility has not deployed ZigBee-equipped smart meters. Various providers offer devices that receive signals and data from the utility via paging, the Internet, a cellular phone network, or the electric power line.

3.3.2 Load Control Devices

"Load control" is control *by the utility* of customer-owned loads. Control commands are generated either at the utility or in a customer-programmed device (as described above) and are executed by the actual control device: a switch controlling the power to the load or a relay that controls the load, such as the relay in a thermostat. Switches are available to control loads in two categories: plug-in loads and wired-in loads.

Plug-In Loads

Typical large plug-in loads, as mentioned earlier, include dehumidifiers, window air conditioners, and chest freezers (to be controlled for short periods only). Though smaller plug-in loads, such as table lamps and fans, are too small to be of direct interest to a utility, they collectively constitute a significant control opportunity for the resident and the utility. These loads typically are equipped for control by the resident as part of an overall response to utility DR events.

Control devices for plug-in loads are widely available from many sources, including hardware and building supply stores, and from online suppliers of automation and control equipment. Typical costs are $20 to $80 per controlled load, plus $50 to $300 for a "hub" or central control and communication box.

Wired-In Loads

Wired-in loads routinely found in load control and DR programs include electric water heaters, air conditioners, pool and spa pumps, and electric strip and thermal storage heaters. These loads typically are served through a circuit breaker and are hard-wired to the supply line. The load control switch must be installed by a qualified electrician between the circuit breaker and the load. Control switches for wired-in loads are usually in plastic weatherproof NEMA-compliant boxes and can be provided with any of various communication technologies, from public cellular to private utility automation network radio.

3.3.3 Ancillary In-Home Devices

It is useful to be aware that, in some cases, the in-home devices described above will not operate reliably without additional equipment, which must be acquired and installed at additional expense. Primary examples are home network range extenders and protocol translators (sometimes called gateways). In residential applications, these devices typically cost less than $200 and can be installed by the resident, but a minority of residential situations may require more intensive effort to achieve reliable communication, incurring on-site technical support for program success.

3.4 Demand Response Program Parameters

3.4.1 Financial

Utilities arrive at the financial incentives embedded in DR programs through a variety of approaches, based on their power supply situations, customer base, and level of sophistication. The following provides a description of the typical incentive structure of DR programs and the typical approach to parameterizing those incentives and price differentials.

Dynamic Pricing and Other Price-Driven Programs

Dynamic pricing programs offer differential rates or a rebate on consumption during prescribed hours during on- and off-peak periods. In particular, dynamic pricing programs under this umbrella involve differing rates or rebates during event periods that are typically prescribed during, and must be triggered by, a particular time prior to the event. The pricing differential typically incorporates some combination of the following:

- Differentials in the cost of energy between on- and off-peak periods and during "super-peak" periods and otherwise. This information can be estimated from utility records regarding generating unit operations and cost characteristics, and power market transactions information or market indices and intelligence.
- Generation costs based on either of the following:
  - Cost of new generating capacity on an amortized basis, allocated across an assumed number of event hours in any year;
  - Wholesale demand rates allocated as above to an assumed number of event hours in a period.
- Transmission costs based on assumed costs of facilities or wholesale transmission billing rates allocated to assumed event hours, as above.
- Distribution costs, determined in a similar fashion as transmission costs.

Direct Load Control (DLC) programs

DLC programs typically are incentivized through either (1) specific dollar amount credits to the monthly bills of participating customers—across the entire year or during months for which events are allowed or expected to occur, and/or (2) rebates on new devices (typically of a particular efficiency threshold) installed with a DLC device. However, there are numerous programs for which no incentive is offered but that achieve some penetration.

The incentive level typically is derived through either an estimate of the benefit of avoided capacity, determined as described above for price differentials, or a survey of the practices of surrounding utilities.

3.4.2 Temporal

DR programs typically have prescribed timing, duration limits, and frequency limits, though not all do. The temporal parameters typically are developed so as to ensure a high probability of avoiding load at the most opportune time—during a system peak, the billing peak (for utilities served at wholesale), or a regional peak. Many programs are limited to a particular season, corresponding with the typical system peak conditions. Dynamic pricing programs that could be characterized as demand response, such as critical peak pricing (CPP), typically are limited to prescribed times of the day or potential event periods (as short as 2−3 hours up to 7 hours). Most DR programs have prescribed limits with respect to the number of events that can be called within a particular month or season. For example, many utilities limit DR events to some maximum number of events per summer season. DLC programs are less likely to have such limits and often are managed by utilities to minimize customer inconvenience and attrition.

3.4.3 Operational Conditions

As mentioned above, DR programs typically have certain prescribed timing characteristics designed to maximize the likelihood that they will be triggered during peak periods that correspond to demand cost incidence. Some DR programs also have prescribed triggers for events, corresponding to system load levels, load levels within the region (e.g., as reported or forecasted by an Independent System Operator, or ISO), or temperature conditions. Most DR programs, however, instead merely have such triggers incorporated into the DR program operator's practice on triggering events. In that case, it is the other prescribed characteristics that the participants solely rely on to anticipate the timing, length, and frequency of events.

3.4.4 Target Loads and Customer Groups

In 2012, the Federal Energy Regulatory Commission (FERC) reported[3] that DR programs in the U.S. had the potential to reduce demand by 66,300 MW. Of that, about 12% was in the residential sector, and nearly all of the rest was in the commercial and industrial sectors.[4]

In the residential sector, DR programs address large and small loads. The large loads are primarily AC, electric space heating (including heat pumps, storage heat, and baseboard or "strip" heat), and pool and spa pumps. These often are controlled directly by the utility when the resident has enrolled in a control program.

Small loads include essentially all other loads in residential service. Any that are discretionary to the resident can be controlled by the resident. DR programs that convey a price or other financial incentive to participants allow each to select what loads to control. Section 3.3.2 describes available devices residents can use to implement such control. Common choices are large loads (if not controlled by the utility), area lighting, dehumidifiers (a relatively large and deferrable load not readily controlled by the utility because it is a plug-in load), and food freezers (which stay cold for just a few hours but cannot be deferred longer).

Significant residential loads that generally are not controlled are well pumps, sump pumps, and electronic loads, such as entertainment and computing. Due to the only marginally deferrable character of food refrigeration and freezing loads, most residents choose not to control them.

Loads in the C&I sector can be divided similarly into those controlled by the utility and those controlled by the user. The diversity of loads is large, making it difficult to list them comprehensively. In general, they include, but are not limited to the following:

- Lighting (both interior and exterior)
- Process machinery (conveyors, mixers, grinders, machining operations, assembly operations, etc.)
- Process heating
- Large-scale space conditioning
- Service operations (escalators, elevators, information and displays, etc.)
- Irrigation and other pumping

3.5 Success Metrics

DR programs can be evaluated based on a combination of estimates regarding the abatement of peak demand and, in some cases, avoided energy, coupled with a valuation analysis regarding the cost to otherwise serve that demand or energy from either traditional supply-side generating resources or via wholesale purchases. Cooperatives can leverage a relatively standardized framework for conducting an analysis of success metrics. This section provides an overview of the central tenets of such a framework, namely (1) the manner in which avoided energy or demand is valued, and (2) financial metrics that compare the cost of the DR program to the value of the avoided energy or demand. Note that this section assumes that the engineering

[3] Federal Energy Regulatory Commission. "Assessment of Demand Response & Advanced Metering." Staff Report. December 2012, p. 22.

[4] The FERC report separated C&I programs from "wholesale" programs by ISOs, regional transmission organizations (RTOs), and other wholesale entities. Since the great majority of load participation in such wholesale programs is composed of C&I users, we combine the wholesale demand reduction with the C&I figure. FERC included agricultural consumption in the C&I sector.

estimates associated with individual DR responses (i.e., kW ratings and technical estimates of abatement) can be readily obtained.

Valuation of Avoided Peak Load/Energy

The key components of avoided cost (or benefits) of a given DR program over a pre-specified time horizon, some of which may not necessarily apply to every program, include the following:

- Avoided or delayed generation or purchased power capacity additions (demand savings);
- Avoided wholesale costs of energy production;
- Avoided transmission/distribution cost (including avoided capital expenditures);
- System loss savings;
- Avoided ongoing operation and maintenance (O&M) costs associated with transmission and T&D system improvements (if any); and
- The value of potential power market sales of resources that are free to serve the external market in place of the energy generation that has been avoided as a result of the program.

From an avoided cost perspective, the bulk of benefits associated with DR programs will arise from avoided demand and energy costs, potentially including avoided or delayed capacity additions costs if the DR program is of sufficient size and scope in participation. Capacity savings represent value in either deferred or avoided investment costs by the utility as well as a reduction in the cost of running expensive peak generation, which may be reflected in a demand tariff. Energy savings represent both immediate and ongoing cumulative benefits associated with the reduction in generation fuel and operating costs as well as losses. Depending on the utility in question, there are typically two key marginal capacity and energy situations that are likely to be encountered for targeted members—specifically, (1) the utility has avoided costly operation of native/existing peaking units; or (2) the utility buys marginal capacity and energy from the market or is a participating member of a G&T, whereby avoided costs can be mapped to an existing demand or energy rate.

In the former case, it is critical to identify the avoided marginal generating resource, either by selecting from a list of pre-defined generic marginal units (e.g., large natural gas combined cycle unit, small gas peaking unit, etc.) with performance characteristics representative of the regional market, or defining the operating characteristics of a specific marginal unit (which could also represent a contract, tariff rate, or market purchase).

To capture avoided demand costs, it is necessary to collect information on marginal generating unit capital and fixed O&M costs to estimate potential capacity savings. To the extent that there is an intermittency in the ability of the DR program to align peak shaving with the utility’s system peak, such issues typically are examined to develop reasonable assumptions for dependable capacity (or the amount of capacity that realistically can be avoided at the time of the utility peak), which then are applied to the requested capacity cost information to determine capacity benefits.

To develop projections of avoided and incurred marginal energy costs, the heat rates of the assumed marginal generating resources (generic or member-defined) are typically multiplied by a (member-defined) forecast of fuel prices plus variable O&M and emission allowance costs (again, either pre- or member-defined) for the marginal unit to derive a total per-unit ($/MWh) marginal average energy cost for these resources. These average per-unit costs then would be multiplied by the projected avoided energy of the DR program (adjusted for marginal losses) to derive total energy cost impacts.

In the absence of such detailed information, a given co-op can review its existing contracts and tariffs to determine the most appropriate energy and demand rates to input into the evaluation model.

To the extent that the other aforementioned elements of avoided cost are present and relevant to a specific utility, most notably the potential for market sales, such estimates can be included as secondary benefits in an economic evaluation framework so as to provide a fair and objective evaluation of potential program benefits. Other examples of secondary benefits include, but are not limited to:

- The monetized value of avoided carbon emissions associated with abatement, using externally derived projections of potential future carbon costs or internal shadow values associated with carbon avoidance;
- The monetized value of jobs created that are associated with DR program implementation; and;
- The downstream economic benefits associated with energy and demand savings that represent an additional amount of disposable consumer income in the general economy.

Program Costs and Key Metrics

From a cost perspective, details regarding DR program cost elements can be developed using detailed information on grant funding and other internal utility costs. A more detailed cost itemization can help to better communicate the overall cost-benefit picture for a given deployment. The main categories of DR program costs can be defined as follows:

- Generic procurement costs associated with the communication network;
- Capital cost of communications devices;
- Capital and staffing costs associated with enhanced IT;
- Installation and program management costs;
- Marketing collateral associated with participant recruitment;
- Lost electric revenues resulting from the avoided peak demand;
- Customer education and public relations costs; and
- Marginal program participation incentive levels (i.e., discounts or rebates for participation) and other ancillary costs, as appropriate.

Understanding success for a given DR program is a function of ensuring that the best available estimate of costs is combined with the best available estimate of avoided costs. While there are numerous approaches to an economic analysis of benefits, there are several industry-standard cost-benefit ratios, which can be defined as follows:

- *Utility Cost Test (UCT)* – A measure of whether the benefits of avoided utility costs are greater than the costs incurred by a utility to implement the DR program.
- *Rate Impact Measure (RIM) Test* – A measure of whether utility consumers that do not participate in a DR program would see an increase in retail rates as a result of other customers participating in a utility-sponsored DR program.
- *Total Resource Cost (TRC) Test* – A measure of whether the combined benefits of the utility and customers participating in the DR program are greater than the combined costs to implement the DR program.

The components of each of these ratios are summarized below. Note that such descriptions are generic in nature, and the exact applicability to a specific DR program will differ, depending on the nature of the measure(s) deployed. Some costs may be equal to zero for a significant number of DR programs.

Utility Cost Test (UCT):

Benefits	=	Avoided Energy Supply Costs (net generation level decreases × marginal energy costs)
	+	Avoided Capital Supply Costs (net generation level decreases × incremental capital costs)
	+	Avoided O&M Supply Costs (net gen. or distrib. level decreases × marginal O&M costs)
	+	Participation Charges
Costs	=	Increased Energy Supply Costs (net generation level increases × marginal energy costs)
	+	Increased Capital Supply Costs (net generation level increases × incremental capital costs)
	+	Increased O&M Supply Costs (net gen. or distrib. level increases × marginal O&M costs)
	+	Utility program costs (administrative costs)
	+	Incentives (utility incentives, rebates, etc.)

Rate Impact Measure (RIM) Test:

Benefits	=	Avoided Energy Supply Costs (net generation level decreases × marginal energy costs)
	+	Avoided Capital Supply Costs (net generation level decreases × incremental capital costs)
	+	Avoided O&M Supply Costs (net gen. or distrib. level decreases × marginal O&M costs)
	+	Revenue Gains (net meter level increases × retail rates)
	+	Participation Charges
Costs	=	Increased Energy Supply Costs (net generation level increases × marginal energy costs)
	+	Increased Capital Supply Costs (net generation level increases × incremental capital costs)
	+	Increased O&M Supply Costs (net gen. or distrib. level increases × marginal O&M costs)
	+	Revenue Losses (net meter level decreases × retail rates)
	+	Utility program costs (administrative costs)
	+	Incentives (utility incentives, rebates, etc.)

Total Resource Cost (TRC) Test:

Benefits	=	Avoided Energy Supply Costs (net generation level decreases × marginal energy costs)
	+	Avoided Capital Supply Costs (net generation level decreases × incremental capital costs)
	+	Avoided O&M Supply Costs (net gen. or distrib. level decreases × marginal O&M costs)
	+	Avoided Participant Costs (avoided capital, O&M, etc.)
	+	Tax Credits
Costs	=	Increased Energy Supply Costs (net generation level increases × marginal energy costs)
	+	Increased Capital Supply Costs (net generation level increases × incremental capital costs)
	+	Increased O&M Supply Costs (net gen. or distrib. level increases × marginal O&M costs)
	+	Incremental Participant Costs (capital costs, O&M, etc.)
	+	Utility DR Program Administrative and General (A&G) Costs

The computations of such ratios should reflect all of the incurred incremental costs and avoided incremental costs (benefits) applicable to the measure in question.

From the perspective of a given co-op, metrics that may be easier to communicate to stakeholders, such as the Net Present Value of Net System Benefits, or the internal rate of return of a given investment, may be used to complement the above cost-benefit analyses. In most cases, the TRC can be made equivalent to the cost-benefit ratio that reflects Net System Benefits, as long as the costs and benefits have been parameterized appropriately to capture the correct utility perspective.

Interpretation of success metrics by members and other stakeholders should be fairly simple by design. All of the relevant avoided costs of the DR program typically are subtracted from the total DR program intrinsic costs in each year. All of these Net System Benefits then are discounted back to today's dollars and added to compute the Net Present Value (NPV) of Net

System Benefits. In a year in which costs outweigh benefits, the benefit-cost ratio will be less than 1.0. This ratio hopefully should be above or equal to 1.0 as the study horizon extends. In general, a DR program that has a positive NPV of Net System Benefits should be implemented because the benefits outweigh the costs in the long run. If a Program has a negative NPV of Net System Benefits, program parameters may need to be re-examined, sensitivities may be necessary, or it may be that the program is simply too expensive relative to the expected demand/energy reductions. Devising a consistent framework for evaluating success in advance of deployment can help a utility ascertain the reasonableness of the level of investment required to achieve a certain amount of DR capability.

Finally, in certain instances, it may also be desirable to determine the number of participating customers required for the system to be cost-effective, given that a broader range of participants can absorb certain fixed and administrative costs of a given deployment more effectively, and that a larger pool of participants will result in a larger amount of abatement. Goal-seek techniques that leverage the above cost-benefit framework or sensitivity analysis can be utilized to determine the point at which the NPV of net program benefits turns positive (i.e., when the program becomes cost-effective, assuming a specific time horizon for the evaluation).

4.0 Review of Previous Empirical Studies of Demand Response

Numerous studies have analyzed the results of dynamic pricing programs—primarily utility-sponsored pilot programs—over the last 10−15 years. The methodologies used to ascertain the significance of and quantify differences in load levels and load profiles, and the results of these studies, are discussed below.

4.1 Study Methodology

Demand savings and price elasticity estimates that are reported as part of many studies of DLC, DP, and other DR programs typically are estimated using regression techniques. The usual approach is to assemble load profile data for both program participants and non-participants (the latter group commonly being referred to as a “control group”) and develop regression equations that seek to explain variations in load levels or characteristics (e.g., ratio of on- to off-peak load) as a function of DR event data; variables capturing enabling technologies; and other variables, including weather conditions, home and appliance characteristics, household characteristics, and day type and seasonal indicators, among others.

While demand savings estimates stand on their own and can be directly useful in gauging the value of some DR programs, elasticity estimates, in the form of both substitution and own-price elasticity, must be combined with pricing information to derive load profile changes resulting from dynamic pricing programs.

For dynamic pricing program evaluations, it is also fairly common for the price ratio to be embedded with additional covariates that capture the influence of other drivers—such as weather conditions, the installation of certain appliances, or the presence of IHDs or other enabling technologies—on the amount by which customers respond to changes in the dynamic pricing.

The elasticity of substitution can be derived from the empirical equation parameter estimates, either directly as the parameter on the price ratio, or the parameter on the price ratio combined with other daily conditions (e.g., weather) multiplied by the respective parameter. This elasticity of substitution is often reported directly as part of pilot program evaluation studies.

4.2 Results

4.2.1 Dynamic Pricing

Figure 1 illustrates the peak demand reductions observed for 80 such programs, grouped by the type of rate and the use of enabling technologies.[5] In general, critical peak pricing (CPP) and peak time rebate (PTR) rates resulted in greater demand reductions than time-of-use (TOU) rates. Enabling technologies generally increased the demand reductions.

