Final Technical Report

AEP OHIO®

gridSMART® Demonstration Project

A Community- Based Approach to Leading the Nation in Smart Energy Use

Department of Energy (DOE) Smart Grid Demonstration Project (SGDP)

Contract Award Number DE-OE0000193

June 2014

Notifications

Acknowledgment

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000193.

Disclaimer

Notice

Use of the Terms Partner and Partnership

The use of the words “partner” and “partnership” herein is intended to indicate a mutually beneficial collegial relationship, rather than a partnership as defined under state law.

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Contents

List of Figures

List of Tables

EXECUTIVE SUMMARY

Project Objectives

The AEP Ohio gridSMART® Demonstration Project (Project) achieved the following objectives:

- Built a secure, interoperable, and integrated smart grid infrastructure in northeast central Ohio that demonstrated the ability to maximize distribution system efficiency and reliability and consumer use of demand response programs that reduced energy consumption, peak demand, and fossil fuel emissions.
- Actively attracted, educated, enlisted, and retained consumers in innovative business models that provided tools and information reducing consumption and peak demand.
- Provided the U.S. Department of Energy (DOE) information to evaluate technologies and preferred smart grid business models to be extended nationally.

Project Description

Ohio Power Company (the surviving company of a merger with Columbus Southern Power Company), doing business as AEP Ohio (AEP Ohio), took a community-based approach and incorporated a full suite of advanced smart grid technologies for 110,000 consumers in an area selected for its concentration and diversity of distribution infrastructure and consumers. It was organized and aligned around:

- Technology, implementation, and operations
- Consumer and stakeholder acceptance
- Data management and benefit assessment

Combined, these functional areas served as the foundation of the Project to integrate commercially available products, innovative technologies, and new consumer products and services within a secure two-way communication network between the utility and consumers. The Project included Advanced Metering Infrastructure (AMI), Distribution Management System (DMS), Distribution Automation Circuit Reconfiguration (DACR), Volt VAR Optimization (VVO), and Consumer Programs (CP). These technologies were combined with two-way consumer communication and information sharing, demand response, dynamic pricing, and consumer products, such as plug-in electric vehicles and smart appliances. In addition, the Project incorporated comprehensive cyber security capabilities, interoperability, and a data assessment that, with grid simulation capabilities, made the demonstration results an adaptable, integrated solution for AEP Ohio and the nation.

Project Impact

The Project accelerated smart grid deployments by improving grid reliability, increasing grid efficiency, lowering consumer energy consumption, reducing peak demand, and significantly reducing carbon emissions. AEP Ohio's gridSMART® initiative integrated a suite of advanced grid technologies into the existing electric network that improved service quality and reliability, lowered energy consumption, and saved money for consumers and AEP Ohio. The new technologies helped AEP Ohio improve efficiencies, identify and respond to outages more quickly, and better monitor and control the operation of the distribution grid.

Overall, the Project showed that implementing AMI technology provided significant cost, reliability, and environmental benefits for the utility and its consumers.

This report provides information about the deployment of gridSMART technologies and includes best practices and lessons learned that can be used to:

- Improve other smart grid deployments
- Drive industry standards development
- Lower the risk of implementing new technologies into existing electrical networks
- Allow for product improvement and commercialization
- Drive consumer behavioral changes through the introduction of new consumer tariffs and programs.

Based on the success of the Project, AEP Ohio has filed a gridSMART Phase 2 (Phase 2) project with the Public Utilities Commission of Ohio (PUCO). This proposed expansion is based on proven and accepted technology solutions. Phase 2 will extend the benefits demonstrated in the Project and deliver additional benefits to a broader set of consumers. Through Phase 2 AMI, AEP Ohio expects to drive significant financial benefits, positively impact customer service and customer satisfaction, improve meter field personnel safety, and reduce environmental impacts. It also will enable demand response (DR) and Competitive Retail Electric Service (CRES) providers to offer consumer programs. Phase 2 DACR is expected to improve Customer Minutes Interrupted (CMI), which will help AEP Ohio consumers annually avoid millions of dollars in lost productivity. Phase 2 VVO is expected to generate significant efficiencies that translate to customer savings.

The following table identifies the Project participants, collaborations, commercialization, and the AMI customer portal.

Project Participants	
Prime award recipient	• Ohio Power Company
Sub-recipients	• Battelle Memorial Institute • Electric Power Research Institute
Federally Funded Research and Development Center Partner	• Pacific Northwest National Laboratory
Academic and Research Organizations	• The Ohio State University • The Ohio State University Fisher College of Business Technology and Entrepreneurship Center
Vendors	• General Electric • Lockheed Martin • Opower • PCS UtiliData • S&C Electric Company • Silver Spring Networks
Key Collaborators	• AEP Ohio Energy Efficiency/Demand Response Collaborative • American Electric Power Service Corporation • National Institute of Standards and Technology • Ohio Consumers Counsel • PJM Interconnection LLC • Public Utilities Commission of Ohio
Project Tools and Products	
Project-Developed Collaboration	• Cyber security information sharing collaborative

Commercialization	• GridCommand™ Active Demand Management
	• GridCommand™ Distribution
	• Smart Grid Dispatch (SGD) engine
	  ▪ Home Energy Manager
	  ▪ Enhanced Programmable Communicating Thermostat

AMI Customer Portal	• Opower's Home Energy Reporting System and Insight Engine

Table 1. Project Participants, Tools, and Products

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1 INTRODUCTION

In 2009, the United States Department of Energy (DOE) awarded a Smart Grid Demonstration Cooperative Agreement to Ohio Power Company (the surviving company of a merger with Columbus Southern Power Company), doing business as AEP Ohio. The AEP Ohio gridSMART® Demonstration Project (Project), award number DE-OE0000193, integrated and evaluated commercially available products, innovative technologies, and new consumer products to understand the economic, environmental, and reliability benefits that could be achieved with scaling such technology to the electrical grid.

This *Final Technical Report* provides insight into the implementation, operation and analytical progression of demonstrated technologies.

1.1 References

References used to prepare this report include:

Document	Date
AEP Ohio gridSMART Demonstration Project Metrics and Benefits Reporting Plan	October 13, 2010
Statement of Project Objectives (SOPO)	January 18, 2013
Instructions For Preparation of Deliverables for Cooperative Agreements Under the Smart Grid Demonstration Program	January 18, 2013
Smart Grid Demonstration Program Guidance for Technology Performance Reports	June 17, 2011
Guidebook for ARRA Smart Grid Program Metrics and Benefits—Smart Grid Demonstration Project	June 2010
AEP Ohio gridSMART Demonstration Project Management Plan (Revision 1)	June 25, 2010
AEP Ohio gridSMART Demonstration Project Quarterly Build Metrics Report	January 31, 2014
AEP 2009 Fact Book	September 30, 2009

Table 2. List of Document References

1.2 Contacts

Name	Role	Telephone
Karen Sloneker	Principal Investigator, AEP Ohio—Director, Customer Service and Marketing	614-883-6677
Scott Osterholt	AEP Ohio—Manager Advanced Distribution Infrastructure gridSMART Project Leader	614-883-6872
Paula Igo	AEP Ohio—gridSMART Project Manager	614-883-7895
Rick Gampp	AEP Ohio—gridSMART Project Comptroller	614-883-6771
Frank Jakob	Battelle Memorial Institute—Project Manager	614-424-4130

Table 3. List of Contacts

1.3 AEP Ohio Demonstration

Ohio Power Company is a unit of the American Electric Power System (AEP), one of the largest electric utilities in the country. Ohio Power Company is commonly referred to as AEP Ohio (AEP Ohio). AEP Ohio and AEP are collectively referred to as AEP in this report.

AEP Ohio was selected because its service area reflects the region and much of the nation in terms of demographic and economic strata, energy consumption patterns, distribution infrastructure, and climate characteristics.

The AEP Ohio territory allows for small-scale and controlled testing of various new technologies and consumer programs in such an environment. The Project integrated these technologies and programs, which included utility-operated distribution system improvements, consumer-managed technology, two-way communications technology, demand management and dispatch technology, and utility-to-consumer interfaces.

1.3.1 Area

Consumers	
Consumers	1.5 million
Communities	890
Counties	61
Distribution	
Distribution Lines	47,000 miles
Transmission	
Transmission Lines	9,200 miles
Generation	
Total Capacity	11,736 MW
Assets	
Total	**$8.3 billion**

Table 4. AEP Ohio Territory Attribute Estimates

Figure 1. AEP Ohio Territory

The Project was located within northeast central Ohio and in the territory formerly served by Columbus Southern Power Company (CSP). This area demonstrates ideal characteristics for implementation and evaluation of grid-enhancing technology. It included a significant number of 13 kV and 34.5 kV circuits; had distribution stations; included diverse consumer income levels; had a good blend of industrial, commercial, and residential accounts; and received a large number of customer service orders.

In this report, the term System area refers to former CSP's territory. The term Project area refers to the area where Project assets, functionality, or programs were implemented, as shown in Figure 2.

Figure 2. Project Area Scope

The table below summarizes the high-level characteristics of both the System and Project areas discussed in this report.

Metric	System area (2009)	Project area
Total number of consumers:		
Residential	667,018	100,000
Commercial & Industrial	81, 866	10,000
Peak load:		
Summer	4,209 MW	800 MW
Winter	3,934 MW	650 MW
Total MWh sales:	**20,623,813 MWh**	**3,500,000 MWh**
Residential	7,303,192 MWh	1,200,000 MWh
Commercial & Industrial	13,320,621MWh	1,000,000 MWh
Total number of substations	136	16
Total number of distribution circuits	673	80
Total miles of distribution line	18,876 miles	3,000 miles
Total miles of transmission line	2,274 miles	0 miles

Table 5. AEP Ohio's gridSMART System and Project areas

1.3.2 Technologies

The Project introduced multiple technology enhancements to the infrastructure of the AEP Ohio Project area, including:

- Advanced Metering Infrastructure (AMI) – Two-way communication enabled meters
- Distribution Automation Circuit Reconfiguration (DACR) – Automation of distribution assets
- Volt VAR Optimization (VVO) – Voltage control and optimization
- Consumer Programs (CP) – Cost-saving opportunities through enhanced communication

The addition of the above technologies served as the foundation to enable two-way communication with consumers and allowed for consumer programs and products. The introduction of these technologies also required comprehensive cyber security and interoperability capabilities for both new and legacy systems.

Explanations of each technology and the extent of its functionality are outlined within the Demonstrated Technology sections of this report.

1.3.3 Benefits

Each technology, or combination of technologies, produced a benefit to the utility and/or electricity consumers. The table below summarizes some of the benefits of these technologies.

Benefit Category	Benefit	Technologies
Economic	Reduced meter operations costs – meter reading routes	AMI
Economic	Reduced meter operations costs – avoided truck rolls	AMI, DACR
Economic	Reduced electricity costs to consumers	CP, DACR, VVO
Economic	Reduced peak load	CP, DACR, VVO
Reliability	Improved outage response time	AMI, DACR
Reliability	Increased number of meters reporting daily	AMI
Reliability	Increased distribution system reliability	DACR
Environmental	Reduced number of truck rolls	AMI, DACR
Environmental	Reduced meter operations vehicle miles	AMI, DACR
Environmental	Reduced CO_2 emissions	AMI, CP, DACR, VVO
Environmental	Reduced pollutant emissions	AMI, CP, DACR, VVO

Table 6. Benefits of Technologies

The Project provided several positive outcomes for AEP Ohio and its consumers.

Consumer benefits:

- Enhanced customer service and satisfaction (for example, through faster, remote service connections, and elimination of estimated bills).
- Opportunity to participate in various consumer programs allowing consumers to:
  - Receive near real-time information about electricity usage.
  - Manage their electricity usage and lower their consumption.
  - Save money with the same level of comfort and service.
- Reduced outage times through the automation of circuit reconfiguration.

AEP Ohio benefits:

- Reduced costs through the elimination of meter reading routes and reduced field visits.
- Improved employee safety.
- Improved system reliability.
- Improved customer satisfaction.
- Reduced peak demand.
- Performed tasks remotely, such as reading meters and restoring service.
- Recognized potential equipment failures or outages, allowing proactive maintenance and repair.

Overall, the Project showed that implementing AMI, DACR, and VVO technologies provided significant cost, reliability, and environmental benefits for the utility and its consumers. The success of this holistic approach to smart grid implementation enabled AEP Ohio to move forward with the gridSMART Phase 2 (Phase 2) filing.

1.3.4 Impact Metric Reference

The table that follows provides a list of metrics by technology. Analysis for each metric is documented in this Final Technical Report.

Impact Metric Reference			
ID	**Scope**	**Description**	**FTR ID**
AMI			
M04	Project	Meter Operations Cost	M04-AMI
M05	Project	Truck Rolls Avoided	M05-AMI
M06	Project	Meter Operations Vehicle Miles	M06-AMI
M07	Project	CO_2 Emissions	M07-AMI
M08	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M08-AMI
M09	System	CO_2 Emissions	M09-AMI
M10	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M10-AMI
M11	Project	Meter Data Completeness	M11-AMI
M12	Project	Meters Reporting Daily	M12-AMI
M29	Project	Outage Response Time	M29-AMI
Consumer Programs			
M01	Project	Hourly Consumer Electricity Usage	M01-CP
M02	Project	Monthly Consumer Electricity Usage	M02-CP
M03	Project	Peak Load and Mix	M03-CP
M07	Project	CO_2 Emissions	M07-CP
M08	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M08-CP
M09	System	CO_2 Emissions	M09-CP
M10	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M10-CP
DACR			
M13	Project	Distribution Circuit Load	M13-CR
M14	Project	Distribution Circuit/Equipment Overload	M14-CR
M15	Project	Deferred Distribution Capacity Investments	M15-CR
M16	Project	Equipment Failure Incidents	M16-CR
M17	Project	Distribution Equipment Maintenance Cost	M17-CR
M18	Project	Distribution Operations Cost	M18-CR
M19	Project	Distribution Circuit Switching Operations	M19-CR
M21	Project	Distribution Restoration Cost	M21-CR
M25	Project	Truck Rolls Avoided	M25-CR
M26	Project	SAIFI	M26-CR
M27	Project	SAIDI/CAIDI	M27-CR
M28	Project	MAIFI	M28-CR
M29	Project	Outage Response Time	M29-CR
M30	Project	Major Event Information	M30-CR
M31	Project	Distribution Operations Vehicle Miles	M31-CR
M32	Project	CO_2 Emissions	M32-CR

Impact Metric Reference			
M33	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M33-CR
M34	System	CO_2 Emissions	M34-CR
M35	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M35-CR
ID	**Scope**	**Description**	**FTR ID**
VVO			
M03	Project	Peak Load and Mix	M03 - VVO
M13	Project	Distribution Circuit Load	M13 - VVO
M15	Project	Deferred Distribution Capacity Investments	M15 - VVO
M16	Project	Equipment Failure Incidents	M16 - VVO
M17	Project	Distribution Equipment Maintenance Cost	M17 - VVO
M20	Project	Distribution Capacitor Switching Operations	M20 - VVO
M22	Project	Distribution Losses (%)	M22 - VVO
M23	Project	Distribution Power Factor	M23 - VVO
M32	Project	CO_2 Emissions	M32 - VVO
M33	Project	Pollutant Emissions (SO_x, NO_x, $PM_{2.5}$)	M33 - VVO
M34	System	CO_2 Emissions	M34 - VVO
M35	System	Pollutant Emissions (SO_x, NO_x, $PM_{2.5}$)	M35 - VVO

Table 7. Impact Metric Reference

2 Demonstrated Technology – Advanced Metering Infrastructure

2.1 Purpose

Advanced Metering Infrastructure (AMI) technology incorporates meters that enable two-way communication between AEP Ohio and consumer premises. These meters use network capabilities to provide detailed, near real-time information and to interact with other external devices that the consumer controls.

Prior to the AEP Ohio gridSMART® Demonstration Project, AEP Ohio operated with analog meters that registered usage and readings at consumer premises. This approach required meter readers to physically observe the meter and collect meter data. Although a few other meter types existed in the Project area, there were no AMI meters.

AEP Ohio's demonstration of AMI meters intended to:

- Prove that the Silver Spring Networks (SSN) technology could function properly in urban, suburban, and rural applications.
- Show efficiencies associated with automated meter reading on a large-scale basis, including real-time meter reading and daily meter reads.
- Demonstrate the effect of AMI meters on meter operations costs.
- Demonstrate remote reconnect and disconnect capabilities, along with program advantages and disadvantages.
- Leverage the two-way communication with meters in the field, network, and back office.
- Study the demographic groups, including multi-unit, residential, commercial, and industrial, with a complete mixture of socioeconomic classes, and their response to different aspects of the AMI meters.
- Evaluate data generated by the AMI meters generate and the best way to use the information, including meter alarms and alerts, power quality information, energy usage, outage notification, and restoration notifications.
- Enable the use of two-way Home Area Networks (HAN) as part of the energy efficiency and demand response programs.
- Exhibit the benefits of receiving real-time information from different operational areas, such as billing, consumer service, engineering, dispatch, meter reading, and credit.
- Reduce or shift electricity demand and consumption through consumer programs.

2.2 Technology

AEP Ohio deployed 110,000 General Electric kV2c and I210+c model meters, including 4-channel recording capability, voltage detection, and ZigBee communication in the Project area. These meters include two-way communication abilities and use a Radio Frequency (RF) mesh network with wireless carrier backhaul communications.

AMI Asset Summary
• 100,000 residential meters • 10,000 non-residential meters • 31 access points • 133 relays

Table 8. AMI Asset Summary

In addition to the meters, the network included a network interface card for each meter, relay, access point, and eBridge. The single-phase residential meters also included a remote connect/disconnect switch. In addition to standard meter functions, AEP Ohio used the AMI system for remote connect/disconnect capabilities, outage reporting, interval data collection, calculation of bill determinants (kWh, kW, kVARh, on-peak, off-peak), power quality monitoring, and consumer programs facilitation. The figure below shows an AMI meter in Power On and Power Off modes.

<table>
<tr><th colspan="2">AMI Meter</th></tr>
<tr><td>Power On</td><td>Power Off</td></tr>
<tr><td>
</td><td>
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</table>

Figure 3. AMI Meters

The meter infrastructure interfaced with back-office systems to collect, measure, and manage meter, consumer, and utility activities. The meter infrastructure included the following integrations:

- UtilityIQ® software (UIQ)
- Marketing and Customer Service System (MACSS) for consumer-associated data management
- Meter Data Management (MDM)
- Distribution Management System (DMS)
- Demand Response Manager (DRM)

The following figure illustrates the AMI system implementation within AEP Ohio.

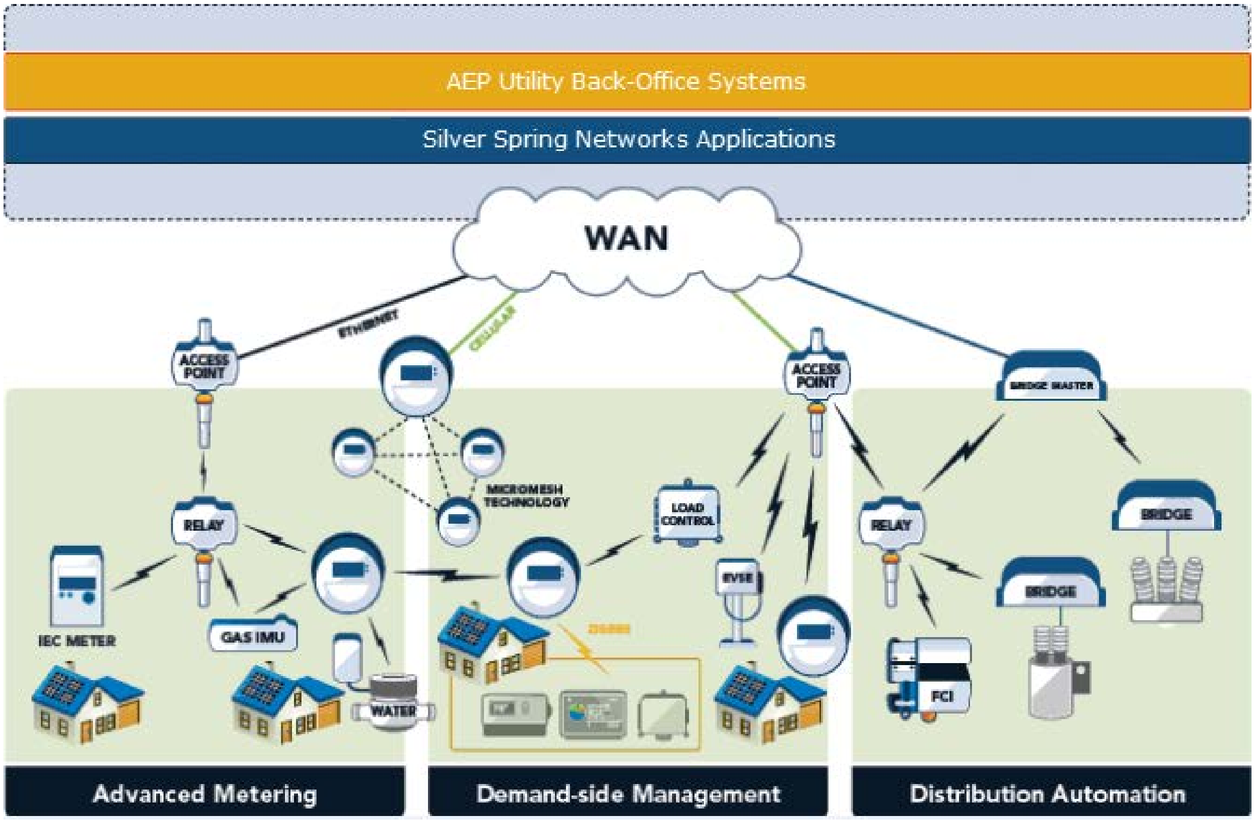

Figure 4. AMI System Illustration

2.3 Approach and Implementation

AEP Ohio installed the meters in an area of central Ohio that had one of the highest bill payment delinquency rates. The intention was to leverage this technology to reduce truck rolls required to perform disconnections for non-payment (DNP) and subsequent reconnections.

To install the meters as quickly as possible, AEP Ohio retained contract resources to install the wireless network and all single-phase meters. AEP Ohio employees installed all poly-phase and instrument-rated meters while contractors were completing the single-phase installations.

As installations were completed, a parallel reading period ensued. The manual reads were compared with the over-the-air reads to ensure that the meter was installed at the correct location and that the meter was reading with 100 percent accuracy. Meter installations were complete by April 1, 2010. AEP Ohio found these meters to be accurate in their out-of-box state, and major manual intervention was not required. As a result, the parallel reading process concluded in June 2010, earlier than planned.

2.4 Impact Metrics Required for AMI

The impact metrics shown in the table below are associated with the AMI technology suite; eight relate to the Project area and two relate to the System area.

Metric ID	Metric Scope	Metric Description	AMI
M04	Project	Meter Operations Cost	M04-AMI
M05	Project	Truck Rolls Avoided	M05-AMI
M06	Project	Meter Operations Vehicle Miles	M06-AMI
M07	Project	CO_2 Emissions	M07-AMI
M08	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M08-AMI
M09	System	CO_2 Emissions	M09-AMI
M10	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M10-AMI
M11	Project	Meter Data Completeness	M11-AMI
M12	Project	Meters Reporting Daily	M12-AMI
M29	Project	Outage Response Time	M29-AMI

Table 9. Impact Metrics Addressing AMI Technology Performance

Refer to the *Metrics Analysis for AMI* section that follows for details.

2.5 Metrics Analysis for AMI

This section provides details for each AMI metric, and includes those requested by the DOE during the definitization of the Cooperative Agreement. Trends were not always observed, however data is presented for each metric.

2.5.1 Meter Operations Cost (M04-AMI)

This metric analyzes savings, incremental and ongoing, resulting from avoiding consumer service truck rolls, eliminating meter reading routes, and reducing meter theft. Also included are the increased costs associated with equipment failure, software licensing, and network maintenance in order to calculate a net savings value.

2.5.1.1 Objective

The purpose of this metric is to understand AMI's impact on the overall cost of AEP Ohio's meter operations.

2.5.1.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- AEP Ohio meter readers typically read one route per day. For calculation purposes, it is assumed that eliminating a route equals eight hours of labor.
- Cost reduction was determined based on conversion factors for vehicle and labor rates.
- Cost reduction did not include potential of savings resulting from truck rolls avoided.

2.5.1.3 Calculation Approach

The following queries and methods were used to generate results:

- Certain types of consumer events, such as check read requests, can be processed remotely by using the AMI system, thereby avoiding a truck roll. A list was compiled of all consumer event order types that lead to an avoided truck roll. The number of truck rolls avoided due to AMI was then calculated based on the number of consumer events with matching order type codes.
- Average mileage per truck roll was calculated by month for each AEP Ohio service center in the Project and System areas. These average mileage values were applied to the count of truck rolls avoided to calculate mileage avoided due to AMI.
- Labor savings from AMI truck rolls avoided per service center, month, and meter funding source were calculated by multiplying the number of truck rolls avoided by an estimated $20 per truck roll.
- Vehicle savings from AMI truck rolls avoided per service center, month, and meter funding source were calculated by multiplying the number of truck rolls avoided by the average vehicle cost per work order completed by each service center and month.
- Labor costs from AMI truck rolls required per service center, month, and meter funding source were calculated by multiplying the number of truck rolls required by $50 per truck roll.

- Vehicle costs from AMI truck rolls required per service center, month, and meter funding source were calculated by multiplying the number of truck rolls required by the average vehicle cost per work order completed by each service center and month.

2.5.1.4 Organization of Results

This section describes the total net-meter operations dollar savings as a result of AMI from: service-related truck rolls avoided, meter reading routes eliminated, meter theft reductions, and meter tampering reductions.

- Service-related truck rolls avoided

  Monthly graphs showing savings and additional costs incurred for vehicle and labor costs are provided in this section. Graphs are then presented for net-labor savings and net vehicle savings. Finally, a graph is presented showing the total dollar value of monthly savings due to truck rolls avoided.

- Elimination of meter reading routes

  Savings analysis based on remote meter readings via the AMI network and the elimination of meter reading routes are provided in this section.

- Reduction in meter theft

  Analysis of the difference in meter theft rates between AMI and non-AMI meters are provided in this section.

- Changes in meter failure rate

  This section contains the analysis of the difference in meter failure rates between AMI and non-AMI meters.

- Software and Network maintenance costs

  This section presents the results from analysis of the ongoing costs associated with the AMI network.

- Revenue Protection

  Results from analysis of the reduction in meter theft achieved through meter tampering detection are described in this section.

2.5.1.5 Data Collection Results

This section shows savings results related to consumer service-related truck rolls, eliminated meter routes, and AEP Ohio’s engineering analysis. In the graphs that follow, DOE represents the approximately110,000 AMI meters that were deployed in the Project area. AEP represents the approximately 22,000 additional AMI meters deployed in the System area.

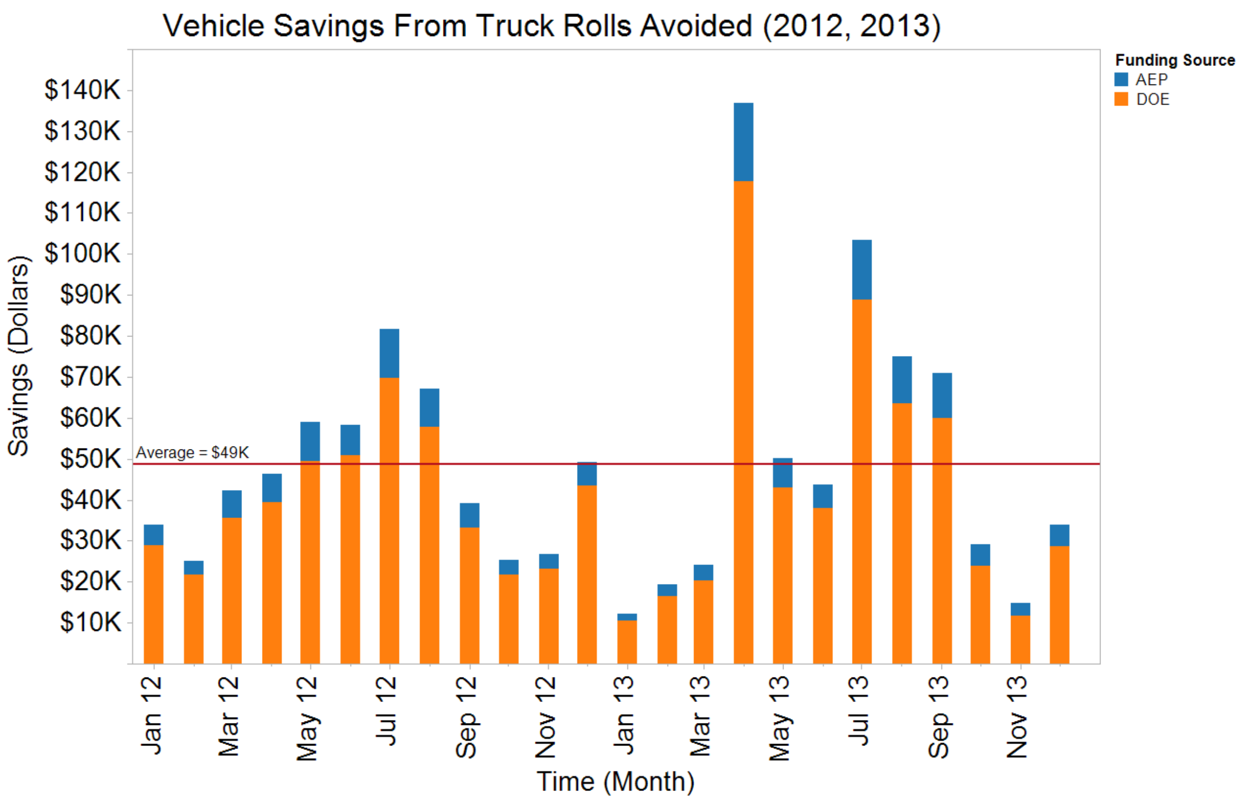

Figure 5. Savings from Reduced Vehicle Costs

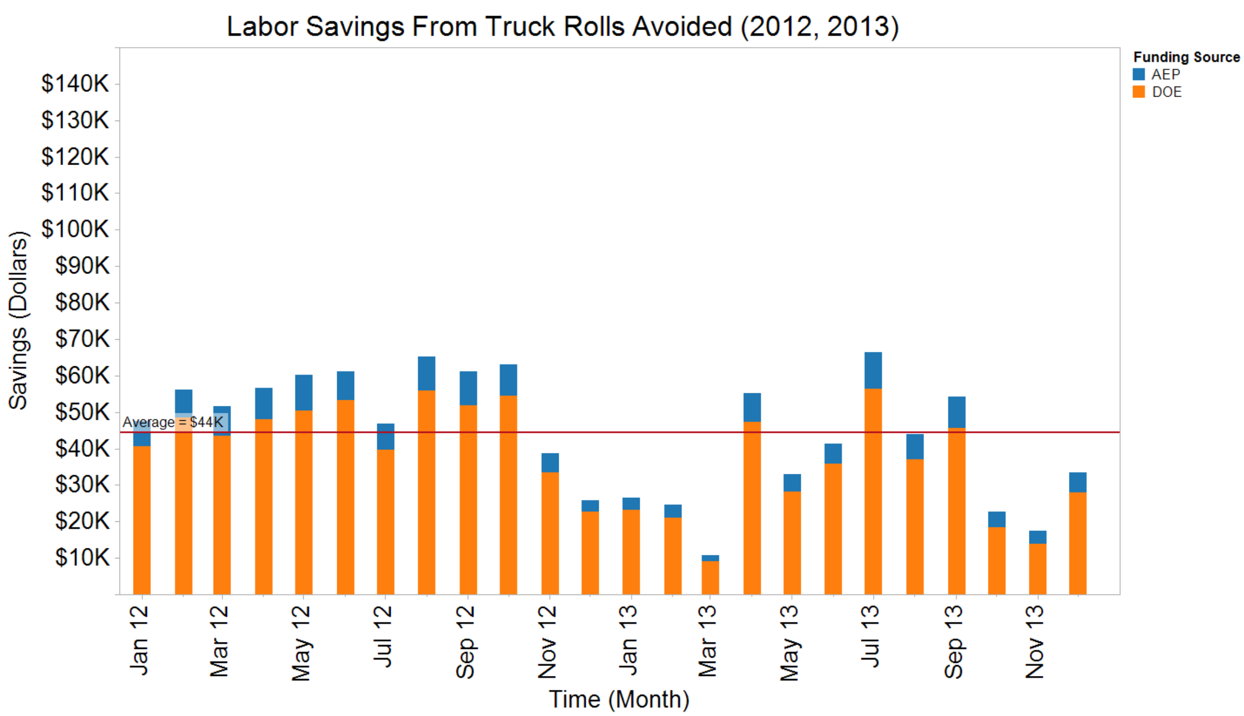

Figure 6. Savings from Reduced Labor Costs

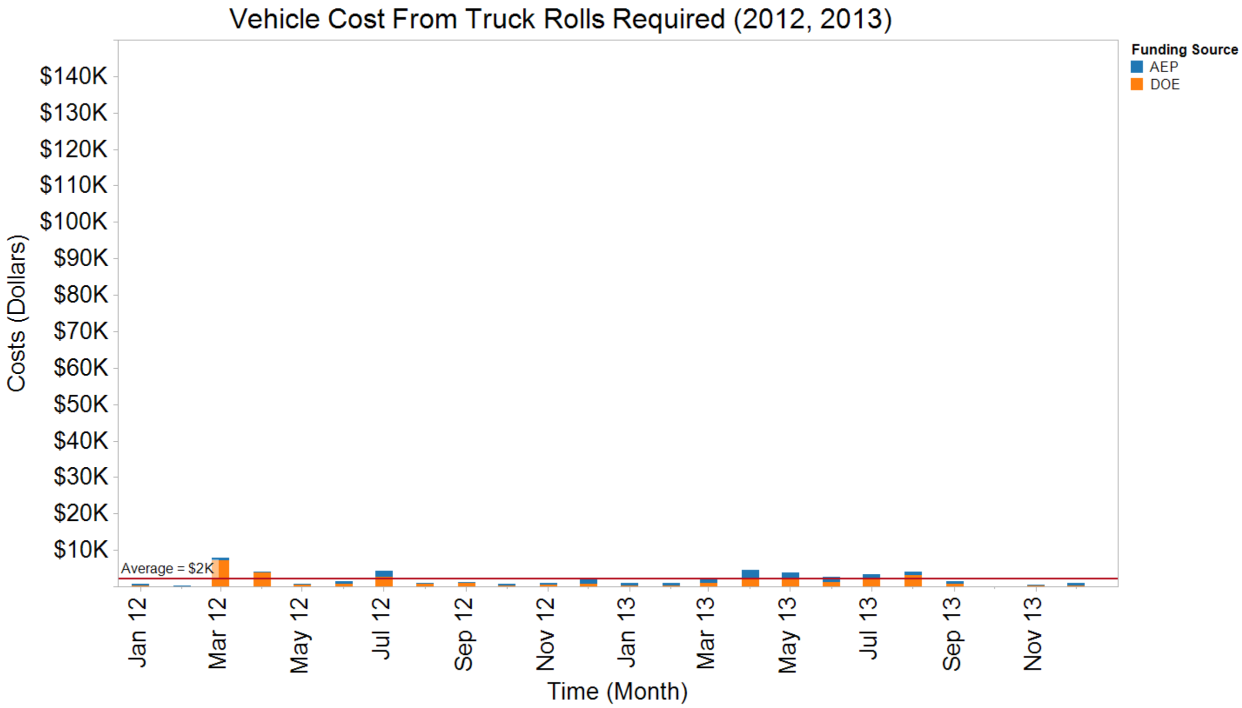

Figure 7. Additional Vehicle Costs from AMI

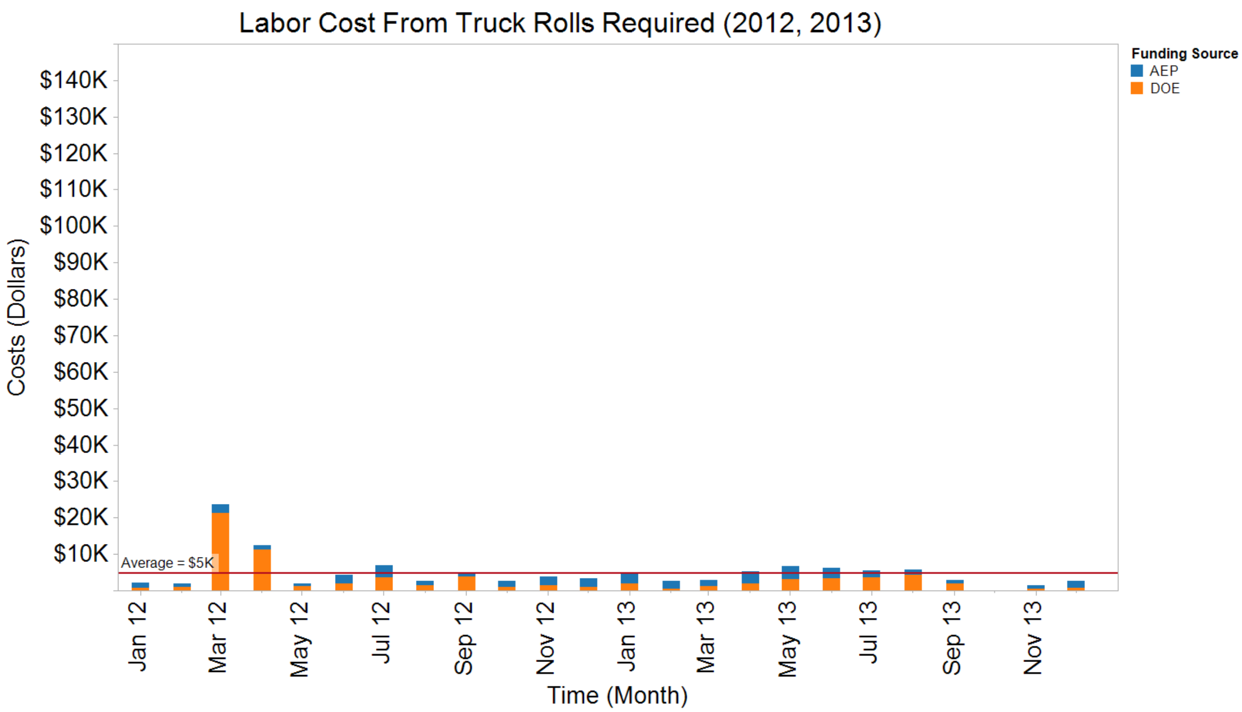

Figure 8. Additional Labor Costs from AMI

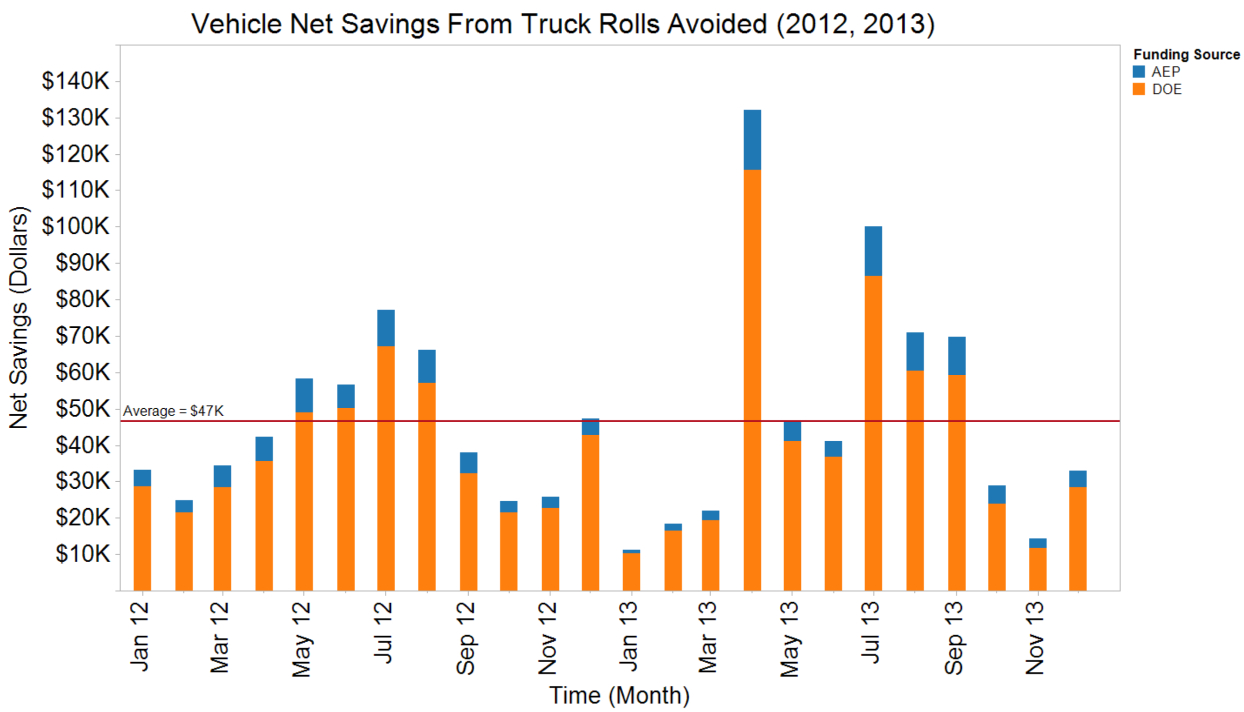

Figure 9. Net Vehicle Savings from Truck Rolls Avoided

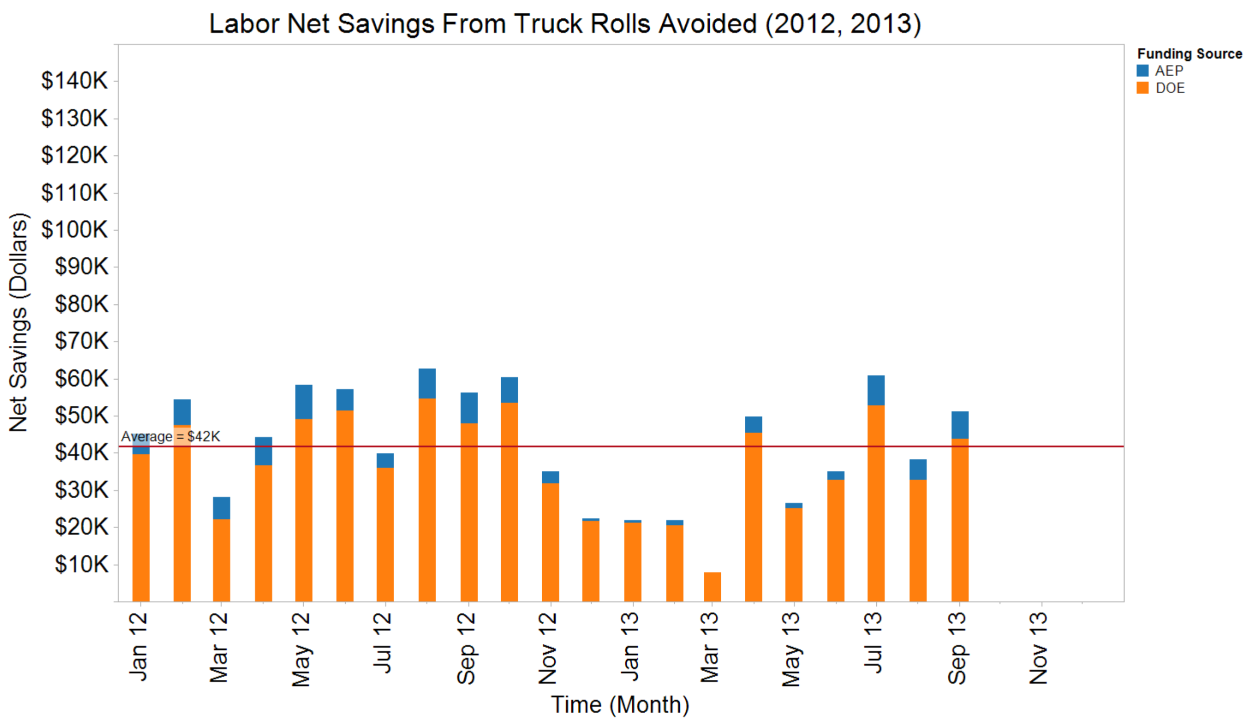

Figure 10. Net Labor Savings from Truck Rolls Avoided

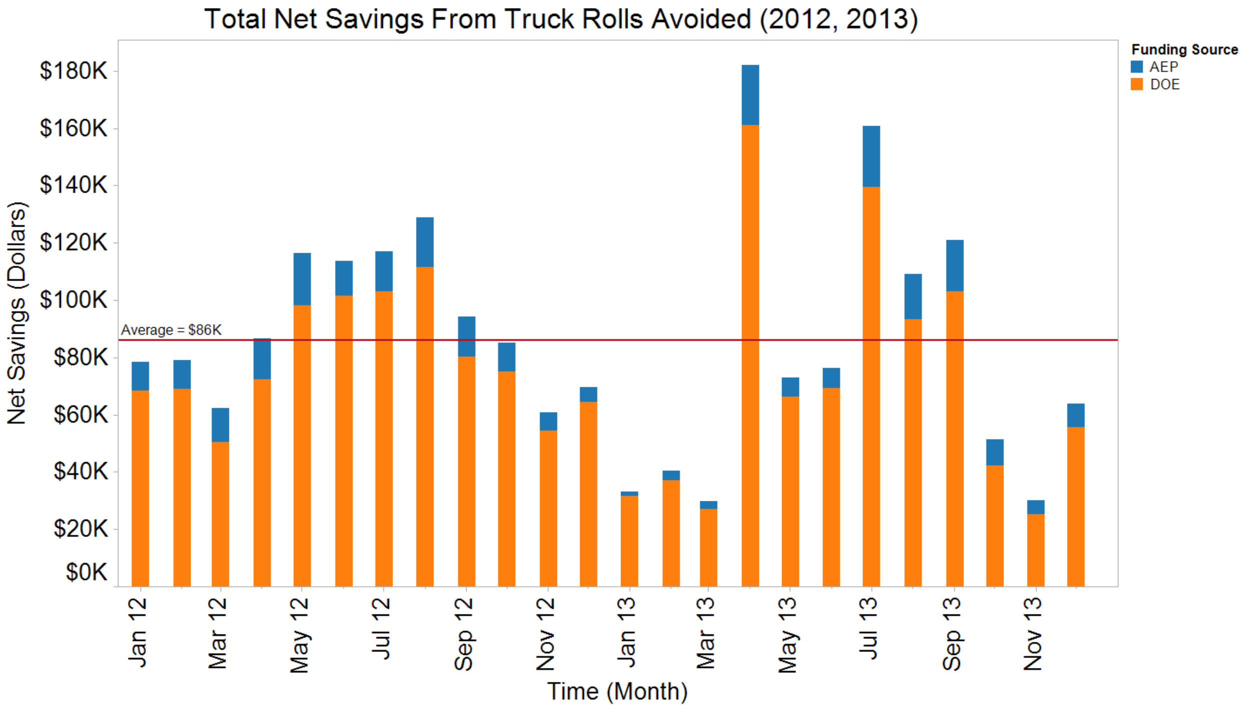

Figure 11. Total Net Savings Associated with AMI Service Truck Rolls Avoided

Results for Consumer Service Related Truck Rolls Avoided

The figure above shows the average monthly net savings due to truck rolls avoided from January 2012 through December 2013 was $85,943, with a total savings of $2,062,628. The population of meters was approximately 132,000 System area meters. The average per meter savings was therefore $7.81 per meter per year.

Cost Savings from Eliminated Meter Reading Routes

Prior to the installation of AMI meters, AEP Ohio had 994 meter reading routes in the Columbus metropolitan area. Through the use of AMI, AEP Ohio was able to eliminate 187 meter reading routes, 100 percent of the meter reading routes in the Project area. AEP Ohio meter readers typically read one route per day. For calculation purposes, it is assumed that eliminating a route equals 8 hours of labor. As a result of installing AMI and eliminating 187 meter reading routes, AEP Ohio has saved 1,301.5 hours in labor and eliminated 10 meter reading positions. In addition, unread meter numbers have improved to 0.3 percent in the Columbus area each month.

The table below outlines the savings due to the elimination of meter reading routes.

Item	Hourly Cost	Total Hours	Total Savings
Meter Reader Salary (2012) - loaded	21.45	1,301.50	$27,917
Vehicle Operations (2012)	7.50	1,301.50	$9,761
Grand Total – Monthly			$37,676
Grand Total – Yearly			**$452,112 (3.43 per meter per year)**

Table 10. Meter Reading Route Elimination Savings

AEP Ohio has filed with the Public Utilities Commission of Ohio (PUCO) for expansion of the AMI project of an additional 894,000 meters. The meter reading efficiencies are projected to increase to approximately $6-$7 million in annual utility savings (adjusted for inflation).

Credit, collections and revenue enhancements through earlier theft detection, lower consumption on inactive meters and greater billing accuracy are projected to lead to an additional $8-$10 million in annual utility savings. Of that amount, $1.5-$2 million annually is operational savings from use of the remote service switch specifically for DNP. The benefits associated with automated DNP require a PUCO waiver for the current process that requires on-site customer interaction. The PUCO would need to consider whether and how the rules would be adjusted to allow for credit disconnects, considering all stakeholder options.

Results for Reductions in Meter Theft and Tampering

Meter Revenue Operations (MRO) is able to quickly identify and mitigate meter theft and tampering, which is a direct result of AMI technology.

Meter Theft

Meter theft occurs when someone removes a meter from its authorized location and uses it elsewhere. Because of AMI technology, MRO is able to locate a stolen meter in near real-time. AEP Ohio uses UtilityIQ® (UIQ) back-office software for meter management. Within 15 minutes, this software sends notifications that an AMI meter is installed in a different location.

Meter Tampering

Meter tampering occurs when a meter or meter base is altered, causing inaccurate recording of that meter's usage, affecting the consumer's bill. With AMI, tampering was identified almost immediately and MRO identified physical tampering schemes, such as jumper placement behind a meter.

Overview

Tampering usually occurs with about 2 to 3 percent of AEP Ohio consumers. With AMI, the goal was to have AEP Ohio respond to tamper alerts within 24 to 48 hours of the first tampering notification. The AMI system sent tampering notifications immediately and enables MRO to respond to tampering orders quickly.

Details

In a 2013 sampling, 163 total tampering calls were identified through AMI and 147 confirmed instances of jumper placement behind the meter. AEP Ohio was able to bill a portion of these account holders for tampering and continued to investigate the remainder.

AEP Ohio's meter tampering operating costs are billed to the tampering consumer. A breakdown of costs is provided below.

Tamper Operating Costs Per Meter	
Investigation Costs	$49.00
Tampering lock installed	$73.00
Meter charge for damages	$125.00
Rebilling of Unmetered Revenue	Varies by account
Minimum Total charged to consumer	$247.00

Table 11. Tamper Operating Costs per Meter

Changes in Meter Failure Rate

AEP Ohio had 3,780 meter failures associated with the AMI implementation, which equated to an approximate failure rate of 0.98 percent during the 3.5 years that the 110,000 AMI meters were installed in the Project area.

Note: This failure rate included the failed diode meters that skewed these numbers initially. However, the problem was diagnosed and corrected.

Software and Network Maintenance Costs

This section contains the analysis of the ongoing maintenance costs associated with operating the AMI network.

Silver Spring Networks' (SSN) AMI fees for the northeast Columbus project are $125,565 per year. This is the annual UIQ maintenance fee for 110,000 AMI meters ($0.095 per meter per month). These recurring fees do not include individual Scope of Work agreements, Online Data Storage (ODS) agreements, and upgrades.

2.5.1.6 Summary

Elimination of truck rolls associated with consumer service calls and the elimination of manual meter reading routes were the major sources of meter operations cost reduction. Both sources included labor and vehicle savings, associated servicing, and reading meters manually. In addition, cost reductions may be realized as meter theft and tampering are identified and mitigated quickly.

The AMI system reduced truck rolls from meter reads and consumer service calls. Customer Service Representatives (CSRs) remotely connected to meters, disconnected meters, and diagnosed consumer issues. For example, AEP Ohio CSRs mitigated billing complaints by accessing and reviewing 15-minute AMI data. Representatives were able to remotely check a meter and review its status. This process often eliminated the need to send a service crew to physically check a meter.

There were more truck rolls as a result of increased consumers' concerns about the accuracy of their bills. These concerns were driven by the increase in information consumers had about their bills. However, this trend was sporadic and it surged on initial installation. Another source of additional truck rolls was AMI-specific maintenance issues (such as communications failures). These additional truck rolls were included in the total number of truck rolls avoided.

The savings from elimination of meter reading routes was fixed, and on a monthly basis, constant. The variability in monthly savings from avoided truck rolls was likely attributable to two major factors – weather events, which drove consumer service calls, and an initial adjustment period as consumers transitioned from traditional meters to AMI meters. There were also concurrent tariff changes with the AMI installation, and that likely drove a short-term increase in consumer service calls seen in February and March of 2012. There were also a number of issues for initial AMI installations that required subsequent truck rolls to correct any installation problems.

2.5.2 Truck Rolls Avoided (M05-AMI)

The AMI system has the potential to reduce the number of truck rolls required through the elimination of meter reading routes and the ability to remotely perform services such as check reads, connections, and disconnections.

2.5.2.1 Objective

This impact metric quantifies the number of truck rolls avoided because of AMI technology. This metric also takes into account the number of truck rolls added that are a result of new information this technology provides. For example, AMI can detect meter tampering and send alerts in near-real time.

2.5.2.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Disconnections for non-payment are excluded from this analysis because AEP Ohio was required to send a representative to consumer premises prior to service disconnection.
- A disconnect for non-payment did not equate to a truck roll avoided.
- One meter reader per truck. (Standard truck is a pick-up truck.)

2.5.2.3 Calculation Approach

Certain types of consumer events, such as check read requests, can be handled remotely via the AMI system, thereby avoiding a truck roll. A list was compiled of all consumer event order types that led to an avoided truck roll. Next, the number of truck rolls avoided because of AMI was calculated based on the number of consumer events with matching order type codes.

The following queries and methods were used to generate results:

- Truck rolls avoided per service center, month, and meter funding source were calculated by multiplying the ratio of miles for a circuit in a service center to total miles for a circuit times the number of consumer events for consumers with AMI meters where the order type that generated the consumer event was any order type except *Excess use on an inactive account*, the meter response to a meter request was not *Error,* and the consumer event type was one of the following:
    - Connect Request
    - Disconnect Request
    - Estimated Bill Complaint
    - High Bill Complaint
- Truck rolls required per service center, month, and meter funding source were calculated by adding the number of truck rolls required from AMI meter events, where the event type was Tamper, to the number of AMI meter requests, where the order request was Read/Solve Access.
- Net truck rolls per service center, month, and meter funding source were calculated subtracting the AMI truck rolls required from the AMI truck rolls avoided.

2.5.2.4 Organization of Results

The following section describes the number of truck rolls avoided due to AMI from the following sources:

- Service-related truck rolls avoided

  This section contains monthly graphs showing the number of truck rolls avoided, as well as the number of new truck rolls required because of AMI. A final graph is presented showing the net number of truck rolls avoided.

- Elimination of meter reading routes

  This section contains a savings analysis that results from the elimination of meter reading routes because meters are read remotely through the AMI network.

2.5.2.5 Data Collection Results

This section shows savings results related to customer service-related truck rolls, eliminated meter reading routes, and AEP Ohio's engineering analysis.

Results for Service Related Truck Rolls Avoided

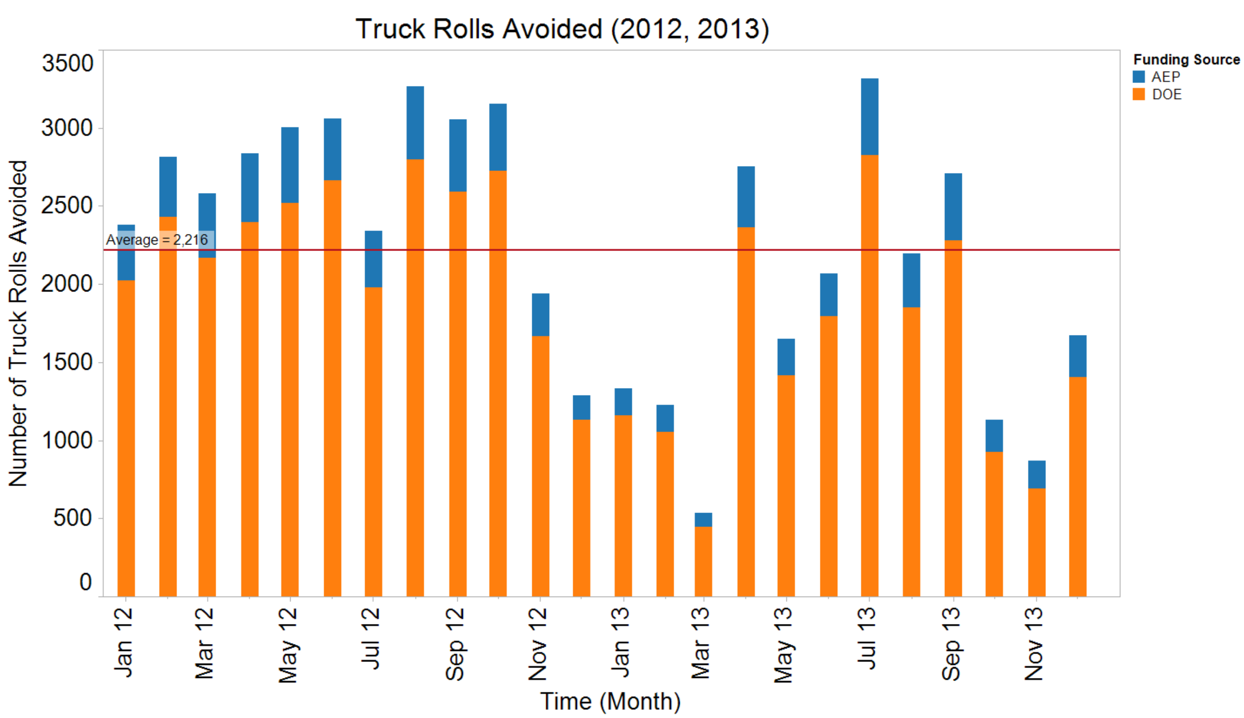

Figure 12. Truck Rolls Avoided Because of AMI

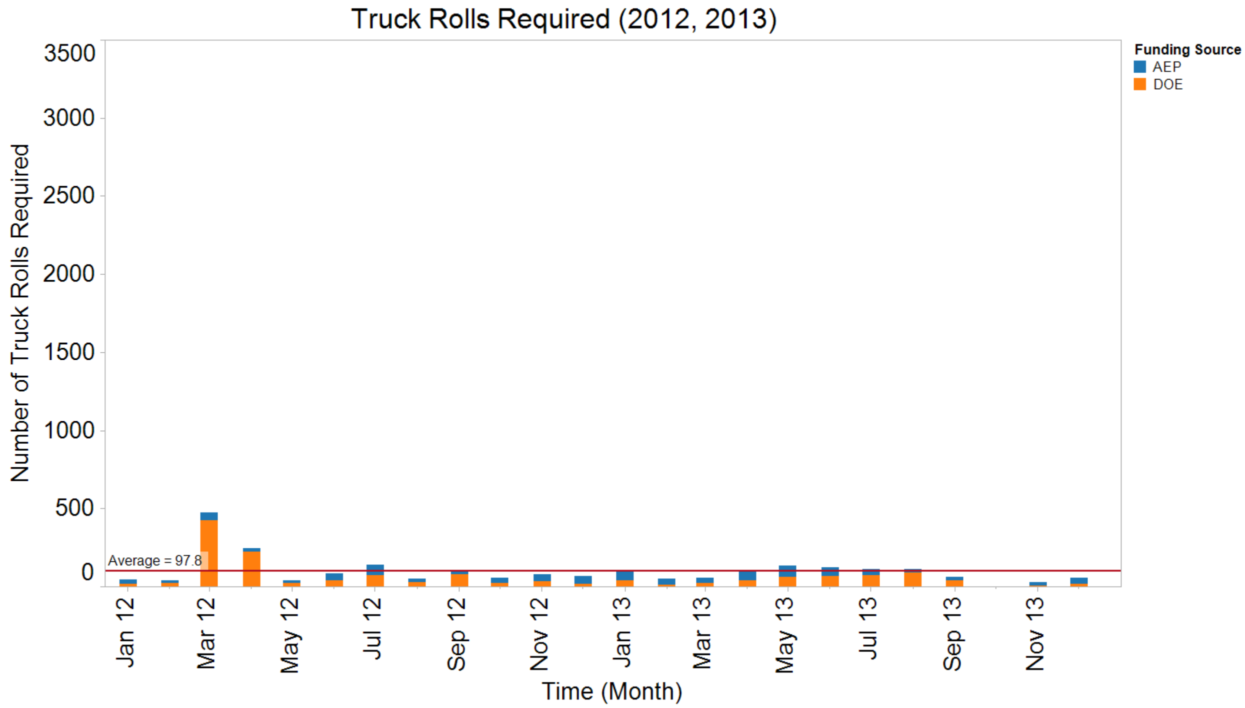

Figure 13. Additional Truck Rolls Required Because of AMI

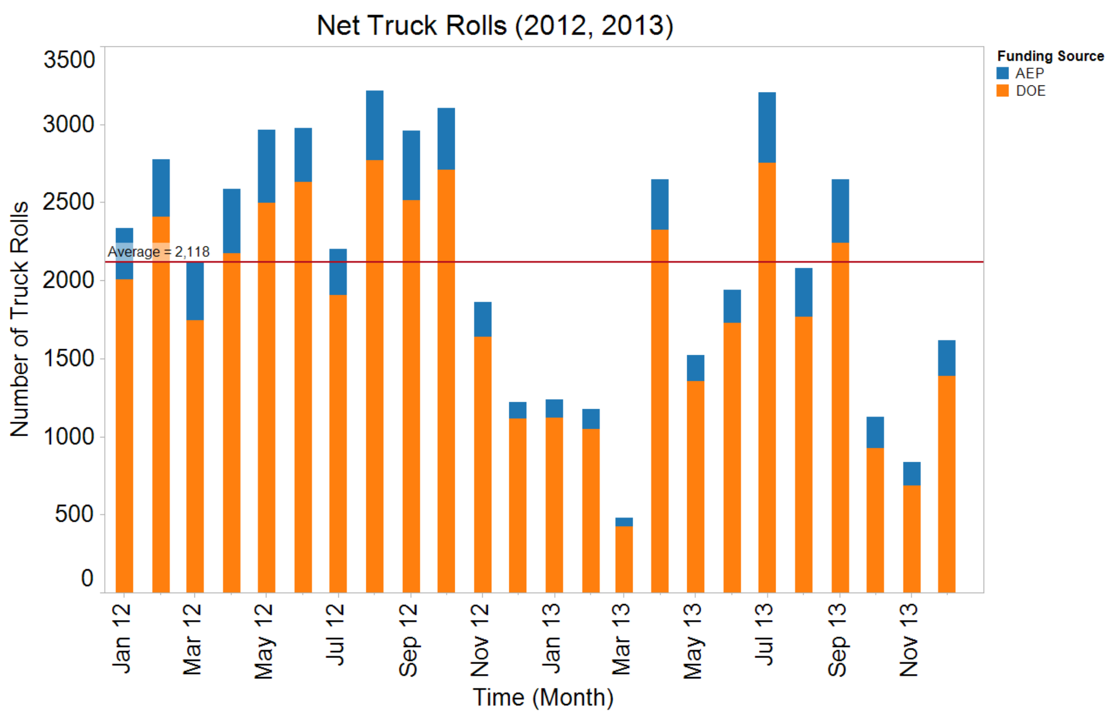

Figure 14. Net Truck Rolls Avoided Because of AMI

The average monthly net count of truck rolls avoided during January 2012 through December 2013 was 2,118 truck rolls per month. The total of number of net truck rolls avoided during January 2012 through December 2013 was 50,825. The 2012 average was 2,526 per month and the 2013 average was 1,709 per month.

2.5.2.6 Results for Eliminated Meter Reading Routes

Prior to the installation of AMI meters, AEP Ohio had 994 meter reading routes in the Columbus metropolitan area. Through the use of AMI, AEP Ohio was able to eliminate 187 meter reading routes in the Project area. This resulted in 163 avoided truck rolls per month, or 1,952 truck rolls avoided per year.

Note that each meter reading route in this area normally required an average of eight hours per route for meter reading activities. Therefore, meter reading truck rolls represent a much larger mileage savings compared with meter service-related truck rolls.

2.5.2.7 Summary

The number of truck rolls avoided per month showed seasonal variation that can be attributed to several factors. For public safety reasons, fewer disconnect (and corresponding reconnect) events occurred during winter months. In April 2013 there was a noticeable increase due to the backlog of disconnects that were not performed during the winter.

2.5.3 Meter Operations Vehicle Miles (M06-AMI)

The AMI system has the potential to reduce the number of truck rolls that AEP Ohio meter operations staff perform through the elimination of meter reading routes and the ability to perform services remotely. These services include meter reading, meter connections, and meter disconnections.

2.5.3.1 Objective

This impact metric provides an estimate of the number of vehicle miles avoided and added because of changes from AMI technology.

2.5.3.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

The AMI system provides the capability to manage certain types of consumer events remotely, which results in mileage eliminated from truck rolls avoided.

2.5.3.3 Calculation Approach

A list was compiled of all consumer event order types that led to an avoided truck roll. The number of truck rolls avoided because of AMI was then calculated based on the number of consumer events with matching order type codes.

Average mileage per truck roll was calculated by month for each AEP Ohio service center in the Project and System areas. These average mileage values were applied to the count of truck rolls avoided to calculate mileage avoided because of AMI.

The following queries and methods were used to generate results:

- Vehicle distances per service center and month for the Meter Revenue Operations (MRO) and Field Revenue Operations (FRO) business units were calculated by summing the vehicle use mileage quantities.
- Average truck roll distances per service center and month for the MRO and FRO business units were calculated by taking the average of the vehicle distances by service center and month for the MRO and FRO business units divided by the number of completed work orders per service center and month.
- The meter operations vehicle miles avoided per service center, month, and meter funding source were calculated by multiplying the AMI truck rolls avoided per service center, month, and meter funding source by the average truck roll distances by service center and month for the MRO and FRO business units.

2.5.3.4 Organization of Results

The following section describes the number of vehicle miles avoided from the following sources:

- Service-related truck rolls avoided

  This section contains monthly graphs showing the number of vehicle miles avoided as a result of the net number of truck rolls avoided.

- Elimination of meter reading routes

  This section contains analysis of vehicle miles avoided as a result of eliminated meter reading routes.

2.5.3.5 Data Collection Results

This section describes savings results related to service truck rolls, eliminated meter routes, and AEP Ohio's engineering analysis.

Results for Consumer Service-Related Truck Rolls Avoided

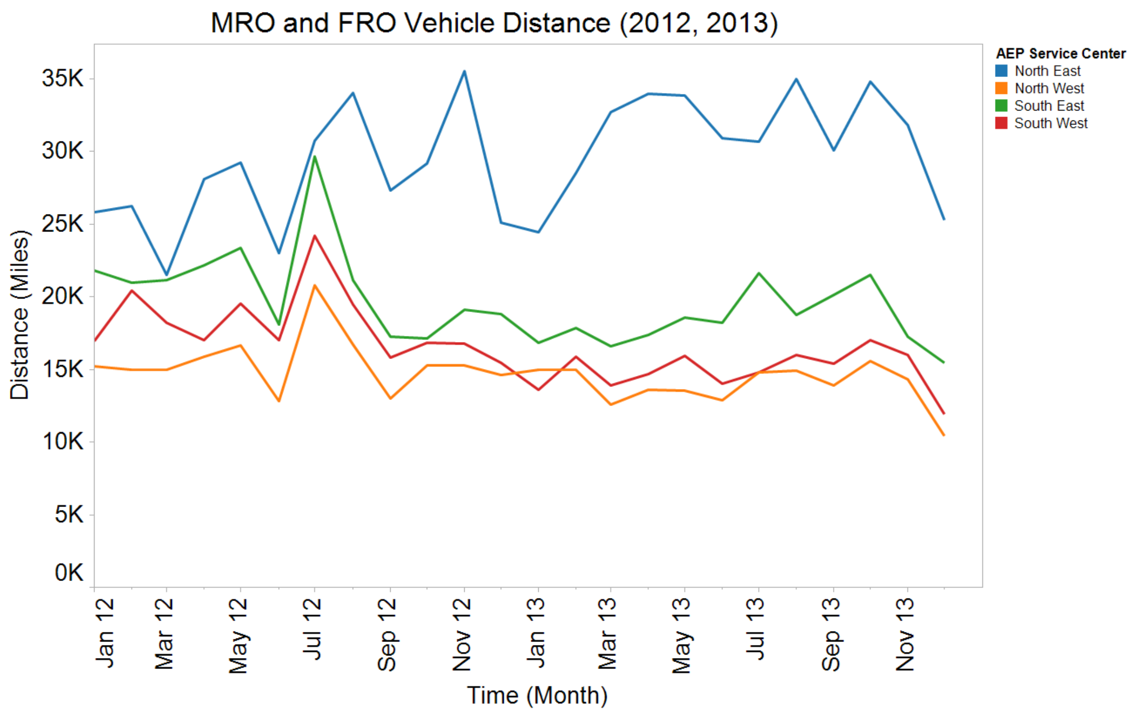

Figure 15. Total Vehicle Distance by Service Center

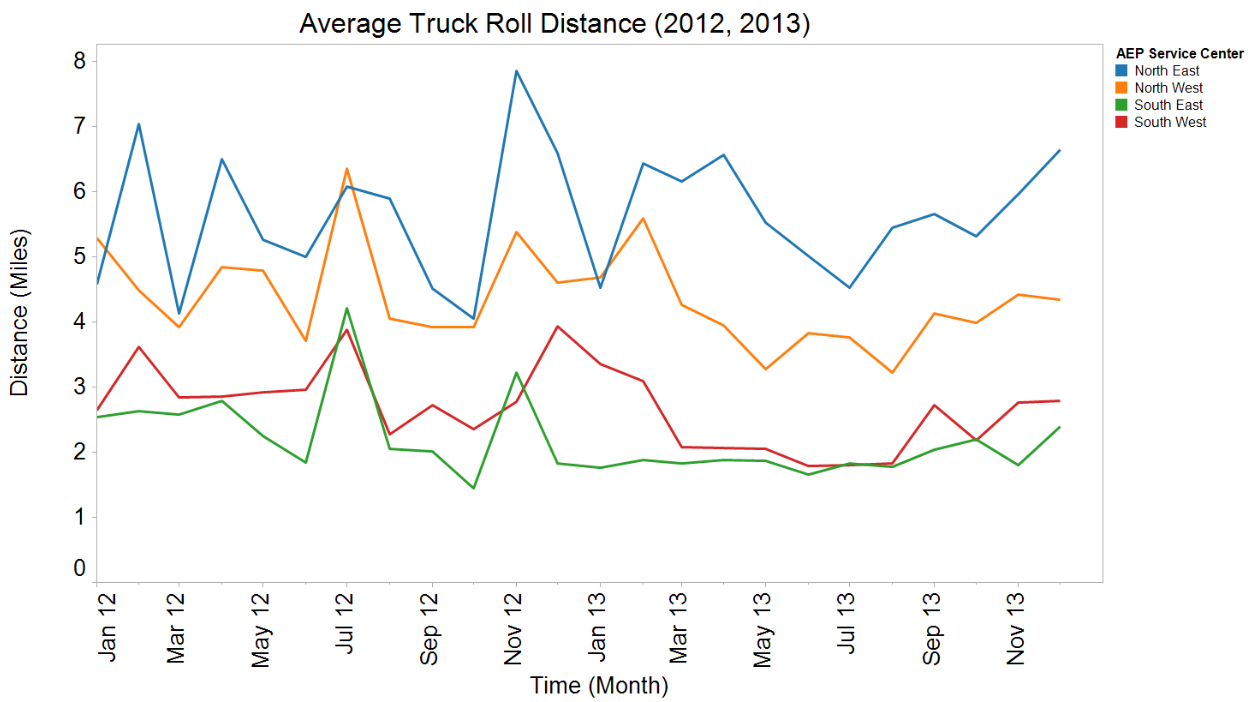

Figure 16. Average Truck Roll Distance by Service Center

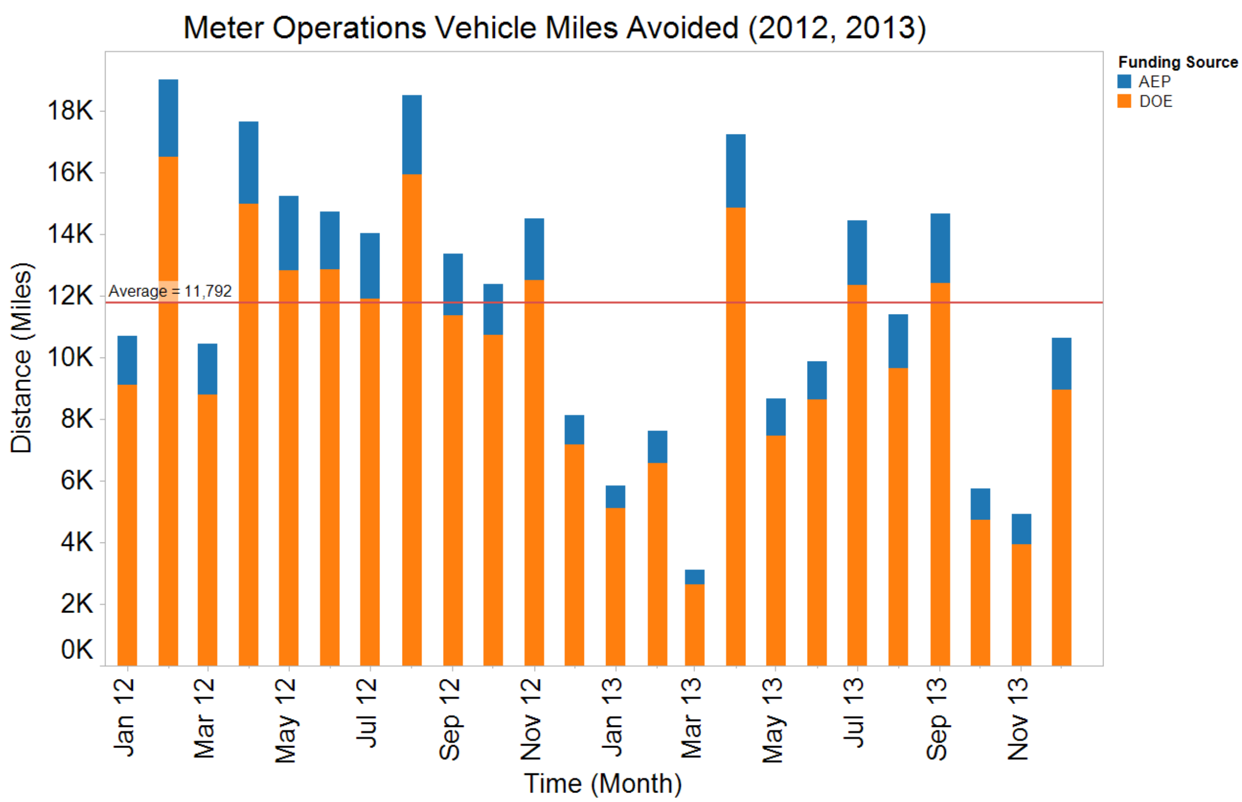

Figure 17. Net Mileage Avoided Due to AMI

The average monthly net mileage avoided from January 2012 through December 2013 was 11,792 miles/month. The total miles avoided for the period of January 2012 through December 2013 was 282,996 miles.

Results for Eliminated Meter Reading Routes

Through the use of AMI, AEP Ohio was able to eliminate 187 meter reading routes in the Project area. This results in a vehicle mileage avoidance of 5,694 miles/month or 68,328 miles per year.

2.5.3.6 Summary

The meter operations vehicle miles avoided were a direct result of eliminating meter reading route vehicle use and eliminating on-site customer trips for connects and disconnects. There was no indication that there was a change in the number of truck rolls or the average mileage per truck roll due to different type of work being performed in the AMI area. The monthly total and average distance per truck roll were fairly consistent within each of the four Columbus service centers across the test period, but varied significantly by service center.

AEP Ohio's Northeast Service Center, which services the Project area, consistently had a higher total vehicle mileage and average truck roll distance than the other three service centers in Columbus. There was no evidence that this was a result of the AMI technology being deployed, but more a factor of the larger geographic layout of the Northeast Service Center coverage.

2.5.4 CO_2 Emissions - Project (M07-AMI)

The AMI system has the potential to reduce the number of truck rolls required through the elimination of meter reading routes and the ability to perform services remotely. Truck rolls avoided results in a reduction of fuel usage.

2.5.4.1 Objective

This impact metric provides an estimate of the CO_2 emissions saved by avoiding truck rolls resulting from AMI functionality.

2.5.4.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- 8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines conversion factor.
  Source: *United States EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-05-001)*
- The only significant impacts on CO_2 emissions due to AMI are achieved through truck rolls avoided because AMI has little direct impact on consumer usage patterns.

2.5.4.3 Calculation Approach

A list was compiled of all consumer event order types that lead to an avoided truck roll. The number of truck rolls avoided due to AMI was then calculated based on the number of consumer events with matching order type codes.

Average mileage per truck roll and average vehicle fuel efficiency were calculated by month for each AEP Ohio service center in the Project and System areas. CO_2 emission avoidance was calculated using fuel efficiency and mileage avoided.

The following queries and methods were used to generate results:
AEP Ohio provided an average fuel economy value for each vehicle. Corrected average monthly fuel efficiencies in miles per gallon per service center, month, and fuel type for vehicles the AEP Ohio Meter Revenue Operations (MRO) and Field Revenue Operations (FRO) business units used were determined as follows:

- Calculating the average of monthly vehicle mileage divided by monthly quantity of fuel for each vehicle.
- Because some suspect monthly vehicle mileage (703,281 miles, for example) was received, if the average of monthly vehicle mileage divided by monthly quantity of fuel divided by the average monthly average fuel economy value was not between 0.5 and 2.0, average monthly average fuel economies were substituted for the average of monthly vehicle mileage divided by monthly quantity of fuel. This calculation provides the corrected average monthly fuel efficiencies.

Tons of CO_2 avoided per service center, month, meter funding source, and fuel type due to truck rolls avoided because of AMI technology were calculated as follows:

- Multiplying the number of truck rolls avoided by the average truck roll distance divided by the corrected average monthly fuel efficiency by (8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines) by 0.00110231131092 (kg to tons conversion factor).

2.5.4.4 Organization of Results

This section contains the results from analysis of CO_2 through the AMI network as follows.

- Customer service-related truck rolls avoided

  This section contains monthly graphs showing the amount of CO_2 avoided due to the net number of truck rolls avoided.

- Elimination of meter reading routes

  This section contains the results from analysis of CO2 avoided due to the elimination of meter reading routes by reading meters remotely through the AMI network.

2.5.4.5 Data Collection Results

This section describes results for service-related truck rolls avoided, eliminated meter reading routes, and AEP Ohio's engineering analysis.

Results for Service-Related Truck Rolls Avoided

The average monthly net CO_2 avoided from January 2012 through December 2013 was 16.91 tons per month, with a total of 406 tons.

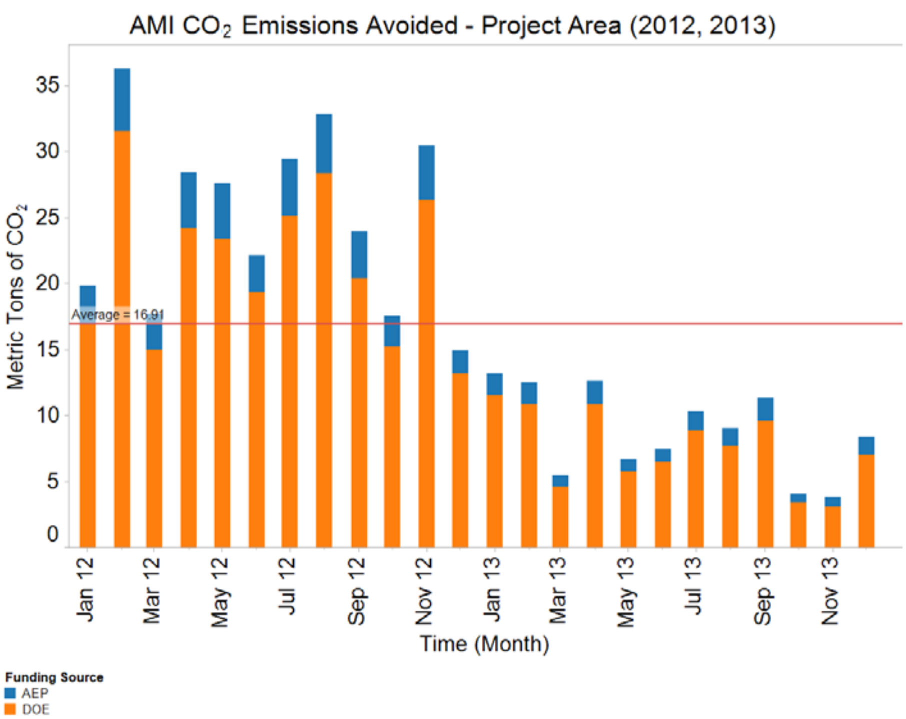

Figure 18. CO_2 Emissions Avoided as a Result of Reduced AMI Truck Rolls

Results for Reduced CO_2 from Eliminated Meter Reading Routes

Through the use of AMI, AEP Ohio was able to eliminate 187 meter reading routes in the Project area. This results in a vehicle mileage avoidance of 5,694 miles/month or 68,328 miles per year. Using an Environmental Protection Agency (EPA) average value of 423 grams of CO_2 per mile (EPA-420-F-11-041) results in 2.408 metric tons of CO_2 avoided per month or 28.903 metric tons avoided per year.

