

Delaware County Electric Cooperative

DR Capability and Predictability

FINAL REPORT | MAY 31, 2014



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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.

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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.

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- 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.

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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.

DISCLAIMER

The views as expressed in this publication do not necessarily reflect the views of the U.S. Department of Energy or the United States Government.

Delaware County Electric Cooperative—DR Capability and Predictability

1. INTRODUCTION

Delaware County Electric Cooperative (DCEC) is testing a Demand Response (DR) program designed to be able to shed demand when requested by the New York Independent System Operator (NYISO). This activity has been supported by the NRECA DOE Smart Grid Demonstration Project through the implementation of advanced metering infrastructure (AMI) and load control switches. Demand response programs for bidding into an ISO market typically have relied on larger industrial-scale customers. However, with the advent of widespread AMI adoption and load control switches for residential devices, it may be possible for distributed residential loads to bid into the market as a cohesive system. DCEC selected water heaters as the best option for its DR program because water heaters have several advantages. They draw a significant amount of load, can store energy thermally, and are commonplace in many homes.

2. RESEARCH OBJECTIVES

- a. Demonstrate how much load—and how quickly—DCEC can reliably shed through a DR program with water heaters.
- b. Determine the best way to apply this technology to decrease costs without compromising member satisfaction.

3. BACKGROUND: THE NRECA/CRN SMART GRID DEMONSTRATION PROJECT

a. *NRECA Overview*

NRECA received a \$34 million Smart Grid Demonstration research grant from DOE in 2010. The resultant project, coordinated by NRECA's Cooperative Research Network (CRN), purchased the necessary equipment on behalf of NRECA's participating member cooperatives. Ancillary services related to the equipment are contracted directly between the supplier and NRECA's member cooperatives. Electric distribution cooperatives have been evaluating the potential benefits of new technologies that could help increase operational efficiencies and improve service. Twenty-three of NRECA's member electric cooperatives have deployed more than 250,000 smart grid components across the country to test the value of the new technologies for cooperative consumer-members.

b. *DCEC Overview*

DCEC of Delhi, New York, is a non-profit rural electric cooperative serving more than 5,300 member locations in 21 towns across four counties—Delaware, Schoharie, Otsego, and Chenango. Formed in 1941 as a corporation and converted in 1942 to a cooperative, DCEC has been a staple of its community for more than 70 years. Its employees now manage more than 800 miles of line, compared to just 8.2 miles in 1944. Its primary mission is to provide a safe, reliable, and cost-effective electric power supply to its members.

4. EXECUTIVE SUMMARY OF RESULTS

a. *Principal Findings*

Two series of tests were performed for this study, one in summer 2013, and one during the following winter. For both tests, control data also were collected during the same time period. During the summer tests, the demand curve for both the control and test data followed a similar trend of a decline followed by a rebound for the period of time sampled. However, during the period that the DR program was active, the demand reduced at 2.5 kW/minute, compared to the 1.2-kW/minute reduction tested in a control group without the DR program. On average, the inflection point of the test data was 55 kW lower and 80 minutes earlier than the control data. However, following the trough, the test loads rebounded faster and at the end of the period measured 112 kW higher than the control loads. Each additional water heater in the study lowered demand by an average of 0.6 kW during the test. This is in line with the findings of other studies of DR programs.

The winter tests were less conclusive—demand dropped 5.5 kW/min in the control studies and 6.3 kW/min during the tests. This is an increase of only 0.8 kW/min in the demand reduction rate. During the time period sampled, demand first increased and then decreased steadily. There was no indication that the DR program had a noticeable impact on when demand began to drop.

b. *Recommendations*

Based on the results of the test and the baseline provided by the control data, this DR program seems best suited for peak-shifting or bidding into the ISO market as a short-term DR program. The rebound effect that follows the DR program makes it unlikely that total load will be reduced.

c. *Further Research*

Further research is needed to test the reliability of this program in different situations. This research should focus on running the program at different times of the day and during different seasons. This is needed for two reasons. First, this program relies on the use of water heaters, which are subject to daily patterns of use; most hot water is used in the evening or mornings. Second, temperature affects hot water use, although this variable will be primarily seasonal.

5. LITERATURE/TECHNOLOGY REVIEW

a. *Previous Approaches to Residential Direct Load Control*

Using water heaters to shed load at a specific time is an example of Demand-Side Management (DSM), which encompasses a host of techniques and technologies to optimize energy use on the consumer side. DSM includes Energy Efficiency (EE) measures, Time-of-Use pricing, Demand Response, and Spinning Reserve.¹ These measures are intended to change the demand curve to benefit the utility by either reducing or shifting load. Energy must be produced in a quantity great enough to satisfy the single highest point of demand safely; in meeting this requirement, significant

¹ (Palensky and Dietrich, 2011, p. 381)

amounts of energy are wasted, however. By bringing the peak lower and the “troughs” higher, less energy production is needed to meet high peaks.² In addition to being more efficient, the ability to reduce load reliably when necessary can help lower the incidence of rolling blackouts. In California a rolling blackout occurred in June 2000 because a 50,000-MW system was short 300 MW, an amount that represented 0.006% of the total load.³ Had an effective DSM program been in place to reduce demand by the necessary amount, the blackout could have been avoided. Events like this cost utilities more than just money—consumer satisfaction and trust also are lost when the grid does not perform reliably.

b. *DLC Approach to DR*

The application of DSM studied in this paper is most accurately classified as a DR program using a Direct Load Control (DLC) approach, in which the utility operator has control over the customers’ water heaters and can determine the most optimal time to shed their load. In contrast, other DR programs require direct member participation and often offer incentives to encourage energy-saving behavior at specific times. For example, to get consumers to adjust their thermostats at peak demand times, a utility may offer a rebate on their electricity bills, but the utility cannot mandate conservation or remotely turn off an appliance under these conditions. DSM, whether consumer or utility controlled, is different from energy efficiency measures, which lower demand by a specific amount across the load levels. As opposed to EE measures, DSM (and specifically DLC in this study) does not lower energy consumption, just the demand at a given time. This leads to a rebound, or payback effect, of increased demand following the period of load shed. **Figure 1**—inserted only for demonstrative purposes—illustrates this impact on demand over time as well as the difference between DSM and EE measures:

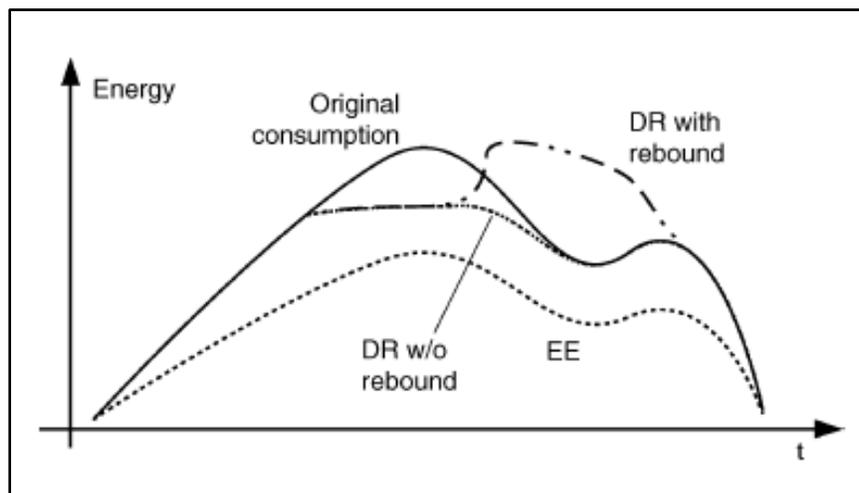


Figure 1.⁴ Impact on Demand over Time and Difference between DSM and EE Measures

² (Saffre and Gedge, 2010, p. 300)

³ (Saele, 2011 p. 102)

⁴ (Palensky and Dietrich, 2011, p. 382)

c. *Previous DLC Water Heater Studies*

A study in Norway estimated the payback effect for the hour following the DR program to be 0.2 kW per household or water heater (typically, there is only one water heater per household).⁵ This means that utility operators need to be careful when instituting a DR program to avoid creating a new peak in demand as they shift load.

The other primary issue is shedding load for such a period of time that it inconveniences consumers; only certain appliances lend themselves to this task. For example, a refrigerator DR program to directly control the temperature of the appliance might leave consumers' food too warm if the system is left to idle for too long. Many appliances do not make good targets for DLC, despite being used widely and having a substantial power factor, because they have no way to store energy (e.g., TVs) or the consumer is concerned that the program might negatively impact them (e.g., A/C units). However, electric resistance water heaters make a good target for DR programs because they consume a significant amount of energy (up to 30% of household loads in some areas); the heating element of a water heater typically is a resistor, making it simple and flexible to turn on and off; and water's high heat capacity allows it to act as a thermal energy storage device, meaning that it can be turned off for longer periods of time without any consumer dissatisfaction.⁶ An ideally operated DR program would average out energy consumption in such a way that consumers' actions would be unaffected but still provide ample peak reduction or shifting for the utility.

Another area of interest for DR is the amount of load that can be shifted. This is essentially a function of how many consumers are participating, the power rating of the water heater, and the load factor of the appliances. Previous testing done in Norway found average demand reductions from 0.5 kW to 1 kW for each standard electrical water heater and 2.5 kW for hot water space heating systems.^{7, 8}

American water heaters tend to have a slightly higher power rating than their European counterparts, by about 1 kW, meaning that the per water heater reduction would be even higher. However, efficiency policies often advocated in the U.S., which seek to ban the manufacturing or installation of electric resistance water heaters may, if successful, threaten the viability of using these residential water heaters for DR programs. Another factor is the increasing ubiquity of smart meters and appliances, which will make deploying DR programs easier and more cost-effective.

⁵ (Torgeir, 2009, p. 1)

⁶ (Diao, 2012 p. 1)

⁷ (Torgeir, 2009, p. 20)

⁸ (Saele, 2011, p. 107)

6. METHODOLOGY

Under the Smart Grid Demonstration Project, DCEC performed DR tests using residential water heaters. A total of 20 tests were performed for this study. Ten tests were run throughout summer 2013, starting on June 25 and ending on August 8; another 10 tests were run during the winter of 2013–2014, starting on November 24, 2013 and ending on February 10, 2014. The study group included 573 water heaters of varying sizes (30 gallon, 50 gallon, 80 gallon, and a farm class), but with similar heating element power ratings (3–3.8 kW for the non-farm classes and up to 4.5 kW for the farm classes). Each class of water heaters was divided into seven subgroups (except for the farm class, which is divided into two) for organizational purposes during the DR program. These subgroups then were recombined to form 16 “blocks” of roughly equal size that were used throughout the test to ramp the water heaters on and off the program. During the DR program, commands to shed were sent out to an entire block at one time and then unshed together after a specified amount of time had passed.

System load data were collected every 5 minutes for 6.5 hours during each test day and included the demand of each of the four feeders, the aggregate demand, the percentage of each type of water heater in “shed mode,” and the step of the test (each step corresponded to the number of blocks of water heaters in shed mode according to a defined matrix). The DR program itself functioned by shedding water heaters on and off (shedding a water heater means turning off its load control switch so that it cannot be turned on). However, the data collected do not show whether or not a water heater entering shed mode was off or on, or whether it would have turned on during shed mode or not. This means that shedding a water heater does not guarantee a reduction in demand, but only that it cannot be turned on. The key takeaway here is that areas with a more frequent water heating load will be able to shed more load at any given time.

Data collection began an hour before an initial command was sent out to water heaters to begin entering shed mode. In most tests, data collection began at 11:00, and the initial command was at 12:00 (a few tests started as late as 11:15, pushing all events back by a corresponding amount). The initial command was always to go to step 8 (out of the 16 total steps), which shed eight blocks of water heaters—roughly 50% of the water heaters. After beginning, another block was shed every 5 minutes, as the steps increased, until step 16, when 100% of the water heaters were shed. All water heaters remained in shed mode for 1 hour—marginally longer in some tests. After the full shed, the water heaters gradually were “unshed,” or allowed to turn back on. The return to service of the water heater loads was staggered by using the step matrix and set-time delays in the defined blocks to minimize the establishment of a subsequent peak loading condition. Similar to the stepping up process, the system stepped down once every 5 minutes. The goal was to avoid a condition in which all of the water heating equipment returned to service at the same time, which could have amounted to a coincident loading peak. However, unlike the shedding process, which is determined by signals sent to the different water heater blocks, the unshedding process occurred after a specified time frame. If the utility wanted to keep a water heater block in shed mode, another shed command had to be sent.

The stepping down process took 80 minutes, until there were no water heaters left in shed mode. Data were collected for another 2.5 hours after all of the water heaters were unshed to assess the amount of “load payback” or increase in demand due to the DSM program. Data collection ended for most tests at 17:30, although tests that started later also ran later.

The winter tests were conducted in the same manner, but began collecting data around 17:00 and started the DR program an hour later. Data were collected continuously until midnight. The program used the same stepping up and stepping down system but increased the length of the full shed for some tests.