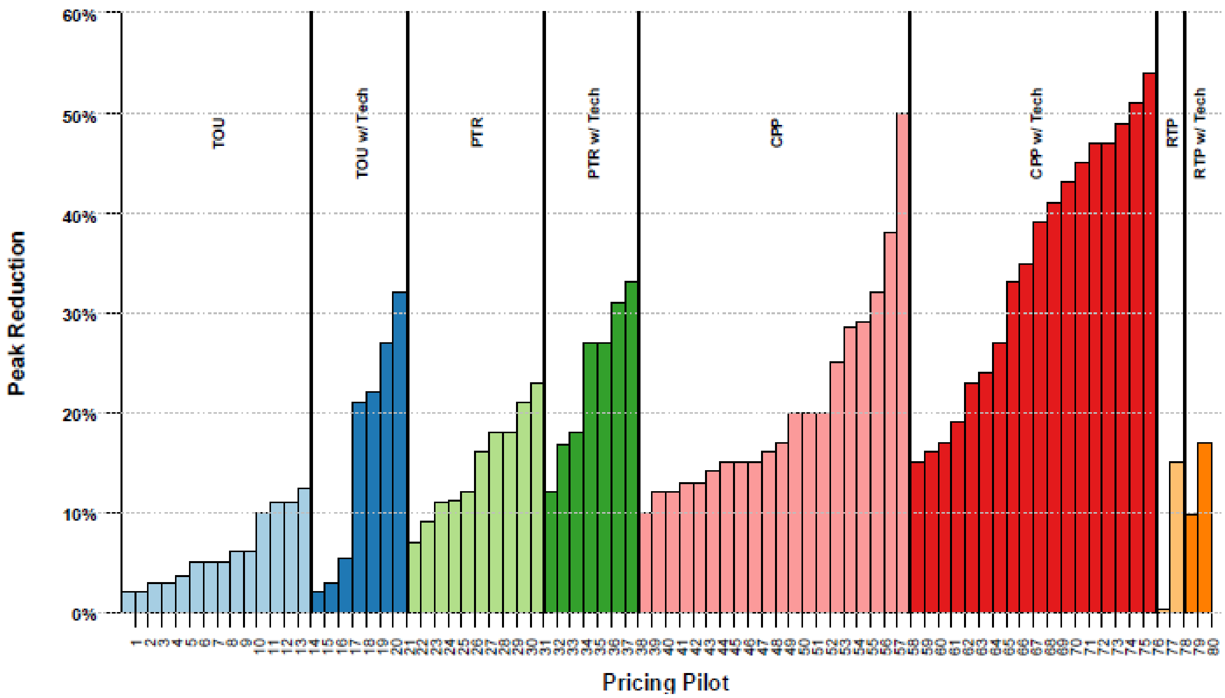


Figure 1. Peak Reduction by Rate Type and Technology for Dynamic Pricing Pilots[6]

A 2011 paper on the subject of dynamic pricing showed that, of 109 pricing programs from 24 different utilities, the median peak demand reduction was 12%. For those programs that used enabling technologies, the median peak demand reduction was 23%. While most of these were pilot programs and used various implementation approaches (e.g., different experimental structures, varying rates, on-/off-peak time periods, participant enrollment approaches, use of control groups, etc.), they generally showed similar price responsiveness from consumers. **Figure 2** depicts the peak reduction for a subset of the pilot programs, including the differences between programs that included enabling technologies (Technology Curve) and those that did not (Price-Only Curve). In both cases, the trend is for increasing reductions in demand as the difference between on-peak and off-peak prices increases (Peak to Off-Peak Price Ratio). The rate of greater reduction decreases at higher levels of peak to off-peak ratio.[7]

[5] L. Wood. Institute for Electric Efficiency. "Dynamic Rates and Smart Meter Benefits." Presented to MACRUC, July 26, 2011.
[6] Ibid.
[7] Faruqui, A., and J. Palmer. "Dynamic Pricing of Electricity and Its Discontents." August 3, 2011, p. 4.

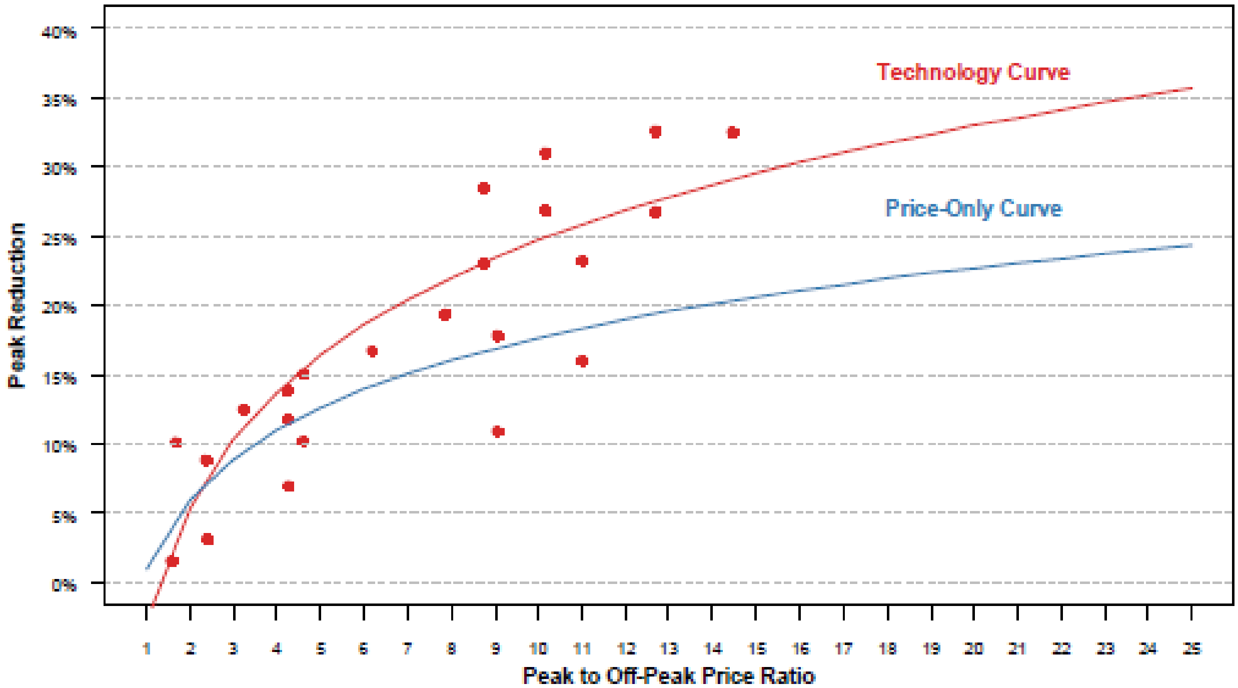


Figure 2. Peak Reduction by Rate Type and Technology for Dynamic Pricing Pilots[8]

Another measure of the responsiveness of consumers to dynamic prices is referred to as price elasticity. The extent to which customers shift electricity demand from on-peak to off-peak time periods can be quantified by the substitution elasticity, while the reduction in demand relative to the relevant price can be quantified by the own-price elasticity. Substitution elasticity is defined as the percentage change in the peak to off-peak demand ratio resulting from a 1% change in the peak to off-peak price ratio. Own-price elasticity is defined as the percentage change in peak demand resulting from a 1% change in price. The most prevalent measure of response to dynamic pricing is the substitution elasticity, presumably due to its more complete characterization of demand response to varying on-peak length and price differential, which are not addressed via own-price elasticity and would result in greater variations of estimated elasticity across programs with varying characteristics.

Based on the variety of studies and programs reviewed, estimates regarding elasticity of substitution varied from as low as essentially zero, or no response, to a high of approximately 0.35 (in absolute terms). There seemed to be no definitive variation across program types, which included TOU, CPP, and PTR programs.

Figure 3 illustrates the variation in demand reductions as a function of peak to off-peak price ratios for various elasticities based on CPP rate programs (demand reductions typically would be somewhat less for TOU programs that involve much longer on-peak periods). As discussed previously, the inclusion of enabling technologies like IHDs and programmable communicating thermostats (PCTs) typically was demonstrated to increase elasticity, or measured response, by 10−50%.

[8] Ibid.

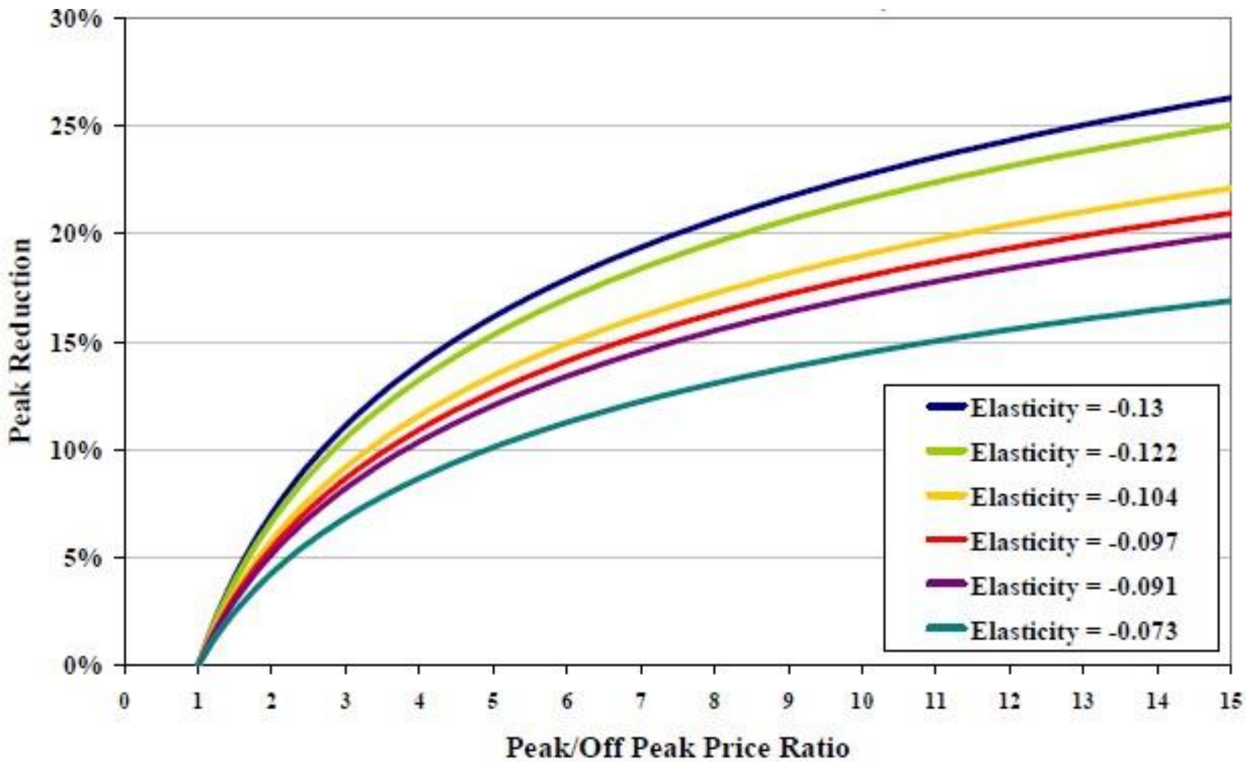


Figure 3. Peak Reduction, by Rate Type and Technology for Dynamic Pricing Pilots[9]

While the focus of the various pilot programs has been on demand reduction or load shifting, the pricing programs have had varying effects on energy use. Most studies of residential dynamic pricing pilots reflect that TOU, CPP, and similar pricing programs result in a reduction in energy consumption, although some studies have demonstrated a positive impact on energy consumption. However, the estimated changes in consumption were typically less than 5%.[10, 11]

4.2.2 Direct Load Control

The Lawrence Berkeley National Laboratory (LBNL) conducted a 2007 study to determine a widely applicable set of savings estimates for AC and water heater DLC programs within the footprint of PJM. Duty cycle models were constructed to examine a wide range of potential switch cycling strategies (27%, 43%, 50%, 67%, 75%, 87%, and 100%). Demand savings estimates were developed using a regression approach, capturing temperature humidity indices (THI) from nearby weather stations across the various cycling strategies, and tabularized for use by the participating utilities. The results of this analysis suggest the following for AC and water heater programs:

- At a THI of 84°F, the estimated demand reduction on air conditioning DLC for the 15-minute time period that ends at 5 p.m. ranged from a low of 0.37 kW for the 27% cycling strategy to a high of 2.06 kW at 100% cycling. The 50% cycling strategy was estimated to yield savings of 0.80 kW.

[9] Faruqui, A., and J. Palmer. "Dynamic Pricing of Electricity and Its Discontents." August 3, 2011 p. 4.
[10] Newsham, G.R., and B.G. Bowker. "The Effect of Utility Time-Varying Pricing and Load Control Strategies on Residential Summer Peak Electricity Use: A Review." NRC-CNRC Institute for Research in Construction. 2010, p. 15.
[11] Goldman, C. et al. "Coordination of Energy Efficiency and Demand Response." *LBNL*, January 2010, pp. 2–12.

- For customers with a seasonal AC of less than 1,600 kWh, the estimated demand savings for air conditioning DLC at a THI of 84°F ranged from a low of 0.21 kW for the 27% cycling strategy to 1.34 kW for the 100% cycling strategy. For large users (i.e., those with a seasonal use greater than or equal to 1,600 kWh), the demand savings ranged from a low of 0.48 kW for the 27% cycling strategy to 2.61 kW for the 100% cycling strategy.
- For DLC of water heaters, analysis was focused on the 100% cycling strategy, with an average estimated load reduction for summer weekday periods at hour ending 4 p.m. of 0.24 kW and for winter weekdays at hour ending 7 a.m. of 0.64 kW.

The Minnesota Department of Commerce, Division of Energy Resources conducted a 2013 Demand Response and Snapback Impact Study. The study was focused on the "snapback" impact of demand response, which can be defined as the increase in energy and demand in the hours immediately following a DR event, as well as research on estimated impacts of various DR programs.

The study utilized three methods of investigation: research on previous studies related to demand response, gathering and analyzing aggregate system load and DR data from two large Minnesota utilities during demand control days, and using energy modeling to analyze various DR controls as applied to typical residential and small commercial buildings. The analysis in this study focused entirely on facilities and utilities located in Minnesota and used weather data from three Minnesota climates.

The technologies used for demand response that exhibit snapback were found to be air conditioner cycling, water heater curtailment, and electric heating cycling. Other often-used technologies do not have snapback effects due to the nature of their operations. These include ice storage, electric heating thermal storage, and on-site generation.

The results of this analysis produced deemed energy and demand savings values for demand response and snapback for entire utilities, residential air conditioner cycling, water heater curtailment (in both winter and summer peaks), electric heat cycling, and electric heating thermal storage, as well as commercial packaged rooftop unit ice storage. These deemed savings values were intended to be used as estimates for utilities to determine the energy and demand impacts of DR technologies.

The results of this study show that, although most DR events produce significant snapback, there is still a net energy savings. **Table 2** has been extracted from the study report and summarizes the residential energy modeling results for a typical Minnesota home.

Table 2. Summary of Estimated Savings and Snapback − Residential[12]

Measure Description	Net kWh Savings	kW Savings	Snapback kWh	Snapback Peak kW
AC Cycling	0.71	0.30	0.72	0.34
Elec. Heat Cycling	3.11	1.42	5.49	1.97
Water Heater − Summer	0.40	0.60	2.71	2.71
Water Heater − Winter	0.09	0.84	2.03	2.03
Electric Thermal Storage	0.0	25.8	0.0	0.0

[12] "Minnesota Department of Commerce Final Report – Demand Response and Snapback Impact Study." August 2013.

4.2.3 Smart Appliances

The use of major appliances with enabling technologies provides an opportunity to further reduce peak demands. As noted previously, consumers have shown a willingness to modify the usage of appliances; however, this response generally has required active participation. Under an automated DR scenario involving smart appliances, it is anticipated that the response could be enhanced. For example, the Northwest GridWise Test Demonstration Projects used automated control of selected equipment (e.g., heating equipment, water heaters, clothes dryers) to respond either to pricing or other signals (e.g., electric power system frequency). The results generally showed the effectiveness of the approach for automated load shedding/shifting and acceptance by the participants.[13] A study by the Pacific Northwest National Laboratory estimated the benefits of smart appliances, including their potential as a "spinning reserve" resource in addition to load shifting and related energy savings impacts.[14] General Electric (GE) tested a number of "demand responsive enabled appliances" and a home energy management system in advance of the roll-out of its smart appliance product line. In a test on smart DR-enabled refrigerators in four homes, GE reported demand reductions of 27%.[15] The impact of smart appliances on home energy use and overall demand profiles depends on the load shedding/load reducing strategies elected. For example, run times/duty cycles can be modified, temperature settings can be adjusted, and water usage can be modified—all of which can have different effects. However, due to the relatively recent roll-out of smart appliances, there has been little experience on the actual DR impacts of these appliances.

5.0 Overview of Select Co-op DR Programs

The following discussion summarizes the nature and nuances associated with the DR programs deployed by those co-ops interviewed for this study. The discussion is organized into the following main categories, on a "by co-op" basis:

- *Program Structure and Application Protocols* – High-level program information and intelligence regarding the manner in which customers were recruited. Program longevity; customer presentment and program development approach; and parameters that constitute a DR event.
- *Enabling Technologies and Devices* – Types of enabling technologies used to enhance customer and load response to DR events.
- *Implementation and Operating Issues* – Feedback from our interviews regarding logistics and operating issues, as applicable.
- *Data Compilation and Reporting* – Preliminary synopsis of the data compilation and reporting that has been undertaken by a given co-op. Further follow-up and interaction with co-ops currently is underway that will shed further light on the nature and extent of the data made available through the Study Data and Asset Tracking System (SDATS) that directly maps to a given co-op's programs. Refer to Section 7 of this report for a detailed review of available data by co-op.

[13] D.J. Hammerstrom. "Pacific Northwest GridWise Demonstration Projects. Part I. Olympic Peninsula Project." October 2007. PNNL-17167.

[14] Sastry, C., V. Srivastava, R. Pratt, and S. Li. "Use of Residential Smart Appliances for Load Shifting and Spinning Reserves, Cost/Benefit Analysis." December 2010.

[15] The pilot program was operated in cooperation with Louisville Gas & Electric (LG&E) and involved 42 DR-enabled appliances in 15 GE employee homes (see Najewicz, D., "Demand Response Enabled Appliances/Home Energy Management Systems." Presentation to NREL, Golden, CO, October 1, 2009.)

- *Choice of Performance/Impact Metrics* – Nature and extent of program performance tracking, metrics collected on abated demand and associated savings, or any other approach to gathering feedback on program performance, up to and including the solicitation of feedback from program participants.

It is important to note that we have not independently verified the information or accounts associated with each description below, the content for which was derived exclusively from our interviews with key co-op representatives. Furthermore, in some cases, it is evident that SGDP funding was used to enhance capabilities or bolster investment in programs that may already have been in place for a given organization. In such instances, we have taken care to focus as much as possible on the exact programs within the SGDP umbrella to minimize overlap. However, given the opportunity to interface with participating co-ops, we have gathered some ancillary intelligence on DR programs that has been infused into this section with due consideration of both the confidential nature of certain information and the need to focus primarily on SGDP-related investments/outcomes.