2.5.4.6 Summary

The CO_2 emissions avoided were a direct multiple of truck roll miles avoided. As a result, the variations and differences in CO_2 emissions over time and service area were consistent with the variations in truck rolls avoided and average truck roll mileage.

2.5.5 Pollutant Emissions - Project area: SO_X, NO_X, and $PM_{2.5}$ (M08-AMI)

The AMI system has the potential to reduce the number of truck rolls required through the elimination of meter reading routes and the ability to perform services remotely, such as meter reading, service connection, and disconnection. Truck rolls avoided can lead to reduced pollutant emissions from vehicles.

2.5.5.1 Objective

This impact metric provides an estimate of the amount of pollutant emissions saved by avoiding truck rolls due to the functionality of AMI technology.

2.5.5.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- California Air Resources Board (CARB) limit value of 0.05 grams of Nitrogen Oxides (NO_X) per mile was used.

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 50,000 mi*

- 0.01 g $PM_{2.5}$ emissions/mi conversion factor

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 100,000 mi*

- 0.165 g SO_X emissions/gallon for gas engines, 0.0963 g SO_X emissions/gallon for diesel engines conversion factor

  Calculated from: sulfur content of gasoline = 30 ppm

  Source: *U.S. EPA 40 CFR parts 80, 85, and 86 AMS-FRL-6516-2*

  Sulfur content of ULSD diesel fuel = 15 ppm

  Source: *U.S. EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-00-057)*

  Molecular weight of SO_2 = 64 g/mole

  Density of gasoline = 2.75 kg/gallon

  Density of diesel fuel = 3.21 kg/gallon

2.5.5.3 Calculation Approach

Certain types of consumer events, such as check read requests, can be handled remotely using the AMI system, thereby avoiding a truck roll. A list was compiled of all consumer event order types that lead to an avoided truck roll. The number of truck rolls avoided due to AMI was then calculated based on the number of consumer events with matching order type codes.

Average mileage per truck roll and average vehicle fuel efficiency were calculated by month for each AEP Ohio Service Center. Pollutant emission avoidance was calculated using fuel efficiency and mileage avoided.

The following queries and methods were used to generate results:

- Average monthly fuel efficiencies in miles per gallon per month and fuel type for vehicles the AEP Ohio MRO and FRO business units used were determined by calculating the average of monthly vehicle mileages divided by monthly quantity of fuel for each vehicle. If the average of monthly vehicle mileages divided by monthly quantity of fuel divided by the average monthly average fuel economy value was not between 0.5 and 2.0, average monthly average fuel economies were substituted for the average of monthly vehicle mileages divided by monthly quantity of fuel to calculate the corrected average monthly fuel efficiencies.
- Kilograms of SO_X avoided per service center, month, meter funding source, and fuel type due to truck rolls avoided attributable to AMI technology were calculated by multiplying the number of truck rolls avoided times the average truck roll distance divided by the corrected average monthly fuel efficiency times either 0.165 g SO_2 emissions/gallon for gasoline engines or 0.0963 g SO_2 emissions/gallon for diesel engines e times 0.001 (g to kg conversion factor).
- Kilograms of NO_X avoided per service center, month, meter funding source, and fuel type due to truck rolls avoided attributable to AMI technology were calculated by multiplying the number of truck rolls avoided times the average truck roll distance times 0.05 g NOx emissions/mi times 0.001 (g to kg conversion factor).
- Kilograms of particulate matter ($PM_{2.5}$) avoided per service center, month, meter funding source, and fuel type due to truck rolls avoided attributable to AMI technology were calculated by multiplying the number or truck rolls avoided times the average truck roll distance times 0.01 g $PM_{2.5}$ emissions/mi times 0.001 (g to kg conversion factor).

2.5.5.4 Organization of Results

The following section describes the amount of pollutants avoided due to AMI from the following sources:

- Consumer service-related truck rolls avoided
- This section contains monthly graphs showing the amount of pollutants avoided as a result of the net number of truck rolls avoided.
- Elimination of meter reading routes

  This section contains the results from analysis of pollutants avoided due to the elimination of meter reading routes by reading meters remotely through the AMI network.

2.5.5.5 Data Collection Results

This section shows results for consumer service-related truck rolls, eliminated meter routes, and AEP Ohio's engineering analysis.

Service-Related Truck Rolls Avoided

- The average monthly net NO_X avoided during January 2012 through December 2013 was 0.956 kg/month, with a total of 22.9 kg.
- The average monthly net SO_X avoided during January 2012 through December 2013 was 0.220 kg/month, with a total of 5.3 kg.
- The average monthly net particulate matter ($PM_{2.5}$) avoided during January 2012 through December 2013 was 0.191 kg/month, with an annual total of 4.6 kg.

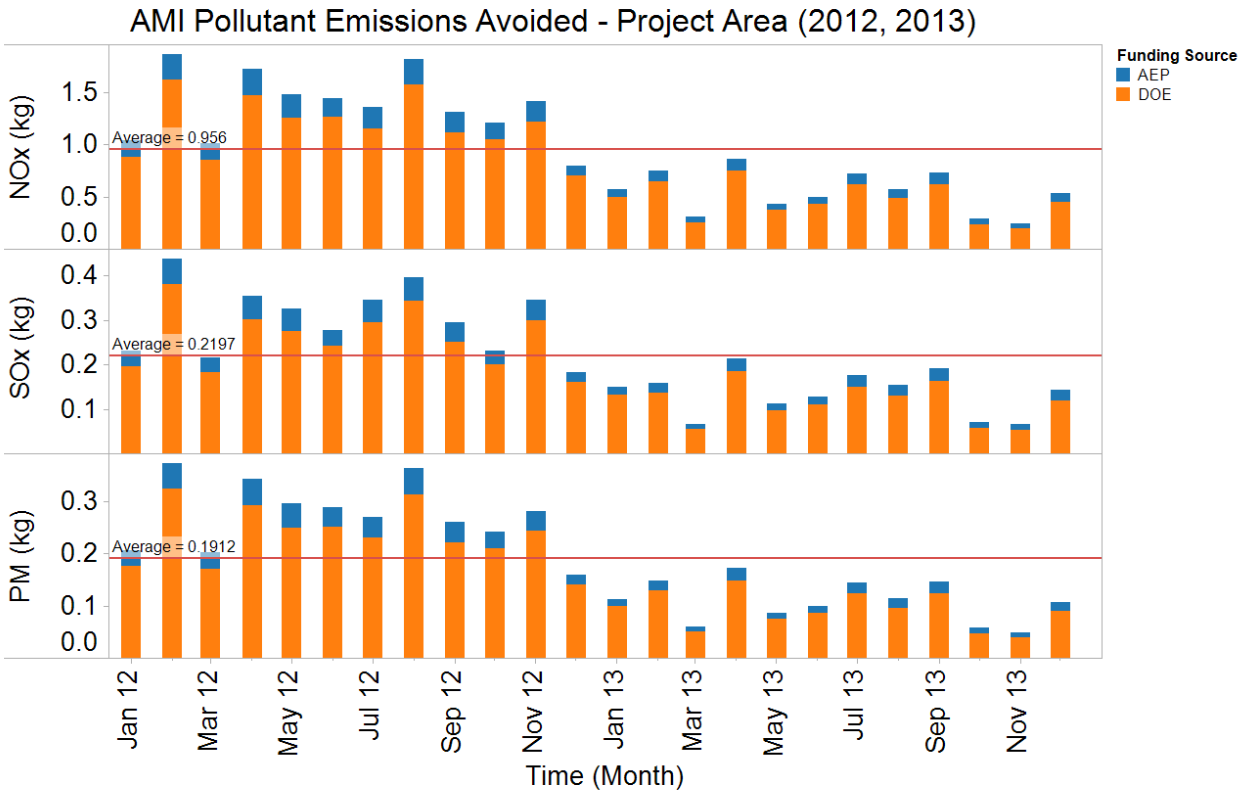

Figure 19. Pollutants Avoided Resulting from AMI Truck Rolls Avoided

Results for Eliminated Meter Reading Routes

Through the use of AMI, AEP Ohio was able to eliminate 187 meter reading routes in the Project area. This results in a vehicle mileage reduction of 5,694 miles/month or 68,328 miles per year.

Using a CARB limit value of 0.05 grams of NO_X per mile, results in 284.7 g of NO_X avoided per month or 3,416 g avoided per year.

SO_X and $PM_{2.5}$ emissions from light-duty gasoline vehicles, which are typically used for meter reading routes, provided a small contribution to this impact metric.

2.5.5.6 Summary

Pollutant emissions are a direct multiple of truck roll miles avoided. As a result, the variations and differences in pollutant emissions over time are consistent with the variations and differences in truck rolls avoided as well as average truck roll mileage.

2.5.6 CO_2 Emissions - System area (M09-AMI)

The AMI system has the potential to reduce the number of truck rolls required through the elimination of meter reading routes and the ability to perform some services remotely. These services include meter reading, meter connection, and disconnection. Truck rolls avoided can lead to reduced pollutant emissions from vehicles.

2.5.6.1 Objective

This impact metric provides an estimated amount of CO_2 that trucks would emit to perform services that could be performed remotely if AMI technology was extended to the entire System area.

2.5.6.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- 8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines conversion factor was used.
- Meter reading truck tolls follow the same distance ratio as service truck rolls.

2.5.6.3 Calculation Approach

The AMI system provides remote service capabilities for certain types of consumer events. A list was compiled of all consumer event order types that lead to an avoided truck roll. The number of truck rolls avoided due to AMI was then calculated based on the number of consumer events with matching order type codes.

Average mileage per truck roll and average vehicle fuel efficiency were calculated by month for each AEP Ohio service center in the Project and System areas. Project area CO_2 emission avoidance was calculated using fuel efficiency and mileage avoided. This emission avoidance was then extrapolated to the System area based on number of consumers and average truck roll distances for each non-Project service center.

The following queries and methods were used to generate results:
The calculation that follows was used to determine avoided tons of CO_2 per service center and month if AMI technology were deployed throughout the AEP Ohio System area:

Truck rolls avoided per consumer in the Northeast Service Center were multiplied by the number of consumers without AMI technology per month times the average truck roll distance.
This value was divided by the corrected average monthly fuel efficiency times (8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines) times 0.00110231131092 (kg to tons conversion factor).

2.5.6.4 Organization of Results

The following section describes the amount of CO_2 that could be avoided if AMI was deployed to the entire System area from:

- Service-related truck rolls

  This section contains monthly graphs showing the amount of potential CO_2 avoided as a result of a potential reduction in truck rolls.

- Elimination of meter reading routes

  This section contains the analysis results from potential CO_2 avoided due to the elimination of meter reading routes. Meters are read remotely through the AMI network.

2.5.6.5 Data Collection Results

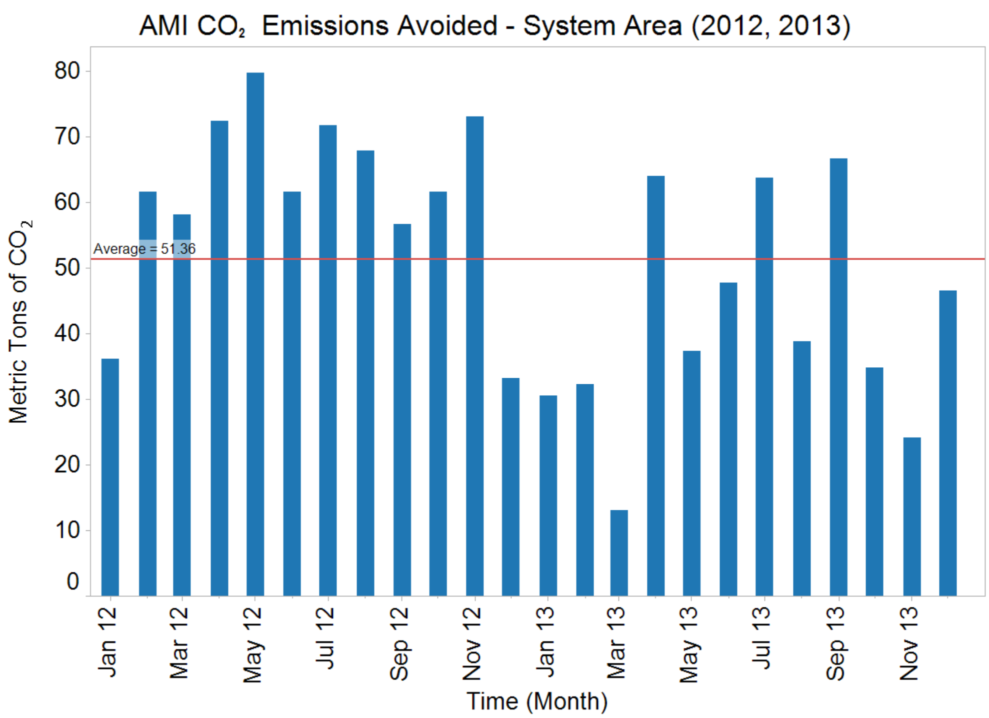

Figure 20. Potential CO_2 Avoided in System Area Due to AMI Truck Rolls Avoided

Results for Service-Related Truck Rolls Avoided

The average potential monthly CO_2 avoided for January 2012 through December 2013 was 51 tons per month, with a potential total of 1,232 tons if AMI were expanded to the entire System area.

2.5.6.6 Summary

CO_2 emissions are a direct multiple of truck roll miles avoided. As a result, the variations and differences in CO_2 emissions are consistent with truck rolls avoided and average truck roll mileage.

2.5.7 Pollutant Emissions - System area: SO_X, NO_X, and $PM_{2.5}$ (M10-AMI)

The AMI system has the potential to reduce the number of truck rolls required through the elimination of meter reading routes and the ability to perform services remotely, such as meter reading, meter connection and disconnection.

2.5.7.1 Objective

This impact metric provides an estimate of the amount of pollutants that would have been emitted by trucks to perform services that could be avoided if AMI technology was extended to the entire System area.

2.5.7.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- A CARB limit value of 0.05 grams of NO_X per mile was used.

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 50,000 m*i

- 0.01g $PM_{2.5}$ emissions/mi conversion factor

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 100,000 mi*

- 0.165 g SO_X emissions/gallon for gas engines, .0963 g SO_X emissions/gallon for diesel engines conversion factor

  Calculated from: sulfur content of gasoline = 30 ppm

  Source: *U.S. EPA 40 CFR parts 80, 85, and 86 AMS-FRL-6516-2*

  Sulfur content of ULSD diesel fuel = 15 ppm

  Source: *U.S. EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-00-057)*

  Molecular weight of SO_2 = 64 g/mole

  Density of gasoline = 2.75 kg/gallon

  Density of diesel fuel = 3.21 kg/gallon

- NOx and SO_X emissions from light duty meter reading vehicles are considered negligible. All presented reductions in NO_X and SO_X are a result of service truck rolls.

2.5.7.3 Calculation Approach

Certain types of consumer events, such as check read requests, can be handled remotely by the use of the AMI system, thereby avoiding a truck roll. A list was compiled of all such consumer event order types. The number of truck rolls avoided due to AMI was then calculated based on the number of consumer events with matching order type codes.

Average mileage per truck roll and average vehicle fuel efficiency was calculated by month for each AEP Ohio service center in the Project and System areas. Project area pollutant emission avoidance was calculated using fuel efficiency and mileage avoided.

This emission avoidance was then extrapolated to the System area based on number of consumers and average truck roll distances for each non-Project area service center.

The following queries and methods were used to generate results:

- Kilograms of SO_X per service center and month that would be avoided if AMI technology were deployed throughout the AEP Ohio System area due to truck rolls avoided were calculated by multiplying the truck rolls avoided per consumer in the Northeast Service Center times the number of consumers without AMI technology per month times the average truck roll distance times either 0.165 g SO_2 emissions/gallon for gasoline engines or 0.0963 g SO_2 emissions/gallon for diesel engines, times 0.001 (g to kg conversion factor)
- Kilograms of NO_X per service center and month that would be avoided if AMI technology were deployed throughout the AEP Ohio System area due to truck rolls avoided were calculated by multiplying the truck rolls avoided per consumer in the Northeast Service Center times the number of consumers without AMI technology per month times the average truck roll distance times 0.05 g NO_X emissions/mi times 0.001 (g to kg conversion factor).
- Kilograms of particulate matter ($PM_{2.5}$) per service center and month that would be avoided if AMI technology were deployed throughout the AEP Ohio System area due to truck rolls avoided were calculated by multiplying the truck rolls avoided per consumer in the Northeast Service Center times the number of consumers without AMI technology per month times the average truck roll distance times 0.01 g $PM_{2.5}$ emissions/mi times 0.001 (g to kg conversion factor).

2.5.7.4 Organization of Results

The following section describes the amount of pollutants that could be avoided if AMI was deployed to the entire System area from the following sources:

- Service-related truck rolls avoided

  This section contains monthly graphs showing the amount of potential pollutants avoided due to truck rolls avoided.
- Elimination of meter reading routes

  This section contains the analysis of potential pollutants avoided due to the elimination of meter reading routes if AMI were extended to the entire System area.

2.5.7.5 Data Collection Results

As derived under Metric M09, System area meter reading potential mileage avoided is equal to 371,071 miles/year. Using a CARB limit value of 0.05 grams of NO_X per mile results in the potential for 18.6 kg NO_X avoided per year.

SO_X and $PM_{2.5}$ emissions from light-duty gasoline vehicles, which are typically used for meter reading routes, provided a small contribution to this impact metric.

- The average potential monthly net NO_X avoided was 3.50 kg/month, with a total of 84.0 kg.
- The average potential monthly net SO_X avoided was 0.858 kg/month, with a total of 20.6 kg.
- The average potential monthly net $PM_{2.5}$ avoided was 0.700 kg/month, with a total of 16.8kg.

Service-Related Tuck Rolls Avoided

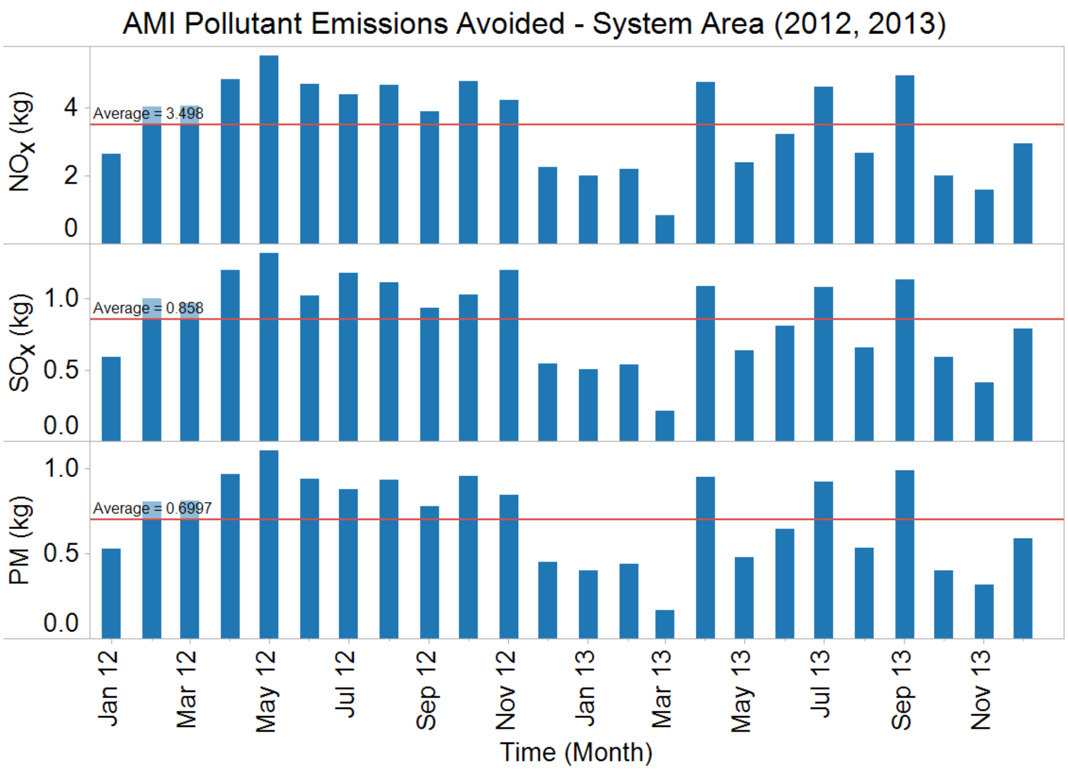

Figure 21. Potential Pollutants Avoided in System Area Due to AMI Truck Rolls Avoided

2.5.7.6 Summary

Pollutant emissions are a direct result of multiple truck roll miles avoided, and in this case are scaled to the System area. As a result, the variations and differences in pollutant emissions over time are consistent with the same in truck rolls avoided and average truck roll mileage.

2.5.8 Meter Data Completeness (M11-AMI)

2.5.8.1 Objective

AMI technology has the potential to provide near real-time meter data to the utility. This impact metric reports the percentage of successfully received meter readings through the AMI system.

2.5.8.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Any estimated readings are not counted as successful.
- Total expected readings are based on the number of active AMI consumers.

2.5.8.3 Calculation Approach

The following queries and methods are used to generate results:

- AMI readings received per meter and date were calculated by counting the number of non-estimated readings in the Input Data Category (IDC).
- AMI readings expected per meter, date, meter type, meter funding source, circuit, and substation were calculated by counting the number of intervals per day for normal and daylight savings on/off days times the number of AMI consumers.
- AMI readings missed per meter, date, meter type, meter funding source, circuit, and substation were calculated by subtracting the number of AMI readings received from the number of AMI readings expected.

2.5.8.4 Organization of Results

The following section describes the completeness of data reported through the AMI system as follows:

- Interval readings successfully reported through the AMI network

  This section contains graphs showing the number of meter readings expected vs. the number received each day.

- Accuracy of reported meter data

  This section contains AEP Ohio's results from analysis of meter data accuracy including their procedure for spot checking meters in the field.

2.5.8.5 Data Collection Results

Interval Readings Reported Through the AMI Network

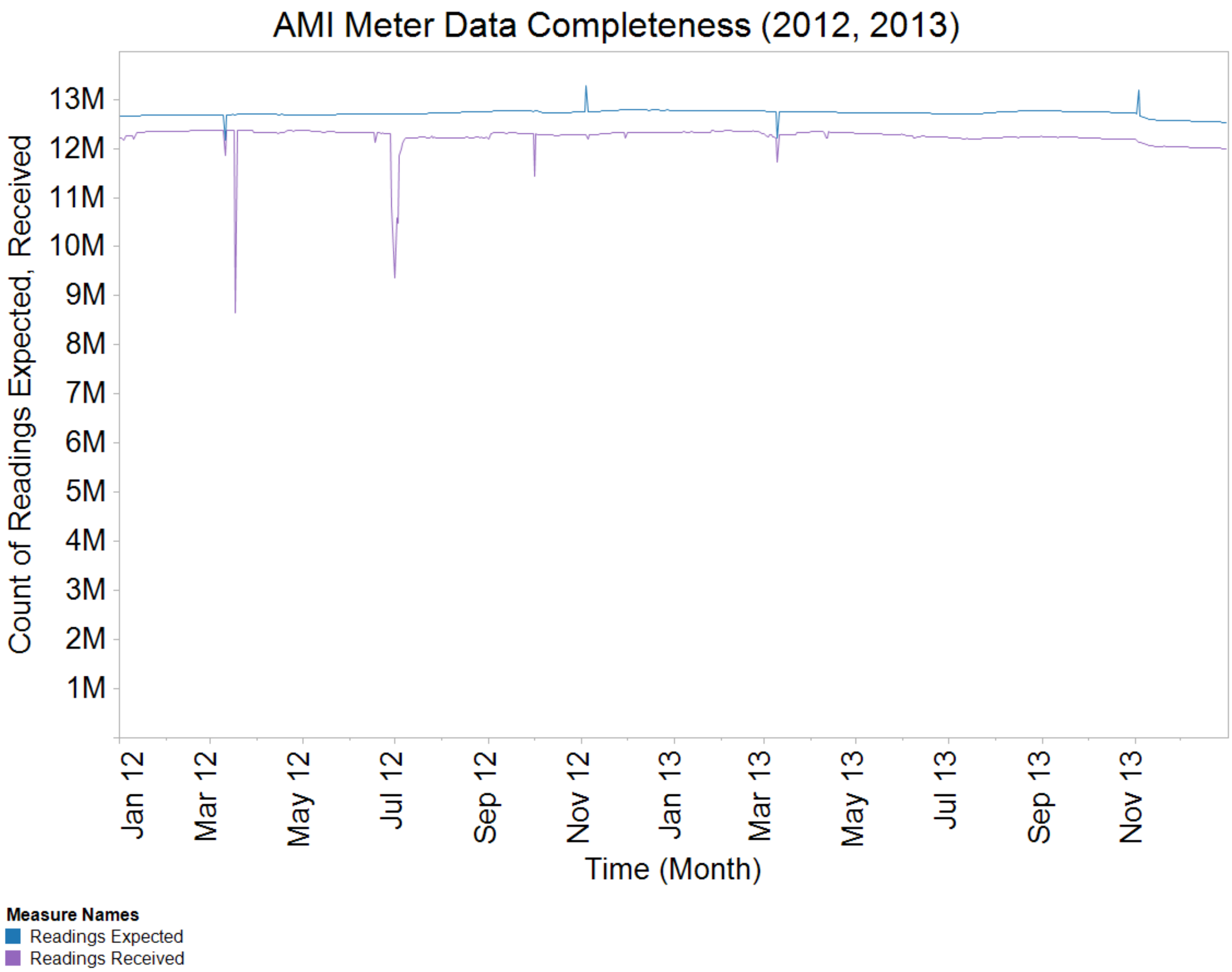

Figure 22. AMI Interval Readings Expected and Received Daily

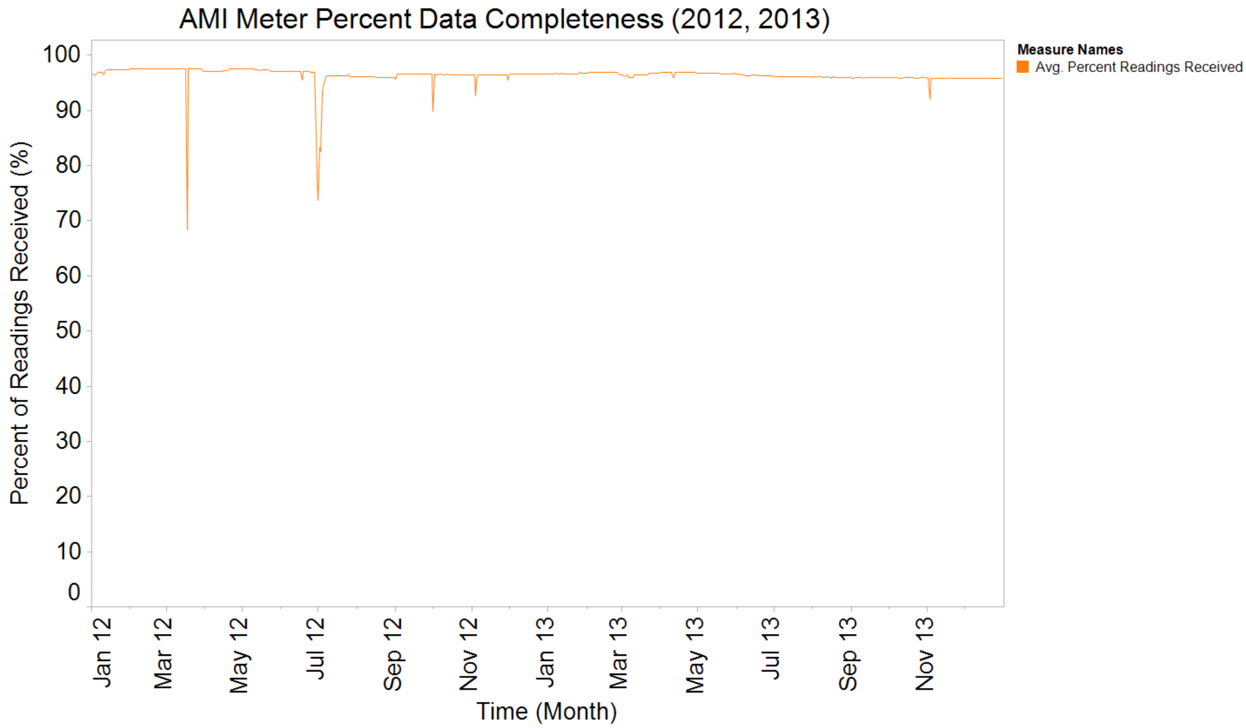

Figure 23. Percentage of Expected AMI Interval Readings Received Daily

2.5.8.6 Summary

More than 131,000 meters on 89 circuits are fully populated with AMI meters. On average, 95 percent of the expected readings have been received from these circuits. The highest average is 97.5 percent and the lowest average is 88 percent. More than 82 circuits exceeded 92.5 percent.

Meter data completeness is consistent throughout the Project period, with a few exceptions resulting from power outages, back-office system outages, or communications network outages. In such cases, the missed readings are for short durations, with the exception of prolonged recovery for some meters after the Derecho storm in late June 2012.

2.5.9 Meters Reporting Daily (M12-AMI)

AMI technology has the potential to provide near real-time meter data to the utility.

2.5.9.1 Objective

This impact metric reports the number of AMI meters that successfully receive meter data, at least once per day, through the AMI system.

2.5.9.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Estimated readings are not counted as successful.
- Total expected readings are based on the number of active AMI consumers.

2.5.9.3 Calculation Approach

This metric presents the number of AMI meters that successfully report at least one 15-minute interval reading per day.

The following queries and methods were used to generate results:
AMI readings missed per meter, date, meter type, meter funding source, circuit, and substation were calculated by subtracting the number of AMI readings received from the number of AMI readings expected.

2.5.9.4 Organization of Results

The following section describes the completeness of data reported through the AMI system. The specific aspect of data completeness analyzed under this metric is the number of meters successfully reporting at least once per day.

2.5.9.5 Data Collection Results

Results for Interval Readings Reported Through the AMI Network

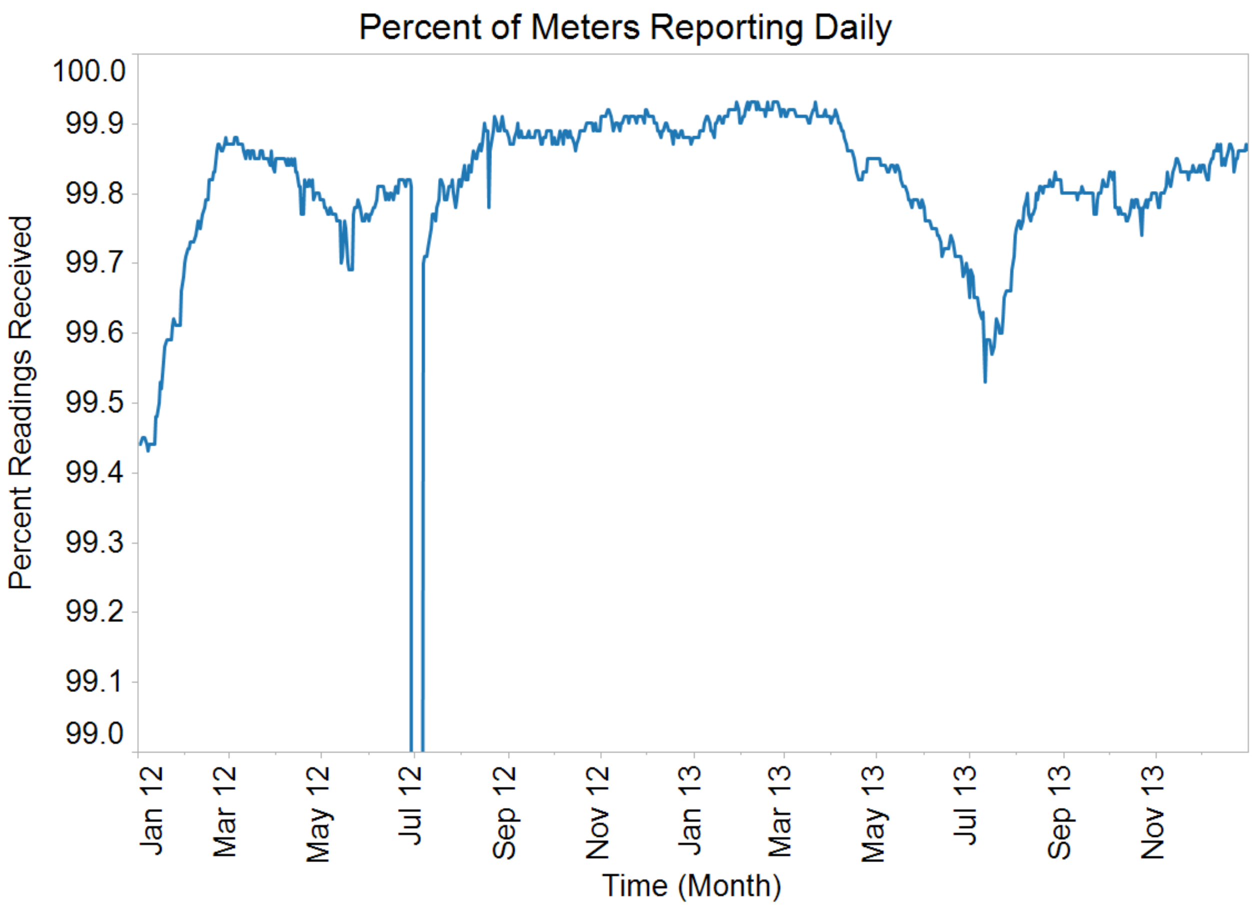

Figure 24. Percent of AMI Meters Reporting Each Day

2.5.9.6 Summary

Meters reporting daily remained relatively high and consistent over the Project time period. This metric does not include short-term communications outages or lost packets, since each meter is required to report a minimum of once per day, unlike the Meter Data Completeness (M11-AMI) metric. The exceptions were associated with major outages, including the late June 2012 through early July 2012 Derecho storm and the associated recovery.

2.5.10 Outage Response Time (M29-AMI)

2.5.10.1 Objective

The AMI system has the ability to notify AEP Ohio of consumer power outages in near real-time. This notification is expected to precede the first consumer-reported outage.

2.5.10.2 Assumptions

This section does not apply.

2.5.10.3 Calculation Approach

This section does not apply.

2.5.10.4 Organization of Results

This section does not apply.

2.5.10.5 Data Collection Results

Refer to the next section, *Outage Response Times and Last Gasp Study*.

2.5.10.6 Outage Response Times and Last Gasp Study

The AMI technology was evaluated to determine if meters automatically reporting outages were beneficial to the outage reporting and restoration process.

2.5.10.7 Evaluation of AMI Ping/Poll Functionality

A ping signal sends a query to a meter to determine if it is in service. A poll signal sends a query to a meter to determine the single phase line to line voltage (240v) on the source side of the meter. Poll capability is not yet available for multiphase meters. The ability to ping/poll meters was incorporated into AEP's PowerOn application. PowerOn is a web-based outage management application.

Studies were performed to track the daily number of dispatchers using ping/poll, and the number of results that returned within one minute. Results varied between a high of 79 percent to a low of 41 percent (technical problems existed skewing results for that month). The overall average for the period was 65 percent of ping/poll queries returning within one minute. Evaluation of the AMI ping/poll features in PowerOn yielded the following results, with associated benefits:

Everyday Use

- The poll feature was useful for consumer voltage complaints or voltage concerns on a given circuit.
- The ability to ping a single meter was useful for single-premises outages.

Storms Use

- The ability to ping multiple meters was beneficial.
- AMI meters were queried to indicate that restoration was complete, which was beneficial for consumer communication.
- Evaluation during the June 29, 2012 Derecho demonstrated that the use of AMI ping/poll can be integrated into major storm restoration efforts to reduce time and effort and maximize employee efficiency.

Evaluation of AMI Meter Outage Processing System

The AMI Meter Outage Processing System was evaluated during daylight hours into late September 2012. Dispatch engineers noticed that recloser and breaker operations created spikes in meter traffic due to simultaneous, rapid powering down and up of multiple meters. This in turn increased the network delay and various communication problems. In the PowerOn system, this led to several false orders created that escaped the filters. In distribution automation (DA) the high volumes of meter messages (primarily power up) were sometimes conflicting with Distribution Automation (DA) signals to operate equipment and report status back to the control center. These conflicts caused communication losses for the DA operation.

The solution formulated was to implement a sleep timer for meter power up messages. That is, these messages would wait a predetermined time (set at five minutes) to send their messages. The five-minute delay would allow the DA commands and status indications to pass without competing with meter messages for communication resources.

The sleep timer was added on September 21, 2012. Following implementation, additional problems were discovered in that the power up message shows the power up time as the actual time plus five minutes (the time the message is sent, not actual power up time). This problem has not yet been resolved and for this reason AMI Meter Outage Processing was disabled until a solution could be found.

2.5.10.8 Evaluation of Meter Disconnects

AEP Ohio is also working through a business process issue associated with consumer disconnects. When a consumer is disconnected, either for nonpayment or a consumer request for home repairs/maintenance, an order is created in the Order Processing System (OPS) for the meter disconnect. At that time a reconnect order is also created by the system, as the consumer will be reconnected the vast majority of the time. When two OPS orders are created for the same consumer, the OPS filter does not properly filter the AMI meter from reporting an outage to Trouble Entry Reporting System (TERS) and consequently PowerOn. This condition requires correction before AMI Meter Outage Processing is fully implemented.

2.5.10.9 Results

Some AMI meter features provided benefits for service restoration and were incorporated into the business culture in 2012. Outage Reporting remains a challenge.

- The ability to determine if a consumer's service is energized (ping) and remotely read the meter voltage (poll) provide good benefit for service restoration, particularly in storms. AMI's ping/poll functionality provides an important tool to better manage outages affecting AMI consumers, and is useful for managing the distribution system. Everyday use of ping/polls increases work crew efficiency and results in truck rolls avoided. The use of Ping/Poll during storms is helpful for verifying outage extent and provides valuable input for Outage Management System (OMS) modeling.
- AMI meter-generated outages predicted correctly according to operating company rules a majority of the time.
- Generally, AMI filters worked as designed.
- Many system integration issues were resolved.
- Test results reveal that using AMI meters to report outages has not yet proven beneficial to the business. Test periods in 2012 revealed multiple technical and business challenges that must be overcome before AMI outage reporting will prove successful.
- During major storms the use of the AMI Meter Outage Process would be a hindrance as it would increase traffic on the Outage Management System.

2.5.11 Order Type Evaluation

In addition to the required metrics for AMI, Meter Revenue Operations managers analyzed order type patterns before and after AMI meters were installed. The statistics that follow show that several order types have decreased significantly in AMI territory. Data does not represent a one-for-one correlation of an order to a specific meter.

Meter Order Types				
Order Type	**Description**	**Years**	**Totals**	**Observations**
CL01	ELEC W/O FIELD READ	2007	45,249	Field order readings are now automated using UIQ, resulting in a 75 percent reduction in CL01s.
		2008	43,927	
		2009	42,645	
		2010	27,006	
		2011	8,905	
		2012	8,755	
		2013	4,756	
		Total	181,243	
CL20	ELEC WITH REMOTE READ	2010	8,904	• The CL20 Order type was not available prior to AMI. • This order type is related to order type CL01.
		2011	29,375	
		2012	27,511	
		2013	16,285	
		Total	82, 075	
CL30	REMOTE READ AND DE-ENERGIZE	2010	2,395	• The CL30 order type was not available prior to AMI. • There were some dips in 2012 and 2013, but quantities stayed above the 2010 count of 2,395.
		2011	7,770	
		2012	6,876	
		2013	4,149	
		Total	21,190	
DN01	FLD READ & DISCONNECT	2007	6,450	This order type represents an unauthorized use of electricity and required a meter reading service call prior to AMI.
		2008	4,947	
		2009	5,194	
		2010	2,605	
		2011	521	
		2012	439	
		2013	247	
		Total	20,403	

Meter Order Types				
Order Type	**Description**	**Years**	**Totals**	**Observations**
DN10	REMOTE READ & DE-ENERGIZE	2010	1,531	• This order type was not available prior to AMI technology. • DN10s are related to DN01 order types.
		2011	3,665	
		2012	2,390	
		2013	1,556	
		Total	9,142	
IO11	EXCESS USE INACT ACCT	2007	714	AEP Ohio back-office personnel were able to identify consumers who are using electricity on inactive accounts. This resulted in truck rolls avoided and loss reduction.
		2008	567	
		2009	360	
		2010	281	
		2011	100	
		2012	41	
		2013	12	
		Total	2,075	
IO12	ENERGY RECOVERY	2007	477	This order type represents recovery from meter tampering. With AMI, tampering was discovered in near real-time, which resulted in a decrease in tampering.
		2008	620	
		2009	598	
		2010	647	
		2011	241	
		2012	307	
		2013	324	
		Total	3,214	
IO40	CHECK READ/RE-READING	2007	6,697	Prior to AMI, this order type required a truck roll in most cases.
		2008	7,237	
		2009	5,948	
		2010	3,387	
		2011	3,235	
		2012	1,631	
		2013	832	
		Total	28,967	

Meter Order Types				
Order Type	**Description**	**Years**	**Totals**	**Observations**
IO41	READ & SOLVE ACCESS	2007	474	Prior to AMI, this order type required a truck roll. Access issues and physical limitations were significantly reduced with AMI remote meter reading.
		2008	441	
		2009	754	
		2010	440	
		2011	41	
		2012	36	
		2013	55	
		Total	2,241	
OP20	ELEC WITH REMOTE READ	2010	689	This order type is associated with consumers moving into new premises. An OP20 was performed remotely with AMI, which resulted in truck rolls avoided.
		2011	2,584	
		2012	2,559	
		2013	1,674	
		Total	7,506	
OP30	REMOTE READ & ENERGIZE	2010	3,284	This order type is associated with a consumer move and service reconnection. An OP30 was performed remotely with AMI, which resulted in truck rolls avoided.
		2011	11,876	
		2012	11,368	
		2013	6,671	
		Total	33,199	
OP97	ELEC CONNECT AT SERVICE	2007	217	Prior to AMI, technicians had to travel to the service location and cut a pole to complete this operation. With AMI,
		2008	244	
		2009	241	
		2010	161	

Meter Order Types				
Order Type	**Description**	**Years**	**Totals**	**Observations**
		2011	54	OP97 orders were performed remotely.
		2012	59	
		2013	27	
		Total	1,003	
RN01	FIELD READ AND CONNECT	2007	6,678	These orders have been reduced as a result of AMI technology. Prior to AMI, technicians had to travel to a site to read and connect a meter.
		2008	6,721	
		2009	7,062	
		2010	3,485	
		2011	1,365	
		2012	1,370	
		2013	827	
		Total	27,508	
RN10	REMOTE READ & ENERGIZE	2010	1,894	This order type is related to RN01. As RN01 orders are reduced, RN10 orders increased as a result of AMI remote read and energize (connect) capabilities. **Note:** Energize is a synonym for connect.
		2011	14,501	
		2012	14,296	
		2013	10,228	
		Total	40,919	
Data for 2013 represents January through July				

Table 12. AMI Order Type Evaluation

2.6 AMI Conclusions

AEP Ohio was able to eliminate 100 percent of the meter reading routes (187 routes) in the area where AMI was deployed. AMI also enabled AEP Ohio to reduce costs associated with meter operations activities. For example, through the use of remote service switch capabilities that enable secure connection and disconnection of electric service to consumer premises from the utility back office, AEP Ohio was able to reduce field visits associated with standard move in/move out orders.

AEP Ohio was able to leverage this technology to reduce truck rolls required to perform disconnections for DNP and subsequent reconnections.

The AMI deployment nearly eliminated the need for AEP Ohio to estimate monthly consumer electricity usage, resulting in a higher read rate in the Project area. The reduction of estimated bills led to greater billing accuracy and improved consumer satisfaction. When a consumer requested service termination, the AMI meter was read remotely and a final bill was sent without delays caused by manual reads. AMI meters equipped with a remote service switch enabled power to be turned on or off remotely. As a result, consumers could have service turned on in minutes, rather than waiting days.

From a reliability perspective, meters were queried to get an indication of whether a consumer had power. This indication was useful to troubleshoot consumer issues. In addition, there were some environmental benefits associated with reduced vehicle emissions as a result of reduced vehicle miles traveled.

Overall, the Project showed that implementing AMI technology provided significant cost, reliability, and environmental benefits for the utility and its consumers. Consumers in the System area were satisfied with the AMI technology and installation process. Less than 0.01 percent of consumers in the Project area requested to opt out of the technology, or experienced RF interference.

2.6.1 AMI Meter Outage Processing System

The AMI Meter Outage Processing System was evaluated during daylight hours into late September 2012. Dispatch engineers noticed that recloser and breaker operations created spikes in meter traffic due to simultaneous, rapid powering down and up of multiple meters. This increased the network delay and contributed to various communication problems. In the PowerOn system, this led to several false orders created that escaped the filters, which required modifications to the existing filters.

In Distribution Automation (DA) the high volumes of meter messages (primarily power up) were sometimes conflicting with DA signals to operate equipment and report status back to the control center. These conflicts caused communication losses for the DA operation. This issue has not been resolved. For this reason, AMI Meter Outage Processing System was disabled.

2.6.2 Meter Disconnects

AEP Ohio is also working through a business process issue associated with consumer disconnects. When a consumer is disconnected, either for nonpayment or a consumer request for home repairs/maintenance, an OPS order is created for the meter disconnect. At that time a reconnect order is also created by the system, as the consumer will be reconnected the vast majority of the time. When two OPS orders are created for the same consumer, the OPS filter, a subset of the Meter Outage Process filters, does not properly filter the AMI meter from reporting an outage to TERS and consequently PowerOn. This condition requires correction before AMI Meter Outage Processing is fully implemented.

2.7 Lessons Learned

This section describes lessons learned for AMI technology. Lessons learned are provided for Technology, Implementation, and Operations.

2.7.1 Technology

- Ensure network is designed and operational before meters are installed. Network optimization is essential as soon as all meter installations are completed.
- Recognize the importance of having temperature sensors on the meters' microprocessors. AEP developed a process to ensure that sensor data is monitored and actionable.
- Improve meter tracking process, including scrap meters for auditing purposes.
- Develop good test cases and ensure due diligence up front. Test cases apply to meters and systems, network software, and communication card (firmware).
- Monitor access points, relays, and components for performance and downtime.
- Perform a gap analysis on reporting tools and systems to identify what is needed for optimum performance. Develop or purchase new tools where in-house technology does not exist.
- Identify the best way to obtain and manage large quantities of AMI data for analytics and reporting, which requires expertise, tools, and planning.
- Use the beneficial AMI ping/poll functionality. AEP is working with multiple vendors to enhance this functionality.

2.7.2 Implementation

- Develop a strong project communication plan. It is a critical component to project success. All project team members, consumers, and stakeholders must be included.
- Install network equipment including access points and relays prior to meter installation
- Develop meter installation schedule considering meter blackout dates.
- Provide detailed instructions to the installation contractors. Quality control and oversight are important. This is critical for equipment installation and commissioning. For example, there were meter socket issues, but they were corrected midway through the implementation by having the installation contractor provide additional photos of meter sockets before and after installation. This is now an industry standard.
- Develop and improve stringent processes to gauge and mitigate interdependencies when new technologies are implemented.
- Perform a cost benefit analysis to determine best implementation model. Vendor-managed and vendor-hosted technology implementation is the most cost effective strategy for AEP Ohio.
- Collaborate with vendors to enhance products and implementation.

- Provide necessary training and tools for expanded roles and responsibilities.
- Perform a root cause analysis as technological issues arise to gain understanding and make improvements.

2.7.3 Operations

- Consider changes in management needs when deploying the AMI Meter Outage Processing in dispatching centers. The following are some of the changes to consider:
  - Business processes within the Distribution Dispatch Center (DDC) need to be established for handling single meter AMI outages with no associated consumer calls before dispatching a service vehicle.
  - Unless benefit can be realized for using AMI Meter Outage Processing in major storms, processes must be in place to disable the functionality before the storm enters the service territory.
- Clarify and document roles and responsibilities in the project plan.
- Collaborate with vendor representatives. Emerging technology requires frequent management consultation to ensure the accuracy and depth of their product knowledge.
- Know the consumer. Keep messages simple, concise, and benefit-driven.
- Provide an education process for internal and contract resources to enable them to act as ambassadors of the technology that strengthens consumer acceptance.
- Integrate AMI ping/poll functionality into major storm restoration efforts to reduce time and effort and maximize employee efficiency.
- Implement a sleep timer for meter power up messages to reduce communication losses for distribution automation operations. These messages will transmit at a predetermined time (set at five minutes). The five-minute delay would allow the DA commands and status indications to pass without competing with meter messages for communication resources.

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3 DEMONSTRATED TECHNOLOGY – CONSUMER PROGRAMS

3.1 Purpose

The AEP Ohio gridSMART® Demonstration Project included the deployment of digital Advanced Metering Infrastructure (AMI) electric meters to the approximately 110,000 premises in the Project area to replace their existing analog electric meters. AMI meters feature 2-way communications between the consumer and the utility, the ability to measure and record usage in sub-hourly increments, and the ability to integrate supportive technologies such as programmable communicating thermostats, load control devices, and in-home displays into home area networks.

The analog meters produce usage data only on a billing cycle basis with no accessible time of usage information, hence residential rates are primarily based on average cost of service. AEP Ohio’s standard tariff is a flat seasonal tariff with a declining block distribution rate in winter months and represents the average cost of electricity for generation and distribution.

The actual cost of service is variable based primarily on the generation mix required to meet demand. Residential energy usage varies by season, day of week, and time of day, with AEP Ohio residential load normally reaching maximum values during late afternoon periods on the hottest summer days. The incremental cost of supplying this peak load is much greater than the cost of serving normal load as high variable cost generation needs to be kept available and run to serve these high load hours.

With the deployment of AMI meters, tariffs were designed to more accurately reflect the underlying variability of the cost of service. Such variable price tariffs ranged from time-of-day rates, where the cost of electricity was lower during off-peak periods and higher during times of peak use, to real-time pricing programs, where rates most nearly aligned with actual wholesale market prices reflected in the locational marginal prices (LMP) of electricity.

AEP Ohio’s deployment of AMI electric meters set the stage for a program to test several consumer programs that could impact utility generation and performance as well as consumer behavior. Using time-of-day tariffs and direct load control (DLC) riders, consumer programs were developed and implemented as an experimental part of the Project.

The introduction of these new consumer programs provided participating consumers with the opportunity for cost savings because of the technology’s two-way communication functionality. Consumers were able to make choices based on the way electric rates varied throughout the course of a day. Depending on the program they were enrolled in, they had differing ways of interacting with the technology to make their choices. These consumer programs included time-of-use prices, critical peak price events, DLC events, and real-time pricing. Several experimental time-of-day tariffs and DLC riders were tested in order to determine at what level these tariffs and riders, either directly or indirectly, might reduce a consumer’s electricity usage and reduce load for the utility.

Participants had the opportunity to more closely monitor their electric use and have greater control over their monthly electric costs by shifting usage from higher price periods to lower price periods or by reducing the demand on the electrical system during peak periods. From a utility perspective, a major goal of these consumer programs was to lower costs and peak demand during peak periods of high generation cost by altering the hourly loads for various residential consumer classes without negatively impacting customer satisfaction.

Because the rate structures and technologies being introduced were new to most of AEP Ohio's consumers, it was important that AEP Ohio provided consumer education and awareness programs to encourage participation in the programs.

3.2 Consumer Programs and Enabling Technologies

Consumer programs required program creation that integrated the supporting technologies including AMI, in-home devices, and enabling networking and software. Several programs emerged from that development effort that were installed and activated for consumer enrollment and participation. Upon consumer subscription, AEP Ohio equipped residences in the Project area with auxiliary devices designed to provide usage, pricing, and event information, as well as the technical capabilities to respond to that information. These devices were essential to the implementation of consumer programs.

Tariffs were approved for the various programs and branded for marketing purposes. The table below provides a brief comparison of the programs:

Market Name	Program Description
eVIEW	Consumer usage feedback device
SMART Shift	Two-tier time-of-day
SMART Shift Plus	Three-tier time-of-day with critical peak pricing events
SMART Cooling	Direct load control, thermostat only
SMART Cooling Plus	Direct load control with load control switch
SMART Choice	Real-time pricing with double auction
Standard Residential	Flat tariff with declining block rate, average cost

Table 13. Consumer Programs Descriptions

3.2.1 eView℠

The eView program consisted of providing consumers with an in-home device that interacted with the smart meter to provide the consumer with current electrical usage and pricing information, enabling them to make decisions about their energy consumption. The device communicated with the smart meter through wireless technology. Consumers could see the average price of electricity and how much they were using and were encouraged to experiment by turning various household appliances on and off to see the difference in usage and costs. The device held usage and average cost data in memory for 30 days, which helped consumers who wanted to make comparisons and estimate upcoming bills.

Later in the Project, eView devices were offered to consumers who signed up for the other consumer programs.

3.2.2 SMART Shift℠

The SMART Shift program was a two-tiered pricing option for the consumer that did not require any additional equipment. Participants were provided with information to actively monitor and choose whether they would shift their electric usage to an off-peak time by being charged a lower rate for electricity consumed before 1 p.m. and after 7 p.m. weekdays and on weekends during the summer months (June to September). Electricity usage between 1 p.m. and 7 p.m. was charged at the higher rate, which could influence consumer behavior and impact utility peak electricity consumption curve. The program was designed to enable consumers to lower their bills by shifting usage from the higher priced time periods to the lower priced time periods.

3.2.3 SMART Shift Plus[SM]

The SMART Shift Plus program was a three-tiered pricing option that offered the consumer incentives to modify their electric usage patterns during peak load times on weekdays of the summer months (June to September). An in-home display (IHD) and optional Programmable Communicating Thermostat (PCT) were installed in the consumer's home to accommodate participation in the program. The PCT gathered and displayed information about how much electricity was being consumed and how much it cost. The IHD displayed the current electricity use and rate and notified consumers when a critical price period was occurring. Consumers were then able to choose how and when to conserve electricity, or shift usage from one period to another, that would result in savings on their bills.

The tariff for this program permitted AEP Ohio to declare up to 15 critical peak pricing (CPP) events when AEP Ohio was experiencing unusually high demand. CPP events were not to exceed 5 hours per day during the calendar year. Energy consumed during these events was charged at a substantially higher rate, thus encouraging consumers to reduce their demand for power at times it cost AEP Ohio the most to produce.

Pricing for non-CPP times had three tiers with only a few cents difference between those tiers. All pricing tiers are depicted in the table below.

Rate Level	Hours
Low	Midnight – 7 a.m. 9 p.m. – midnight And Weekends
Medium	7 a.m. – 1 p.m. 7 p.m. – 9 p.m.
High	1 p.m. – 7 p.m.
CPP	As called – up to 5 hours each event and up to 15 events per year

Table 14. SMART Shift Plus Pricing Tiers

3.2.3.1 Smart Appliances

As part of the SMART Shift Plus program, the deployment of 33 Smart Appliances was included in the experiment. The General Electric (GE) smart appliances that were installed in 20 homes were:

- Washer
- Dryer
- Range
- Refrigerator
- Electric water heater

The appliances were equipped with circuitry that communicated with the SMART Shift Plus power display device and allowed the consumer to see in real time how much electricity was being used. When the SMART Shift Plus device detected a higher price for power, the appliances responded accordingly. During a price increase or a defined critical peak period when usage costs were higher, the appliances were programmed to respond as follows.

If…	Then…
The appliance was not running when a SMART Shift Plus unit signaled increased prices or a critical peak time began…	The appliance didn't run at all unless the consumer chose to override the programming using the appliance controls.
The appliance was already running when a SMART Shift Plus unit signaled increased prices or a critical peak time began…	The appliance went into energy-saver mode which curbed energy usage by slowing appliance power and lengthening the duration of the appliance cycles. If desired, the consumer was able to override this programming by using the appliance controls.

3.2.4 SMART Cooling[SM]

SMART Cooling was a direct load control (DLC) program, which enabled the utility to control electricity demand at the consumer's premises by remotely adjusting the PCT that was installed upon enrollment in the program. At times of peak energy demand from May through September between the hours of noon and 8 p.m., AEP Ohio was permitted to declare up to 15 non-emergency events. An additional 10 PJM Interconnection LLC (PJM) emergency events also could be declared during these months.

During these events, AEP Ohio remotely adjusted participating consumer PCTs up to four degrees higher than the consumer's programmed setting for a time period of up to five hours. Consumers could then elect to accept the increased setting and receive a bill credit, or they could override the setting and forfeit the credit.

3.2.5 SMART Cooling Plus^{SM}

This program was an add-on to the SMART Cooling program by installing a load control switch (LCS) in addition to the IHD and PCT devices. The LCS was installed on electric water heaters, pool pumps, or hot tubs as additional power demand that could be managed remotely. These consumers were offered an incentive to reduce demand by allowing the utility to interrupt the devices during DLC events. Consumers with water heaters and hot tubs could experience 15 additional events during the months of October through April. Consumers had the ability to opt out during DLC events.

3.2.6 SMART Choice^{SM} (Real-Time Pricing with Double Auction)

This program provided consumers the opportunity to participate in real-time pricing based on supply and demand for their particular power circuit. Pricing occurred every five minutes for each circuit included in the program. Consumers participated by using the home energy manager (HEM) and the enhanced programmable communicating thermostat (ePCT). For detailed information about this consumer program, see the *Demonstrated Technology – Real-Time Pricing with Double Auction* chapter of this document.

3.3 Approach and Implementation

Prior to development of the consumer programs, AEP Ohio determined that market research was required to understand which program features would appeal to consumers in the Project area. Consumer education requirements were also identified. Consumer demographic information was obtained and focus groups were conducted as the programs and technologies were developed. This approach provided a more effective rollout of the consumer programs, provided consumers with a better understanding of the various enabling technologies, and provided AEP-Ohio with information about which programs appealed to different types of consumers.

3.3.1 Market Research and Consumer Segmentation

One objective of the market research was to match consumer demographics with programs that would appeal to them and enable AEP Ohio to identify target markets for future programs and implement cost effective marketing strategies. The approach taken was to divide the Project area residential consumers into different marketing strata. Each stratum was created to be a proportional demographic representation of the Project area, containing all categories of residential consumers. A control group was also assigned as a baseline against which to measure the effectiveness of the various consumer programs. The control group consumers were not solicited for program participation so they received no marketing or educational materials. The resulting stratification model is illustrated in the following figure.

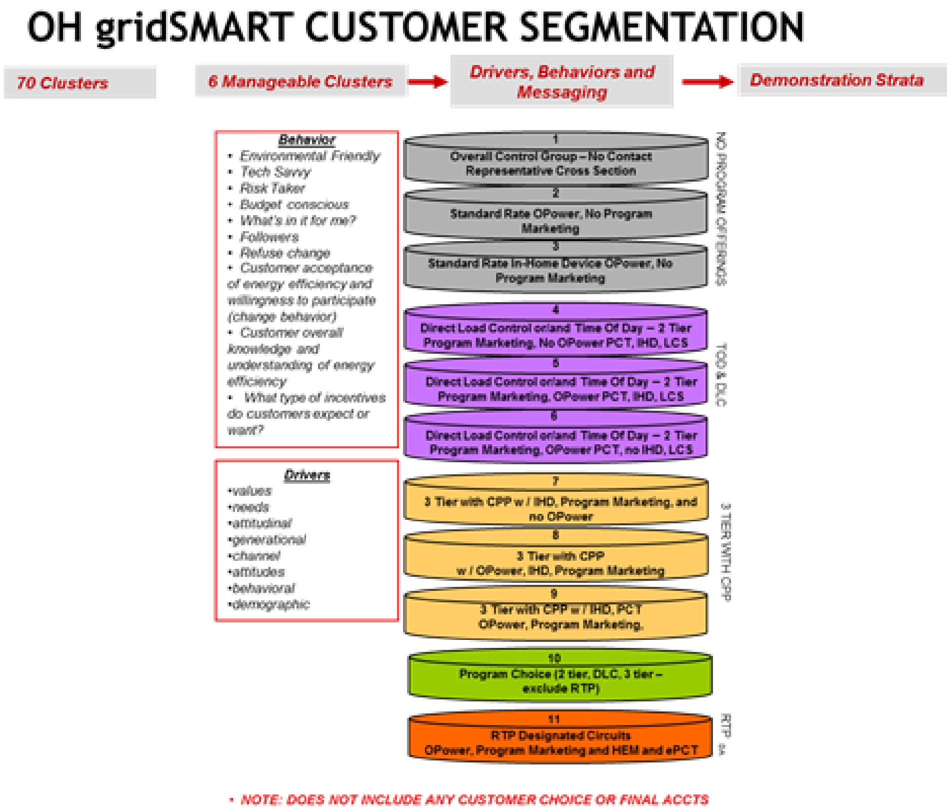


Figure 25. Consumer Segmentation

The residential consumers were divided into six different demographic groups for purposes of marketing and analysis. Following are the groups and their definitions:

Group Name / Number	Description
Optimizers (11 clusters)	Comprised of affluent, middle-aged homeowners, mix of married/single, mostly without children. This group represents approximately 17.3 percent of AEP Ohio's consumer base and 18.3 percent of budget billing consumers. Approximately 18.5 percent were high or extremely high users of electricity. This group was generally interested in energy efficiency programs, though none of the clusters were identified as being environmentally conscious.
Budget Stretchers (9 clusters)	This group consisted of low and middle income, mostly young renters, and single and without children. They represented approximately 12.7 percent of the consumer base and roughly 3.2 percent of budget billing consumers. This group was interested in energy efficiency programs with two of the nine clusters being identified as environmentally conscious.
Big Bills (8 clusters)	This group consisted of wealthy, middle-aged homeowners, married with some having children. Approximately 13.3 percent of the consumer base and around 19.1 percent of budget billing consumers are in this group. High or extremely high users of electricity represented 31.2 percent of the group. Many were interested in reducing their bills, but were busy with families, careers, etc., which limited the time they were willing to commit to reduced usage efforts. One of the eight clusters was identified as being environmentally conscious.
Remaining Budget Billed (16 clusters)	This group consisted of households with a mix of incomes, late middle-aged and senior, both married and single, and with or without children. They represented 21 percent of the consumer base and 38 percent of budget billing consumers. High or extremely high users of electricity represented 11.8 percent of the group. Since many were on fixed incomes, they were interested in ways to reduce their usage and save money. Two of the 16 clusters were identified as being environmentally conscious.
Remaining with Children (9 clusters)	This group consisted of mostly low to middle income families with children. They were both young and middle-aged and most owned their homes. They represented 17.5 percent of the consumer base and 10.7 percent of budget billing consumers. High to extremely high users of electricity represented 13.5 percent of this group. These households were generally busy with family and were not concerned with energy efficiency. None of the clusters were identified as environmentally conscious.
Remaining without Children (17 clusters)	This group was very diverse in their incomes, ages and home ownership status. It also contained both married and single homes without children. They represented 18.2 percent of the consumer base and 10.7 percent of budget billing consumers. Nine percent were high or extremely high users of electricity. These households were not generally concerned with energy efficiency. Two of the 17 clusters were identified as being environmentally conscious.

Table 15. Demographic Groups Identified for Marketing Purposes

3.3.2 Marketing Strategy

Residential consumers received smart meters as part of the Project, which was the enabling technology for development of the consumer programs. One of the main objectives that AEP Ohio established as part of the experimental design was to actively attract, educate, enlist, and retain consumers in consumer programs that provide tools and information to reduce cost, consumption, and peak demand. The primary marketing objective was to educate the consumer on the technology, the benefits to the consumer, and assist them in saving energy costs and being environmentally responsible. A complete marketing communications plan was necessary to provide that education, create awareness, and drive consumer program participation.

Using extensive market research and the resulting consumer segmentation, AEP Ohio was able to intelligently target specific demographics for each consumer program being implemented in the Project area. That market intelligence also helped ascertain the marketing channels and tactics that were used. For example, it was not feasible to use mass media – television, radio, and print – because those channels would advertise to people who were not part of the demonstration area or demographic. Thus, list management was used to direct specific marketing messages to the various consumer strata throughout the marketing effort.

Several different marketing channels were employed so that all eligible consumers were aware of their options:

- Web
- Direct mail
- Telemarketing
- Email
- Door-to-door
- Community events
- gridSMART Mobile

AEP Ohio experimented with different types of outreach to discover the best method or combination of methods to communicate with its consumers based on both the nature of the Project as well as the competition for electric service in the Project area. AEP Ohio focused on direct mail and was motivated to test different marketing channels

3.3.3 Consumer Outreach and Education

A key component to obtaining consumer interest and enrollments was to educate consumers about the programs and the potential opportunities for those consumers. AEP Ohio adopted a multi-channel approach to consumer education. Initial mailings were sent to each consumer informing them about the upcoming Project. Follow-up mailings with mostly educational information about smart meters were sent periodically for several months thereafter to entice and build interest for the upcoming technologies. AEP Ohio used a multi-channel approach to consumer outreach and education that included the gridSMART Website, gridSMART mobile, and a school teaching program within the Project area.

3.3.3.1 gridSMART Website

AEP Ohio expanded the Website content of www.aepohio.com to include information about gridSMART and consumer programs. The Website provided details about the Project as well as links to the different consumer programs available. The programs became open for online enrollment as they were rolled out to the Project area.

Figure 26. AEP Ohio gridSMART Demonstration Project Website

3.3.3.2 gridSMART Mobile

In addition to the Website and ongoing direct mail campaigns, AEP Ohio created the gridSMART Mobile unit as shown below.

Figure 27. gridSMART Mobile

This custom-built recreational vehicle (RV) contained six interactive exhibits designed to educate consumers about different aspects of the Project. Upon entering the vehicle, consumers were able to view a brief computer-driven, multi-media presentation. This presentation consisted of a video explaining the basics of the Project accompanied by a unique sound and light presentation that included a realistic display of thunder and lightning.

Following the presentation, participants received an introduction to smart meters, which was the impetus for consumer programs. This display provided a side-by-side comparison of the smart meter and the traditional meter and explained the benefits of using smart meters.

Other exhibits in the mobile unit included a unique seven-foot-long sliding computer monitor that allowed visitors to explore all components of AEP Ohio's holistic smart grid approach, including a variety of new technologies meant to help identify power outages, restore service faster, and make the distribution network more efficient. Visitors also could test their knowledge by competing in an interactive gridSMART trivia game.

When the Project's focus turned to enrolling consumers in the programs, the mobile unit was modified to be more of an enrollment site with more space designated for consumers to sign up for the programs in person.

3.3.3.3 Other Education

AEP Ohio worked with the Ohio Energy Project to develop and implement the gridSMART Education Program with 40 teachers and their students and families in 25 schools located throughout the Project area. Energy curriculum emphasized the new technologies and programs while correlating them to Ohio's Science Content Standards. This partnership supported learning objectives to help students with standardized assessments, and it raised awareness about the gridSMART technologies for potential participants within the Project area.

3.3.4 Enrollments

AEP Ohio chose to pilot the consumer programs first with selected employees that resided within the demonstration area. This type of live testing helped work out some of the potential issues that might have otherwise impacted consumer satisfaction. Once that testing was complete, the rollout of the programs to consumers began.

Upon completion of equipment testing and successful trials at AEP Ohio and in AEP employee homes in the Project area, programs were offered to consumers designated for program offerings under the stratification method described above in the Market Research and Consumer Segmentation subsection.

AEP Ohio used several methods to communicate to its consumers regarding enrollment in Consumer Programs. In considering the cost of using various methods and programs, AEP Ohio considered the following factors:

- Cost per enrollee
- Number of expected enrollees
- Return on investment

While implementing the Project, the utility market in Ohio moved from a regulated utility market to a competitive retail market. As of March 1, 2012, there were 14 competitive retail electric service (CRES) providers actively serving consumers in AEP Ohio's service territory, which meant they were potentially within the Project area as well. This shift to a competitive market had an impact on enrollments for consumer programs because consumers who enrolled with a CRES provider could no longer participate in the gridSMART Consumer Programs.

3.3.4.1 Consumer Acceptance

When consumers contacted AEP Ohio directly regarding potential program enrollment, each consumer was asked how they found out about the program and the primary motivation for pursuing program enrollment. Most consumers learned about the program from the program mailers, and most participated primarily to save money. The following illustrations provide the responses to those questions.

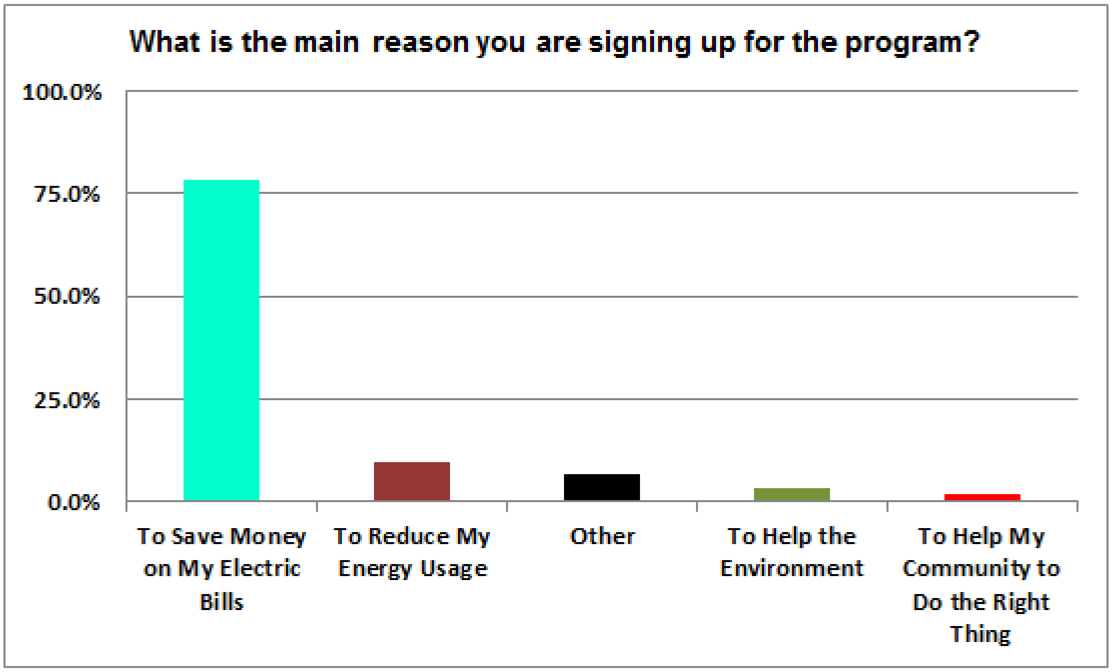


Figure 28. Consumer Enrollment Survey Results

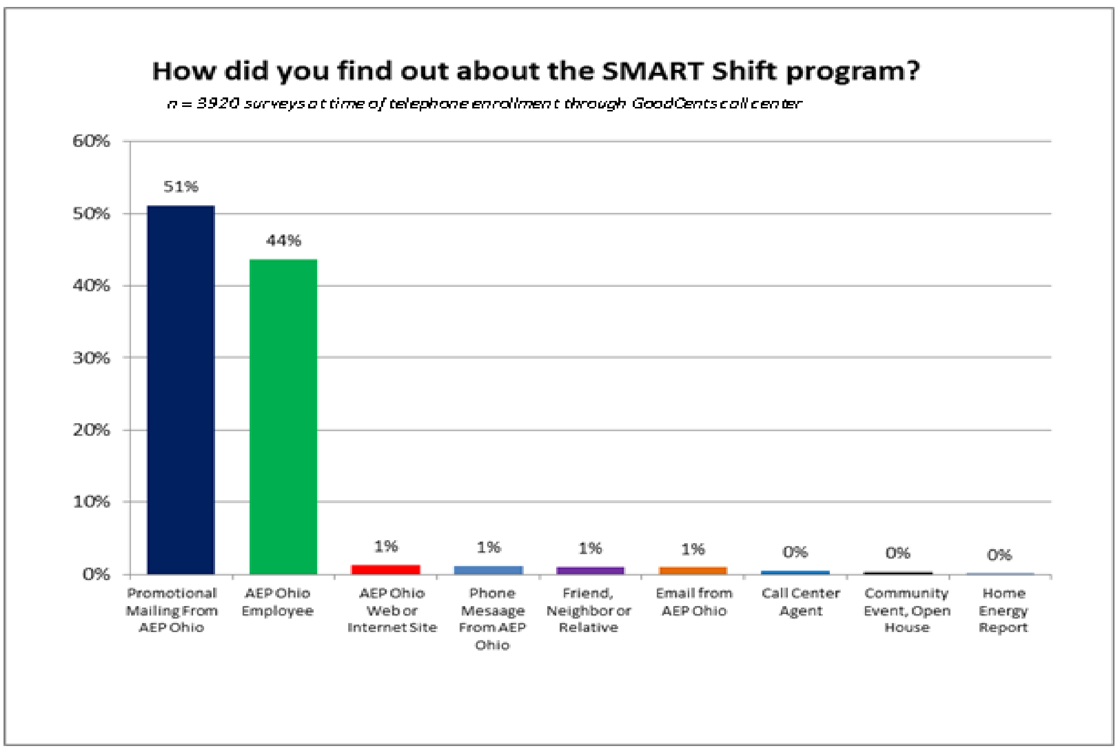


Figure 29. Consumer Awareness Survey Results

3.3.4.2 Customer Satisfaction

AEP Ohio conducted consumer satisfaction surveys throughout the course of the Project to better understand the consumers who were participating in the various programs. The survey results shown below indicated that the majority of participants wanted to reduce their electricity usage and realize the benefits of that reduction with lower monthly electric bills. When surveyed at the conclusion of the programs, the survey results showed that most participants perceived an impact on their monthly electric bills. Overall, these results are an indication that people like having the tools to reduce usage and costs and are likely to accept and participate in future consumer programs offered in the electric utility industry.

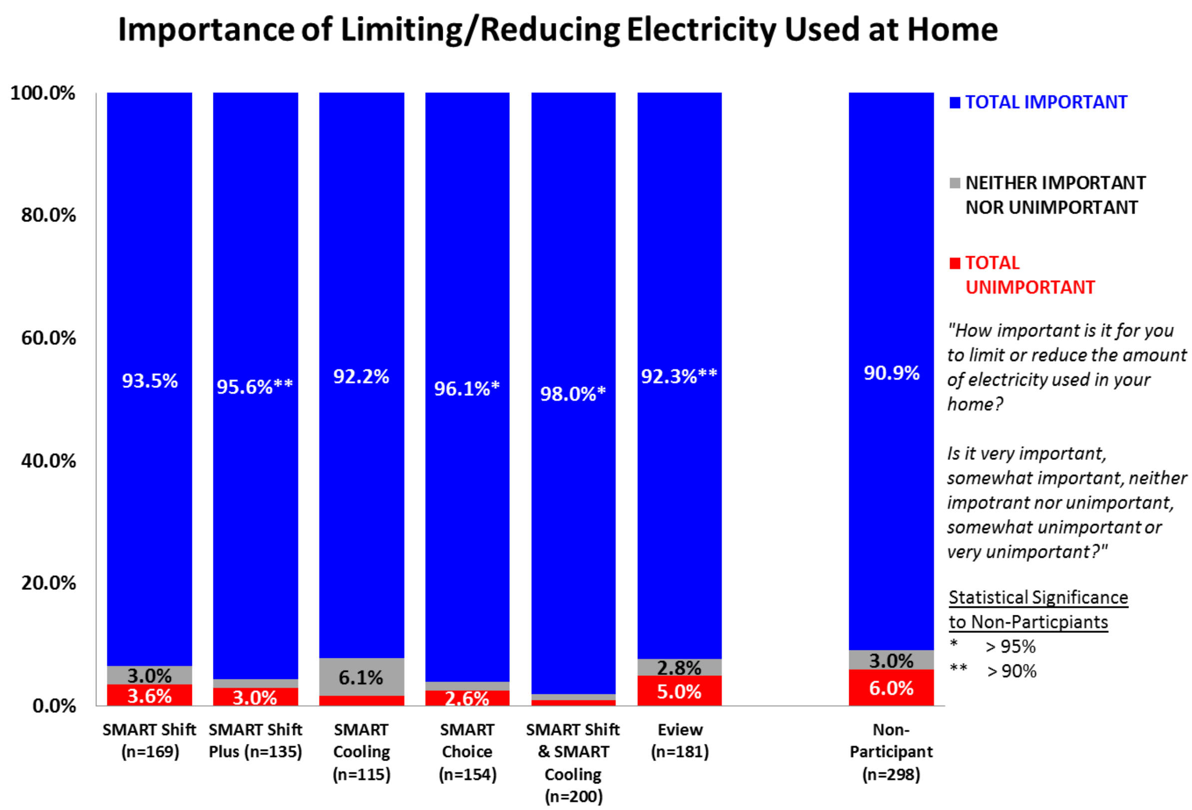


Figure 30. Survey Results - Importance of Limiting/Reducing Electricity Used at Home

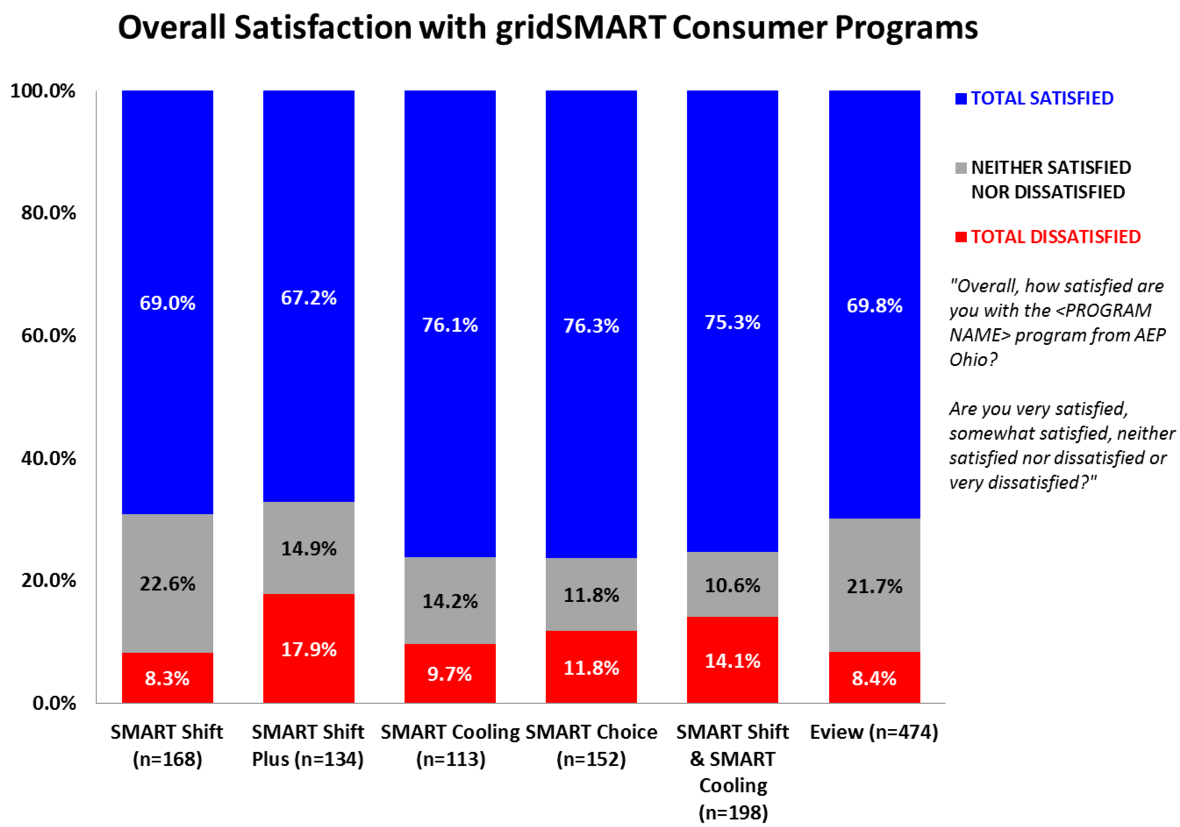


Figure 31. Survey Results - Overall Satisfaction with gridSMART Consumer Programs

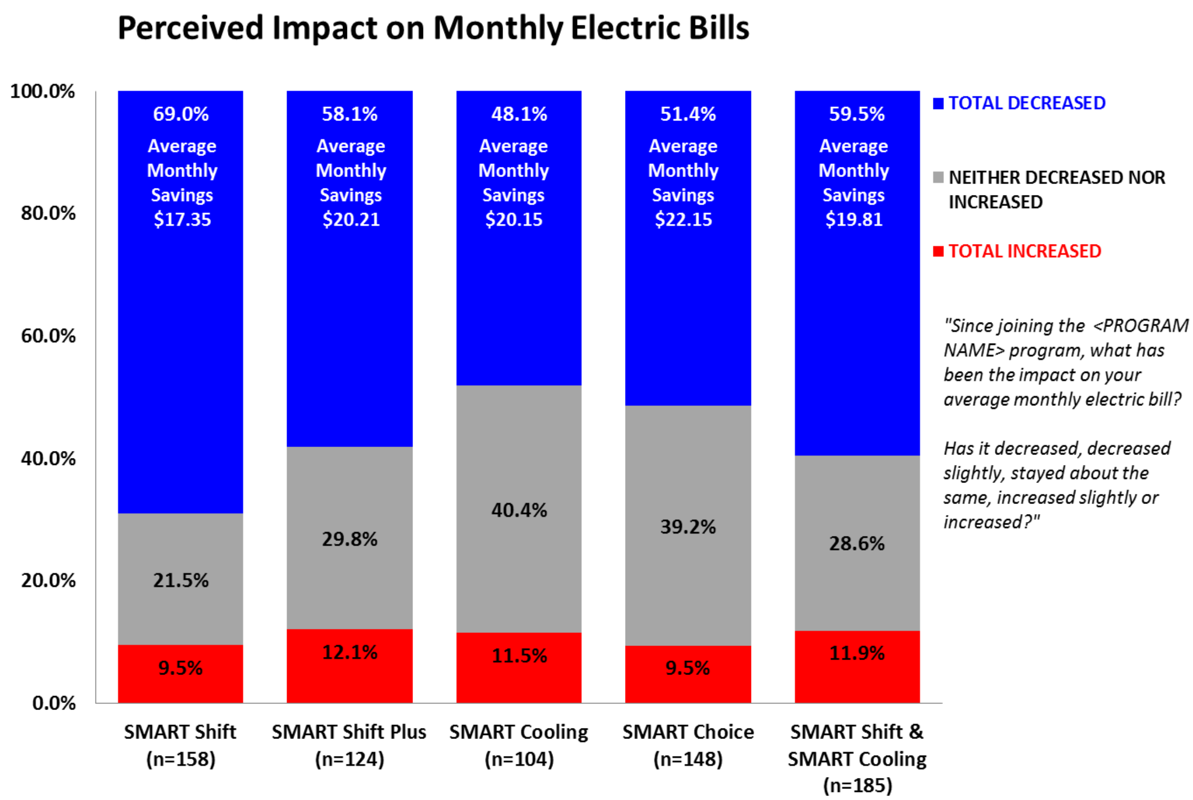


Figure 32. Survey Results - Perceived Impact on Monthly Electric Bills

3.4 Analysis

The primary objectives of the Consumer Programs technologies in this demonstration project were:

- To demonstrate consumer use of demand response programs to reduce energy consumption, peak demand, and fossil fuel emissions.
- To actively attract, educate, enlist, and retain consumers in innovative business models that provide tools and information to reduce cost, consumption, and peak demand.