Along with the test data, 14 days of load-level data without the DR program were provided—seven from the summer and seven from the winter. These data, collected from the same feeders and at the same intervals (every 5 minutes), were the control data for the experiment. This allowed for a baseline comparison of how the demand curve would have looked without the DR program.

In addition to the process outlined above, there are several important points about the study.

First, the blocks used to control which water heaters were shed were created because DCEC uses a Power Line Carrier (PLC) communications system that cannot accommodate requests to all of the blocks if they were to be initiated simultaneously. This limited how quickly demand could be reduced through this program because not all of the water heaters could be shed at once. Second, the shedding schedule operated in a “round robin” mode, also known as “first-in, first-out.” In this system, the first block of water heaters shed at step 1 would be the first block unshed at a later time. For example, at Step 14, the command sequence would shed 86% of the 30/40-gallon units, 86% of the 50-gallon units, 100% of the 80-gallon units, and 100% of the farm units. If the system stayed at step 14, unshed 30-, 40-, and 50-gallon units would be commanded to be shed to maintain the 86% value, whereas those that had been in shed mode the longest would time out and be allowed to return to normal operation. The 80-gallon and farm units would remain in shed mode, as allowed by the set-time delays. The command sequence would have knowledge of the subgroups in shed and would move to the unshed subgroup as needed according to the system strategy matrix, following set time delays. All of this was done to avoid inconveniencing one group of members with longer shed times.

Finally, an error source exists in each of our samples, originating with the sampling process in DCEC's data acquisition system. DCEC's feeder measurements do not register changes in demand smaller than 48 kW, 24 kW, 21 kW, or 19.2 kW, depending on which feeder it measures. While this quantization noise is relatively small, it could cause sampling error because the signal from this program also is small; each block should reduce demand by only 20 kW when shed, while the error is 17.5 kW RMSE. The error is largely ignored for this analysis because it is normally distributed around zero and, with a sufficient sample of tests, averages out to a negligible factor.

7. ANALYSIS

The primary goal was to find out how much load could be reduced, and in what time frame. Thus, the first analysis was conducted to show how demand changes as water heaters are shed. **Table 1** shows the slope of the relationship between demand and percentage of water heaters in shed mode.

Table 1. Slope of Relationship between Demand and Percentage of Water Heaters in Shed Mode

Date	Test No.	Weekday	Total kW Reduction at 100% Shed	Hours to Inflection Point
6/25/2013	1	Tuesday	21.84	1.82
7/5/2013	2	Friday	498.53	41.54416667
7/15/2013	3	Monday	345.45	28.7875
7/16/2013	4	Tuesday	307.96	25.66333333
7/17/2013	5	Wednesday	401.92	33.49333333
7/18/2013	6	Thursday	266.11	22.17583333
7/30/2013	7	Tuesday	324.36	27.03
7/31/2013	8	Wednesday	420.84	35.07
8/2/2013	9	Friday	384.1	32.00833333
8/8/2013	10	Thursday	640.71	53.3925
Test Averages:			356.814	29.7345

This shows that, for each additional 1% of water heaters shed, demand dropped by 3.56 kW. Given that there were 573 water heaters in the study, this averages out to 0.6 kW per water heater—a number similar to the reduction found in previous studies. This shows that for almost every test, demand drops during the implementation of the DR program, but we need to know the time frame of this effect as well.

Figure 2 provides an overview of all of the summer demand curves; the curves showing averages are bold. Time is shown in 5-minute intervals to correspond with the frequency of data collection (labeled “Time Step”).