5.1 Clarke Electric Cooperative

Program Structure and Application Protocols

Clarke Electric Cooperative (Clarke) in Iowa has roughly 5,000 customers and an approximate system peak demand of 20 MW (alternating between summer and winter peaking). Annual energy sales are 90,000 kWh. Clarke is served by the Central Iowa Power Cooperative (CIPCO), a 12-member G&T.

Clarke's program consists of a direct load control pilot with 80 participants. During the summer months of June, July, and August, Clarke controls water heaters and central air units between the hours of 4−7 p.m. on weekdays *every other time* the outside temperature exceeds 92˚F. Water heaters are cycled every 30 minutes, and central air units are cycled every 15 minutes. The rationale for program choice was predicated on the fact that AC and water heating end-uses are more prevalent and thus the largest sources of electricity usage during peak periods. The CIPCO summer peak typically occurs between 4–6 p.m., and is the primary demand billing determinant for Clarke. The winter period (see below) was chosen for simplicity/consistency with the control period for the summer, although Clarke recognized that the peak demand savings would be negligible or nonexistent during that period.

During the winter months of December, January, and February, Clarke controls water heaters between the hours of 4−7 p.m. on weekdays *every other time* the outside temperature is below 15˚F. Water heaters are cycled every 30 minutes. There are no limits to the number of events that can be called.

Clarke sent out a detailed letter soliciting participation from members. Clarke targeted 90 participants initially but retained 80 for the pilot program. Member-consumers received communications, including email, regular mail, post cards, and recruitment of walk-ins. The Clarke newsletter also mentioned the program. CIPCO assisted Clarke with the development of a random sample of potential participants to target. The pool of potential participants was strategically catalogued to focus on potential participants that currently had an electric water heater and who were most likely to have higher AC usage in the summer period. Customer presentment focused on the potential to help the co-op save money and incentives for participation, as well as a detailed letter that included contact information for Clarke representatives and a full description of the main enabling technology (further described below).

The participants were provided with incentives. Clarke committed to reward the members for allowing Clarke to control their AC units and water heaters for the summer months by crediting the account being controlled. The amount credited was set at $40, credited to the account in June of each of the two years. Clarke also planned to reward the members for allowing Clarke to control their water heaters for the winter months by crediting the account being controlled. The amount was set at $20, credited to the account in December of each of the two years. Incentives were derived based on benchmarking of nearby utility practices, most notably Alliant. Clarke reported that it provided enhanced incentives to obtain sufficient pilot participation quickly, given the compressed overall deployment schedule.

Enabling Technologies and Devices

Clarke deployed a power line communication (PLC) over an AMI system. The DLC system was the last component of the system added. A given event is programmed and kicked off before the Clarke office closes. Clarke also installed the technology on some devices within the Clarke office for testing purposes.

Clarke’s main enabling technology from the customer perspective was a Load Control Receiver (LCR). When Clarke was not controlling load, participants would see only a green light lit up on their LCRs. When the above-cited outside temperature conditions were met, and Clarke was engaging in DLC, customers saw a red indicator light lit up on their LCRs.

Implementation and Operating Issues

Installation of the equipment began immediately after Clarke obtained participants. The Clarke operations department led the installation of the load control devices. Clarke made an effort to use one device to control both AC and water heater load whenever possible. The Clarke team created procedures and processes to run the Yukon system for testing individual and groups of LCRs, in addition to remote testing. Cooper Industries was retained to provide training, programming, and support of the Yukon system, working the load control devices in the field.

Clarke did not report any significant operating issues. There were some early issues related to the AMI system that were solved. The system is reportedly working very smoothly.

Data Compilation and Reporting

Clarke provided all necessary account information, such as the following:

- Current and past usage data
- Current and past temperature data
- Control dates
- Control times
- Interval data from the meters in the group

The Clarke Operations Assistant compiles the data and submits the information as scheduled.

Choice of Performance/Impact Metrics

Clarke has not yet completed detailed analysis of performance or developed specific impact metrics. Clarke’s expectation is that, given its relatively small size and the small scale of the pilot, it is not reasonable to go to great lengths to determine such program parameters or develop an economic evaluation framework. As noted above, incentives were designed at a level that would ensure sufficient participation, given the compressed overall pilot schedule. Clarke anticipates that analyses conducted by others (e.g., Leidos, NRECA/CRN) will provide good information on its program.

With respect to feedback on program performance, Clarke provided detailed contact information for Clarke staff to all participants, including a direct cell phone number for participants to call in case they had significant issues. Clarke reports that there were several minor complaints that were entirely related to customer equipment failure, as opposed to the nature and extent of the DR program itself. Clarke reports that there has been virtually no attrition.

Clarke does not have any significant plans to adopt additional DR programs at this time. Any additional DR program implementation would need to be reviewed and endorsed by CIPCO prior to deployment.

5.2 Flint

Program Structure and Application Protocols

Flint has approximately 83,000 total customers. The Flint DR program consists of demand reduction via an IHD, which was deployed to 150 customers. There were also 150 customers that did not have an IHD but were informed of events via email and text message. The reasoning behind this dichotomy was to test for differences in efficacy of the program directly attributable to the presence of an IHD. There are also 150 customers that served as a control group. All participants in the IHD-based program were solicited on an opt-in basis.

Flint already has an existing DLC program, with nearly 20,000 DLC devices installed on various end-uses, such as ACs, water heaters, and irrigation systems. All of Flint’s customers are on an AMI system. To select participants for the IHD program, accounts/meters were stratified into different groups to ensure a statistically representative sample of participants.

Flint’s program was active through 2013, but the current status of the program is being evaluated. From June 1−September 30, based on Flint’s review of its load forecast over the period 3–7 p.m., events would be called, with no limit on the number of events. Flint reports that, given the mild winter weather experienced recently, there has been a need for only two prescribed events over the past year – specifically, a 3-hour event and a 4-hour event, when both IHD and DLC program participants were activated.

Customers were recruited for the program via a contest that provided free appliances as a giveaway. Flint received 1,200 responses to the contest, and a winning customer was selected. Customers were presented with the event signals through IHDs or regular communication channels, as noted above. In addition, a dinner was held to discuss the benefits of the program and answer any questions that participants may have had about the program. This was done in parallel with hand delivery of IHDs to homes. Flint leverages various marketing materials to manage its existing DLC programs, such as direct mail, an initial signup incentive, and a credit on the participant bill. For the IHD program, customers were provided with a credit rate of $0.87/kWh, reduced during a given event. However, the rate was applied to an estimate of the difference between usage during the event and the estimated usage that otherwise would have occurred. This estimate was derived using a “past-look” algorithm that estimates what usage would have been otherwise and then credits the customer for that amount of abated energy.

Enabling Technologies and Devices

Flint deployed 150 IHDs as part of the SGDP study exercise. This was the main enabling technology regarding the customer. The participant was the main catalyst for reducing energy consumption during the events in question.

Implementation and Operating Issues

Flint does not report any operational or implementation issues with the IHDs. The IHD program was implemented predominantly as a study exercise. The core idea was to examine how voluntary, incentive-based programs compared to its existing DLC customer base and determine whether significant behavioral differences existed between an opt-in and an opt-out program structure.

Data Compilation and Reporting

Flint reports that all interval data have been posted within SDATS.

Choice of Performance/Impact Metrics

Flint reports that it is experiencing very little attrition, estimated to be less than or equal to five participants in the IHD program to date. There have been no direct follow-up efforts by Flint to obtain feedback from participants on the program. However, pending executive review, it is Flint's intention to continue with its existing DLC program and strive to sign up additional customers.

5.3 Corn Belt Cooperatives

The Corn Belt Cooperatives in Iowa include Corn Belt Power G&T and its members, Calhoun, Iowa Lakes, Midland/Humboldt, and Prairie Energy.

Program Structure and Application Protocols

The Corn Belt cooperatives are defined as Corn Belt Power Cooperative (Corn Belt), a G&T that comprises the member co-ops of Iowa Lakes Electric Cooperative, Midland Power Cooperative (now merged with the Humboldt Regional Electric Cooperative (REC)), Boone Valley Electric Cooperative, Prairie Energy Cooperative, Franklin Rural Electric Cooperative, Butler County Rural Electric Cooperative, Raccoon Valley Electric Cooperative, Calhoun County Rural Electric Cooperative, and Grundy County Rural Electric Cooperative. Corn Belt also serves the North Iowa Municipal Electric Cooperative Association (NIMECA). The summaries presented herein are based on interviews conducted with representatives from Corn Belt, Calhoun, Prairie Energy, and Midland, as well as follow-up information from Iowa Lakes.

Corn Belt administers a DLC program for water heaters, irrigation pumps, and storage heat. Corn Belt's water heater program is nearly 2 years old and is active all year long. Based on co-op interviews, there are currently 200 load control switches installed at Midland and 700 switches installed at Prairie Energy. The program is ongoing, and the NRECA grant, as a follow-on to a pilot program that was in place in 2008 with Iowa Lakes, provided for installation of additional switches and the deployment of newer and better technology than the neighboring G&Ts that have mature LM programs. Member co-ops cannot ignore the specific demand response signals/events. However, customers can call ahead during the holidays or other times when they do not wish to be controlled. The members can also work with individual customers to deactivate individual switches. The member co-ops report that they do not typically initiate independent control events above and beyond those administered by Corn Belt. There were no IHDs purchased as part of this program.

Water heaters are subjected to either full (100%) or partial (duty-cycle) control (e.g., 80%), as deemed appropriate. Corn Belt is responsible for projecting when control will begin so as to abate peak demand, and control occurs based on that subjective determination. Each month, Corn Belt analyzes the previous month and the same month from a year earlier to decide what the control threshold will be for that month. Typically, after the first control event in a given month, the system automatically steps in and implements control when demand reaches that level for the remainder of the month. However, there are exceptions, constituting manual overrides initiated by Corn Belt in the event of long control duration with expected higher loads later in the month. There are no limits on the number of events that can be called in a given month. However, the strategy taken by Corn Belt has been to cycle units to increase the amount of time that control can take place with minimal disruption or customer inconvenience.

Development of rebate levels was based on neighboring utility practices, some of which have been deploying similar programs for more than 20 years. Corn Belt did not want to engage in "reinvention" of program parameters that have been deployed successfully elsewhere.

Given that the program is opt-in, there is diversity in customer presentment and incentive levels across the member co-ops. Based on the interviews conducted, the following is a high-level summary of customer interaction:

- For Midland, customers are opt-in and either are part of the water heater discount program or, if they have older water heaters, are approached separately (with no discount offered) to participate in the program for purely altruistic reasons;
- For Calhoun, marketing was conducted to members to volunteer" to sign up; this process resulted in minimal interest; and
- For Prairie Energy, its marketing program mirrored Midland, and Prairie reports that the program typically is not refused when marketed properly.

Customers are provided with a discount on the cost of a more expensive water heater in exchange for signing up for the program and allowing switches to be installed. The member co-ops are tasked with minimizing customer inconvenience.

Enabling Technologies and Devices

The Corn Belt program is predicated on a Yukon communication system. A two-way Express Com system sends a signal from Corn Belt to the member systems, and the individual member co-op Yukon system then sends the downstream signal to member customers. The Cooper/Cannon Demand response system serves as the connection between the G&T Yukon head end to the distribution co-op Yukon head-end system, and then sends a downstream signal to the individual customer switch. The control signal is a power line carrier modulation, sent on the power lines to all loads by equipment installed in the co-ops' substations. The aforementioned switches were installed subsequent to the Iowa Lakes pilot as a direct result of the NRECA grant.

Implementation and Operating Issues

The program's implementation was driven by the need to abate the Corn Belt peak demand as billed by Basin Electric. The demand rate for Corn Belt does not vary seasonally, and the member co-ops are billed based on their coincident peak with Corn Belt. Water heating is the main end-use that can contribute to peak reduction in all 12 months. Corn Belt did not report any specific implementation or operating issues. There were some data compilation/reporting challenges, as noted below.

Data Compilation and Reporting

Corn Belt's existing SCADA system provides full load intelligence. Corn Belt can manually intervene in the automatic system calls on events, as described above. Corn Belt reports that interval and event data are in the SDATS system. That data currently are being subjected to review. Corn Belt will provide its Load Management Operating Manual for review. In addition, Corn Belt will provide a tabular history of estimated DLC impacts on monthly peak for the duration of the program. Based on interviews conducted, there were some reports of data compilation and reporting challenges, as follows:

- Midland reports that there were some communication issues in getting kWh consumption reads in for billing. Midland believes that this problem was related to the operation of the PLC. There were also some challenges related to the merger of Humboldt REC and Midland, both of which had legacy Yukon systems.
- Iowa Lakes had similar challenges relating to data quality/transmission issues. Iowa Lakes will be compiling an abbreviated data set for analysis that reflects a sample of load over a 2-year period.
- Calhoun has had some difficulty with its meter communications and is in the process of making improvements to line data repeaters. Calhoun also will be providing a condensed data set for analysis.

Based on the interviews conducted, follow-up is being undertaken to ensure that event data are provided in concert with the interval data in SDATS.

Choice of Performance/Impact Metrics

Corn Belt reports that there has been no formal tracking of metrics or cost-benefit analysis conducted. Corn Belt receives a monthly report from the distribution co-ops on the number of switches installed, and estimates monthly impacts based on the control percentage, an assumed diversity percentage, and an assumed average kW rating. Because switches can only store data for approximately 36 hours, a more manual and continuous process would be necessary to fully extract actual event data from the switches.

Corn Belt does note that, based on customer pushback, the 100% control for the water heater program motivated it to adjust the cycle to 80% during control periods. Calhoun notes that there are challenges related to program participation when homes are sold to new owners.

There has been no formal communication plan to solicit feedback on the program or any customer surveys conducted. Corn Belt reports virtually no attrition. However, based on the interviews conducted, the following is an overview of performance-related feedback from the customer perspective:

- In Midland, a few people have called to express concerns (two calls out of all switches installed); one was related to the water heater itself and was unrelated to load control performance, and the other was related to a control event; Midland anticipates conducting a survey at some point soon, but there is no strict survey timeline.
- Prairie Energy has 700 switches installed, and only a handful of people complained about running out of hot water – some 50-gallon water heaters were moved to a lower-duration cycle to conserve hot water.
- For Calhoun, there were some concerns with the program but they have been very limited. Since the switches were deployed recently, in the spring 2014, the program is still in its early stages. To the extent that the program is extended to irrigation and storage heat, it will be done outside of the current NRECA grant.

In the medium term, Corn Belt is prepared to focus on AC and storage heater control. However, the individual member co-ops have not taken on these additions at this time. Iowa Lakes already has IHDs in place, and other co-ops are considering similar additions. The IHDs display a colored signal (green to yellow to red) to signify closeness to a potential peak, which in theory entices participants to avoid/delay hot water end-use. Currently, there is no peak pricing program. However, a handful of C&I customers do receive a price signal and are on a coincident peak rate. It remains to be seen whether such a program would be more widely marketed/introduced in the future.

5.4 Minnesota Valley Electric Cooperative

Program Structure and Application Protocols

Minnesota Valley Electric Cooperative (MVEC) has 43,000 customer meters, comprising 36,000 members spanning very rural to suburban areas. MVEC recently replaced 11,000 one-way LM devices with two-way receivers. This investment was helpful in alleviating the non-functional receivers, which MVEC estimates represented between 15% and 25% of the older receivers. MVEC notes that reliance on hourly data was an unreliable approach for determining which receivers were not functioning (as the interval was too long). With the new equipment, MVEC can obtain feedback from the load control receivers, making it relatively easy to detect failures.

MVEC also worked with Great River Energy and Basin Electric on a DR management system comprising new head-end software. The intent of the investment was to help abate peak demand in the summer, much like a standalone commercial customer.

The investments made were all a function of buttressing the existing MVEC DR program. This program is a DLC structure for AC, water heater control, and battery peak shaving. Water heating control occurs at night for peak shaving. AC cycling occurs in the summertime for the same reason, generally over the hours of 1–5 p.m. Heating control occurs in the winter, with batteries discharged to abate peak on an as-needed basis (typically several times a day). The program is permanent and has been in place for 20 years. There are currently 8,500 participants, with 8,000 of those having AC control, and the remainder having water heater and space heating control. The program is administered on an opt-in basis. There are certain limits to the number of events that can be called, as reported by MVEC.

Participants are provided with a discounted rate on the sub-metered portion of their bills (e.g., AC/heat pump). Customers are charged their basic rate for general service. Additionally, metered AC customers receive a 10% discount on their overall monthly energy bill. Regarding customer presentment and recruitment, MVEC did not engage in any additional recruitment or communication of program benefits to existing participants, given that the program has been in place for well over 20 years. However, one customer presentment technique that has been in place for quite some time relates to an energy savings line item on customer bills that shows "zero savings" for non-participants. MVEC also mails out a yearly energy report to bolster participation.

Enabling Technologies and Devices

The main enabling technology invested in is the aforementioned two-way receivers. The MVEC demand response program is operated via a power line communications system (which differs from a power line carrier system). The prior radio frequency system signal was intermittent and would not work consistently. In addition, MVEC also invested in support software, as described above.

Implementation and Operating Issues

MVEC does not report any significant operational or implementation issues. The program was implemented 20 years ago to provide rate relief and avoid costly demand charges. MVEC's bill is in part derived from its transmission peak with Great River Energy. The Basin Energy peak typically occurs between 1 p.m. and 9 p.m., and is also a billing determinant.

Data Compilation and Reporting

MVEC data as compiled in SDATS are currently being subjected to review (as available). MVEC reports that data initially uploaded to SDATS were less than optimal, as certain system challenges were being addressed. MVEC will be creating a smaller, concise data set for analysis. The data will provide identification of program types and include data for non-participants.

Choice of Performance/Impact Metrics

As a result of these new investments, MVEC estimates that there has been a 1-MW increase in water heater control capacity, and a 10–15% improvement on AC control devices. However, MVEC does note that 500 participants quit the program when the initial change out of load control receivers was attempted. In addition, between 50 and 100 customers per year are estimated to be irritated by AC cycling (out of all participants).

MVEC currently has plans for increasing its saturation rate, which stands at 46% across all current DR programs. MVEC is introducing three new programs—specifically, (1) a Wi-Fi-enabled EnergyHub device to set back thermostats for up to 4° for 3 hours, up to 7 days per month; a (2) a behavioral "beat the energy peak challenge" over the period 5–9 p.m., with cash prizes awarded to the winning participant; and (3) a pre-pay option of $5 if the customer reduces consumption during the peak, which MVEC reports was received favorably by half of all existing participants.

MVEC reports that it conducts periodic studies of its existing DR portfolio, which helps drive the rates associated with the program. The most recent study conducted was in 2011, which guarantees program rates through the year 2014. A new study of the program to lock in rates for the next cycle may be done at a later point.

5.5 Delaware County Electric Cooperative

Program Structure and Application Protocols

Delaware County Electric Cooperative (DCEC) in New York State has 5,300 meters and 840 miles of distribution lines. DCEC has a large number of seasonal accounts representing vacationers from urban areas of New York, which account for approximately 40% of its membership.