To understand whether the demonstration project achieved those objectives, analysis was conducted using a control group against the consumer segments defined at the beginning of the Project. It is important to understand exactly what was measured and why. The following metrics provide an analysis and some comparison of the consumer programs experiment.

3.5 Impact Metrics Required for Consumer Programs

Consumer Programs and supporting devices had the potential to influence consumer usage patterns by enabling consumer control. Utilities could provide incentives for consumers to modify their usage and behavior to reduce peak loading and enable load shifting. Consumers in various account classes, demographic groups, and strata were expected to modify their behaviors and consumption patterns as a result of participating in any of the consumer programs offered.

The following impact metrics are associated with the consumer programs technology set. Five are related to the Project area, and two are related to the Systems area.

Metric ID	Metric Scope	Metric Description	Consumer Programs
M01	Project	Hourly Consumer Electricity Usage	M01-CP
M02	Project	Monthly Consumer Electricity Usage	M02-CP
M03	Project	Peak Load and Mix	M03-CP
M07	Project	CO_2 Emissions	M07-CP
M08	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M08-CP
M09	System	CO_2 Emissions	M09-CP
M10	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M10-CP

Table 16. Impact Metrics Addressing Consumer Programs Technology Performance

Refer to the *Metrics Analysis for Consumer Programs* section that follows for details.

3.6 Metrics Analysis for Consumer Programs

This section provides details for each Consumer Programs metric, and includes those requested by the DOE during the definitization of the Cooperative Agreement. Trends were not always observed, however data is presented for each metric.

Please note that Project area and System area metrics related to emissions did not include the potential impact of shifting load over 24 hours.

3.6.1 Hourly Consumer Electricity Usage (M01-CP)

This impact metric illustrates the average consumer's usage profile based on demographics and the premises' location.

3.6.1.1 Organization of Results

All load profile data for this metric include information from 2012 and 2013.

Various views of data were selected to quantify and visualize this impact metric. The key parameters of interest include time, account class, and the account's applicable tariff. For residential accounts, applicable demographic data were used.

The time varying aspect of consumer behavior is addressed by:

- Aggregating data by three seasons- Summer, Winter and Autumn/Spring combined
- Aggregating data for different day types into three groupings
- Weekdays – Monday through Friday
- Saturday
- Sunday
- Graphing usage data as a function of each hour of the 24-hour day

The account class was set as the three traditional groupings of consumers: Industrial, Commercial and Residential. Residential consumers were categorized by account class, tariff, and demographic.

3.6.1.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Usage patterns were relatively consistent across spring and fall seasons.
- Usage patterns were relatively consistent across all weekdays.
- The Standard Residential tariff was a reasonable proxy for the baseline consumption patterns of consumers on program tariffs.

3.6.1.3 Calculation Approach

This impact metric provides an analysis of average daily usage patterns for consumers grouped by combinations of day of week, season, demographic, and tariff.

The following queries and methods were used to generate results:
The hourly consumer electricity usage was calculated by averaging hourly consumer electricity usage into 24 hourly bins.

3.6.1.4 Data Collection Results

Hourly Load Profiles by Account Class: Summer/Winter, Industrial and Commercial

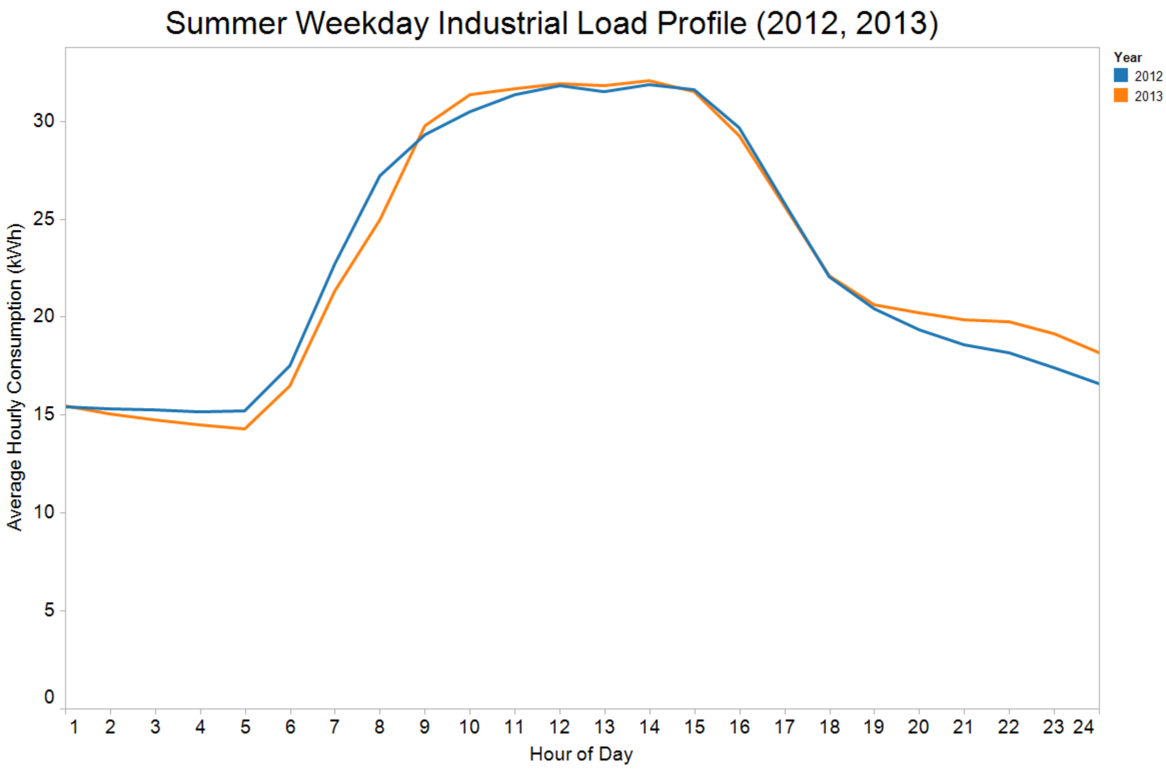


Figure 33. Summer Industrial Hourly Load Profile (Weekday)

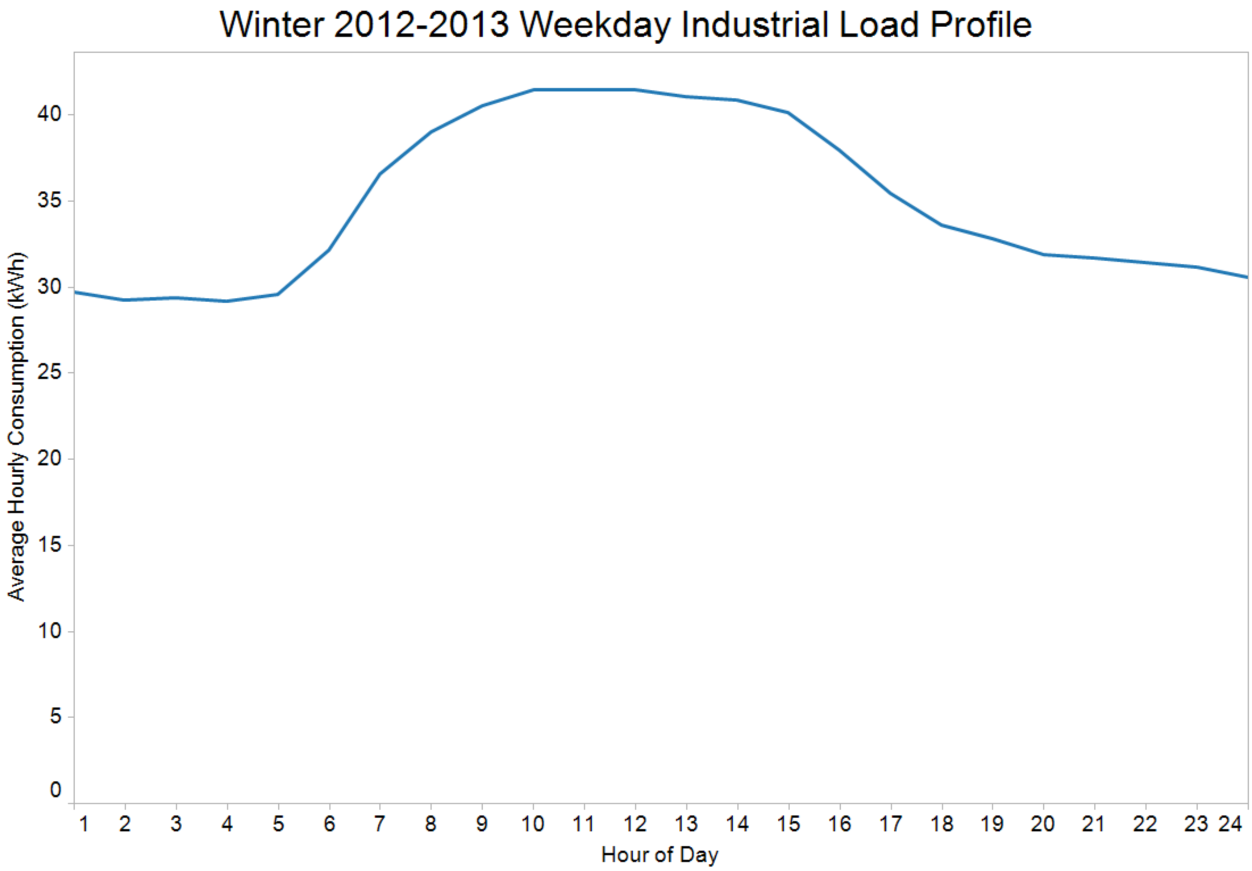


Figure 34. Winter Industrial Hourly Load Profile (Weekday)

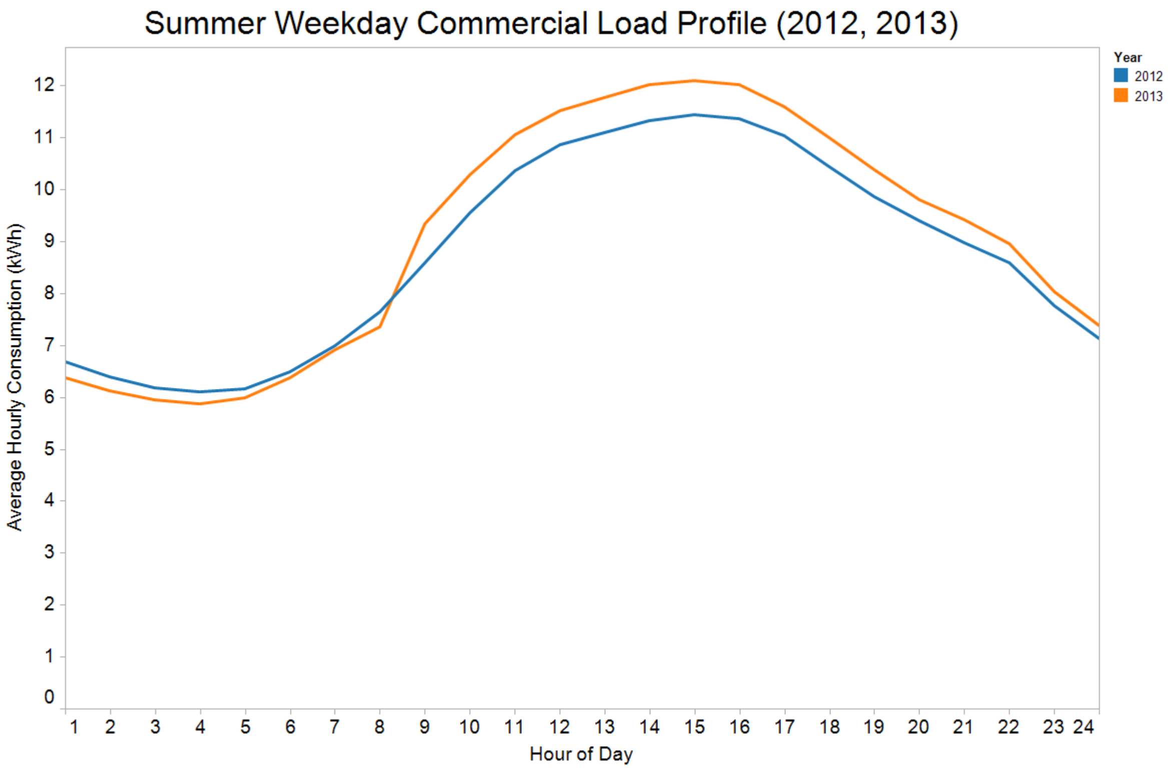


Figure 35. Summer Commercial Hourly Load Profile (Weekday)

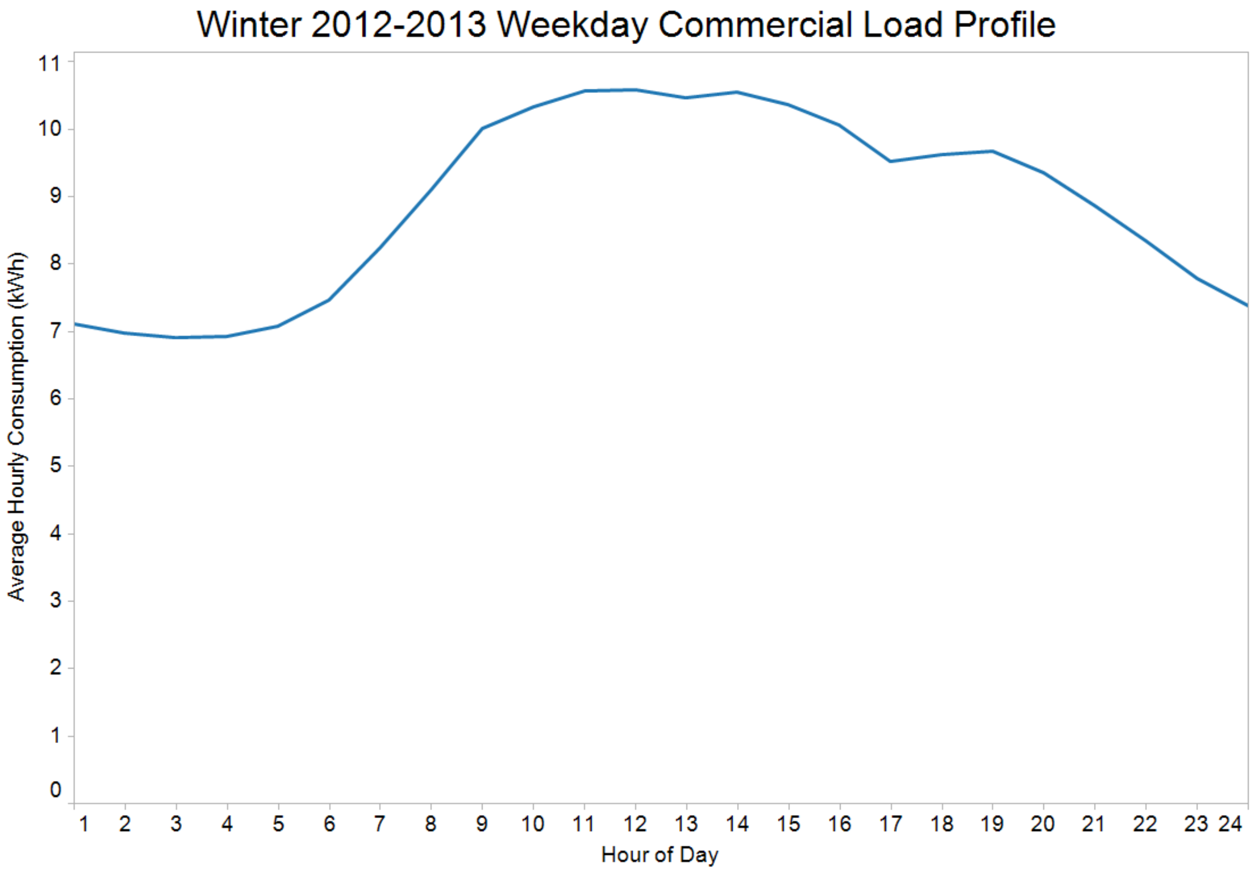


Figure 36. Winter Commercial Hourly Load Profile (Weekday)

Weekday Hourly Residential Load Profiles by Tariff for Each Season

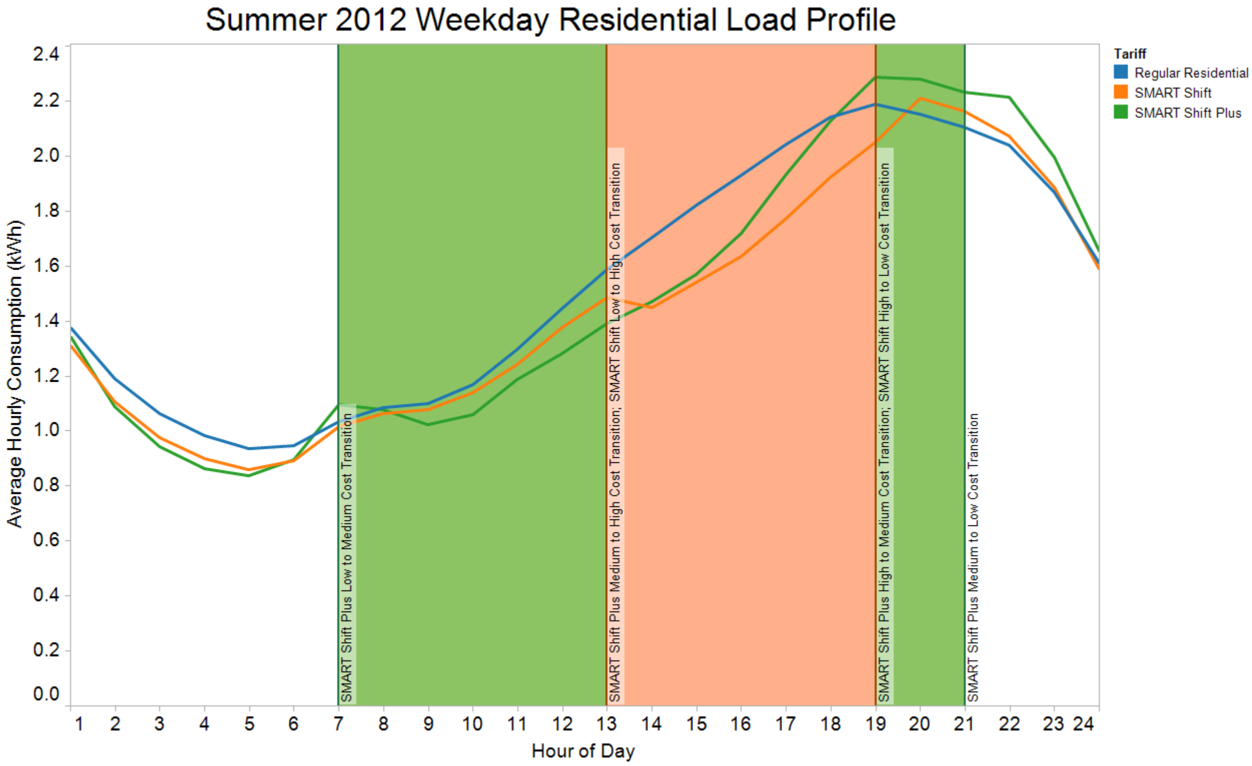


Figure 37. Summer Hourly Load Profile by Tariff (Weekday 2012)

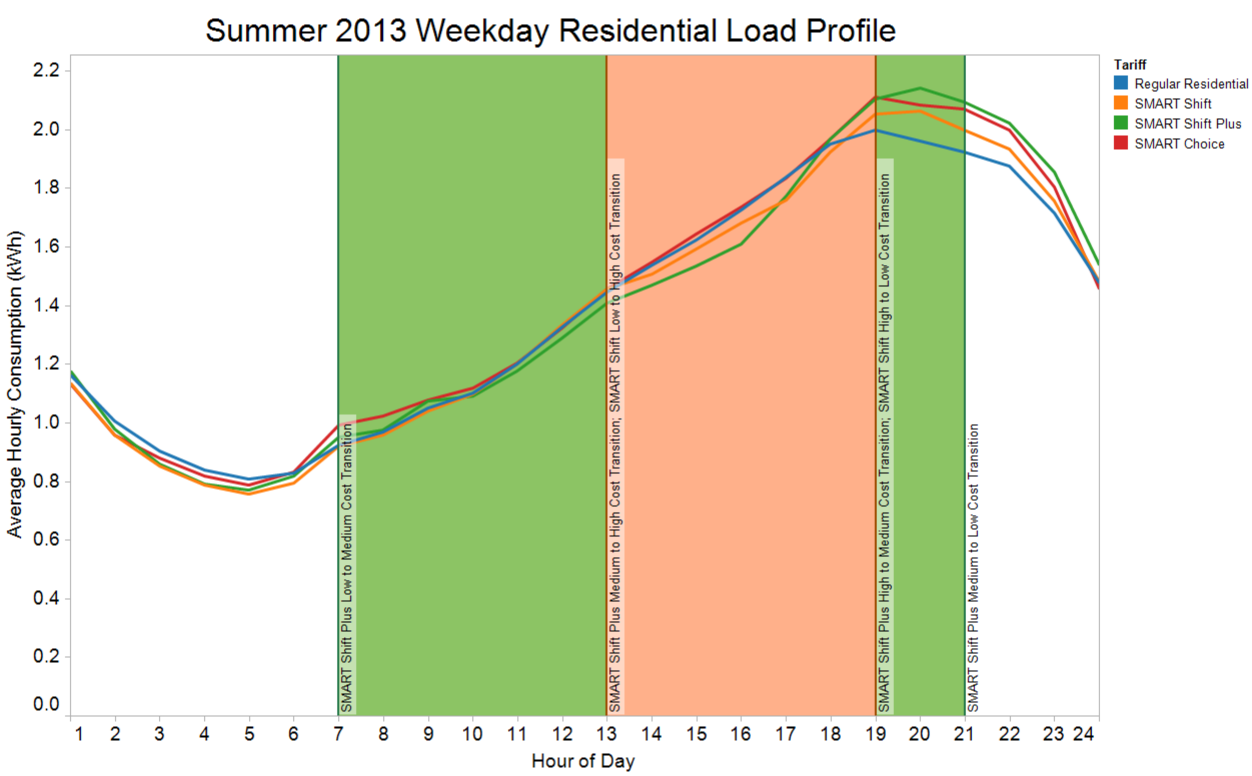


Figure 38. Summer Hourly Load Profile by Tariff (Weekday 2013)

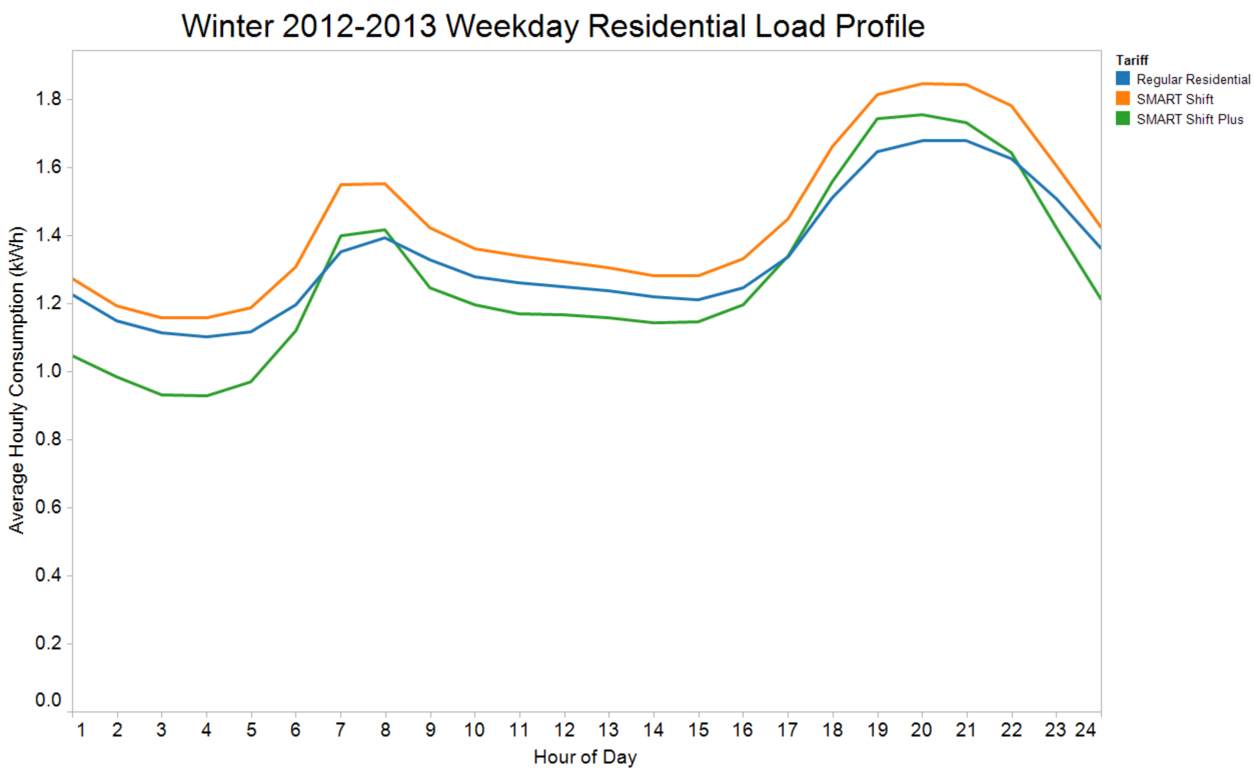


Figure 39. Winter Hourly Load Profile by Tariff (Weekday)

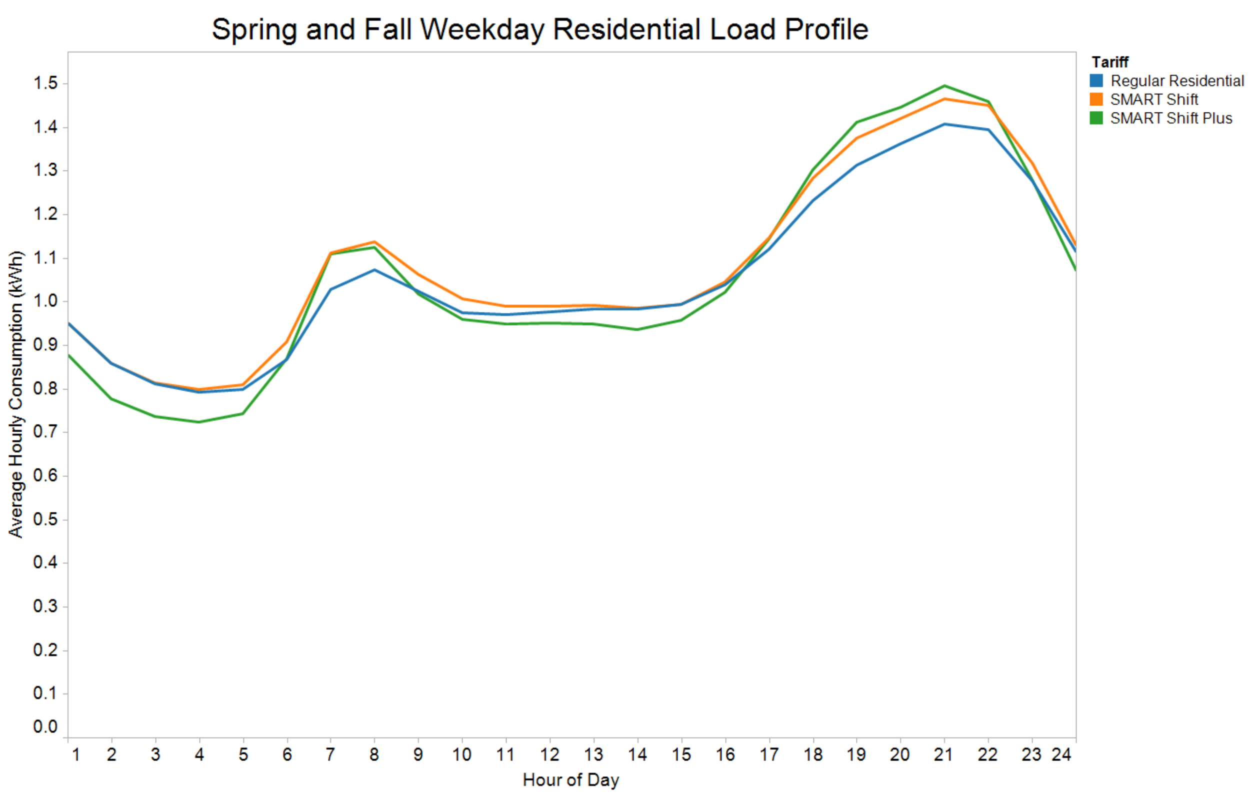


Figure 40. Autumn/Spring Hourly Load Profile by Tariff (Weekday)

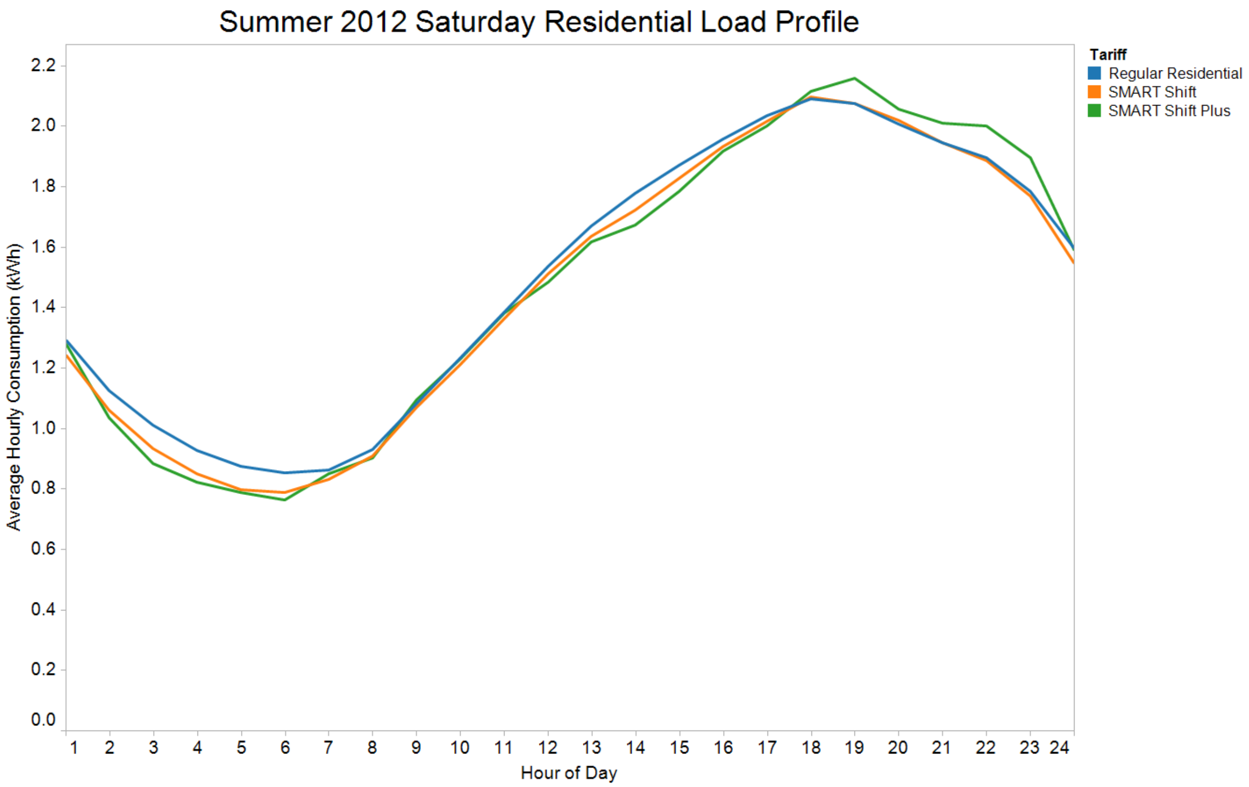


Figure 41. Summer Hourly Load Profiles (Saturday 2012)

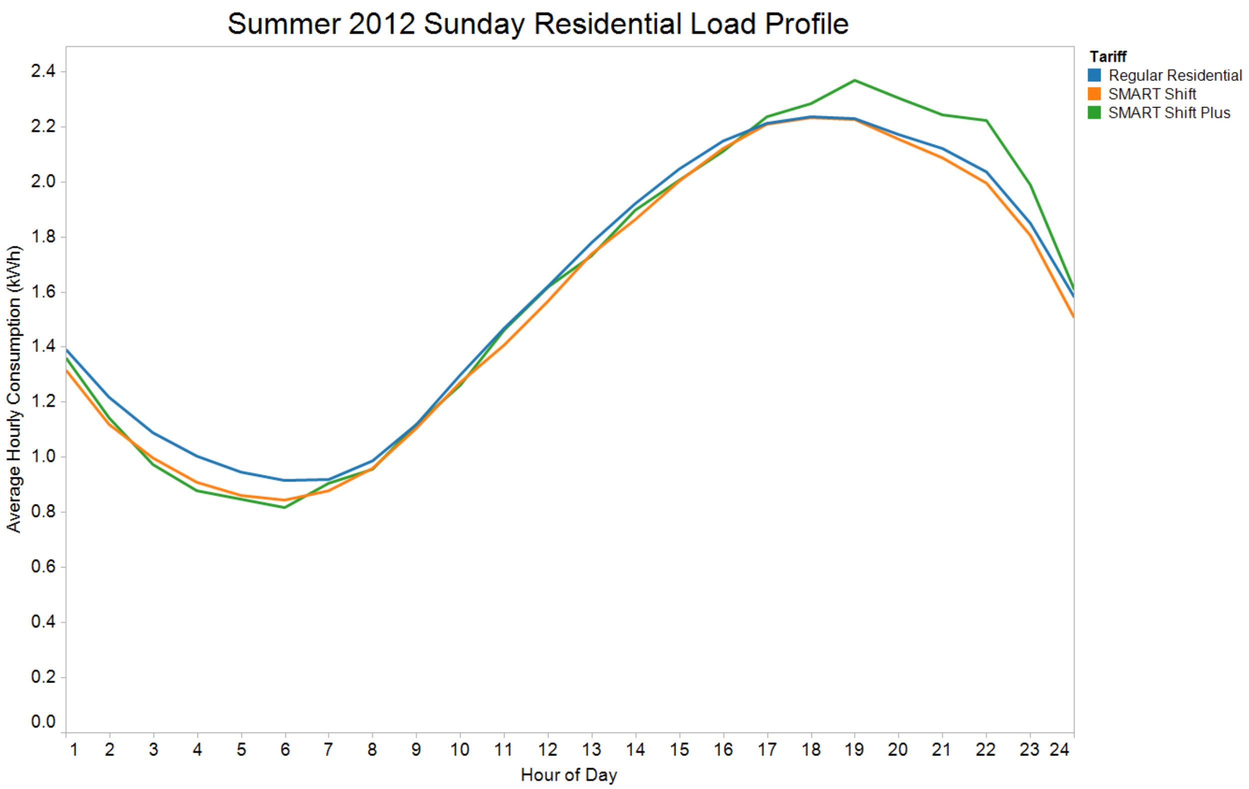


Figure 42. Summer Hourly Load Profiles (Sunday 2012)

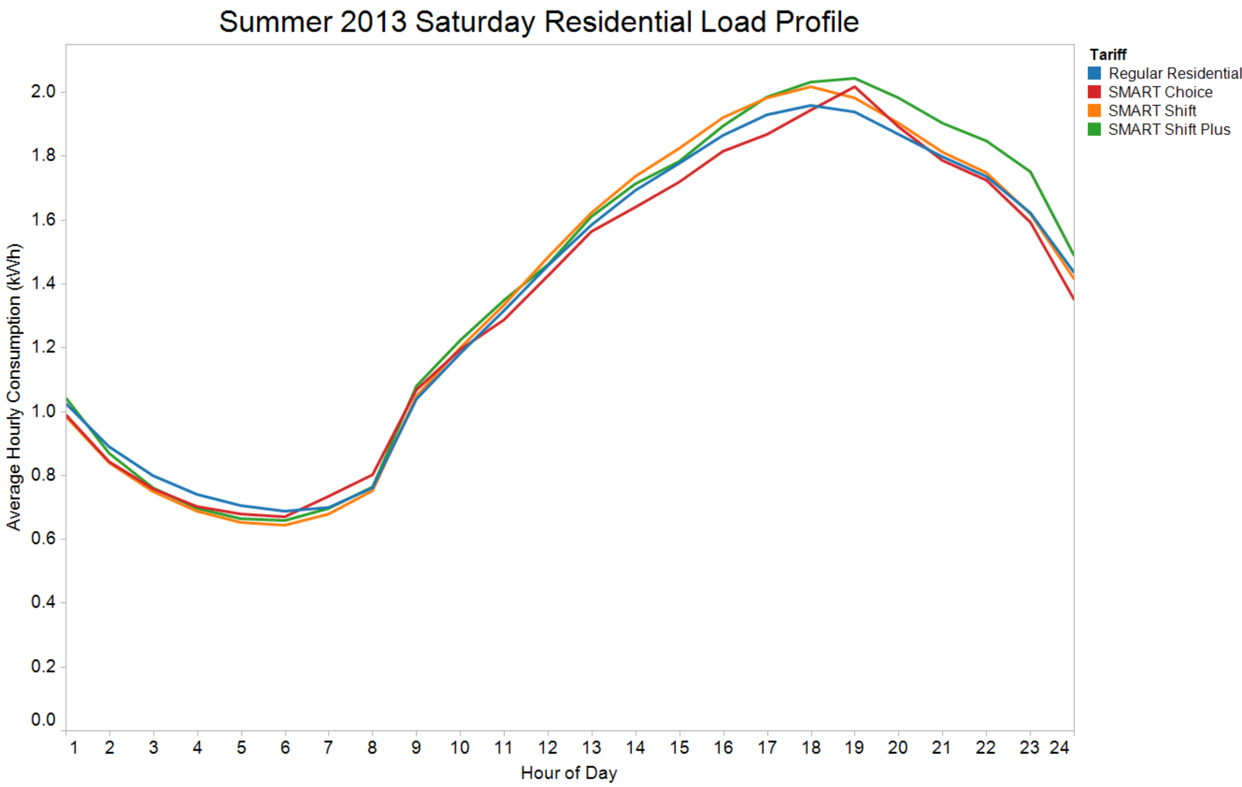


Figure 43. Summer Hourly Load Profiles (Saturday 2013)

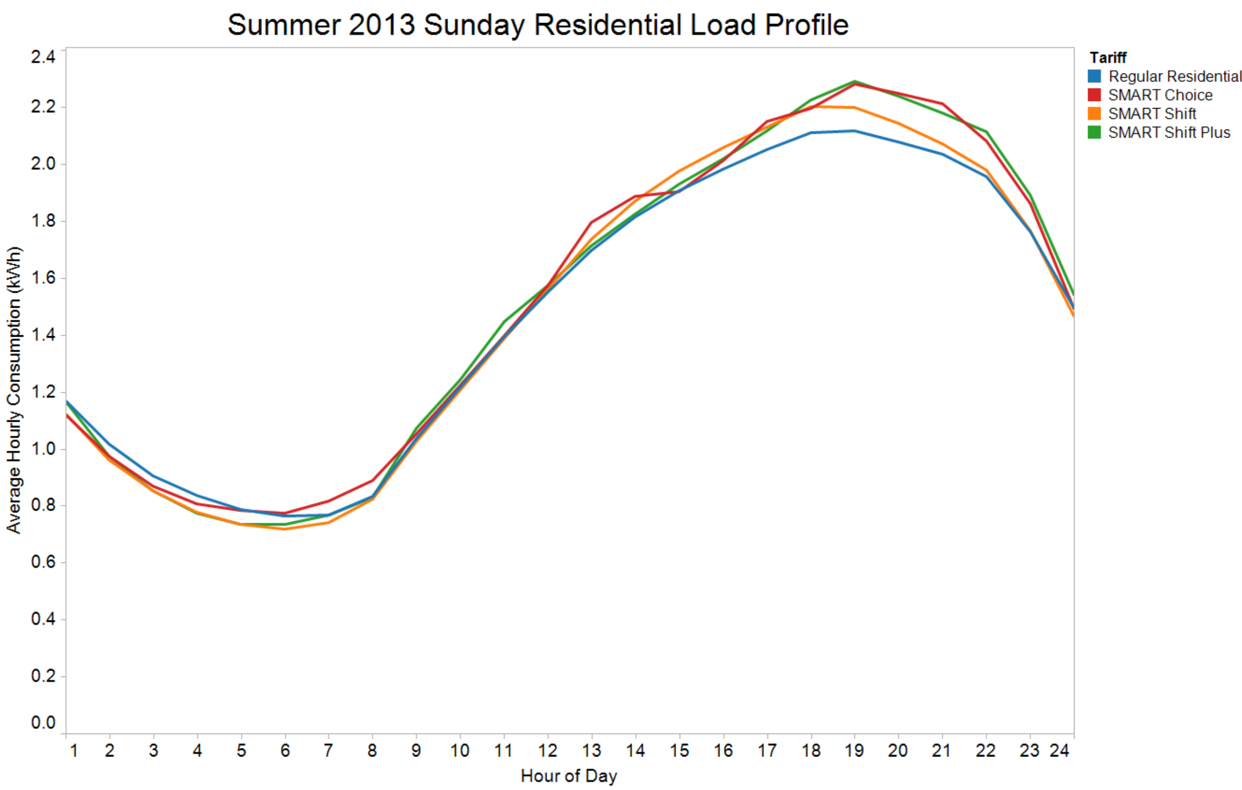


Figure 44. Summer Hourly Load Profiles by Tariff (Sunday 2013)

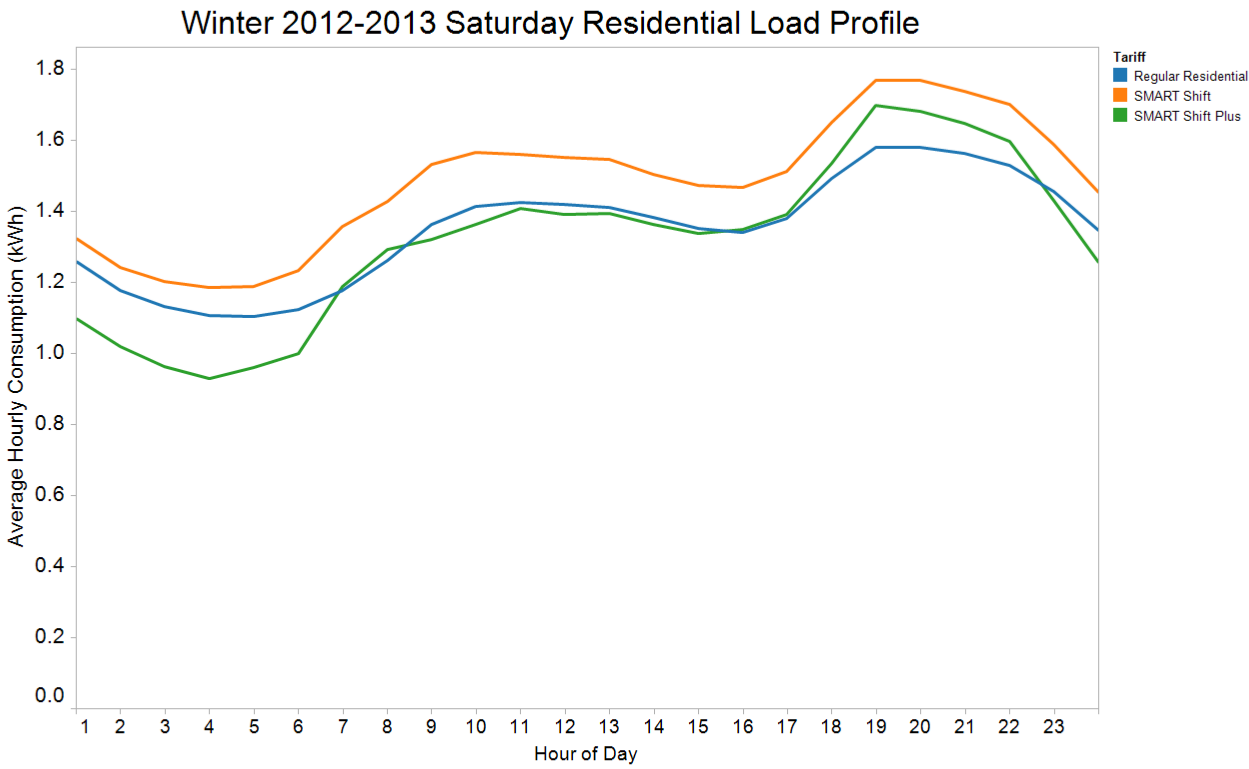


Figure 45. Winter Hourly Load Profiles by Tariff (Saturday)

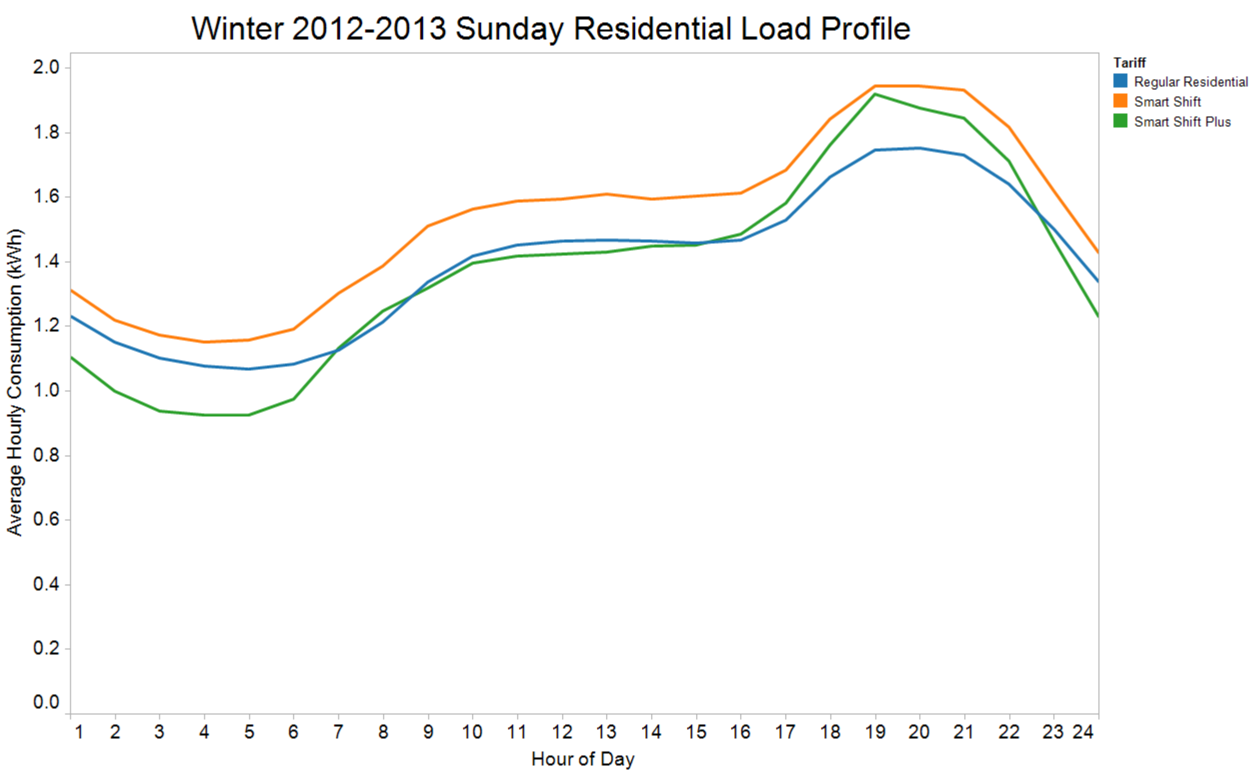


Figure 46. Winter Hourly Load Profiles by Tariff (Sunday)

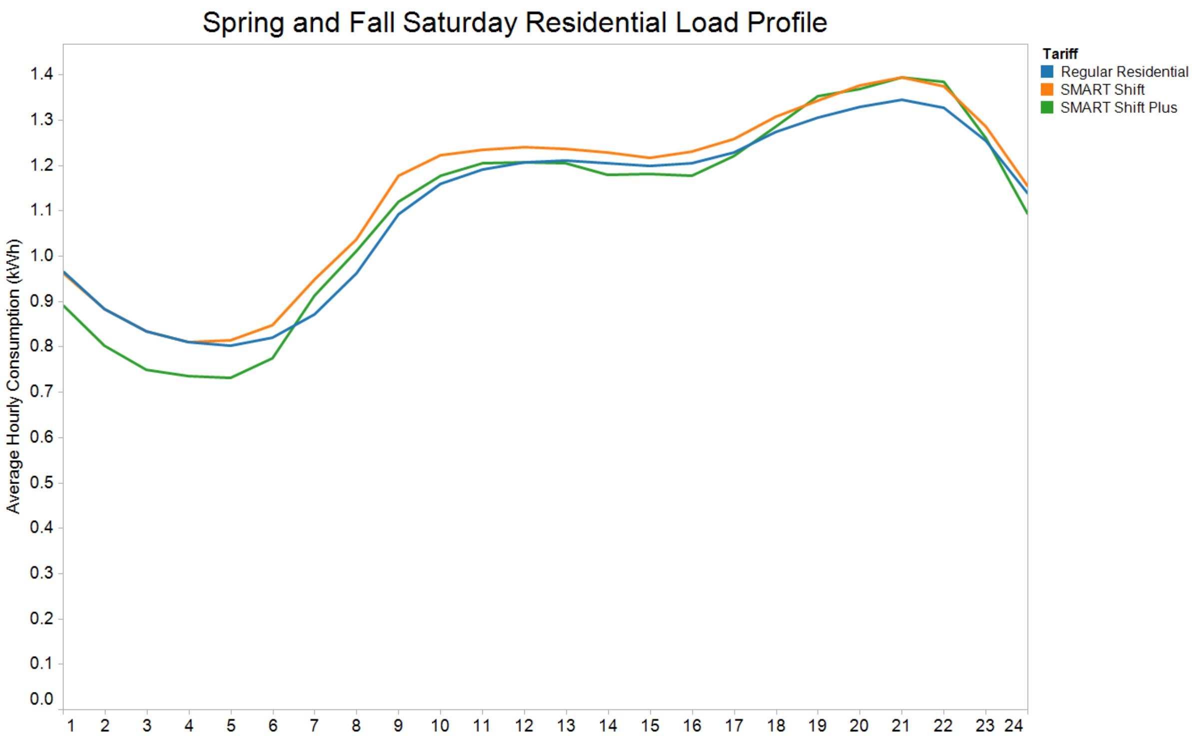


Figure 47. Autumn/Spring Hourly Load Profiles by Tariff (Saturday)

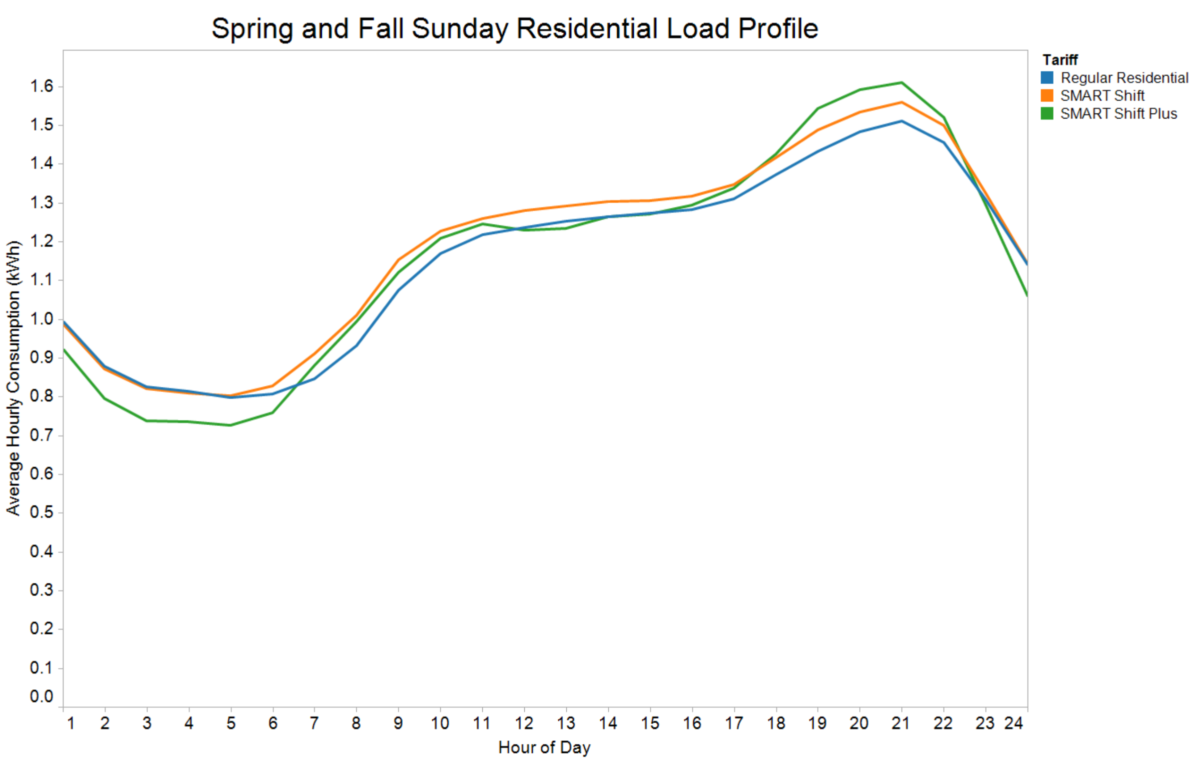


Figure 48. Autumn/Spring Hourly Load Profiles by Tariff (Sunday)

3.6.2 Conclusions

3.6.2.1 Load Shapes by Consumer Class and Season

Industrial loads had a large differential in peak and off-peak usage patterns, with a fast rise in loads between 6 a.m. and 9 a.m. and a subsequent drop in load around 5 p.m. They also had higher winter usage and a slightly less pronounced peak, with an approximate 20 percent higher peak in the winter compared to the summer. Commercial loads in the Project area had an afternoon peak around 3 p.m., with a much broader peak in the winter.

Residential loads had an evening peak, which changed from about 7 p.m. in the summer to 9 p.m. in the winter; this change was driven primarily by the switch from air conditioning (which moved peak consumption to earlier in the day), to heating (which pushed peak consumption to the evening hours). The spring and autumn residential load shapes exhibited a similar (although lower) evening peaking pattern as the winter season. The additional impacts of less daylight and more heating load contributed to a winter peak that was over 20 percent higher than in the spring/autumn. The summer peak was over 40 percent higher than the autumn/spring peak due to the large residential air conditioning load. This increase was despite the fact that there was a reduction in lighting loads due to additional daylight availability in the summer in the Project area.

3.6.2.2 Tariff Impacts

The time-of-day (TOD) tariffs (SMART Shift and SMART Shift Plus) each defined the peak period to be from 1 p.m. to 7 p.m. from June 1 to September 1. Both the SMART Shift and SMART Shift Plus consumers had lower consumption than the standard residential tariff (flat rate) consumers during the peak time periods in 2012. In 2013 however, the SMART Shift and SMART Shift Plus consumers had lower consumption during the first hours of the peak period and higher consumption during the last 2 hours and higher overall peak. After the peak period (approximately 7 p.m. to midnight) the time-of-day consumers' consumption was greater than the flat rate consumers in 2012 and 2013.

In the winter, the SMART Shift consumers had higher overall usage and a similar load shape compared to standard residential consumers. SMART Shift Plus consumers had a lower overnight and mid-day usage with sharper morning and evening peaks compared to standard residential consumers. During winter months, standard residential consumers were charged a declining block rate; SMART Shift and SMART Shift Plus consumers were charged a flat rate that was lower than the standard residential tariff.

The autumn/spring load profiles appeared similar across all three tariffs, with the TOD consumers exhibiting higher morning and evening peaks.

The TOD behavior may have been driven by PCTs, which allowed consumers to program different set points for specific time periods within a day. A typical PCT program had specific morning and evening time periods (representing the times consumers prepared for work/school and return home), which may have resulted in the higher consumption for the TOD/CPP consumers during the morning and evening time periods.

3.6.3 Monthly Consumer Electricity Usage (M02-CP)

This impact metric measures the cost impact to electricity consumers as a result of various consumer programs.

3.6.3.1 Organization of Results

This metric presents average monthly bills for residential, commercial, and industrial consumer classes for the years 2011 through 2013. The residential graphs are distinguished by tariff and demographic and depict residential monthly average costs. The first residential graph shows the average monthly bill per consumer by tariff. The second graph shows the average monthly bill per consumer by demographic.

3.6.3.2 Assumptions

Please see the Calculation Approach for this metric.

3.6.3.3 Calculation Approach

This impact metric provides an analysis of average bill amount and average energy consumption for consumers grouped by demographic and marketing stratum.

The following queries and methods were used to generate results:

- Average monthly consumer electricity usage was calculated by averaging the billed usage for the ending month of the billing period for all residential consumers on the standard residential tariff.
- Average monthly consumer electricity usage per tariff was calculated by averaging the billed usage for the ending month of the billing period for all residential consumers on the standard residential, SMART Shift, and SMART Shift Plus tariffs.
- Average monthly consumer cost was calculated by averaging the billed amount for the ending month of the billing period for all residential consumers on the standard residential tariff. These data points were not normalized for rate changes occurring within the period.
- Average monthly consumer cost per tariff was calculated by averaging the billed amount for the ending month of the billing period for all residential consumers on the standard residential, two-tier TOD, and three-tier TOD with SMART Shift Plus tariffs.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration: http://hurricane.ncdc.noaa.gov/pls/plclimprod/poemain.accessrouter?datasetabbv=DS3505&countryabbv=&georegionabbv=

3.6.3.4 Data Collection Results

Residential Monthly Cost Data

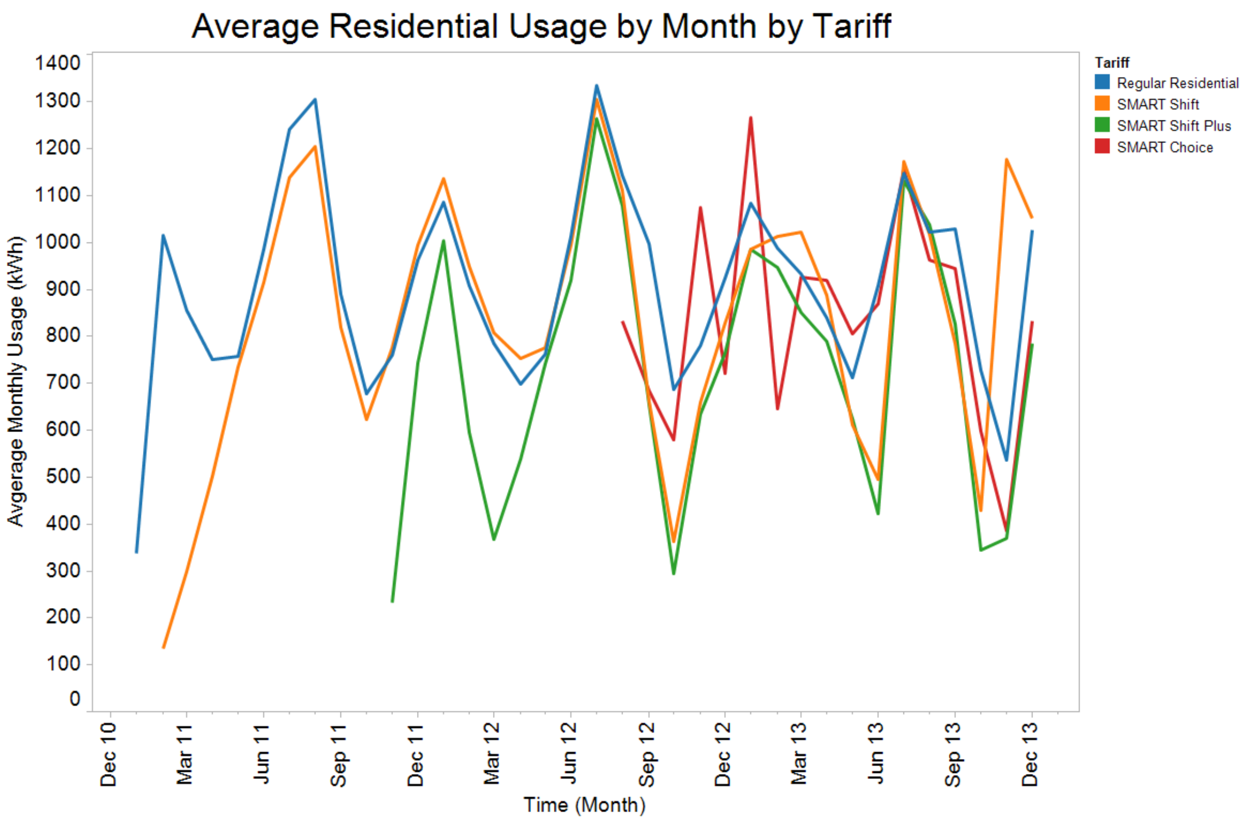


Figure 49. Average Residential Monthly Usage for Tariffs

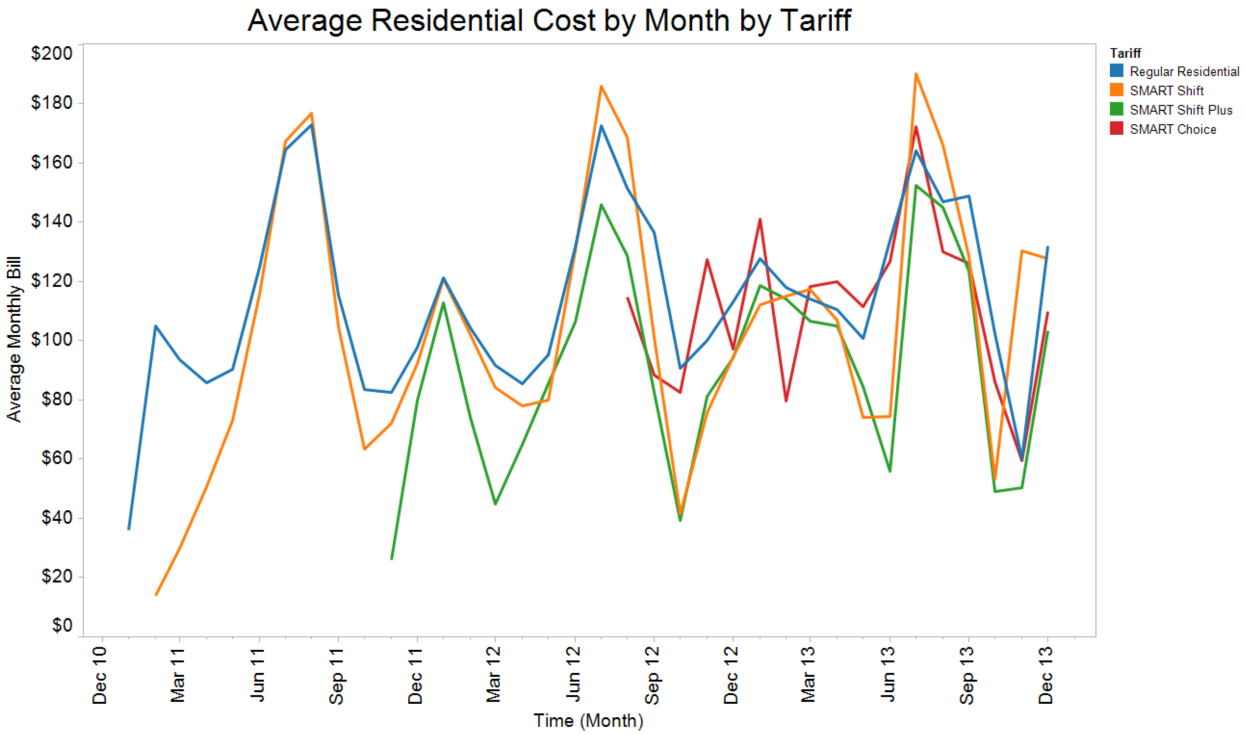


Figure 50. Average Residential Monthly Bill Amount for Tariffs

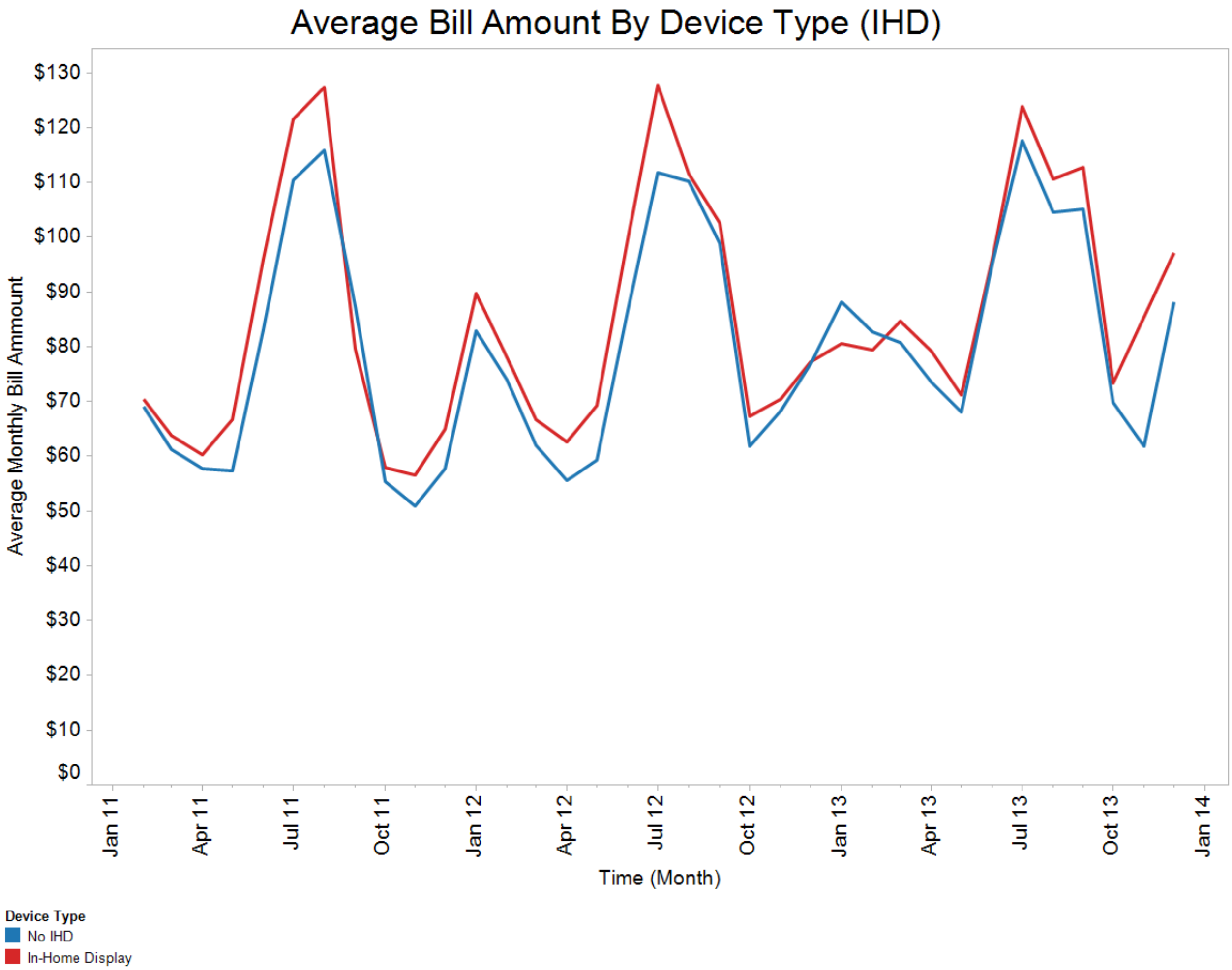


Figure 51. Average Residential Monthly Bill Amount for Consumers With vs. Without eVIEW

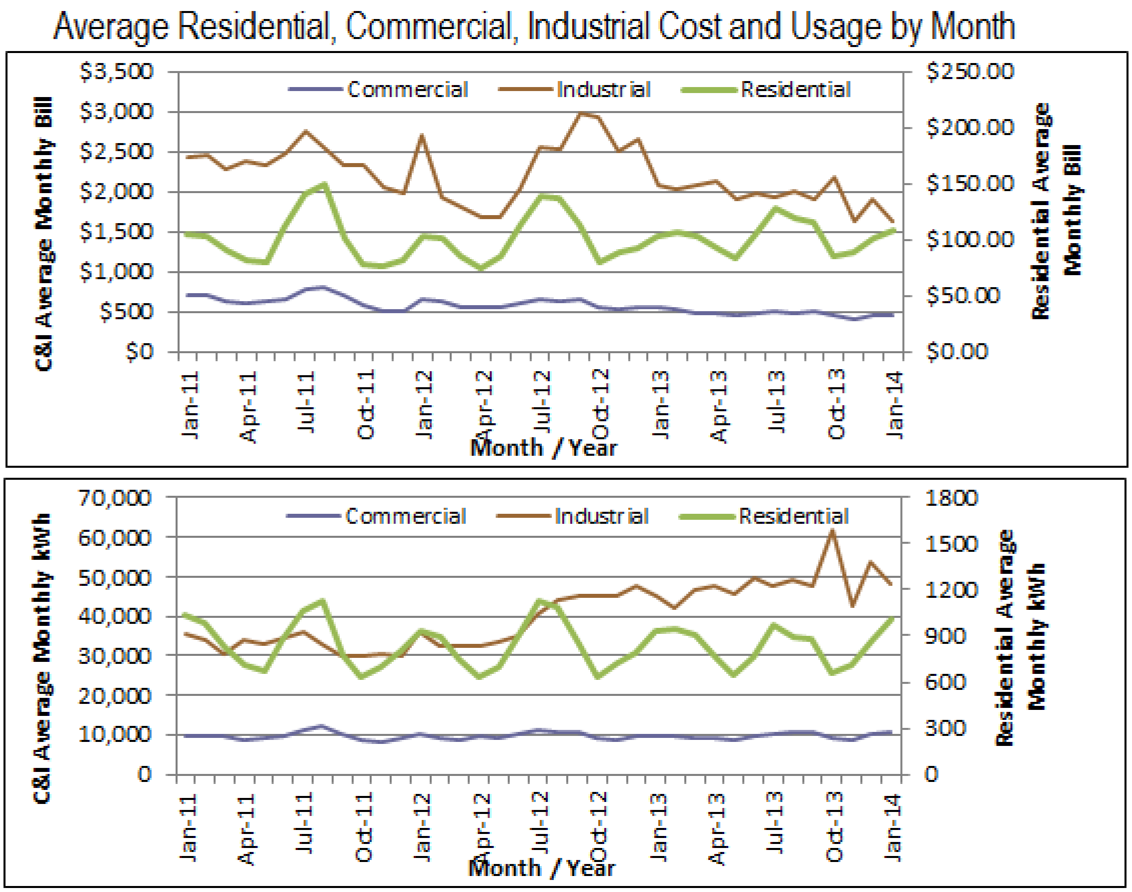


Figure 52. Comparison of Residential, Commercial, and Industrial Monthly Bill Amounts

Enrollments in eVIEW commenced in February 2012 and increased in 2013 due to canvassing efforts. The monthly enrollment and removal counts are presented in the figure below.

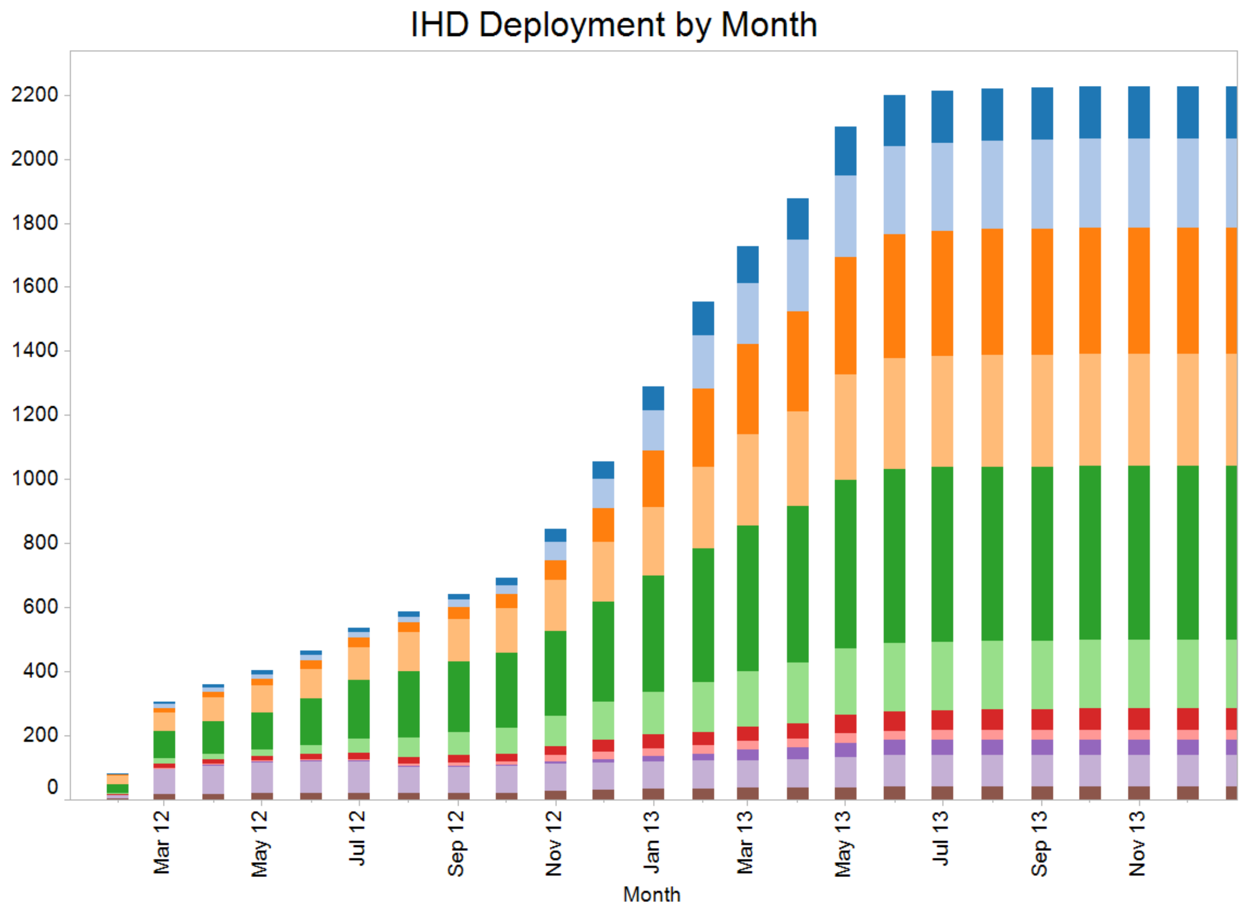


Figure 53. eVIEW In-Home Display Device Deployment by Month

Marketing Stratum

- Overall Control Group – No Contact Representative Cross Section
- Standard Rate, In-Home Device, OPOWER, No Program Marketing
- RTP Designated Circuits, some OPOWER, Program Marketing, and IHD/HEM/ePCT
- RTP Random, Program Marketing, and IHD/HEM/ePCT
- Standard Rate, OPOWER, No Program Marketing
- 3 Tier with CPP w/ IHD/PCT, WH Controller, Program Marketing
- 3 Tier with CPP, No OPOWER, Program Marketing, and IHD
- 3 Tier with CPP, OPOWER Program Marketing, and IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT, IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, No OPOWER PCT
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT

Enrollments in SMART Shift commenced in February 2011 and increased in 2013 due to canvassing efforts. The monthly enrollment and removal counts are presented in the figure below.