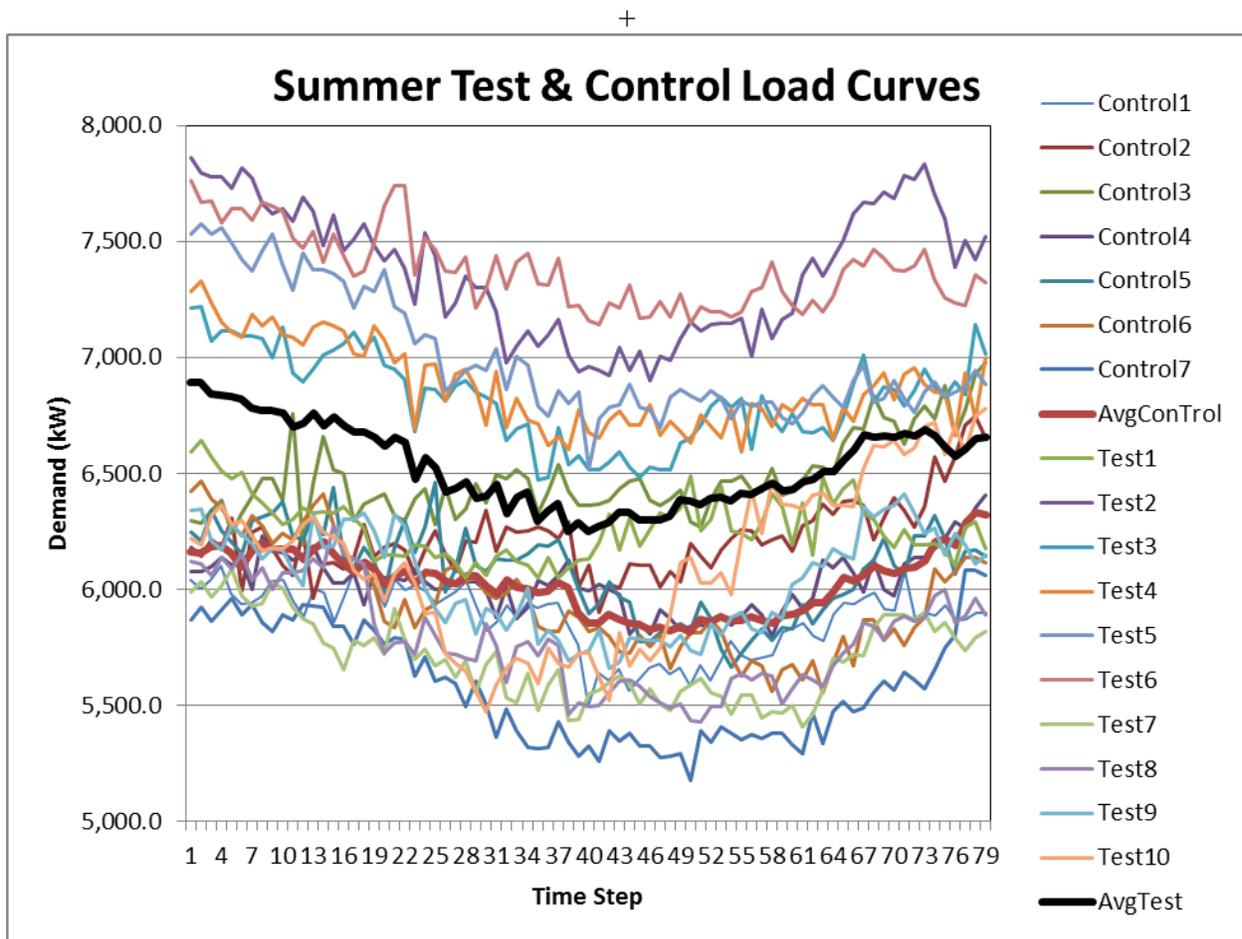


Figure 2. Overview of All Demand Curves

From these data, it is difficult to see trends or patterns amidst the noise. However, for both sets of data, the averages of the test and control data over the period the test was conducted and normalized by their starting value (**Figure 3**) display a U-shaped pattern. While both lines have a similar trend, the test data drop further and more sharply than the control data.

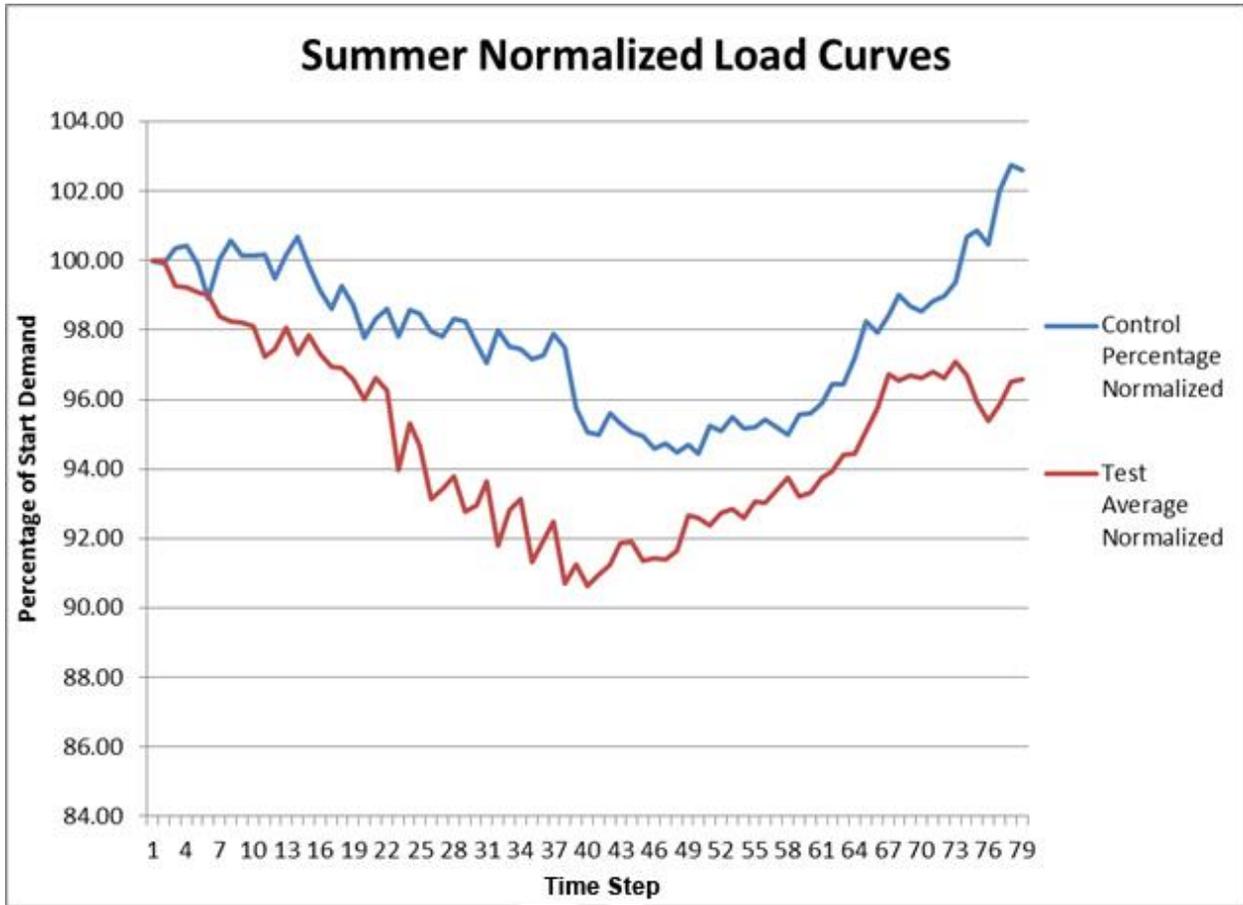


Figure 3. Averages of Test and Control Data over Test Period, Summer

In contrast, the winter data shown in **Figure 4** have a very different load shape, which starts lower, rises, and then steadily decreases (only the averages of the control and test data are shown).