DCEC made a significant investment to buttress its existing DR program, which has been in place for 20 years. The program is predominantly focused on water heater control, and DCEC reports that AC load is not significant enough to warrant deployment of a DR program. DCEC monitors load from its main purchase points in 5-minute periods and projects system demand. Dispatch of demand response is controlled via a matrix. Load response/reduction is assessed and dispatched based on how much load control is deemed necessary (utilizing the existing Survalent SCADA system). The new technology for DLC uses a very low ultra-narrow band form of power line carrier, and block timing as a dispatch solution. DCEC merged or integrated the old and new systems to maintain the old matrix functionality resident in the SCADA programming. DCEC also installed new IHD devices (described further below).

Currently, there are 600 participants on a water heater DLC program. Additionally, there are 50 participants who have an IHD but not directly controlled water heaters. DCEC reports that it has very little AC load or other controllable load. There are also 100 participants with no DLC or an IHD (this serves as a control group). The DR program is active year round and is intended to improve system load factor. The program is administered on an opt-in basis. The program is active at any time of the day. Time-supervised demand shedding thresholds are set by the Assistant Manager (operator), based on his experience with the operation of DLC with respect to historical system demand levels. Typically, shedding is enabled during the historical morning and evening peak hours. The operator may also place the DLC system in the shedding mode, if needed. Typically, the shedding function is limited to twice per day; however, depending on system conditions, no shedding may take place on a daily basis. Durations are generally limited to approximately 4 hours in length, depending on the level of shedding needed to meet threshold limits.

Customers are provided with an incentive of $4 per month all year round for participating in the DLC program. There is no additional incentive associated with the IHD. Customers were recruited for the program via direct mail and newsletter advertisements, in addition to mention of the program at the DCEC annual meeting.

Enabling Technologies and Devices

In addition to the installation of the new DLC service, DCEC also installed IHDs as enabling devices. The IHDs use a ZigBee wireless connection that shows kWh consumption. The customer has the ability to select different display parameters in the IHD related to energy consumption, including color coding of the display background.

DCEC engaged in testing the DR system (10 separate tests were run) during the summer of 2013, and 10 additional tests in the winter of 2013−2014.

Implementation and Operating Issues

DCEC implemented the program to help control the cost of its New York Power Authority (NYPA) demand charge for hydro capacity and energy through load factor improvements. Furthermore, NYPA goes into the market to purchase energy for DCEC's load in excess of its hydro allocation. This excess or incremental energy is more costly than the hydro-based energy, and the need for incremental energy is greatest during the winter period. Managing its load factor reduces incremental energy purchases while simultaneously increasing hydro-based energy purchases from NYPA to the greatest extent possible.

DCEC reports that the time it takes to transmit all load shed commands on the new power line carrier system, due to its very low transmission data rate, is 45 minutes. The TS 2 system was designed primarily for an AMI application, with very limited capabilities for real-time applications.

Data Compilation and Reporting

DCEC has been reporting hourly load data to NRECA's Study Data and Asset Tracking System (SDATS) based on (1) 100 customers with DLC; (2) 50 customers with an IHD (no overlap with DLC); and (3) 100 participants with no DLC or IHD, serving as the control group for approximately 1 year. The DCEC SCADA system contains event data related to the percentage of load shed in a spreadsheet format. These data are not in SDATs and will be critical to analysis of the DCEC data. Other DCEC data currently are under review. DCEC reports that it used one feeder (representing approximately 384 customers) and dumped 6 months of hourly data into the SDATS system prior to the inception of the DLC and the IHD installations as a trial operation of the newly installed AMI system.

Choice of Performance/Impact Metrics

DCEC reports that it has saved approximately $50,000‒$60,000 over a 10-month period as a result of the investment. To track program performance, a formal questionnaire was sent out to IHD customers. DCEC received 34 survey responses. Feedback on ease and usefulness of the IHD was generally favorable.

While there has been no formal follow-up to obtain feedback on the new investments within the program, DCEC reports that there has been some very limited attrition as a result of certain customers needing to ensure proper water temperature for downstream end-uses. Some dairy farms reportedly dropped out of the program due to water temperature problems in their production process. It should be noted that there are not a significant number of farm accounts, and this distinction is not captured in the data reported to SDATS (as this is not anticipated to have a significant impact from an analytical perspective).

DCEC does not conduct any formal cost-benefit analysis on the program or tracking of benefit-cost ratios. Deployment of the program was based on the perception that water heating as an end-use would result in the biggest DR capability. DCEC does estimate its demand savings and load factor improvements on a monthly basis.

6.0 Review of Available Program Data

6.1 Study Data and Asset Tracking System (SDATS)

SDATS is a web-based central data repository system developed to collect both asset and study data and reports in a timely fashion, enabling efficient DOE reporting and program analysis.

Project data collected in SDATS consist of the procurement, receipt, installation, and experiential information (“Asset Data”) for all assets with a value greater than $5,000 procured through the NRECA SGDP. It also includes the build, impact, and baseline data (“Study Data”) that are used for cost-benefit analyses by the NRECA study team and DOE. Study data are broken down further into “low-frequency” and “high-frequency” data. Low-frequency data are entered through a web interface called the SDATS. High-frequency data, such as meter interval and SCADA data, are uploaded by co-ops to a secure file upload site.

6.2 SDATS Data

We have carefully reviewed the following required groups of data within SDATS to be used for the proposed statistical and econometric analyses.

- Customer Systems Build Metric Data
- AMI and Customer Systems Impact Metric Data
- Meter Location Data
- Meter Interval Data
- DR Event Data

6.2.1 Customer Systems Build Metric Data

These metrics represent the number of installations of various customer system devices, such as in-home displays, web portals, DLC devices, smart appliances, programmable controllable thermostats, home area networks, and energy management devices, both at project and system levels. We extracted these data from a recent build metric report (Q2-2013) from SDATS. Data have been thoroughly reviewed and found to be in good condition, with no major data anomalies.

6.2.2 AMI and Customer Systems Impact Metric Data

These metrics reflect system impacts and benefits due to the installation of AMI and customer systems. A number of these metrics and associated data are relevant to the proposed statistical and econometric analyses, such as co-op coincident/system peaks. Some of the required data have been collected from recent semiannual reports (H1-2013) from each co-op and reviewed for data completeness. However, some co-ops missed reporting certain fields of required information in their reports. Supplemental data was requested by the co-ops for analytical purposes and is detailed further below.

6.2.3 Meter Location Data

These data contain various attributes of individual meters (meter locations), such as meter identification number; customer identification number; installation date; in-service date; feeder identification number; customer class; data acquiring frequency; data polling frequency; flags to indicate different features of meters, such as power quality monitoring, tamper detection, remote disconnect, etc.; and flags to indicate the participation in specific DR programs, such as IHDs, DLC for water heaters, DLC for ACs, web portal access, programmable controllable thermostats. Available meter location data for each co-op were collected and reviewed. There are some data anomalies, explained in detail in the next sub-section.

6.2.4 Meter Interval Data

These data contain different intervals of meter reading (kWh) data with date and time stamp. An exhaustive review of data available from SDATS revealed several data anomalies, explained in detail in the next sub-section. **Table 3** lists high-level stats of meter interval data extraction from SDATS for those co-ops reporting.

Table 3. Statistics of Meter Location and Interval Data Extraction from SDATS

	Meter Location Data	Meter Interval Data		
	Number of Meters	Number of Records	Interval	Duration
Calhoun Co. ECA, IA	1,844	Approx. 5000	Monthly	May-12 to Jun-12
Clarke EC, Inc., IA	12,394	Approx. 2.5 Million	5 min, 15 min, and Hourly	Mar-12 to Dec-12
Delaware County EC, NY	617	Approx. 2.7 Million	Hourly	Jan-12 to Mar-13
Delta Montrose EA, CO	No Data	No Data	No Data	No Data
Flint EMC, GA	59,690	Approx. 8.7 Million	Daily	Aug-11 to Mar-12
Humboldt REC (Midland), IA	2,037	Approx. 8.0 Million	Hourly	Jan-12 to Sep-12
Iowa Lakes EC, IA	9,655	Approx. 133 Thousand	Daily	Jan-12 to Jun-12
Owen EC, Inc., KY	No Data	No Data	No Data	No Data
Prairie Energy Co-op, IA	4,993	Approx. 17.7 Million	Hourly	Jan-12 to Sep-12
MVEC, MN	42,541	Approx. 24.1 Million	Hourly	Mar-12 to Aug-12

6.2.5 DR Event Data

These data contain DR event information, such as start of the event date/time stamp, end of the event date/time stamp, anticipated kW demand reduction, and actual kW demand reduction. Most co-ops have not reported these data in SDATS, and we are working directly with them and in some cases, their G&T, to request the data.

6.3 Data Quality Issues

As shown in **Table 3**, the extent and amount of data received across the co-ops varies and, importantly, the apparent quality or reasonableness of the data also varies.

6.3.1 Meter Location Data

The meter location data generally were understandable and useful. However, there were limited instances of apparent confusion regarding the fields that were intended to capture participation in DR programs. In a couple of instances, data were incorrectly entered and either reflected no participation in programs or the use of additional equipment (e.g., IHDs, PCT) not actually installed.

6.3.2 Customer Load Data

The following are the primary data quality issues impacting usefulness of the load data:

- A few co-ops uploaded data of only a daily or monthly frequency, which is not very useful for analysis of impacts on load profiles or energy consumption due to DR events.
- One co-op uploaded data that appear to represent daily cumulative meter readings rather than interval reads. While it seems likely that these values could simply be subtracted to yield the daily interval kWh, it was never resolved what the data actually represented, and there were a considerable number of missing data points. However, as discussed below, the co-op in question agreed to work on providing a new data set.
- Due to the limitations of the AMI system, some hourly load data were in whole numbers, which yield insufficient variation across many hours for the typical residential and small commercial customers, the loads of which are frequently less than 1 kW.
- For most of the co-ops that did provide hourly customer profile data, the data include numerous instances of potentially erroneous zero load intervals and anomalous spikes, as well as missing values.

It appears that many co-ops experienced data transmission issues over PLC communication systems, particularly early in the deployment of AMI equipment, which tends to cause missing and anomalous readings to be captured in the downstream systems. Issues such as line noise are also likely culprits in these cases. One of the co-ops reported that bandwidth was insufficient to transmit the load profile data, and that it was difficult at times simply to capture the consumption readings used for billing purposes. One of the co-ops reported that its communication issues were improved by the installation of additional repeaters along the distribution lines, although for many co-ops, it appears that data transmission from the substations back to the master station was also a problem.

In our experience, these sorts of communication issues are common to PLC systems and require the ongoing attention of an experienced operator of the equipment to monitor data feeds, ensure complete coverage on an ongoing basis, and engage in frequent re-uploading of anomalous data points. It is likely that co-op staff was stretched to afford this kind of attention and would require ongoing feedback on data review to engage in a secondary uploading process.

It also was noted that some co-ops, in consultation with NRECA, suspended uploading data to SDATS because of these data issues.

6.3.3 Conclusions

Calls were made to each co-op for which data quality issues or missing data were evident. Participating co-ops compiled additional data deemed useful in the study of the success of their DR programs. We received additional event data across the co-ops, as well as samples of customer load profile data from which to ascertain the tractability of formats and engage in a larger-scale compilation of customer load profile data. For at least one of the co-ops, the load profile collection capability of meters was disabled at some point, so no profile data can be captured from historical periods up to this point. The remaining sections of this report summarize the objectives, approach, and results of our detailed econometric analysis of all available co-op data.

Appendix A contains a detailed description of our proposed DR Planning Model, including an overview of types of programs covered, inputs, and outputs. This model and associated analysis process represent a simple yet complete method for estimating the value of deploying various DR program types at cooperative utilities. Only a portion of the data needed to fully populate the model was available from co-op DR deployments. Therefore, our goal is to leverage the data available to the greatest extent possible and subsequently identify additional data needed to fully build out a complete DR Planning Model that supports analyses of all relevant DR types and is empirically driven.

7.0 Statistical and Econometric Analyses of Cooperative DR Program Data – Testing the Theoretical Basis for Demand Response

7.1 Testing the Theoretical Basis for Demand Response—Overview of Analysis Objectives

The theoretical basis for DR programs is a function of several commonly accepted assumptions. (1) It is assumed that a utility can engage in load control events over a period of time that aligns with its system or wholesale billing peak, thereby saving the utility and its customers money on costly wholesale peaking purchases. (2) The impact of a given load control event in kW reductions represents a significant reduction, typically based on general rules of thumb regarding appliance peak load and diversity, and the extent of control cycling. (3) A DR program can be administered in a cost-effective manner, in that the cost of abatement (infrastructure capital cost, participant incentives, and ongoing administrative costs) is less than the cost of otherwise having to meet that demand with traditional generating resources. The effectiveness of the program also rests on the premise that any “rebound” in load in periods succeeding or preceding the load control event do not cancel out savings gained during the period of control, and that targeting larger customers leads to larger returns (i.e., the best “bang for the buck” for demand response is generally achieved by targeting large customers).

This study utilized econometric analysis (described further in Section 7.2) to test a subset of these premises. By gathering empirical data in the form of hourly loads from participating co-ops and conducting analytical tests, the theories above are allowed to “confront” the data, so that it can be determined whether they are supported either fully or partially in real-world deployments. Although certain of the above premises may be obvious in a theoretical context, they are anything but obvious in practice. Obtaining objective estimates of abatement and evaluating theories provides significant value in terms of future investment decisions related to demand response. Such decisions can be made based on empirical evidence instead of theoretical assumptions that may or may not be supported by the data.

Table 4 provides a summary of the key research questions underpinning the theoretical basis for demand response, giving a high-level overview of which analysis objectives were covered in the study and the approach to achieving each research objective.

Table 4. Summary of Research Objectives

Research Question	Within Scope of Analysis?	Analytical Approach
Are load control events called during appropriate peak period times?	Yes	Compare duration of load control event data to peak timing data (where available).
Are load control kW reductions statistically significant?	Yes	Perform econometric analysis on hourly meter data from participating co-ops, controlling for hourly and weather variation.
Are there any significant load rebound effects either before or after the period of load control?	Yes	Examine leading or trailing edge hours in the econometric analysis for statistically significant and positive parameters.
Are full cycling and/or a focus on larger customers warranted as a function of larger abatement gains?	Yes	Conduct econometric analysis on isolated meters that are larger than average; conduct tests of variables that measure the percentage of load cycled (where data are available).
Are demand response programs cost-effective?	No	Refer to Section 10 below and Appendix A for a full description of a proposed DR screening tool that would address this question.

7.2 Analytical Approach and Data Sources

As mentioned above, econometric models were developed to estimate the parameters of interest. The primary functional form of the theoretical equation for these types of analyses is typically as follows:

$$\ln Yi,t = \alpha + \beta 1 \ln X1i,t + \beta 2 \ln X2i,t + \ldots + Bn \ln Xni,t + \epsilon i.t$$

Where,

Yi,t – The load characteristic of interest for customer i and day t

Xni,t – Explanatory variables for customer i and day t (discussed below)

α , βn – Parameters to be estimated via regression

$\epsilon i,t$ – The amount of error in the equation's estimate of Yt

As the data analyzed generally comprised customer loads and characteristics by customer and by day, they conform to what commonly are referred to as "panel data." Fixed effects panel estimation was the primary form of analysis conducted on each co-op's data set.

The econometric analyses attempted to explain variations in customer loads during DR events relative to loads for other hours/days, and as a function of a series of explanatory, or independent variables. The dependent variable, or variable explained in these analyses, was the customer load during the DR event. This approach leveraged as many attributes of the programs and technologies as possible.

Explanatory variables typically include those regarding the relevant electric rates (for dynamic pricing programs), customer attributes, event conditions, and weather conditions. The set of available explanatory variables initially contemplated was the following:

- Ratio of on- to off-peak electric rates (for dynamic pricing programs)
- Installation of "enabling technologies," or devices to assist the customer in awareness of DR events or reacting to events (e.g., IHD, programmable communicating thermostat, text alerts, etc.)
- Installation of AC and/or electric heat
- Installation of other appliances (e.g., electric water heating)
- Daily weather conditions (maximum temperature, temperature-humidity index, and/or preceding day maximum temperature)
- Seasonal variables (e.g., month of year)
- Day-type variables (e.g., day of week)

In practice, the set of possible explanatory variables initially contemplated as control variables was larger than what actually was available from the co-op data. As these were all direct control programs, there were no pricing-related parameters, and as no data were available regarding customer characteristics outside of program participation, the equations tended to be relatively sparse as to explanatory variables. The primary parameter of interest was a simple binary variable defining the control event, typically controlling for participation in the applicable program by combining the control event and participation binaries into a single binary variable. These equations sometimes were supplemented by equations specific to participant groups and even individual meters, for testing purposes.

Leidos compiled meter and event data from the subset of co-ops. Data were available for highly disparate periods and stretches of time across the co-ops. Generally, we were able to capture sufficient overlap between the meter data and the event data to test for event impacts, but there were significant periods of meter and/or event data for which overlap between the two was not available.

We supplemented these data with weather data from a nearby weather station, both to control for weather variation—where the appliance subject to control was not significantly weather sensitive (e.g., water heating), and to capture the impact of weather variation on the controlled load—where the appliance was highly weather sensitive (e.g., air conditioning). Data collected included daily high and low temperature, humidity, and precipitation. High and low temperature data were used to derive daily heating and cooling degree days,[16] which was the primary weather variable utilized in the analysis.

The analysis process was inherently iterative, with varying combinations of explanatory factors being posed, estimated, and reviewed for explanatory power and statistical validity as compared to other combinations. Once the best combination of explanatory variables and their estimated parameters was ascertained, the econometric model for a given co-op was finalized. As necessary and in alignment with the objectives listed in Section 7.1 above, alternative models were created to address differing research objectives, which are summarized in Section 8 below.

[16] Heating and cooling degree days are standardized measures of weather deviations in daily average temperature from a base, typically 65°F, summed over any period of interest. Heating degree days represent cool weather, and cooling degree days represent warm weather.

8.0 Statistical and Econometric Analysis Results

The methodology described above was applied to the subset of participating co-ops that we were able to engage and that provided complementary and/or supplemental data relative to data contained in SDATS.

8.1 Summary of Findings

The tables below capture estimated parameters, which represent the average kW savings that can be expected on a per-participant basis during a load management event, for hours during which LM events tended to occur across the co-ops, as well as hours viewed as being in the critical period of likely significant impacts due to higher coincidence of consumption for the end-uses in question. The tables are organized by the type of control program, with **Table 5** providing an overview of estimated impacts of water heater control programs and **Table 6** providing impacts of AC control programs. To the extent that a given hour was not within the control period of the co-op in that row or was otherwise not captured in the analysis, that cell is grayed out. To the extent that a co-op did not engage in a particular load control program, that entity is not shown in the table. Table 7 shows the combined impacts for AC and water heating programs—for some co-ops, all participants were in both programs, so the impacts of water heater and AC programs could not be determined separately. To the extent that no significant impact associated with load control was estimated for a particular hour or overall, "N/S" is shown in that particular table element.