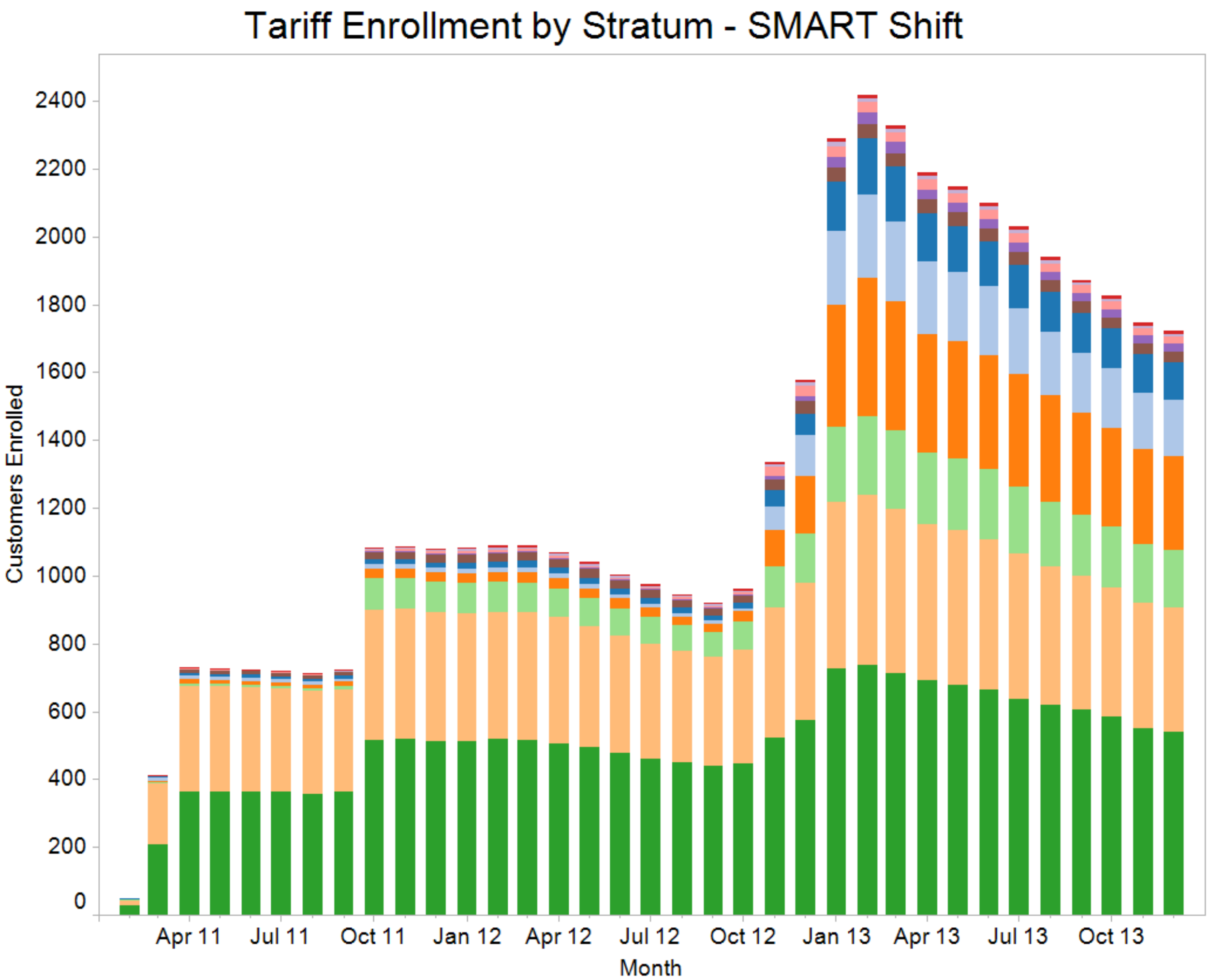


Figure 54. Consumer Enrollment by Month - SMART Shift

Marketing Stratum

- Overall Control Group – No Contact Representative Cross Section
- Standard Rate, In-Home Device, OPOWER, No Program Marketing
- RTP Designated Circuits, some OPOWER, Program Marketing, and IHD/HEM/ePCT
- RTP Random, Program Marketing, and IHD/HEM/ePCT
- Standard Rate, OPOWER, No Program Marketing
- 3 Tier with CPP w/ IHD/PCT, WH Controller, Program Marketing
- 3 Tier with CPP, No OPOWER, Program Marketing, and IHD
- 3 Tier with CPP, OPOWER Program Marketing, and IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT, IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, No OPOWER PCT
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT

Enrollments in SMART Shift Plus commenced in November 2011 and increased in 2013 due to canvassing efforts. The monthly enrollment and removal counts are presented in the figure below.

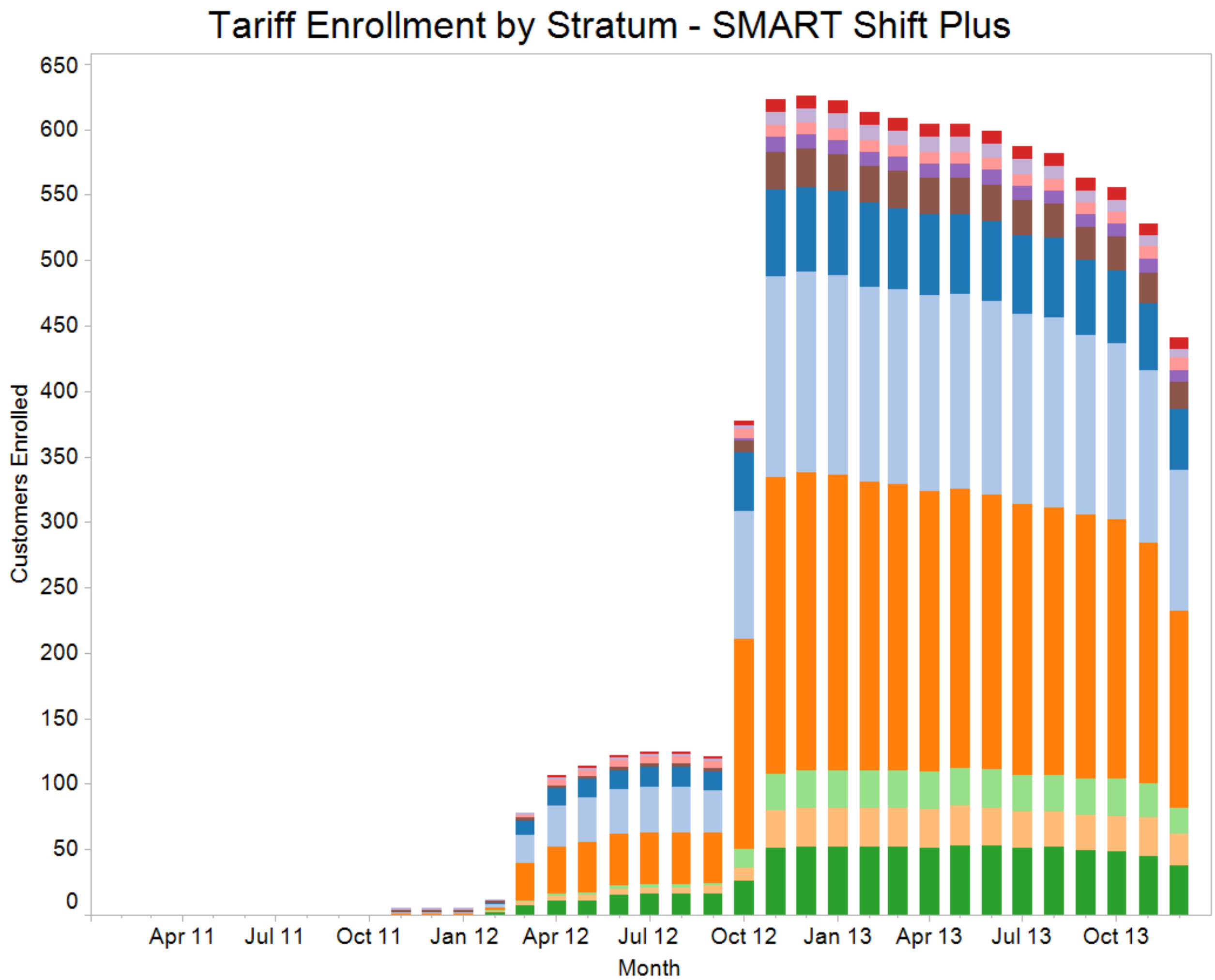


Figure 55. Consumer Enrollment by Month - SMART Shift Plus

Marketing Stratum

- Overall Control Group – No Contact Representative Cross Section
- Standard Rate, In-Home Device, OPOWER, No Program Marketing
- RTP Designated Circuits, some OPOWER, Program Marketing, and IHD/HEM/ePCT
- RTP Random, Program Marketing, and IHD/HEM/ePCT
- Standard Rate, OPOWER, No Program Marketing
- 3 Tier with CPP w/ IHD/PCT, WH Controller, Program Marketing
- 3 Tier with CPP, No OPOWER, Program Marketing, and IHD
- 3 Tier with CPP, OPOWER Program Marketing, and IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT, IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, No OPOWER PCT
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT

Enrollments in SMART Cooling commenced in April 2011 and increased in 2013 due to canvassing efforts. The monthly enrollment and removal counts are presented in the figure below.

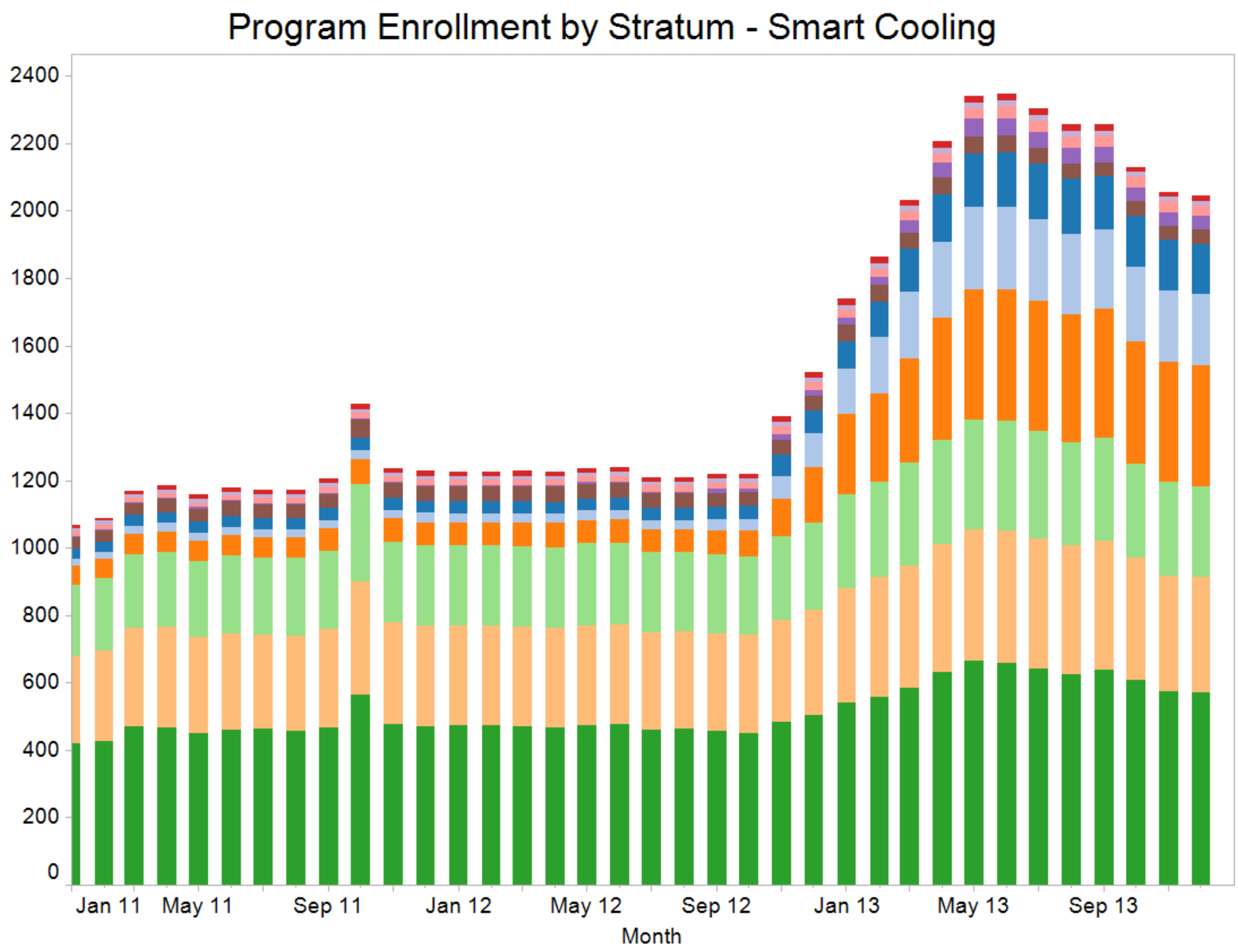


Figure 56. Consumer Enrollment by Month - SMART Cooling

Marketing Stratum

- Overall Control Group – No Contact Representative Cross Section
- Standard Rate, In-Home Device, OPOWER, No Program Marketing
- RTP Designated Circuits, some OPOWER, Program Marketing, and IHD/HEM/ePCT
- RTP Random, Program Marketing, and IHD/HEM/ePCT
- Standard Rate, OPOWER, No Program Marketing
- 3 Tier with CPP w/ IHD/PCT, WH Controller, Program Marketing
- 3 Tier with CPP, No OPOWER, Program Marketing, and IHD
- 3 Tier with CPP, OPOWER Program Marketing, and IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT, IHD
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, No OPOWER PCT
- Direct Load Control and/or Time of Day – 2 Tier, Program Marketing, OPOWER PCT

Following a successful canvassing effort in 2013, enrollment efforts stopped after June 1, 2013 when the summer season began and data collection needed to be stabilized. The monthly enrollment and removal counts are presented in the figure below.

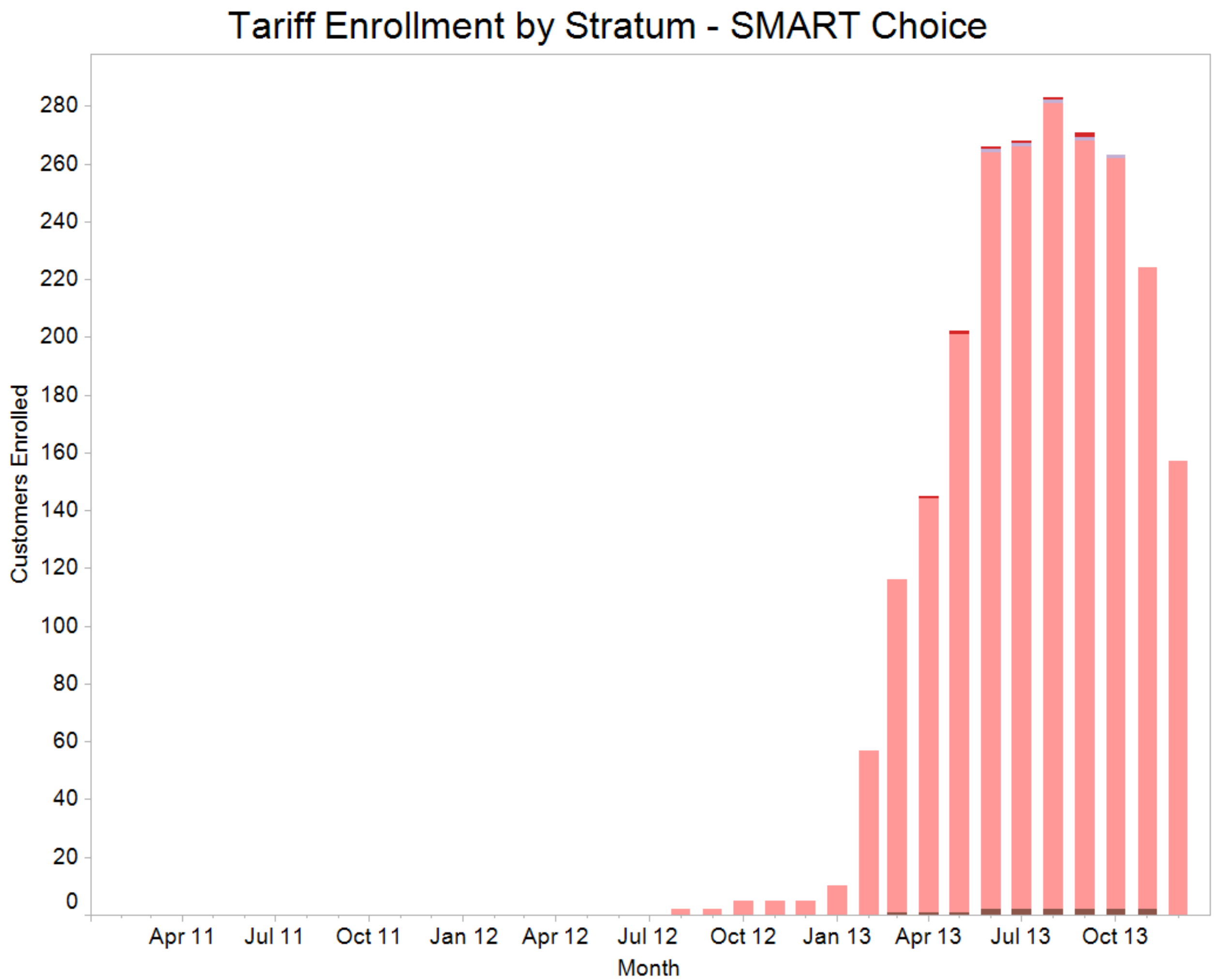
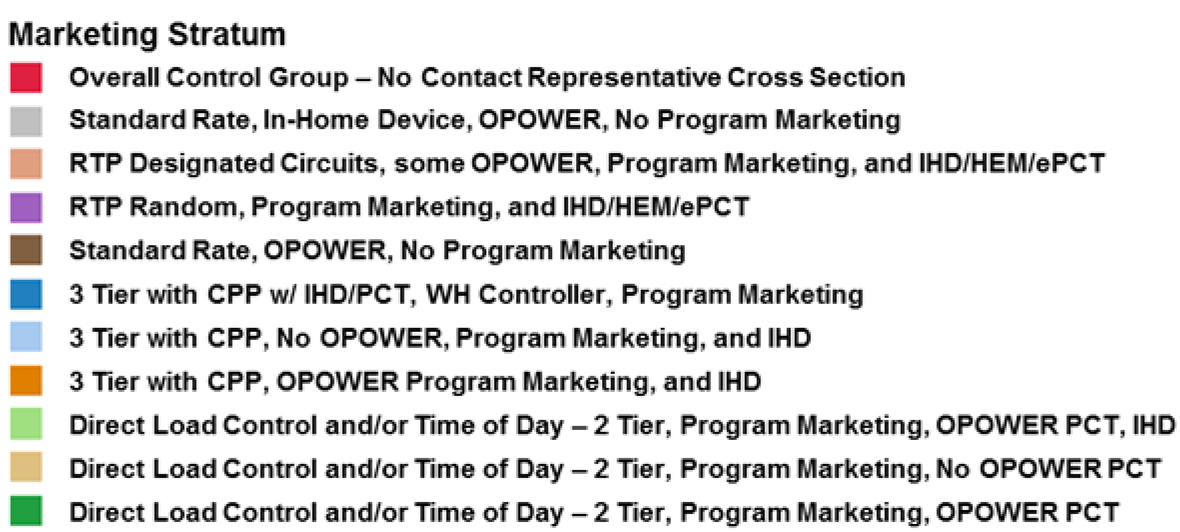


Figure 57. Consumer Enrollment by Month - SMART Choice



3.6.4 Peak Load and Mix (M03-CP)

This impact metric examines the impact of the various consumer programs on the daily usage peaks. This impact metric compares the impacts across account classes, such as residential, commercial, and industrial. Various consumer strata and demographic data were used to determine which programs had the most impact on peak load and mix.

3.6.4.1 Organization of Results

This impact metric assesses the ability of programs, tariffs, and technologies to influence consumers to shift their load away from traditionally typical peak periods.

The key parameters of interest included time, account class, the account's applicable tariff, and for residential accounts, applicable demographic data.

- The time variant aspect of the data was handled by graphing data as a function of each hour of the day.
- Account class was set as the three traditional groupings of consumers – industrial, commercial and residential.
- Residential consumers were categorized by account class, tariff, and demographic.
- Three key demographic groups were identified with the remainder of the consumers placed in one of three groups
- Consumers on a fixed billing program
- Consumers with and without children in the household
- Consumers without children in the household
- Commercial and Industrial Monthly Average

3.6.4.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- For consumers on a program tariff, the most significant peak reductions occur on DLC and CPP event days.
- The Regular Residential tariff is a reasonable proxy for the baseline consumption patterns of consumers on program tariffs.

3.6.4.3 Calculation Approach

This impact metric provides an analysis of average daily usage patterns during selected peak days for consumers grouped by tariff.

The following queries and methods were used to generate analysis and graphs:

- Peak load and mix was calculated by averaging hourly consumer electricity usage into 24 hourly bins.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration here: http://hurricane.ncdc.noaa.gov/pls/plclimprod/poemain.accessrouter?datasetabbv=DS3505&countryabbv=&georegionabbv=
- Direct Load Control events per meter were selected based on the type of Direct Load Control device installed on a consumer's premises.

3.6.4.4 Data Collection Results

Usage Data by Account Class and Hour of the Day for the Peak Week

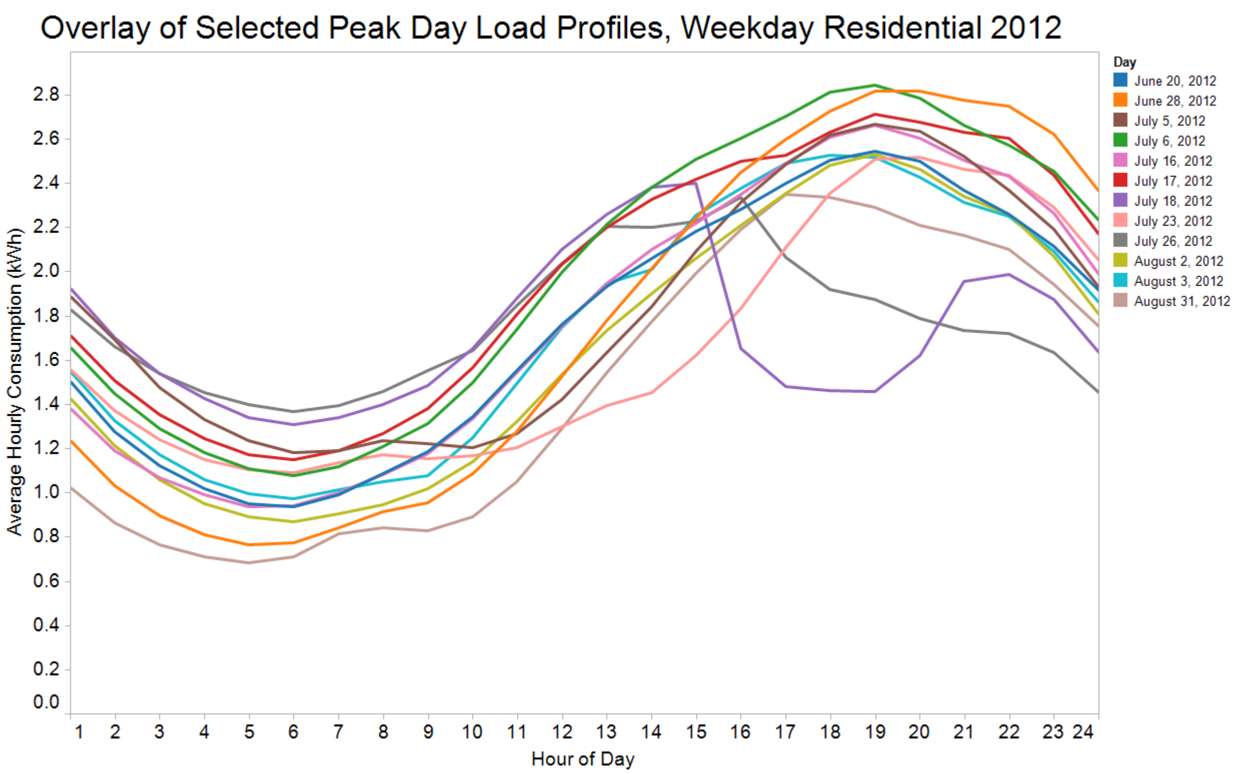


Figure 58. Overlay of Peak Load Days - Residential 2012

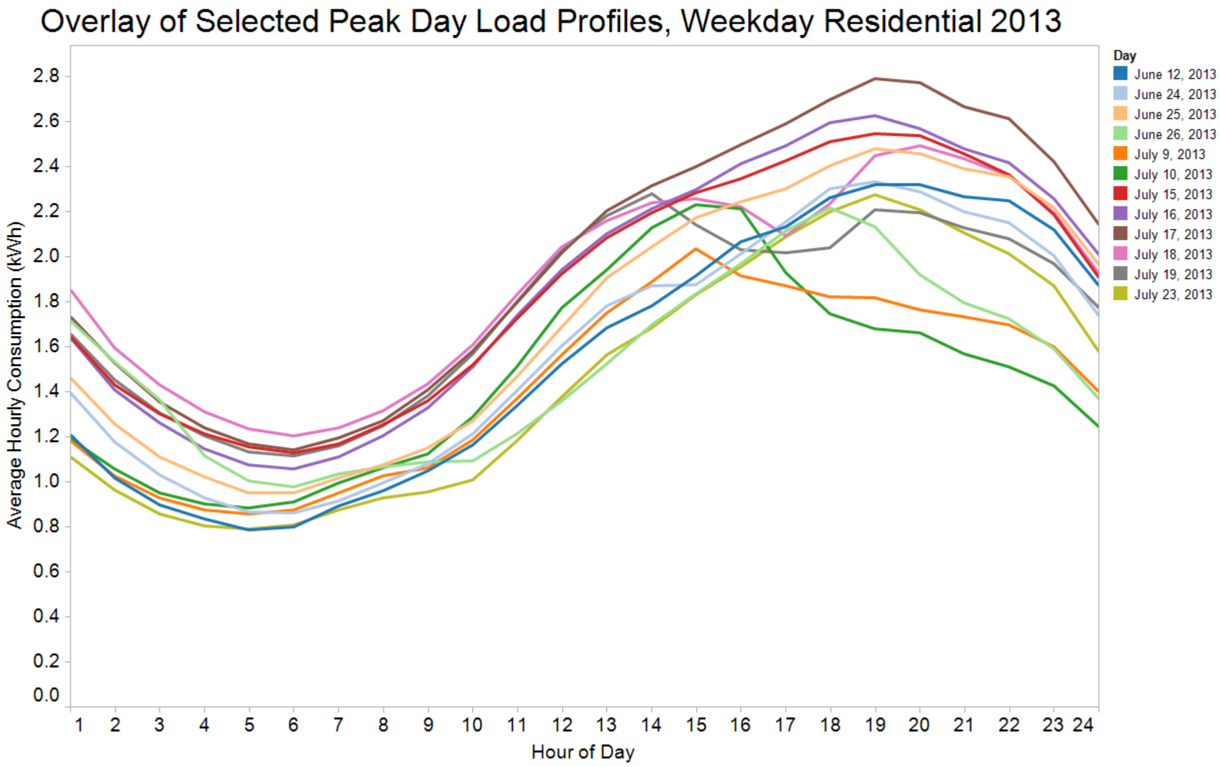


Figure 59. Overlay of Peak Load Days - Residential 2013

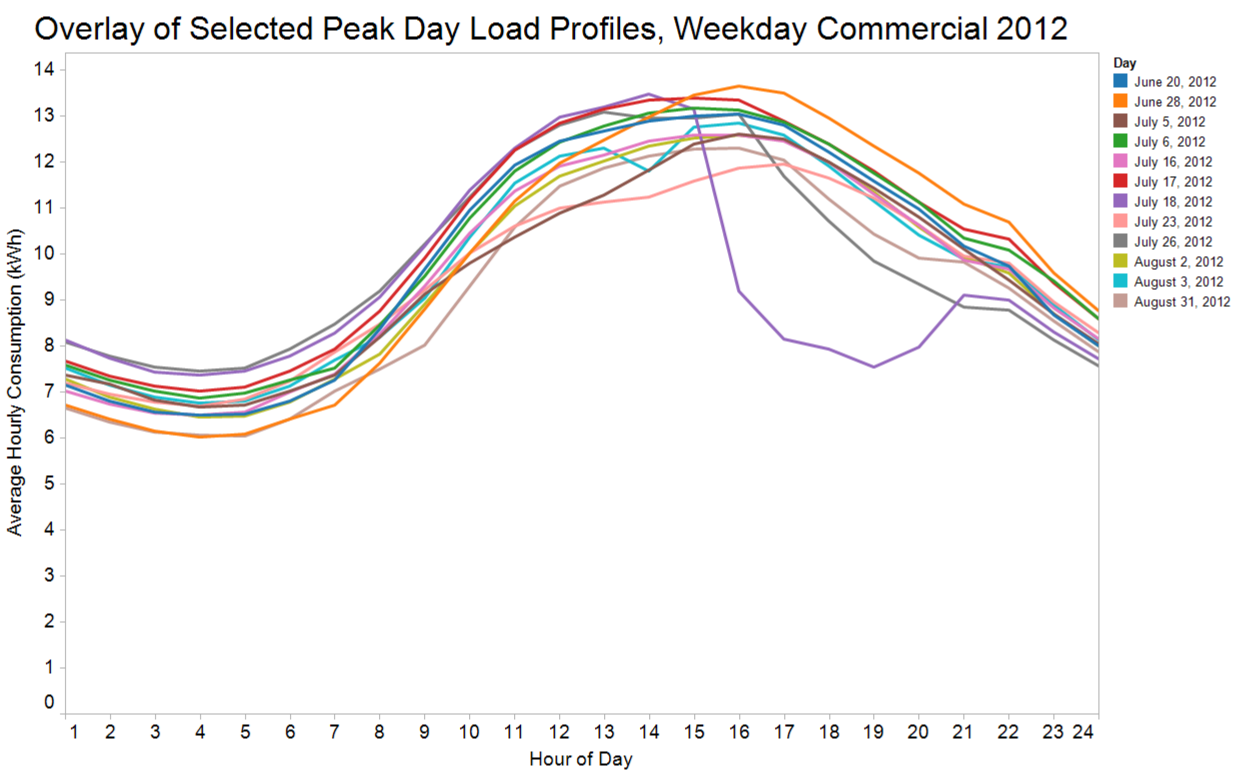


Figure 60. Overlay of Peak Load Days - Commercial 2012

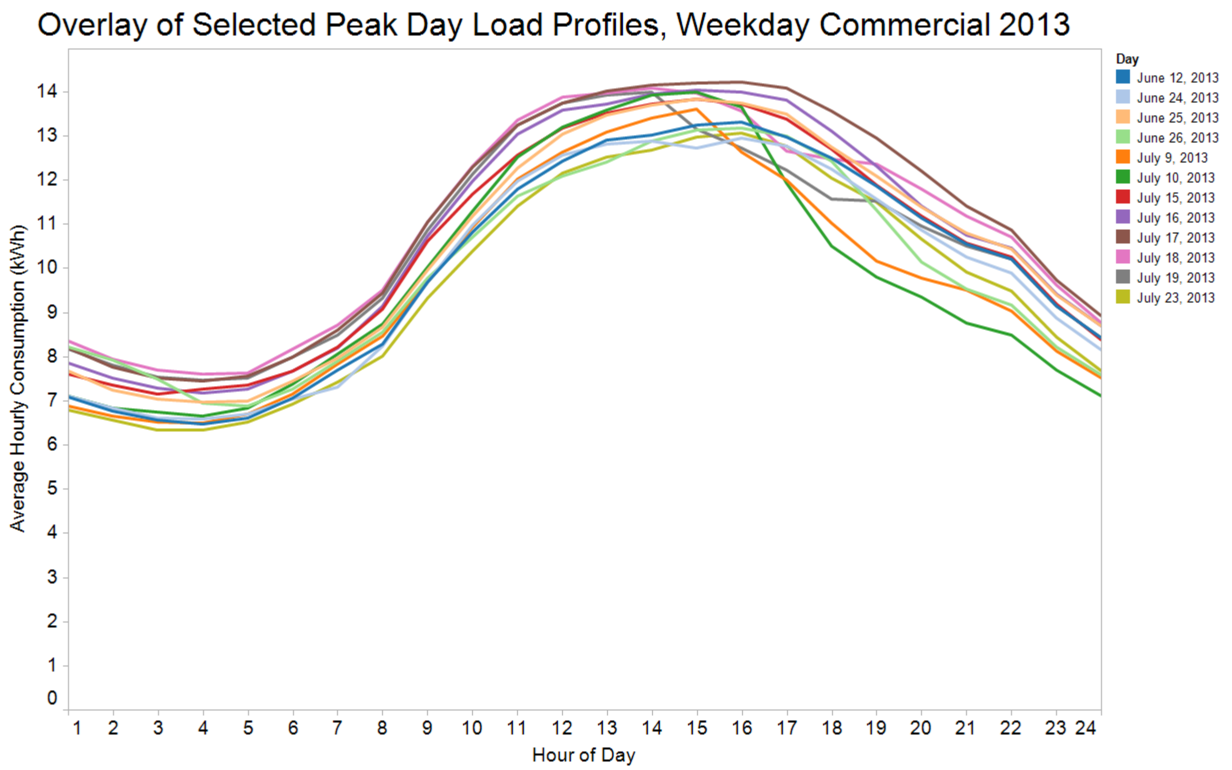


Figure 61. Overlay of Peak Load Days - Commercial 2013

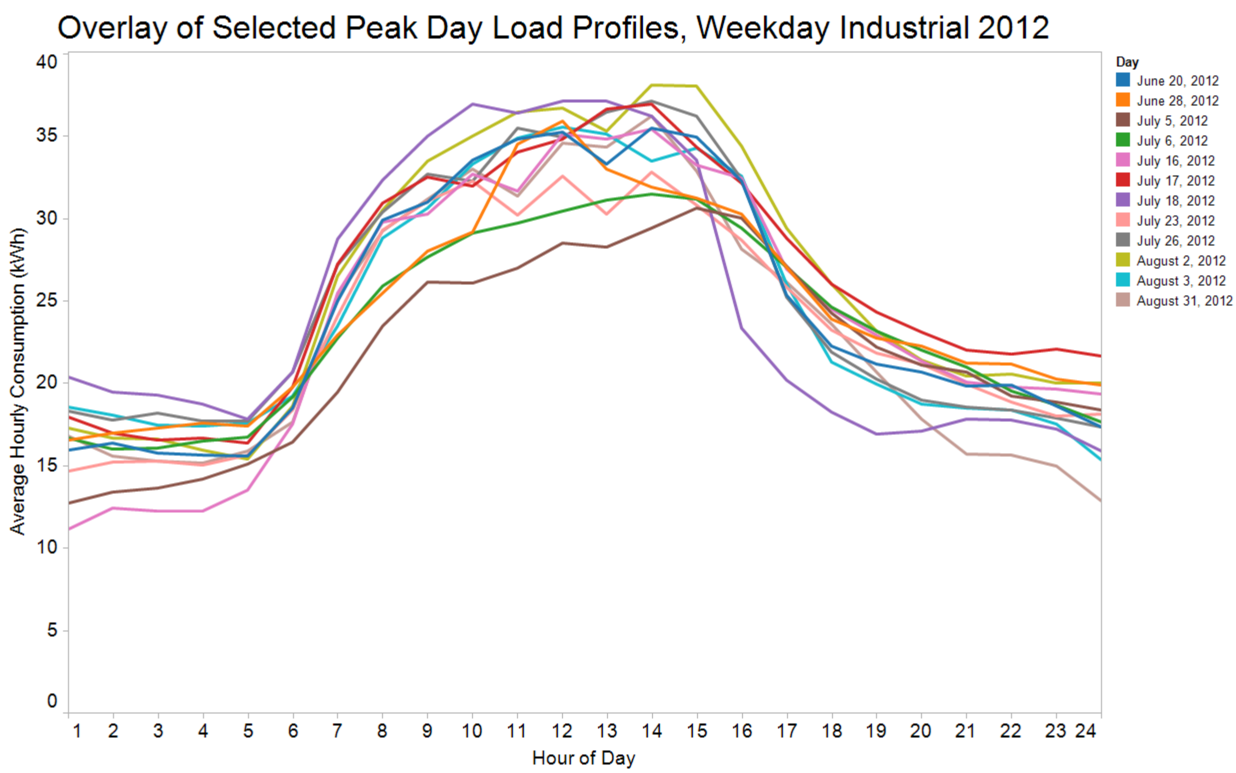


Figure 62. Overlay of Peak Load Days - Industrial 2012

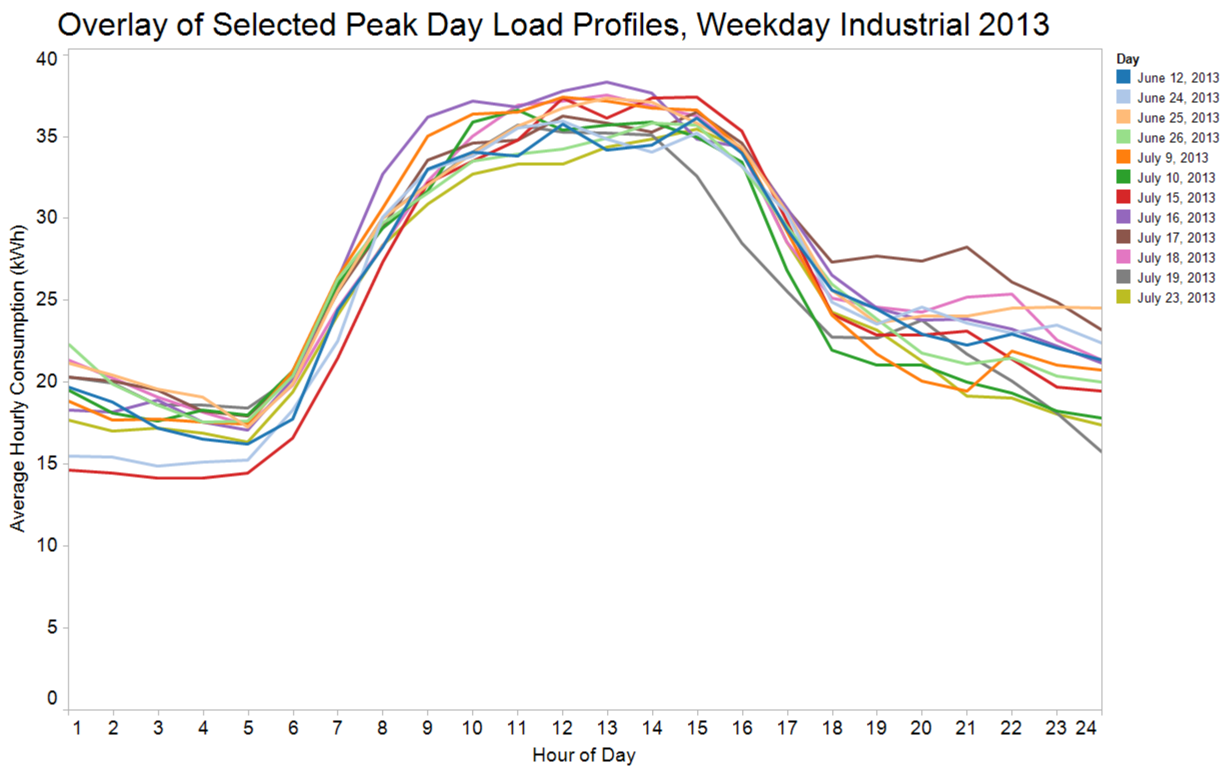


Figure 63. Overlay of Peak Load Days - Industrial 2013

Load Profile Data by Account Class for the Peak Day

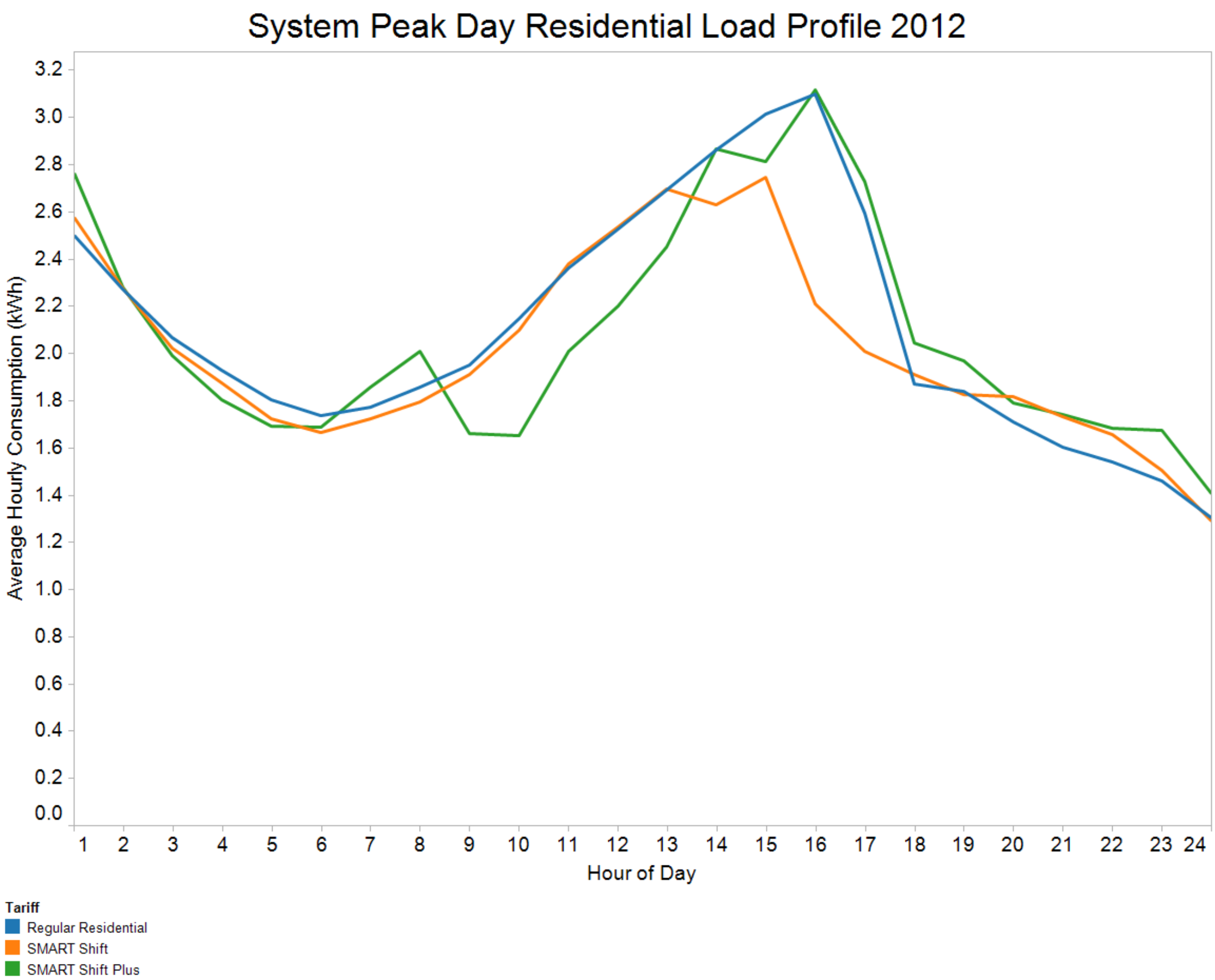


Figure 64. Residential Load Profile for System Peak Day - June 29, 2012

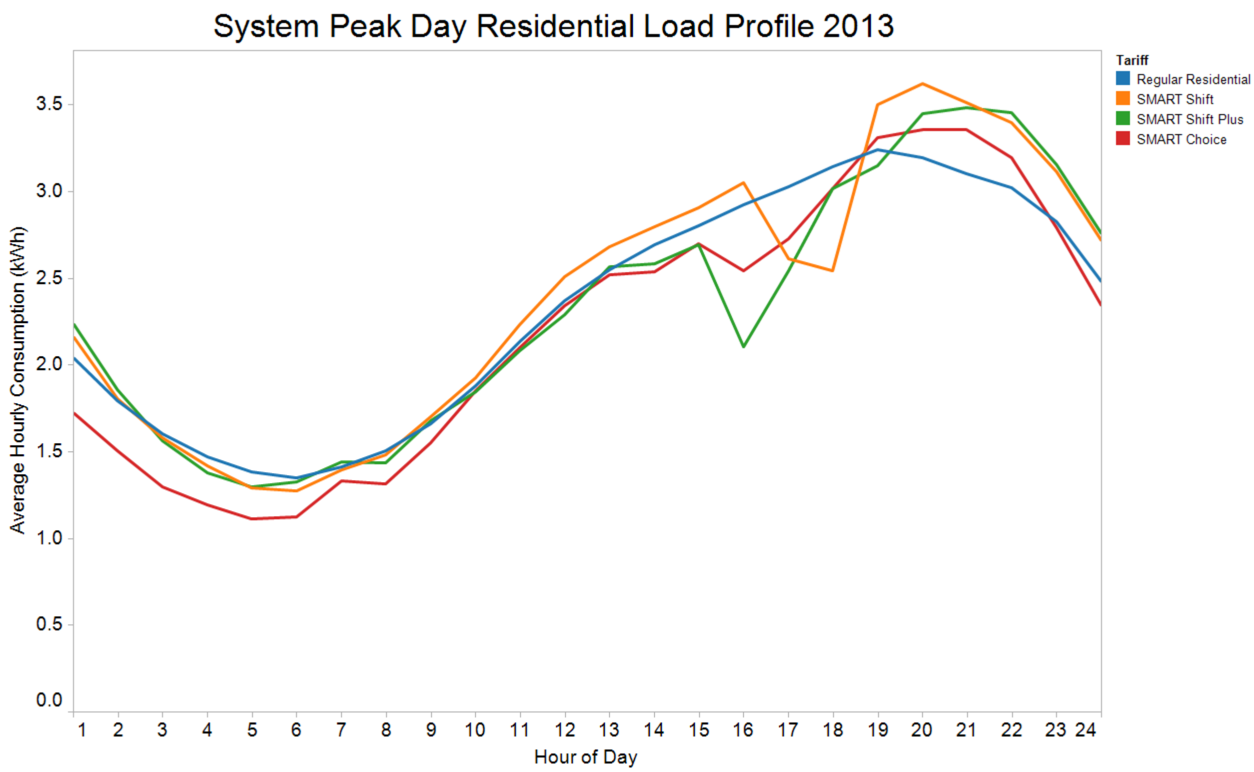


Figure 65. Residential Load Profile for System Peak Day - July 17, 2013

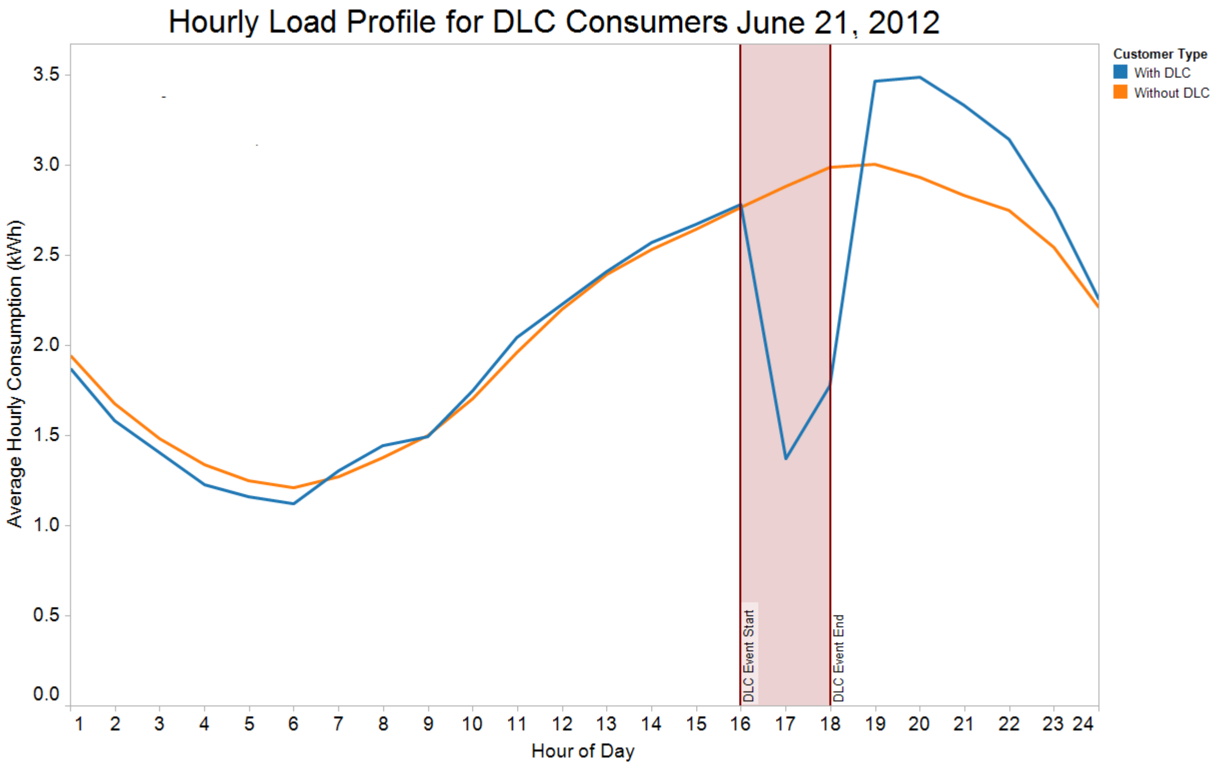


Figure 66. SMART Cooling DLC Event - June 21, 2012

6/21/2012 DLC Event Summary		
Average Event Load Reduction	1.338	kW / consumer
Peak Load Rebound	-0.605	kW / consumer
Event Energy	2.676	kWh / consumer
Rebound Energy	-2.422	kWh / consumer

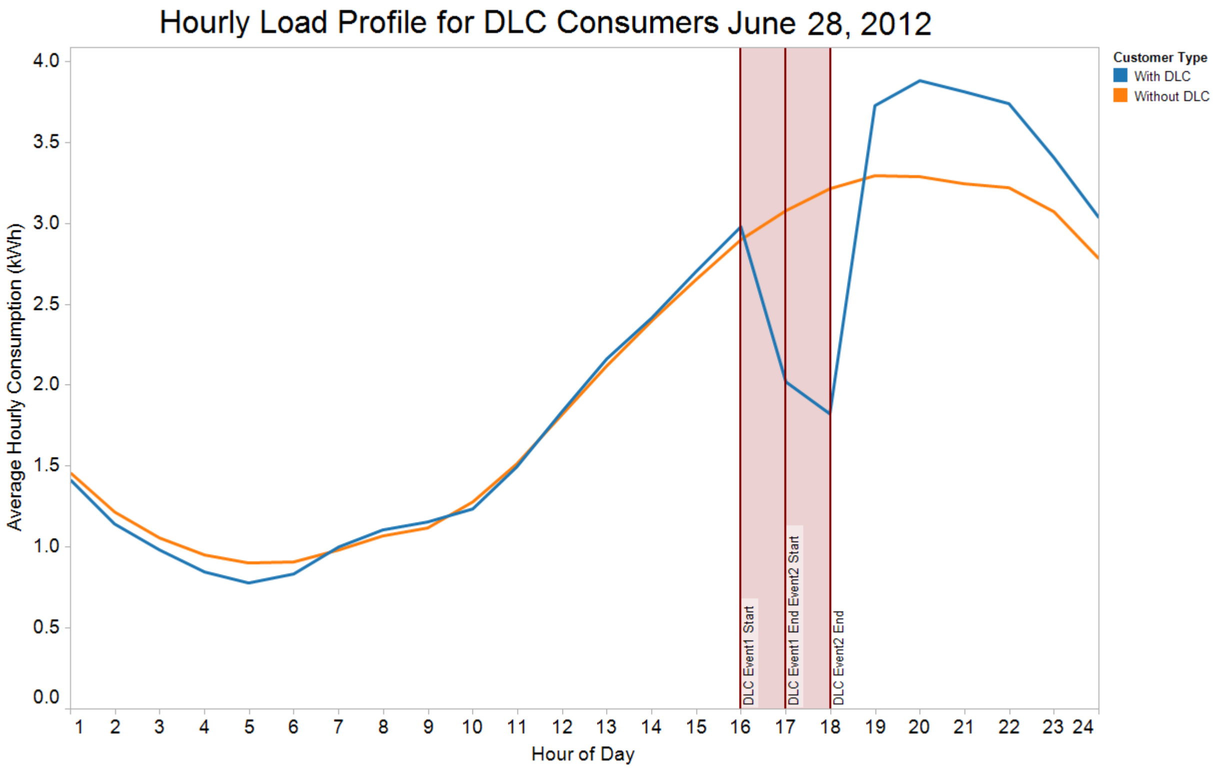


Figure 67. SMART Cooling DLC Event - June 28, 2012

6/28/2012 DLC Event Summary		
Average Event Load Reduction	1.173	kW / consumer
Peak Load Rebound	-0.696	kW / consumer
Event Energy	2.345	kWh / consumer
Rebound Energy	-3.283	kWh / consumer

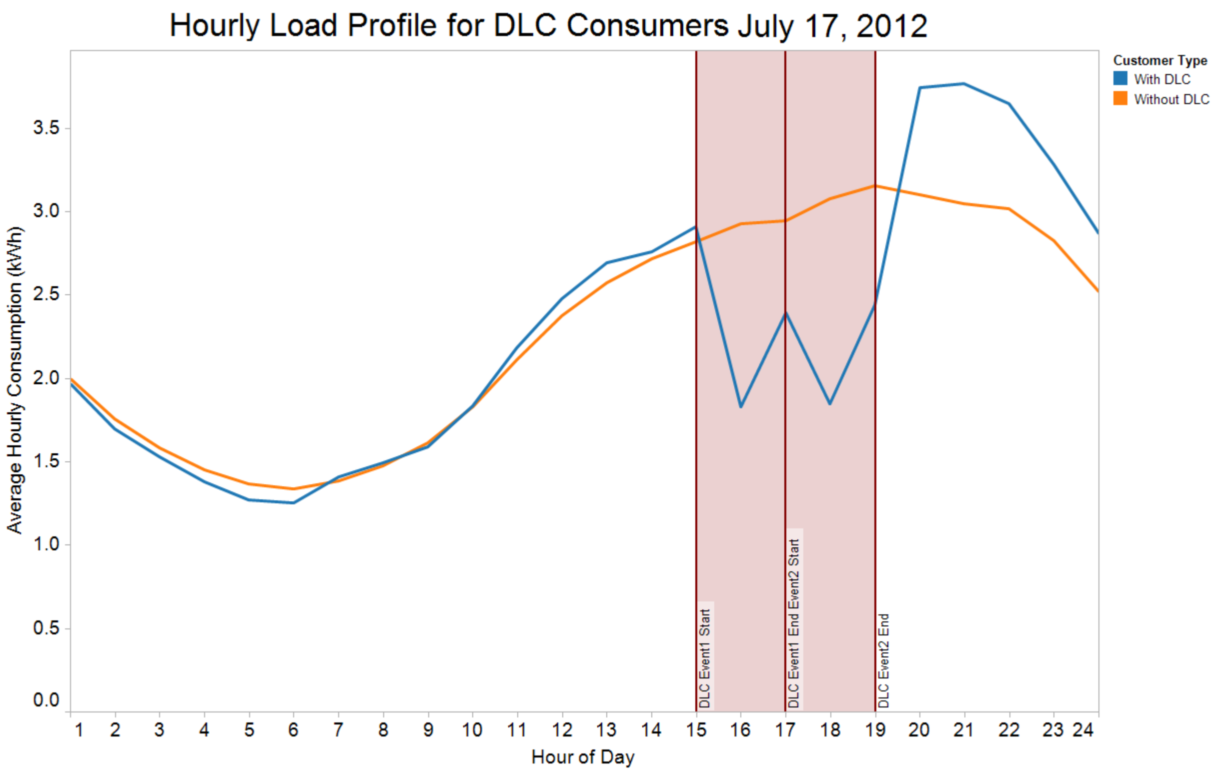


Figure 68. SMART Cooling DLC Event - July 17, 2012

7/17/2012 DLC Event Summary		
Average Event1 Load Reduction	0.814	kW / consumer
Average Event2 Load Reduction	0.956	kW / consumer
Peak Load Rebound	-0.748	kW / consumer
Event1 Energy	1.628	kWh / consumer
Event2 Energy	1.912	kWh / consumer
Rebound Energy	-2.916	kWh / consumer

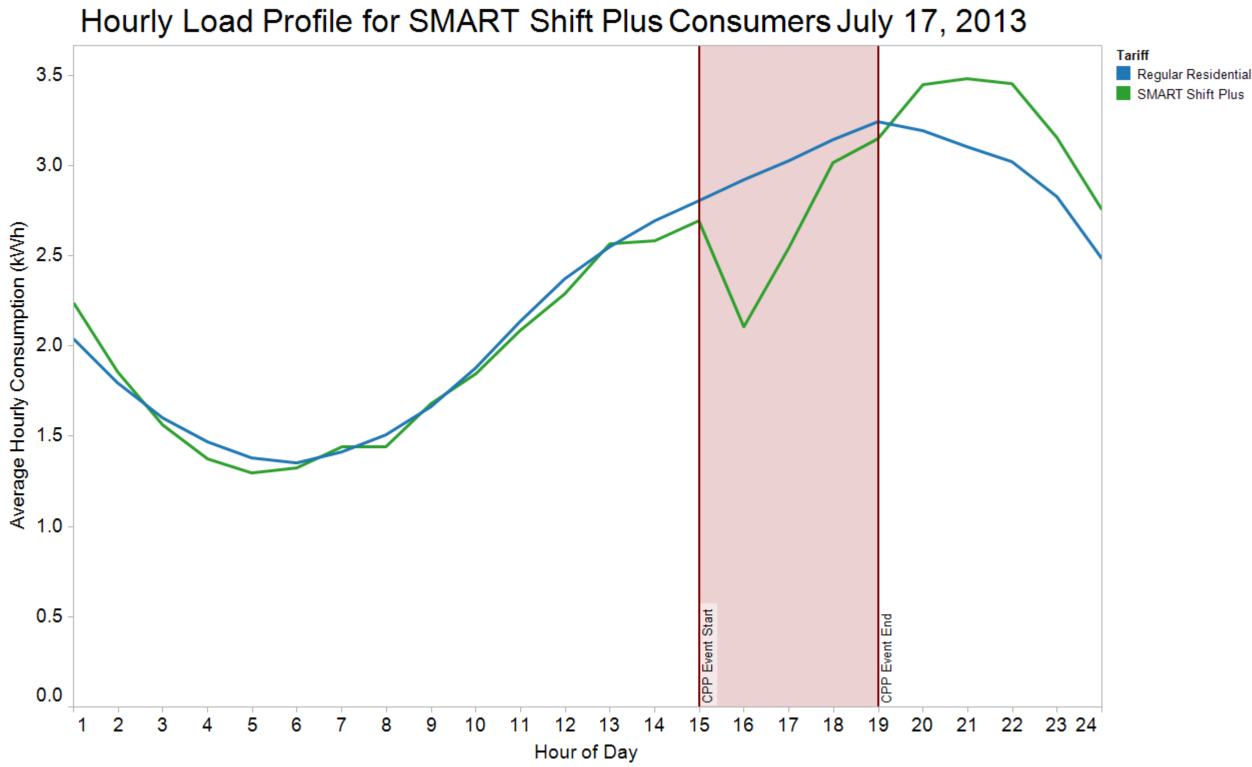


Figure 69. SMART Shift Plus CPP Event - July 17, 2013

7/17/2013 CPP Event Summary		
Average Event Load Reduction	0.338	kW / consumer
Peak Load Rebound	-0.484	kW / consumer
Event Energy	1.352	kWh / consumer
Rebound Energy	-1.919	kWh / consumer

3.6.4.5 Summary

The load and temperature curves for residential, commercial, and industrial consumers for the selected CPP and DLC event days demonstrate a fairly consistent response to the events. For both programs, the length of the events had a significant impact on the average reduction in KW over the event. For two hour events, consumers provided around 1.2-1.3 KW of average reduction across the duration of the event, while for four hour events, this number was reduced to ~0.6 to 0.8 KW. The variations can be attributed to temperature and other weather factors as well as variations in consumer behavior and the initial temperatures of the residences at the start of each event due to HVAC cycling randomness.

The post-event rebound behavior was also fairly consistent across both programs in terms of KW, and overall there was little or no net KWh savings. Some of this behavior can be attributed to the loss of diversity in the HVAC cycling across the population of participants, which was evidenced by the lower overall consumption for these consumers during the early morning hours following an event. Once the events ended, the majority of the HVAC turned at nearly the same time, their natural hysteresis resulted in the overall average indoor temperature across the population being lower than normal once the post-event cycling had occurred. Thus, there was overall fewer overnight cycles occurring for the population.

The consistency of the behavior across the DLC and CPP consumers was attributed to the method of response for both. In both cases, the HVAC thermostat set point was set back in response to the event. The default CPP adjustment was equal to the typical DLC setback, and the consistency of the CPP response indicated that consumers were not reprogramming the setback settings but left them on the default setting.

3.6.5 Project CO_2 Emissions (M07-CP)

This impact metric examines the impact to CO_2 emissions resulting from changes in consumer usage behaviors in the Project area. In principle, the reduction of energy use or shifting of energy use to different times of day had an impact on the CO_2 emitted by the generation fleet. This impact metric compares the impacts against account classes, such as residential, commercial, and industrial. Various consumer strata and demographic data were used to determine which programs had the most impact to CO_2 emissions.

3.6.5.1 Organization of Results

This metric presents the impact of Consumer Programs on CO_2 emissions by quantifying the difference in energy consumption from new tariffs and technologies versus traditional residential flat-rate electric tariffs.

CO_2 Emissions Avoided by Month

This metric is displayed as a graph that shows the CO_2 emissions avoided by the consumers on the experimental for SMART Shift, SMART Shift Plus, and SMART Choice.

3.6.5.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Differences in CO_2 emissions per kWh due to shifting load from peak to off peak times are insignificant compared to the total CO_2 avoided through kWh reductions.
- CO_2: 0.00068956 tons/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Regi*on

3.6.5.3 Calculation Approach

Load reduction was calculated as the difference between usage for consumers on an experimental tariff versus usage of similar consumers on the standard residential tariff. These results are reported for consumers grouped by demographic and by stratum.

Load reduction was translated into CO_2 reduction using typical generation emissions factors.

The following queries and methods were used to generate the analysis:

- Energy consumption reductions per month
- Consumer class
- Consumer stratum
- Consumer demographic
- Tariff

The calculation was done by subtracting the average billed hourly usage for residential consumers not on the standard residential tariff from average billed hourly usage for residential consumers on the standard residential tariff for the same month, consumer class, consumer stratum, and consumer demographic.

Tons of CO_2 avoided per month, consumer stratum, consumer demographic, and tariff for consumer programs were calculated by multiplying the amount of CO_2 emissions avoided by the ratio of all consumers on a circuit to residential consumers not on the standard residential tariff.

3.6.5.4 Data Collection Results

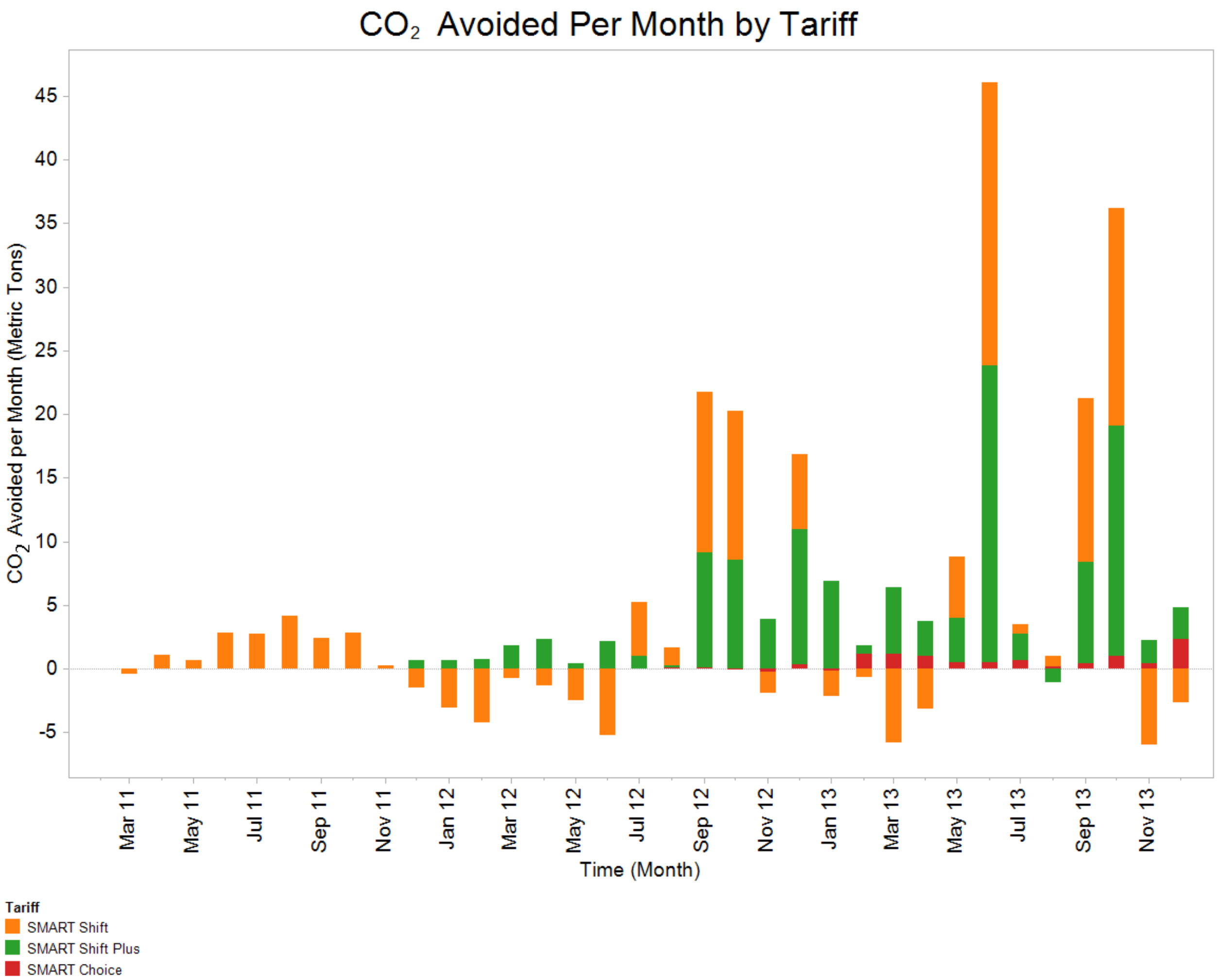


Figure 70. Monthly CO_2 Emissions Avoided or Contributed by Three Tariffs

3.6.5.5 Summary

Since the TOD and TOD/CPP consumers used less overall energy than the consumers on the standard residential tariff they contributed to lower CO_2 emissions. Based on this simple comparison, consumer programs resulted in nearly 196 metric tons of CO_2 reductions during the Project time period. Establishing pre-tariff baselines for the TOD/CPP and TOD consumers allowed for a more accurate accounting of these reductions.

From the data available, it appears that the TOD tariff encouraged conservation in the summer months yet may have led to slightly increased energy consumption (and thereby CO_2 emission) in the winter when the rates are lower than the standard tariff. Both TOD and CPP tariffs showed small values of CO_2 reduction when they were first introduced and larger values of reduction after they had been in place for several months. This was most likely due to a combination of an increase in the number of consumers participating in each tariff along with changes in behavior as consumers gained a better understanding of how to adjust their usage patterns for maximum savings.

3.6.6 Project Pollutant Emissions (M08-CP)

This impact metric examines the potential impact on pollutant emissions resulting from changes in consumer usage behaviors. In principle, the reduction of energy use or shifting of energy use to different times of day had an impact on the pollutants emitted by the generation fleet. This impact metric compares the impacts against account classes, such as residential, commercial, and industrial in the Project area. Various consumer strata and demographic data were used to determine which programs had the most impact to pollutant emissions.

3.6.6.1 Organization of Results

This metric presents the impact of consumer programs on pollutant emissions by quantifying the difference in energy consumption from new tariffs and technologies against traditional flat-rate electric tariffs.

Pollutant emissions avoided by month

This metric is displayed as a graph that shows the pollutant emissions avoided by the consumers in the Project area on the experimental tariffs SMART Shift, SMART Shift Plus, and SMART Choice.

3.6.6.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Differences in pollutant emissions per kWh due to shifting load from peak to off peak times are insignificant compared to the total pollutant emissions avoided through kWh reductions.
- SOx: 0.00263084 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- NOx: 0.00117934 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- $PM_{2.5}$: 0.001 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*

3.6.6.3 Calculation Approach

Load reduction due to consumer programs was calculated as the difference between usage for consumers on an experimental tariff versus usage of similar consumers on the standard residential tariff. These results are reported by tariff by month.

Load reduction was then translated into pollutant reduction using typical generation emissions factors.

The following queries and methods were used to generate the metric analysis:

- Energy consumption reductions per month, consumer class, consumer stratum, consumer demographic, and tariff based on consumer programs were calculated by subtracting the average billed hourly usage for residential consumers not on the standard residential tariff from average billed hourly usage for residential consumers on the standard residential tariff for the same month, consumer class, consumer stratum, and consumer demographic.

- Kilograms of NO_X avoided per month, consumer stratum, consumer demographic, and tariff for consumer programs were calculated by multiplying the energy consumption reductions by 0.00117934 (kilograms per kWh).
- Kilograms of $PM_{2.5}$ avoided per month, consumer stratum, consumer demographic, and tariff for consumer programs were calculated by multiplying the energy consumption reductions by 0.001 (kilograms per kWh).
- Kilograms of SO_X avoided per month, consumer stratum, consumer demographic, and tariff for consumer programs were calculated by multiplying the energy consumption reductions by 0.00263084 (kilograms per kWh).

3.6.6.4 Data Collection Results

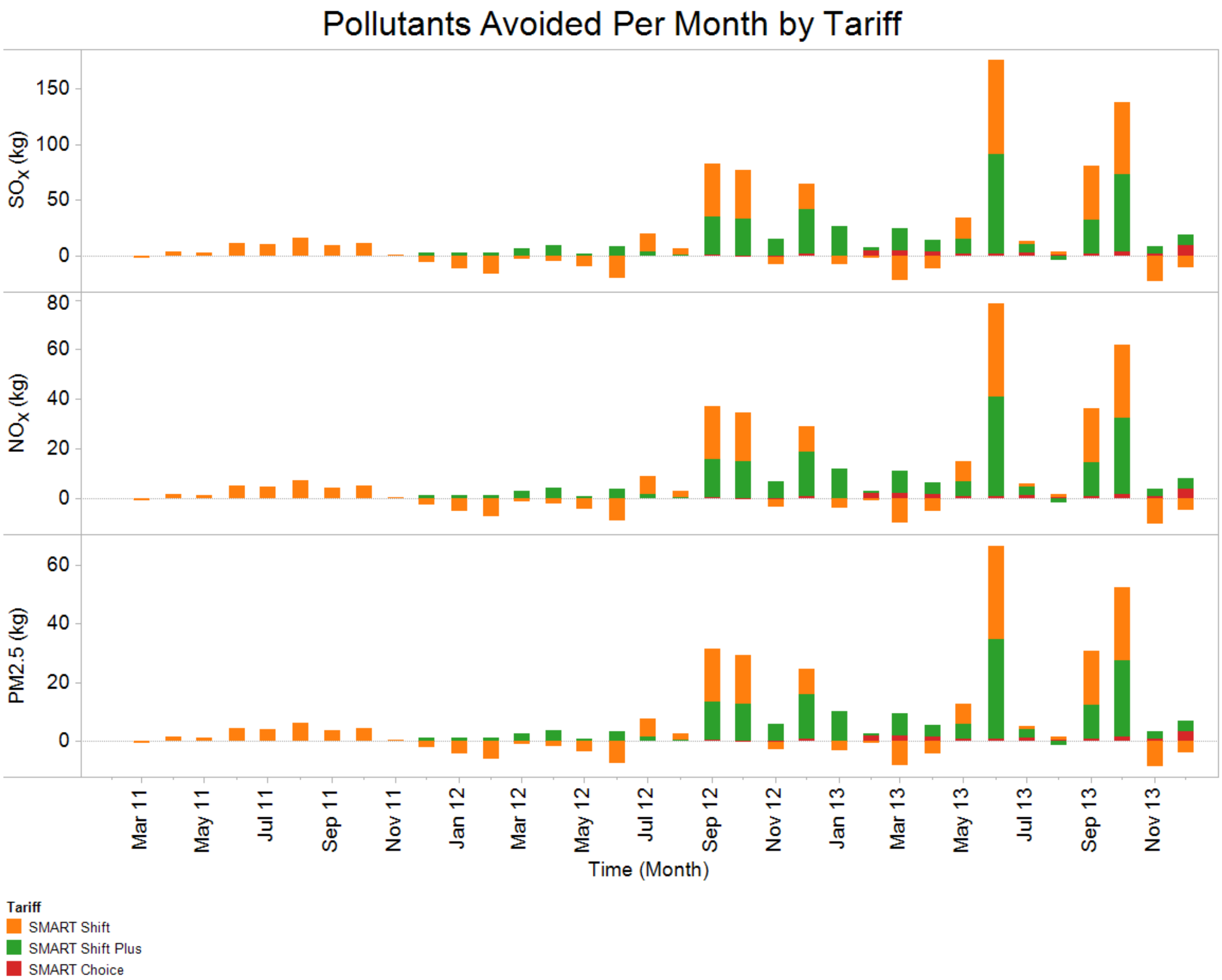


Figure 71. Monthly Pollutant Emissions Avoided or Contributed by Three Tariffs

3.6.6.5 Summary

NO_X and SO_X emissions reductions behaved the same as the CO_2 emissions reductions. Both the TOD and TOD/CPP consumers consumed less overall energy. Based on a comparison of these consumers' consumption to that of standard residential consumers, consumer programs resulted in approximately 749 kg of SO_X, 335 kg of NO_X, and 284 kg of $PM_{2.5}$ reductions during the Project time period. The attribution of these reductions to the particular tariff was verified by baseline analysis for both consumer populations.

From the data available, the TOD tariff encouraged conservation in the summer months yet may have led to slightly increased energy consumption (and thereby pollutant emission) in the winter, when the rates were lower than the standard tariff. Both TOD and CPP tariffs showed small values of pollutant reduction when they were first introduced and larger values of reduction after they had been in place for several months. This reduction was most likely due to a combination of an increase in the number of consumers participating in each tariff along with changes in behavior as consumers gained a better understanding of how to adjust their usage patterns for maximum savings.

3.6.7 System CO_2 Emissions - System area (M09-CP)

This impact metric examines the potential impact to CO_2 emissions resulting from consumer usage behaviors in the System area. In principle, the reduction of energy use or shifting of energy use to different times of day should have an impact on the CO_2 emitted by the generation fleet. This impact metric compares the impacts against account classes, such as residential, commercial, and industrial. Various consumer strata and demographic data were used to determine which programs have the most impact to CO_2 emissions.

3.6.7.1 Organization of Results

This metric presents the impact of consumer programs on CO_2 emissions by quantifying the difference in energy consumption from new tariffs and technologies versus traditional flat-rate electric tariffs.

CO_2 Emissions Avoided by Month

This metric is displayed as a graph that shows the CO_2 emissions avoided by the consumers projected into the System area as if they were on the experimental tariffs SMART Shift, SMART Shift Plus, and SMART Choice.

3.6.7.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Consumer behavior changes due to program tariffs would be similar for consumers outside the Project area.
- CO_2: 0.00068956 tons/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Re*gion

3.6.7.3 Calculation Approach

The following queries and methods were used to generate results:
Load reduction was calculated as the difference between usage for consumers on an experimental tariff versus usage of similar consumers on the standard residential tariff. These results are reported for consumers grouped by demographic and by stratum.

Load reduction was translated into CO_2 reduction using typical generation emissions factors. This reduction was then extrapolated onto the System area based on the ratio of total circuit load between the Project and System areas.

Tons of CO_2 avoided per month, consumer stratum, consumer demographic, and tariff for Consumer Programs were calculated by multiplying the energy consumption reductions by 0.00068956 (tons per kWh).

3.6.7.4 Data Collection Results

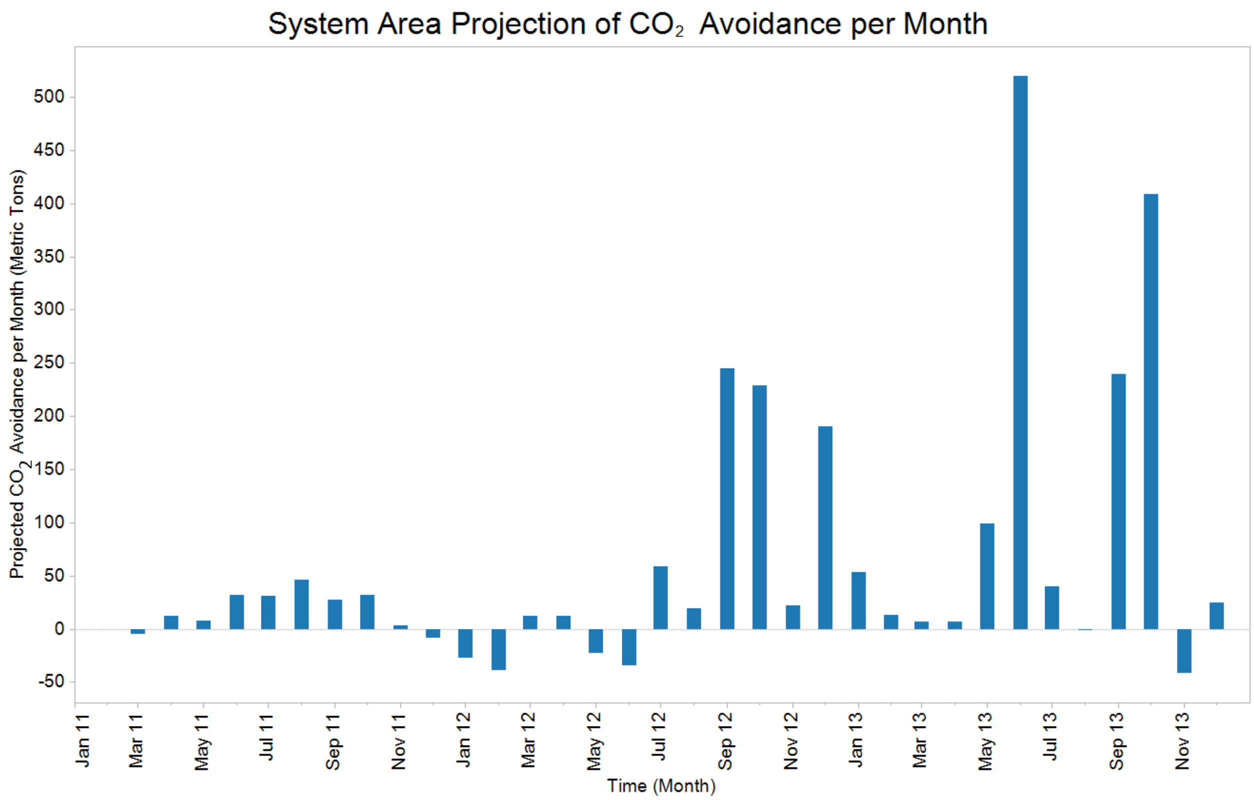


Figure 72. Monthly Projected Potential CO_2 Emissions Avoided or Contributed by Three Tariffs

3.6.7.5 Summary

The System area CO_2 reductions were an extrapolation of the Project area CO_2 reductions. This resulted in 2,212 metric tons of CO_2 avoided in the System area over this two year period. This extrapolation assumed that the current percentages of consumers on each tariff for the Project remained constant as they were extended to the entire System area. Additional reductions could be achieved by extending the tariffs to higher percentages of consumers although the result may not be linear.

From the data available, it appeared that the TOD tariff encouraged conservation in the summer months, yet may have led to slightly increased energy consumption (and thereby CO_2 emission) in the winter when the rates were lower than the standard tariff. Both TOD and CPP tariffs showed small values of CO_2 reduction when they were first introduced and larger values of reduction after they had been in place for several months. This was most likely due to a combination of an increase in the number of consumers participating in each tariff along with changes in behavior as consumers gained a better understanding of how to adjust their usage patterns for maximum savings.

3.6.8 System Pollutant Emissions (M10-CP)

This impact metric examines the potential impact on pollutant emissions if consumer programs were extended to the System area. In principle, the reduction of energy use or shifting of energy use to different times of day may have an impact on the pollutants emitted by the generation fleet. This impact metric compares the impacts against account classes, such as residential, commercial, and industrial in the system area. Various consumer strata and demographic data were used to determine which programs have the most impact to pollutant emissions.

3.6.8.1 Organization of Results

This metric presents the impact of consumer programs on pollutant emissions by quantifying the difference in energy consumption from new tariffs and technologies versus traditional flat-rate electric tariffs.

Pollutant emissions avoided by month

This metric is displayed as a graph that shows the pollutant emissions avoided by the consumers projected into the system area as if they were on the experimental tariffs SMART Shift, SMART Shift Plus, and SMART Choice.

3.6.8.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Consumer behavior changes due to program tariffs would be similar for consumers outside the Project area.
- SO_X: 0.00263084 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- NO_X: 0.00117934 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- $PM_{2.5}$: 0.001 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*

3.6.8.3 Calculation Approach

The following queries and methods were used to generate results:
Load reduction due to consumer programs was calculated as the difference between usage for consumers on an experimental tariff versus usage of similar consumers on the standard residential tariff.