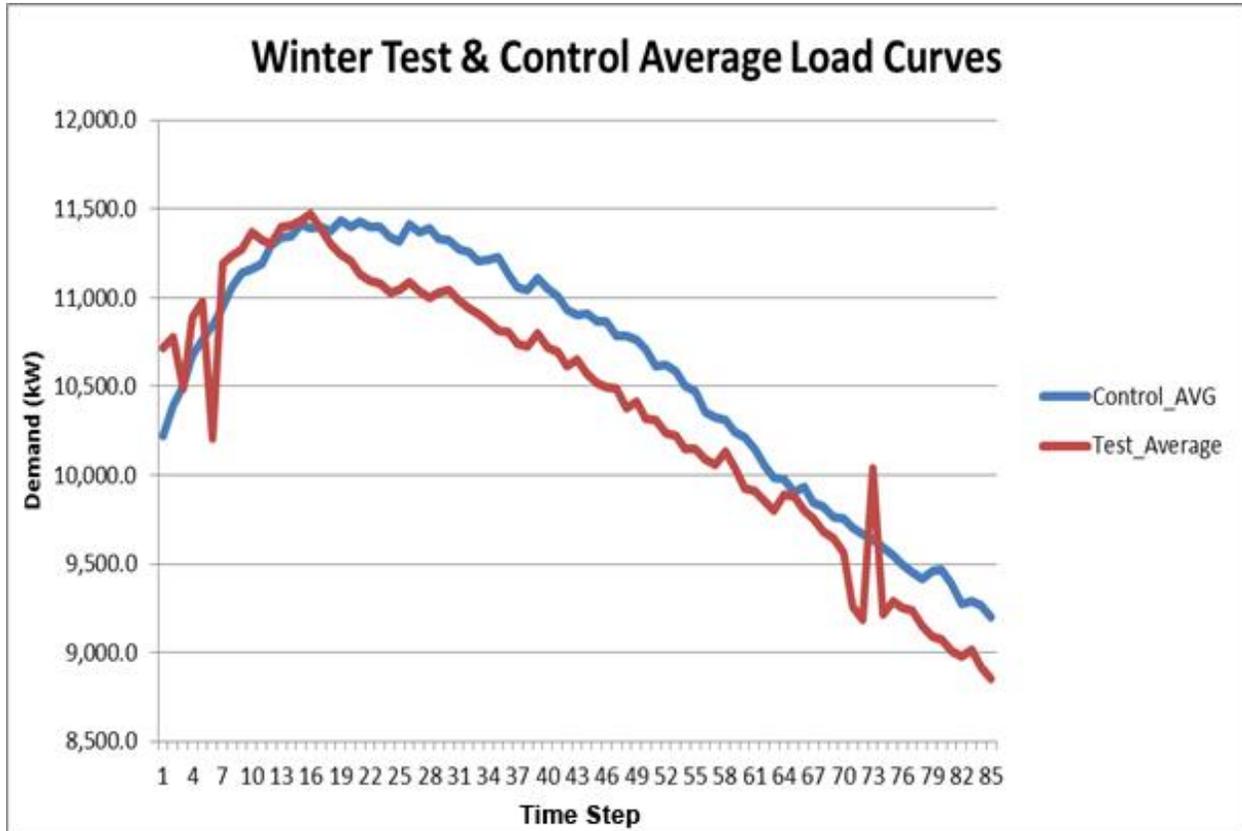


Figure 4. Winter Test and Control Average Load Curves

The next challenge was to find the inflection point of the DR program—when does demand start trending upward again? In an ideal world, this point would be at the end of step 16, right before water heaters start cycling out of shed mode. However, for various reasons, including system lag and other demand factors, the bottom of the curve does not exactly match the end of the DR full shed mode. To find the inflection point between where the demand is decreasing and increasing, the moving R-squared product was calculated. This means that every data point inside the middle 50% was assumed to be the potential inflection point; the linear regressions on either side then were calculated, and the R-squared values of each side were multiplied together. The point associated with the greatest of these products was selected as the true inflection point. This method ensured that each side had the greatest optimal linear fit, but not at the expense of making the other side a poor fit. The moving-R method then was applied to the control data to see how the breakpoints and rates of change compared to baseline data. See Appendix A for more information on the moving R-squared technique.

In **Figure 5**, the graphs of each test result show how demand changed over time during the test. The left vertical axis is demand in kW, the right vertical axis is the R-squared product of that point (corresponding to the gray line), and the horizontal axis is the time stamp in 5-minute intervals (for example, “40” corresponds to 3 hours and 20 minutes after the start of data

collection, or 14:20 in most tests). The first vertical red line marks the start of the load shedding, the second red line is the start of the “full-shed” (all water heaters are in shed mode), and the third red line marks the end of the full-shed as the water heaters begin coming back online. The red squares are demand readings during the downward reduction, and blue squares are demand readings as demand begins to rise again. The point between the red and blue squares is the inflection point, based on the product of their R-squared values.