Table 5. DLC Event Estimated kW Impacts—Water Heater Programs

Cooperative	# of Meters	# of Events	Overall	Hour Ending						
				7 a.m.	8 a.m.	9 a.m.	4 p.m.	5 p.m.	6 p.m.	7 p.m.
Clarke	80	7	-0.1					N/S	-0.2	N/S
DCEC	254	27	N/S	0.2[17]	-0.2	-0.1				-0.4
ILEC	317	97	-0.2	N/S	-0.3	N/S			-0.4	-0.6
PEC	530	372	N/S	N/S	0.4	N/S	-0.1	N/S	N/S	0.2

Table 6. DLC Event Estimated kW Impacts—AC Programs

Cooperative	# of Meters	# of Events	Overall	Hour Ending					
				3 p.m.	4 p.m.	5 p.m.	6 p.m.	7 p.m.	8 p.m.
Clarke	80	7	-0.2			-0.3	-0.3	-0.1	

Table 7. DLC Event Estimated kW Impacts—Combined AC & Water Heater Programs

Cooperative	# of Meters	# of Events	Overall	Hour Ending					
				2 p.m.	3 p.m.	4 p.m.	5 p.m.	6 p.m.	7 p.m.
FEMC	500	2	0.117		-0.2	-0.1	N/S	0.1	0.5
MVEC	190	15	-0.2		-0.3	-0.2	-0.2	-0.3	

[17] Parameter is positive and significant. It is reported herein for completeness and likely is due either to higher overall load levels during that period that tend to crowd out the impact of the LM event, a load "rebound" effect (as described above), or to bias due to an omitted variable that cannot be measured.

It is important to note that some of the parameters in **Tables 5**, **6**, and **7** may be positive. These parameters are reported for completeness and generally are driven from (1) higher overall load levels during that period that tend to crowd out the impact of the LM event (control periods and groups notwithstanding); (2) omitted variable bias that may impact the precision of the parameter estimates; or (3) to the extent that the hour falls along the edge of a load control event in an adjacent hour, some amount of load "rebound" due to the adjustment of load, resulting from control/cycling in surrounding hours.

It is also important to note that in most cases, control groups (or meters that were not participants in a given DR program) were available. In addition, every day of meter data for a control group that was not a load control event day was effectively used to estimate a load "baseline," or the amount of kW that could be expected (which would vary based on hourly variables inserted into the model to control for per-hour variation). If the variable or variables that isolated load control events or other thresholds were statistically significant, they were found to be so over and above baseline control variables. As mentioned above, these baseline control variables included hour-of-the-day and weather variables designed to control for weather-induced variation that is separate from variation due to load control.

To aid in the interpretation of the data above and the data upon which they are based, **Figure 4** below provides a comparison of hourly loads for control and non-control days averaged across all participating customers for Clarke Electric Cooperative. Average load data shown reflect approximately 60 meters over 7 control days and 21 non-control days with similar climate conditions.[18] As shown below, the control days exhibit lower load levels in the key load control hours to some degree, most notably the hours ending 17, 18, and 19, with some load rebound evident in the hours ending 20 through 24. In addition, higher loads are also evident in the hours preceding the event, presumably illustrating customers being familiar with the control parameters and perhaps pre-cooling the home heading into a control event. For the purposes of this figure, the non-control days are isolated to similar temperature days and participating customers to produce a useful baseline reflecting similar cooling requirements and customers with air conditioning (non-participating customers may not have air conditioning).

[18] As mentioned previously, the summer portion of Clarke's load management pilot reflected control events on every *other* day meeting certain temperature thresholds (on a forecasted basis) during summer months and a requirement for participants to have central air conditioning.

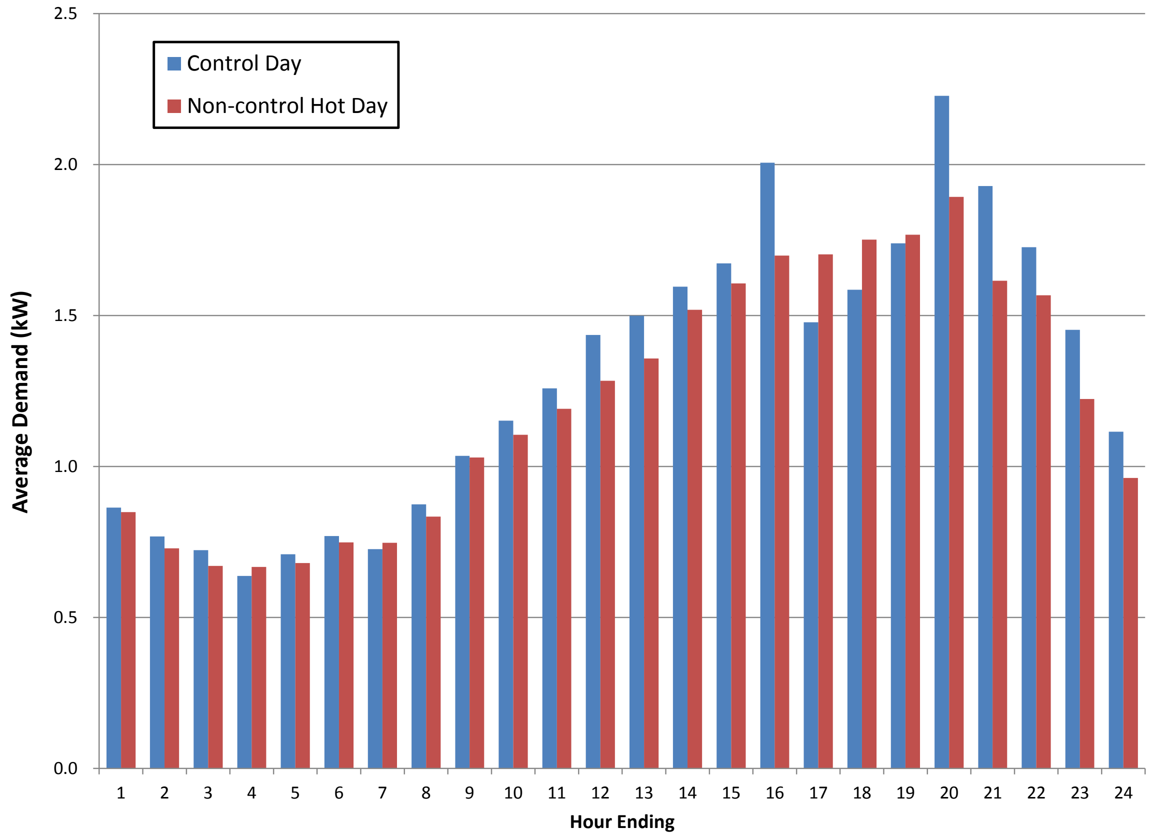


Figure 4. Comparison of Control vs. Non-Control Days with Similar Weather Conditions

The subsections below capture cooperative-specific program details and associated findings to provide more information regarding the numerical results and highlight key challenges associated with the analysis of each co-op's data, including thresholds required to generate significant findings (either through isolation of particular groups or compartmentalization of certain tiers of kW readings, as applicable).

8.1.1 Clarke Electric Cooperative

The Clarke data included 80 meters: 43 were participants in the AC control program only, 22 were in the water heater control program only, and 15 were in both programs. Accordingly, there were no non-participating customers. Control events during 2013, the only year for which data were provided, totaled seven events. As the control events were triggered by particular weather events on every other instance of such weather events, there were the same number of non-control days with similar weather conditions, which were included in the analysis as a baseline. There were numerous duplicate meter data observations, which were removed from the data set prior to analysis. Clarke meter data exhibited anomalous spikes in the loads of several meters, which were excluded from certain equation specifications to ensure that these potentially erroneous observations were not impacting the results.

Overall, impacts of load management were statistically significant, particularly for hours the ending 5 p.m. and 6 p.m. LM impacts were more significant upon isolating the data set for customers that were participating in either the water heater or AC program (i.e., using the non-control days as the only baseline rather than non-participating customers). It is possible that the perfect correlation between the coincident water heater and AC control events made it impossible for the statistics software to separate out the impacts of these programs. It is also possible that the effective baseline of non-control days for participating customers was more effective at isolating the control impact than the cross-sectional differences across non-participating customers (both those not participating in the particular program or in either program). In addition, there was evidence of both a statistically significant load rebound subsequent to the control period (as much as three hours after the control period) and higher loads in the hour preceding control periods, presumably due to pre-cooling of the home based on participant experience with the control program on preceding control days. These positive impacts in the hours surrounding the control period are readily visible in Figure 4 above.

8.1.2 Flint

FEMC meter data included more than 500 accounts; approximately 130 were in each of the following groups:

- Standard water heater and AC load control program
- Water heater and AC control program with notification of events via an IHD
- Water heater and AC control program with e-mail and text notification of events
- Baseline group with no load control

In August 2013, there were two load control events, spanning 3–7 p.m.

The hourly data available for Flint was reviewed and generally found to be reasonable. To ensure that empty cells or zero meter reads did not have an undue influence on our analysis, we generated an adjusted hourly meter read data set that excluded missing or “0” fields. This nuance did not appear to have a significant impact on the findings.

The data available for analysis for Flint was limited to the afternoon and evening hours, which makes it more difficult to find sufficient variation across the various groups and presents some econometric challenges when attempting to isolate hours and certain groupings. These challenges notwithstanding, the analysis reflects the following:

- During certain key hours and for certain key ranges of kW reads, most notably the customers that are larger than 13 kW, LM events were found to have a statistically significant impact on load.
- We have experimented with various combinations of isolated hours to determine how the threshold constraint changes the results; in general, the impacts of LM events are less significant for the smaller domain of kW readings, but become increasingly significant as the hour approaches 19 (7 p.m.) and the kW ratings are above 13.
- The above analysis suggests that, during evening peak periods, the program is having a statistically significant impact on the range of possible peak hours. The results shown in Table 7 reflect that generally, there was a statistically significant and perceptible abatement impact in the early hours of combined control when all kW reads for all meters were analyzed in one model.

8.1.3 Iowa Lakes

ILEC meter load and control event data spanned October–December 2013. Meter load data included approximately 300 meters, all of which were participants in the water heater control program.

Load control events totaled nearly 100, although days during which there was control included as many as 4–5 events, many of them in nearby time intervals. The periods of control were across many hours but were most heavily focused in the early morning (hours ending 7 a.m. and 8 a.m.) and early evening hours (hours ending 6 p.m. and 7 p.m.). There were multiple control events for various groupings of water heaters, specified as "primary," "secondary," and "tertiary." For purposes of this analysis, only the primary water heater control events were analyzed.

The meter data included many meters with highly volatile and potentially anomalous load patterns. For purposes of the results provided in the tables above, 12 accounts were excluded from the analysis due to potentially erroneous data.

As evidenced by the results tables, statistically significant impacts of load control events were found in several daytime and evening hours, as well as overall, across all hours.

8.1.4 Prairie

The Prairie data set was generally reasonable. Initial econometric analysis was halted to investigate bracketed meter reads subsequently found to be separately metered heating load. After this investigation, those observations were excluded from the data set, and the econometric analysis was refreshed. Exclusion of the separate meters resulted in parameters for abatement that generally were larger and more in alignment with expectations. Based on the revised analysis, the following represent some overarching findings relative to the data set:

- The impact of load control over the aggregated hourly period was not statistically significant.
- Water heater participants, in certain isolated hours, did not have statistically significant amounts of abatement.
- The hours found to be statistically significant as to control periods were not necessarily bounded within the domain of hours that would be considered typical peak or control periods. (A possible exception is 8 p.m., which reflects hour 21, given the manner in which the time stamps for the data set were structured.)
- As evidenced by Table 5, some amount of statistically significant rebound impacts were also found in certain hours.
- The data were spliced in an effort to understand whether generally larger kW readings were subject to larger incremental abatement estimates. For the hours in question, load control events that align with meter reads of 10 kW or less generally were found to have a lower abatement impact than the estimated impact over the entire data set.

8.1.5 Minnesota Valley Electric Cooperative

For MVEC, the econometric data translation process that converts the data set into a dated panel for analysis initially identified some duplicated meter stamps and time stamps, which was believed to indicate that there were duplicates in the data set (same meter ID and same time stamp more than once). This prevented the software from doing a full panel translation and, as an alternative, "cell IDs" were created to ensure that each cross-sectional element was unique. The focus of our analysis was on the cycling of AC units; the "dual-fuel" meter reads were excluded from the analysis. Data were available for both the participation of a given meter and the percentage associated with the cycling of the end-use.

Leidos engaged in a more thorough data review and uncovered that the duplicate records were caused by a lack of precision in certain isolated time stamps, wherein the hour in question was not being read properly by our statistics software. We adjusted the format of the raw data and replicated our earlier analysis with a full panel data set to ensure the consistency of the findings.

The key findings associated with the MVEC data set are as follows:

- When kW readings were in the smaller range (less than 2 kW in a given hour) and during key hours in which LM events took place, there was a small and statistically significant impact associated with abatement.
- Weather data, including maximum and minimum temperatures and heating and cooling degree days, were included in the analysis, and cooling degree days in particular worked to control some of the weather-related variation in the data, after which LM participation was found to be statistically significant. In models that capture either temperature or degree day measures, the omitted variable bias associated with estimates that may not reflect control for sources of weather variation was considerably lower.
- The level of participation appears to matter—and generally in the expected direction (i.e., only load management percentages greater than 0.5 were statistically significant).

8.1.6 Delaware County Electric Cooperative

DCEC meter data spanned approximately January through July 2013, excluding March 2013, while the event data were available only for March through mid-April 2013. Another 10 tests were run during the winter of 2013−2014, starting on November 24, 2013 and ending on February 10, 2014. The meter data reflected consumption readings in whole kW, with the majority of readings of either 0 or 1 kW, reflecting rounding of readings to the nearest kW and an overall lack of precision (i.e., no difference between 0.1 kW and 0.4 kW or between 0.5 kW and 0.99 kW). The 27 control events were concentrated in the morning, from the hour ending 7 a.m. to noon and the evening, from the hour ending 7 p.m. to as late as 11 p.m., frequently occurring in both morning and evening hours on the same day. The data set was populated with "LM_XX" variables that captured specific events, as well as "LM_YY" variables that captured participation across various retail groups (e.g., farms). While this additional information was tested to determine the possibility of discerning differences in participation across groupings, there was no significant difference between the central variable that controlled for LM events and the other variables. This is likely to be driven in part by the lack of precision in the underlying kW reads.

Statistically significant impacts of LM events were sparse and typically not significant across the hours of control. Hours that were statistically significant tended to be focused around the typical periods of hot water usage in households, in the mid-morning and early evening hours, as shown in **Table 4** above. It is likely that the lack of precision of the meter data, along with the more typical data vagaries across the co-op data sets, limited the ability of the statistics software to detect load differences.

8.1.7 Overall Findings – Insights on the Theoretical Basis for DR

Based on the overall set of analyses completed by co-op, the following are some overarching themes regarding the findings, which represent high-level insights on certain theoretical bases for demand response as detailed in Section 7:

1. Load control events, when initiated, do result in statistically significant impacts for hours in which it is reasonable to anticipate a utility will peak. These impacts generally are in the same range for per-device, per-event kW savings across the entities in the analysis.
2. When the data for meters that had larger average kW readings were analyzed separately, there were larger statistically significant amounts of abatement. This is in general alignment with theoretical expectations, in that larger meters and larger customers are more

likely to achieve tangible reductions in load (i.e., reductions that can be teased out of the data) from load control programs.

3. Full control or cycling, or event criteria that generally cycle to a greater degree were found to be statistically significant in terms of abatement of kW. This suggests that partial cycling may be less effective at obtaining significant levels of abatement, and is in alignment with theoretical expectations.
4. There was a statistically significant rebound effect identified in certain co-op's models.
5. Weather data were extremely useful for controlling for variation when developing estimates of abatement and controlling for the impact of weather variation and the reduced parameter bias that results from models carefully infusing weather data into the analysis.

Demand Response Program Success in Abating Peaks

The value of a load control program lies in the utility's ability to control load during peak load hours—either the utility itself or its wholesale provider, if its demand charges are based on a coincident peak. This is due to the fact that capacity costs are driven from the utility's peak demand value, whether directly through a wholesale power supply contract or indirectly through generation assets built to meet a previously forecasted peak demand. In addition, capacity costs are driven by electricity demand during relatively few hours. Consequently, abatement that does not align with the utility peak or coincident peak provides only avoided energy cost, but no avoided demand cost.

Load control needs to occur in a sufficient number of hours to provide assurance of actually abating the utility's peak demand or the wholesale demand billing hour. However, the number of load control events cannot be unbounded, as frequent disruption of end-user comfort likely will lead to program participant attrition. Control cycling of less than 100% during control hours reduces this disruption considerably but also reduces the overall abatement.

To properly evaluate the economics of a load control program, this imperfection in the alignment of control events and peak load events should be taken into account. The reality is that peak periods cannot be forecasted with perfect accuracy, and the success of load control event timing typically is not known until well after the fact. In cases of wholesale power supply contracts for which monthly demand costs are driven by a single coincident peak hour (or annual demand costs, over a few summer months), capturing the full demand abatement benefits typically requires fewer hours of control. This proposition can be complicated by cases in which a host of the supplying utility's other wholesale customers also are "chasing" the peak.

In an effort to determine the co-ops' success at controlling loads during peak load periods, Leidos requested peak timing data from our contacts for the period overlapping the deployment of the load control program in question, at a minimum, or additional data, if available. Data regarding the timing of peak load events were available for three co-ops, DCEC, MVEC, and PEC. Data also were available on peak timing for Basin Electric Cooperative during 2012 and most of 2013, which were provided by Corn Belt Power Cooperative, and represent the basis for wholesale demand billing for the Corn Belt co-ops, including PEC. Of the 26 total peak events taken from these data, load control was called during 19, or 73%, of them. While Flint provided data regarding its top 10 load hours for 2013, they were not exactly comparable to data from the other co-ops, and it appeared likely that load control event data were not sufficiently available for this purpose. As PEC provided the longest time series of both monthly peak demand and control events, these data are most representative of that co-op and, in essence, of the Corn Belt

Power Cooperative—Corn Belt Power Cooperative initiates load control events. The data show that control events were successful at hitting the majority of peak events. However, as noted in the discussion of the econometric analysis of customer loads, statistically significant impacts on customer loads were found during only a subset of control event hours.

It is important to note that, while on the surface, comparing the recorded peak to the domain of load control events is one indicator of the possible success of a load control program, it is entirely possible that engaging in load control for a given hour actually reduced demand in an hour *that otherwise would have been the actual peak*. To more fully test whether a given program's control events matched the hypothetical peak that would have occurred absent the load control, it would be necessary to "gross-up" the relevant hourly load profile based on hourly estimated impacts. These hourly load data were not requested from the participating co-ops and, for the Corn Belt co-ops, could not be obtained from the wholesale provider in question, whose loads also would have been impacted by other wholesale customers engaging in load management. Such an analysis was beyond the scope of this project.