Load reduction was translated into pollutant reduction using typical generation emissions factors, and was extrapolated to the System area based on the ratio of total circuit load.

The following queries and methods were used to generate the analysis and graphs:

- Kilograms of NO_X per month, circuit, and consumer demographic that would be avoided if Consumer Programs were deployed throughout the System area were calculated by multiplying the kilograms of NO_X emissions avoided by the ratio of all consumers on a circuit to residential consumers not on the standard residential tariff.

- Kilograms of $PM_{2.5}$ per month, circuit, and consumer demographic that would be avoided if consumer programs were deployed throughout the System area. These were calculated by multiplying the kilograms of $PM_{2.5}$ emissions avoided by the ratio of all consumers on a circuit to residential consumers not on the standard residential tariff.
- Kilograms of SO_X per month, circuit, and consumer demographic that would be avoided if consumer programs were deployed throughout the System area. These were calculated by multiplying the kilograms of SO_X emissions avoided by the ratio of all consumers on a circuit to residential consumers not on the standard residential tariff.

3.6.8.4 Data Collection Results

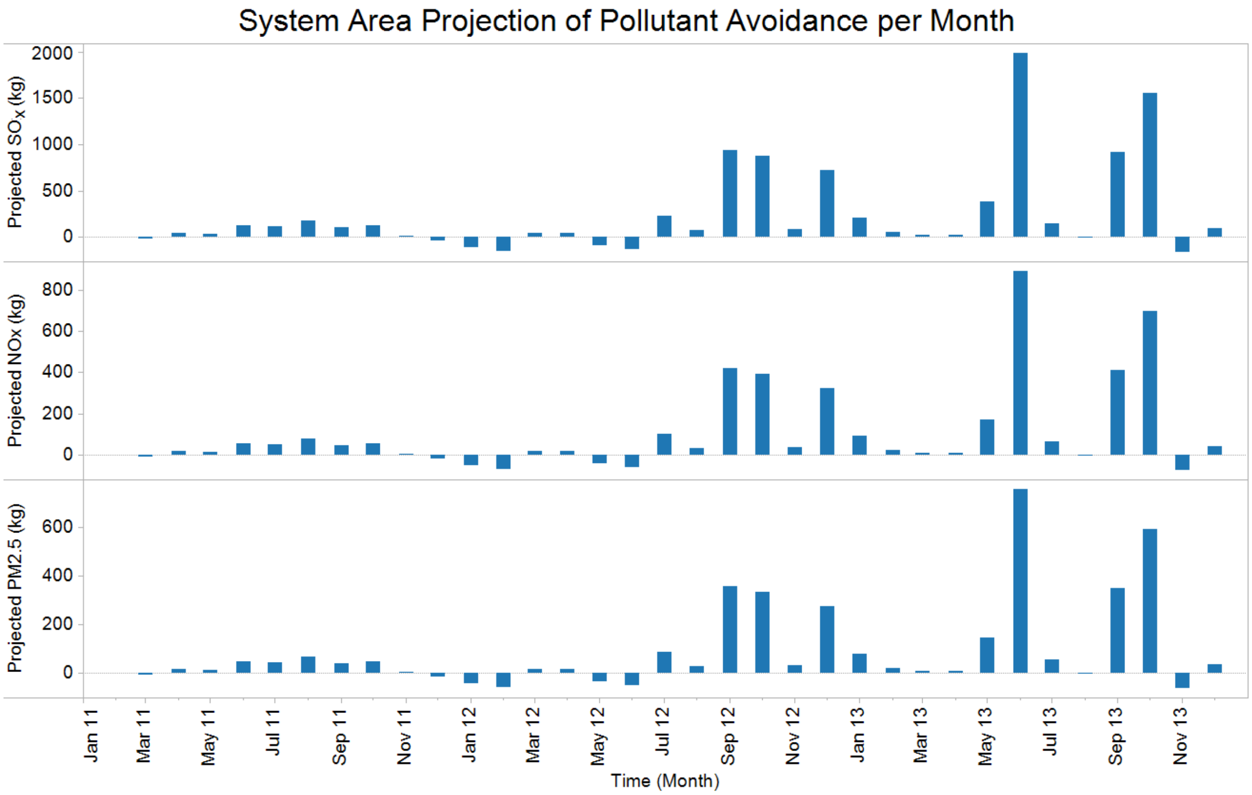


Figure 73. Monthly Projected Pollutant Emissions Avoided or Contributed by Three Experimental Tariffs

3.6.8.5 Summary

The system NO_X and SO_X reductions are an extrapolation of the Project area NO_X and SO_X reductions. This calculation resulted in approximately 8,442 kg of SO_X, 3,787 kg of NO_X, and 3,207 kg of $PM_{2.5}$ reductions in the System area during this two year period. This extrapolation assumed that the current percentages of consumers on each tariff for the Project remain constant as they are extended to the entire System area. Additional reductions can be achieved by extending the tariffs to higher percentages of consumers although the result may not be linear.

SMART Shift resulted in conservation during the summer months with mixed results in the winter months when the rates were lower than the standard tariff. SMART Shift Plus resulted in greater conservation on a per customer basis and SMART Choice had minimal overall impact.

The increase in the year one to year two total avoidances were directly related to the significant increase in participation for all the tariffs in year two.

3.6.9 Comparison of Average Energy and Demand Impacts

Below is a comprehensive comparison of the results of the Consumer Programs impacts.

Summer 2012	Premises	Average Hourly Per Premises Energy (kWh) Impact	Average Per Premises Demand (kW) Impact
SMART Shift	877	-0.3	-0.3
SMART Shift Plus	108	-0.1	-0.2
SMART Cooling Events	898	-1.2	-1.5
eVIEW	318	-0.1	-0.2

Summer 2013	Premises	Average Hourly Per Premises Energy (kWh) Impact	Average Per Premises Demand (kW) Impact
SMART Shift	1848	-0.1	-0.2
SMART Shift Plus	619	-0.2	-0.3
SMART Shift Plus/CPP Events	619	-0.6	-0.7
SMART Cooling Events	1966	-1.1	-1.2
SMART Choice	217	-0.1	-0.2
eVIEW	1573	0.1	0.0

- Premises counts are for analysis purposes only and include those premises that were active in the tariff/program from June 1 to September 30 of the analysis year and are not representative of the total enrollment in these programs
- During high-cost hours for tariff-based consumer programs or event hours for event-based consumer programs
- Excludes SMART Cooling Event Dates
- Excludes SMART Shift impacts on those SMART Shift premises that also have SMART Cooling
- SMART Shift/Standard Tariff Consumers
- Excludes SMART Shift impacts on those SMART Shift premises that also have eVIEW
- Excludes SMART Shift Plus CPP Event Dates

3.7 Consumer Programs Conclusions

The Project provided useful information about consumer programs linked to AMI-driven technologies. It demonstrated that programs can be successfully implemented, but significant changes to back-office IT systems and business processes were required. The results indicated that consumers would participate in programs when given adequate information and enabling technologies. Dedicated customer service representatives were essential to handle significant call volume and address concerns as a high priority. Some consumers were motivated to modify their energy usage patterns when provided with appropriate tools and the potential for savings on their electric bills. However, overall energy usage impacts from these programs were minimal.

The SMART Shift and SMART Shift Plus programs exhibited lower energy and demand impacts in 2013 than they did in 2012. A milder weather season in 2013, an increased number of participants in 2013, less program communication in 2013, or a combination of those factors may have contributed to the difference in 2013 results.

Consumers participating in the SMART Cooling Program significantly reduced their demand during thermostat adjustment events. This reduction resulted in approximately twice the demand reductions achieved by those in SMART Shift Plus Program equivalent Critical Peak Pricing events. Thermostat adjustment provided the largest demand reduction for approximately the first hour. As temperatures in participants' homes began reaching the new thermostat set-points, HVAC operations resumed. This indicated that proper timing of the events and thermostat adjustment to coincide with AEP Ohio's peak load conditions was a critical component for program success.

Overall, program participants were satisfied with their experience. Customer satisfaction ratings ranged 67 to 76 percent, depending on the program. Program participants perceived an average savings of $20 per month on their summer electricity costs.

3.8 Lessons Learned

3.8.1 Technology

- Perform thorough testing of all equipment and software in collaboration with vendor suppliers to ensure its readiness for implementation with consumers.
- Engage internal resources to assist with field testing of new technology and equipment to get meaningful feedback that further evolves the programs.

3.8.2 Implementation

- Form close working relationships with vendors and partners from the beginning to ensure strong knowledge transfer, thus creating internal subject matter experts.
- Allow sufficient time in the project plan to ensure the technology and processes are tested and ready for public implementation to save time and costs and preserve positive consumer perceptions.
- Provide in-depth training for participating consumers to help them better understand how to use the equipment and what to expect prior to or at the time of installation.
- When developing and implementing this kind of new technology, be sure to provide in-depth communication and training to regulators, so they better understand the full extent and impact of the tariffs and riders being requested. This Project required regulatory approval for various tariffs associated with the consumer programs. AEP Ohio met with regulators throughout the program onset to review tariff designs, potential participant impacts and overall program goals. Modifications to most of the programs resulted from these reviews.
- Carefully plan time-sensitive pieces of the proposed tariffs and riders to ensure coordinated timing with the actual rollout of technology and equipment to consumers.

3.8.3 Operations

- Consumer service groups and representatives must be fully trained and ready to support consumer inquiries immediately upon installation of new equipment and implementation of programs. An example of specialized training is ping/poll functionality.
- A focus on tight communication between the various impacted areas is necessary to ensure readiness for upcoming called events and pricing.
- The scope and depth of this new technology requires cooperation and communication across impacted functional teams.

4 DEMONSTRATED TECHNOLOGY – REAL-TIME PRICING WITH DOUBLE AUCTION

4.1 Purpose

The Real-Time Pricing with double auction (RTP_{da}) project was an experimental, collaborative research project between American Electric Power (AEP), AEP Ohio, Battelle, and Pacific Northwest National Laboratory (PNNL).

Branded as SMART Choice^{SM}, the RTP_{da} program offered participating consumers an opportunity to take advantage of variable electric prices over the course of a billing cycle. The RTP_{da} consumer program gave the electricity consumer choices to effectively manage their own power usage in a more intelligent and informed manner. The program offered a complete demand response system that collected real-time market prices, so consumers could self-manage their power usage based on market price and comfort settings they controlled on their thermostats.

Throughout the operations phase of the project, RTP_{da} experiments were performed and analysis was conducted to assess the impacts and effectiveness of the research project based on the following objectives:

- Identify energy and demand changes.
- Determine benefits for both consumer and utility.
- Determine ability to manage distribution circuit load during congestion events.
- Determine technical and operational feasibility of a large scale deployment.
- Document lessons learned, technical and operational gaps, and overall consumer experience and satisfaction.

4.2 Technology

The RTP_{da} program was a complex combination of several internal and external systems and data sources, many of which were linked together for the first time. The interdependent data flow between devices and systems was critical for RTP_{da} to function properly.

RTP_{da} participation was predicated on the consumer having an AMI meter. In addition, consumers were given two pieces of hardware – a Home Energy Manager (HEM) and an enhanced Programmable Communicating Thermostat (ePCT). The HEM was the central premises controller that contained the integral logic that allowed RTP_{da} to function properly.

4.2.1 Home Energy Manager (HEM)

The HEM was a customized piece of hardware that communicated with the following:

- AMI meter at the consumer's home
- ePCT
- Smart Grid Dispatch (SGD) system at AEP's operations center

The HEM monitored and controlled the ePCT within the home based on settings the consumer selected.

To ensure security, the HEM used Secure Sockets Layer (SSL) encrypted communications to send information to and from the SGD application via a cellular network. To further enhance security, a unique security certificate for each HEM was created. This security certificate was verified against the list of valid certificates and against the list of certificates that had been revoked before any communication took place.

4.2.2 Enhanced Programmable Communicating Thermostat (ePCT)

The customized ePCT was controlled by the HEM, provided real-time control of the HVAC temperature setting, and acted as the interface between the HEM and the consumer. The ePCT display provided the consumer with the estimated price for electricity, in $/kWh, for the 5-minute interval.

4.2.3 Real Time Pricing Integration Layer

The Real-Time Pricing Integration Layer (RTPi) was critical to all RTP_{da} functions (see figure below). The RTPi was a complex platform used to route data between back office applications, including Meter Data Management (MDM), AEP Cost Engine (ACE), and SGD.

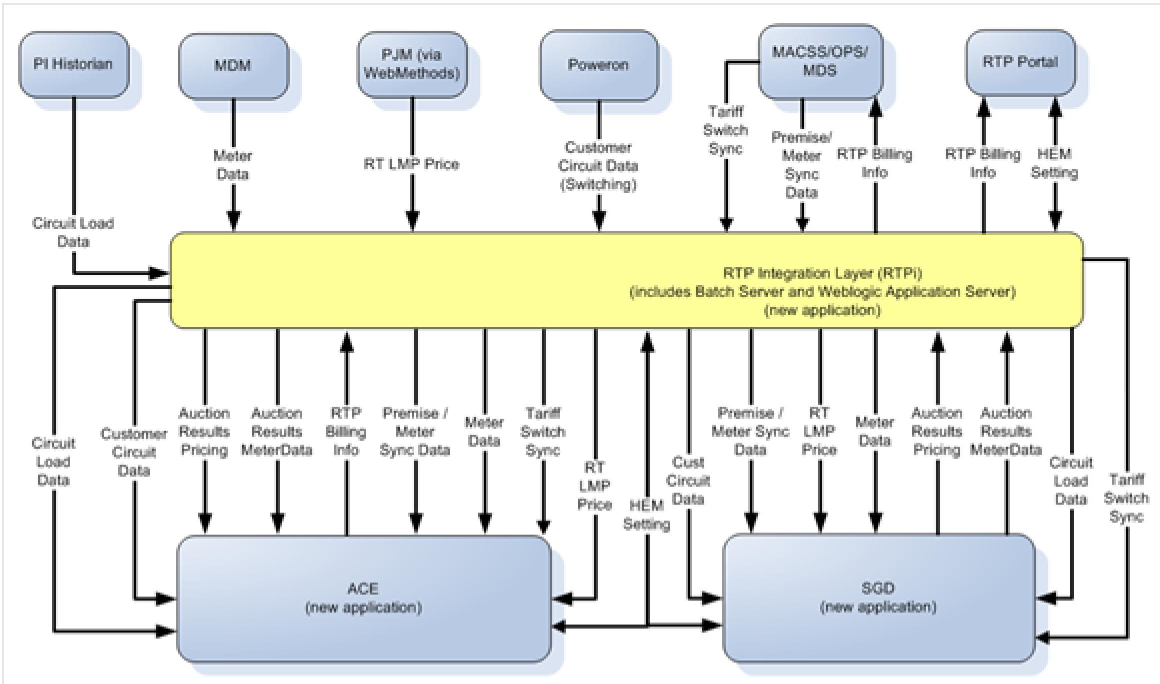


Figure 74. RTPi

4.2.4 Smart Grid Dispatch

The Smart Grid Dispatch (SGD) subsystem functioned as the primary interface between the HEM and AEP's back office systems via the RTPi. The SGD managed the auction process for the markets within the RTP_{da} program.

For the RTP_{da} program, consumers who were served from one of four AEP Ohio distribution circuits within the Project area were eligible to participate. Each of the four distribution circuits was considered a separate market; the four individual markets ran simultaneously. The SGD managed the electricity market for each distribution circuit.

4.2.4.1 Performance Monitoring and Control User Interface

The Performance Monitoring and Control (PMC) application was the utility interface into the SGD. The PMC allowed the authorized utility operator to adjust system settings as well as view pertinent real-time data. The figure below illustrates the home page of the PMC and available features.

Figure 75. PMC Home Page

PMC Functionality

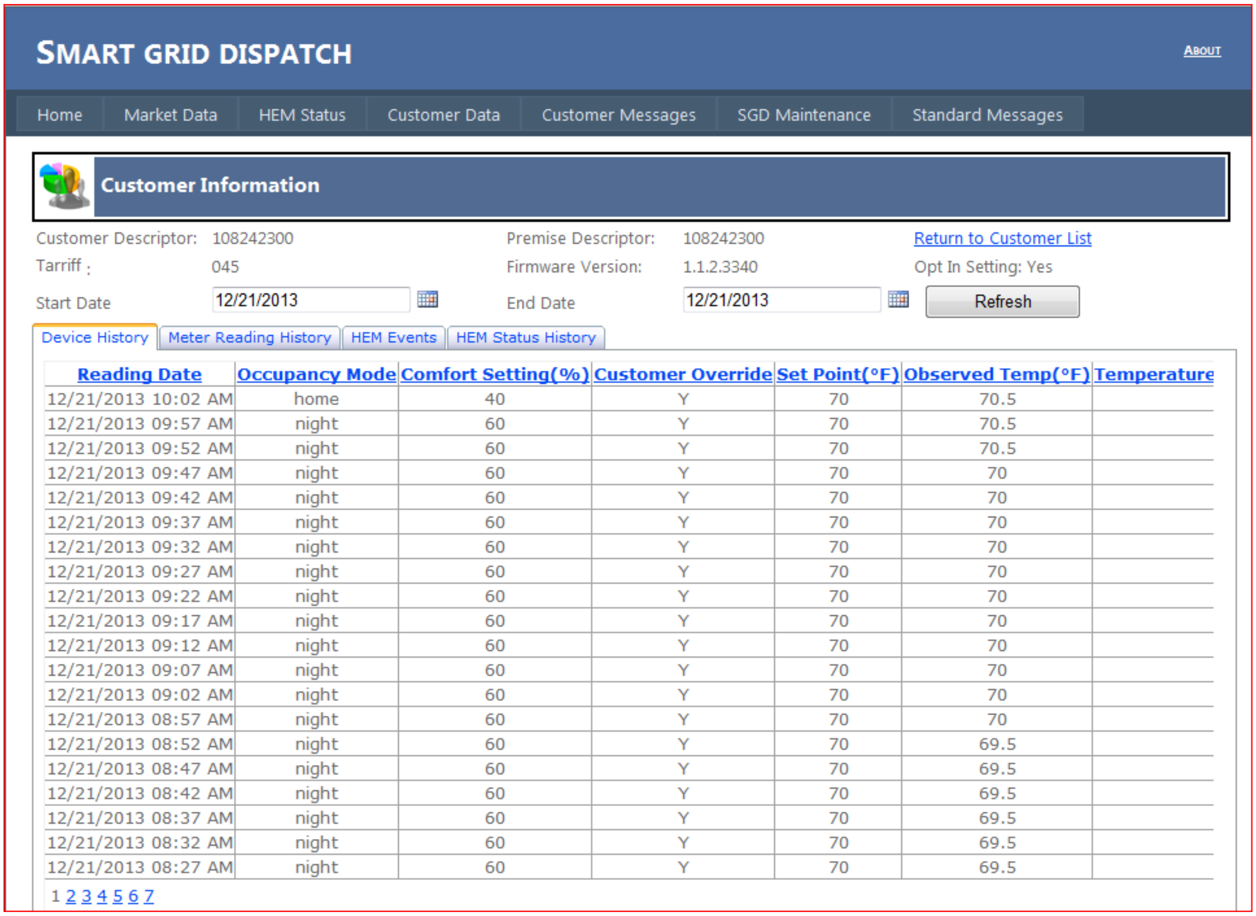
The Market Data function provided a view of historical cleared price data for each distribution circuit presented in graphical form. The operator could click on any point on the graph and view the supply and demand curves for a particular 5-minute interval.

The HEM Status function allowed authorized operators to view the HEMs by status. Operators could also view HEM events for a particular date range. Examples of HEM events included loss of cellular communication and hardware events.

The Consumer Information function allowed the operator to view various pieces of information and data related to an RTP_{da} participant such as:

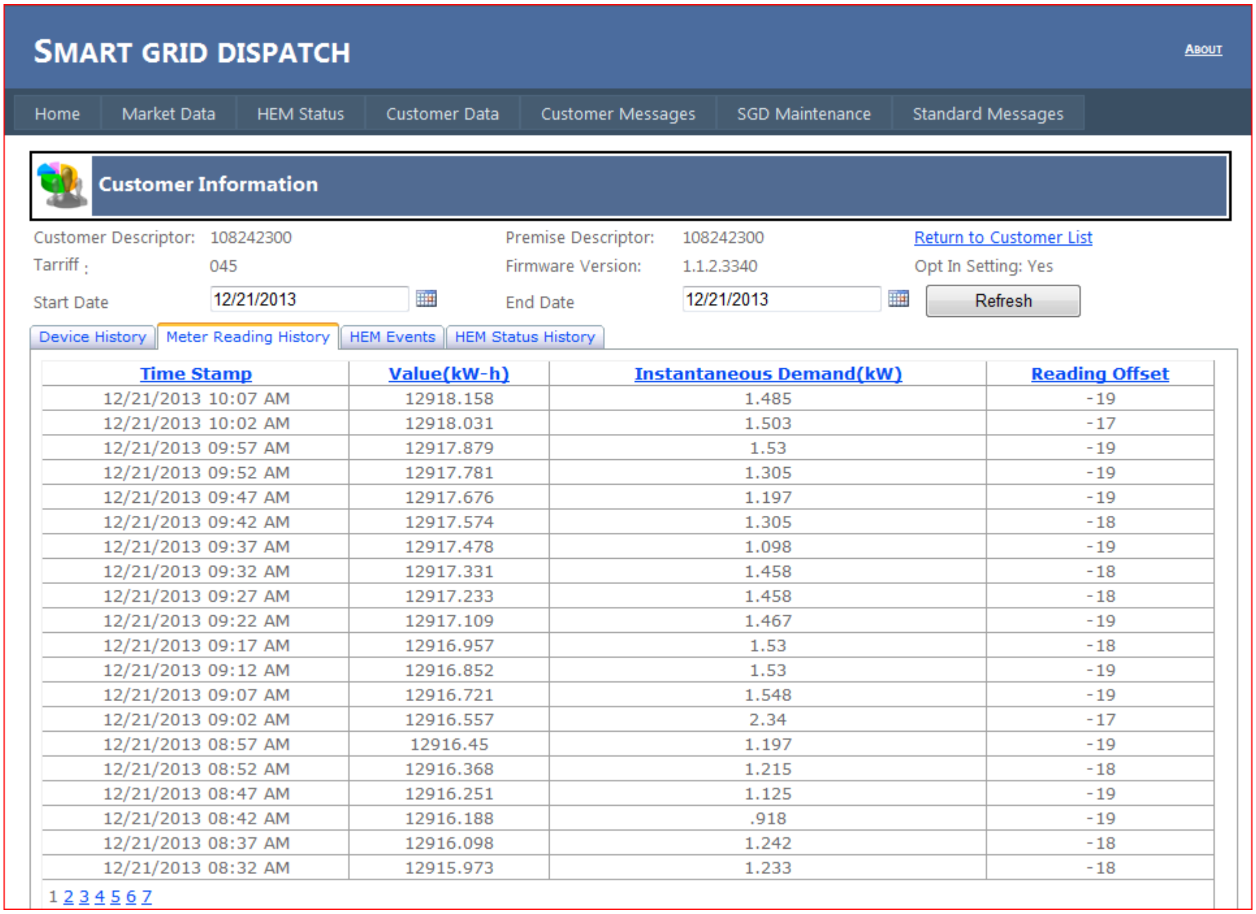
- Device history information including Occupancy Mode (home, away, or night), Comfort Setting (slider setting from 0 percent to 100 percent), thermostat set-point, whether or not the thermostat was in override mode, and the observed temperature in the home.
- Meter reading history information including meter register read, reading time stamp, and instantaneous demand reading in kW.
- HEM events and status history

The following figures show two views of the Consumer Information screen.



Reading Date	Occupancy Mode	Comfort Setting(%)	Customer Override	Set Point(°F)	Observed Temp(°F)	Temperature
12/21/2013 10:02 AM	home	40	Y	70	70.5	
12/21/2013 09:57 AM	night	60	Y	70	70.5	
12/21/2013 09:52 AM	night	60	Y	70	70.5	
12/21/2013 09:47 AM	night	60	Y	70	70	
12/21/2013 09:42 AM	night	60	Y	70	70	
12/21/2013 09:37 AM	night	60	Y	70	70	
12/21/2013 09:32 AM	night	60	Y	70	70	
12/21/2013 09:27 AM	night	60	Y	70	70	
12/21/2013 09:22 AM	night	60	Y	70	70	
12/21/2013 09:17 AM	night	60	Y	70	70	
12/21/2013 09:12 AM	night	60	Y	70	70	
12/21/2013 09:07 AM	night	60	Y	70	70	
12/21/2013 09:02 AM	night	60	Y	70	70	
12/21/2013 08:57 AM	night	60	Y	70	70	
12/21/2013 08:52 AM	night	60	Y	70	69.5	
12/21/2013 08:47 AM	night	60	Y	70	69.5	
12/21/2013 08:42 AM	night	60	Y	70	69.5	
12/21/2013 08:37 AM	night	60	Y	70	69.5	
12/21/2013 08:32 AM	night	60	Y	70	69.5	
12/21/2013 08:27 AM	night	60	Y	70	69.5	

Figure 76. Consumer Information - Device History Screen



Time Stamp	Value(kW-h)	Instantaneous Demand(kW)	Reading Offset
12/21/2013 10:07 AM	12918.158	1.485	-19
12/21/2013 10:02 AM	12918.031	1.503	-17
12/21/2013 09:57 AM	12917.879	1.53	-19
12/21/2013 09:52 AM	12917.781	1.305	-19
12/21/2013 09:47 AM	12917.676	1.197	-19
12/21/2013 09:42 AM	12917.574	1.305	-18
12/21/2013 09:37 AM	12917.478	1.098	-19
12/21/2013 09:32 AM	12917.331	1.458	-18
12/21/2013 09:27 AM	12917.233	1.458	-18
12/21/2013 09:22 AM	12917.109	1.467	-19
12/21/2013 09:17 AM	12916.957	1.53	-18
12/21/2013 09:12 AM	12916.852	1.53	-19
12/21/2013 09:07 AM	12916.721	1.548	-19
12/21/2013 09:02 AM	12916.557	2.34	-17
12/21/2013 08:57 AM	12916.45	1.197	-19
12/21/2013 08:52 AM	12916.368	1.215	-18
12/21/2013 08:47 AM	12916.251	1.125	-19
12/21/2013 08:42 AM	12916.188	.918	-19
12/21/2013 08:37 AM	12916.098	1.242	-18
12/21/2013 08:32 AM	12915.973	1.233	-18

Figure 77. Consumer Information – Meter Reading History Screen

The Consumer Messages and Standard Messages function allowed the utility to initiate messages to consumers, such as program welcome messages or notifications of upcoming congestion test events. Messages could be sent to the ePCTs of the entire RTP_da consumer group or to a subset of consumers.

The SGD Maintenance function provided access to the following features:

- Circuit Parameters
- Tariff Parameters
- Global Parameters

The circuit parameters included the rated circuit capacity, the circuit capacity percent, and retail cost multiplier (RCM). The circuit capacity percent was lowered during the RTP_{da} experiments to artificially induce congestion on distribution circuits. If the product of rated circuit capacity and circuit percent capacity resulted in a value lower than current circuit load, the circuit would go into congestion.

The RCM price ($44.25/MWH divided by the average PJM locational marginal price) was used to calculate the auction clearing price during non-congestion intervals (the locational marginal price multiplied by the RCM). The figure below shows an example of circuit parameters data.

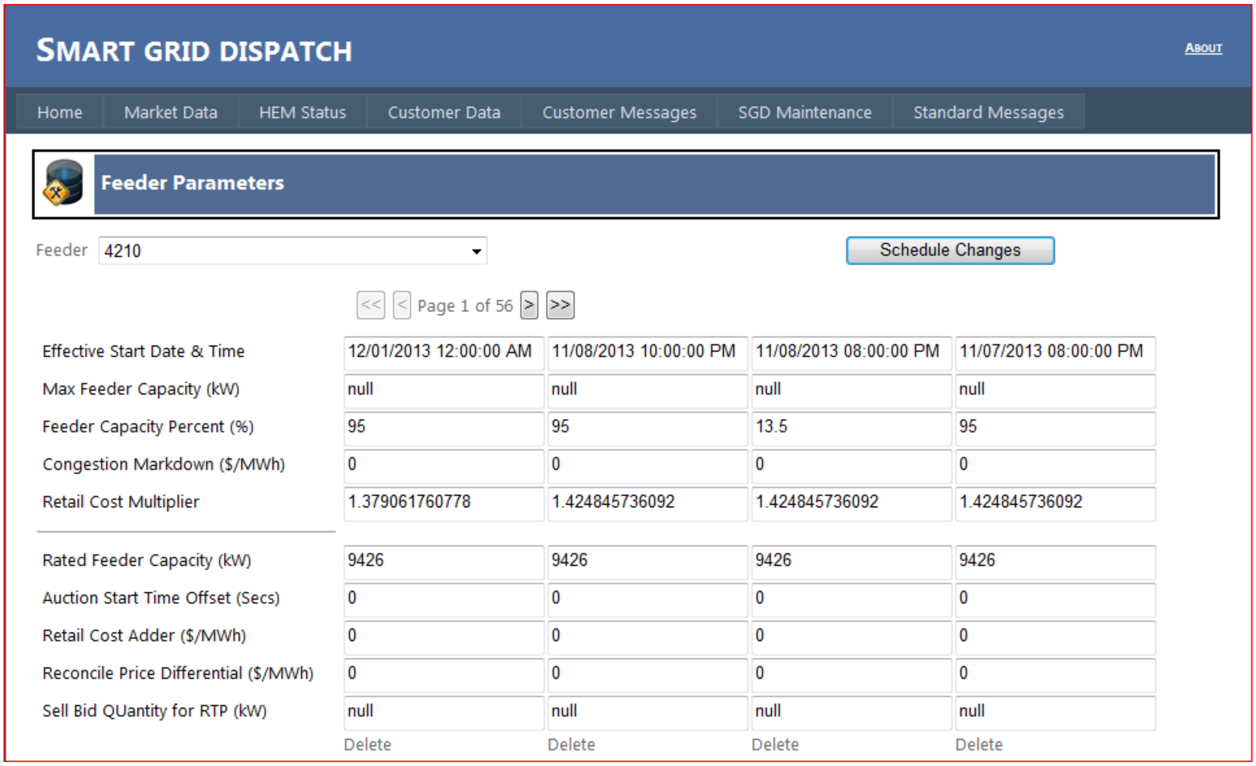


Figure 78. Circuit Parameters Screen

The Tariff Parameters function allowed the operator to define other riders and taxes that would apply to the consumer's bill; these would be added to the cleared price to determine an estimated cost of electricity. Updated riders and taxes were provided each month during the program and input into the Rider Tax field in the Tariff Parameters screen. The total (cleared price + rider tax) displayed on the consumer's thermostat every 5 minutes to give the consumer an estimate of the current cost of energy in $/kWh.

Security

Access to the PMC interface was restricted to authorized users. Windows-based authentication verified access to the application and Active Directory credentials established on the Domain Controller authenticated each user and determined the level of access.

There were three major categories of access – SGD Admin, SGD Support and SGD Field Rep. The roles are defined below:

- SGD Admin –a limited number of users were designated with this access level since an SGD Admin could change, add, and delete parameters within the PMC as well as decommission HEMs.
- SGD Support –Information Technology (IT) personnel were designated with this access level. SGD Support users could view information and control firmware changes in the HEMs.
- SGD Field Rep – provided read-only access to authorized employees who needed to view information in the PMC.

4.2.5 HEM Bids

The ePCT was configured by the consumer during installation to address their preference for comfort and economy. For each programmed period of operation, the homeowner specified their desired temperature (T_{Set}), their minimum and maximum temperature (T_{Min}, T_{Max}), and their preference for more comfort or more savings through the slider bar. Their slider selection was represented by the slope (*k*).

The HEM received the 5-minute market price of electricity from the SGD. The HEM kept track of an average price of electricity (P_{avg}). The average was calculated over the previous 24-hour period and was updated each interval to adjust for trends in pricing. The HEM then generated a bid for the associated location. The bid was based on complex algorithms that included but was not limited to the current market price and factors from the ePCT.

In the figure below, an elevated cleared price (P_{clear}) caused the ePCT to offset the set temperature in the house to $T_{Offset\ Set}$ from T_{Set}. Because the observed temperature in the house, $T_{Observed}$, was lower than the offset set temperature, the bid price (P_{bid}) from the HEM was lower than the cleared price. Because the bid price is less than the cleared price the HEM did not win the auction and the HVAC did not run during that interval.

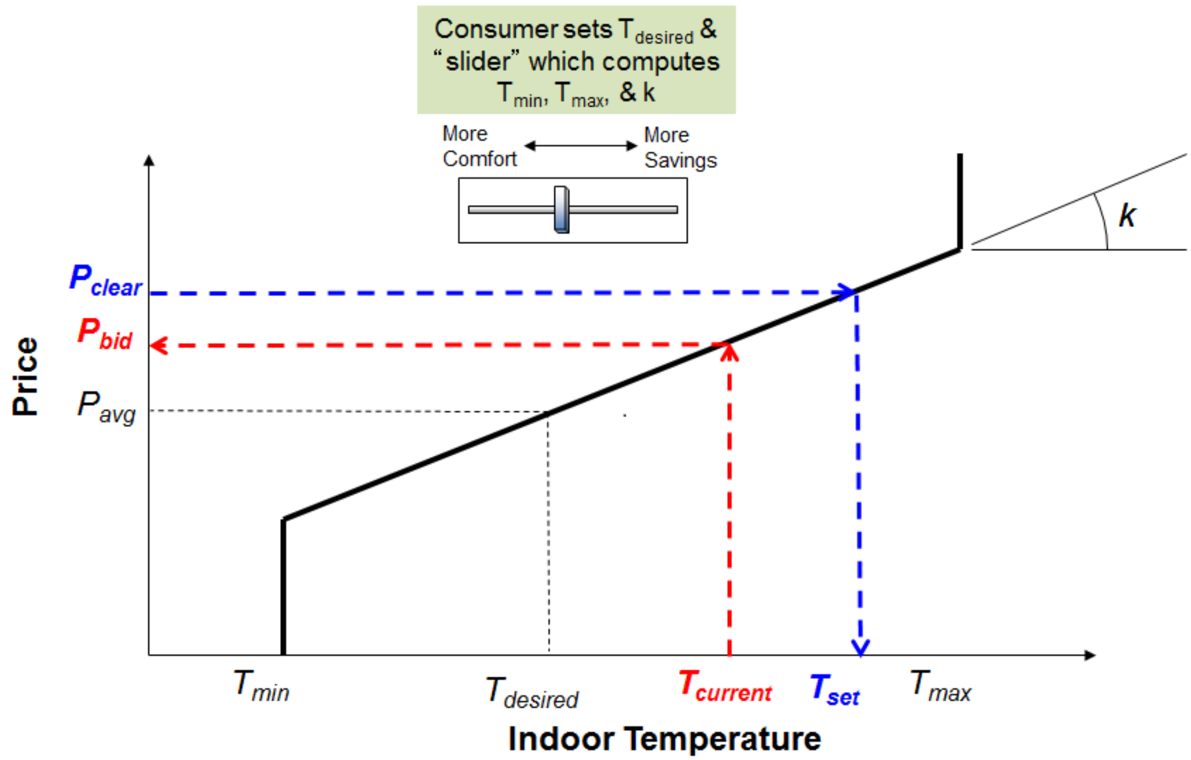


Figure 79. Bid Algorithm Calculation

4.2.6 Auction Process

The SGD aggregated the bids from all households on a given distribution circuit to develop the demand curve. The SGD also developed a supply curve which was a function of the real-time, 5-minute wholesale electricity price from PJM (the Regional Transmission Operator for this region), the RTP_{da} tariff, and other factors. A cleared price was established by the intersection of the two curves. This cleared price became the new prevailing retail real-time cost for electricity for the next 5-minute period. For illustrative purposes, the figure below shows the supply and demand curves which were generated by SGD using a complex set of algorithms.

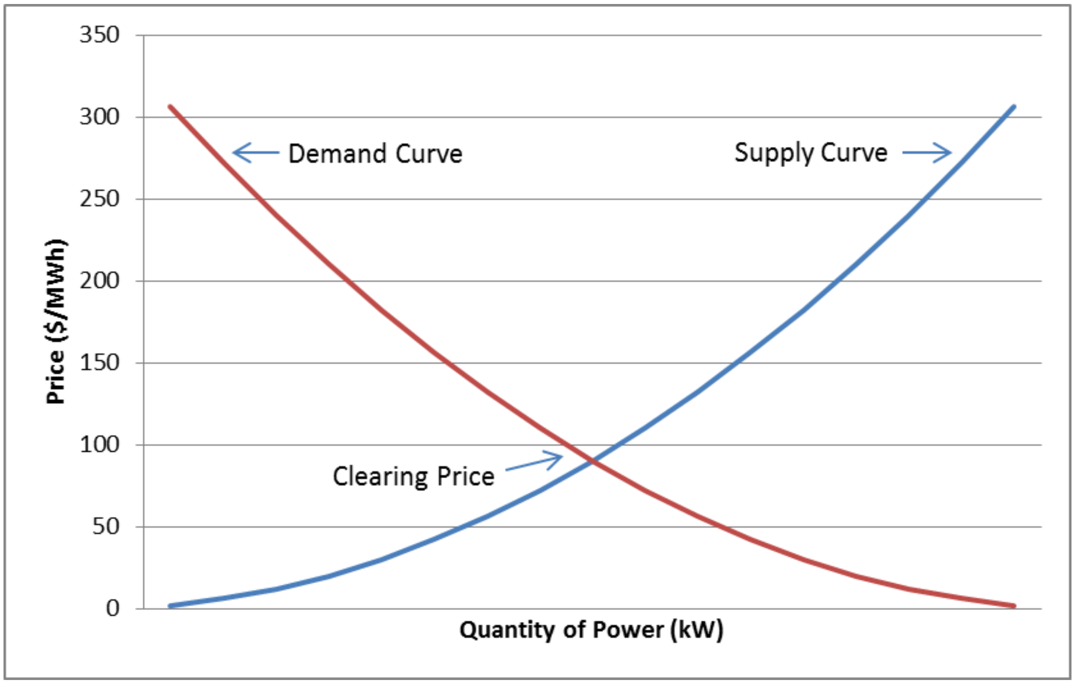


Figure 80. Illustrative Example of Supply Curve, Demand Curve and Cleared Price

The red curve represents the aggregated demand for power during the next increment of time (for example, 5 minutes) and the blue curve represents the supply side of power generation

Energy costs to the consumer increased under certain conditions:

- When demand on a circuit was high, causing it to exceed the circuit congestion limit.
- When the local market price of energy was high.

SGD managed 288 auctions each day for each circuit in the Project area; one for each 5-minute period during a 24-hour day.

Double-auction was a process where bids to buy power (from the HEM) and bids to sell power (from utility) were submitted independently.

4.2.7 AEP Cost Engine

The AEP Cost Engine (ACE) determined the energy cost portion of the consumer's electric bill. ACE used the following types of data to determine the energy cost, including but not limited to:

- Consumer circuit ID
- The 5-minute interval usage
- The associated 5-minute cleared price
- Consumer's bid
- Congestion status

ACE aggregated the cost of energy for each of the 5-minute periods of the billing cycle. ACE then computed any credits the consumer may have earned. There were two possible credits available to the consumer:

- RTP incentive – available when the consumer voluntarily reduced their usage during a congestion event.
- RTP rebate – to ensure the consumer paid no more per KWh than other non RTP_{da} consumers on the same circuit. This provision ensured revenue neutrality.

This data was sent to the AEP billing engine for inclusion on the consumer's monthly electric bill.

4.3 Approach and Implementation

4.3.1 Development and Testing

The SGD and the PMC were developed by Battelle, and the interfaces into the back office systems were developed by AEP.

Due to the complex nature of this experimental program, AEP Ohio elected to perform extensive testing of the RTP_{da} technology before introducing it to the general population of consumers. A fully functioning internal production evaluation environment was installed and AEP employees were invited to participate. This phase of evaluation was called the Virtual Operations Test (VOT), which allowed AEP to exercise the software with real consumers to ensure the technology operated as expected. After the successful VOT, the RTP_{da} program was rolled out to AEP Ohio consumers in the RTP_{da} Project area.

4.3.2 Consumer Outreach – Education, Marketing and Enrollment

$RTP_{da,}$ marketed as SMART Choice^{SM}, was included in the overall outreach plan for consumer programs. See the Consumer Programs chapter for additional information.

4.3.3 Customer Service

Customer service was a high priority for AEP Ohio. In addition to AEP Ohio's normal customer service, the following steps were taken to ensure RTP_{da} consumers were satisfied with the experimental program.

- Due to the complex nature of the RTP_{da} program, all enrollments and equipment installations were closely monitored.
- The primary contact for the RTP_{da} consumers was an outside organization (call center) that was specifically trained on the RTP_{da} operation. A dedicated toll free number was provided to all RTP_{da} consumers.
- AEP Ohio internal resources were available 24 x7 to answer any questions the call center could not resolve or inquiries from consumers who contacted AEP Ohio directly.
- A service representative was dispatched immediately to resolve any issues with the installed equipment, up to and including replacement of a device.

4.3.4 Consumer Survey Results

Consumers participating in the RTP_{da} offering were surveyed at selected points in time in order to quantify their overall satisfaction with the program. AEP contracted with an independent third party research firm for most of the consumer research reported here.

The final survey was administered to eligible RTP_{da} participants (HEM and ePCT installed and functional for a minimum of 30 days) as of 12/02/2013. Of the 256 eligible RTP_{da} consumers there were 154 completed surveys. The focus of this survey was to gauge participant final perceptions of the program.

Overall satisfaction with the RTP_{da} program was at 76.4 percent (total "satisfied" and "very satisfied" responses), the highest level measured over the three RTP_{da} participant surveys. This represents a slight gain from the 69.8 percent recorded in the SMART Choice Survey #2 and a return to the early satisfaction level of 73.8 percent noted in SMART Choice Survey #1.

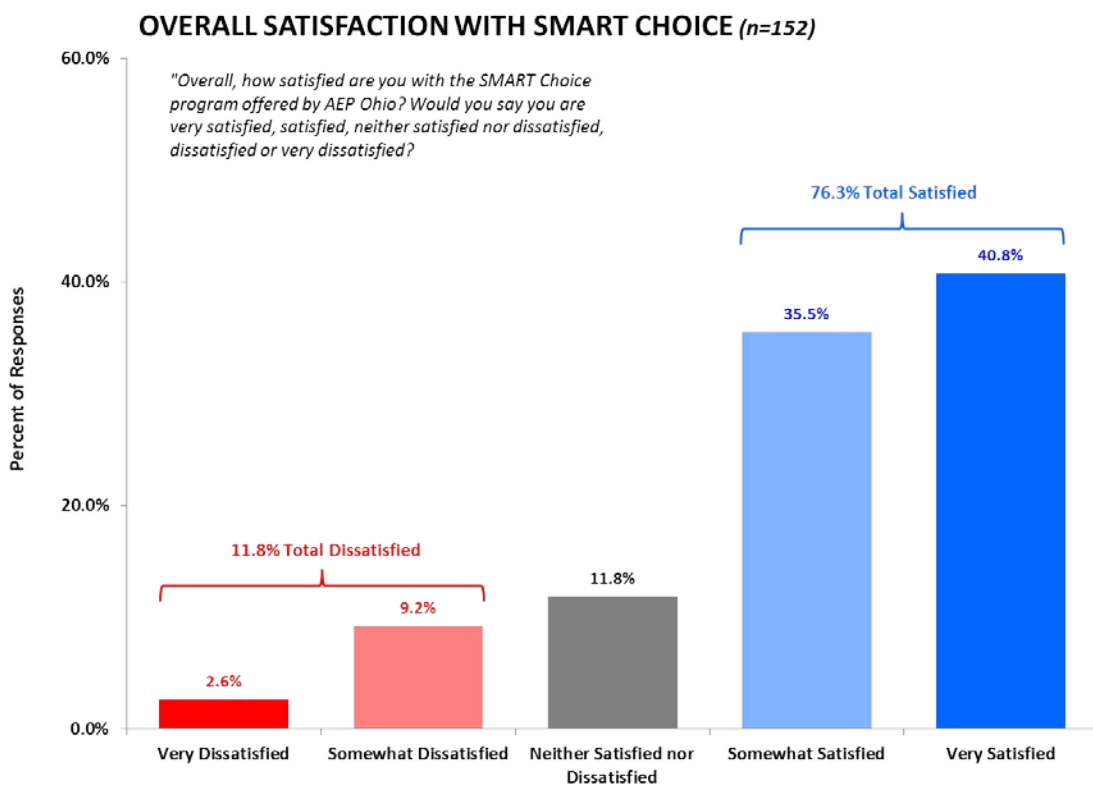


Figure 81. Overall Satisfaction with SMART Choice (RTP_{da})

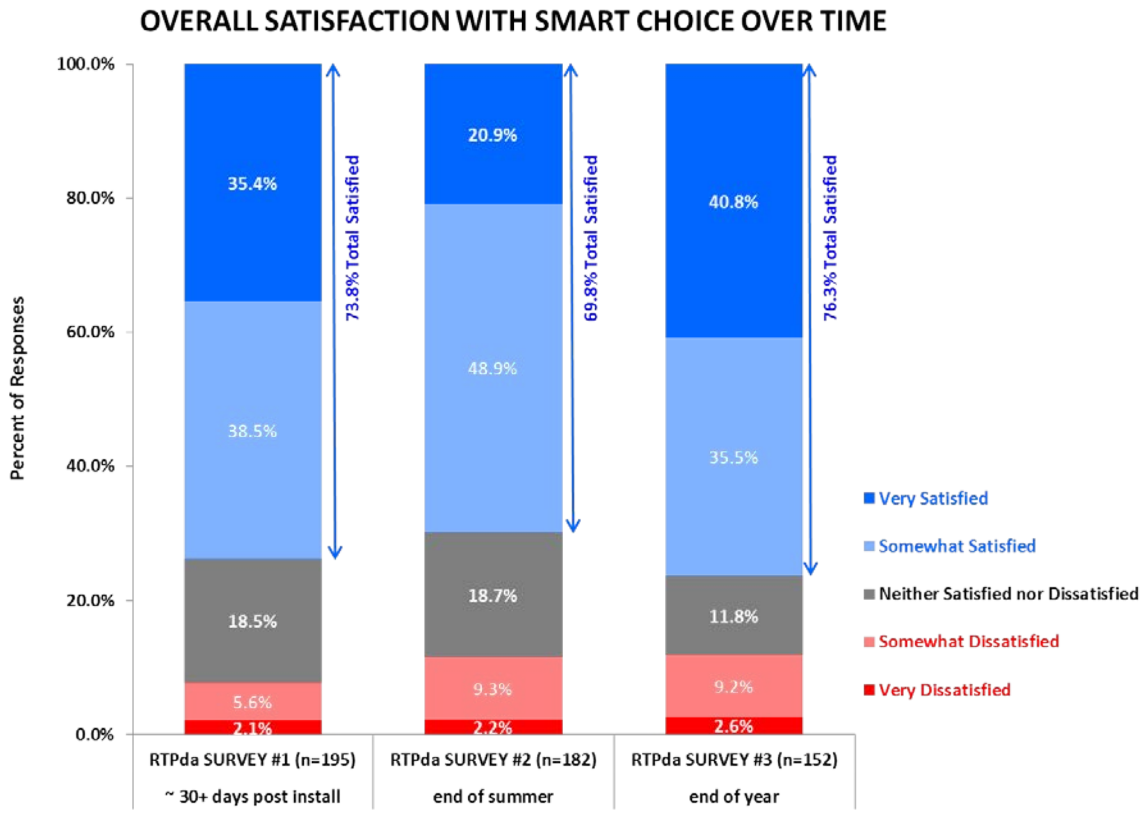


Figure 82. Overall Satisfaction with SMART Choice (RTP_{da}) Over Time

When participants were asked about the perceived impact of the RTP_{da} program on their monthly electric bills, about half (51.4 percent) indicated it either 'decreased slightly' (37.2 percent) or 'decreased' (14.2 percent). The average reduction in the monthly bills attributed to the RTP_{da} program for these individuals was $22.15. Some respondents (9.5 percent) indicated that the program resulted in their monthly electric bills either "increased slightly" (6.1 percent) or "increased" (3.4 percent) with the average monthly increase at $22.23.

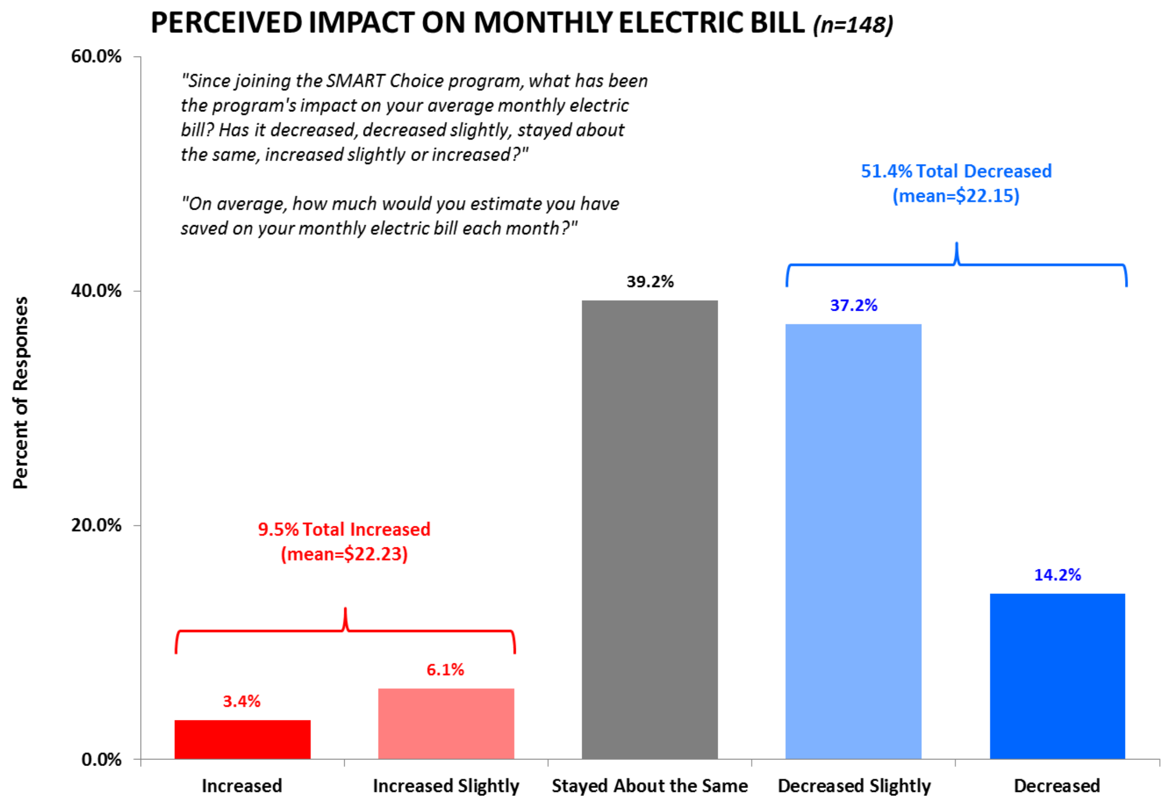


Figure 83. Perceived Impact on Monthly Electric Bill

4.4 Data Collection Results

This section is broken out into three levels to detail the impacts and performance and their propagation in the RTP_{da} project.

- The most basic level is the HEM at consumer premises. This is the primary building block of the entire RTP_{da} system. This level contains the consumer response to market fluctuations and circuit congestion.
- The next higher level is the aggregation of all HEMs on a circuit. At a circuit level the utility starts to see how the aggregated HEMs impact the distribution network. The utility can see the impact during peak load hours, congestion events and high price periods.
- The highest level is the circuits aggregated to a program level. At this level the utility can see the impacts across multiple circuits and can determine the overall average impact. This allows the utility to perform comparative analysis against the other consumer programs.

4.4.1 Experiments

4.4.1.1 Non-Experiment

During normal operation of the RTP_{da} project, the HEM monitored the cost of power to the consumer at 5-minute intervals. At each interval the HEM adjusted the set temperature of the ePCT and the bid price based on the cleared price and the observed temperature in the house. If the price fluctuated significantly during an interval, the HEM offset the set temperature in the ePCT to reduce the power consumed during the higher price interval.

4.4.1.2 Experiments

For the RTP_{da} project, experiments were initiated to test the functionality of the system as well as to test consumer response to pricing events. During an experiment, artificial congestion was placed on the circuits using the PMC application. The simulation was accomplished by lowering the rated circuit capacity of each distribution circuit to a point that was lower than the current circuit load. This artificially induced congestion caused the pricing portion of the double auction algorithm to reach the price cap of $1,000/MWh, which was a user-defined default setting in the PMC. The pricing spike caused the HEMs to offset the set temperature in the ePCT based on consumer-defined slider settings. To fully test system functionality, these experiments were performed over a broad span of days and times. In total, 96 experiments were run, providing a total of 293 hours of testing.

The table below presents a density chart of the experiments performed during the RTP_{da} program over various timeframes. As an example, of the 293 hours of testing performed, 12.35 percent of the total hours were performed on a Sunday with 4.53 percent of the total hours done on a Sunday between 3 p.m. and 5:55 p.m.

	12am - 5:55am	6am - 8:55am	9am - 11:55am	12pm - 2:55pm	3pm - 5:55pm	6pm - 11:55pm	Total
Sunday	0.00%	1.23%	1.23%	4.12%	4.53%	1.23%	12.35%
Monday	0.00%	0.00%	0.82%	1.99%	8.68%	3.74%	15.23%
Tuesday	0.00%	0.82%	0.38%	3.29%	11.90%	2.47%	18.87%
Wednesday	0.41%	2.88%	1.17%	3.53%	5.63%	0.69%	14.31%
Thursday	0.00%	0.82%	1.54%	2.13%	10.67%	3.70%	18.87%
Friday	0.00%	0.82%	0.34%	2.74%	1.65%	4.94%	10.50%
Saturday	0.00%	0.41%	3.70%	3.70%	1.23%	0.82%	9.88%
Total	0.41%	7.00%	9.19%	21.51%	44.29%	17.60%	

Table 17. RTP_{da} Experiments Density Chart

The figure below is an expanded graphical representation of the table above. The majority of events (approximately half of the total experiment hours) were conducted between 3 p.m. and 5:55 p.m. This time frame was typically when AEP Ohio experienced a peak load hours event.

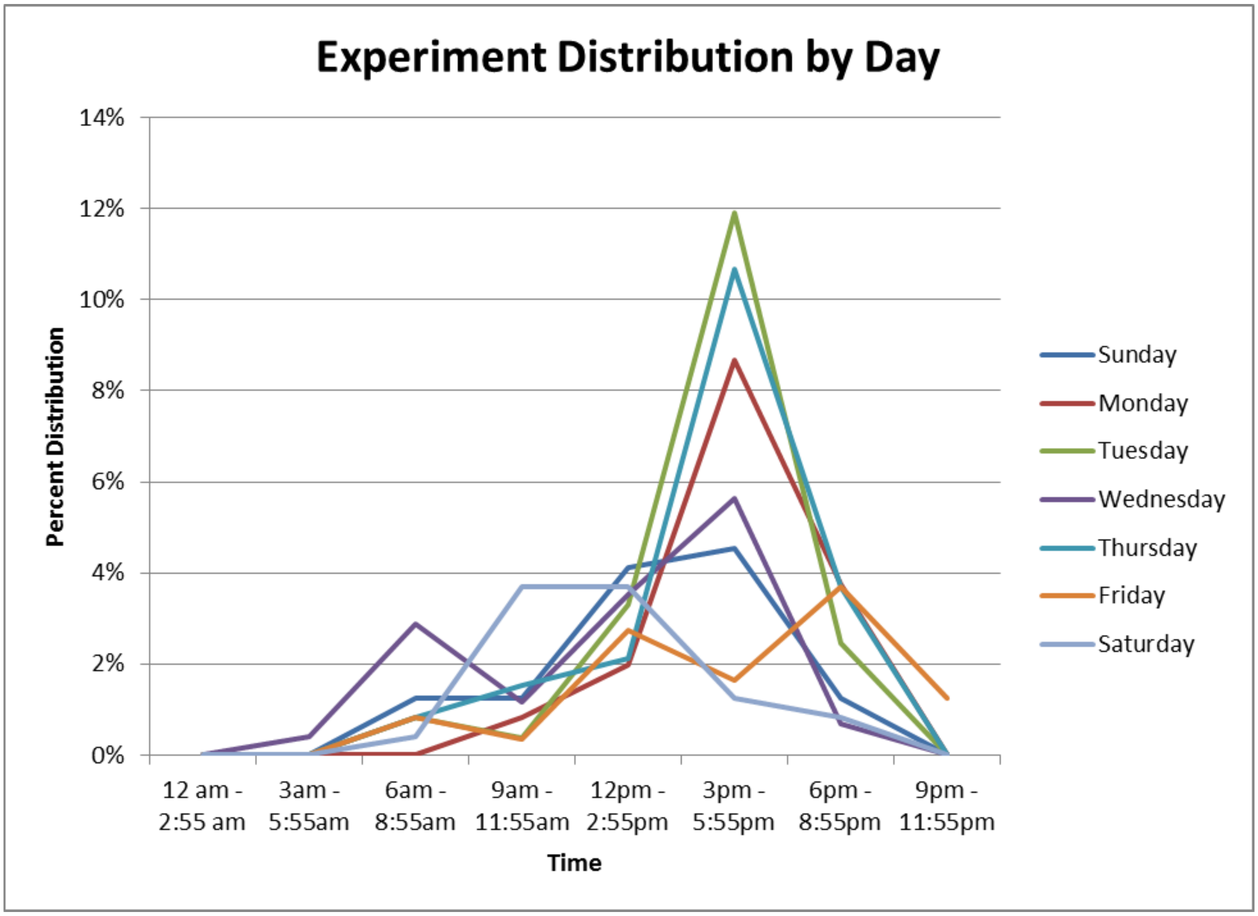


Figure 84. Hourly Distribution of RTP_{da} Experiments

The figure below illustrates the hourly distribution of RTP_{da} experiments; some congestion events were induced to coincide with Critical Peak Price (CPP) events.

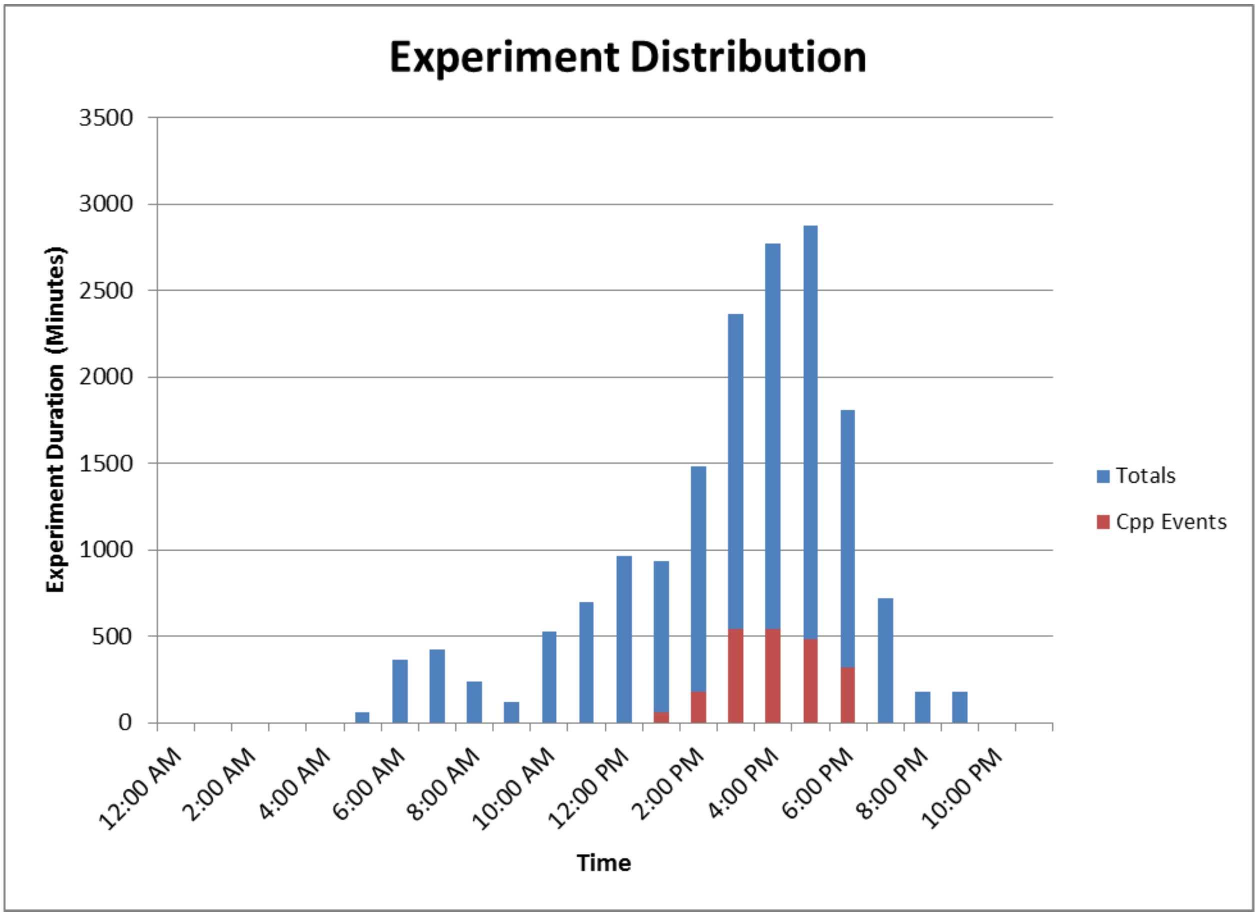


Figure 85. RTP_{da} Experiment Distribution by Day and Time

4.4.2 Consumer Level - HEMs

4.4.2.1 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The described behavior of a HEM was applicable during the summer season.
- During the summer season, there was no restriction on time of the experiments or the duration.
- The described behavior of a HEM applied to HEMs that had been commissioned and were fully operational.
- The described behavior of a HEM applied to HEMs that were not placed on hold via the ePCT by the consumer.

4.4.2.2 Hot Day

On days with elevated temperatures, the HEM responded as anticipated and reacted to Locational Marginal Price (LMP) price spikes. On days when artificial congestion was induced these reactions were much more pronounced. When the HEM registered that the cleared price hit the price cap, it offset the set temperature of the ePCT to the maximum offset based on the consumer settings. As time progressed, the observed temperature inside the premises increased due to the elevated exterior temperature. In response, the HEM began to increase the bid price during each auction. The observed temperature in the premises continued to climb reaching the new set temperature. Once the observed temperature exceeded the offset set temperature, the HEM instantaneously increased the bid price to the maximum placing the HEM into a *must-run* state. During the must-run state, the HEM kept the bid price equal to or higher than the cleared price. In a must-run state the HEM will not issue any further temperature adjustments to the ePCT.

At the end of the experiment or when congestion was no longer an issue, the cleared price would begin to fall. This change caused the set temperature of the ePCT to return to its programmed value. The HEM stayed in a must-run state until the observed temperature was less than or equal to the set temperature, and the HEM lowered its bid price and returned to normal participation in the auctions.

The figure below illustrates a HEM-level view from a non-experiment hot day.

- When the observed temperature (red line) was less than the set temperature (dark blue line) the bid price (green line) was less than the cleared price (purple line). In these intervals the HEM had not won the auction.
- When the observed temperature was higher than the set temperature, the bid price was greater than or equal to the cleared price. In these intervals, the HEM won the auction. On this day there was no experiment scheduled, so the LMP was the major influencing factor on the oscillation in the set point.

This effect occurred at approximately 11 a.m. through 4 p.m. as the LMP (light blue line) fluctuated. This fluctuation caused the cleared price to fluctuate proportionately. As the cleared price rose and fell during this period, the set temperature mirrored the movement, shifting the temperature up during higher priced intervals and back down during lower priced intervals.

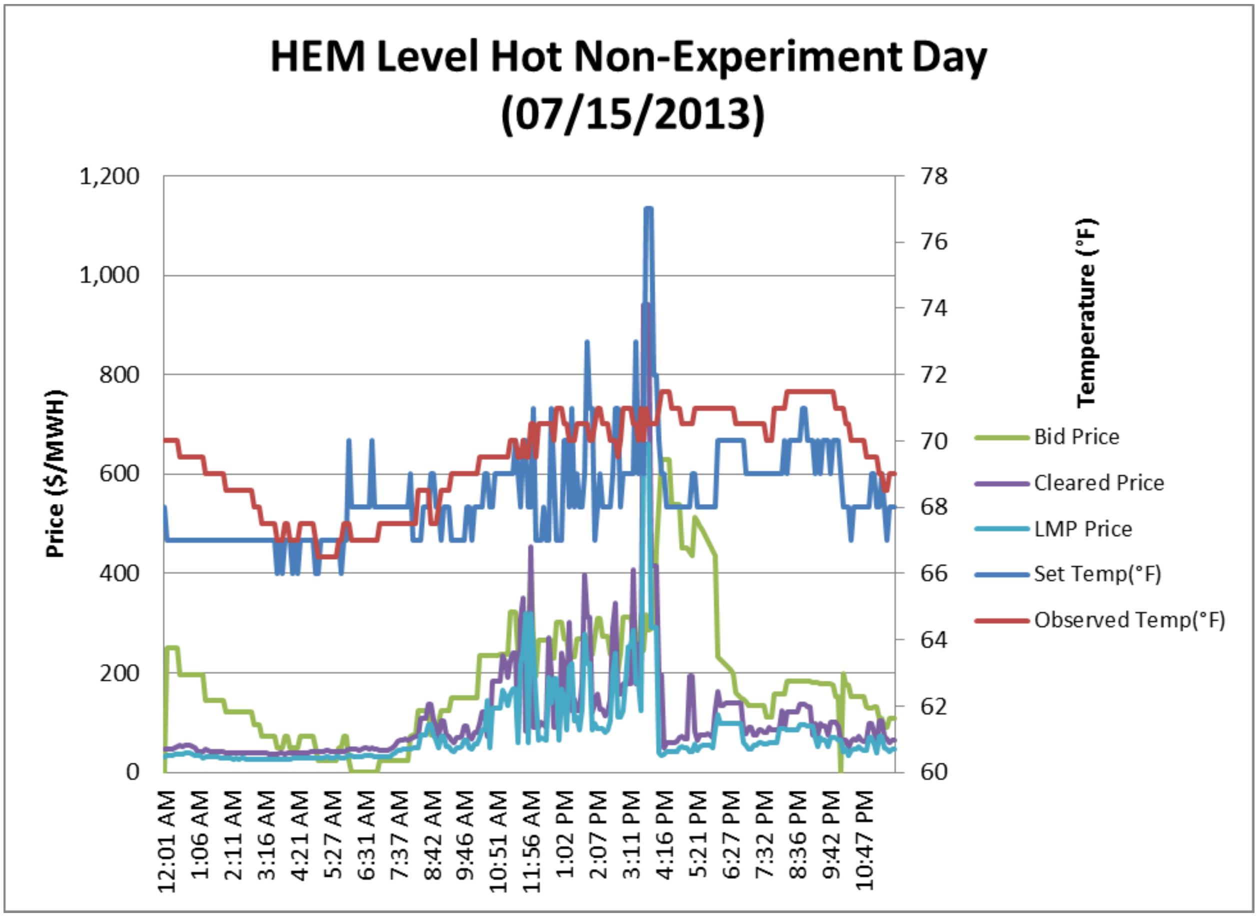


Figure 86. HEM Level Hot Non-Experiment Day

The figure below illustrates a HEM level view from an experiment on a hot day.

- When the observed temperature (red line) was less than the set temperature the bid price (green line) will be less than the cleared price, (purple line). In these intervals the HEM had not won the auction.
- When the observed temperature is higher than the set temperature the bid price will be greater than or equal to the cleared price. In these intervals the HEM won the auction. On this day the, prior to the experiment, the set temperature in the house (dark blue line) fluctuates slightly during the day based on the cleared price and the consumer's slider settings. At 1 p.m. a congestion event started and the cleared price offset to the max bid price independent of the LMP price (light blue line).

During this event the set temperature offset from 68°F to 77°F. During the event the observed temperature climbed causing the bid price to rise. At approximately 4 p.m. there was a change in the consumer setting that caused the set temperature to drop to 73°F. The new set temperature was lower than the observed temperature causing the bid price to spike to the max bid price. With the cleared price equal to the bid price, the HEM won the auction and began to cool the house. The observed temperature was greater than the set temperature for the remainder of the day as the house rebounded from the experiment.

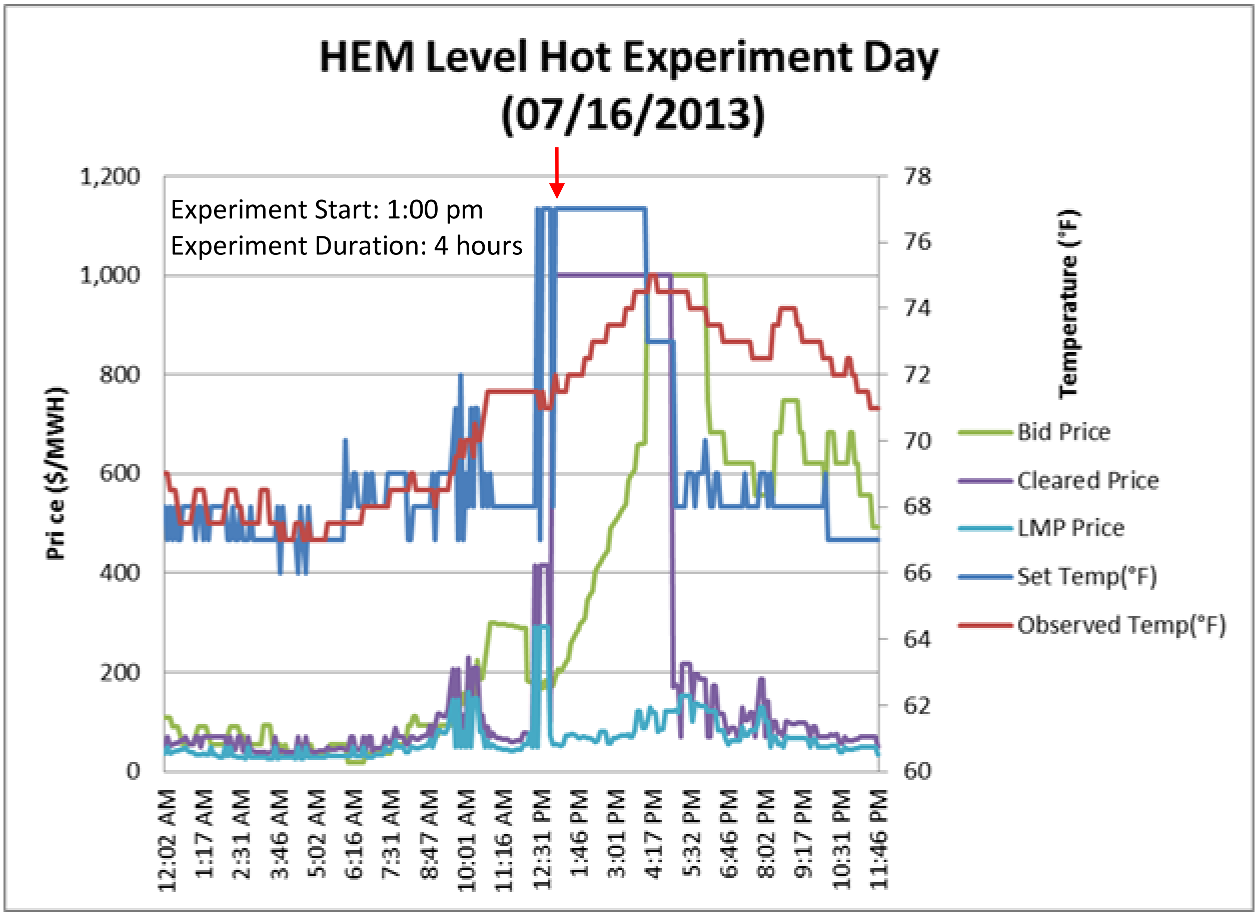


Figure 87. HEM Level Hot Experiment Day

4.4.2.3 Cold Day

On an experiment day with lower outside temperatures, the consumer level system reacted as expected. At the point where congestion was applied to the circuit, the cleared price responded by increasing to the price cap. The set temperature of the house offset to the maximum allowed temperature. However, the reduced exterior temperature caused the interior temperature of the premises to rise at a much slower pace. The HEM responded by keeping the bid price lower than what was observed during hot days. Consequently, the HEM never reached a must-run state leading to a reduced premises temperature recovery time after the congestion event.

The figure below illustrates a HEM-level view from a non-experiment cold day.

- When the observed temperature (red line) was less than the set temperature, the bid price (green line) was less than the cleared price (purple line). In these intervals, the HEM did not win the auction.
- When the observed temperature was higher than the set temperature, the bid price was greater than or equal to the cleared price. In these intervals, the HEM won the auction.

On this day there was not an experiment scheduled, so the LMP was the major factor impacting the set temperature. On this day the LMP did not fluctuate through a wide range, which caused fewer set temperature changes than on the hot day. During this day there were only a few intervals in the morning when the observed temperature was higher than the set temperature causing the bid price to raise past the cleared price.

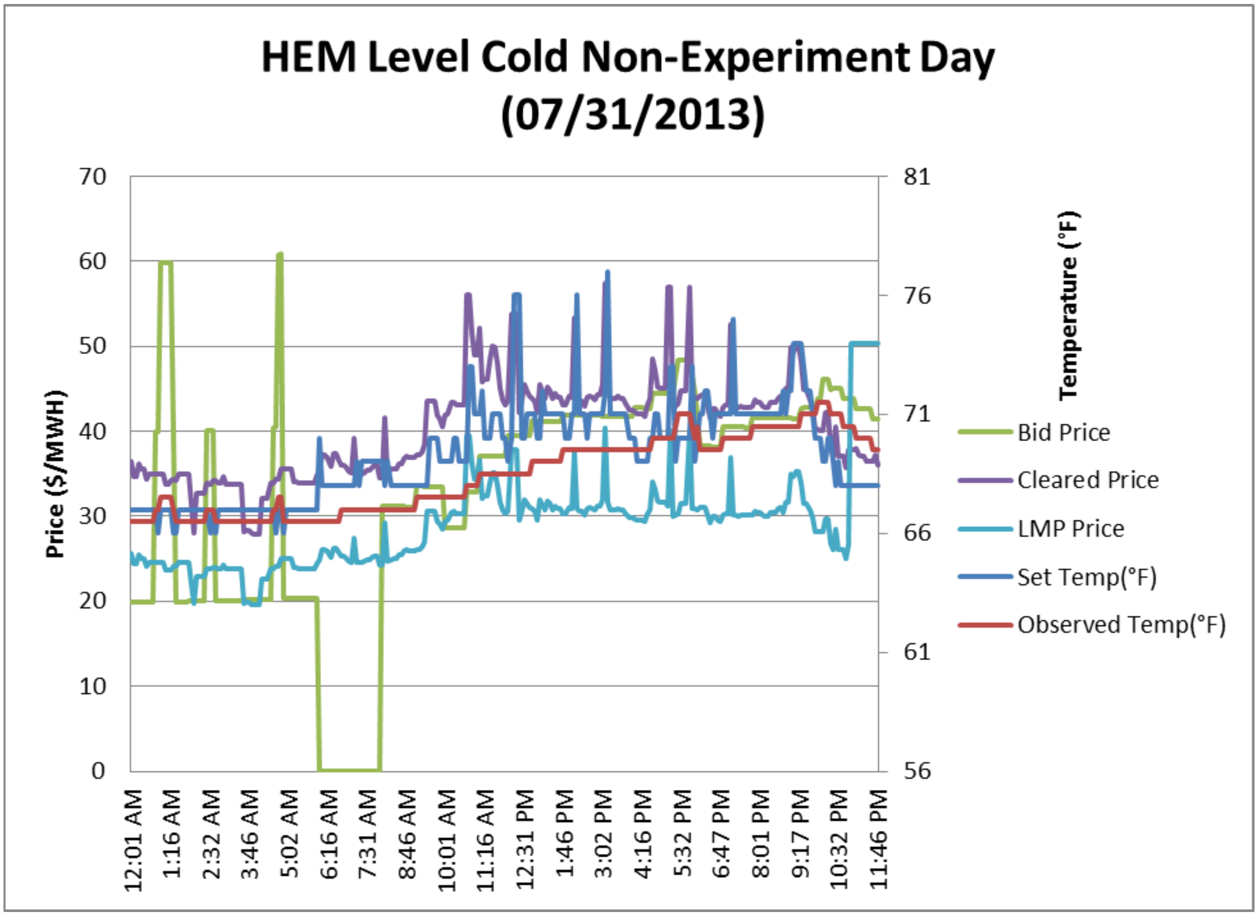


Figure 88. HEM Level Cold Non-Experiment Day

The figure below illustrates a HEM level view from an experiment on a cold day.

- When the observed temperature (red line) was less than the set temperature, the bid price (green line) was less than the cleared price (purple line). In these intervals, the HEM did not win the auction.
- When the observed temperature was higher than the set temperature, the bid price was greater than or equal to the cleared price. In these intervals the HEM won the auction. At 5 a.m. a congestion event started causing the cleared price to rise to the max bid price thereby causing the set temperature to rise from 68°F to 75°F.

During this event there was not a significant climb to the observed temperature because of the colder outdoor temperature. Because there was not a significant climb to the observed temperature, the bid price remained much lower during the experiment. The experiment was released at 7 a.m. Because there was little deviation to the observed temperature, there was little to no rebound period after the event.

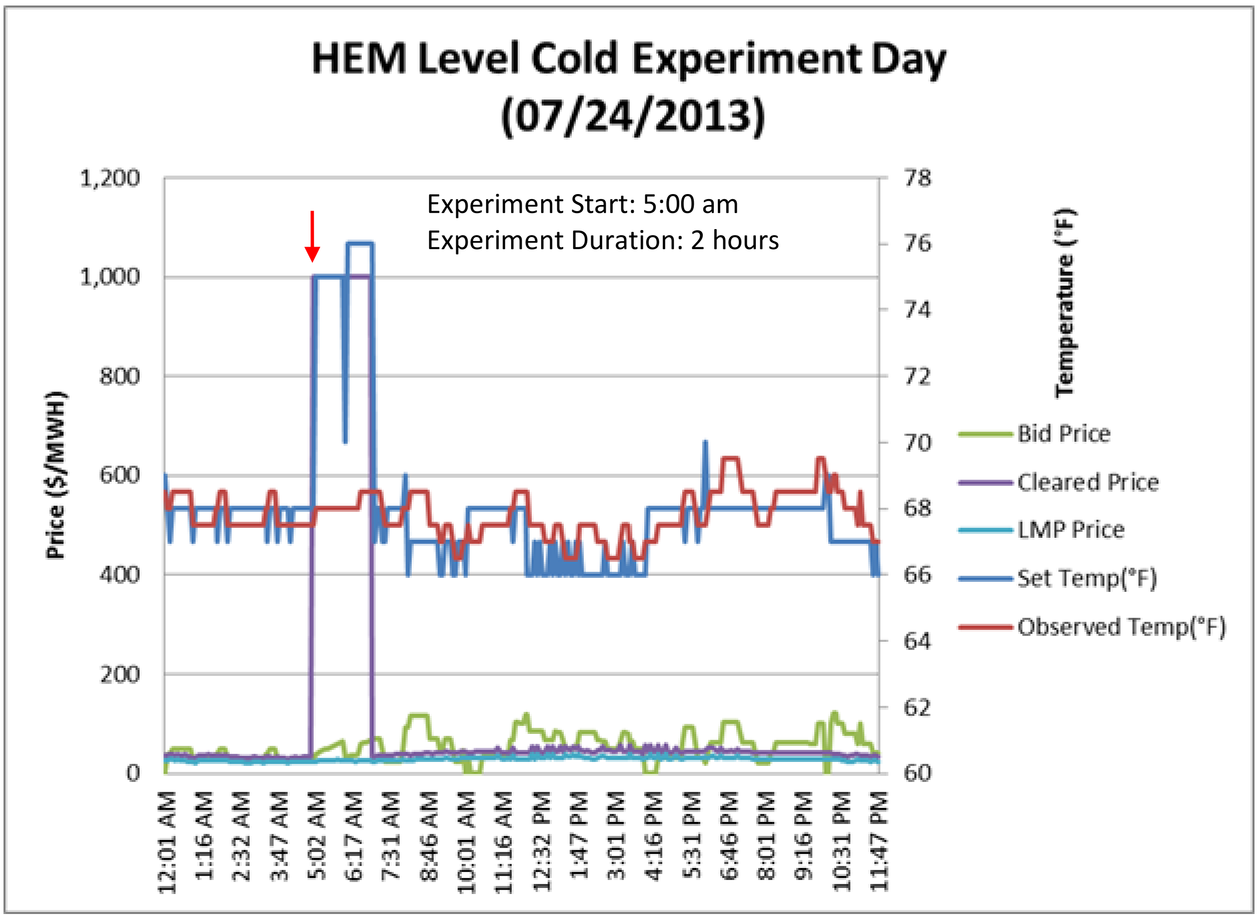


Figure 89. HEM Level Cold Experiment Day

4.4.3 Distribution Circuit Level

4.4.3.1 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The described behavior of a circuit applied during the summer season.
- During the summer season, there was no restriction on time of the experiments or restrictions on the duration of the experiments.
- During the experiments, no RTP load shifted from the experiment circuits.
- The described behavior of the circuit applied to intervals when there were no communication or back office data issues.