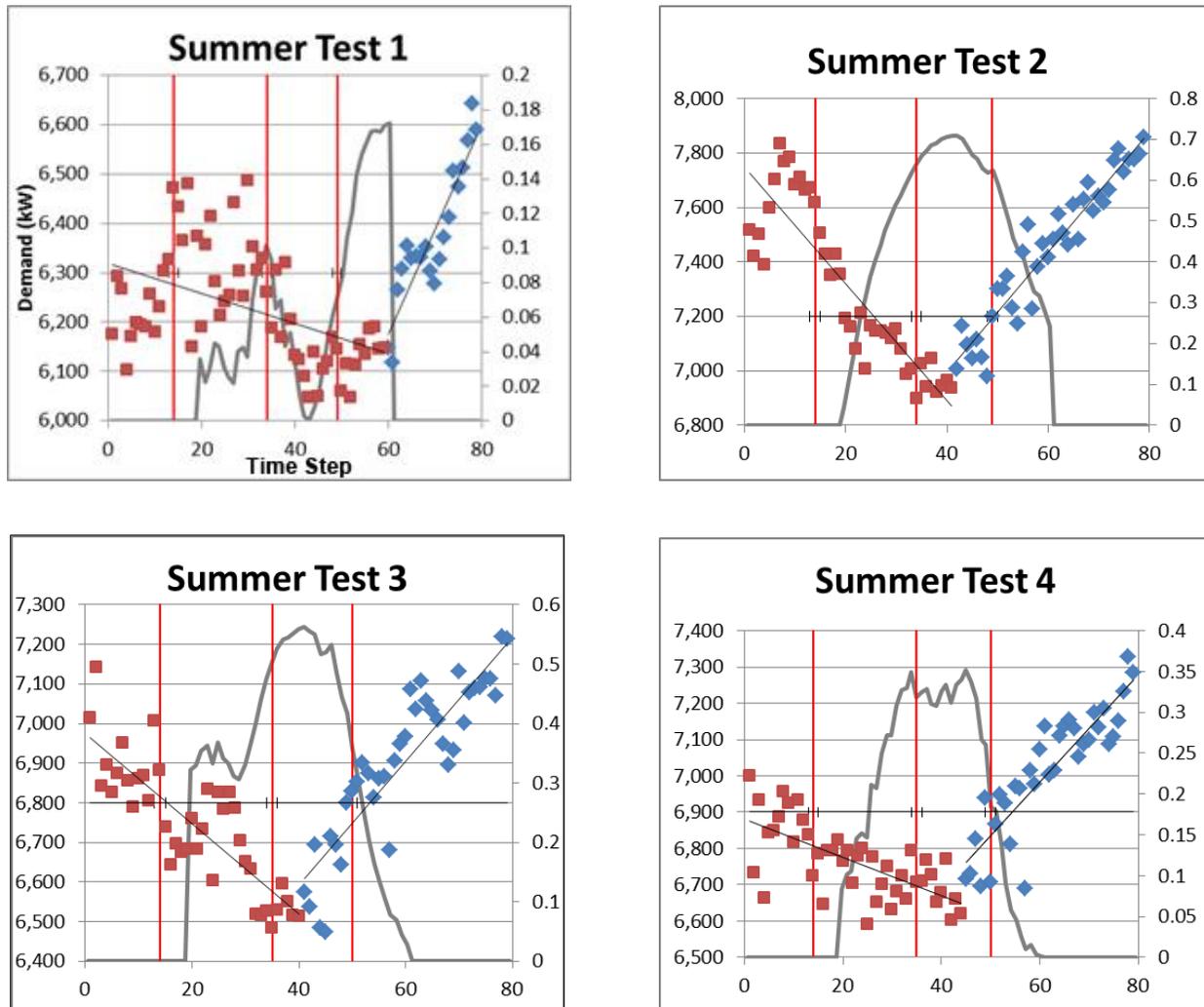


Figure 5. Demand Changes over Time during Each Test

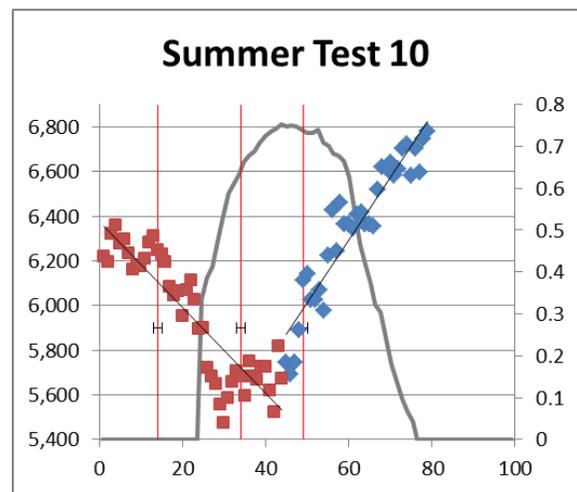
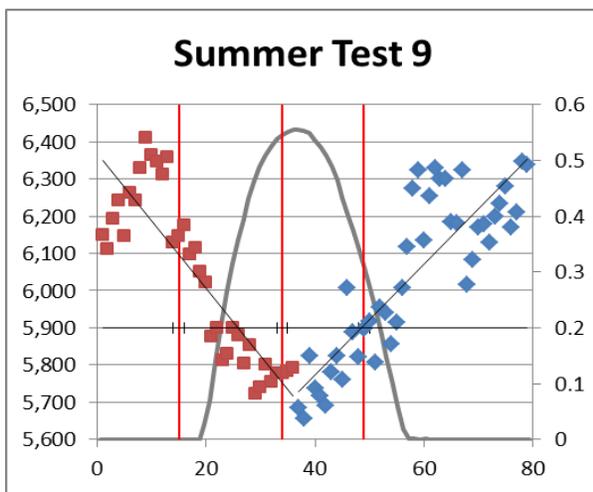
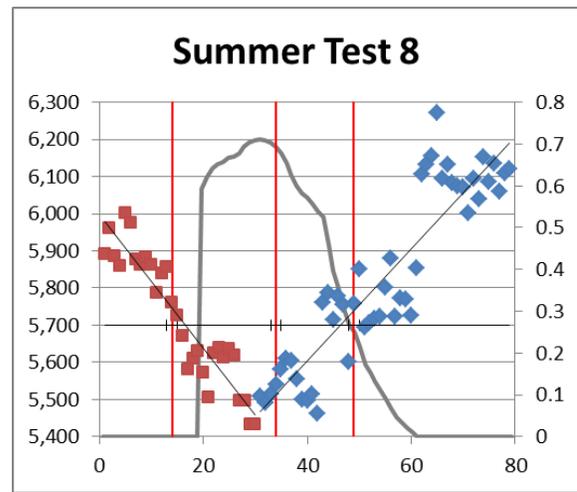
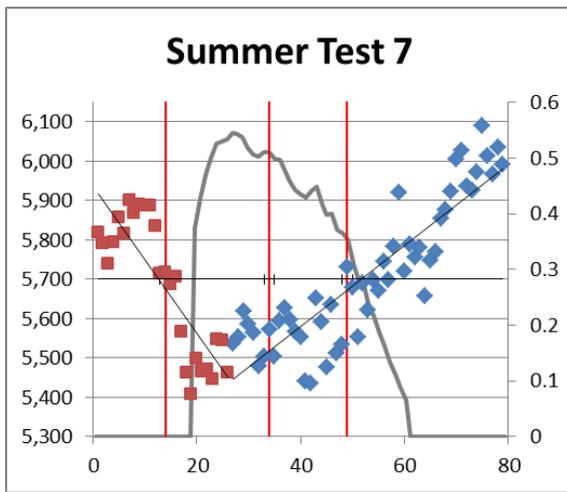
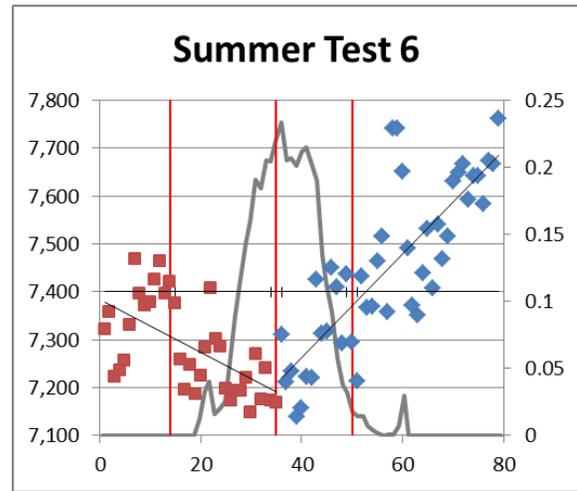
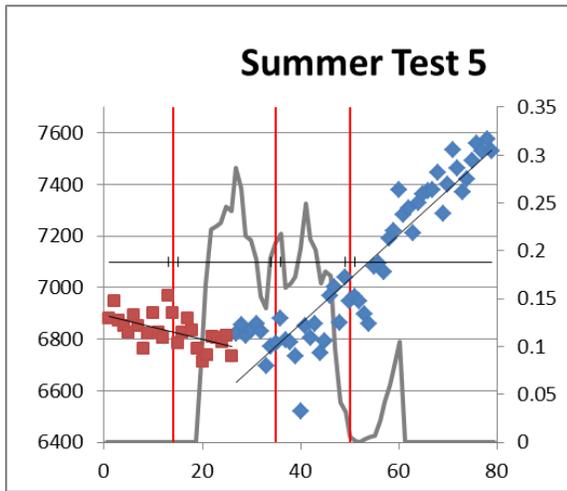


Figure 5. Demand Changes over Time during Each Test (continued)

The important characteristics of the data displayed above are how quickly demand falls and rises, and the location of the inflection point (or breakpoint). **Table 2** lists these numbers for all of the test and control data for summer.