The results of our review suggest that the majority of the peak events analyzed were covered by load control. However, a key consideration, because only a subset of the control event hours was found to contain a statistically significant impact, is this: *the analysis suggests that utilities should take care to include conservative estimates of abatement in any future cost-benefit analyses*. Such estimates should capture discounting factors to account for the peak demand coincidence of the abatement and other net-to-gross factors that result in lower actual estimates of abatement, compared to theoretical rules of thumb or engineering-based estimates of end-use loads.

9.0 Observed Data Challenges and Issues—Econometric Analysis

In prior sections of the report, we summarized challenges regarding the collection, manipulation, and amalgamation of data for purposes of rendering those data suitable for econometric analysis. In addition to these, we uncovered other data challenges and issues after the onset of the econometric analysis. Given the large volume of data and the somewhat disparate nature of the control event data available, Leidos went through a secondary quality control process as the data were being subjected to initial specifications within Eviews and as part of the development of panel data sets (described in prior sections of this report) within Eviews.

The following is a list of the additional challenges encountered during the econometric analysis:

- Event data for several co-ops were not in the desired format required by the analysis. We had to simplify the data to bring them to the desired format and subsequently created other threshold variables within Eviews as deemed appropriate.
- In one co-op's data set, a few of the MeterIDs had a special character (bracket "[]") along with a numeric meter number that was discovered when attempting to create the panel data set within Eviews. After discussion with the co-op member, we realized that the brackets represent separate metering for heating. These separate meters were excluded from the analysis.
- Some co-ops' data sets had duplicate meter reading entries with different kW values for a similar MeterID and DateTime stamp. We had to remove these entries to create a consistent data set for the analysis.
- Some co-ops' meter reading data had zero values for the kW field. It was difficult to find out whether the zero values are actual kW or rounded-off values because some co-ops'

meter data management systems round off the kWh readings to the nearest integer values or simply are not capable of capturing double precision values. To address the potential impact of this nuance on the analysis, we generated adjusted kW time series that excluded zero values, and ran the analysis using both data sets. As noted above, this nuance does not appear to have any impact on our findings, which is mostly due to the volume of observations in any given equation.

10.0 Nexus between Analysis Results and DR Screening Tool

The econometric analysis conducted in this project is a critical element of the Leidos vision for a Demand Response Planning Model, which is described in extensive detail in Appendix A. **Figure 5** provides a more high-level overview of the key components of the screening tool architecture.

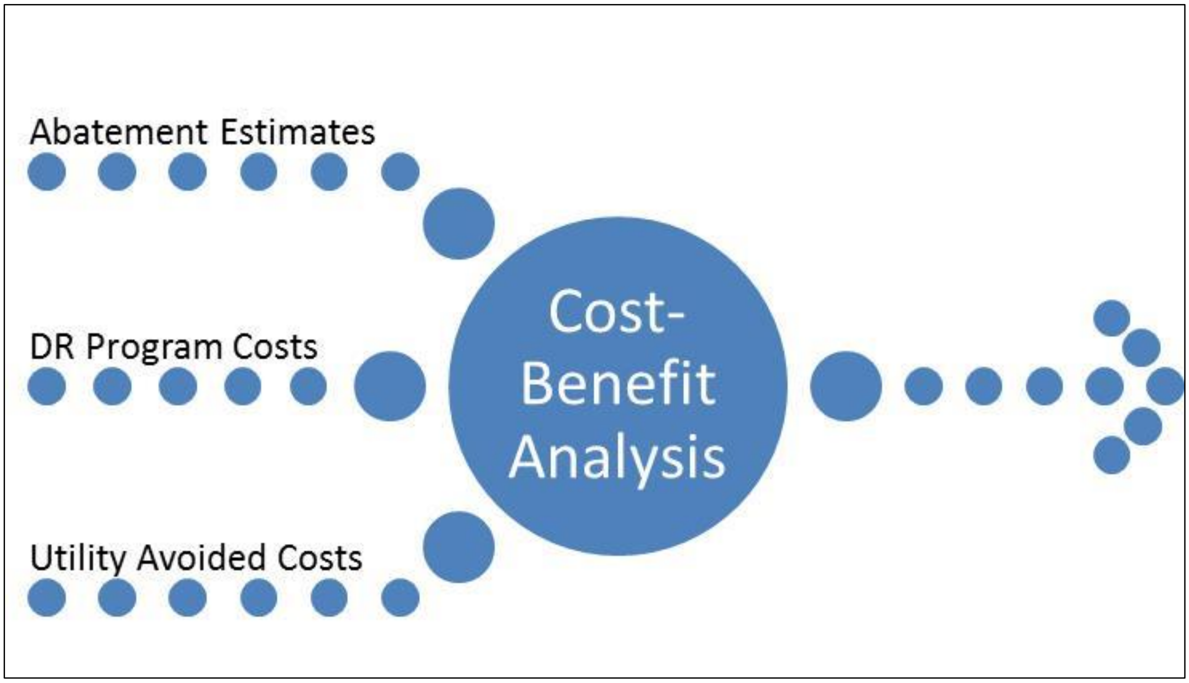


Figure 5. Top-Level Demand Response Planning Model Architecture

The econometric analysis conducted in this project provides (or can be manipulated to provide) the following critical assumptions to the planning model:

- If all else is equal, the per-unit, per-event, hourly kW abatement for a variety of load control programs, either in aggregate (for all hours), or for specific hours.
- Details on which hours can be assumed to be statistically significant, in general, or based on the specific portfolio involved, which can inform assumptions that vary based on the type of program assessed and the range of hours over which load control events are anticipated to be initiated by the utility involved.
- The likelihood that load control events resulting in statistically significant impacts align with utility peaks, which can inform discounting factors associated with peak coincidence for cost-benefit analyses.

As evidenced in **Figure 5**, this domain of intelligence/information can be considered one-third of the triumvirate of assumptions required to objectively evaluate a DR program (or the universe of "abatement estimates"). The other two key components can be defined as (1) information on avoided costs, which typically are based on wholesale demand charges or more detailed estimated costs of power supply; and (2) detailed cost estimates associated with the all-in cost to deploy the demand response program, including core equipment, information technology/architecture, marketing and incentives, maintenance and repairs, and the long-term administrative and general costs associated with maintaining customer relationships and procuring new participants.

The construction of a robust DR planning model is the logical extension of the work summarized in this project. Refer to Appendix A for further details on other sources of data and more detailed discussions of suggested model architecture, inputs, and outputs.

11.0 Lessons Learned

Based on the direct contact with participating co-ops, the review and manipulation of data as based on SDATS and follow-up information provided by individual co-ops, the results of the econometric analysis described above, and the Leidos vision for a downstream screening tool, the following are some lessons learned from our research endeavor.

1. ***Cooperatives would benefit from further education and tools to assess the costs and benefits of programs prior to deployment***. Leidos did not encounter any participating co-op that had engaged in cost-benefit analysis prior to deployment of the programs, which suggests that each entity based its deployment decisions either on prior experience with existing DR programs already in place or through more high-level judgment techniques. In an incentivized (or demonstration-based) context, this approach provides sufficient coverage of options, and indeed, co-ops were successful in obtaining statistically significant hourly impacts associated with their load control programs, as detailed above. However, were the utility to finance such an endeavor on its own, further analysis should be conducted to estimate the total resource costs of a given program compared to the utility's avoided power supply costs (or wholesale demand charges) and to examine the impact of the deployment on non-participants. The screening tool Leidos proposes to construct is predicated upon designing a user-friendly framework to engage in these types of analyses.
2. ***A common standard or rubric for data management, scrubbing, and reporting capabilities, which leverages the power of SDATS, would allow for more efficient long-term tracking of DR program performance***. Leidos engaged in a greater-than-anticipated effort in extracting data from the SDATS system and working with individual co-ops to understand, catalogue, and scrub meter data. Additionally, the nature and extent of reporting into the SDATS system appears to have been executed in different ways across the various entities. A common set of guidelines for how to review and scrub the information would greatly expedite future investigations into the efficacy of DR programs over a much longer period of time. Such guidelines are critical precursors to the econometric analysis, which itself can be refreshed as time progresses and the program matures as to both the command that utilities have over anticipating the timing of load control events and the customer relationship management required to maintain a successful program.

3. ***Utilities should embed conservative estimates of load control impacts on a per-unit basis into their evaluations***. As evidenced by our modeling results, the efforts to generate load control events that are commensurate with the system peak are generally aligned with expectations. However, the process is not perfect, and additionally, the ability of a given event to achieve a statistically significant impact in a given hour varies based on the type of program and the individual utilities involved. These results reinforce the notion of incorporating discount factors for peak coincidence, persistence, and net-to-gross issues, and applying them to engineering-based estimates of the technical abatement potential of load control devices.
4. ***Utilities may be able to attract participants without significant monetary incentives*.** In some instances, entities provided similar feedback on the methods and incentives used to attract program participants. A commonly heard element of this approach was to hold town hall meetings or "get the word out" in informal ways, with the core message being that participating in the program is helping the member's co-op, and consequently the community served by that co-op, to save money. The consumer reaction when presented with the program opportunity indicates that messaging strategies targeted toward the intrinsic benefits of load control may be a complementary tactic that can offset or reduce the need for direct financial incentives or credits. While compensatory incentives are unlikely to be phased out, the costs associated with attracting and maintaining program participants may be able to be reduced with the right communications platform.

Appendix A: Demand Response Planning Model

A.1 Purpose

Numerous demand response (DR) studies have been conducted over the past few decades in various regions of the United States. The outcomes and lessons learned from many of these pilots and theoretical research studies have published a wide spectrum of results. It is the NRECA's desire not to repeat or restudy this arena but to glean from it, the best of the existing research findings to frame an approach to develop an easily accessible yet robust DR cost-benefit evaluation model that will enable co-ops to evaluate the relative effectiveness of competing demand response programs.

Specifically, this meta-analysis and accompanying model will enable electric co-ops to understand the demand response potential that their specific class of customers will be able to provide, gauge the benefits of the DR, and quantify the costs of implementing such a plan. DR implementation results and data from the NRECA Smart Grid Demonstration Project will be leveraged for this analysis and tool development.

The overarching purpose of the DR model as based on the collective vision of NRECA and Leidos is to devise a tool that will accomplish the following:

- Provide a warehouse of cost estimates for a portfolio of potential DR programs (which are defined below)
- Provide algorithms and assumptions from which the load impacts of the portfolio of DR programs can be estimated, taking into account customer attributes, environmental conditions (e.g., weather conditions, seasons, day of the week, etc.), and the technical or engineering realities associated with a given program;
- In the absence of user-provided data specific to the co-op, leverage representative assumptions regarding the cost of abated marginal energy or peak demand to monetize the overall load impacts
- Combine the cost of the program, the estimated avoided costs (benefits) of the program, and assumptions or analysis regarding potential participation rates for the program to compute benefit-cost ratios, discounted payback periods, and return on investment estimates that consider the most significant model factors ("first order effects"), with appropriate data proxies where necessary

The model will carefully balance inputs and assumptions formulated into outputs within the model itself with, as appropriate, exogenous estimates of certain key assumptions (such as adoption rates). Preliminarily, it is anticipated that research into existing empirical studies will drive the majority of model logic, with boundary constraints limited to estimates of program participation, which will be an exogenous user input that will allow model users to devise scenarios of their choosing. At a very basic level, the model will internally develop the unitary benefit-cost ratio, net present value of system benefits, and internal rate of return for a single instance implementation of every DR program within the pre-defined portfolio.

The remainder of this document details (i) a model overview that defines the DR programs we contemplate the tool will cover, provides the perspective from which the evaluation will be conducted, and delineates preliminarily contemplated inputs and outputs, ; (ii) the approach to be taken to devise model inputs, (iii) a high-level overview of the proposed model's processes, sequencing, and architecture, including details on how the ultimate benefits, costs, and return on investment calculations will be summarized, and (iv) the data that is anticipated to be required to execute the model. Finally, a discussion of next steps, given the information contained in this paper is also provided.

A.2 Model Overview

The core elements of the model development process that will define the model boundary are the types of DR programs the model will cover, the perspective of the cost-benefit evaluation, and the main model inputs and outputs. Each issue is summarized below, with the global understanding that the model boundary will be reviewed and refined during analysis and modeling activities, and that the items summarized herein are intended to provide us with sufficient specificity from which to finalize the model architecture.

Types of DR Programs Covered

The model will be able to provide coverage of the following DR programs:

- Direct Load Control, which in the residential sector will be constrained to the most top-of-mind programs, specifically, water heater, HVAC, pool pumps, and irrigation pumps, and for which up to 7 additional programs will be considered in the commercial and industrial sector;
- Seasonal Time of Use;
- Critical Peak Pricing (or time of use with a price differential during critical peak periods); and
- Peak Time Rebates.

The model will be parsimonious, in the sense that users will be able to model one program at a time, and will be able to generate multiple iterations of the model to compare various scenarios or alternative programs against one another using a set of consistently derived outputs (defined preliminarily below).

Perspective of the Evaluation

There are differing perspectives that can be taken when evaluating a given DR program from an economic standpoint. The seminal literature on DR programs generally categorizes these perspectives into one of the following categories:

- The utility administering the program
- The participant in the program
- The ratepayer who is not a participant in the program
- Society in general and/or the external environment as it pertains to the public good resulting from abatement of demand and energy through participation in the program

Based on feedback from NRECA and research and discussions within the Leidos team, the model as proposed will focus on the perspective of the utility administering the program. However, it should be noted that this perspective does not imply that the model will ignore the impact of specific rate differentials and incentive payments on participation and ultimate response. These issues will be of paramount importance, as they will serve as key inputs for specific programs that will allow for an objective evaluation of costs and benefits.

Preliminary Model Inputs

The following is a list of preliminarily contemplated model inputs. Some inputs will be directly derived and entered by the model user (“exogenous inputs”), whereas other inputs will require extensive research in order to parameterize the model and afford the user the requisite intelligence to render the model meaningful under a variety of contexts (“endogenous inputs”). The list below covers exogenous inputs, and the Approach section that follows details the proposed thought process, research, and analysis required to derive the endogenous inputs. In some cases, flexibility will be provided to the user to select default values derived endogenously in lieu of direct input intervention, and those redundancies are listed in parentheticals in the list.

- General information regarding the utility, case number/title
- Retail class in question that DR program is being applied to and the number of customers in that retail class
- Estimated baseline energy use and peak demand contribution of a given customer within the retail class in question (to be buttressed by default values derived from within the model)
- Type of DR program desired to be evaluated
- Estimated costs of the DR program for inception and ongoing maintenance (but only to the extent the user wishes to override endogenous model inputs)
- Study period desired for the analysis (to be bounded based on a reasonable "upper bound" for the DR portfolio based on research and analysis and in partnership with NRECA)
- Tolerances for discounted payback period (if applicable)
- Rate differentials for the specific program (as applicable)
- Estimated demand rate (at peak) and marginal energy cost for the utility in question (to be supplemented by a template in the model that will guide the user through derivation of such rates, if desired)
- Estimated participation rates in the given program (to be supplemented by default values based on research and analysis underpinning the program in question)
- Specific nuances of a given program or selections to narrow down the specific retail customer base ("attributes") that serve as levers for both estimated demand and energy savings and participation rates, that will be active and available for user interaction if the program is selected and inactive otherwise (refer to the Approach section for a listing of such attributes)
- Intelligence/assumptions about weather or seasonal elements of a given program (time of day, seasonal details, weather assumptions, etc.) that have a direct impact on participation and demand/energy savings (to be supplemented with "typical" conditions associated with deployment of a given DR program based on legacy implementations in the literature)

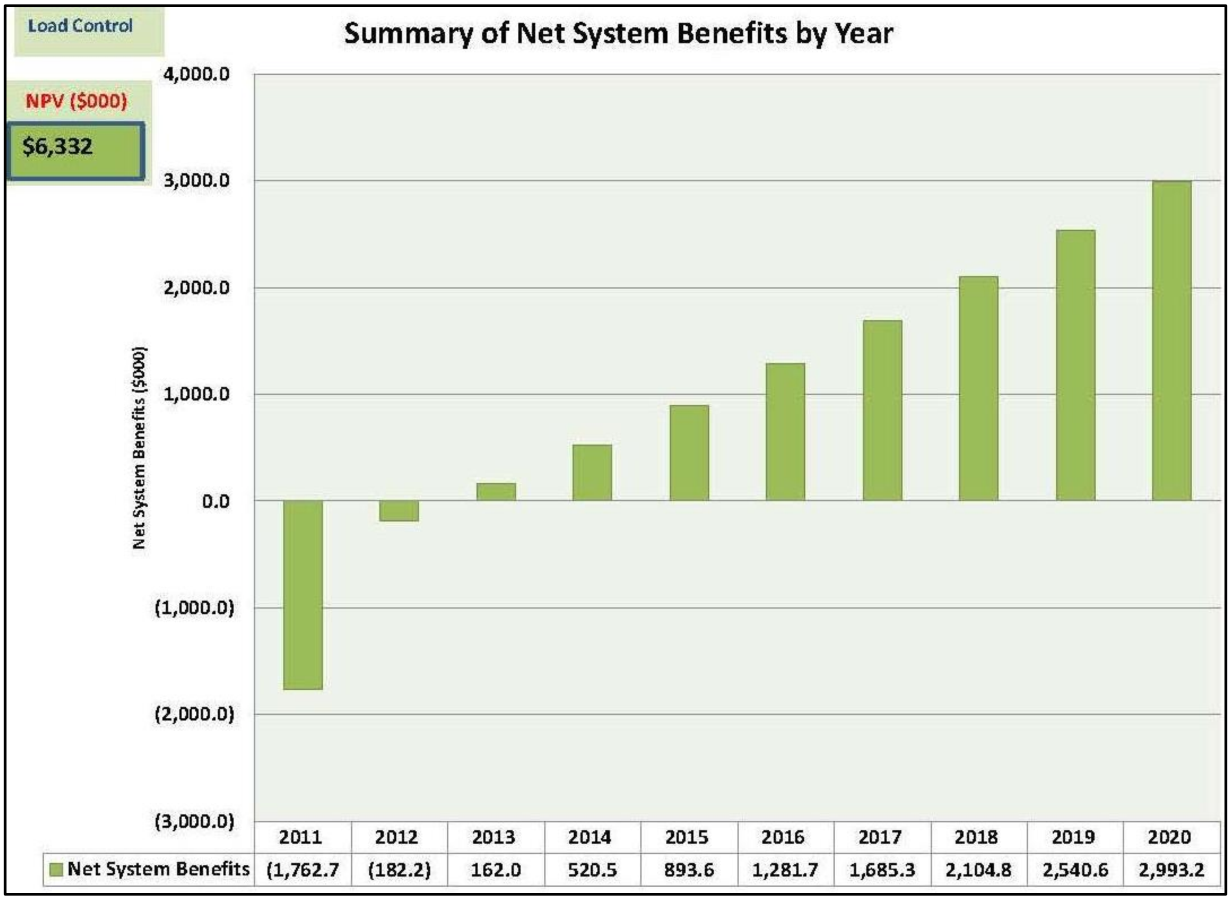
Preliminary Model Outputs

Given the exogenous user inputs and the endogenous model inputs (the approach for which is detailed below), the model will produce the following key outputs:

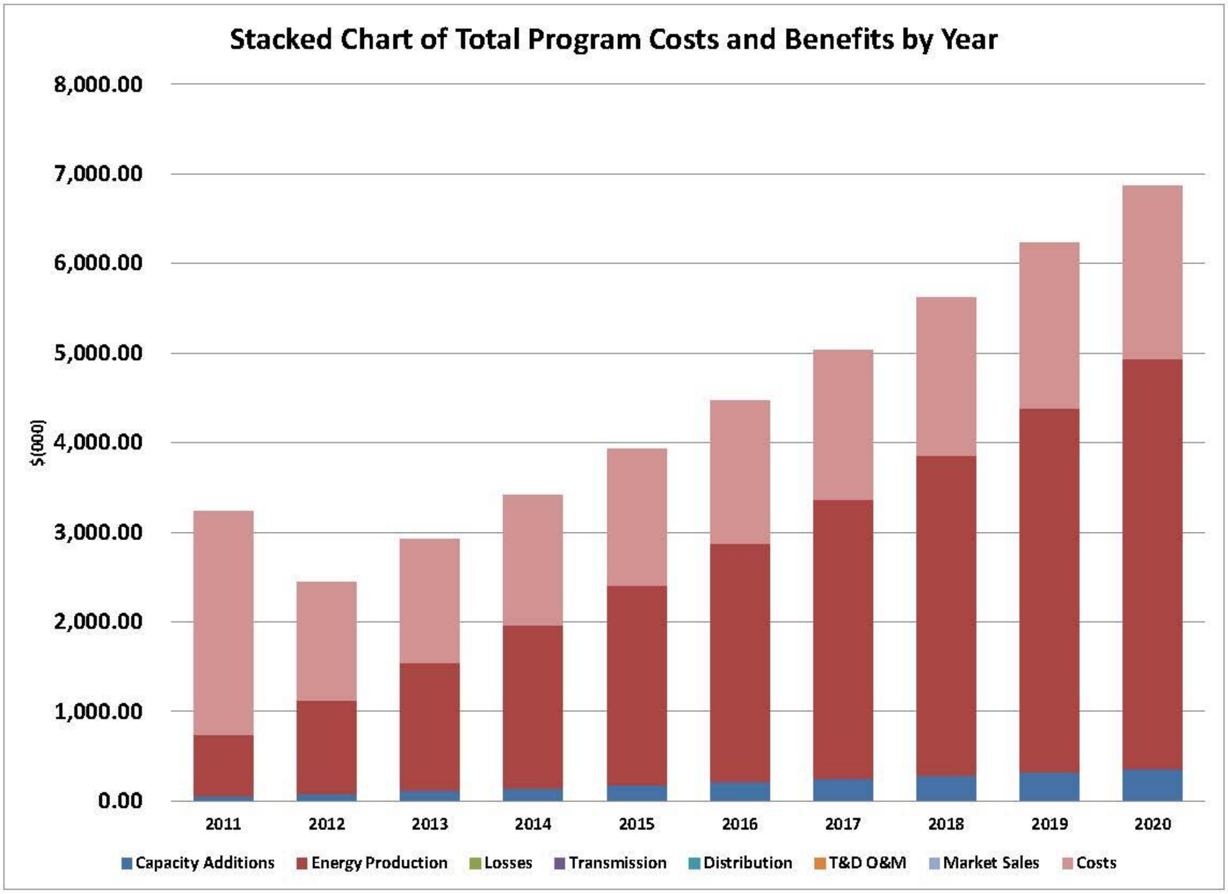
- Annual and overall energy/demand saved and/or energy shifted to shoulder hours (during study period)
- Net system benefits on a by-year and Net Present Value (NPV) basis, defined as the difference between total benefits and total costs of the DR program;
- Benefit-cost ratios (e.g., Total Resource Cost Test), which can be used to determine estimated program payback periods and/or serve as a litmus test for whether a program is implemented;
- Additional financial return metrics, most notably internal rate of return (IRR), which can be compared to the utility's IRR if it were to invest in programs other than DR; and
- Graphical outputs summarizing net system benefits on a by-year and NPV basis.

The figures below represent example mock-up of outputs that will be derived from the model.

The first figure summarizes the net system benefits and NPV of a mock program by year over an example study period. Up-front net benefits are negative as a result of the investment, but over time, as the marginal cost of energy abated increases and the up-front investment amortization period ends, there is a significant upside.



The second figure compartmentalizes the elements of cost and avoided cost in a stacked bar chart. Consistent with the above example, the cost bar is larger at project onset in this mock example, and the benefits from the elements of avoided cost considered (which are preliminarily defined further below) increase over time.



It is important to stress that the model outputs will be informed by feedback from NRECA stakeholders to refine these preliminary outputs in terms of both aesthetics and priorities related to financial metrics, and that, given a robust cataloguing of the appropriate costs and benefits of a given program, calculation of various industry standard benefit-cost ratios can be accomplished by combining the appropriate cost and avoided cost (benefit) elements together.

A.3 Approach to Gathering Endogenous Model Inputs

Overall, several important aspects must be considered when establishing a methodology to quantify the costs and benefits of demand response which have direct consequences in terms of the key endogenous model inputs for each DR measure, which are as follows:

- The elasticity of substitution for a given retail class that results in energy savings/shifted to off-peak periods and peak demand savings;
- Energy and demand baselines by retail class;
- Typical weather or seasonal conditions for deployment of a given DR program;
- Program costs (direct and ongoing);
- Participation rates (which allow for the allocation of certain fixed costs over a greater contingent of program participants); and
- The relationship between up-front investment/incentive levels or price differentials and participation.

Some obvious questions that must be addressed in order to parameterize the model with these endogenous inputs are:

- What customer attributes are important?
- What are the customer response sensitivities?
- What environmental conditions are relevant?
- Which DR treatments are the most effective?
- What drives the cost of the programs and implementation details?

With these questions in mind, and with the intent to develop a relatively simple initial model, we intend to focus our research on the population of co-op customers in each retail class (residential and commercial/industrial/agricultural) that is likely to provide load curtailment and participate in the DR programs, and quantify the impact of participation of those customers in the aforementioned portfolio of DR programs. We will establish a set of assumptions and perform analysis as needed that we will apply to the aforementioned specific customer attributes and then derive expected customer responses. Given reasonable assumptions regarding the nexus of these factors with actual customer activity and the savings to be achieved when deploying DR, DR program costs will be estimated as well as the DR benefits to the co-op, and these will determine the overall return on investment.

To define the appropriate customer population that will be the focus of our research, numerous attributes will be considered. Some of these attributes are fully relevant and others may not be germane enough to a parsimonious treatment of costs and benefits to warrant inclusion. Some key characteristics that have been identified in various studies are discussed below. We propose to bifurcate the retail space into residential customers and the collective commercial/industrial/ agricultural customer base when examining key attributes that will be used to derive the endogenous assumptions for each class by DR program. In addition, other key attributes outside of the retail distinctions will also be considered in the development of our endogenous inputs, most notably the elasticity of substitution. These factors, as well as the mathematical construct proposed to derive elasticity of substitution, are both detailed in the Model Architecture section below.

Residential Customer Attributes

This class of customer is likely the largest and most significant demand response group for many co-ops. As such, determining the simplest model will depend on what information is available about these customers. It all comes down to the ability to model their electric demand and predict that use over various conditions. Certain attributes that are drivers for consumption and, more importantly, curtailment will be considered and proxy attributes that may be substituted, if any, will be conceptualized. The majority of the specific customer data is expected to be obtained from the co-ops and augmented with a few proxy sources if necessary. The following attributes will be considered for residential customers as they pertain to measurement or estimation of DR impacts, and also for participation potential.

Attribute	Description
Energy Awareness	How energy conscious are the residents? Are they familiar with the impacts of energy production and the degree to which this affect s price and the environment? Would this level of awareness drive the customers to step up their level of participation if it will lower costs or preserve the environment?
Income level	Is the income level a predictor of their consumption? Does income play a part in how motivated the customer is with respect to demand response signals? Can a home value estimate be an accurate proxy? Alternatively, can the proportion of electricity cost relative to income in a region (ZIP code or census tract) be used to determine how much abatement of consumption matters?
Owner or renter	Does ownership have a positive effect on DR?
Single or multi-family	How do the different densities of homes affect DR?
Number of occupants	Certainly, a greater electric demand is expected as the number of occupants increases, but does this inversely affect DR participation? Will they adjust their lifestyle to save a few dollars?
Urban or rural	Does the location play a part? Can ZIP code be an accurate proxy?
Electric price	Does the price per kWh that the customer routinely pays make a difference? Existing retail rates can be used for this purpose as well as for valuation of avoided energy.
Electric energy consumption (per home)	Does the amount of electricity consumed affect a customer's reaction to pricing signals? Research suggests that low-consumption customers do indeed respond to DR programs. Their responses tend to be about the same percentage reductions in demand and energy as larger consumption accounts

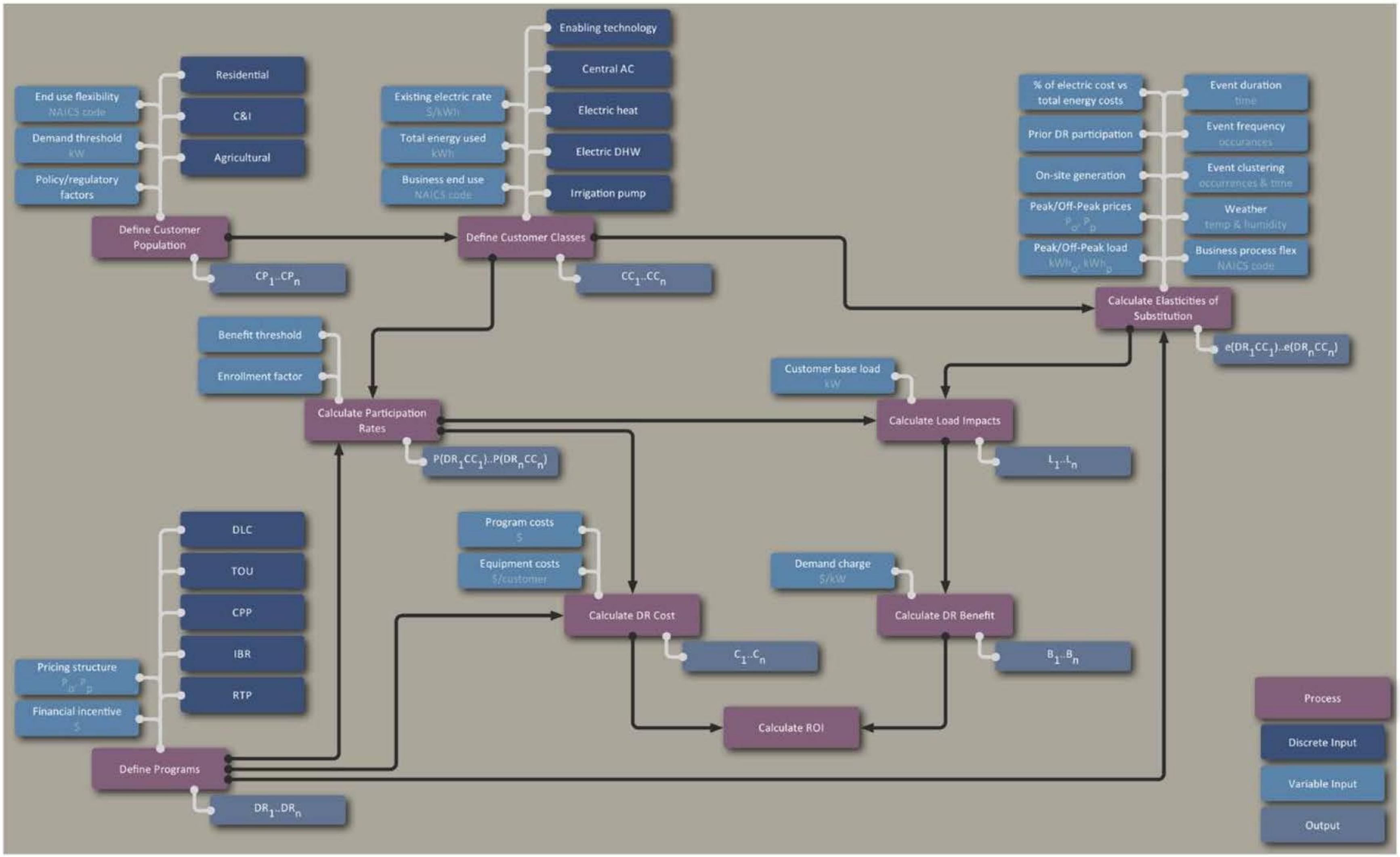
Commercial, Industrial, & Agricultural Customer Attributes

This class of customer, although typically fewer in number compared to the residential class, can individually have significant demand. They behave much differently and more diversely than residential customers and can be more difficult to model. The following attributes will be considered for commercial and industrial customers as they pertain to measurement or estimation of DR impacts, and also for participation potential.

Attribute	Description
Size of business	This will drive the overall consumption and, to some degree, the amount of curtailment possible.
Electric price	Does the price per kWh that the customer routinely pays make a difference? Are there specific commercial tariffs that may be counterintuitive with respect to DR?
Electric energy consumption (per sq. ft.)	Does the amount of electricity consumed affect a customer's reaction to pricing signals? Does a low consumption customer even have the ability to lower consumption any further?
End use	This perhaps is the primary factor in determining the potential DR. Does the business operate 24/7? Is electricity the fundamental energy source in the production of the end product? Does the business operate with multiple production shifts and have the ability to be flexible with its manufacturing process?

A.4 Model Architecture

The conceptual model addresses the above questions, and is depicted in the figure below.



The foundation of the model is driven by the baseline energy consumption of DR program participants. This provides the basis for determining the potential demand response from those participants. The discussion that follows provides a chronology of how the model will go about leveraging exogenous and endogenous inputs to derive the ultimate model outputs.

Define Customer Population and Classes for Analysis

The process begins by identifying the customer population for the DR program to be evaluated, as based on user entry. We propose to bifurcate the customer base into residential and commercial/industrial/commercial classes.

The model's endogenous assumptions will take care not to lump in customers that either cannot or will not participate in any demand response program. Customers that rely on electricity for critical operations are an example of a specific group (hospitals, data centers, restaurants, etc.) that may not be demand response eligible.

The purpose of this first step is to reduce the overall customer base into a smaller, demand response eligible subset that will be considered in the cost/benefit analysis. We believe that the bifurcation suggested will allow us to compute a representative elasticity of substitution that characterizes how a particular customer class will respond to a given DR program while keeping the model relatively simple in terms of structure.

Define Programs

Next, the model will consider the possible demand response pricing programs that are to be included in the analysis, as based on user selection and the aforementioned portfolio of DR programs. Various demand response treatments coupled with the desired pricing structures define the set of programs that drive the set of calculated elasticities. This element of the process will also define the costs of each program (either direct incentive costs, equipment subsidies, or ongoing administrative costs, as applicable) as a function of the specific program and the retail class selected by the user. Refer to the Data Requirements section of this paper for suggested sources of cost data.

Calculate Participation Rates

Based on the user input defining the targeted customer classes and the desired DR programs, the estimated participation rates will be calculated. As participation in utility DR programs can be fluid and vary from year to year, we intend to calculate these for each customer class/DR program pair based on a meta-analysis of existing literature for benchmark programs of like structure and customer base. Furthermore, as mentioned above, the user will have the full flexibility to revise or adjust our default model values based on their particular insights and estimates of penetration potential.

Calculate Elasticities of Substitution

Given the user-defined customer class and DR program, the response characteristics must be estimated. How will the targeted customer class respond to a price signal, given the relevant attributes and environmental and event conditions? How much of their on-peak energy will be moved to the off-peak period, and how much peak reduction can be expected? This will be a fundamental calculation within the model and will require significant research to (i) establish the attributes and environmental and event conditions that should be reflected in the model, and (ii) parameterize these factors as a part of the estimation of the by-participant impact of a given DR program.

Several demand response studies have documented the customer attribute, environmental, and event conditions that are dominant in determining the load response, in terms of elasticity of substitution, to DR events. As we anticipate estimating the DR impacts on an elasticity basis, the list below does not include price differentials between on- and off-peak, but the price differential is a significant driver. The key attributes denoted below are preliminarily proposed to comprise the "nuances" of a specific program, and the user will be able to use these nuances as levers in the model to utilize differing elasticity of substitution assumptions to the extent the model's endogenous calculation of the elasticity of substitution is informed by a given attribute. Note herein that retail class distinctions will also inform the elasticity of substitution calculation.

Key Attributes of DR Programs

Attribute	Description
Event duration	The duration of the demand response event drives the response rate; short events are more effective than longer events
Event frequency	Initially, demand response participation may be good, but as the frequency of events increases, the participation level decreases
Event clustering	As with the previous two event types, clustering is a combination of the two. Numerous events over a span of several days can be exhausting to the customer. As the clustering intensifies, customers begin to opt out of the DR program
Weather	As expected, both temperature and humidity play a significant role in demand response participation and the duration of these weather conditions is also significantly correlated with response.
Electric cost ratio	This attribute is the magnitude of the electric energy cost divided by the total energy cost for a customer. . Some customers may have a mix of electric and oil or natural gas energy consumption, and the percentage of electric consumption to service their energy needs affects how they view their ability to lower their overall energy costs. Energy costs as a proportion of total income (residential) or revenue potential during requested times of DR deployment (commercial/industrial) may also factor into the propensity of the participant to curtail load.
Prior DR participation	Studies have also concluded that those customers that have either participated in a previous demand response program or are "energy cost" conscious are more active DR participants.
On-site generation	The presence of generation at a customer site is a strong indicator of positive participation. It allows the customer to continue their consumption, most likely a business operation, and reduce demand from the distribution system.
Business process flexibility/end use	There is evidence that from a business process perspective, if the operation has the flexibility to move end uses to different times of the day, then demand response participation is feasible. This can be accomplished with processes that may be able to run on an alternate shift, after hours, or deferred to the next day.
Automation of response	Response rates tend to be significantly better if there is equipment that can automatically manage the response for the participant, such as automated thermostats for residential customers.

Methodology for Computing Elasticity of Substitution

The model will deploy an econometric approach to compute elasticity of substitution. This approach will leverage as many of the above attributes as possible. However, it is likely that additional discrete adjustments to elasticity to capture certain attributes will be made based on the prevailing literature and/or expert judgment when sufficient data does not exist to infuse that attribute into the analysis.

The typical econometric analysis seeks to explain variations in customer loads during DR events, relative to loads in other hours, as a function of a series of explanatory, or independent variables. The dependent variable, or variable explained in these analyses, is typically the ratio of the average load during the DR event to the average load during other hours, or the "Peak Load Ratio." Explanatory variables typically include variables regarding the relevant electric rates, customer attributes, event conditions, and weather conditions, as detailed above. The primary analytical method is typically a multivariate econometric analysis, which quantifies the isolated impacts of a large number of a priori specified variables on the ratio of load during event hours to load during non-event hours.