4.4.3.2 Calculation Approach

The RTP_{da} project had participants on four different distribution circuits. The system allowed for the tracking and recording of:

- Responsive load – the sum of all the RTP_{da} HVAC loads on the circuit.
- Active load – the amount of responsive load that cleared to run in the market period – participation in an auction.
- Inactive load – the amount of responsive load that did not clear to run in the market period – nonparticipation in an auction.
- Unresponsive load – the total circuit load minus the responsive load during the market period on the circuit.

The RTP_{da} circuit loads included the unresponsive load, which were those consumers not participating in the RTP_{da} program, and the responsive load or those consumers who were enrolled in the program. The active load and inactive load values were included in the responsive load portion of the circuit. These values represented the load on the circuit that contributed to the RTP_{da} load. At a circuit level, these values are the sum of all of the HEMs participating at each interval. During a congestion event these load values responded according to market prices and the user settings on each ePCT on that circuit.

The load response was based on several criteria. During a congestion experiment the resources were purposefully engaged. At the start of the experiment, the responsive load was reduced as the HEMs offset their set temperatures due to the price increase. As the experiment continued, the responsive load remained suppressed, reducing the total load on the circuit. On a hot day the observed temperatures in the premises climbed. Because of the individual HEM settings, the houses on the circuit reached their offset set temperature at different times. The load slowly ramped back up in the congestion period as the resources were exhausted. If the congestion were to remain in place on the circuit, all of the resources on the circuit would eventually become exhausted and the load reduction on the circuit would be minimal.

These results were obtained by inducing congestion on days when peak demand reduction was needed. On days that peak demand reduction was required, the consumer was typically consuming power with their HVAC because of the high outside temperatures. The induced congestion released those power resources allowing maximum reduction. This method was used on several days during the experimental period. On a day with high forecasted loads, congestion events were scheduled to coincide with the critical peak pricing (CPP) program. A congestion event was also used during the PJM emergency demand response event to assist with overall load reduction.

The results on a cooler day are slightly different. As with the hot day, an initial responsive load reduction occurred at the start of the experiment. The cooler temperatures reduced the initial load reduction because of a smaller number of resources consuming power. The lower temperatures diminished the ramp up of the resources during the congestion event, allowing the congestion to hold longer on the circuit without the resources being exhausted.

The following figure illustrates a circuit level view from a hot non-experiment day. The blue line represents the total load on the circuit and the red line represents the total load minus the RTP load. On this day the load curve was a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon. The green line represents the RTP load. During this day the RTP load was only responding to PJM prices. If there was a spike in the PJM price the circuit saw a reduction in RTP load. For example, the PJM price spiked from 3:40 to 3:50 p.m. from $124 to $660. This spike caused the RTP load reduction highlighted in the figure with the red circle. The RTP load fluctuated for the remainder of the day due to PJM prices.

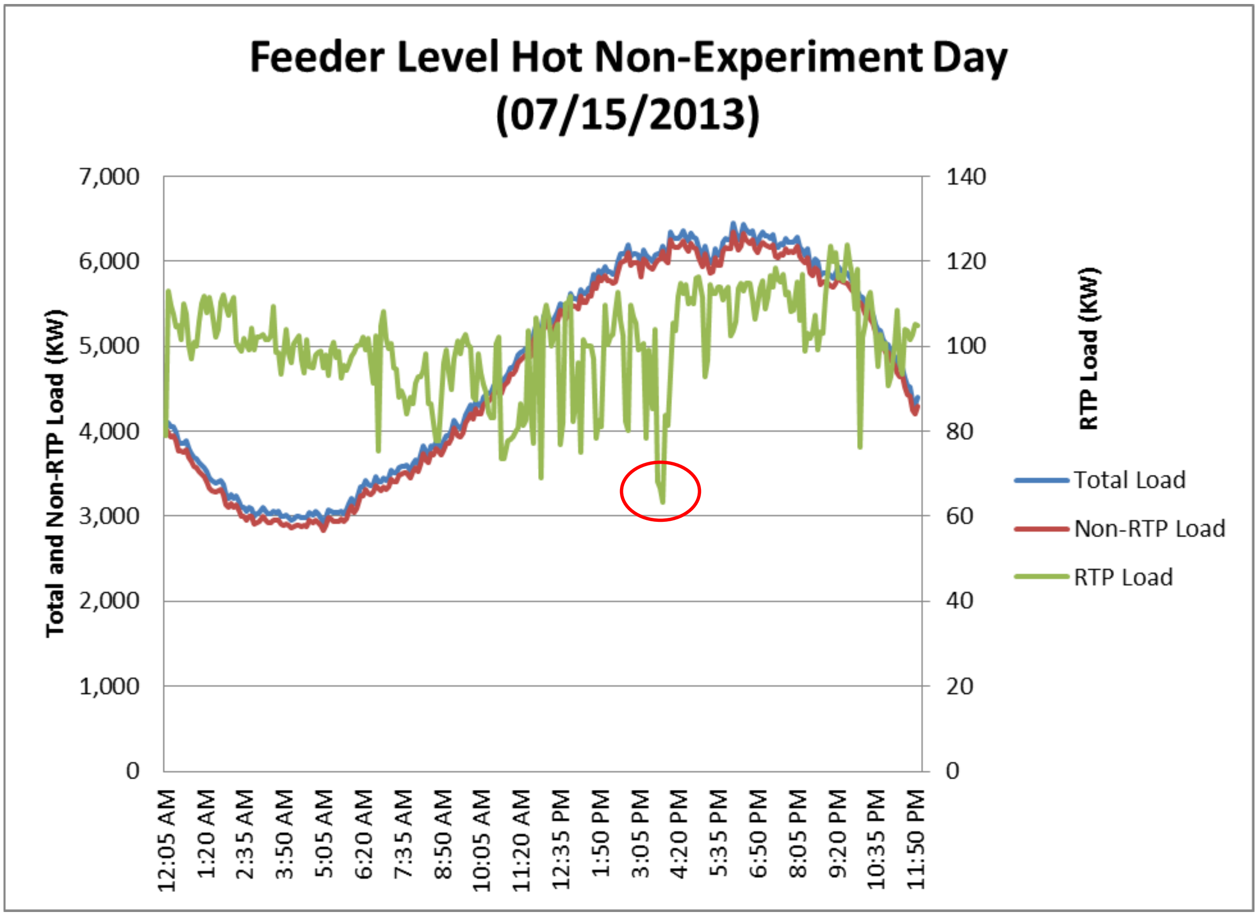


Figure 90. Circuit Level Hot Non-Experiment Day

The figure below illustrates a circuit level view from a non-experiment cold day. The blue line represents the total load on the circuit and the red line represents the total load minus the RTP load. On this day the load curve was close to a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon; however, it is slightly flatter than a typical summer curve because of the colder temperatures. The green line represents the RTP load. During this day there were no significant reductions and the overall RTP load was down because of the colder temperatures. The RTP load fluctuated for the remainder of the day due to PJM prices.

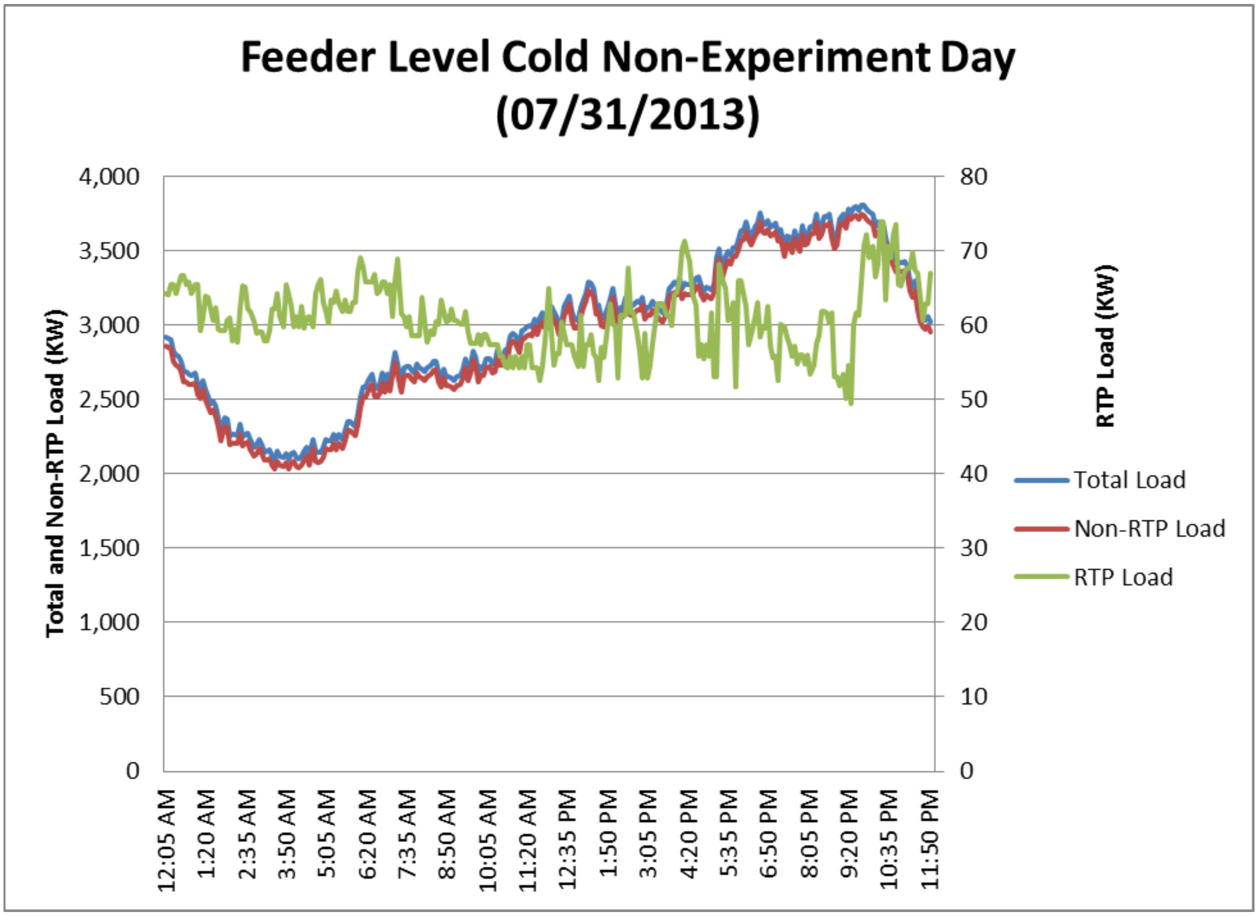


Figure 91. Circuit Level Cold Non-Experiment Day

The figure below illustrates a circuit level view on a hot day. The blue line represents the total load on the circuit, and the red line represents the total load minus the RTP load. On this day the load curve was a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon. The green line represents the RTP load. During non-experiment hours, the load fluctuation was minimal; however, there was a significant reduction of load shortly before the experiment due to a sharp increase in the PJM price. Once the experiment started at 1 p.m. there was another reduction in RTP load from approximately 100 kW to 60 kW. An overall reduction was sustained through the duration of the experiment; however in this experiment, at approximately 3 p.m., the RTP load started to slowly climb because the HEMs were reaching a must-run state. The RTP load reduction continued until the end of the experiment, and the load was released at 5 p.m. The RTP load fluctuated for the remainder of the day due to PJM prices.

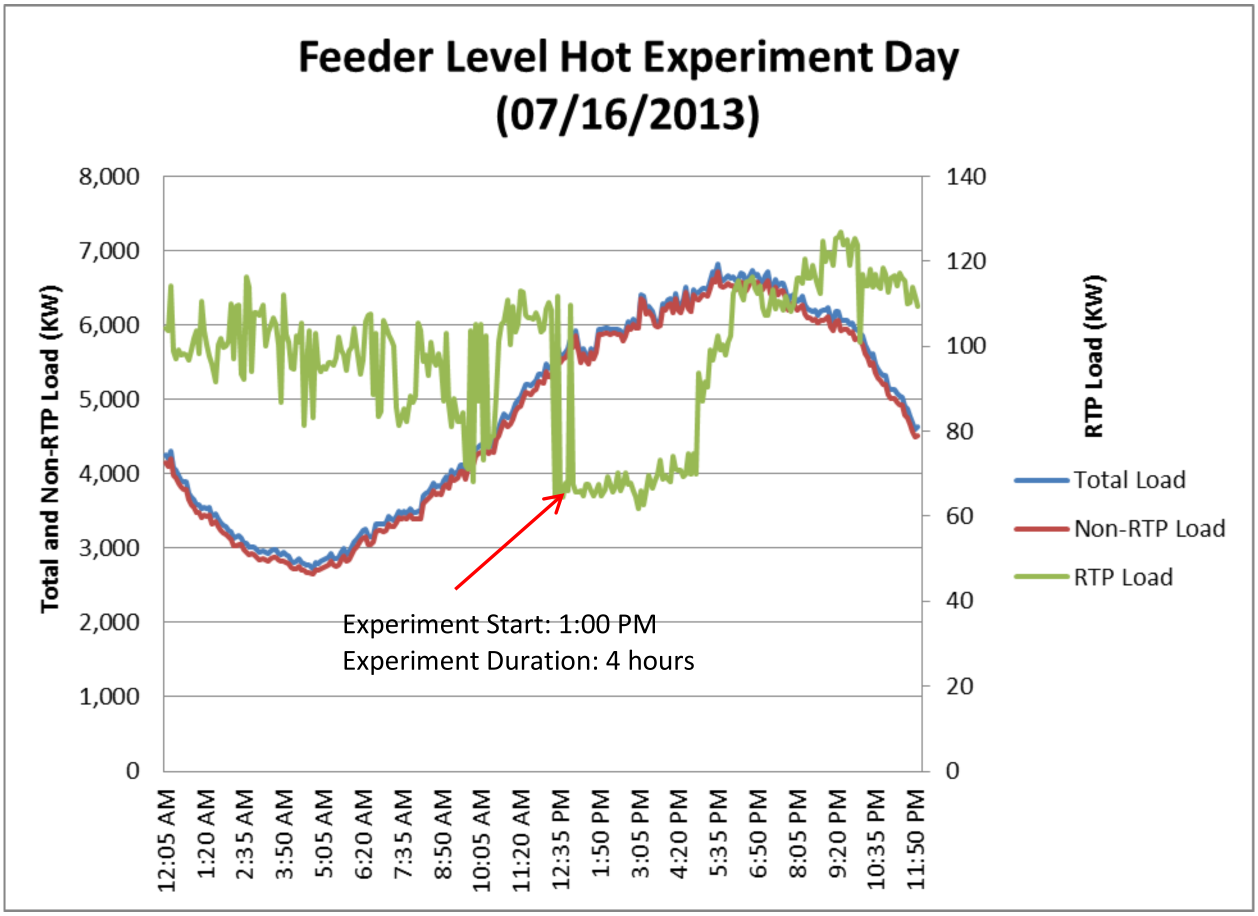


Figure 92. Circuit Level Hot Experiment Day

The figure below illustrates a circuit level view on a cold day experiment. The blue line represents the total load on the circuit, and the red line represents the total load minus the RTP load. On this day the load curve was a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon; however, the total load was reduced because of the cooler temperatures. The green line represents the RTP load. At 5 a.m. the experiment started, and the RTP load was reduced on the circuit from approximately 85 kW to 72 kW. This reduction was sustained through the experiment duration of 2 hours. At 7 a.m. the RTP load was released. The circuit saw a rebound from the RTP load for a short duration. The RTP load fluctuated for the remainder of the day due to PJM prices.

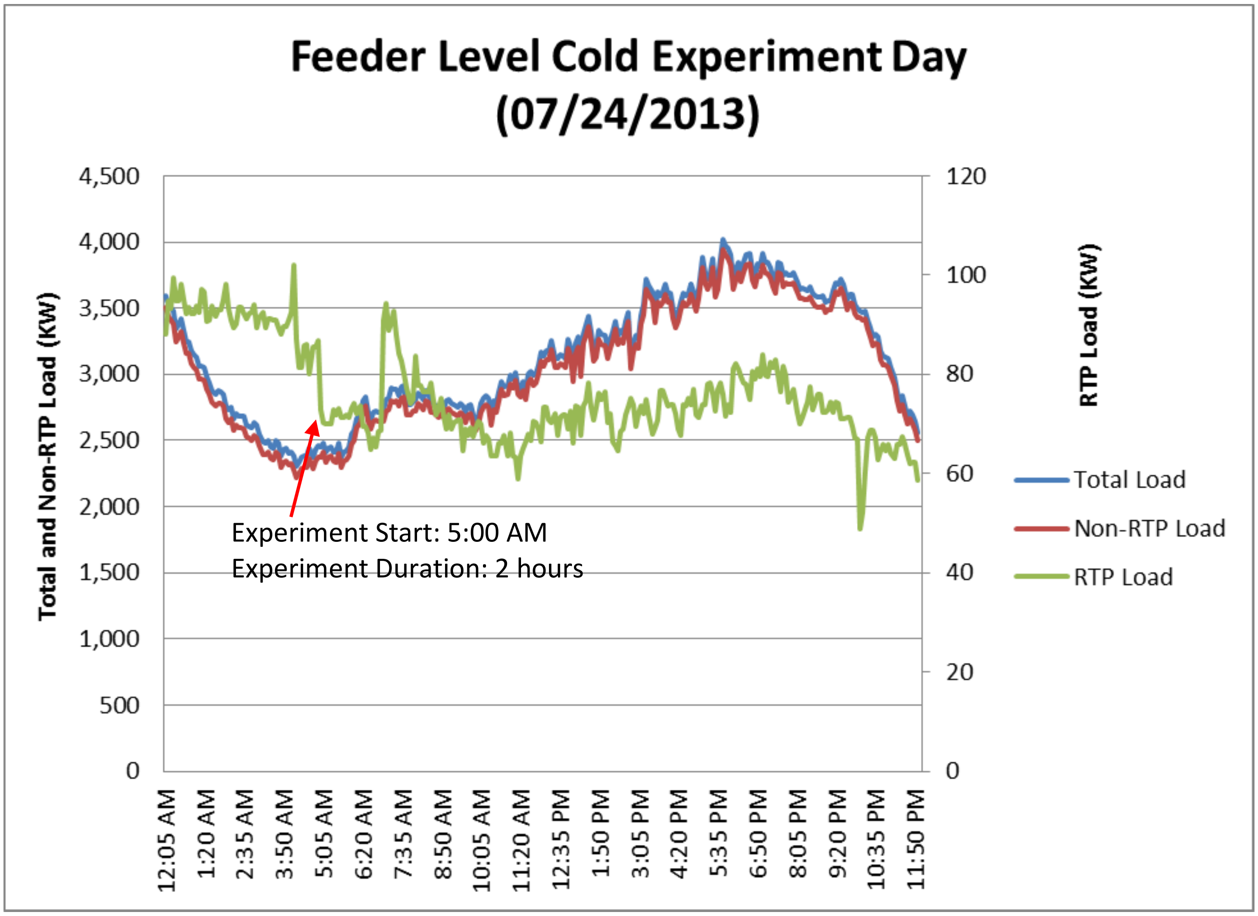


Figure 93. Circuit Level Cold Experiment Day

The figure below illustrates a circuit level view of an experiment on a holiday. The blue line represents the total load on the circuit, and the red line represents the total load minus the RTP load. On this day the load curve was a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon. The green line represents the RTP load. During non-experiment hours the load fluctuation was minimal. At 10:15 a.m. congestion was induced on the circuit. The RTP load responded, and there was a reduction in RTP load dropping from approximately 90 kW to 55 kW. As the experiment progressed, the load reduction was fairly constant for the duration of the experiment. At 12:10 pm the congestion was released, and the RTP load rebounded on the circuit. The RTP load fluctuated for the remainder of the day due to PJM prices.

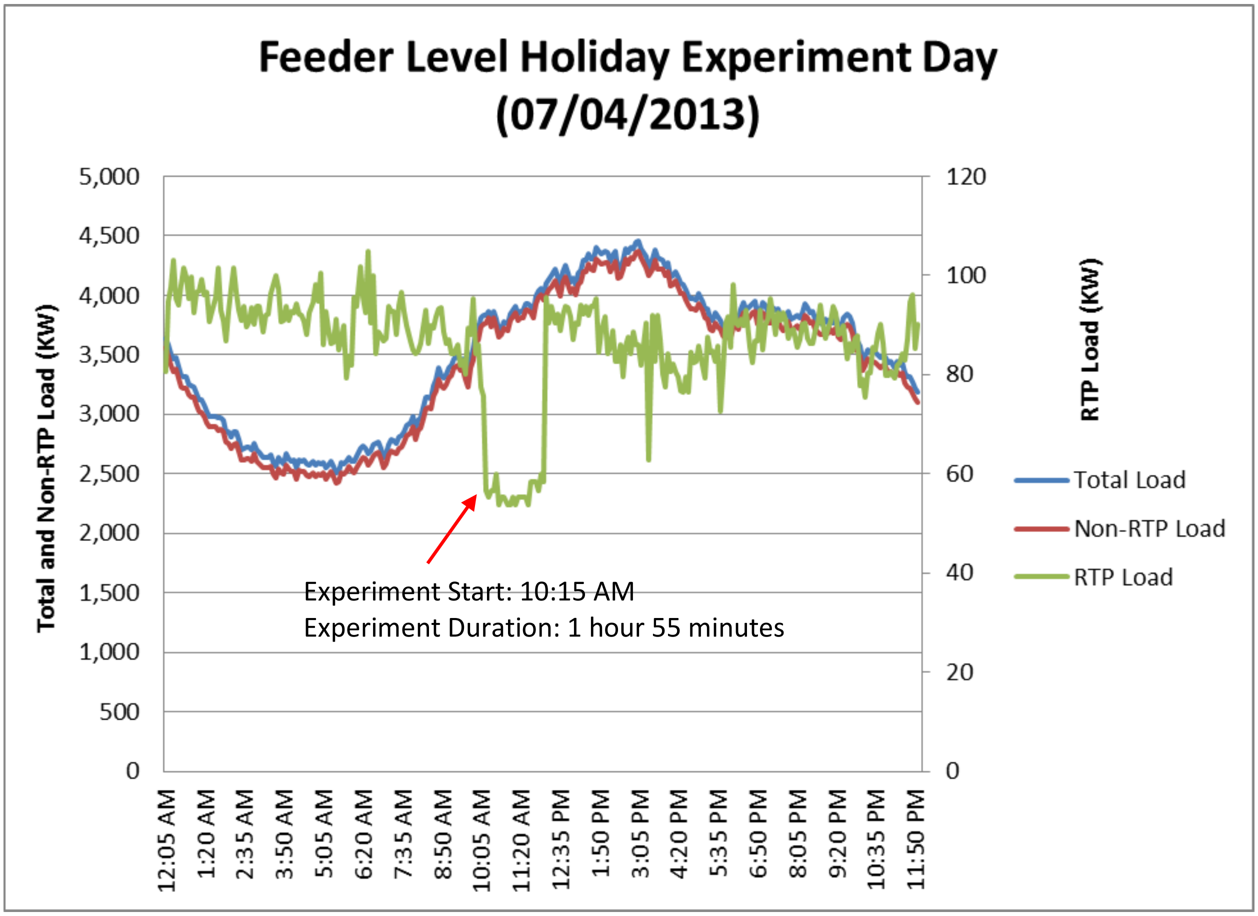


Figure 94. Circuit Level Holiday Experiment Day

The figure below illustrates a circuit level view of an experiment on a PJM emergency day. The blue line represents the total load on the circuit, and the red line represents the total load minus the RTP load. On this day the load curve was a typical summer curve with low circuit load during the morning hours and the load peaking during mid to late afternoon. During this day PJM called an emergency event starting at 1:30 p.m. and lasting until 7:30 p.m. The green line represents the RTP load. During non-experiment hours, the load fluctuation was minimal with a slight price spike prior to the experiment causing a reduction for a short interval. At 3 p.m. the experiment started, and the RTP load reduced from approximately 115 kW to 85 kW. The reduction was sustained with a slight climb in RTP resources for the 4-hour duration of the experiment. At the completion of the experiment, the resources rebounded. The RTP load fluctuated for the remainder of the day due to PJM prices.

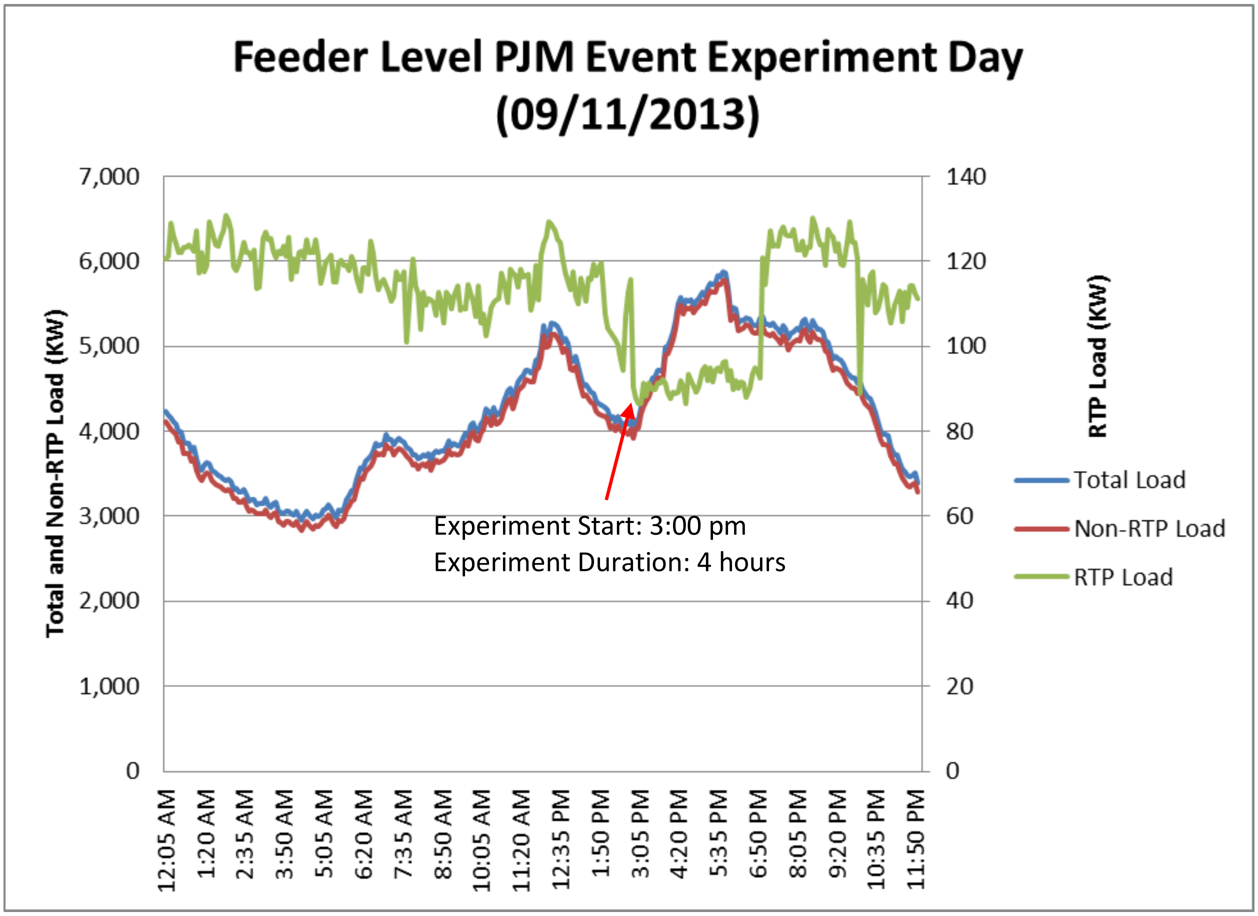


Figure 95. Circuit Level PJM Event Experiment Day

4.4.4 Consumer Program Level

The RTP_{da} data from all four distribution circuits was aggregated in order to calculate the overall average consumer energy and demand impacts at the consumer program level. The energy and demand impacts were calculated by comparing the average RTP_{da} premises hourly usage to the average hourly usage of a control group composed of comparable standard tariff consumers (see section 4.x for a full description of the calculation approach using control groups). The consumer program level of analysis provides insights into the impacts of RTP_{da} as a tariff rather than just a series of experiments.

4.4.4.1 RTP_{da} – Overall Impacts

This metric examines the overall impacts of the RTP_{da} program on consumers' energy usage and demand. This metric measured the average changes in consumer consumption during various periods of the day on experiment weekdays and weekends, and non-experiment weekdays and weekends. It also included two RTP_{da} experiment days – the summer 2013 peak day and a PJM emergency event day.

4.4.4.2 Organization of Results

This metric assessed the ability of RTP_{da} and associated technologies to influence consumers to decrease or shift their energy usage away from high-cost periods of the day.

For the analysis of the average experiment weekdays (Figure 96) and weekends (Figure 97) and non-experiment weekdays (Figure 98) and weekends (Figure 99), a high-cost period was defined as the hours from 1 p.m. to 7 p.m. For the summer 2013 peak day (Figure 100) and a PJM emergency event day (Figure 101), the analysis used the high-cost periods of the day as determined by the program experiments.

The key parameters of interest included experiment and non-experiment days (regardless of the time of day of the event), day types (weekdays and weekends), peak day and PJM emergency day, hour of the day and hourly kWh usage.

4.4.4.3 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

This impact metric provided an analysis of the average hourly RTP_{da} premises energy reduction between 1 p.m. and 7 p.m., the total average daily kWh reduction for RTP_{da} premises, and the maximum daily kW reduction for the average RTP_{da} premises for:

- Experiment weekdays and weekends
- Non-experiment weekdays and weekends
- The summer 2013 peak day
- A PJM emergency event day

4.4.4.4 Calculation Approach

The following queries and methods were used for the analysis:

- Average hourly kWh reduction was calculated by averaging hourly usage by day type (event days, non-event days, weekdays, weekend days, summer peak day and PJM emergency day) for RTP_{da} premises and control group premises, and taking the hourly average of the differences between the groups of premises between 1 p.m. and 7 p.m.
- Total average daily kWh reduction energy was calculated by averaging hourly usage by day type for RTP_{da} premises and control group premises, and taking the hourly average of the differences between the groups of premises for the entire day.
- Maximum daily kW reduction was calculated by averaging hourly usage by day type for RTP_{da} premises and control group premises, and taking the maximum hourly difference between the groups of premises between 1 p.m. and 7 p.m.
- Only those RTP_{da} consumers participating in the program for the period of June 1, 2013 and September 30, 2013 were included in this analysis. To include those consumers that were enrolled for only part of the summer would have required recalculating the control group for each unique set of consumers.

4.4.4.5 Energy and Demand Analysis – Summer 2013

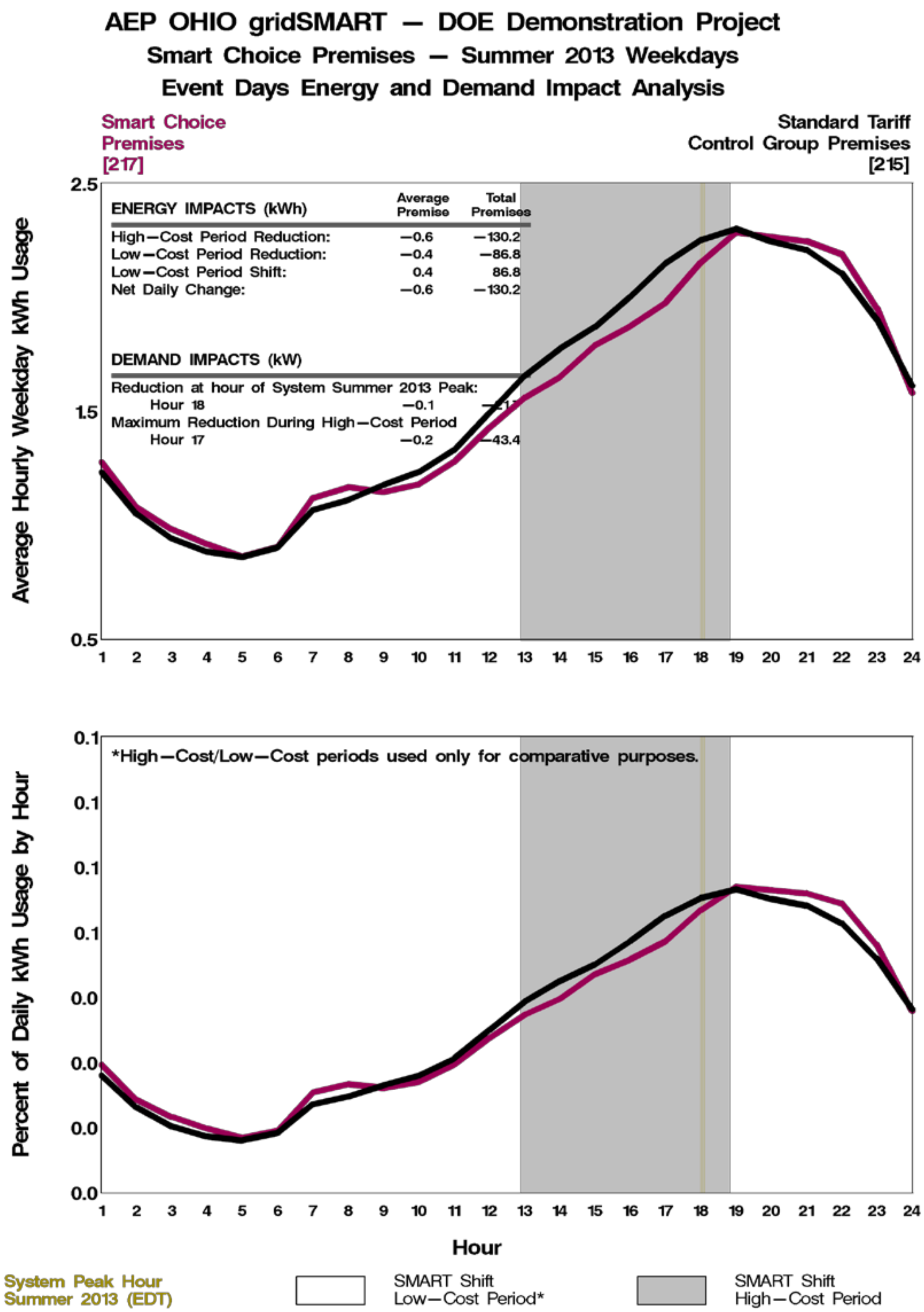


Figure 96. Event Days - Summer 2013 Weekdays

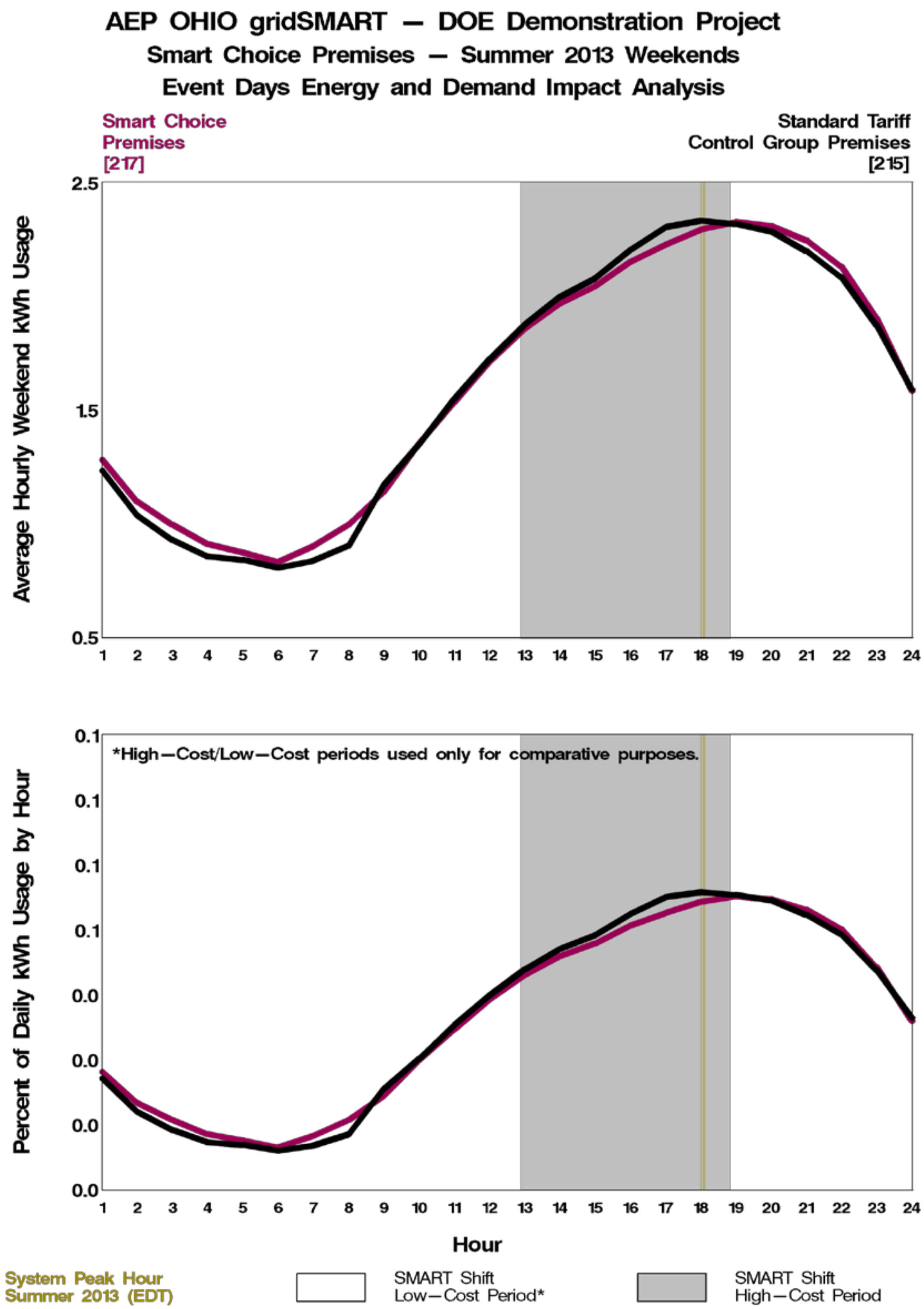


Figure 97. Event Days - Summer 2013 Weekends

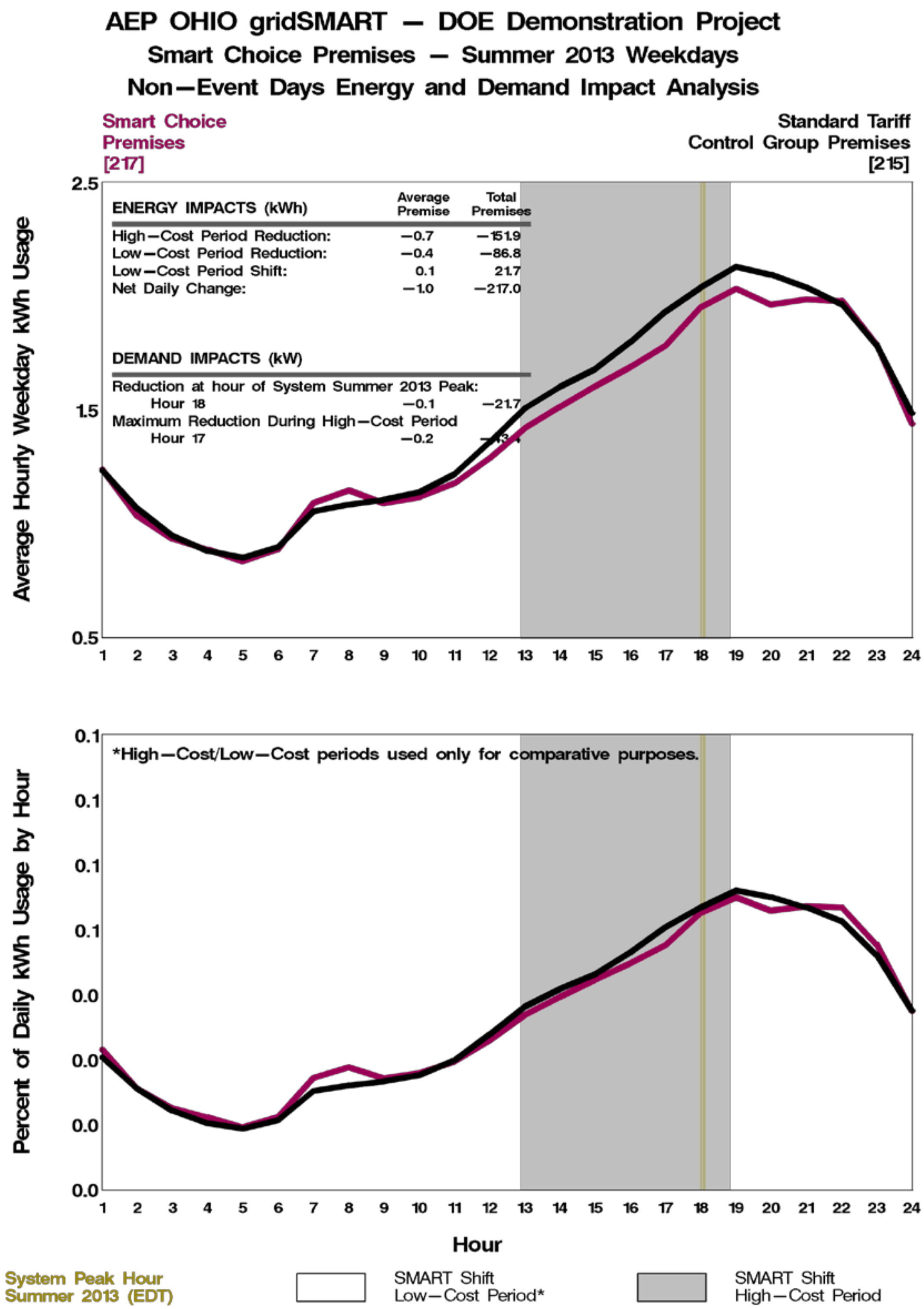


Figure 98. Non Event Days - Summer 2013 Weekdays

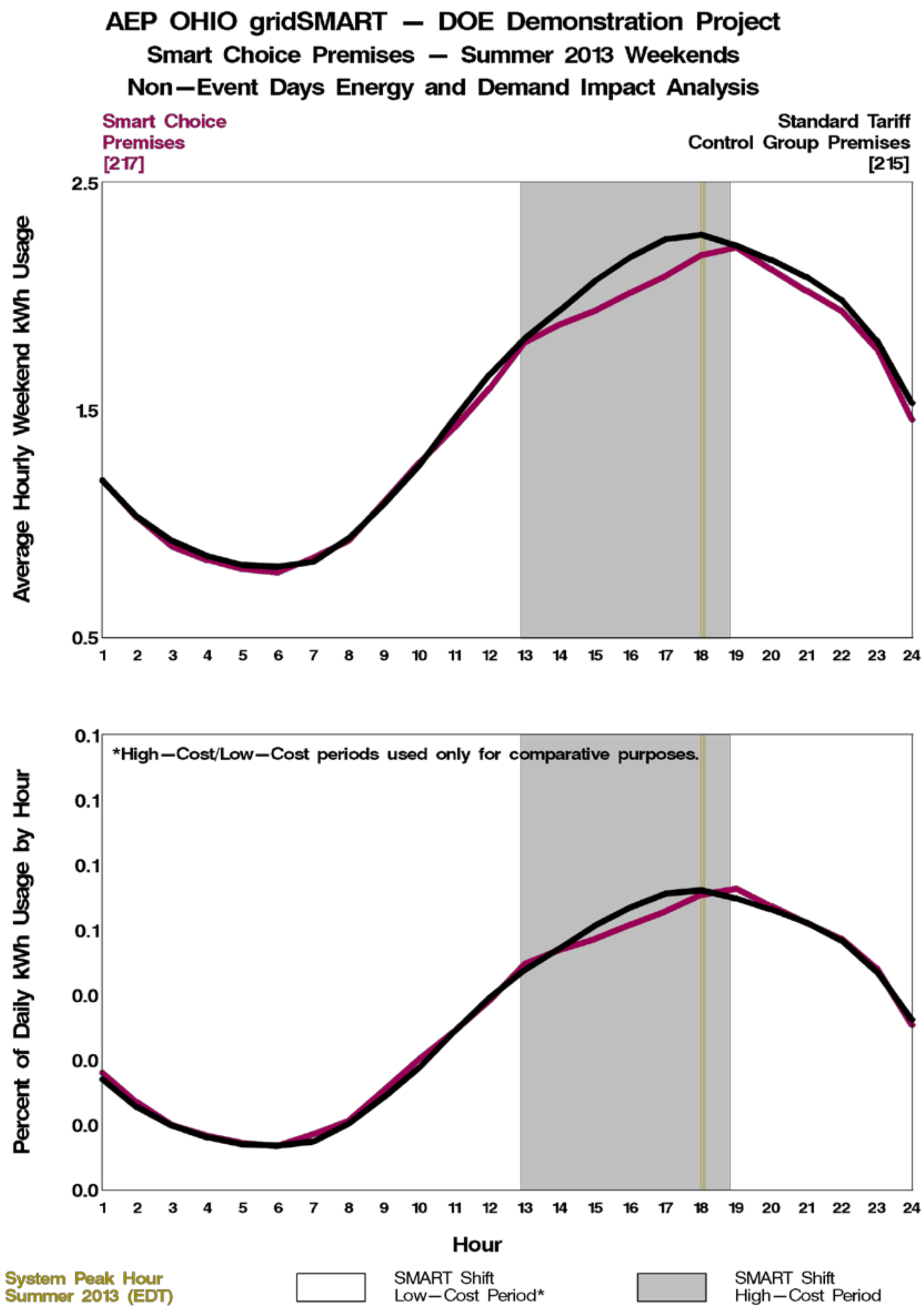


Figure 99. Non Event Days - Summer 2013 Weekends

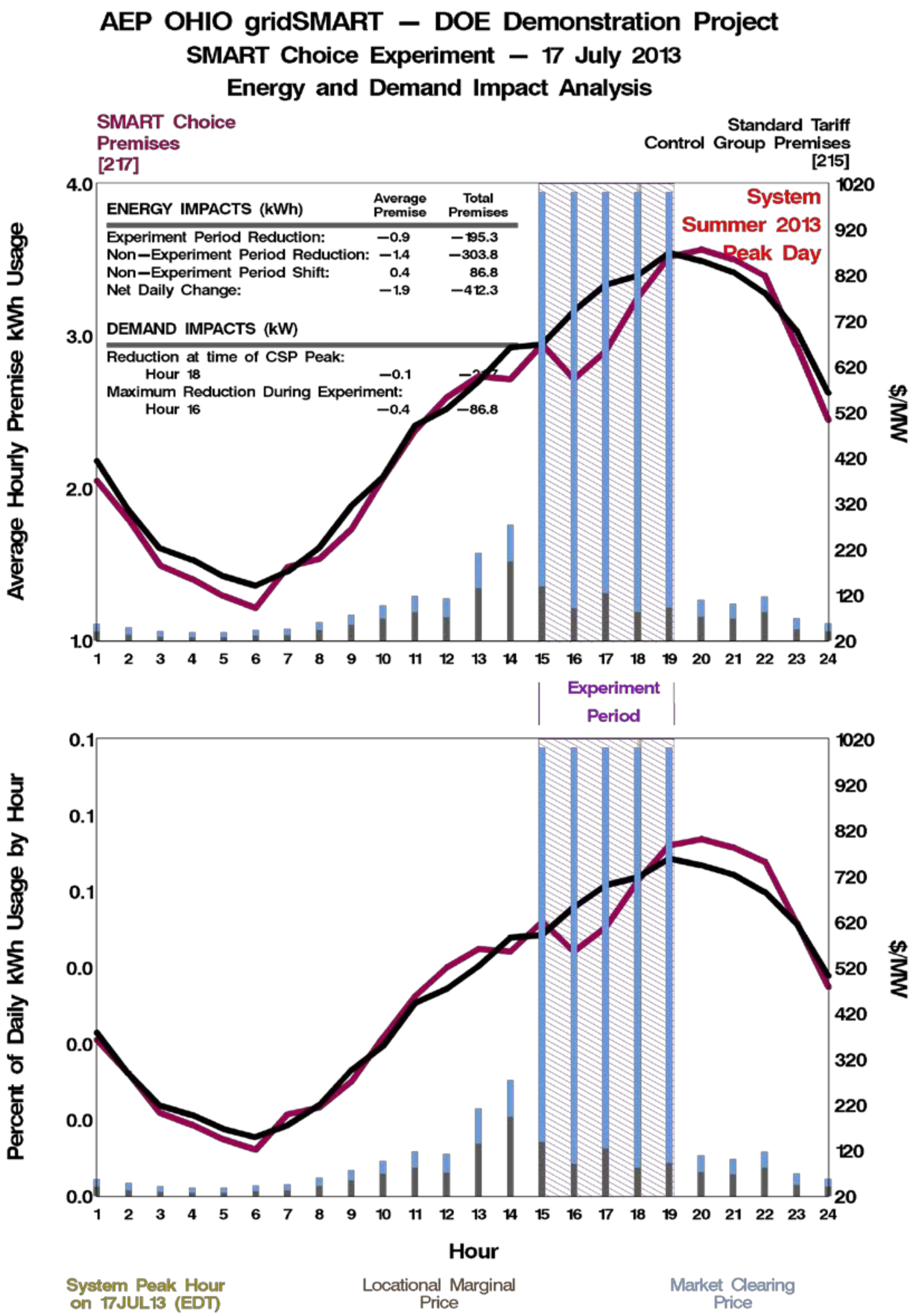


Figure 100. Peak Event Day - July 17, 2013

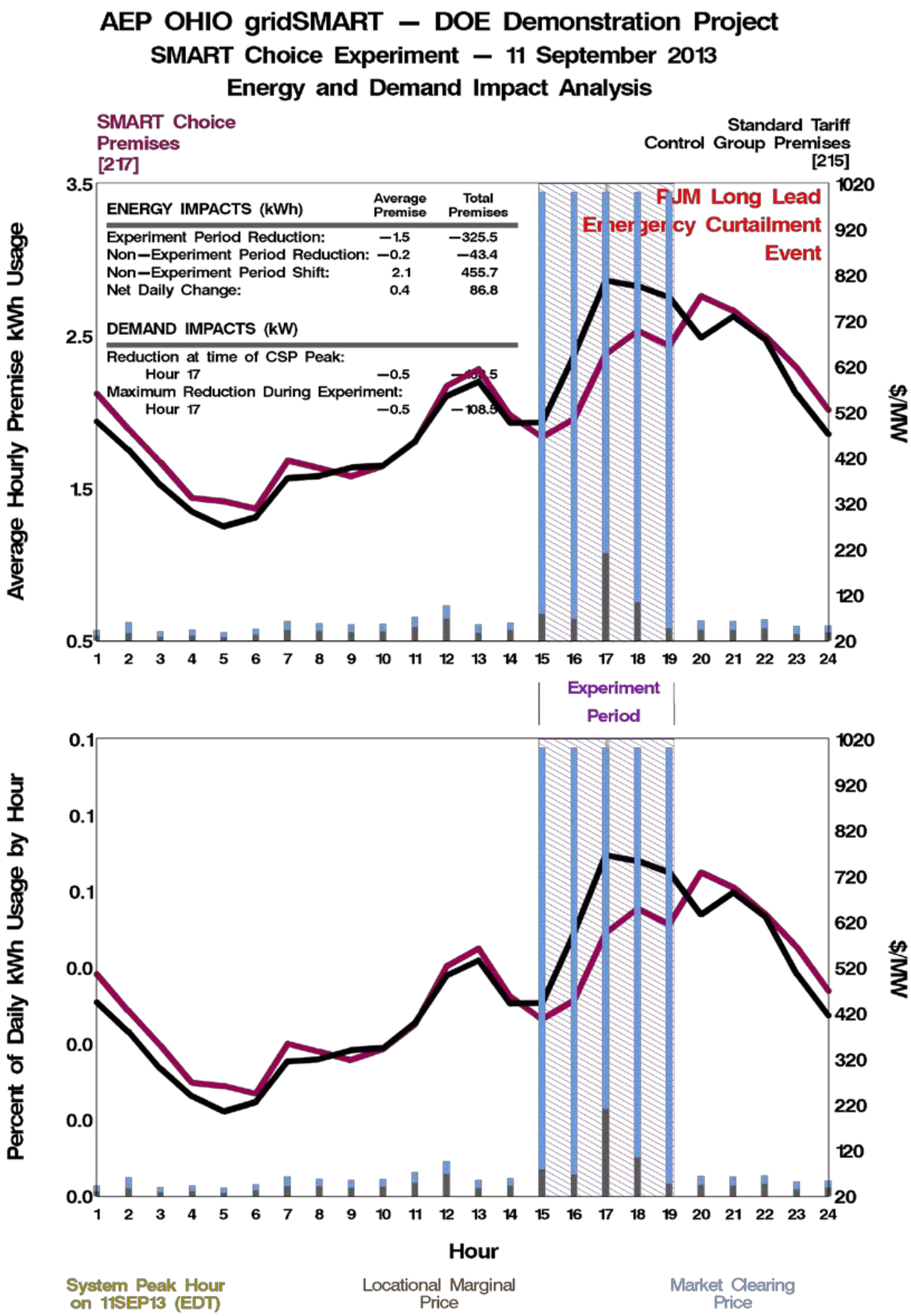


Figure 101. PJM Event Day - September 11, 2013

4.4.4.6 Data Collection Results

RTP_{da} consumers reduced their average hourly consumption by 0.1 kWh between the hours of 1 p.m. and 7 p.m. on experiment weekdays and weekends. They reduced their average hourly consumption by the same amount on non-experiment weekdays. There were no observed changes in RTP_{da} average hourly kWh consumption on non-experiment weekends.

There were similar results regarding the maximum kW reduction between these hours as well. These observations are not inconsistent given the possible distribution of the RTP_{da} experiments across all hours of all days which tended to spread consumption impacts of the experiments over a wider range of hours. That there was an observed reduction in kWh consumption is perhaps indicative of the self-selection bias of these consumers that actively opted into this program.

When this analysis is applied to specific days when there were RTP_{da} experiments, the impacts of the program were more clearly observed.

RTP_{da} experiments were conducted on AEP's summer peak day of July 17, 2013 between 3 p.m. and 6 p.m. and on the PJM emergency curtailment event day of September 11, 2013 between 3 p.m. and 6 p.m.

The reduction in the observed average hourly kWh consumption of RTP_{da} consumers during the hours of the experiments on these days was 0.3 and 0.4 kWh respectively. The max kW reduction during the hours of the experiments on these days was 0.4 and 0.5 kW respectively.

Total daily kWh reduction measured the extent to which consumers shifted their kWh consumption from high-cost to low-cost periods of the day or reduced their kWh consumption altogether. For non-experiment weekdays and weekends, consumers decreased their total daily kWh consumption, but on experiment weekdays, consumers shifted their kWh consumption to the low-cost hours of the day. On the AEP summer peak day, consumers decreased their total daily kWh consumption more than on the average days. On the PJM emergency curtailment day, consumers tended to shift their kWh consumption to the lower-cost period of the day.

Day Types		Average Hourly kWh Reduction[1]	Total Daily kWh Reduction	Max kW Reduction[1]
Experiment Days	Weekdays	0.1	0.6	0.2
	Weekends	0.0	0.3	0.1
Non- Experiment Days	Weekdays	0.1	1.0	0.2
	Weekends	0.1	1.0	0.2
Peak Day[2]	n/a	0.3	1.9	0.4
PJM Emergency Day[3]	n/a	0.4	0.4	0.5

Table 18. Energy and Demand Analysis - Summer 2013

Notes:

- Between 1 p.m. and 7 p.m., the SMART Shift Plus high-cost period used for comparison purposes only.
- Peak day was Wednesday, July 17.
- PJM emergency day was Wednesday, September 11.

4.5 RTP_{da} Conclusions

Real-Time Pricing with double auction was an experimental or beta project to understand what it would take to make this technology a viable program offering to the general public. There were several positive outcomes of the program:

- The theories behind the algorithms were proven correct. The HEMs generated bids, SGD accumulated the supply information and auctions took place. The price the consumer paid for energy varied with each 5-minute interval during the day.
- During a congestion event, load on the congested circuit was reduced by the participating RTP_{da} consumers. As the interval prices increased, the premises thermostat was adjusted to reduce demand. This is evident in the figures contained in the Distribution Circuit Level section of this chapter.
- Consumer response was observed by the consumer's participation in the auctions through the ePCT settings.
- In general, the consumer comments were positive and satisfaction with the RTP_{da} program was high.

In addition to the positive outcomes, there were challenges to overcome before a full deployment could be considered.

- Some consumers who wanted to participate in the RTP_{da} program could not because of the lack of cellular service at their premises. This lack of cellular coverage impacted the number of participating consumers, thereby reducing the amount of potential RTP_{da} load on a circuit. Although cellular service was the most cost effective and easiest to implement for the Project, other technologies should be explored.

- Often multiple trips to a consumer's premises were required in order to get the equipment installed, commissioned, and fully functional. After installation, continuous monitoring was required to ensure the equipment remained in a fully functional state.
- There were challenges in getting the real-time data processed through the legacy back office applications and back to the consumer premise in a timely manner. To account for this delay, a workaround was implemented that offset the 5-minute pricing by two intervals or ten minutes. In other words, the real-time 5-minute LMP for an interval ending at 12:05 was used for the auction with a timestamp of 12:15.
- The combined cost of the ePCT, HEM, and cellular communication for individual premises was too costly for the utility to absorb without some cost recovery mechanism such as in the tariff, through an additional rider, or by increasing the pricing in the tariff to recoup the cost of equipment and installation.
- Other consumer programs had greater financial value to the consumer and the utility than the RTP_{da} program. For detailed results, see the Consumer Programs chapter of this report.

4.6 Lessons Learned

4.6.1 Technology

- Software development needs to be done with the utility's perspective to ensure it is properly aligned with operational functions.
- Thorough testing of software and equipment is essential in preparation for rolling out a complex technology.

4.6.2 Implementation

- Collaboration and preparation is essential to manage an experimental, collaborative research project. With this type of project, allowing enough time for research and development is essential to meet objectives. The use of proven project management tools is effective to develop the technologies and ensure collaboration.
- Develop clear communications to provide expectations to vendors for user acceptance testing processes and feedback mechanisms.
- Select vendors and service providers that more closely align with program goals that accommodate effective collaboration and consistent outcomes and deliverables.
- When performing updates to a user interface, application, or device, the documentation must be updated accordingly. Documentation enhances consumer support as well as back office operations.

4.6.3 Operations

- Consistent communications between devices is dependent on a reliable cellular network. Although cellular service was the most cost effective and easiest to implement for the Project, other technologies should be explored.
- Align software development goals with ongoing operational systems.

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5 Demonstrated Technology – Distribution Automation Circuit Reconfiguration

5.1 Purpose

Distribution Automation and Circuit Reconfiguration (DACR) operating in conjunction with the Distribution Management System (DMS) leveraged two-way communication and infrastructure improvements to improve reliability. Automatic network reconfiguration quickly restored power to de-energized loads, even under complex circuit arrangements that were not suitable for simple loop schemes. DACR control systems could transfer loads automatically between circuits after an outage. This reduced outage times by allowing these networks to automatically respond to fault conditions and outages. It encompassed many system-wide control objectives in the distribution system, including:

- Improved circuit reliability and customer experience.
- Provided enhanced service restoration.
- Enabled data sharing with adjacent control areas.
- Enabled communications link failure detection.
- Demonstrated enhanced situational awareness.
- Demonstrated two-way communication among devices with DMS, central control center visibility, and automated outage recovery.
- Demonstrated equipment sensors that provided near real-time condition/status.
- Used integrated back office systems to provide remote and automated data collection, analysis, visualization, and action.
- Improved effectiveness of traditional protection practices.

5.2 Technology

DACR provided a system to remotely monitor, coordinate, and operate distribution circuit equipment, working behind the scenes to keep the power on. DACR automatically detected fault conditions and outages and strategically rerouted the paths of electricity within the electrical grid. For consumers, this resulted in improved reliability with fewer outages and quicker restoration times. DACR reduced the number of consumers impacted by an outage as well as decreased the amount of time consumers were without power by rerouting the flow of electricity. Any remaining outage areas were identified by the technology and crews were dispatched efficiently, which reduced restoration time.

Distribution substation breakers and line reclosers were designed to attempt to clear a fault by de-energizing the line for a few seconds to see if the fault cleared. If the fault persisted, the recloser de-energized the line and locked out until repairs were made and it was manually switched back in.

Traditional circuit reconfiguration was based on distribution loop schemes that were effective for well-defined circuits. These schemes traditionally operated without communication by monitoring voltage at each switch to detect outages and restore loads. The drawback of using a loop scheme was that control decisions relied only on loss of voltage. DACR leveraged communications and coordinated control to improve reliability. DACR generally included Supervisory Control and Data Acquisition (SCADA), remote sensors, monitors, switches, digital relays, and controllers with embedded intelligence. The Distribution Automation Controller (DAC) was the intelligence behind DACR. All of the available circuit routes were programmed into each DAC. Together, these components gathered near real-time information to provide fault location, outage isolation, circuit reconfiguration, service restoration, and remote equipment monitoring. When a fault occurred, the DAC looked at data from all devices in its control. It then:

- Determined which line section was faulted.
- Identified devices that could be switched to isolate that section and restored power to the un-faulted sections.
- Checked to make sure no sections were overloaded.
- Commanded the devices to switch.

After performing these steps, the DAC sent a message to the Distribution Dispatch Center (DDC) to update the Distribution Management System (DMS) and the Outage Management System (OMS). This reconfiguration was designed to occur within two minutes.

During storms it was necessary to locate multiple fault locations, make repairs, and switch consumers back into service after repairs were made. DACR combined with DMS and OMS enabled the DDC operators to view outage locations and monitor how the DACR system isolated the problem areas. This visualization allowed the DDC operators to perform remote switching to restore service in addition to what the DACR logic was able to accomplish automatically. The remote switching was done without dispatching distribution line crews to the switch locations and expedited restoration of service to the consumer.

The following figure provides a schematic diagram for a typical DACR system.

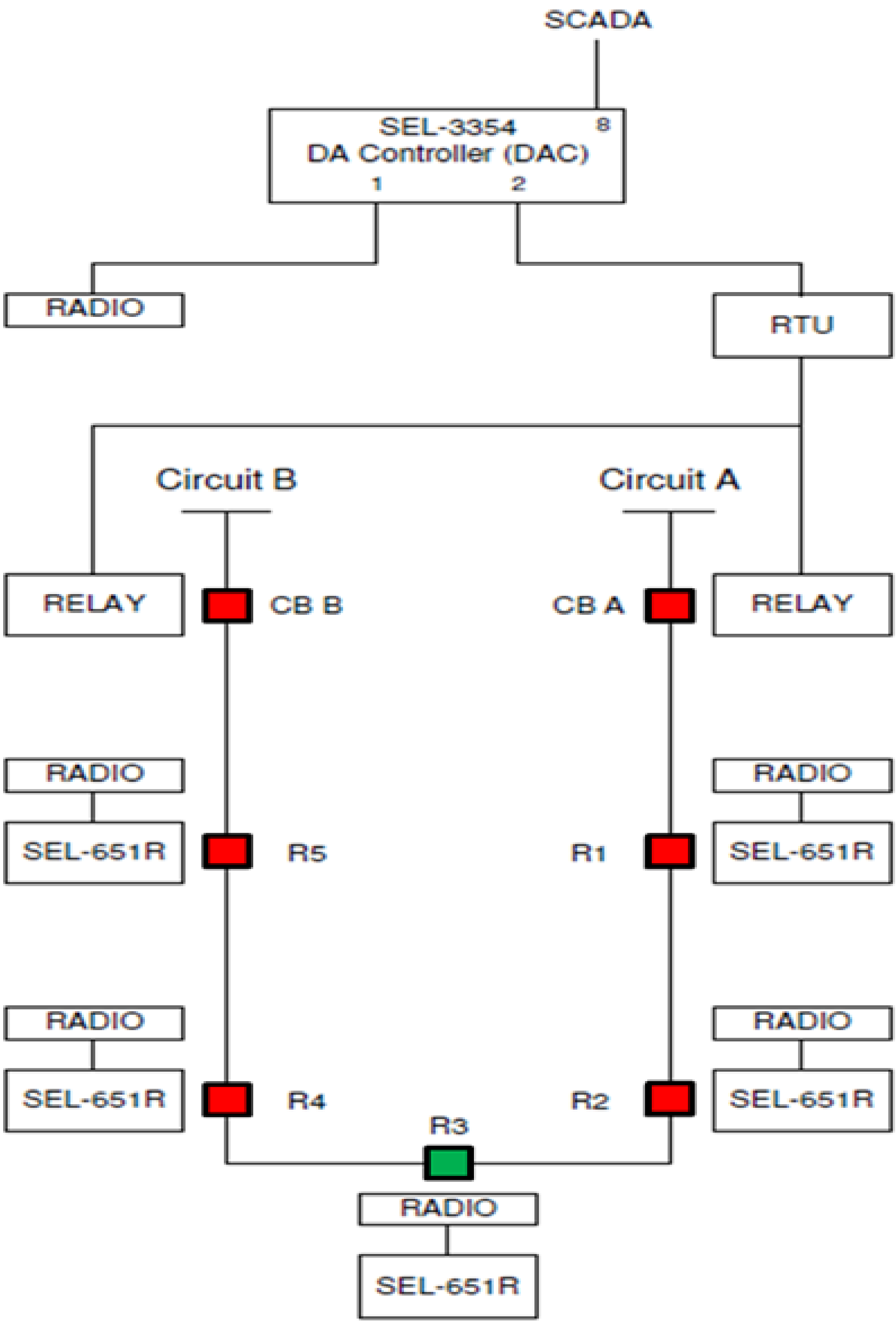

Figure 102. Example DACR System Architecture.[1]

[1] A more detailed discussion of DACR than is practical here is available in: Greer, R., Allen, W., and Dulmage, A., "Distribution Automation Systems With Advanced Features," 55th Annual IEEE Rural Electric Power Conference, Chattanooga, TN, 2011.

5.3 Approach and Implementation

The AEP Ohio gridSMART Demonstration Project deployed DACR on 70 circuits in the Project area. As the DACR system was being designed, it was determined that line devices on the 70 circuits would be upgraded to allow for two- way communication, monitoring, and control via the DMS system. Monitoring and control capability was available on circuit breakers, reclosers, regulators, and capacitor banks. This allowed visualization of the distribution system conditions at all times and enabled proactive correction activities through remote switching of devices or crew dispatch.

The DACR system was monitored by the DMS, which provided alarms and visualization of the outage area to the DDC operators. This resulted in reduced outage times. Each DACR deployment included equipment from Schweitzer Engineering Laboratories (SEL) and G&W Electric (G&W). Replacement of existing station circuit breaker relays with SEL-351S relays enabled SEL DACs to function as controllers for circuits with circuit reconfiguration capability. On these circuits, DACs communicated with SEL-651R recloser controls, which were connected to G&W Viper reclosers. G&W Viper reclosers, SEL-651R recloser controllers, and SEL-3354 Distribution Automation Controller (DAC) automatically reconfigured circuits, isolated faulted line segments, and restored power to customers affected by an outage.

These systems used the DAC deployed in substations to communicate with recloser controllers on circuits associated with each station. When a recloser opened for a permanent fault, the recloser controller communicated with the substation DAC via a wireless mesh radio network, enabling the DAC to make decisions based on the state of the faulted circuit. The DAC then commanded the applicable normally closed recloser(s) on the other side of the faulted section of the line to open. When possible, it also instructed a normally open recloser at a tie point to an energized circuit to close and restore power to the open isolating recloser.

5.4 Impact Metrics Required for DACR

The following 19 impact metrics are associated with the DACR suite of technologies; 17 relate to the Project area and 2 relate to the System area.

Metric ID	Metric Scope	Metric Description	DACR
M13	Project	Distribution Circuit Load	M13-CR
M14	Project	Distribution Circuit/Equipment Overload	M14-CR
M15	Project	Deferred Distribution Capacity Investments	M15-CR
M16	Project	Equipment Failure Incidents	M16-CR
M17	Project	Distribution Equipment Maintenance Cost	M17-CR
M18	Project	Distribution Operations Cost	M18-CR
M19	Project	Distribution Circuit Switching Operations	M19-CR
M21	Project	Distribution Restoration Cost	M21-CR
M25	Project	Truck Rolls Avoided	M25-CR
M26	Project	SAIFI	M26-CR
M27	Project	SAIDI/CAIDI	M27-CR
M28	Project	MAIFI	M28-CR
M29	Project	Outage Response Time	M29-CR
M30	Project	Major Event Information	M30-CR
M31	Project	Distribution Operations Vehicle Miles	M31-CR
M32	Project	CO_2 Emissions	M32-CR
M33	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M33-CR
M34	System	CO_2 Emissions	M34-CR
M35	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M35-CR

Table 19. Impact Metrics Addressing DACR Technology Performance

Refer to the *Metrics Analysis for DACR* section that follows for details.

5.5 Metrics Analysis for DACR

This section provides details for each DACR metric, and includes those requested by the DOE during the definitization of the Cooperative Agreement. Trends were not always observed, however data is presented for each metric.

5.5.1 Distribution Circuit Load (M13-CR)

5.5.1.1 Objective

This impact metric examines circuit load for all circuits in the DACR Project area to historical data for the same circuits to identify the impact of DACR on circuit loads.

5.5.1.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

On an operational circuit, DACR will not influence circuit load. However, DACR improves reliability so the circuit will operate a higher percentage of the time.

5.5.1.3 Calculation Approach

The following queries and methods were used to generate results:

- Circuit load was measured as the instantaneous real power supplied to a circuit's voltage regulator, measured in kW. Power at the circuit regulator was recorded every 15 minutes for each of the three phases (A, B, C). Instantaneous real power was computed as the sum of real power over all three phases.
- Circuit load per circuit, substation, and time were collected.
- Substation load per substation and time were calculated by summing the load of circuits originating at substations.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration.

5.5.1.4 Organization of Results

This section provides circuit load graphs showing the total circuit load for each DACR Project area circuit. Each graph shows percentile results for real power, reactive power, and apparent power for all circuits in the Project area.

5.5.1.5 Data Collection Results

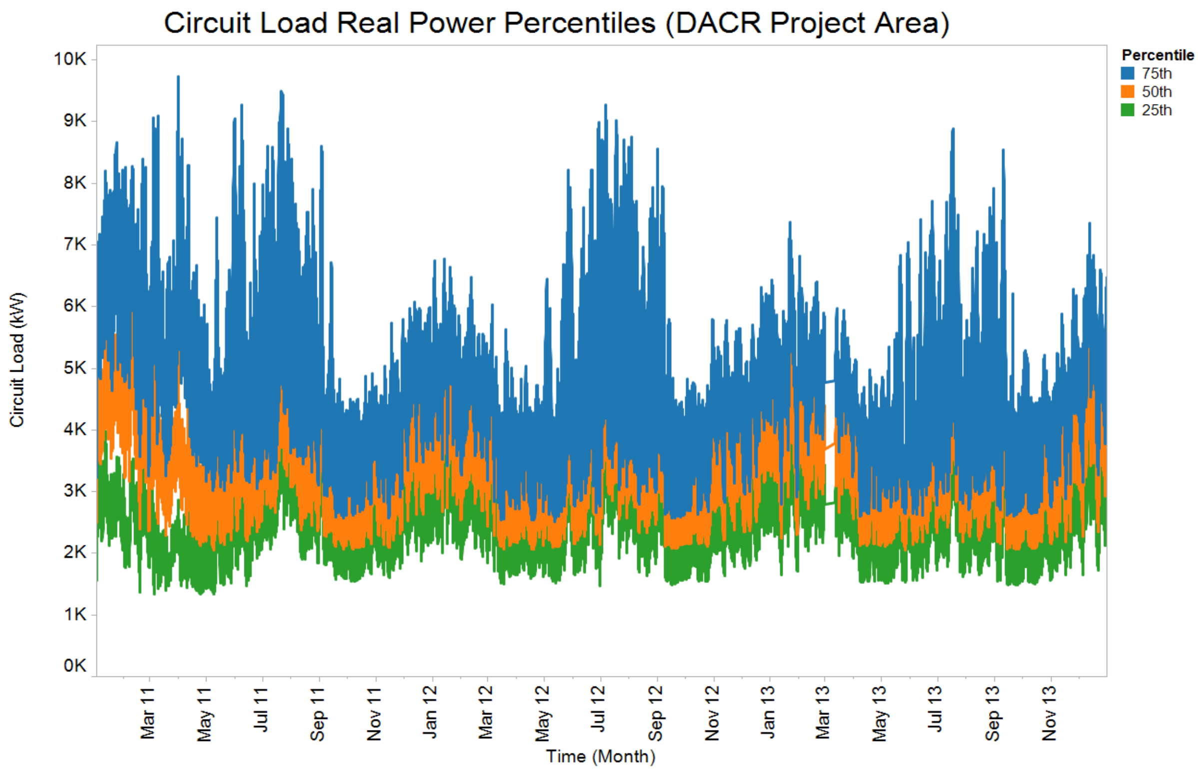

Figure 103. Circuit Load Real Power Percentiles (DACR Project)

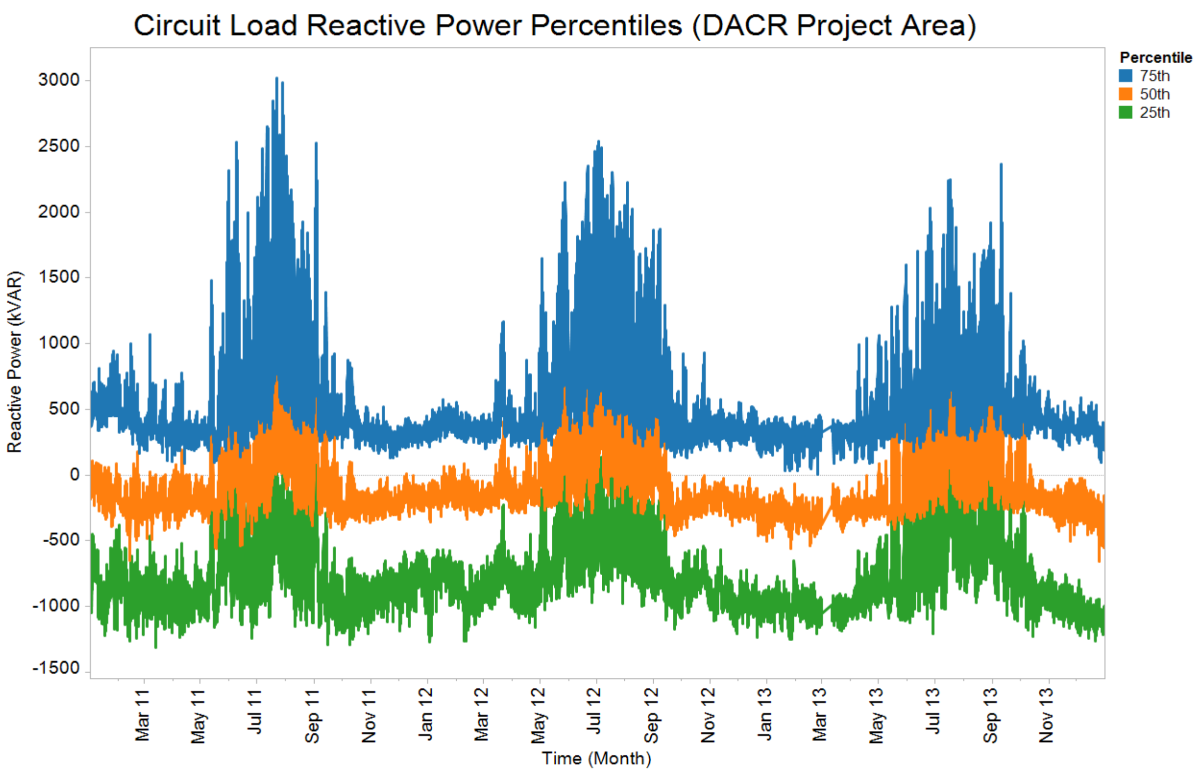

Figure 104. Circuit Load Reactive Power Percentiles (DACR Project)

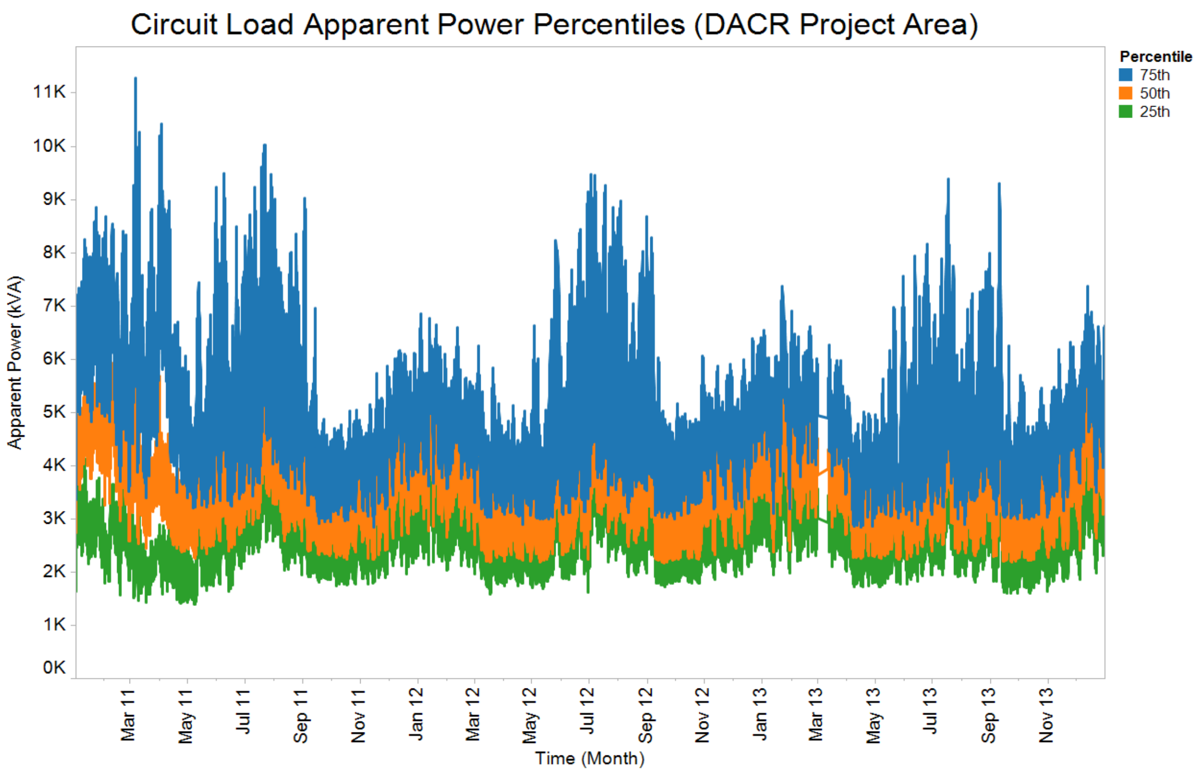

Figure 105. Circuit Load Apparent Power Percentiles (DACR Project)

5.5.1.6 Summary

As anticipated, there was no influence on normal Distribution Circuit Load due to DACR.

5.5.2 Distribution Circuit or Equipment Overload Incidents (M14-CR)

5.5.2.1 Objective

This impact metric reports equipment overload events within the Project area in order to quantify any reduction in the number of overload events on circuits with DACR capability.

5.5.2.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Circuit and substation SCADA reports, event logs, and direct equipment notifications/alarms recorded switching operations performed to relieve equipment overloading. Any such events that resulted in equipment failure contributed to the cumulative count total.