Table 2. Rise and Fall of Demand, and Inflection Points, Summer Data

Date	Test No	Weekday	Inflection Point	Rate of Decrease kW/min	Rate of Increase kW/min	Total kW Demand Reduction	Total kW Demand Increase
Summer Test Data:							
6/25/2013	1	Tuesday	60	-0.61	4.22	-139.95	400.79
7/5/2013	2	Friday	42	-4.28	4.41	-599.06	815.96
7/15/2013	3	Monday	41	-2.29	3.12	-308.48	591.96
7/16/2013	4	Tuesday	45	-1.05	2.96	-162.96	503.95
7/17/2013	5	Wednesday	27	-0.96	3.46	-62.26	898.98
7/18/2013	6	Thursday	36	-1.10	2.16	-121.37	465.09
7/30/2013	7	Tuesday	27	-3.74	2.06	-243.24	534.46
7/31/2013	8	Wednesday	31	-3.58	3.01	-304.20	721.92
8/2/2013	9	Friday	37	-3.62	2.98	-398.22	625.00
8/8/2013	10	Thursday	45	-3.84	5.59	-595.26	950.47
Test Averages:			39.1	-2.51	3.40	-313.33	650.86
Summer Control Data							
6/26/2013	1	Wednesday	48	-1.66	2.14	-281.39	331.42
6/27/2013	2	Thursday	38	0.46	2.74	55.22	562.56
7/2/2013	3	Tuesday	70	0.53	5.26	148.68	236.82
7/11/2013	4	Thursday	54	-1.07	3.74	-213.90	466.98
7/12/2013	5	Friday	54	-1.84	4.31	-367.12	538.58
7/29/2013	6	Monday	60	-2.53	5.75	-581.21	546.71
8/5/2013	7	Monday	56	-2.92	5.91	-613.28	679.93
Control Averages:			54.28571429	-1.29	4.27	-259.46	527.06

This information confirms that there is a distinct difference in the rates of change. The DR program reduced demand at almost twice the rate of the control group (2.5 kW/minute and 1.28 kW/minute, respectively) and reached the local minimum in a much shorter time frame (80 minutes, on average). As shown in **Figure 6**, visualizing these data using the averages of the summer data clearly shows the impact of the load-shedding program:

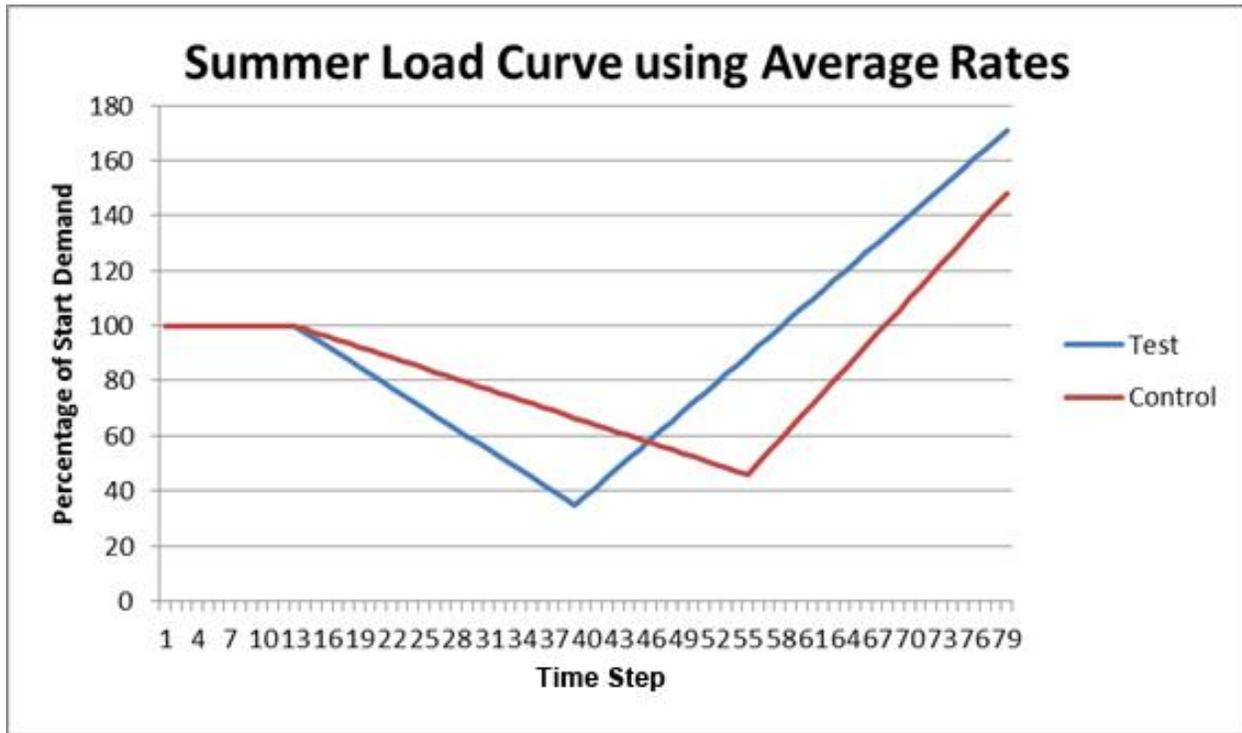


Figure 6. Rates of Change for DR Program and Control Group, Data Averages, Summer

The winter data have a very different load profile, and the impact of the program was neither as pronounced nor coincident on the inflection point. For these tests, the important characteristics were the rate of change during the test period and after the test, as compared to control data over the same time frame. **Table 3** lists these numbers for all of the test and control data for winter.

Table 3. Rise and Fall of Demand, and Inflection Points, Winter Data

Date	Test No	Weekday	Inflection Point	Rate of Decrease during Test Period kW/min	Rate of Decrease after Test Period kW/min
Winter Test Data:					
11/24/2013	1	Sunday	7	-7.68	-11.37
11/30/2013	2	Saturday	8	-6.50	-12.32
12/12/2013	3	Thursday	16	-3.96	-10.30
12/27/2013	4	Friday	16	-7.04	-9.73
12/31/2013	5	Tuesday	17	-4.91	-3.93
1/30/2014	6	Thursday	n/a	-3.01	-2.60
2/5/2014	7	Wednesday	n/a	-4.30	-9.38
2/9/2014	9	Sunday	n/a	-4.74	-12.03
2/10/2014	10	Monday	n/a	-3.20	-8.39
Test Average of Test 1-5			16	-6.30	-9.47
Winter Control Data					
1/17/2014	1	Wednesday	19	-3.14	-5.94
1/19/2014	2	Thursday	9	-8.60	-10.22
1/20/2014	3	Tuesday	17	-6.52	-5.64
1/21/2014	4	Thursday	10	-5.13	-5.27
1/24/2014	5	Friday	15	-3.94	-7.52
1/26/2014	6	Monday	9	-7.59	-7.09
1/27/2014	7	Monday	19	-3.87	-8.13
Control Average			13	-5.54	-7.12

The winter data are less complete than the summer data due to sampling difficulties. Test 8 was conducted during a different time frame, and tests 6–10 started at various times before the control and other tests. For these reasons, they are discounted from the winter average but still included in the table to show how their rates of change compare.