The primary functional form of the theoretical equation is typically as follows:

$$\ln Yi,t = \alpha + \beta 1 \ln X1i,t + \beta 2 \ln X2i,t + \ldots + Bn \ln Xni,t + \epsilon i.t$$

Where,

Yi,t – The load characteristic of interest for customer i and day t

Xni,t – Explanatory variables for customer i and day t (discussed below)

α , βn – Parameters to be estimated via regression

$\epsilon i,t$ – The amount of error in the equation's estimate of Yt

As the data set to be analyzed will generally comprise customer loads and characteristics by customer and by day, it conforms to what is commonly referred to as "panel data."

The potential explanatory variables are typically tested for their ability to explain variations in the ratio of on- to off-peak average loads include the following (which are generally aligned with the attributes listed above):

- Ratio of on- to off-peak electric rates
- Installation of "enabling technologies," or devices to assist the customer in awareness of DR events or in reacting to events (e.g., in-home display, programmable communicating thermostat, text alerts, etc.)
- Installation of air conditioning or electric heat
- Installation of other appliances (e.g., electric water heating)
- Daily weather conditions (maximum temperature, temperature-humidity index, and/or preceding day maximum temperature)
- Seasonal variables (e.g., month of year)
- Day type variables (e.g., day of week)
- Housing type (e.g., single- vs. multi-family)
- Type of occupancy (full- vs. part-time)
- Extent of daytime home occupancy
- Household income
- Household education attainment
- Household size and composition (e.g., number of persons, number of children, percent of household between 13 and 18 years of age)
- Technological proclivity of household decision makers (e.g., early adapters vs. laggards on the product adoption curve)

The analysis process is inherently iterative, with varying combinations of explanatory factors being posed, estimated, and reviewed for explanatory power and statistical validity as compared to other combinations. The modern standard of practice for multivariate statistical modeling involves the notion that "theory must confront the data." It is a critical part of the process to delineate what theories, intuition, or engineering expectations exist relative to particular socioeconomic or demographic conditions, that can then be cross referenced with the empirical model to put those theories to the test. In some cases, adequate data regarding a variable of interest will not be available, which will require inference from other related variables or the use of a proxy of some kind.

Once the best combination of explanatory variables and their estimated parameters are arrived at, the resulting equation can be combined with assumed values for the explanatory variables to produce estimates of load impacts (i.e., the percentage of load shifted from on- to off-peak). For purposes of reporting a single elasticity value, it is typically necessary to populate certain explanatory variables (e.g., weather conditions) and solve for the resulting combined parameter on the price ratio. For example, weather conditions are likely to be related to the extent of the impact of dynamic prices on load characteristics. In order to report a single elasticity value, an assumption must be made for the weather conditions that are representative of the typical conditions that are relevant—for example, an average summer day or summer peak day might be utilized.

The empirical research on the impacts of DR programs typically indicates price elasticities that are in a reasonable range and statistically significant. The range of price elasticity estimated from the load data of participating customers has ranged from approximately -0.05 to -0.30. Most of these studies have shown greater elasticities in the presence of in-home displays and other enabling devices.

Calculate Monetized Benefits of Substitution

Based on the estimated elasticity of substitution for a given stratum of participating customer, the estimated peak demand abated and energy saved or shifted to off-peak hours will be monetized. As noted above, certain assumptions involved in the calculation will either be a function of default values endogenous to the model, user overrides, or templates designed to aid the user in determining the appropriate basis for valuation. Valuation of benefits will be achieved using the following avoided cost protocol:

- Abated peak demand will be valued at either the demand rate of the prevailing utility for the given customer class (if applicable) or the capacity cost of the marginal resource that would otherwise serve that load; as some customer classes are billed based on demand rates, benefits will be greater for those customer classes
- Energy saved will be valued at the marginal energy cost, either based on rate ratchets for on-peak energy or, if not applicable, the general energy charge (e.g., residential)
- Energy estimated to be shifted to shoulder hours will be valued only to the extent the specific customer class is subject to price discrimination based on peak/off-peak consumption; otherwise, there are no monetized savings, as the consumption is merely shifted and not saved.
- The key components of avoided cost (or benefits) that are preliminarily contemplated for evaluation over a pre-specified time horizon, some of which may not necessarily apply to every DR option contemplated, include:

- Avoided or Delayed Generation or Purchased Power Capacity Additions (demand savings);
- Avoided Costs of Energy Production (including avoided emissions costs);
- Avoided Transmission/Distribution cost (including avoided capital expenditures);
- System Loss savings;
- Avoided ongoing O&M costs associated with Transmission and Distribution system improvements (if any); and
- The value of potential power market sales of resources that are free to serve the external market in place of the energy generation that has been avoided as a result of the DR Program.

To the extent that adjustments need to be made to the list above to capture specific nuances of a given DR measure, such changes will be made, while balancing the need to develop conclusions about the costs and benefits of the program using a standardized method that reflects the current standard of practice in the electric utility industry, and that can easily be compared across different options.

From an avoided cost perspective, it is anticipated that the bulk of benefits will arise from avoided demand and energy costs, potentially including avoided or delayed capacity additions if the program is of sufficient size and scope in terms of participation. Capacity savings represent value in terms of either deferred or avoided investment costs by the utility as well as a reduction in the cost of running high-cost peaking generation. Energy savings represent both immediate and ongoing cumulative benefits associated with the reduction in generation fuel and operating costs of supply-side resources as well as losses. As most co-ops purchase their power, the users will be able to enter their own estimate of power supply costs for both demand and energy. However, we propose to make the modeling framework flexible enough to capture both key marginal capacity and energy situations that are likely to be encountered, specifically, (i) the utility has avoided operation of native/existing generation or abated the need for additional generating capacity, or (ii) the utility buys marginal capacity and energy from the market, whereby avoided costs can be mapped to an existing demand or energy rate.

Default values endogenous to the model for avoided demand and energy costs will be developed as supplemental and supportive of user-defined costs. As it is highly likely that almost all model users will have a good handle on their specific power supply costs, the analysis of default values will be sufficiently high level as to not divert excessive resources to the estimation process in lieu of focusing on higher priority model elements.

To capture endogenous avoided demand costs, the model will contain information from third party sources on the representative alternative supply side generating unit's capital and fixed O&M costs to estimate potential capacity savings. To the extent there is an intermittency in the ability of the measure to align peak shaving with the utility's system peak, such issues will be examined at a high level, and it is anticipated that NRECA will be able to assist Leidos with developing reasonable assumptions for dependable capacity (or the amount of capacity that can realistically be avoided at the time of the utility peak).

To develop projections of avoided and incurred marginal energy costs, the heat rate of the assumed alternative marginal generating resource (defined based on research of existing third-party databases) will be multiplied by a forecast of fuel prices plus variable operating and maintenance and emission allowance costs to derive a total per-unit ($/MWh) energy cost for the alternative supply-side resource. These average per-unit costs would then be multiplied by the projected avoided energy of the measure (adjusted for marginal losses) to derive total energy cost impact. In each case (demand and energy), a template will be provided as an option to the user to populate these more detailed statistics in lieu of direct entry of demand and energy rates, such that the user controls the inputs, but the model still computes the ultimate costs endogenously. The user will essentially have three choices in terms of validation (direct input of costs, use of defaults, or provision of needed information to recompute assumptions endogenously).

To the extent other elements of avoided cost are present and relevant, most notably the potential for market sales, the model will provide an input range for utilities to enter estimates of market sales potential into the model, so as to provide a fair and objective evaluation of potential DR program benefits. Default market prices at a high level by region of the country also will also be provided as an option.

Calculate Benefit-Cost Ratios, Internal Rate of Return, Net Present Value, and Discounted Payback Period

The model's internal logic will carefully review model inputs as gathered and delineated above and examine the resulting DR program evaluation model findings for reasonableness. Results for each measure will include the following (which are identical to the aforementioned model outputs from above):

- Annual and overall energy and demand saved and/or energy shifted to shoulder hours (during the study period);
- Net system benefits on a by-year and Net Present Value (NPV) basis, defined as the difference between total benefits and total costs of the DR program;
- Benefit-cost ratios (e.g., Total Resource Cost Test), which can be used to determine estimated program payback periods and/or serve as a litmus test for whether a program is implemented;
- Additional financial return metrics, most notably internal rate of return (IRR), which can be compared to the utility's IRR if it were to invest in programs other than DR; and
- Graphical outputs summarizing net system benefits on a by-year and NPV basis.

Interpretation of model results by NRECA and other stakeholders will be fairly simple by design. The model will sum all of the avoided costs of the measure that are relevant and subtract the total measure's intrinsic costs in each year to arrive at Net System Benefits each year. These Benefits then all will be discounted back to today's dollars and added to compute the Net Present Value (NPV) of Net System Benefits. In a year in which costs outweigh benefits, the Benefit-Cost ratio will be negative. This will generally be the case in the first year of a program, when implementation costs are incurred but benefits have not had time to accumulate. For productive programs, this ratio will be above or equal to 1.0 as the study horizon extends. A measure that has a positive NPV of Net System Benefits is a program where benefits outweigh the costs in the long run. If a measure has a negative NPV of Net System Benefits, program parameters may need to be reexamined, sensitivities may be necessary, or it may be that the program is simply too expensive relative to the value of expected demand/energy reductions.

It will be critical to devise model calculations with an emphasis on the benefits and cost for the utility in question. There are industry-standard benefit-cost ratios that can be brought to bear, such as the Total Resource Cost Test, the Rate Impact Measure Test, etc. to evaluate impacts. As the model will calculate and summarize all relevant first-order costs and benefits, calculating alternative benefit-cost ratios from various perspectives (utility, utility and G&T, the participant, society, etc.) will be a natural consequence of the model structure. Based on NRECA feedback, the impact on the utility will be the priority perspective captured in the model. Alternative benefit-cost ratios, if deemed valuable, will be summarized as part of the results interface/tables of the model.

A.5 Approach to Gathering Endogenous Model Inputs

The model requires accurate data to drive the results, defining both the cost of the demand response program(s) and the benefits of such programs. It is clear that some required data may not exist or, if it does exist, the accuracy may come into question. For the areas where data do not exist or are not available for model consumption, substitutes and/or proxy data will be considered as a best fit for the specific inputs to the model.

Customer Population

To screen out the customer accounts that are not likely candidates for a demand response program, data about these customers is required. From a residential perspective, it is reasonable to assume that the majority of customers would be eligible and there is nothing compelling about their electric use that would immediately indicate that they could not contribute to demand response. It might however, be an option to eliminate the very low consumption customers from the mix, as the investment required to provide the hardware and in-home devices might be greater than the load reduction savings over several years. From that perspective, the payback period could be considerable. In this case, given the account demand data, a minimum threshold can be established that considers only those residential customers above a certain demand to be included in the customer population. Customers that may be on energy-assistance or other types of levelized billing programs or lower-income customers may also be able to be filtered out. With that said, in an effort to provide a holistic and inclusive set of assumptions when evaluating a given program, the model will give the utility the key economic metrics inclusive of such customers to the extent desired by the user utility.

Commercial and industrial customers should be viewed with a slightly different approach. There will be groups of customers that will not be likely candidates for a demand response program. Here, we would want to screen out the likes of hospitals, restaurants, and other end use customers that are clearly not capable of reducing their loads.

Given that many co-ops are located in rural regions of the country, the agricultural customer base could be a significant contributor to demand response.

The table below defines the data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Business end use		NAICS code	NAICS code
Demand threshold	Average demand (co-op supplied)	Average demand (co-op supplied)	Average demand (co-op supplied)

Programs

The data input requirements for the aforementioned list of DR programs the model will cover will be derived from various studies conducted across the nation. Data will need to be gathered for these specific demand response programs and the intelligence gathered must provide the necessary pricing structure for the desired programs in the model.

The table below defines the program data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Pricing structure	On/off peak price (study/user based)	On/off peak price (study/user based)	On/off peak price (study/user based)
Financial incentive	$ (study/user based)	$ (study/user based)	$ (study/user based)

Customer Class

The customer class process segments the customer population (as delineated above) into classes that have similar response characteristics. These are primarily based on how the customer uses electricity, how load reduction is implemented (via informational channels or direct control), and by particular sensitivities of customers. Generally, the energy use indicates the number and size of electric loads in the home and this can also align with the magnitude of household energy costs that are electric based rather than other fuel-based (like natural gas heating and cooking). Particular customer data will be required to support the classification and the model will categorize these with some knowledge of what *Elasticities of Substitution* are available.

The business activity of large customers is strongly correlated to their willingness to participate and thus, to how they might respond. Information on these customers' lines of business is available in the form of North American Industry Classification System (NAICS) codes. These codes distinguish groups of customers with similar energy usage characteristics, and we will use them to target likely customer groups for the commercial, industrial, and agricultural segment.

The table below defines the data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Electric loads by end use	Major electric load devices (co-op supplied)	Major electric load devices (co-op supplied)	Major electric load devices (co-op supplied)
Existing electric tariff rate	$/kWh (co-op supplied)	$/kWh & $/kW (co-op supplied)	$/kWh & $/kW (co-op supplied)
On-peak energy	On-peak kWh (co-op supplied)	On-peak kWh (co-op supplied)	On-peak kWh (co-op supplied)
Off-peak energy	Off-peak kWh (co-op supplied)	Off-peak kWh (co-op supplied)	Off-peak kWh (co-op supplied)
Total energy cost	$ (co-op supplied)	$ (co-op supplied)	$ (co-op supplied)
On-site generation		Capacity (co-op supplied)	Capacity (co-op supplied)
Business type		NAICS code	NAICS code
Enabling technology	Device type (study/user based)	Device type (study/user based)	Device type (study/user based)

Participation Rates

The customer penetration rate is inherently very fluid and tends to change from year to year. Existing customers may drop out after a couple of years and others will join in any given year. Some may rejoin if the program changes and/or implements new incentives. Based on these factors, it will be more practical to estimate the participation rate based on the typical year of a single mature program, given there is data for such a program. Given data from previous demand response deployments, the enrollment factor can be one method to establish the appropriate value for the model.

Several methods in estimating participation rates have been documented from various studies, such as Expert judgment (or Delphi), Translated experience, Benefit threshold, and Choice model. Each one has advantages and disadvantages and can take considerable effort and experience to gain useful results. We will choose the method that is suitable for the model and reinforce a simple approach, allowing user input in the assumptions ultimately used.

The Benefit threshold approach might appear to be the best choice, as it strives to base the participation rate largely on the customer's expectation of benefits. It doesn't rely on data from previous program implementations and therefore, makes this an attractive option. It does, however, require assumptions on the benefit level that will encourage participation. A prudent approach will be to develop a high/med/low benefit level that will define a high/med/low participation rate for the model to apply.

The table below defines the participation-related data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Benefit threshold	$ Savings/month (study/user based)	$ Savings/month (study/user based)	$ Savings/month (study/user based)
Enrollment factor	Typical rate from published studies (study/user based)	Typical rate from published studies (study/user based)	Typical rate from published studies (study/user based)

Elasticities of Substitution

The data required to develop the elasticity of substitution for each customer class is dependent on customer response from programs that have been implemented and studied. Without this type of data, it is difficult to estimate how customers may respond to demand response programs. Within the NRECA community, more than a dozen demand response demonstration programs slated for implementation and we will draw on those results to perform the estimation of elasticity for the model. If the data is insufficient to provide the essential input then other relevant published demand response pilots – of which there are numerous – will be explored.

Layered upon those base sensitivities, several other response factors will be estimated and used to adjust the base elasticities. Our approach will be to determine a high/med/low effect that will help illustrate the range of DR potential rather than target a single point. To the extent elasticity of substitution methods are not tractable for a given measure, load impacts will have to be estimated in a more discrete fashion as discussed above.

The table below defines the preliminarily contemplated data needed for each customer category. Refer to the discussion above regarding the analytical approach to determining elasticity of substitution, as there may be additional data needs uncovered as the execution of that approach moves forward.

Attribute	Residential	Commercial & Industrial	Agricultural
% Electric cost/total cost	Electric & Gas bill (co-op supplied)	Electric & Gas bill (co-op supplied)	Electric & Gas bill (co-op supplied)
Prior DR participation	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)
On-site generation		Capacity (co-op supplied)	Capacity (co-op supplied)
Ratio on-peak to off-peak price	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)
Ratio on-peak to off-peak load	Customer demand history (co-op supplied)	Customer demand history (co-op supplied)	Customer demand history (co-op supplied)
Event duration	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)
Event frequency	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)
Event clustering	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)	Prior DR program results (co-op supplied)
Weather	Historical records (external data)	Historical records (external data)	Historical records (external data)

Baseline Customer Loads

The load impact calculation relies on the customer base load during planned demand response events. This will require access to customer demand history broken down into on-peak and off-peak consumption.

The table below defines the data needed for each customer category. The model will invite the user to input these values and, if the user does not have them, will substitute default values based on U.S. regional averages.

Attribute	Residential	Commercial & Industrial	Agricultural
Customer base load	Customer demand history (co-op supplied)	Customer demand history (co-op supplied)	Customer demand history (co-op supplied)

DR Cost

To calculate the demand response program cost, the model will leverage existing NRECA DR demonstration costs and nationwide studies of demand response implementations. As with other key inputs, the user will have the ability to override default values.

The table below defines the data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Program costs	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)
Equipment costs	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)	Prior DR program details (co-op supplied)

DR Benefit

Refer to the above discussion for how benefits will be valued, and the three choices given the user related to marginal energy and demand rates used to value abatements.

The table below defines the data needed for each customer category:

Attribute	Residential	Commercial & Industrial	Agricultural
Demand charge	Co-op $/kW charge (co-op/study supplied)	Co-op $/kW charge (co-op/study supplied)	Co-op $/kW charge (co-op/study supplied)
Energy charge	Co-op $/kW charge (co-op/study supplied)	Co-op $/kW charge (co-op/study supplied)	Co-op $/kW charge (co-op/study supplied)

A.6 Summary

Our approach to DR cost-benefit evaluation will allow the NRECA's co-ops to simulate the effectiveness of defined DR programs and drive the model to quantify the cost and benefit results. It will leverage input data, from the individual co-ops, that will establish the specific attributes of customer base and energy supply costs that are critical to the analysis. Within the model, elasticities of substitution will be modeled through various existing demonstration programs, both within the NRECA membership and out in the industry (as needed). The user will have the capability to enter and adjust several parameters in the model that will enable a comprehensive analysis of what programs will be effective at differing levels of customer participation.

This initial conceptual model approach is based on the congruence of a number of methods and studies performed in various jurisdictions throughout the country. It is prudent that the next steps in vetting our model approach is to conduct a review with the NRECA and determine if we meet the expectations of method, functionality, and data access assumptions. We would also prefer to expose the defined user interaction with a few of the co-ops and solicit their feedback in how we envision the model to be used by them. We anticipate that with that feedback in hand we will then finalize the approach, architecture, and methodology.