5.5.2.3 Calculation Approach

The following queries and methods were used to generate results:

- Equipment overload events per equipment, equipment type, circuit, substation, and time were collected.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration.

5.5.2.4 Organization of Results

This metric was intended to present a table of circuit overload events reported within the DACR Project area. No such events occurred during the Project.

5.5.2.5 Data Collection Results

No overload events occurred during the Project. DACR did not influence the number of equipment overload events.

5.5.2.6 Summary

DACR did not influence the number of equipment overload events.

5.5.3 Deferred Distribution Capacity Investments (M15-CR)

5.5.3.1 Objective

This impact metric provides a description of all distribution capacity investments that were deferred due to distribution automation.

5.5.3.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Semi-annual variance analysis of distribution capital investment plan was performed.

5.5.3.3 Calculation Approach

No planned or deferred distribution capacity investments occurred within the DACR Project area; therefore, no calculation approach was necessary.

5.5.3.4 Organization of Results

This metric is a study of deferred distribution capacity investments due to circuit reconfiguration distribution automation.

5.5.3.5 Data Collection Results

AEP Ohio reviewed planned projects in Distribution Load Forecasting where DACR circuits would be involved. No projects were deferred as a result of DACR. DACR did not influence distribution capacity investments.

5.5.3.6 Summary

DACR did not influence distribution capacity investments.

5.5.4 Equipment Failure Incidents (M16-CR)

5.5.4.1 Objective

This impact metric provides counts of equipment failure events within the Project and System areas in order to quantify the effects DACR has on equipment failures.

5.5.4.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Circuit and substation SCADA reports, event logs, and direct equipment notifications/alarms recorded switching operations performed to relieve equipment overloading. Any such events that resulted in equipment failure contributed to the cumulative count total. Failures for the following equipment types in this report included:

- Capacitor Banks
- Distribution Transformers
- Reclosers
- Switches
- Voltage Regulators

Other equipment types had no failures.

5.5.4.3 Calculation Approach

The following queries and methods were used to generate results:

- Equipment failure events per date, equipment type, circuit, and substation were collected by linking equipment compatible units to circuit equipment types.
- Equipment failure rate was calculated by the total number of failures divided by the total number of installations for each equipment type.

The part of the System area excluding the footprint of the Project area was referred to as the non-Project area.

5.5.4.4 Organization of Results

This metric shows equipment failure event information grouped by equipment type by month and equipment failures associated with substations in the Project area compared to the non-Project area. Each graph shows the quantity of equipment failures on the vertical axis and separates the columns by either type of equipment, month, or substation.

5.5.4.5 Data Collection Results

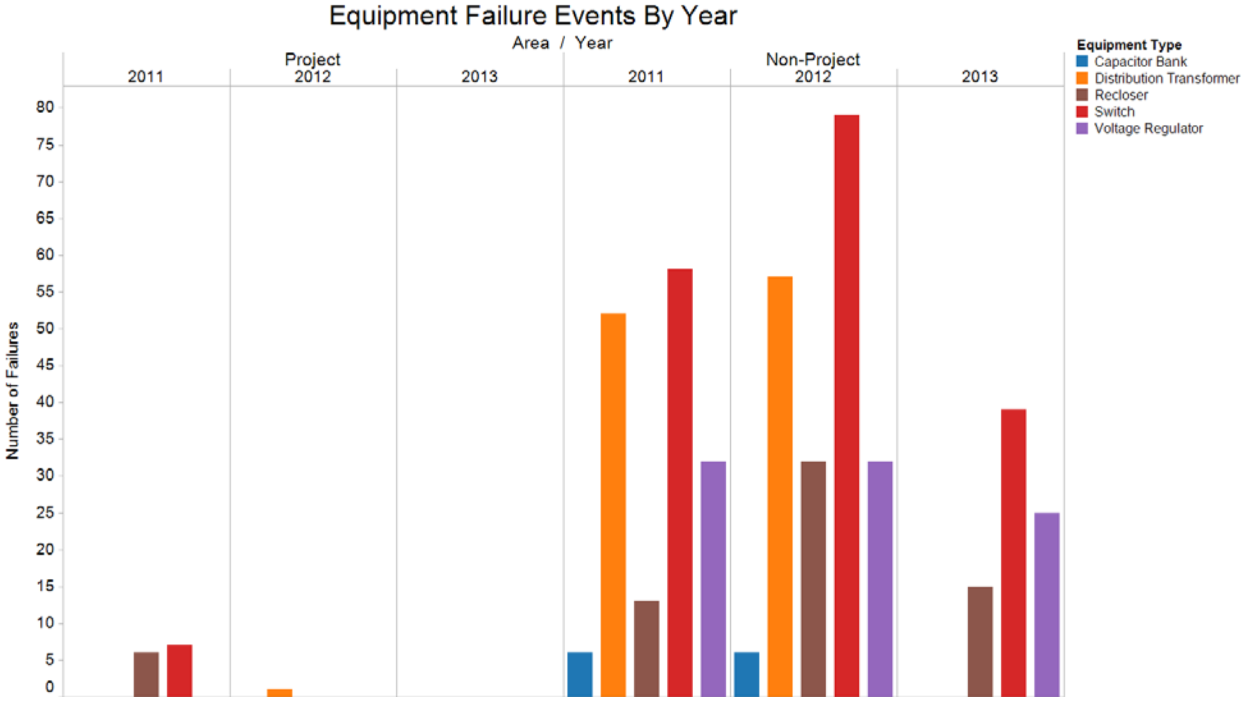

Figure 106. Equipment Failure Events by Year (Project vs. Non-Project Area)

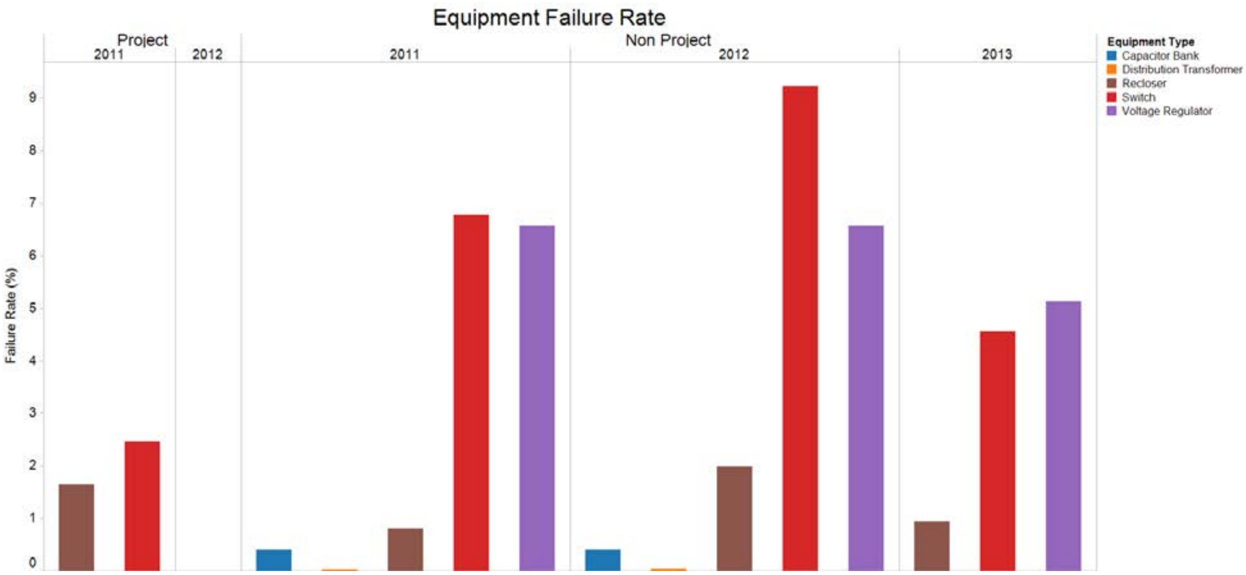

Figure 107. Equipment Failure Rate by Year (Project vs. Non-Project Area)

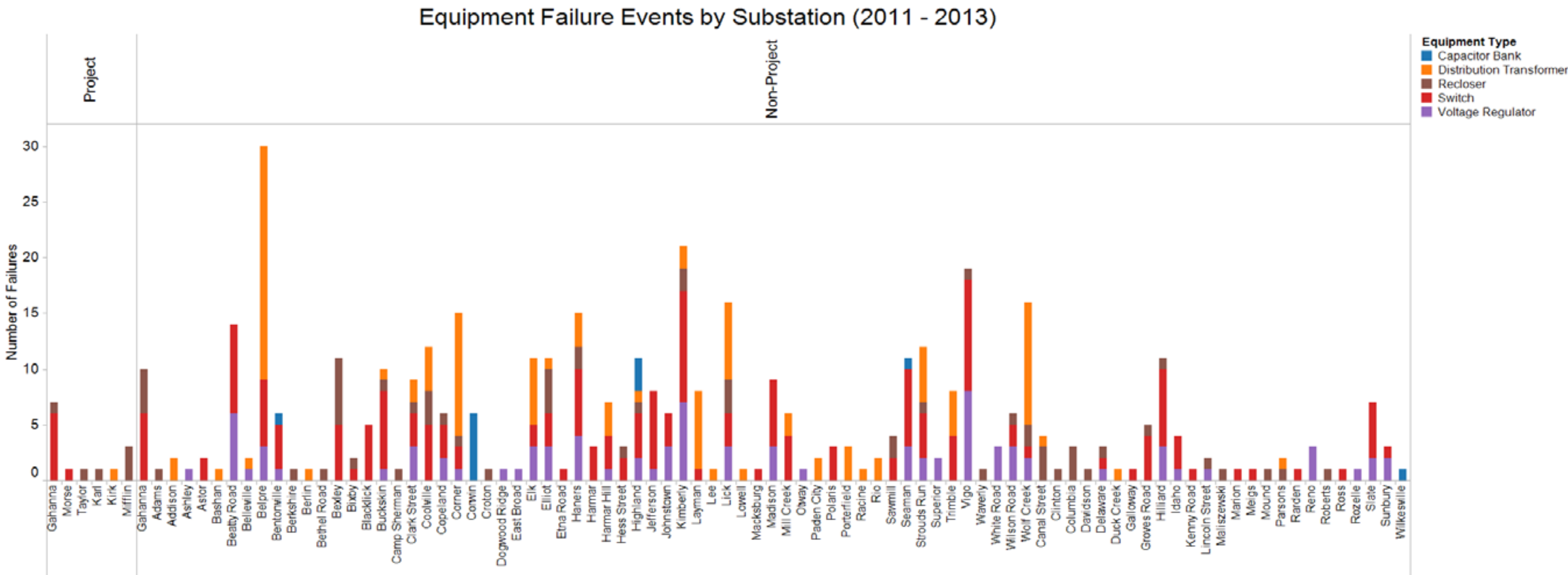

Figure 108. Equipment Failure Events by Substation (Project and Non-Project Area)

5.5.4.6 Summary

No increase in equipment failure events was evident from the data.

5.5.5 Distribution Equipment Maintenance Cost (M17-CR)

5.5.5.1 Objective

This impact metric provides monthly cost data for distribution maintenance activities throughout the Project and System areas.

5.5.5.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Maintenance assumptions identified here are solely for the purpose of this reporting metric and do not follow traditional AEP Ohio accounting policies.

Maintenance costs in the Project area included:

- Non-warranty asset replacement of capacitors, regulators, reclosers, and associated controls or protective devices
- Estimated inspection
- Equipment failures
- IT infrastructure maintenance
- Telecommunications infrastructure

Maintenance costs in the non-Project area included:

- Total asset replacement costs on capacitors, regulators, reclosers, and associated controls or protective devices
- Inspection programs including repairs
- Equipment failures

The part of the System area excluding the footprint of the Project area was referred to as the non-Project area.

5.5.5.3 Calculation Approach

The following queries and methods were used to generate results:

Distribution equipment maintenance labor, material, vehicle fleet, and construction overhead costs per circuit, substation, and work order close date were calculated by summing labor, material, vehicle fleet, and construction overhead costs.

5.5.5.4 Organization of Results

This metric presents monthly average equipment maintenance costs per circuit for both the Project and non-Project areas. Each graph shows average maintenance costs per circuit by month separated by components of construction overhead, labor cost, fleet cost, material costs, and the sum of all four, components. Two graphs are presented; one for the Project area and one for non-Project area.

5.5.5.5 Data Collection Results

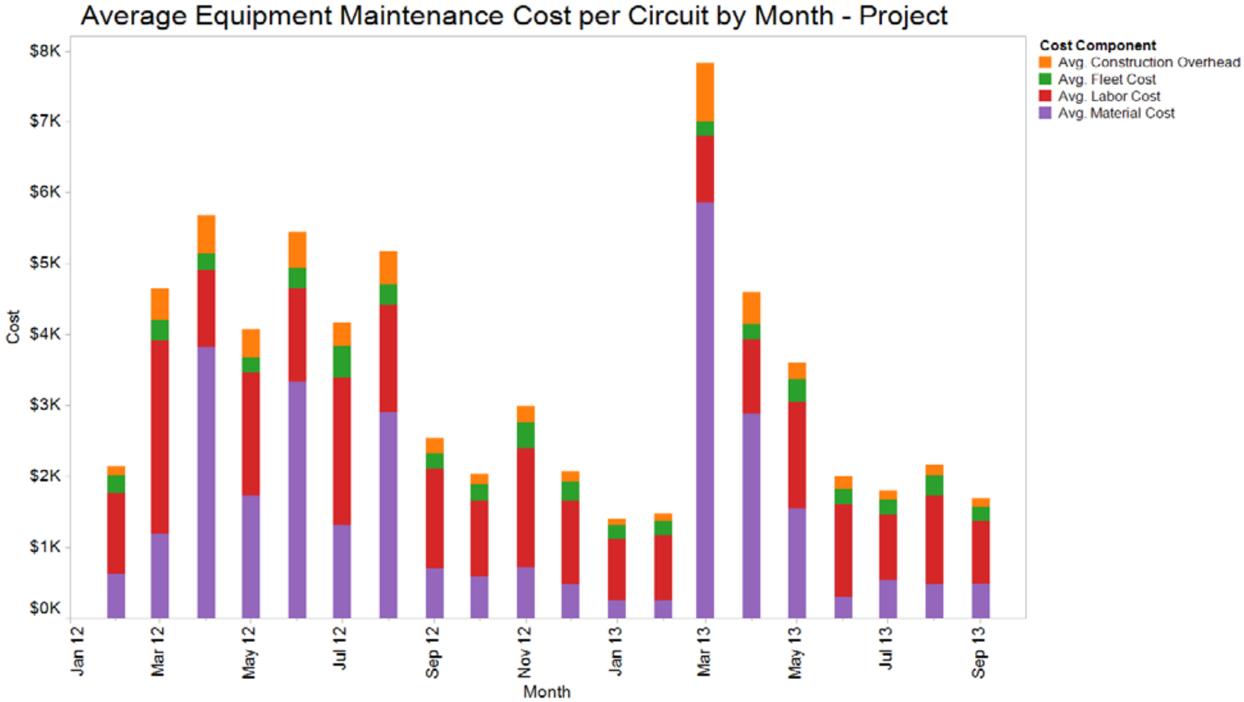

Figure 109. Average Equipment Maintenance Cost per Circuit by Month (Project Area)

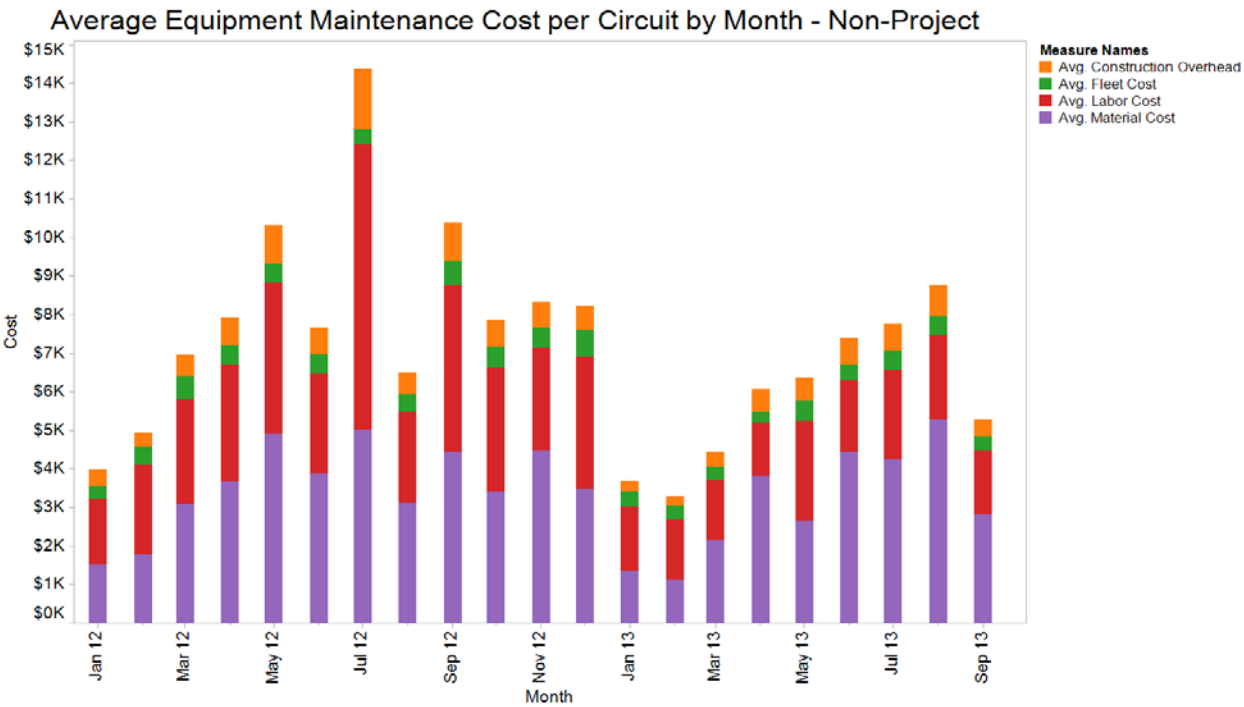

Figure 110. Average Equipment Maintenance Cost per Circuit by Month (Non-Project Area)

5.5.5.6 Summary

The patterns and profiles of costs between the Project area and the non-Project area appear to be within normal month-to-month variation for the Project area. These are based on events in the Project area, and not indicative of impacts of DACR.

5.5.6 Distribution Operations Cost (M18-CR)

5.5.6.1 Objective

This metric provides an estimate of the cost reduction and/or addition achieved by the elimination of inspection programs and reduction in truck rolls due to the installation of the DACR system.

5.5.6.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- Inspection costs were not addressed here. Consequently operation cost reductions were estimated solely from truck rolls avoided.
- Truck roll assumptions:
  - Truck rolls avoided by DACR were due to multi-step outages and scheduled switching events.
  - A short truck roll was 15 minutes and a standard (long) truck roll was 90 minutes.
  - Operations were conducted by one service staff member in one service truck.

5.5.6.3 Calculation Approach

Analysis was conducted by counting the number of remote switching operations and assigning each as either a short or standard truck roll avoided. Standard truck rolls represented a crew traveling from the service center to a switching location. Short truck rolls represented a crew traveling from one switching device to another nearby switching device on the same circuit or on an adjacent circuit. Cost was determined based on conversion factors for vehicle and labor rates.

The following queries and methods were used to generate results:

- Short truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote equipment switching events that occurred during multi-step restoration outages. These were combined with remote recloser switching events that occurred within five minutes of another remote recloser switching events on the same circuit.
- Standard truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote recloser switching events which occurred more than five minutes after another remote recloser switching event on the same circuit that did not occur during an outage with a single restoration step.
- Vehicle savings from truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by summing short truck rolls avoided multiplied by $7.50 per truck roll with standard truck rolls avoided multiplied by $45.25 per truck roll.
- Labor savings from truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by summing short truck rolls avoided multiplied by $15.75 per truck roll with standard truck rolls avoided multiplied by $94.00 per truck roll.

5.5.6.4 Organization of Results

This metric provides savings from avoided truck rolls per month associated with DACR.

5.5.6.5 Data Collection Results

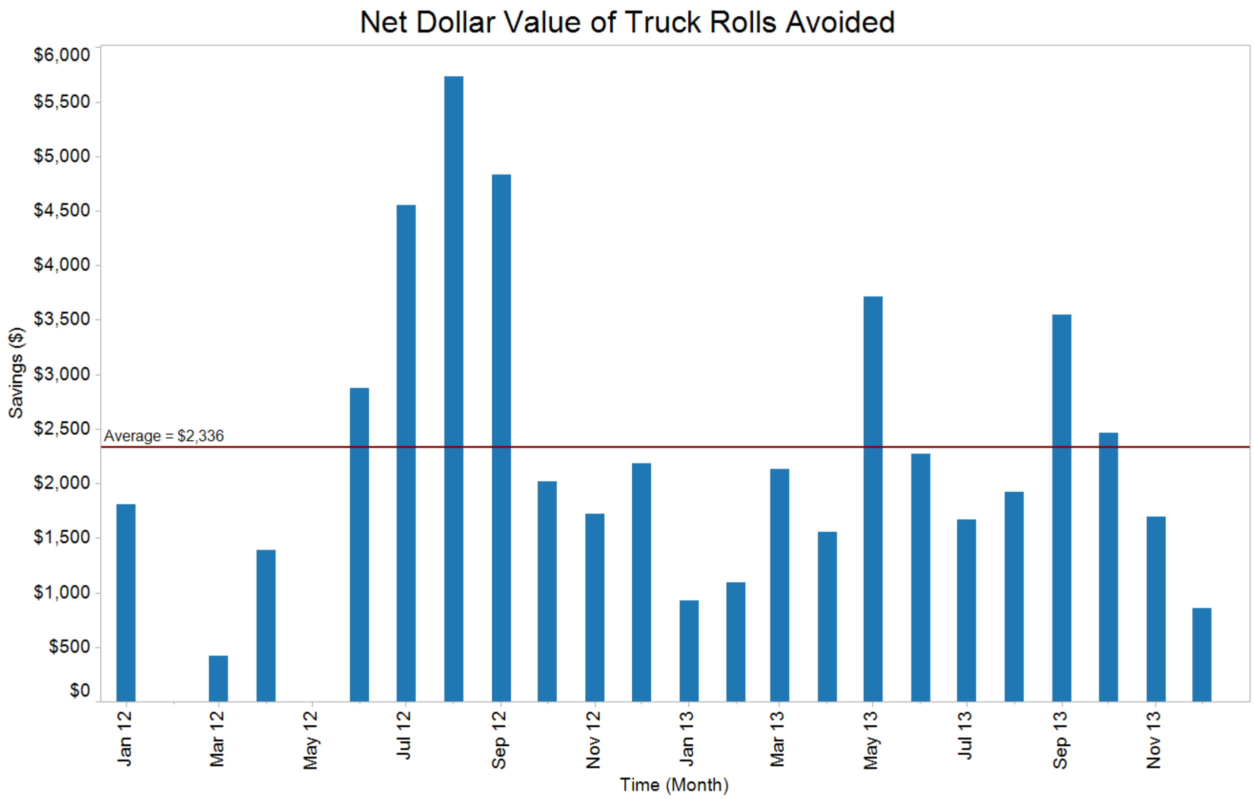

Figure 111. Net Dollar Value of Truck Rolls Avoided

5.5.6.6 Summary

The DACR technology had a greater savings due to avoided truck rolls during the summer months, driven by a combination of a larger number of maintenance operations, construction projects, and weather events occurring in the summer season.

5.5.7 Distribution Circuit Switching Operations (M19-CR)

5.5.7.1 Objective

This impact metric counts the number of switching actions performed by the DACR system and compares these numbers to historical manual switching data to estimate effects on operational costs.

5.5.7.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Data collected prior to the implementation of the DMS system are artificially inflated due to the previous lack of a single system of record for tracking switching events.

5.5.7.3 Calculation Approach

The following queries and methods were used to generate results:

- Equipment switching events per equipment, equipment type, date, current state, circuit, substation, and event type were calculated by counting equipment switching events.
- Short truck rolls avoided attributable to DACR technology were calculated by selecting those remote switching events that occurred during outages that were combined with two recloser switching events within 5 minutes of one another on the same circuit. This analysis was segmented by equipment type, month, circuit, and substation, and excluded outages with a single restoration step.

5.5.7.4 Organization of Results

Switching events are presented as counts of device operations by device type over time.

5.5.7.5 Data Collection Results

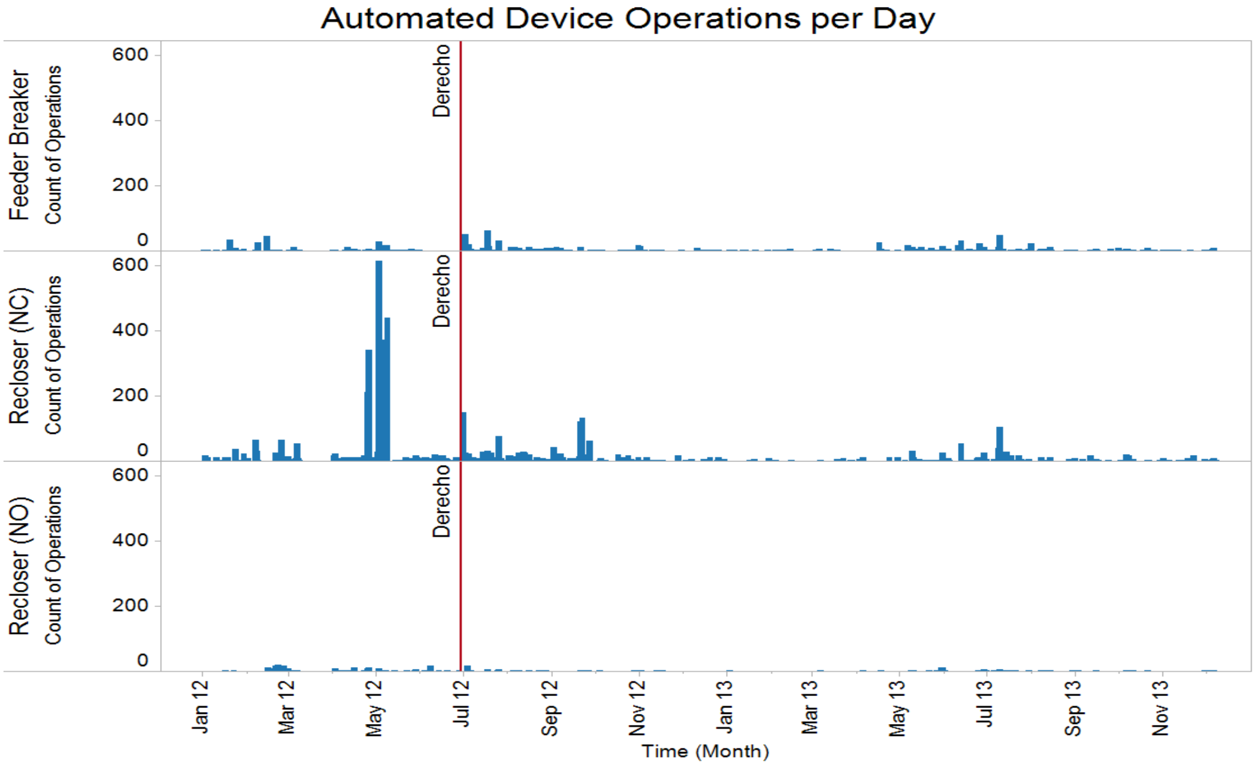

Figure 112. Automated Device Operations per Day

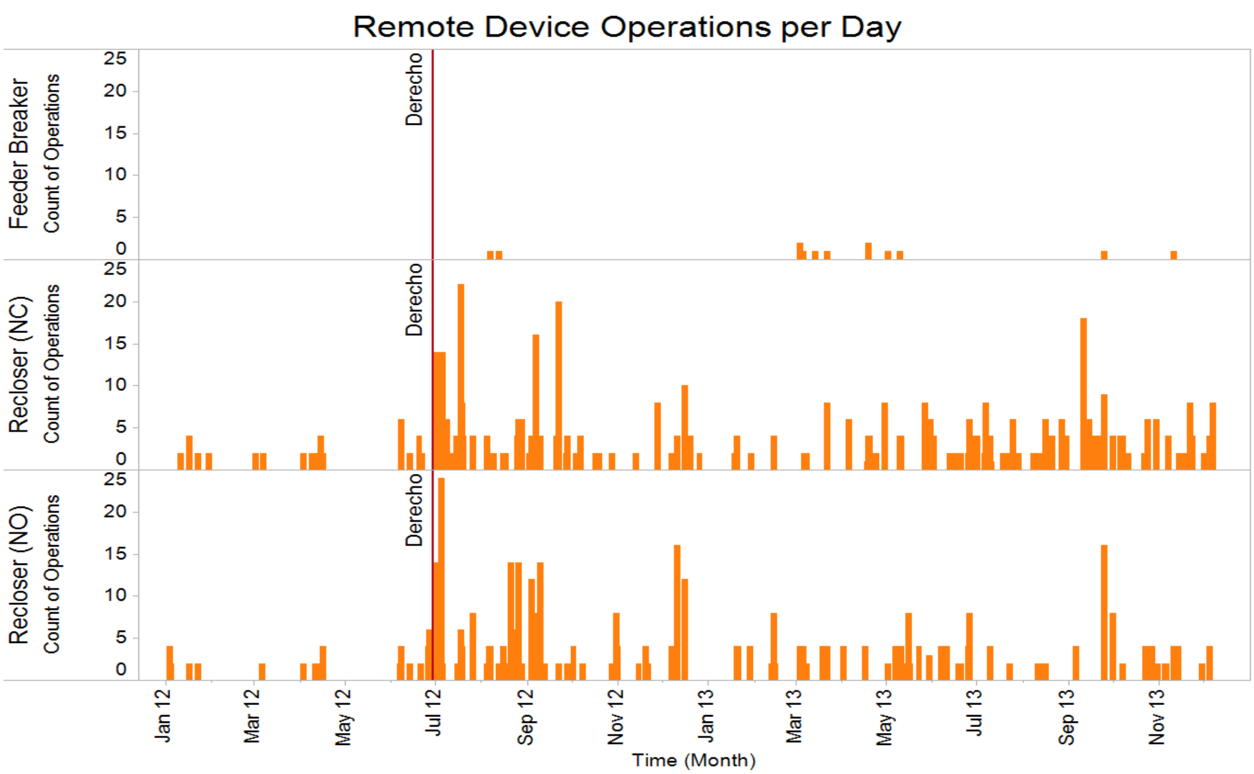

Figure 113. Remote Device Operations per Day

5.5.7.6 Summary

There was insufficient data available to draw conclusions about the overall number of events and whether they were declining as the DACR technology was tuned and operational experience matures, or increasing, and the effect of weather events on the number of switching events.

5.5.8 Distribution Restoration Cost (M21-CR)

5.5.8.1 Objective

This impact metric compares Customer Minutes of Interruption (CMI) avoided for manual switching activities to automated switching by DACR.

5.5.8.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Cost savings for CMI avoided was attributed to achieving reduced labor and associated costs such as reduction in lodging expenses. Using both major and non-major event data from 2005 through 2009, a 5-year average was computed. This extended time period accounts for annual variation caused by weather events.

5.5.8.3 Calculation Approach

Using a charge code set up for restoration on DACR circuits, the following queries and methods were used to generate results:

- Distribution restoration CMI per circuit, substation, outage, and date were calculated by subtracting the time of the first customer call from the time of the outage in minutes multiplied by the number of customers affected by the outage.
- Distribution restoration CMI costs per circuit, substation, outage, and date were calculated by subtracting the time of the first customer call from the time of the outage in minutes multiplied by the number of customers affected by the outage multiplied by $0.052 yields dollars per minute.
- CMI avoided per circuit, substation, and month for non-jurisdictional major event days were calculated by selecting the CMI avoided reported by AEP Ohio.
- CMI avoided costs per circuit, substation, and month for non-jurisdictional major event days were calculated by multiplying the CMI avoided reported by AEP Ohio by $0.052 yields dollars per minute.

5.5.8.4 Organization of Results

This metric presents CMI avoided by DACR and the associated cost savings of reducing CMI. Each graph shows the total customer minutes or equivalent cost impact of avoided CMI by month due to DACR.

5.5.8.5 Data Collection Results

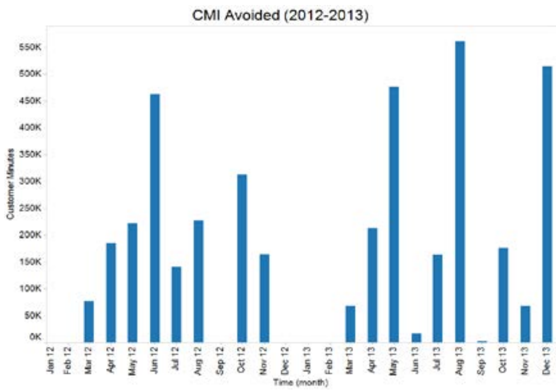

Figure 115. CMI Avoided Due to DACR

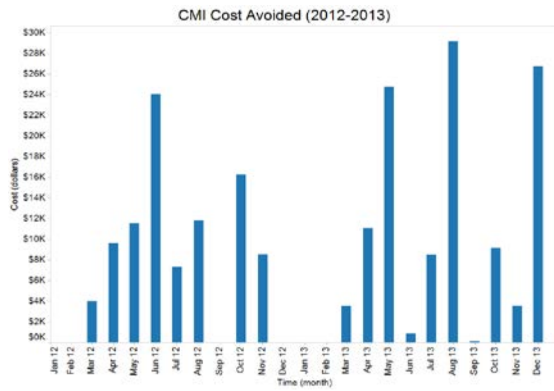

Figure 114. Dollar Value of CMI Avoided Due to DACR

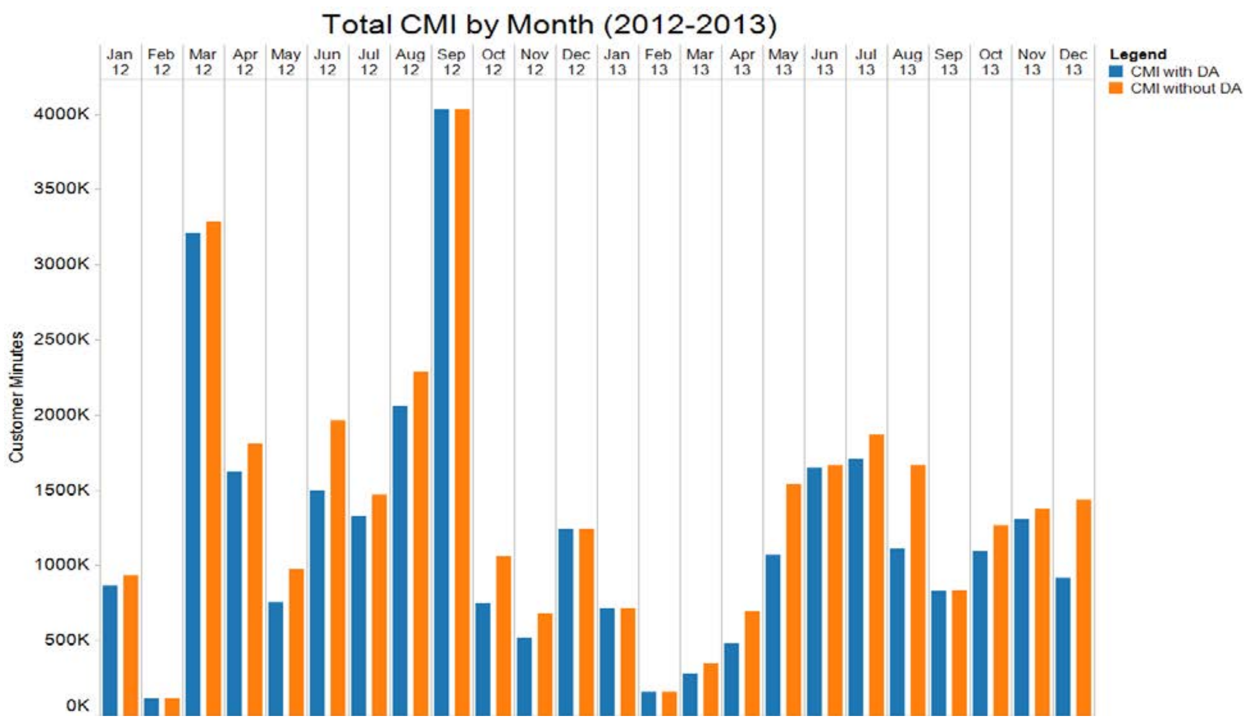

Figure 116. Total Project Area CMI With and Without DACR

5.5.8.6 Summary

DACR was able to successfully reduce CMI when outages occurred in the Project area, which resulted in a corresponding dollar value savings. Some months showed greater savings than others, including some months with no savings. This may be due to the location of the outages on the circuit. Only the outages that were in an area where a circuit reconfiguration was possible were capable of resulting in a CMI reduction. CMI impacts varied in direct proportion to the number of outage events that occurred and were typically driven by weather patterns.

5.5.9 Truck Rolls Avoided (M25-CR)

5.5.9.1 Objective

This metric provides a count of the number of switching actions performed by the DACR system that would otherwise have required a truck roll for manual switching.

5.5.9.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

All circuit reconfiguration events would have been previously performed by a dispatched crew before the installation of DACR.

5.5.9.3 Calculation Approach

Analysis was conducted by counting the number of remote switching operations and assigning each as either a short or standard truck roll avoided. Standard truck rolls represented a crew traveling from the service center to a switching location. Short truck rolls represented a crew traveling from one switching device to another nearby switching device on the same circuit or on an adjacent circuit.

The following queries and methods were used to generate results:

- Short truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote equipment switching events that occurred during multi-step restoration outages. These were combined with remote recloser switching events that occurred within five minutes of another remote recloser switching event on the same circuit.
- Standard truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote recloser switching events which occurred more than 5 minutes after another remote recloser switching event on the same circuit that did not occur during an outage with a single restoration step.

5.5.9.4 Organization of Results

Truck rolls avoided by automated DACR switching may be one of two types: Standard truck rolls represented a crew traveling from the service center to a switching location. Short truck rolls represented a crew traveling from one switching device to another nearby switching device on the same circuit or on an adjacent circuit. These graphs show the total count of short and standard truck rolls avoided by month.

5.5.9.5 Data Collection Results

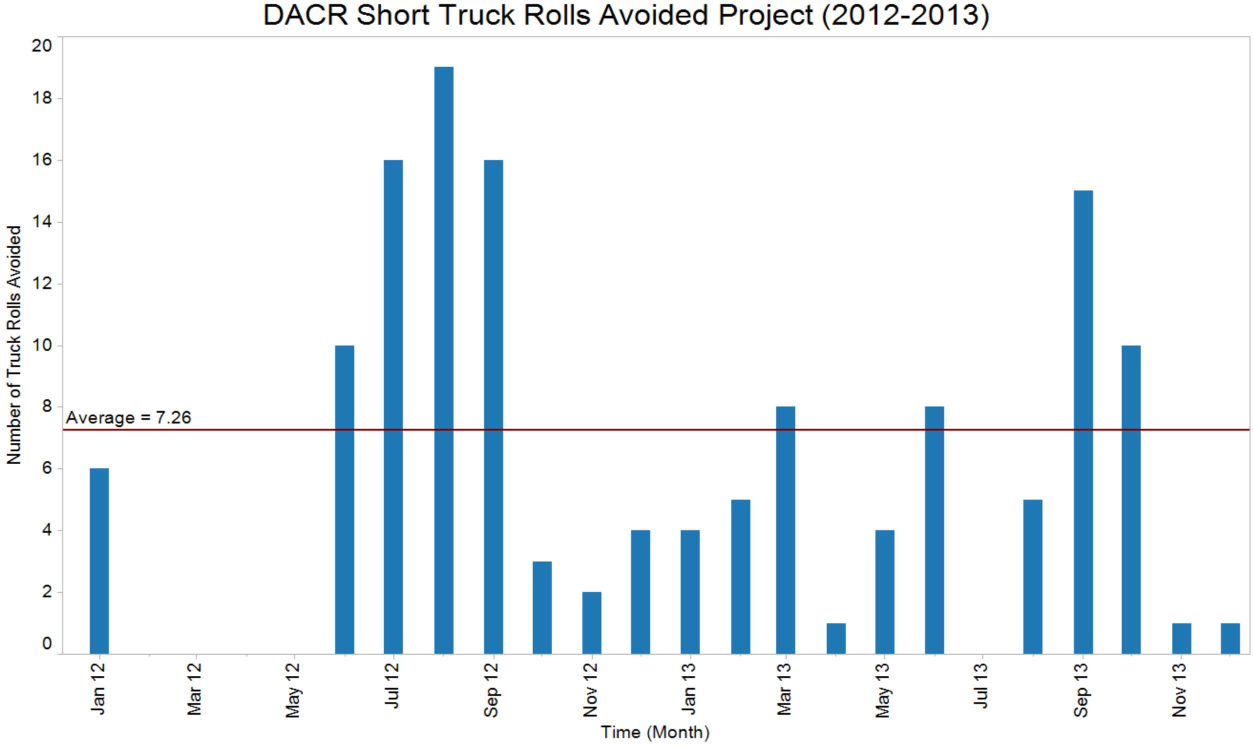

Figure 117. Short Truck Rolls Avoided due to DACR

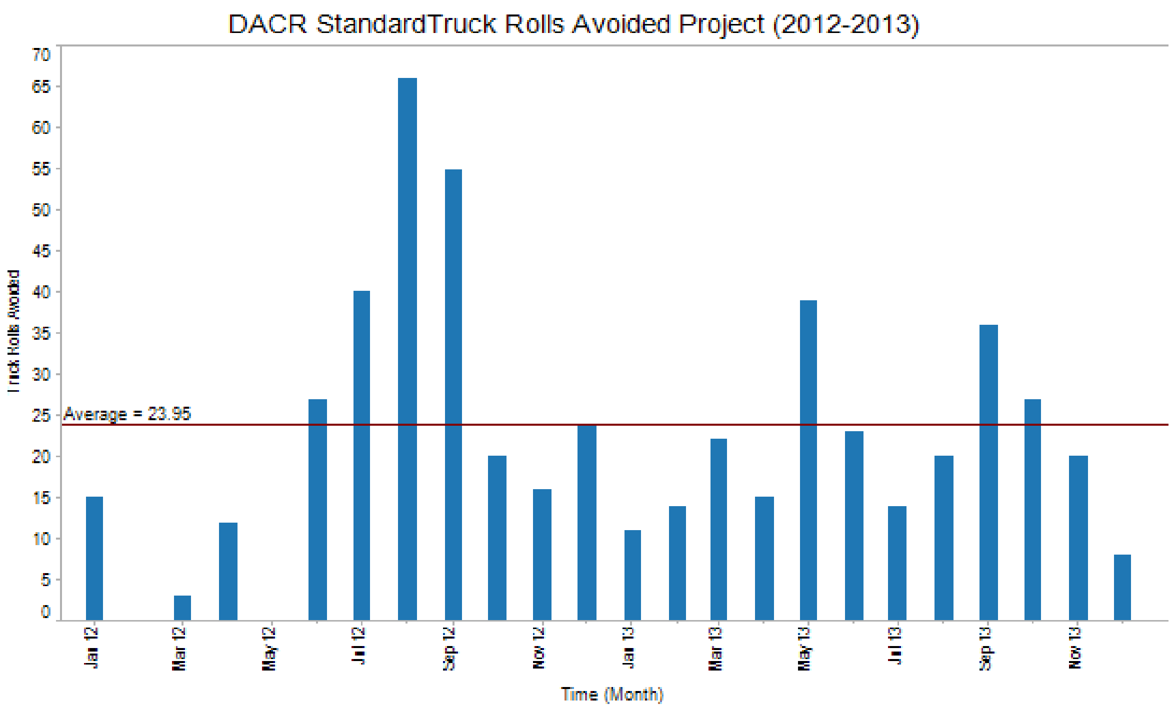

Figure 118. Standard Truck Rolls Avoided due to DACR

5.5.9.6 Summary

Truck rolls were primarily avoided due to the reconfiguration that happened after outages. Therefore the number of truck rolls avoided per month varied greatly depending on weather events. Due to the short duration of the project, the average number of truck rolls avoided over time may not have been consistent with those experienced during the Project.

5.5.10 SAIFI (M26-CR)

5.5.10.1 Objective

This metric provides a report of actual System Average Interruption Frequency Index (SAIFI) for DACR project circuits as well as calculations of what SAIFI would have been without DACR.

5.5.10.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

This analysis assumed that customers restored within five minutes using DACR did not experience a sustained outage, in accordance with IEEE 1366 definitions.

5.5.10.3 Calculation Approach

Actual SAIFI data was reported directly by AEP Ohio. SAIFI without DACR was calculated using customers interrupted (CI) avoided due to DACR.

The following queries and methods were used to generate results. Note that major event days were calculated as defined in IEEE 1366:

- SAIFI With DACR: SAIFI per month, circuit, and substation was calculated by dividing CI excluding major event days by the number of consumers served on the circuit:
  SAIFI = CI / customers served.
- SAIFI Without DACR: SAIFI per month, circuit, and substation was calculated by adding the avoided CI excluding major event days to the CI with DACR excluding major event days and dividing that sum by the number of consumers served on the circuit.

5.5.10.4 Organization of Results

This metric presents a comparison of monthly SAIFI for System area circuits with and without DACR capabilities. The graph and tables show the total SAIFI per month for all Project area circuits.

5.5.10.5 Data Collection Results

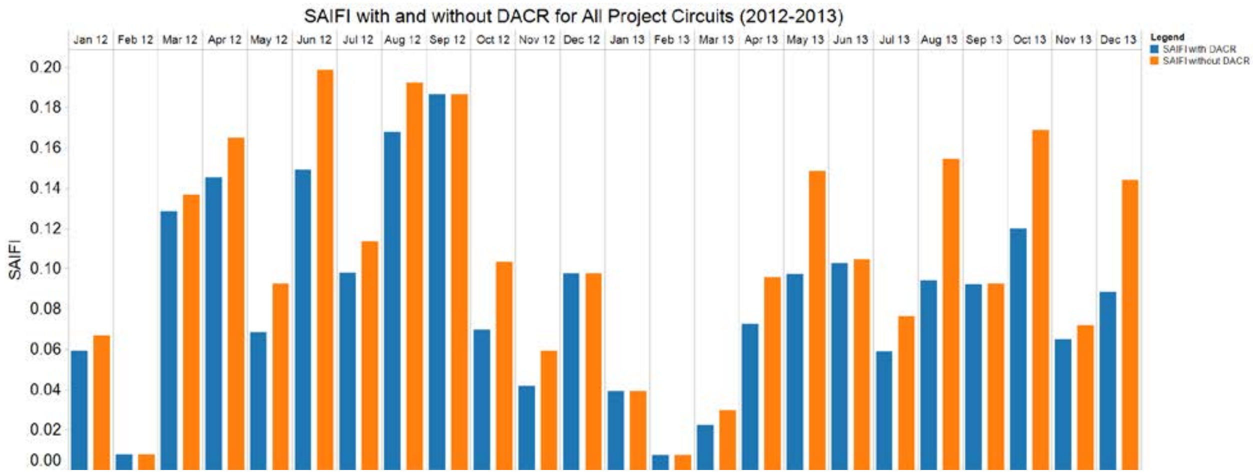

Figure 119. SAIFI with and without DACR for Project Area Circuits

Project Area (70 circuits)				
	Year	With DACR	Without DACR	% Improvement
SAIFI	2011	1.606	1.673	4.0%
	2012	1.226	1.400	12.4%
	2013	0.869	1.151	24.5%

Table 20. SAIFI Comparisons

5.5.10.6 Summary

Project area DACR circuits consistently demonstrated lower SAIFI values than those same circuits without DACR. The DACR impact on SAIFI will vary from circuit to circuit and from year to year depending on the number and location of outages.

5.5.11 SAIDI/CAIDI (M27-CR)

5.5.11.1 Objective

This metric provides a report of actual System Average Interruption Duration Index (SAIDI) and Customer Average Interruption Duration Index (CAIDI) for DACR project circuits as well as a calculation of what SAIDI and CAIDI would have been without DACR. Each graph shows the total SAIDI or CAIDI per month for circuits with and without DACR.

5.5.11.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

This analysis assumed that customers restored within five minutes using DACR did not experience a sustained outage, in accordance with IEEE 1366 definitions.

5.5.11.3 Calculation Approach

Actual SAIDI and CAIDI data were reported directly by AEP Ohio. SAIDI and CAIDI without DACR were calculated using customers interrupted (CI) and customer minutes interrupted (CMI) avoided due to DACR.

The following queries and methods were used to generate results. Note that major event days were calculated as defined in IEEE 1366:

- SAIDI with DACR: SAIDI per month, circuit, and substation was calculated by dividing CMI excluding major event days by the number of customers served on the circuit: SAIDI = CMI / customers served.
- SAIDI without DACR: SAIDI per month, circuit, and substation was calculated by adding the avoided CMI for non-jurisdictional major event days to the CMI with DACR excluding major event days and dividing that sum by the number of customers served on the circuit.
- CAIDI with DACR: CAIDI per month, circuit, and substation was calculated by dividing SAIDI with DACR by SAIFI with DACR: CAIDI = SAIDI / SAIFI.
- CAIDI without DACR: CAIDI per month, circuit, and substation was calculated by dividing SAIDI without DACR by SAIFI without DACR.

5.5.11.4 Organization of Results

This metric presents a comparison of monthly SAIDI and CAIDI for Project area circuits with and without DACR capabilities.

5.5.11.5 Data Collection Results

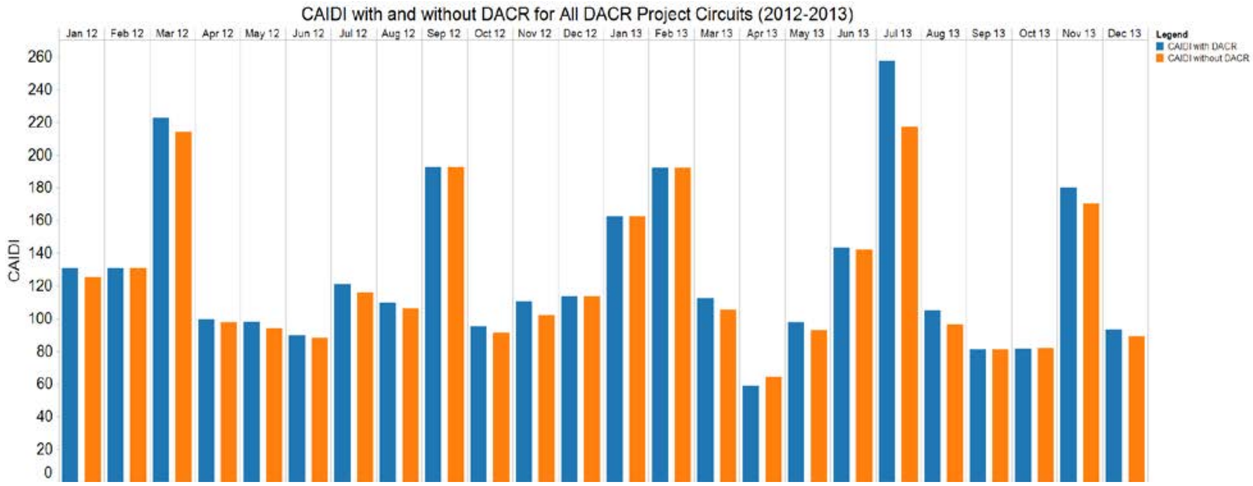

Figure 120. CAIDI with and without DACR for all Project Area Circuits

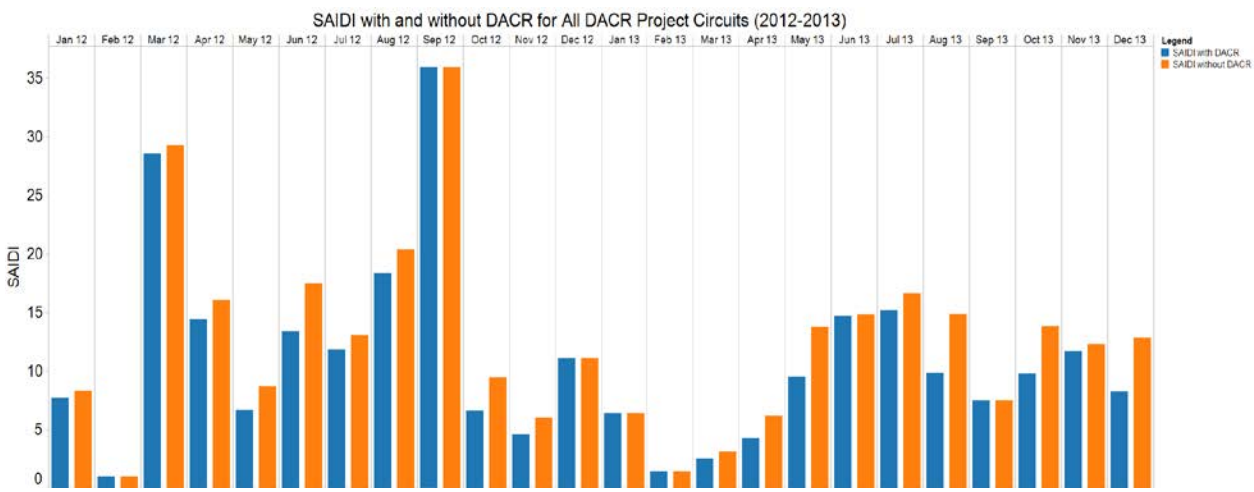

Figure 121. SAIDI with and without DA for All DACR Project Area Circuits

Project Area (70 circuits)				
	Year	With DACR	Without DACR	% Improvement
SAIDI	**2011**	180.9	186.5	3.0%
	2012	161.4	175.7	8.2%
	2013	99.7	123.1	19.0%
CAIDI	**2011**	112.6	111.4	-1.1%
	2012	131.6	125.6	-4.8%
	2013	114.7	107.0	-7.3%

Table 21. SAIDI/CAIDI Comparisons

5.5.11.6 Summary

DACR technology had more impact on SAIDI than on CAIDI. DACR technology reduced the number of impacted consumers and resulted in a reduction in SAIDI, on individual outages. The impact of DACR on the SAIDI of the Project area will vary from year to year depending on the number and location of outages as well as annual weather events. CAIDI measured the average outage duration for only those consumers who experience a sustained outage.

Once DACR technology minimized the impact of an outage, consumers not able to be restored by DACR experienced similar outage duration as consumers on non-DACR circuits. Service that would have been restored quickly in the past could now be restored so quickly that a sustained interruption was not experienced. It appeared that consumers who experienced a sustained outage were interrupted for a longer duration because CAIDI increased. The reason for the increase was that short duration outages were removed from the average that CAIDI represented. The fundamental time to repair each fault/outage was not impacted directly by DACR technology.

5.5.12 MAIFI (M28-CR)

5.5.12.1 Objective

This metric provides an estimation of monthly Momentary Average Interruption Frequency Index (MAIFI) in the Project area.

5.5.12.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Only recloser and breaker operations that resulted in interruptions lasting less than 5 minutes in duration and did not result in a lockout contributed to the MAIFI.

5.5.12.3 Calculation Approach

The following queries and methods were used to generate results:

MAIFI is defined as the number of momentary customer interruptions occurring in a time period divided by the number of customers served.

$$MAIFI = \frac{CI_{mom}}{Customers\_Served}$$

The number of momentary customer interruptions per month was computed in several steps.

1. All customers were assigned to a recloser or breaker zone.
2. The energy state was determined for each zone through time accounting for circuit reconfiguration.
3. Any time a zone was de-energized and then re-energized for a period of 5 minutes or less, momentary customer interruptions were counted for all customers in the zone. Note that momentary interruptions occurring less than 5 minutes before or after a sustained interruption or previously counted momentary interruption were not included in this count.

Once a count of momentary customer interruptions was determined, MAIFI was then computed for each month over the Project area.

5.5.12.4 Organization of Results

This metric presents the monthly MAIFI for Project area circuits.

5.5.12.5 Data Collection Results

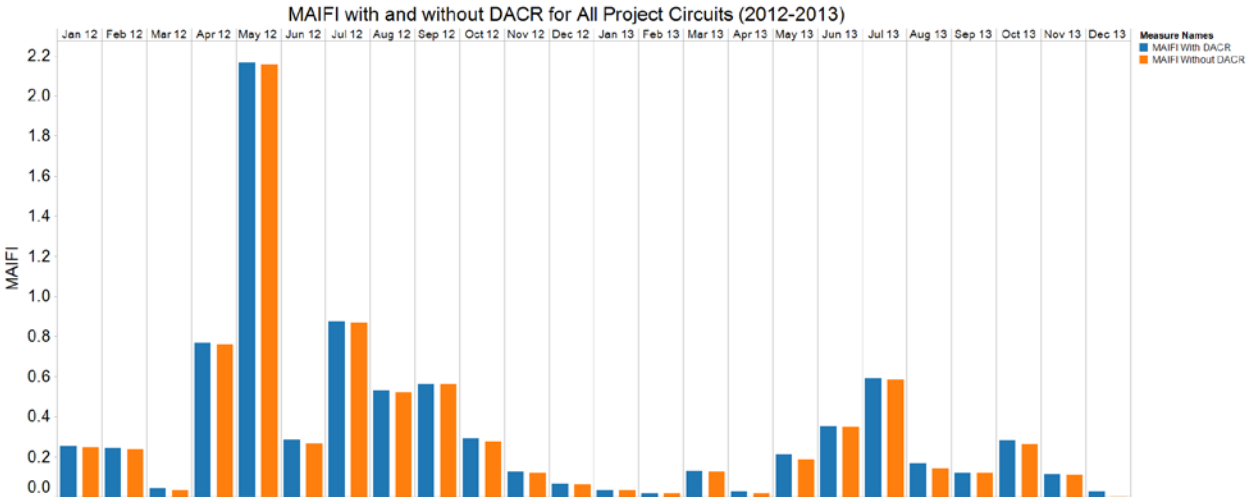

Figure 122. Monthly MAIFI With and Without DACR circuits

5.5.12.6 Summary

Historical data for comparison was not available prior to the Project because AEP did not have a mechanism for tracking MAIFI. This was an example of how distribution automation improved visibility pf AEP's distribution system.

The value of MAIFI with and without DACR showed that circuit reconfiguration contributed a very small increase in the number of momentary interruptions. This was expected because circuit reconfiguration effectively converted sustained outages into momentary interruptions for consumers in zones that were reconfigured.

5.5.13 Outage Response Time (M29-CR)

5.5.13.1 Objective
This metric is intended to gauge the improvement in the response time that occurs as a result of DACR notification.

5.5.13.2 Assumptions
This section contains assumptions made when collecting, analyzing, and presenting the data.

This analysis assumed that outage response time was defined as the time it took for AEP Ohio to become aware that an outage had occurred. This metric did not include the time it took to correct the outage.

5.5.13.3 Calculation Approach
The following queries and methods were used to generate results:

For each outage reported on circuits with DACR installed, the time of the first associated lost-power customer event was compared to the DACR reported outage start time.

5.5.13.4 Organization of Results
Data required for this metric requires reliable matching of customer event calls with specific outages reported by DACR. This customer/DACR event matching was not achievable under the current record keeping system.

5.5.13.5 Data Collection Results
No results are available.

5.5.13.6 Summary
This consumer to DACR event matching was not achievable under the current record keeping system.

5.5.14 Major Event Information (M30-CR)

5.5.14.1 Objective

This metric describes the DACR system's performance and usage during major events that occur during the demonstration period.

5.5.14.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

To demonstrate the impact of DACR on major event service, results achieved during the Derecho event are presented.

5.5.14.3 Calculation Approach

Not applicable

5.5.14.4 Organization of Results

This metric presents the findings of an AEP Ohio produced study of the Derecho event

5.5.14.5 Data Collection Results

The following major events were extracted from a special AEP Ohio study enumerating these events:

- DACR systems had limited ability to restore consumers within the first hour.
- 1,420 consumers on three circuits were restored to service automatically.
- DACR was disabled when the DDC determined the magnitude of damage.
- SCADA switching (53 remote recloser operations) of distribution line devices resulted in:
    - Restoration to service of approximately 10,000 consumers after repairs was completed.
    - Transfer and shedding load from limited circuits in abnormal and extreme loading conditions.
    - Estimated savings of 30-60 minutes per truck roll, resulting in approximately 40 hours of crew time saved where resources could be utilized elsewhere on the System.
    - Utilization of AMI meters to close over 300 outage tickets eliminating the use of field resources for verification.

5.5.14.6 Summary

DACR integration with the Distribution Management System (DMS) had positive impact on outage locating and restoration following major events.

5.5.15 Distribution Operations Vehicle Miles (M31-CR)

5.5.15.1 Objective

This metric provides an estimate of the number of vehicle miles avoided due to DACR and compares it with mileage from a similar area without DACR.

5.5.15.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

All avoided truck rolls would have been dispatched from the normally assigned service center.

5.5.15.3 Calculation Approach

The following queries and methods were used to generate results:

Analysis was conducted by counting the number of remote switching operations and assigning each as either a short or standard truck roll avoided. Standard truck rolls represented a crew traveling from the service center to a switching location. Short truck rolls represented a crew traveling from one switching device to another nearby switching device on the same circuit or on an adjacent circuit.

The following queries and methods were used to generate results:

- Distribution operation vehicle miles per service center, month, vehicle, and vehicle characteristics for sections of circuits with DACR were calculated by multiplying vehicle mileage by the percentage of the circuit with DACR divided by 100. The distribution operation vehicle miles per service center, month, vehicle, and vehicle characteristics for sections of circuits without DACR were calculated by multiplying vehicle mileage by the percentage of the circuit without DACR divided by 100.
- Vehicle miles avoided due to DACR technology per service center, circuit, and month were calculated by summing the sum of urban (5 miles), rural (20 miles), and combination (10 miles) standard truck roll distances for standard truck rolls avoided with the sum of urban (2 miles), rural (4 miles), and combination (3 miles) short truck roll distances for short truck rolls avoided.

5.5.15.4 Organization of Results

This metric presents total vehicle miles avoided due to DACR by month. The graph shows the total miles avoided per month.

5.5.15.5 Data Collection Results

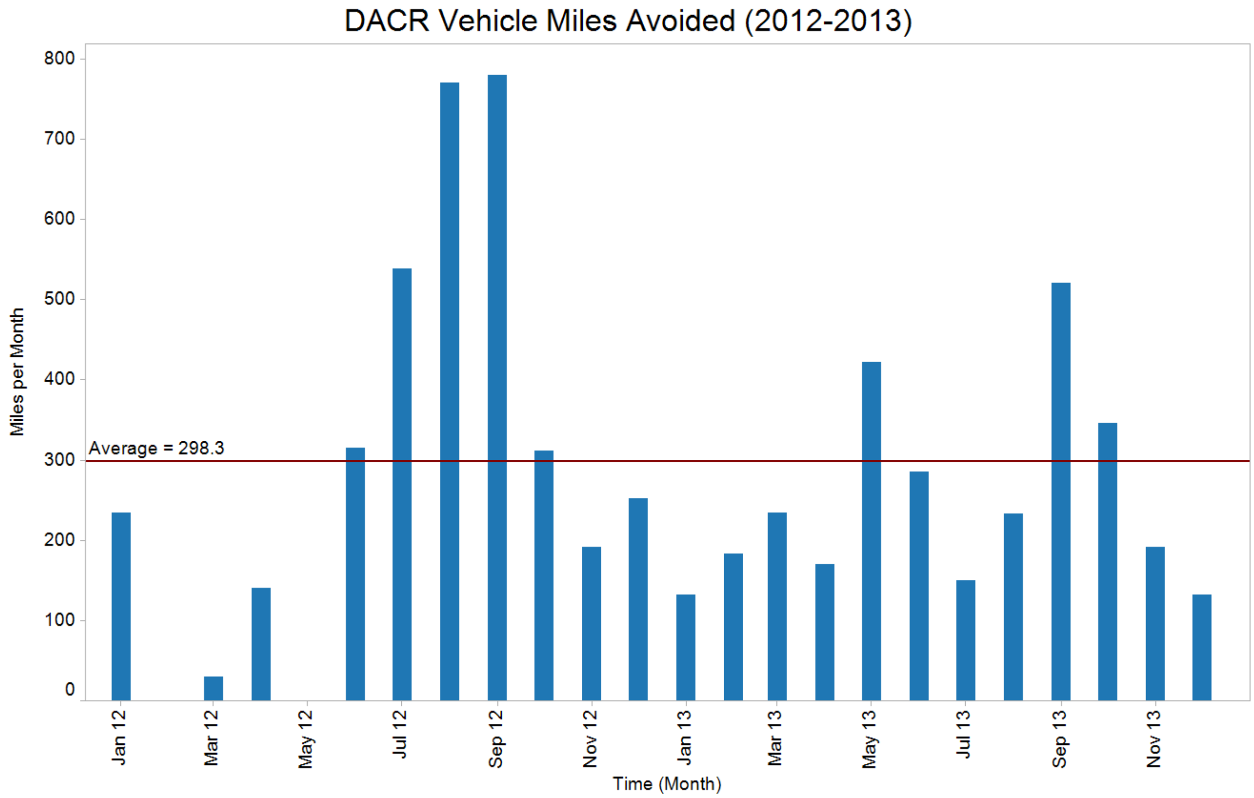

Figure 123. DACR Vehicle Miles Avoided

5.5.15.6 Summary

The DACR system and DMS reduced the number of miles driven to address operational activities. The average number of miles avoided is estimated at 298.3.

5.5.16 CO_2 Emissions - Project area (M32-CR)

5.5.16.1 Objective

This impact metric provides an estimate of the amount of avoided and/or added CO_2 emitted due to reduced driving miles resulting from use of DACR technology.

5.5.16.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The only significant impacts on CO_2 emissions due to DACR are achieved through truck rolls avoided since DACR has little direct impact on consumer usage patterns.
- SO_X: 0.00263084 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- NO_X: 0.00117934 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- $PM_{2.5}$: 0.001 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*

5.5.16.3 Calculation Approach

CO_2 reduction was calculated as a function of vehicle miles avoided using emissions data specific to AEP Ohio's distribution service fleet vehicles.

The following queries and methods were used to generate results:

- Short truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote equipment switching events that occurred during multi-step restoration outages. These were combined with remote recloser switching events that occurred within five minutes of another remote recloser switching events on the same circuit.
- Standard truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote recloser switching events which occurred more than 5 minutes after another remote recloser switching event on the same circuit that did not occur during an outage with a single restoration step.
- AEP Ohio determined an average fuel economy value for each vehicle. Corrected average monthly fuel efficiencies in miles per gallon per service center, month, and fuel type for vehicles used by the AEP Ohio Distribution business unit were calculated by calculating the average of monthly vehicle mileages divided by monthly quantity of fuel for each vehicle. Because some suspect monthly vehicle mileages (i.e., 703,281 miles) were received, if the average of monthly vehicle mileages divided by monthly quantity of fuel divided by the average monthly average fuel economy value was not between .5 and 2, average monthly average fuel economies were substituted for the average of monthly vehicle mileages divided by monthly quantity of fuel to calculate the corrected average monthly fuel efficiencies.

- Tons of CO_2 avoided per service center, circuit, and month due to truck rolls avoided due to DACR technology were calculated by dividing vehicle miles avoided by the corrected average monthly fuel efficiency times (8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines) times 0.00110231131092 (kg to tons conversion factor).

5.5.16.4 Organization of Results

The following section describes the amount of CO_2 avoided due to DACR as a result of truck rolls avoided. The graph shows the amount of CO_2 avoided due to the net number of truck rolls avoided in the Project area.

5.5.16.5 Data Collection Results

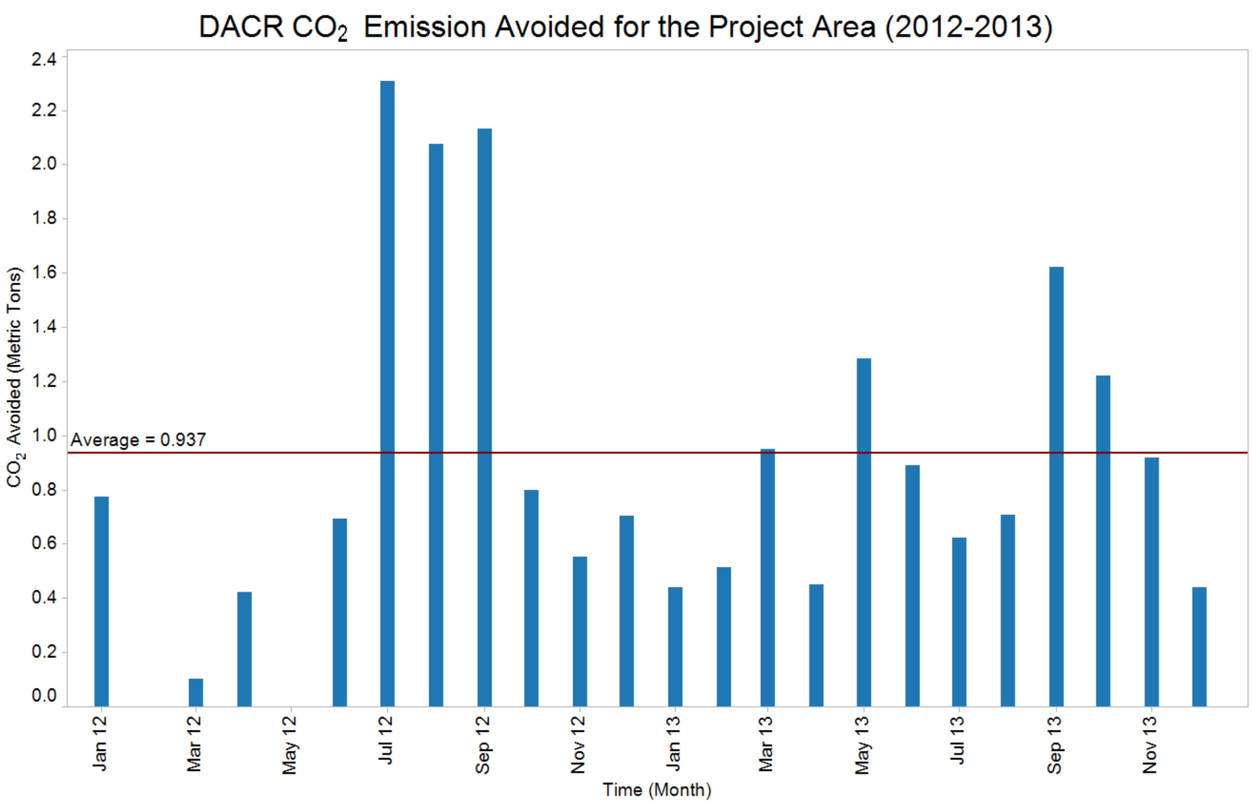

Figure 124. DACR CO_2 Emissions Avoided for the Project Area

5.5.16.6 Summary

Emissions reductions were a direct multiplier of avoided truck miles. CO_2 emissions were primarily reduced by the automated reconfiguration that happened after outages. Therefore the amount of CO_2 emissions reduced per month varied greatly depending on weather events.

5.5.17 Pollutant Emissions - Project area: SO_X, NO_X, $PM_{2.5}$ (M33-CR)

5.5.17.1 Objective

This impact metric provides an estimate of the amount of avoided and/or added pollutants emitted during driving miles due to use of DACR technology.

5.5.17.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

The significant impacts on pollutant emissions due to DACR were achieved through truck rolls avoided as DACR had little direct impact on consumer usage patterns.

- For the purposes of calculating SO_X for this metric, SO_2 emissions from vehicles was used as the measure for that metric.
- A CARB limit value of 0.05 grams of Nitrogen Oxides (NO_X) per mile

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 50,000 mi*

- 0.01 g $PM_{2.5}$ emissions/mi conversion factor

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 100,000 mi*

- 0.165 g SO_X emissions/gallon for gas engines, .0963 g SO_X emissions/gallon for diesel engines conversion factor

  Calculated from: sulfur content of gasoline = 30 ppm

  Source: *U.S. EPA 40 CFR parts 80, 85, and 86 AMS-FRL-6516-2*

  Sulfur content of ULSD diesel fuel = 15 ppm

  Source*: U.S. EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-00-057)*

  Molecular weight of SO_2 = 64 g/mole

  Density of gasoline = 2.75 kg/gallon

  Density of diesel fuel = 3.21 kg/gallon

5.5.17.3 Calculation Approach

Pollutant reduction was calculated as a function of vehicle miles avoided using emissions data specific to AEP Ohio's distribution service fleet vehicles.

The following queries and methods were used to generate results:

- Short truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote equipment switching events that occurred during multi-step restoration outages. These were combined with remote recloser switching events that occurred within five minutes of another remote recloser switching events on the same circuit.
- Standard truck rolls avoided per equipment, equipment type, month, circuit, and substation due to DACR technology were calculated by selecting remote recloser switching events which occurred more than 5 minutes after another remote recloser switching event on the same circuit that did not occur during an outage with a single restoration step.
- AEP Ohio determined average fuel economy value for each vehicle. Corrected average monthly fuel efficiencies in miles per gallon per service center, month, and fuel type for vehicles used by the AEP Ohio Distribution business unit were determined by calculating the average of monthly vehicle mileages divided by monthly quantity of fuel for each vehicle. Because some suspect monthly vehicle mileages (i.e., 703,281 miles) were received, if the average of monthly vehicle mileages divided by monthly quantity of fuel divided by the average monthly average fuel economy value was not between 0.5 and 2.0, average monthly average fuel economies were substituted for the average of monthly vehicle mileages divided by monthly quantity of fuel to calculate the corrected average monthly fuel efficiencies.
- Kilograms of NO_X avoided per service center, circuit, and month due to truck rolls avoided due to DACR technology were calculated by multiplying vehicle mileage avoided multiplied by 0.05 g NO_X emissions per mile multiplied by 0.001 (g to kg conversion factor).
- Kilograms of $PM_{2.5}$ avoided per service center, circuit, and month due to truck rolls avoided due to DACR technology were calculated by multiplying vehicle mileage avoided multiplied by 0.01 g $PM_{2.5}$ emissions per mile multiplied by 0.001 (g to kg conversion factor).
- Kilograms of SO_2 avoided per service center, circuit, and month due to truck rolls avoided due to DACR technology were calculated by dividing vehicle miles avoided by the corrected average monthly fuel efficiency multiplied by (.165 g SO_2 emissions/gallon for gas engines, .0963 g SO_2 emissions/gallon for diesel engines) multiplied by 0.001 (g to kg conversion factor).

5.5.17.4 Organization of Results

The following section describes the amount of pollutants avoided due to DACR as a result of truck rolls avoided. The graph shows the amount of pollutants avoided due to the net number of truck rolls avoided in the Project area.

5.5.17.5 Data Collection Results

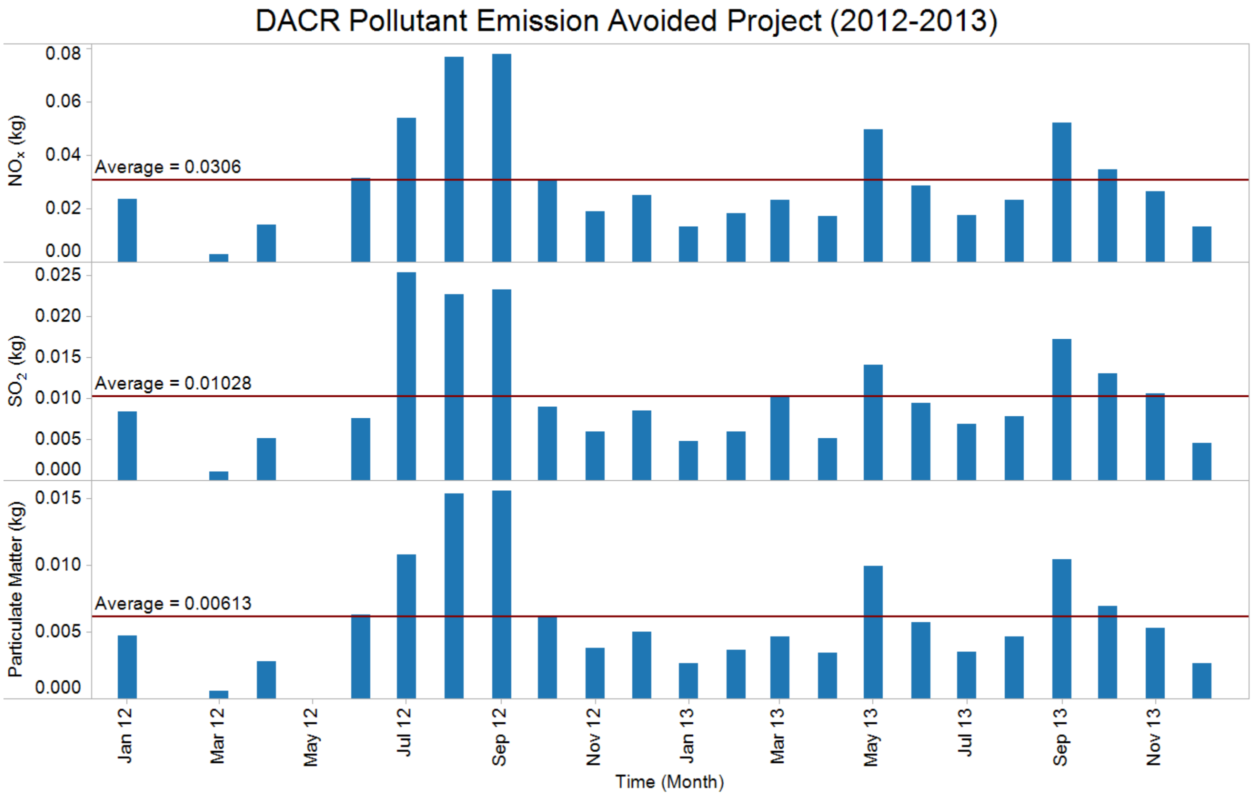

Figure 125. DACR Pollutant Emissions Avoided - Project Area

5.5.17.6 Summary

Emissions reductions were a direct multiplier of avoided truck miles. Pollutant emissions were primarily reduced by the automated reconfiguration that happened after outages. Therefore, the amount of pollutant emissions reduced per month varied greatly depending on weather events.

5.5.18 CO_2 Emissions– System (M34-CR)

5.5.18.1 Objective

This metric provides an estimate of the CO_2 emissions that would be avoided by eliminating DACR related truck rolls throughout the entire System area.

5.5.18.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- DACR impacts were consistent per circuit mile between the Project and non-Project areas.
- 8.8 kg CO_2 emissions/gallon for gas engines, 10.1 kg CO_2 emissions/gallon for diesel engines conversion factor.

  Source: *United States EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-05-001)*

5.5.18.3 Calculation Approach

Project area CO_2 reduction was calculated as a function of vehicle miles avoided using emissions data specific to AEP Ohio's distribution service fleet vehicles. This reduction was then extrapolated to the System area based on the number of circuit miles in each area.

The following queries and methods were used to generate results:
Tons of CO_2 per service center and month that would be avoided if DACR technology were deployed throughout the System area estimated truck rolls avoided were calculated by multiplying the tons of CO_2 eliminated due to truck rolls avoided due to DACR technology multiplied by the ratio of circuit miles without DACR technology to circuit miles with DACR technology.

5.5.18.4 Organization of Results

The following section describes the amount of CO_2 avoided due to DACR as a result of truck rolls avoided. The graph shows the amount of CO_2 avoided due to the net number of truck rolls avoided in the System area.