The winter data show that on average, demand dropped 0.75 kW/min faster during the test than it did for the control (6.3 compared to 5.54), but this is a smaller change than seen earlier. The average inflection points are much closer, and the control inflection average is actually before the test inflection point. This means that running the DR program in the winter is very unlikely to make demand drop sooner. The reasons for the DR program’s lesser impact in the winter are discussed in the next section.

8. DISCUSSION OF RESULTS OF THE DEMONSTRATION

This study did not find any surprises in the amount of demand reduction by shedding water heaters. Similar to the studies conducted in Norway, demand dropped roughly one-half a kilowatt for each water heater shed. The study also showed the impact of the payback effect. Close consideration needs to be given to this phenomenon to avoid accidentally creating a new peak.

During the summer, the data show that the DCEC DR program is capable of reducing load in a timely and predictable fashion. In total, using the load-shedding technology at full shed reduced load by 356 kW from the start, on average. However, this number needs to be put in the context of the control data. The average local inflection point of the test data was 55 kW lower and 80 minutes earlier than the control data's average inflection point.

The winter test results were not as encouraging. Demand dropped less than it did during the summer, and more slowly. Demand only dropped 0.75 kW/minute faster during the tests than the control and did not occur sooner. Possible explanations include the following: fewer water heaters were used during the time of the test, or not as many people were living in the DCEC service territory during that time of the year (many homes there are vacation homes). It should be noted that the findings of this report are specific to the area studied and should not be taken as a general finding that DR programs are less effective in the winter. Further investigation is needed to determine why the program was less effective in the winter than the summer.

Potential uses for this program include peak-shifting and possible bidding into the NYISO market. For peak-shifting, DCEC could affect its own load curve and associated peaks. This could help the co-op smooth and lower demand, thus resulting in lower demand charges from the New York Power Authority (NYPA) and an improved load factor. An improved load factor helps to limit expensive incremental energy purchases during the winter months, at the time when DCEC exceeds its contractual limit for the purchase of low-cost hydro power provided by NYPA. Both of these methods result in financial savings for the cooperative and its consumer-members. Failure of the DR system results in higher demand charges to DCEC and increased purchases of expensive incremental energy for the cooperative in the NYISO market.

A markedly different strategy would be to bid into the NYISO market, either for uniform, contracted reductions or non-uniform sporadic reductions. This study and analysis will assist the co-op in judging whether to approach the NYISO to request the ability to participate or bid as a DR resource through the aggregation of controlled electric domestic water heating, which to our knowledge has not been done historically. Depending on the findings of this study, DR programs similar to DCEC's controlled electric water heating program could be implemented by other distribution cooperatives or municipal electric systems in New York State. Uniform contracted reductions would require DCEC to hard shed demand for the contracted kW level when requested by the NYISO. This is a more consistent and valuable contract. If DCEC was unable to meet the contracted level with the DSM program, other loads would have to be shed. For this application, DCEC would be paid for its reductions as a resource, but if DCEC was unable to meet the level required, there would be monetary penalties or forfeiture of payments. The second option is to participate in the non-binding Emergency Demand Response Program (EDRP) to provide non-uniform sporadic reductions as issued by NYISO. However, DCEC is first and foremost concerned with not compromising consumer satisfaction. While the tests clearly

demonstrate the feasibility of its DR program, it has not yet been tested in all temporal or climatic conditions. Based on this fact, the best course of action is to use the DR program to shift load for its own benefit and participate in the EDRP when convenient. It is important for DCEC to fully characterize the ability of its DR load control program to meet the “step function” expectation that is assumed by the NYISO for any DR participant and, if it is unable to do so, then instead it might judge its value as some sort of “modified” participant.

9. CONCLUSIONS

The DCEC DR program successfully reduced demand in a reliable and predictable manner, but it is of limited capability regarding how much demand it can reduce, given the small differential between the inflection point in demand of the test and control data. Further research is needed to strengthen the reliability aspect of these results by testing the program at different times of the day, weekends, and seasonally. In addition, collecting more control data to create a “typical load curve” for each season would aid in the analysis. If more water heaters were given load control switches and added to the study, the capability of the program should increase as well. As long as large-capacity resistance water heaters continue to be used by consumer-members, cooperatives can make use of DR programs for a variety of purposes. The idea of cooperatives bidding into ISO markets using dispersed residential load controls is an innovative use of Smart Grid technology that is likely to proliferate in the future as DR programs gain more participants and devices.

10. RECOMMENDATIONS FOR FURTHER STUDY

Further avenues for future research and project development are numerous. The test should be conducted again at different times of the day, on weekends, and in different types of weather throughout the year. Conducting the test during the winter showed markedly different results than the summer. As future tests are conducted, regular control data for the same times should be collected on the day following or preceding the test. By running tests throughout the year and comparing the results, DCEC will have a better understanding of its program at different times and be able to leverage it more effectively. Additionally, the program should be expanded to include more residences if possible. A similar study could be undertaken in different locations and using different appliances. For example, tying air conditioning into the program in this location is not likely to be practical as there is little market penetration of residential air conditioning load in the DCEC service area; this could be viable in the warmer southwestern U.S. Future studies will help to strengthen the predictability and capability of these DR programs, however.

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APPENDIX A

The moving R-squared product equation:

$R\text{-squared (all points above breakpoint)} \times R\text{-squared (all points below breakpoint)}$.

This technique works best in the middle of datasets because, as it gets closer to one side of the data, the fit can get very close to one, artificially skewing the results. The calculation was performed in Excel using cell formulas. To the authors' best knowledge, this is an original analytic technique developed by Craig Miller and Thomas Kirk.

The technique does not perform well if the data have more than one curve or if one side of the curve has far fewer data points (this can lead to a very high R-squared value that pulls the inflection point).