5.5.18.5 Data Collection Results

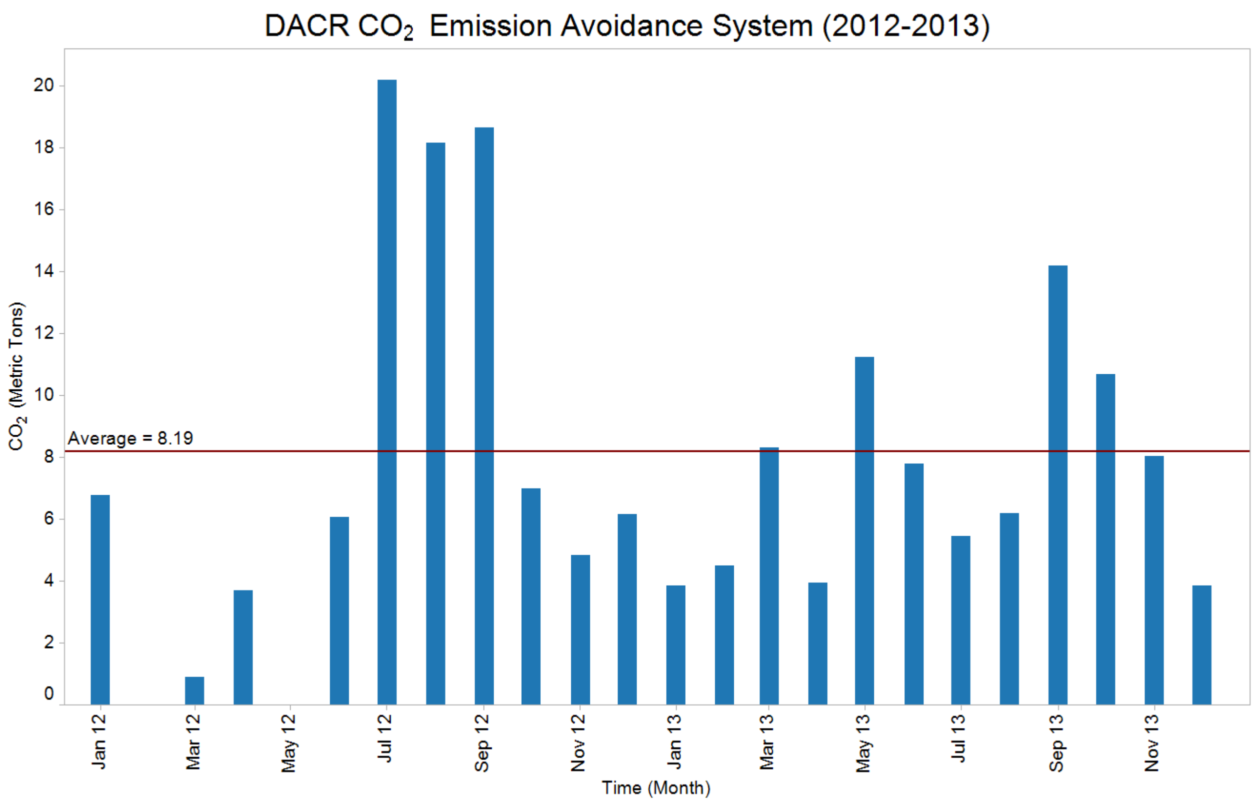

Figure 126. DACR CO_2 Emissions Avoided - System Area

5.5.18.6 Summary

Emissions reductions were a direct multiplier of avoided truck miles. CO_2 emissions were primarily reduced by the automated reconfiguration that happened after outages. Therefore the amount of CO_2 emissions reduced per month varied greatly depending on weather events.

5.5.19 Pollutant Emissions - System area: SO_X, NO_X, $PM_{2.5}$ (M35-CR)

5.5.19.1 Objective

This metric provides an estimate of the pollutant emissions that would be avoided by eliminating DACR related truck rolls throughout the entire System area.

5.5.19.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- DACR impacts were consistent per circuit mile between the Project and non-Project areas.
- A CARB limit value of 0.05 grams of Nitrogen Oxides (NO_X) per mile was used.

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 50,000 mi*
- 0.01 g $PM_{2.5}$ emissions/mi conversion factor

  Source: *United States EPA 40 CFR part 86 Subpart S tier 2 Bin 5 Emissions limits at 100,000 mi*
- 0.165 g SO_X emissions/gallon for gas engines, 0.0963 g SO_X emissions/gallon for diesel engines conversion factor

  Calculated from: sulfur content of gasoline = 30 ppm

  Source: U.S. EPA 40 CFR parts 80, 85, and 86 AMS-FRL-6516-2

  Sulfur content of ULSD diesel fuel = 15 ppm

  Source: *U.S. EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-00-057)*

  Molecular weight of SO_2 = 64 g/mole

  Density of gasoline = 2.75 kg/gallon

  Density of diesel fuel = 3.21 kg/gallon

5.5.19.3 Calculation Approach

Project area pollutant reduction was calculated as a function of vehicle miles avoided using emissions data specific to AEP Ohio's distribution service fleet vehicles. This reduction was then extrapolated to the System area based on number of circuit miles in each area.

The following queries and methods were used to generate results:

- Kilograms of SO_2 per service center and month that would be avoided if DACR technology were deployed throughout the AEP Ohio System area due to truck rolls avoided were calculated by multiplying the kilograms of SO_2 avoided due to truck rolls avoided due to DACR technology by the ratio of circuit miles without DACR technology to circuit miles with DACR technology.
- Kilograms of NO_X per service center and month that would be avoided if DACR technology were deployed throughout the AEP Ohio System area due to truck rolls avoided

were calculated by multiplying the kilograms of NO_X avoided due to truck rolls avoided due to DACR technology by the ratio of circuit miles without DACR technology to circuit miles with DACR technology.

- Kilograms of $PM_{2.5}$per service center and month that would be avoided if DACR technology were deployed throughout the AEP Ohio System area due to truck rolls avoided were calculated by multiplying the kilograms of $PM_{2.5}$ avoided due to truck rolls avoided due to DACR technology multiplied by the ratio of circuit miles without DACR technology to circuit miles with DACR technology.

5.5.19.4 Organization of Results

The following section describes the amount of pollutant avoided due to DACR as a result of truck rolls avoided. The graph shows the amount of pollutant avoided due to the net number of truck rolls avoided in the System area.

5.5.19.5 Data Collection Results

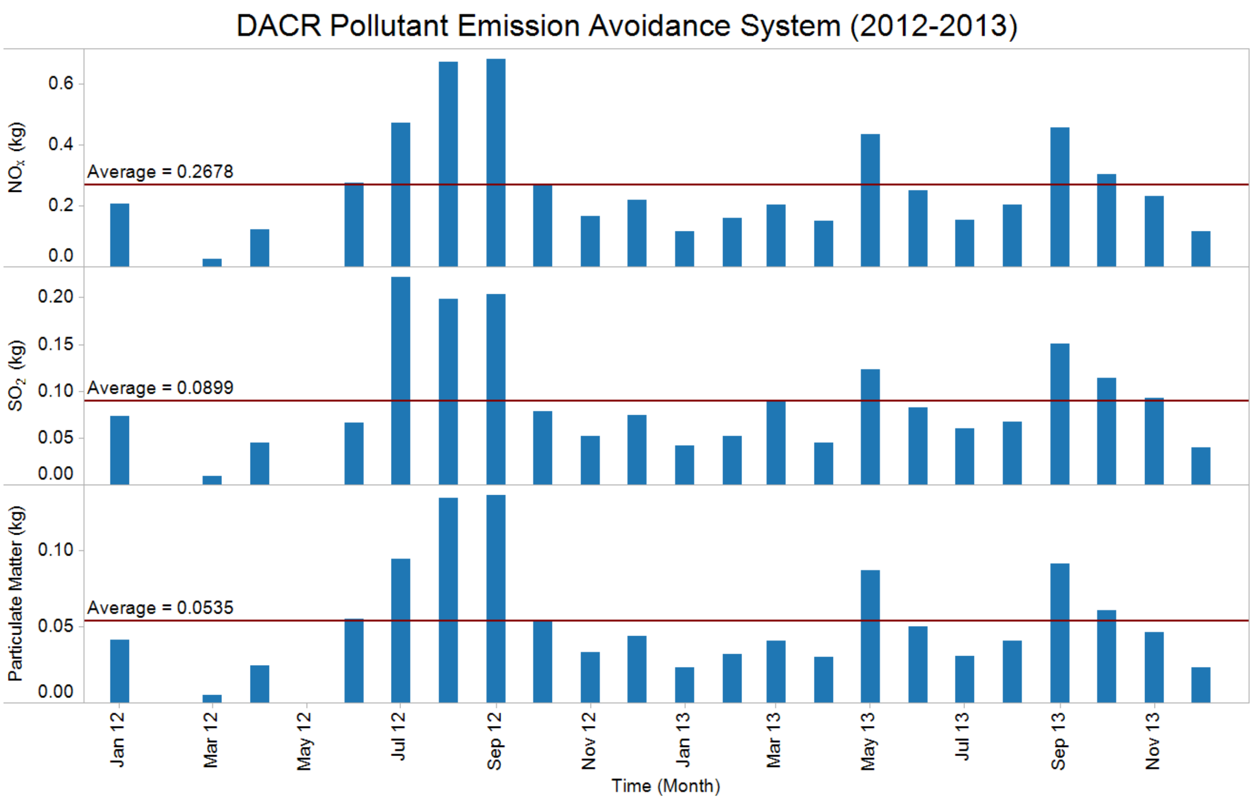

Figure 127. DACR Pollutant Emissions Avoided for System Area

5.5.19.6 Summary

Emissions reductions were a direct multiplier of avoided truck miles pollutant emissions were primarily reduced by the automated reconfiguration that happened after outages. Therefore the amount of pollutant emissions reduced per month varied greatly depending on weather events.

5.6 DACR Conclusions

The most significant advantages of DACR were its impacts to reliability and its use during major events. Excluding major events, the Project, through the deployment of DACR on 70 circuits, was able to reduce Customer Minutes of Interruption (CMI) by 1,602,647 minutes, improving reliability for 19,309 consumers in 2012 and by 2,606,781 minutes, improving reliability for 31,407 consumers in 2013, as shown in the table below.

Project area (70 circuits)						
Year	Outages	Customers Interrupted	Customer Minutes Interrupted	# of Events (Automation Impacted CI)	Customers Restored via Automation	Customer Minutes Avoided
2010	2,244	163,380	17,940,145	n/a	n/a	n/a
2011	1,951	177,147	19,953,044	3	7,427	616,441
2012	1,838	136,741	17,989,775	16	19,309	1,602,647
2013	1,903	96,902	11,116,587	27	31,407	2,606,781

Table 22. DACR Outage Summary

Although weather conditions were the primary driver for changes in SAIFI and SAIDI, AEP Ohio could attribute some improvements of these indices from the DACR deployment. DACR technology had more impact on SAIFI than on SAIDI. DACR technology was typically able to reduce the number of consumers impacted by a specific outage resulting in a reduction in SAIFI. CAIDI represented the average outage duration for only those consumers who experienced a sustained outage and increased slightly.

Once DACR technology minimized the impact of an outage, consumers not able to be restored by DACR experienced similar outage duration as consumers on non-DACR circuits. Service that would have been restored quickly in the past could now be restored so quickly that a sustained interruption was not experienced. It appeared that consumers who experienced a sustained outage were interrupted for a longer duration because CAIDI increased. The reason for the increase was that short duration outages were removed from the average that CAIDI represented. The fundamental time to repair each fault/outage was not impacted directly by DACR technology.

During major events, DACR systems had limited ability to restore consumers within the first hour. DACR was initially disabled to ensure crew safety. When safety conditions were resolved, the system was enabled to aid restoration.

In addition to the reliability benefits described above, the systems also enabled crew labor savings, up to 2 hours per event, and in some instances avoided service calls entirely. This provided opportunities for AEP Ohio to perform additional proactive work on circuits in need of service, further enhancing reliability.

5.7 Lessons Learned

This section describes lessons learned for DACR technology. Lessons learned are provided for Technology, Implementation, and Operations.

5.7.1 Technology

- Implementation of a fully integrated vendor solution eliminates the need for multiple firmware upgrades and system enhancements.
- Provide training and process improvement to achieve the full benefit of the technology.
- Communications or control failures must return the field equipment to local control.
- Review and analysis of large amounts of data are essential to obtain the full benefits of DACR.
- Expand the design of circuit reconfiguration technologies to account for consumers with alternate feed sources, multiple station transformers and switching configurations.

5.7.2 Implementation

- Use compatible interface standards when integrating products to reduce failures and consumer service delays.
- Work closely with selected vendors to enhance existing products and facilitate integration with legacy equipment and systems.
- Develop standardized work processes for testing, configuring and commissioning devices and automation schemes.
- Plan and design the implementation of the voltage sensing equipment to enable installation on a one-pole structure.

5.7.3 Operations

- Standardize technology architecture and upgrades.
- Establish acceptance testing, customer support, and escalation procedures.
- Maintain a comprehensive inventory of spare components.
- Develop a formal process to integrate configuration control.
- Optimize the system to improve performance.
- Continue data collection and analysis to quantify long-term impacts to operations and maintenance costs.

6 DEMONSTRATED TECHNOLOGY – VOLT VAR OPTIMIZATION

6.1 Purpose

Volt VAR Optimization (VVO) is a demand-side management program that reduces energy consumption and demand without consumer interaction or participation. The primary focus of VVO is to reduce circuit demand and energy consumption by flattening and lowering voltage on the circuit while maintaining consumer service voltage standards. As a secondary goal VVO also attempts to provide reactive power support. Consumers realize lower consumption with the same level of comfort and service.

6.2 Technology

Traditionally voltage regulation on a circuit has been achieved by setting the voltage at the beginning of the circuit high enough so that voltages at the end of the circuit remained within acceptable limits. This approach provided acceptable service voltage even during peak load but did not result in the most efficient operation of the circuit. Voltage control devices, both regulators and shunt capacitors, traditionally have been operated using local set points. While the set points may be coordinated, capacitor and voltage regulator controls operate independently without communication to a master control that coordinates their operation. These independently operating, stand-alone devices may not optimize overall system efficiency.

VVO dynamically controls and coordinates multiple devices to manage both voltage and reactive power. System-wide efficiency is achieved by simultaneously coordinating operations using continuous measurements from multiple sensors distributed across the circuit.

The following figure shows a typical VVO implementation with components of the VVO system identified on a map showing the circuit layout.

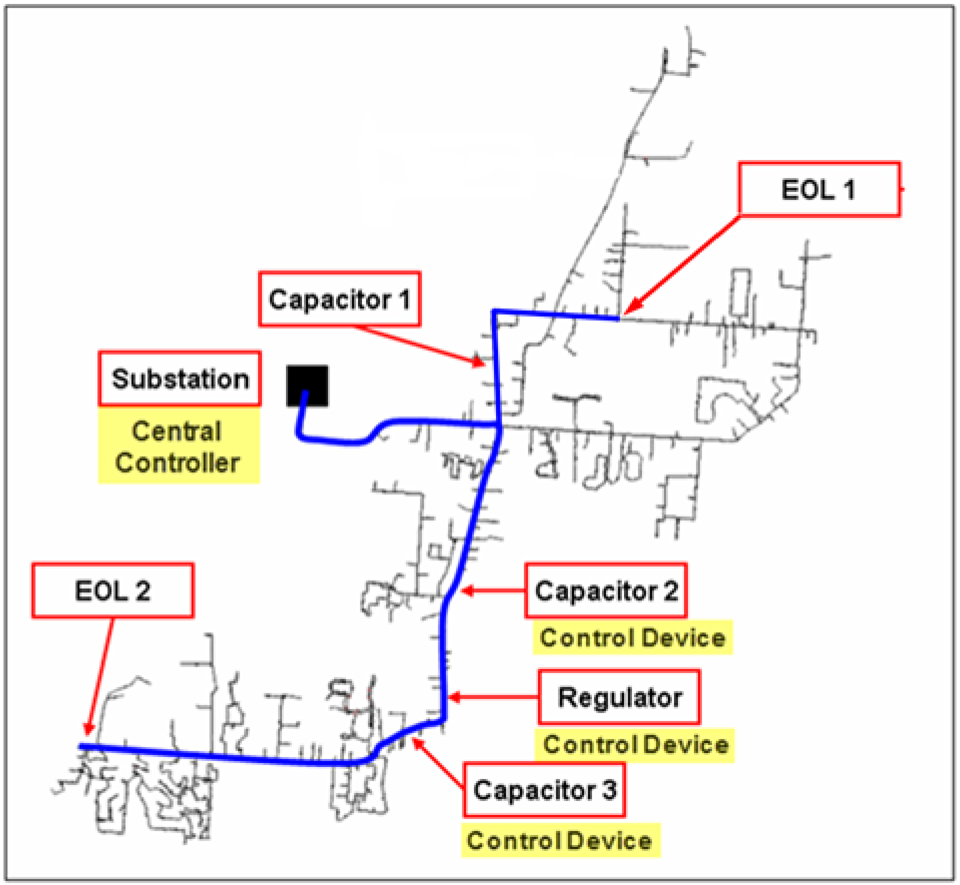

Figure 128. VVO Example

As shown in the VVO example, controls are placed on regulators and capacitors with a central controller installed at the substation. Distributed sensors, including end-of-line (EOL) monitors, supply the central controller with circuit, environmental, or other data. The central controller processes this data and instructs the control devices to adjust voltage and power factor on the line as needed. The controllers and monitors work together to maintain the voltage and power factor at a desirable level, thus reducing overall energy consumption.

6.3 Approach and Implementation

Similar to traditional voltage regulation methods, conceptual approaches to achieve VVO and the commercial systems to implement them vary widely. As part of the AEP Ohio gridSMART® Demonstration Project, two separate VVO systems were deployed.

Because VVO technology was evolving, commercial vendors had no ready-to-go system in place. AEP Ohio selected two vendors in order to gain experience installing the technology and to quantify the energy efficiency and demand reduction results.

One of the systems was General Electric Coordinated Volt VAR Control (CVVC). The CVVC provided command and control for S&C Electric Company's IntelliCAP® capacitor controllers and for Cooper CL6-B voltage regulator controllers while monitoring EOL voltages. Cooper CL6-B controllers operated both circuit voltage regulators and line voltage regulators. IntelliCAP controllers operated switched capacitor banks. The integrated system provided voltage and VAR support to flatten and lower a circuit's voltage profile while promoting unity power factor.

AEP Ohio also deployed the PCS Utilidata VVO system. The PCS system provided command and control for S&C Electric Company's IntelliCAP® capacitor controllers and for Cooper CL6-B voltage regulator controllers while monitoring EOL voltages. Cooper CL6-B controllers operated both circuit voltage regulators and line voltage regulators. IntelliCAP controllers operated switched capacitor banks. The integrated system provided voltage and VAR support to flatten and lower a circuit's voltage profile while promoting unity power factor.

Seventeen circuits, including 13kV and 34.5kV circuits, were selected for VVO installations. AEP Ohio installed the technology, including upgraded controls on existing regulators and capacitors, to determine the effectiveness on non-optimized circuits.

6.4 Impact Metrics Required for VVO

The following impact metrics are associated with the VVO suite of technologies; 10 relate to the Project area and 2 relate to the System area.

Metric ID	Metric Scope	Metric Description	VVO
M03	Project	Peak Load and Mix	M03-VVO
M13	Project	Distribution Circuit Load	M13-VVO
M15	Project	Deferred Distribution Capacity Investments	M15-VVO
M16	Project	Equipment Failure Incidents	M16-VVO
M17	Project	Distribution Equipment Maintenance Cost	M17-VVO
M20	Project	Distribution Capacitor Switching Operations	M20-VVO
M22	Project	Distribution Losses (%)	M22-VVO
M23	Project	Distribution Power Factor	M23-VVO
M32	Project	CO_2 Emissions	M32-VVO
M33	Project	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M33-VVO
M34	System	CO_2 Emissions	M34-VVO
M35	System	Pollutant Emissions (SO_X, NO_X, $PM_{2.5}$)	M35-VVO

Table 23. Impact Metrics Addressing VVO Technology Performance

Refer to the *Metrics Analysis for VVO* section that follows for details.

6.5 Metrics Analysis for VVO

This section provides details for each VVO metric, and includes those requested by the DOE during the definitization of the Cooperative Agreement. Trends were not always observed, however data is presented for each metric.

Please note that Project area and System area metrics related to emissions did not include the potential impact of shifting load over 24 hours.

6.5.1 Peak Load and Mix (M03-VVO)

6.5.1.1 Objective

The VVO dynamically flattens and lowers circuit voltage profiles to reduce energy consumption and demand while maintaining consumer service voltage standards. This impact metric provides an overview of residential electrical demand by circuit and the cumulative effects of VVO for selected circuits and months.

6.5.1.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

For circuits where Advance Metering Infrastructure (AMI) meters were available, peak load was measured as the sum of AMI real power readings. Where AMI was not available, the instantaneous real power supplied to a circuit's voltage regulator, measured in kW, was used. Power was recorded every 15 minutes for each of the three phases (A, B, and C). Instantaneous real power was computed as the sum of real power over all three phases.

- For this metric, peak load and mix includes only residential consumers.
- Hourly VVO On versus VVO Off load was temperature normalized using the approach described in the calculation subsection below. Additional weather factors and behavioral shifts across seasons/weeks were not considered.

6.5.1.3 Calculation Approach

The following queries and methods were used to generate results.

VVO peak load and mix were analyzed in three steps:
1. Determine temperature correction functions.
2. Apply temperature corrections.
3. Bin data into load profiles.

An extract of hourly data was created to select weekday load data from all residential consumers on the circuit being analyzed. Each data point in this extraction consists of a time stamp, average residential load aggregated over the entire circuit, and a temperature value. This data extract was then subdivided into two sets: one set for days during which the VVO system was operated in a day/on day/off sequence, and a second set for days in which the VVO system was operated in a steady on or off state.

Temperature Normalization

Temperature normalizations were determined from the steady state data set. First, the data set was grouped by hour of the day. Then, for each hour, an average load was calculated. Next, each record was assigned a load ratio equal to load reading divided by average load as well as a temperature difference equal to the temperature reading minus 65 degrees F. For each hour, scatter plots were generated showing temperature difference versus load ratio and fitted using third order polynomial curves. The resulting polynomial functions were then used as temperature correction factors in subsequent stages of this analysis.

Temperature Correction

All raw temperature readings from the experimental day/on day/off data set were corrected using third order polynomials described above. Unique correction functions were used for each hour of the day as well as for VVO day/on versus VVO day/off times. All load readings were normalized to the monthly average temperature for each corresponding hour.

Load Profile

Load profile graphs were generated for each month by binning temperature corrected load values from the day/on day/off data set by hour of the day. Separate series were used to show readings when VVO was on versus readings taken when VVO was off.

6.5.1.4 Organization of Results

The following section presents load profile graphs for consumers on VVO circuits. These graphs each contain two lines, one line showing hours in which VVO was on and one line showing hours in which VVO was off. Graphs have been generated for residential consumers from a representative circuit for three months.

6.5.1.5 Data Collection Results

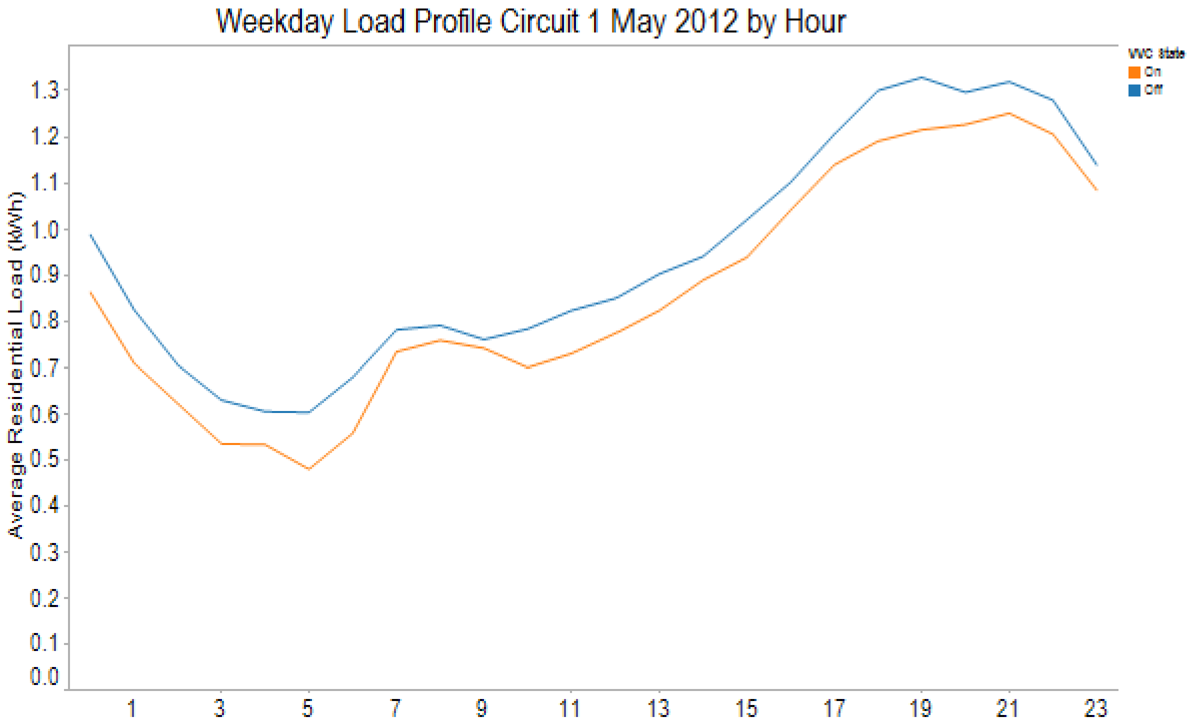

Figure 129. Temperature Normalized Hourly Load with VVO Day/On and Day/Off (May 2012)

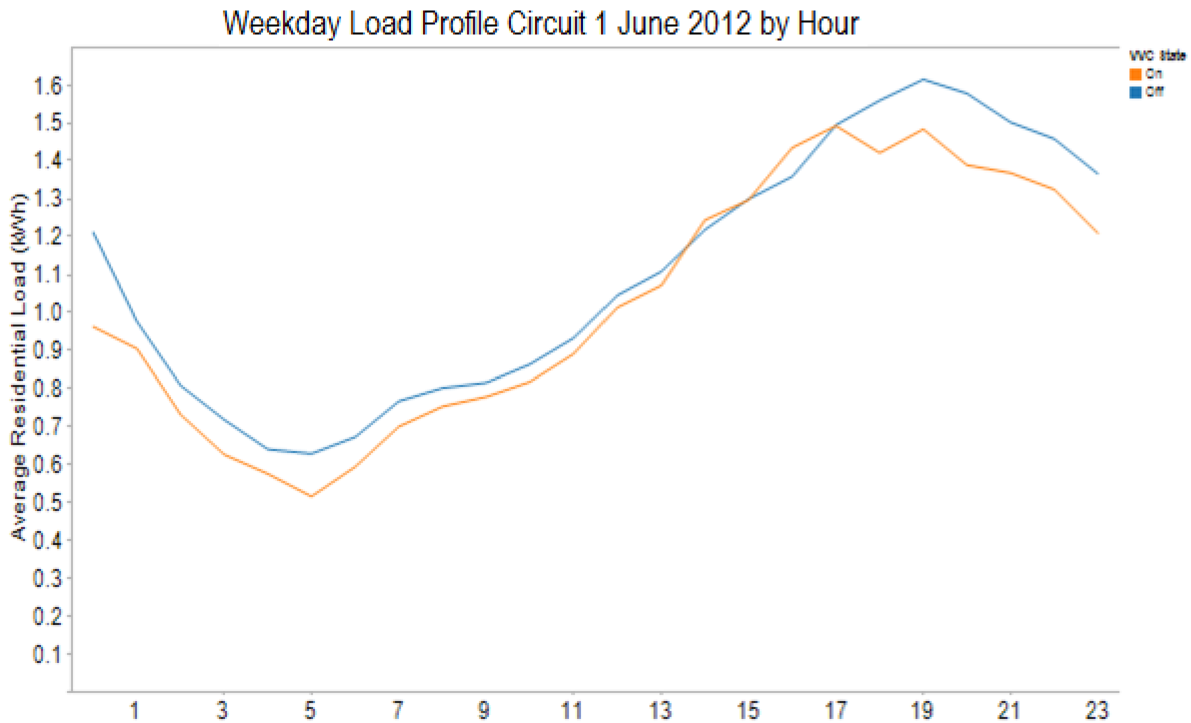

Figure 130. Temperature Normalized Hourly Load with VVO Day/On and Day/Off (June 2012)

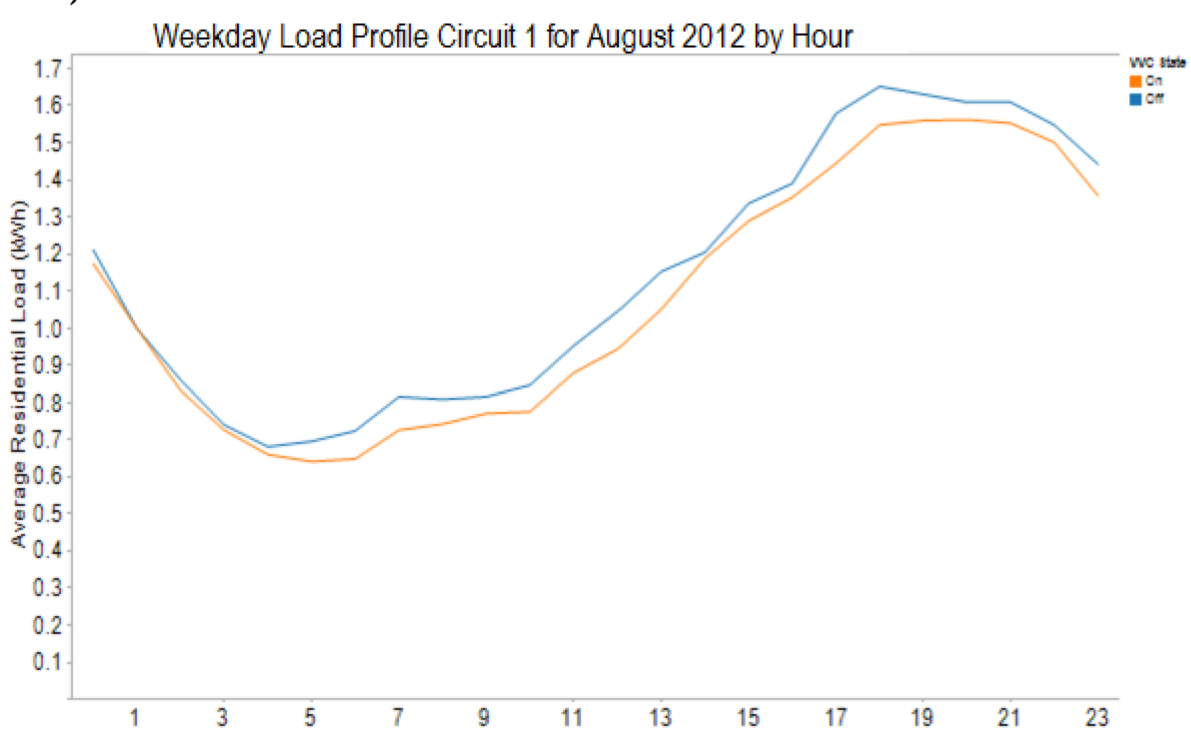

Figure 131. Temperature Normalized Hourly Load with VVO Day/On and Day/Off (Aug 2012)

The preceding graphs represent the impacts of VVO on peak loading.

6.5.1.6 Summary

VVO provided an average of approximately 3 percent reduction in residential load for consumers with AMI meters during the test period.

6.5.2 Distribution Circuit Load (M13-VVO)

6.5.2.1 Objective

VVO is expected to reduce total circuit load by flattening and lowering voltage levels while maintaining consumer service standards. This metric examines the impact of VVO on circuit load.

6.5.2.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

VVO operated using the day/on day/off sequence for extended time periods during the Project. Circuit load was measured as the instantaneous real power measured in kW. Power was metered at the station regulator for each circuit every 15 minutes for each of the three phases (A, B, and C). Instantaneous real power was computed as the sum of real power over all three phases.

6.5.2.3 Calculation Approach

The following queries and methods were used to generate results.

Distribution feed load was analyzed in three steps:

1. Determine temperature correction functions.
2. Apply temperature corrections.
3. Bin data into load profiles.

An extract of hourly data was created to select weekday load data from all residential consumers on the circuit being analyzed. Each data point in this extraction consists of a time stamp, average residential load aggregated over the entire circuit, and a temperature value. This data extract was then subdivided into two sets: One set for days during which the VVO system was operated in a day/on day/off sequence, and a second set for days in which the VVO system was operated in a steady on or off state.

Temperature Normalization

Temperature normalizations were determined from the steady state data set. First, the data set was grouped by hour of the day. Then, for each hour, an average load was calculated. Next, each record was assigned a load ratio equal to load reading divided by average load as well as a temperature difference equal to the temperature reading minus 65 degrees F. For each hour, scatter plots were generated showing temperature difference versus load ratio and fitted using third order polynomial curves. The resulting polynomial functions were then used as temperature correction factors in subsequent stages of this analysis.

Temperature Correction

All raw temperature readings from the experimental day/on day/off data set were corrected using third order polynomials described above. Unique correction functions were used for each hour of the day as well as for VVO day/on versus VVO day/off times. All load readings were normalized to a temperature of 65 degrees F.

Load Profile

Load profile graphs were generated for each month by binning temperature corrected load values from the day/on day/off data set by hour of the day. Separate series were used to show readings when VVO was on versus readings taken when VVO was off.

6.5.2.4 Organization of Results

The following section presents load profile graphs for VVO circuits based on circuit load data. Each graph contains two lines, one showing hours in which VVO was on and one showing hours in which VVO was off. Graphs have been generated separately for each month.

6.5.2.5 Data Collection Results

The figures on the following pages quantify the impact metric for this section.

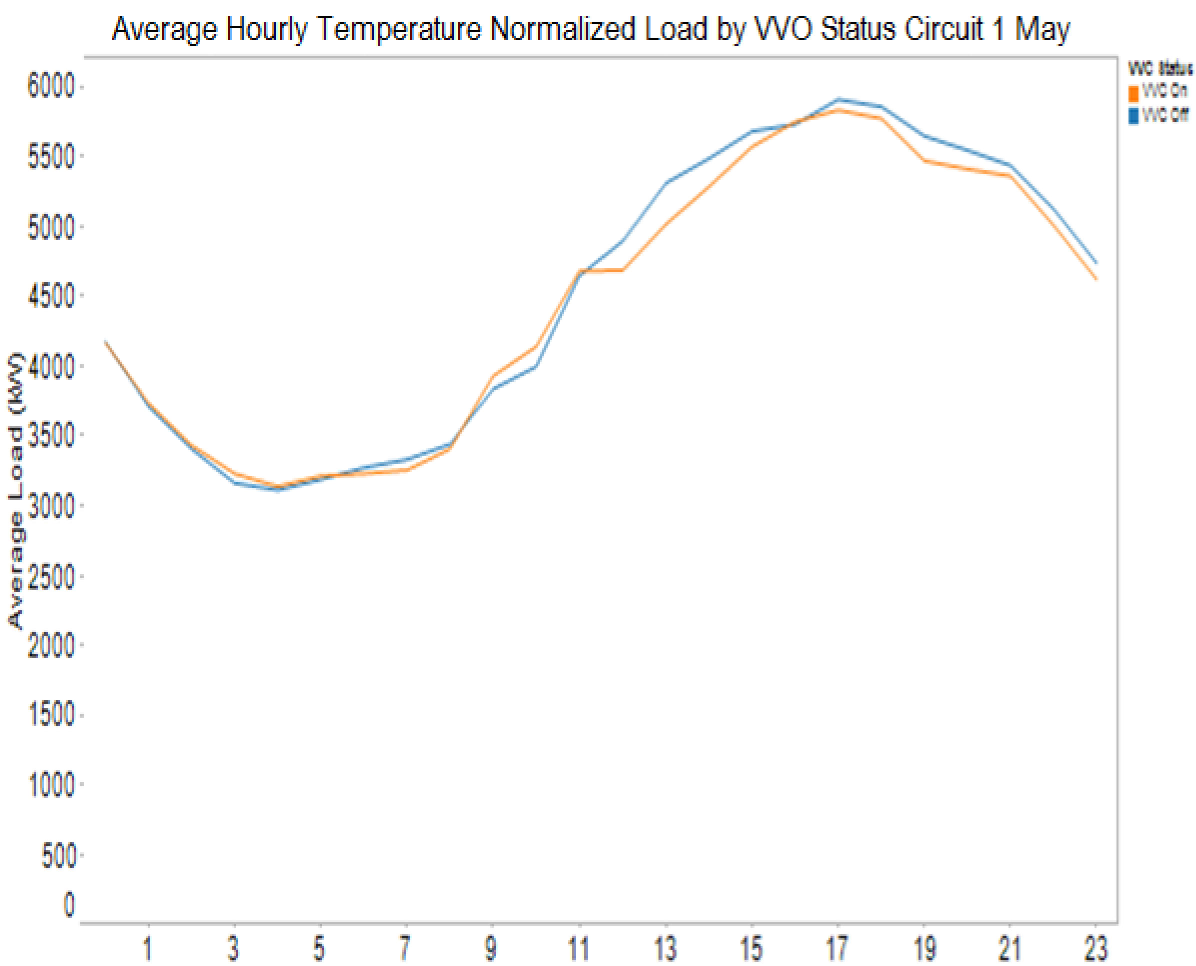

Figure 132. Circuit 1: Circuit Load

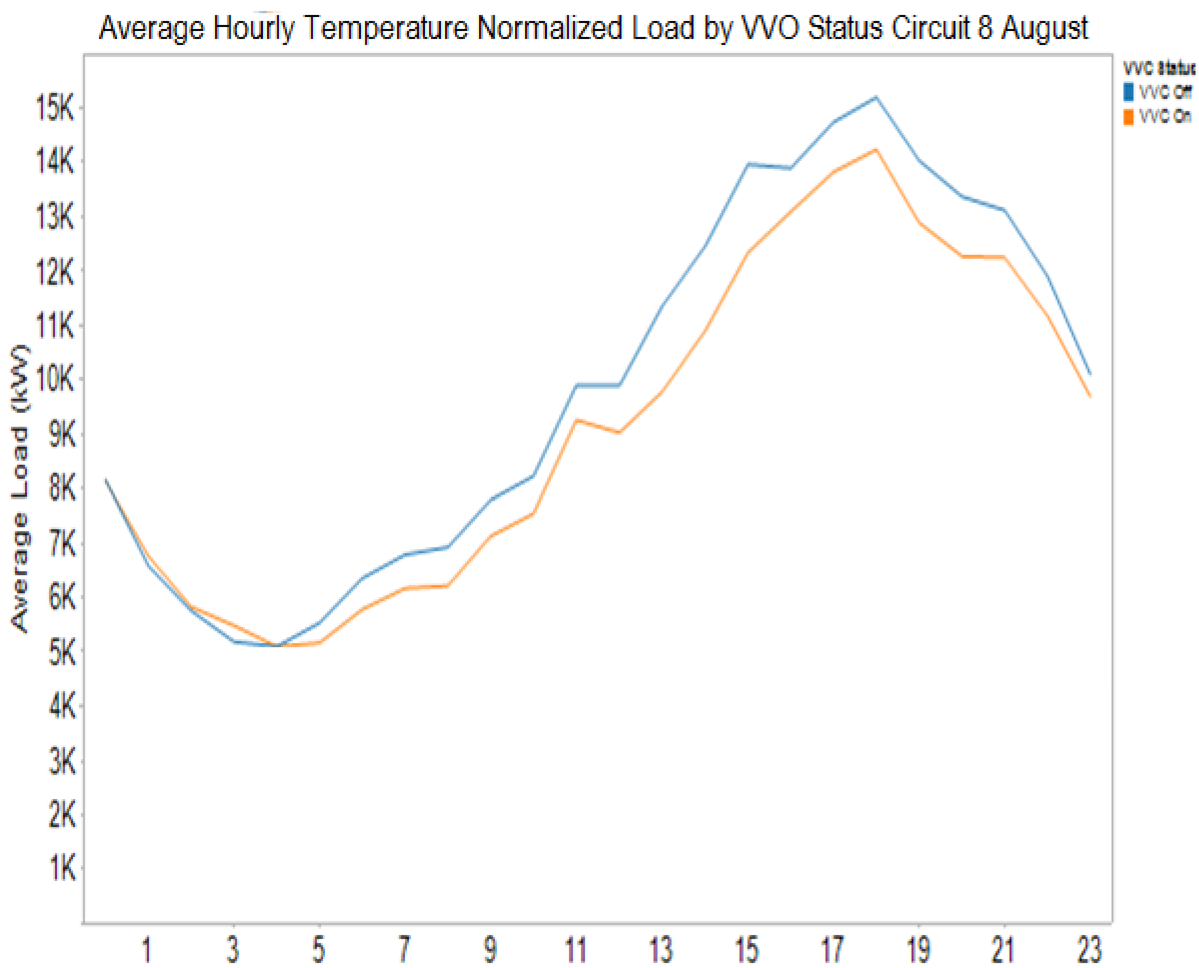

Figure 133. Circuit 8: Circuit Load

The graphs presented above represent the impacts of VVO on distribution circuit load.

6.5.2.6 Summary

VVO provided an average of approximately 3 percent reduction in circuit load.

6.5.3 Deferred Distribution Capacity Investments (M15-VVO)

6.5.3.1 Objective

Utility operators periodically upgrade distribution circuit equipment and systems to satisfy demand and take advantage of improved technology. Those upgrades require significant capital investment and impact the economics of operation. VVO has the potential to achieve benefits that reduce the need for such investments. This impact metric provides a description of all distribution capacity investments that were deferred due to VVO.

6.5.3.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Semi-annual variance analysis of distribution capital investment plan was performed.

6.5.3.3 Calculation Approach

No planned or deferred distribution capacity investments occurred within the Project area. Therefore, a calculation approach was unnecessary.

6.5.3.4 Organization of Results

This metric is a study of deferred distribution capacity investments due to VVO.

6.5.3.5 Data Collection Results

AEP Ohio reviewed planned projects in Distribution Load Forecasting where VVO circuits would be involved.

6.5.3.6 Summary

Within the short duration of the Project, there were no planned distribution capacity investments within the Project area. Therefore, no projects were deferred as a result of VVO. VVO did not influence distribution capacity investments.

6.5.4 Equipment Failure Incidents (M16-VVO)

6.5.4.1 Objective

Frequent VVO equipment operations may result in increased equipment wear. This impact metric provides counts of equipment failure events within the Project and System areas in order to quantify these effects.

6.5.4.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Circuit and substation Supervisory Control and Data Acquisition (SCADA) reports, event logs, and direct equipment notifications/alarms recorded switching operations performed. Any such events that resulted in equipment failure contributed to the cumulative count total. Failures for the following equipment types are included in this report:

- Capacitor Banks
- Distribution Transformers
- Reclosers
- Switches
- Voltage Regulators

6.5.4.3 Calculation Approach

The following queries and methods were used to generate results:

- Equipment failure events per date, equipment type, circuit, and substation were selected by linking equipment compatible units to circuit equipment types.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration.

6.5.4.4 Organization of Results

The following graphs report the number of equipment failure events that occurred on VVO and non-VVO circuits within the Project area.

- Count of Equipment Failures by Year for VVO vs. non-VVO Circuits
  This graph shows the number of equipment failures per year for each type of equipment tracked. The graph is divided into two sections, one showing the 17 VVO circuits, and the other showing the rest of the Project area. This represents a population of approximately 80 circuits.
- Equipment failure rates for VVO versus non-VVO circuits
  This graph shows the number percent failure rate per year for each type of equipment tracked. Failure rates were calculated as a percentage of the population of each device type within the VVO and non-VVO areas. The graph is divided into two sections, one showing the 17 VVO circuits, and the other showing the rest of the Project area. This represents a total population of approximately 80 circuits.

6.5.4.5 Data Collection Results

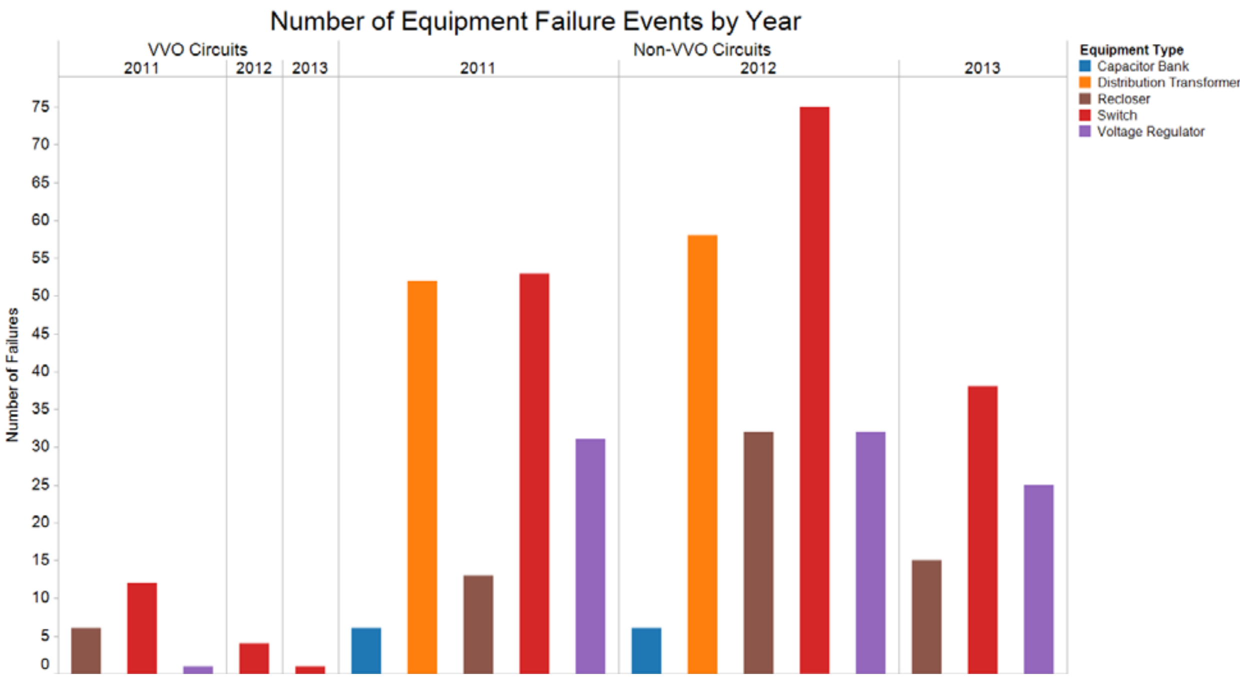

Figure 134. Count of Equipment Failures by Year for VVO vs. Non-VVO Circuits

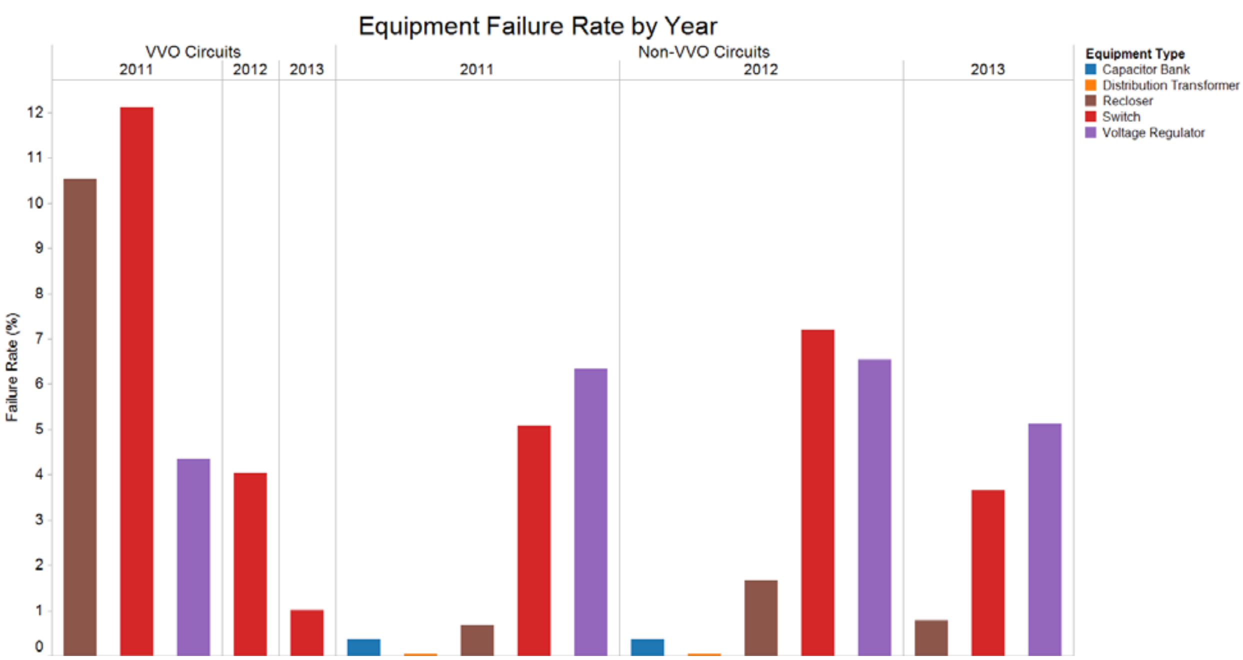

Figure 135. Equipment Failure Rate by Year for VVO vs. Non-VVO Circuits

6.5.4.6 Summary

There are no statistically significant trends in equipment failure rate due to VVO. There was no evidence of either an increase or decrease in failure events attributable to VVO.

6.5.5 Distribution Equipment Maintenance Cost (M17-VVO)

6.5.5.1 Objective

Reduced consumption can result in reduced costs, deferred capital investments, extended equipment life, and reduced fuel consumption. Because VVO reduces consumption, the addition of VVO equipment has the potential to affect maintenance costs. With the intent to capture expected maintenance costs and/or savings associated with maintaining a VVO system compared to traditional distribution operations, this impact metric provides monthly cost data for distribution maintenance activities throughout the Project and System areas.

6.5.5.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Maintenance assumptions identified here are solely for the purpose of this reporting metric and do not follow Generally Accepted Accounting Principles (GAAP).

- Maintenance costs in the Project area include:
    - Non-warranty asset replacement costs on capacitors, regulators, reclosers, and associated controls or protective devices
    - Estimated inspection costs
    - Equipment failures
    - IT infrastructure maintenance costs
    - Telecommunications infrastructure costs
- Maintenance costs in the System area include:
    - Total asset replacement costs on capacitors, regulators, reclosers, and associated controls or protective devices
    - Inspection programs including repairs
    - Equipment failures

6.5.5.3 Calculation Approach

The following inputs were used to generate results:
Distribution equipment maintenance labor, material, vehicle fleet, and construction overhead costs per circuit, substation, and work order close date were calculated by summing labor, material, vehicle fleet, and construction overhead costs.

6.5.5.4 Organization of Results

The following section reports the maintenance related costs incurred on VVO and non-VVO circuits within the System area.

- Equipment maintenance for VVO circuits
  This graph shows the cost in dollars per month within the VVO Project area for each maintenance cost component. This covers a population of 17 circuits.
- Equipment maintenance costs for non-VVO circuits
  This graph shows the cost in dollars per month outside the VVO Project area but within the System area for each maintenance cost component. This covers a population of approximately 700 circuits.

6.5.5.5 Data Collection Results

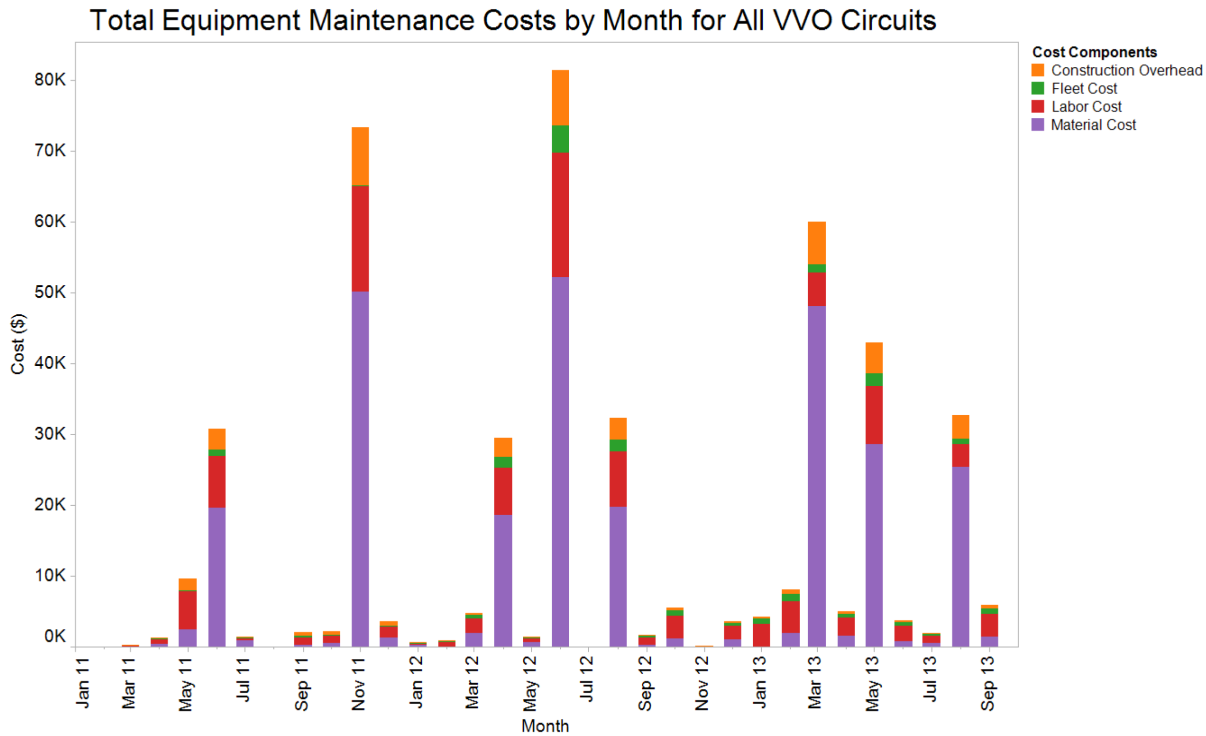

Figure 136. Breakdown of Monthly Maintenance Costs for All VVO Circuits

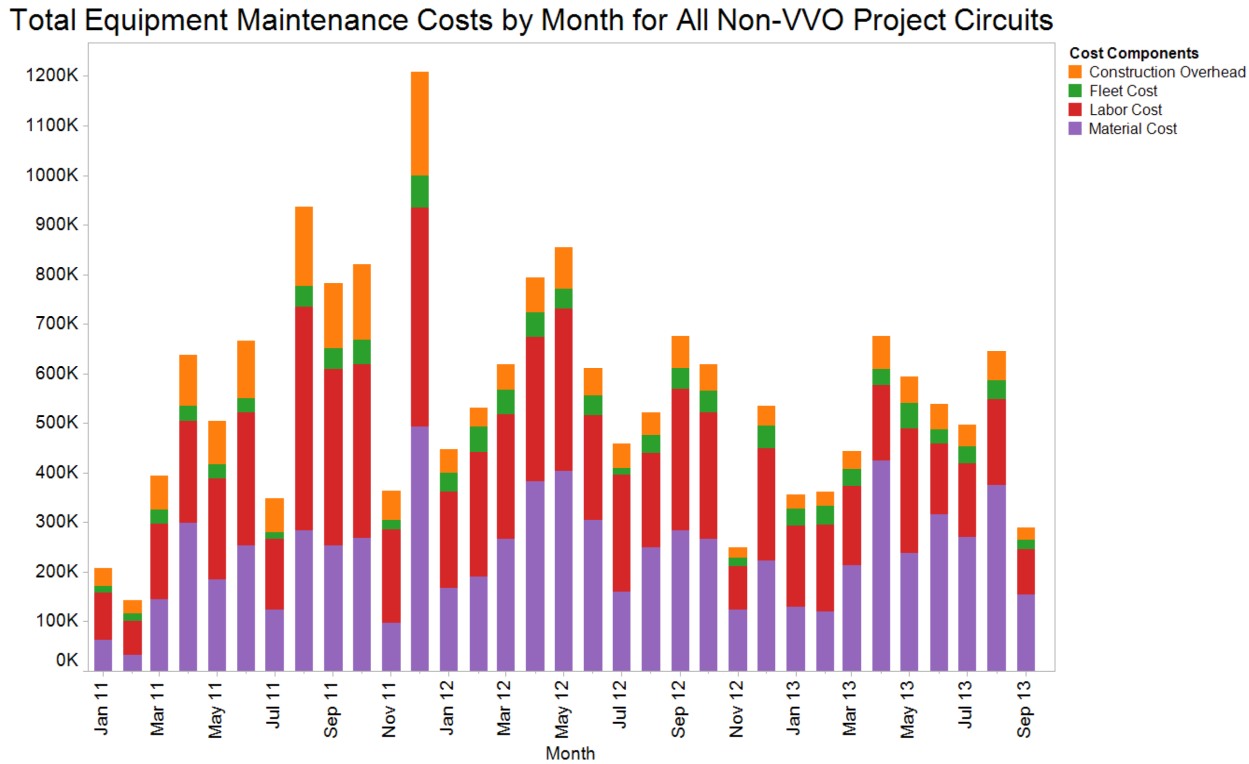

Figure 137. Breakdown of Monthly Maintenance Costs for All Non-VVO circuits

6.5.5.6 Summary

Maintenance costs are driven by factors such as periodic schedules, replacements, and failures. There is no evidence of impact on maintenance costs due to the installation and operation of VVO. A longer term of observation would be necessary to determine definitively if VVO has a measurable impact on maintenance.

6.5.6 Distribution Capacitor Switching Operations (M20-VVO)

6.5.6.1 Objective

VVO controls switched capacitors to achieve targeted power factor settings, switching the capacitors on or off to provide reactive power support. Excessive switching operations may lead to increased maintenance. This impact metric examines the behavior of switched capacitor banks in the Project area by counting how many non-VVO and VVO switching events occurred during the Project period.

6.5.6.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Distribution capacitor switching events per circuit, substation, and day were selected by counting switching events on capacitors.

6.5.6.3 Calculation Approach

The following queries and methods were used to generate results:

- Distribution capacitor switching events per circuit, substation, and day were selected by counting switching events on capacitors.
- The average switching operations per capacitor bank were calculated by summing the total number of capacitor switching operations for a day then dividing by the number of capacitor banks that switched. If a capacitor bank did not switch, then it was not included as part of the average calculation for that particular day.

6.5.6.4 Organization of Results

The following section reports the number of capacitor switching events on VVO and non-VVO circuits within the Project area.

- Average Capacitor Switching Operations per Capacitor Bank

  This graph shows per capacitor averages of switching events per day within the VVO Project area and also for the non-VVO portion of the Project area. The VVO plot covers a population of 17 circuits while the non-VVO plot covers a population of approximately 63 circuits.
- Total Count of Capacitor Switching Operations

  This graph shows counts of switching events per day within the VVO portion of the Project and for the non-VVO portion of the Project.

6.5.6.5 Data Collection Results

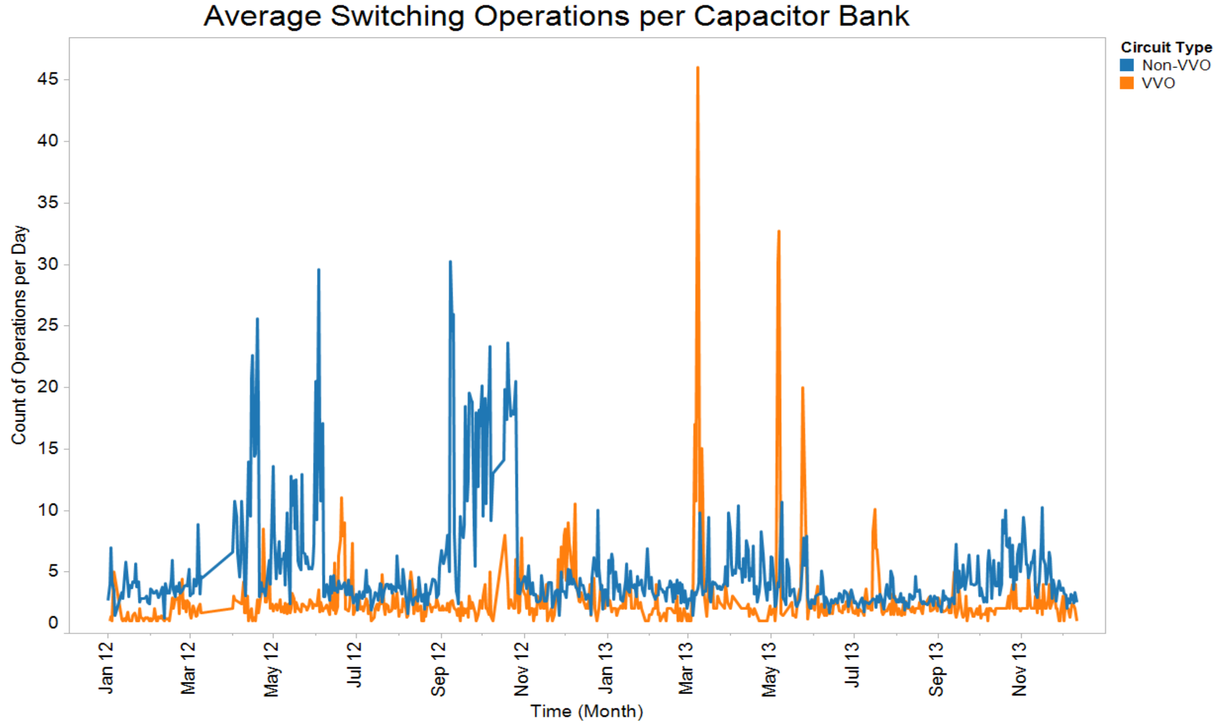

Figure 138. Average Number of Capacitor Switching Events per Capacitor Bank: VVO vs. non-VVO

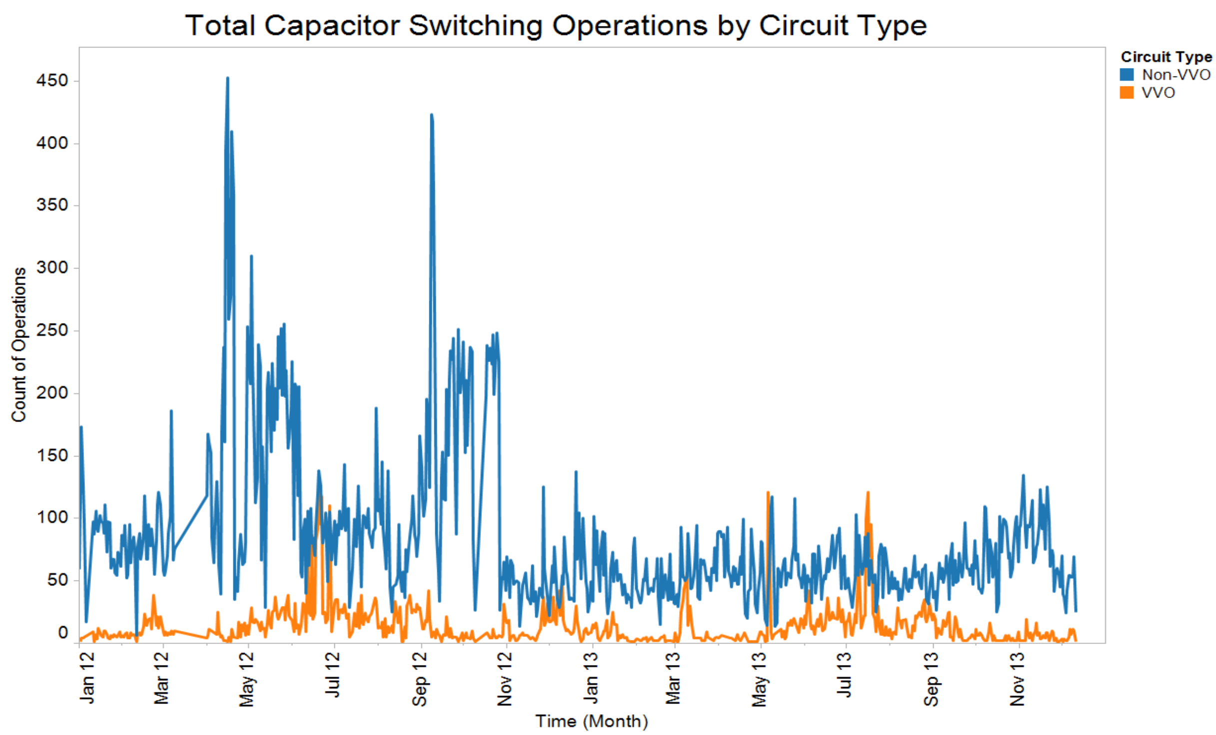

Figure 139. Total Count of Capacitor Switching Events for VVO: All Non-VVO Circuits

6.5.6.6 Summary

On average, VVO circuits had fewer capacitor switching events than non-VVO circuits in the Project area. Several factors may have contributed to this result, including variations across circuit configurations. It was also possible that non-VVO circuits were more likely to experience oscillatory behavior due to the distributed nature of their local control, where individual set points may have triggered multiple events in a short period of time.

The figure labeled *Average Number of Capacitor Switching Events per Capacitor Bank: VVO vs. non-VVO* shows a small number of capacitors switching sufficient number of times to appear as spikes. Further explanations of the three days in which spikes occurred include:

- On March 8, 2013 a single capacitor bank opened 23 times and closed 23 times resulting in 46 operations. None of the other 48 capacitor banks on VVO circuits operated on March 8, 2013. The average switching operations for March 8, 2013 is shown as 46 and appears as a spike.
- On May 7, 2013 there were 3 capacitor banks that operated. Two of the capacitor banks had 32 operations each and the other capacitor bank had 34 operations. None of the other 46 capacitor banks on VVO circuits operated on May 7, 2013. The average switching operations for May 7, 2013 is shown as 32.67 and appears as a spike.
- On May 24, 2013 there was 1 capacitor that operated 20 times. None of the other 48 capacitor banks on VVO circuits operated on May 24, 2013. The average switching operations for May 24, 2013 is shown as 20 and appears as a spike.

6.5.7 Distribution Losses (M22-VVO)

6.5.7.1 Objective

VVO reduces circuit demand by flattening and lowering circuit voltages, primarily by using voltage regulators. At the same time, VVO actively controls capacitor banks to maintain circuit power factors near unity.

Electrical loss in the circuit can be investigated using the difference between power provided by the circuit regulator and the total power delivered to the consumer loads. This impact metric presents the difference between circuit load measured at the substation via the SCADA system and the metered load measured through AMI. The net result is the total non-AMI metered load on the circuit. Distribution losses are a component of total non-AMI metered load and are expected to be impacted by VVO.

6.5.7.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

There are many elements that contribute to differences between circuit load data and the summation of AMI metered data for each circuit. These factors include:

- Consumers without AMI meters (mechanical meters)
- Unmetered load, such as street lights
- Electricity theft
- Circuit line losses

Note: Factors that AMI does not measure are considered non-technical losses. AMI does not measure consumers without AMI meters, unmetered load, or electricity theft. Factors that AMI does measure are considered technical losses. AMI does measure circuit line losses.

6.5.7.3 Calculation Approach

The following queries and methods were used to generate results:
Using concurrent measurements available on 15-minute intervals, Distribution losses were calculated by subtracting total real AMI power from real circuit power. This represents both technical and non-technical losses. Next, a comparison was made showing changes in non-AMI metered load associated with VVO status (on versus off).

The following queries and methods were used to generate results:
Distribution unmetered load, energy theft, and losses were calculated by subtracting the 15-minute interval readings from AMI meters on a circuit from the circuit load measured at the circuit regulator. These calculations were repeated per circuit, by VVO controller status, and by time.

6.5.7.4 Organization of Results

- AMI meter penetration by circuit
  This graph shows the percentage of meters that are AMI meters on each VVO circuit. Further analysis of non-AMI metered load is conducted only for circuits that have at least 90 percent AMI meter penetration.

- Calculation of non-AMI metered power
  This graph illustrates the calculation of non-AMI metered power by showing measured circuit load, a summation of the AMI interval data for that circuit, and the non-AMI metered power for a representative distribution circuit. Non-AMI metered power is calculated as circuit load minus AMI summation.

- Non-AMI metered load
  The following section shows the non-AMI metered load on selected VVO circuits. More detailed analysis is provided for times during which AEP Ohio implemented a day/on day/off sequence. This strategy consists of alternately enabling and disabling the VVO system for 24-hour periods in order to demonstrate differences in circuit load, consumer energy consumption, and losses.

A table of statistics is provided for circuits that exhibit day/on and day/off behavior.

6.5.7.5 Data Collection Results

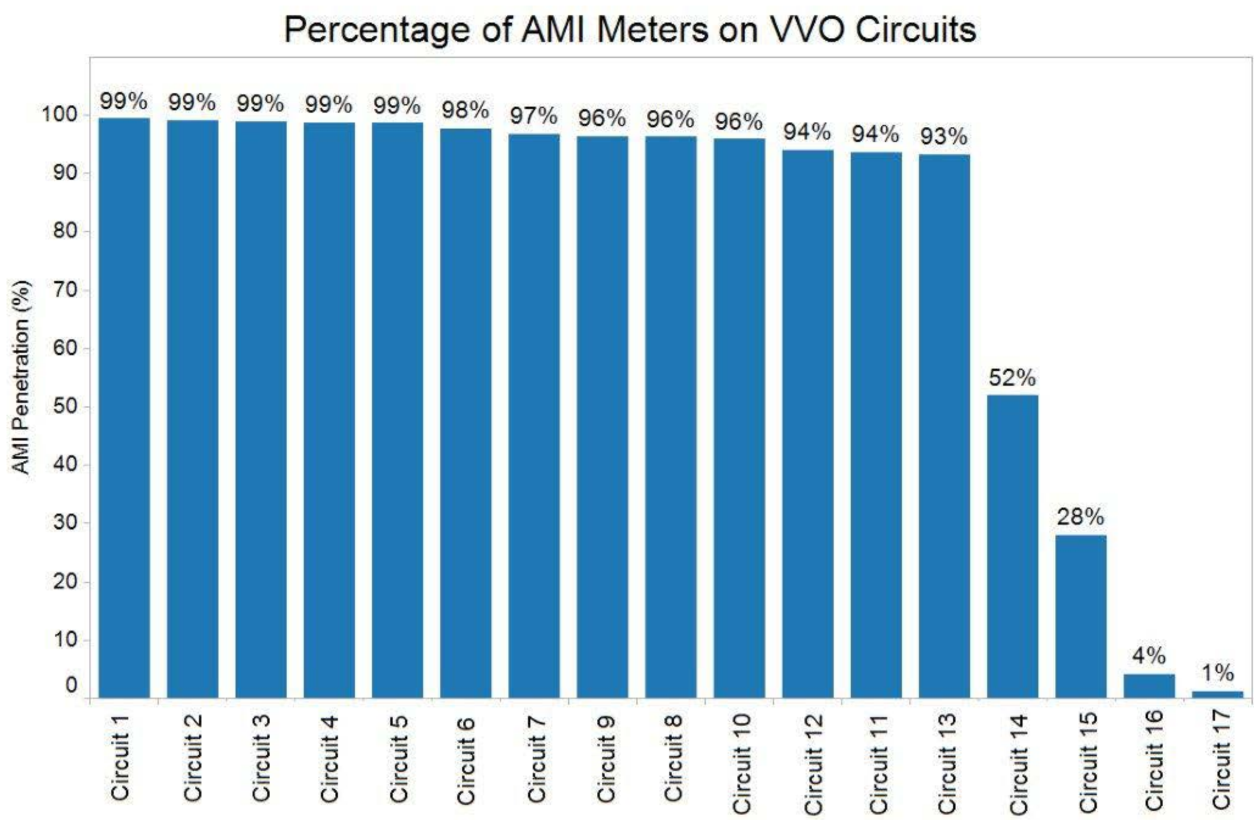

Figure 140. Percentage of AMI Meters for Each VVO Circuit

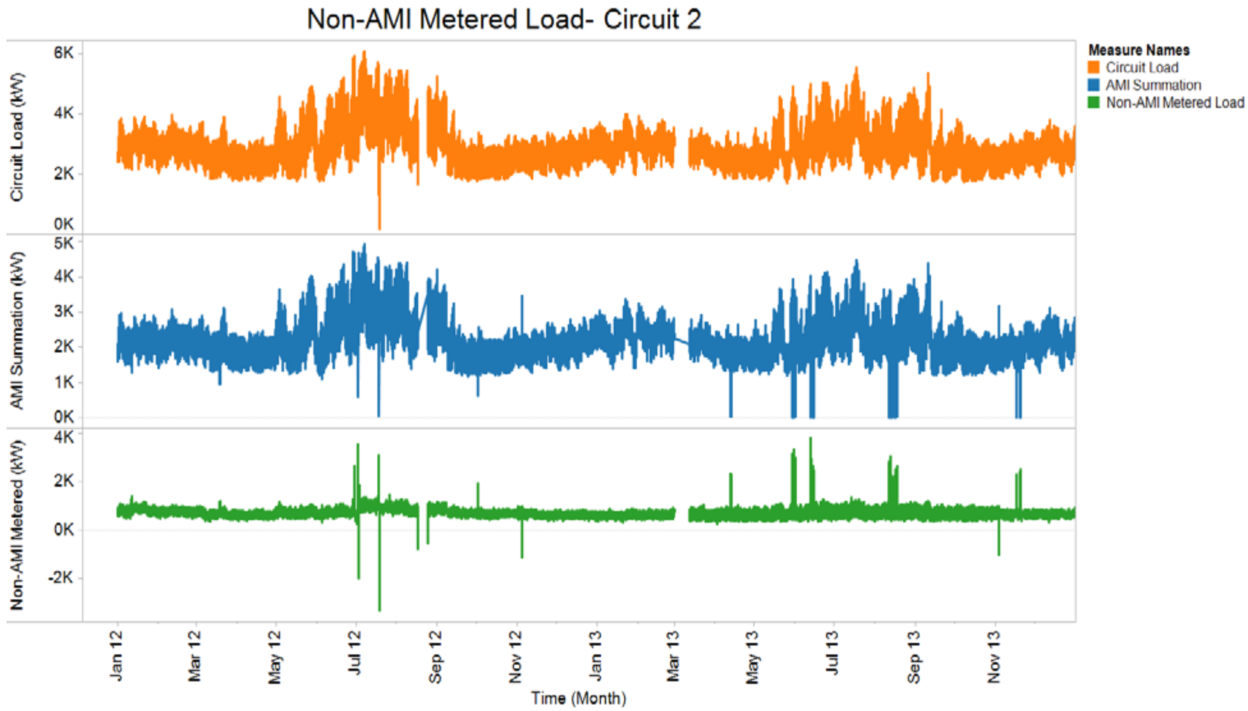

Figure 141. Circuit 1: Calculation of Non-AMI Metered Power

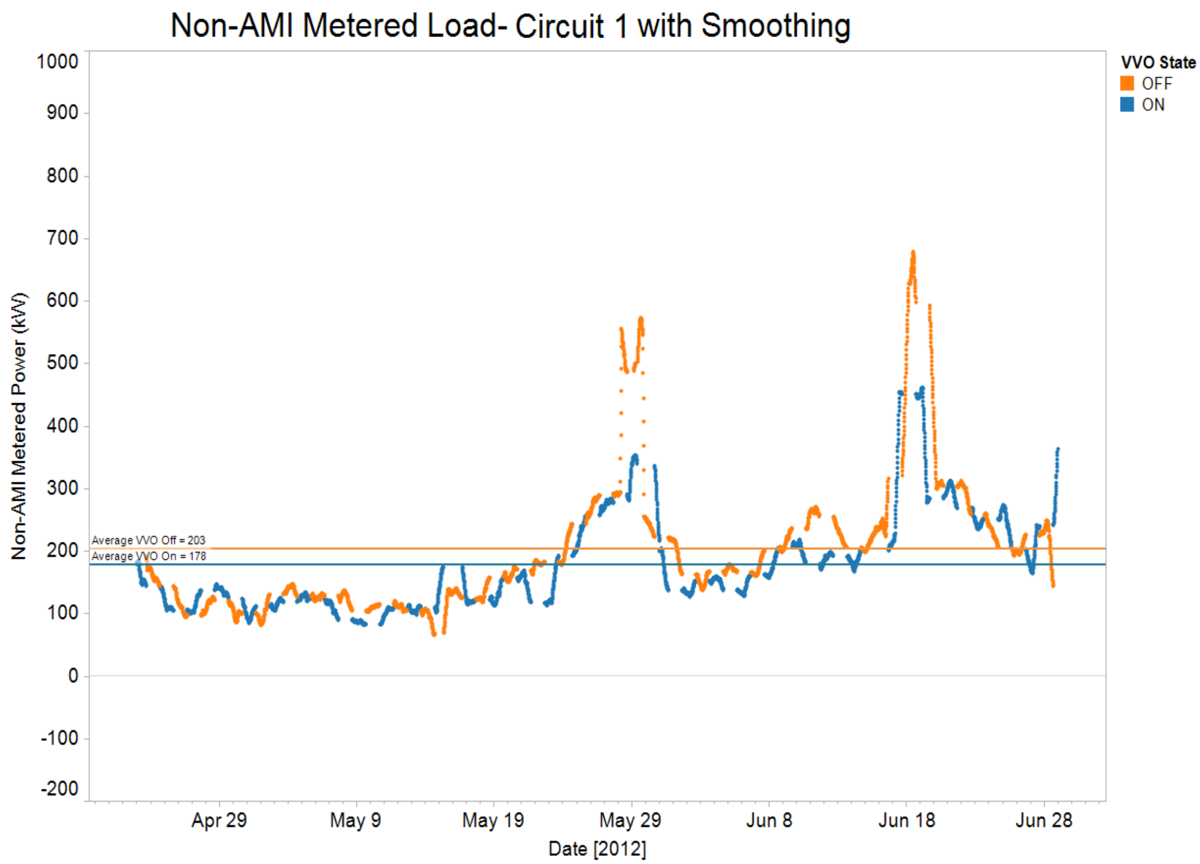

Figure 142. Circuit 1: Non-AMI Metered Power vs. Time

The summary statistics for Circuit 1 are:

Circuit 1		
Volt-VAR Status	**Avg Power**	**% Difference**
On	171.0187	
Off	192.2625	11.0%
Outliers Removed		
On	171.0187	
Off	183.4525	6.8%

Table 24. Circuit 1 Statistics

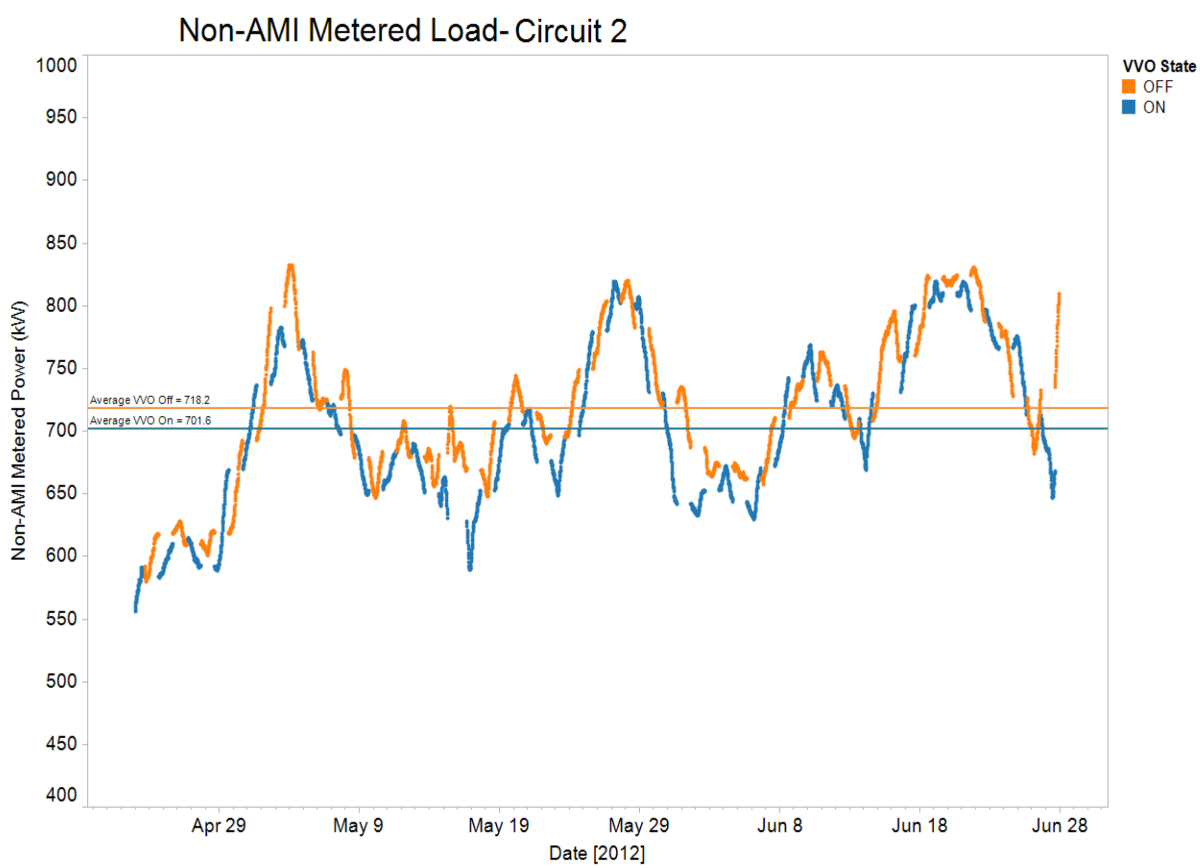

Figure 143. Circuit 2: Non-AMI Metered Power vs. Time (Apr-Aug)

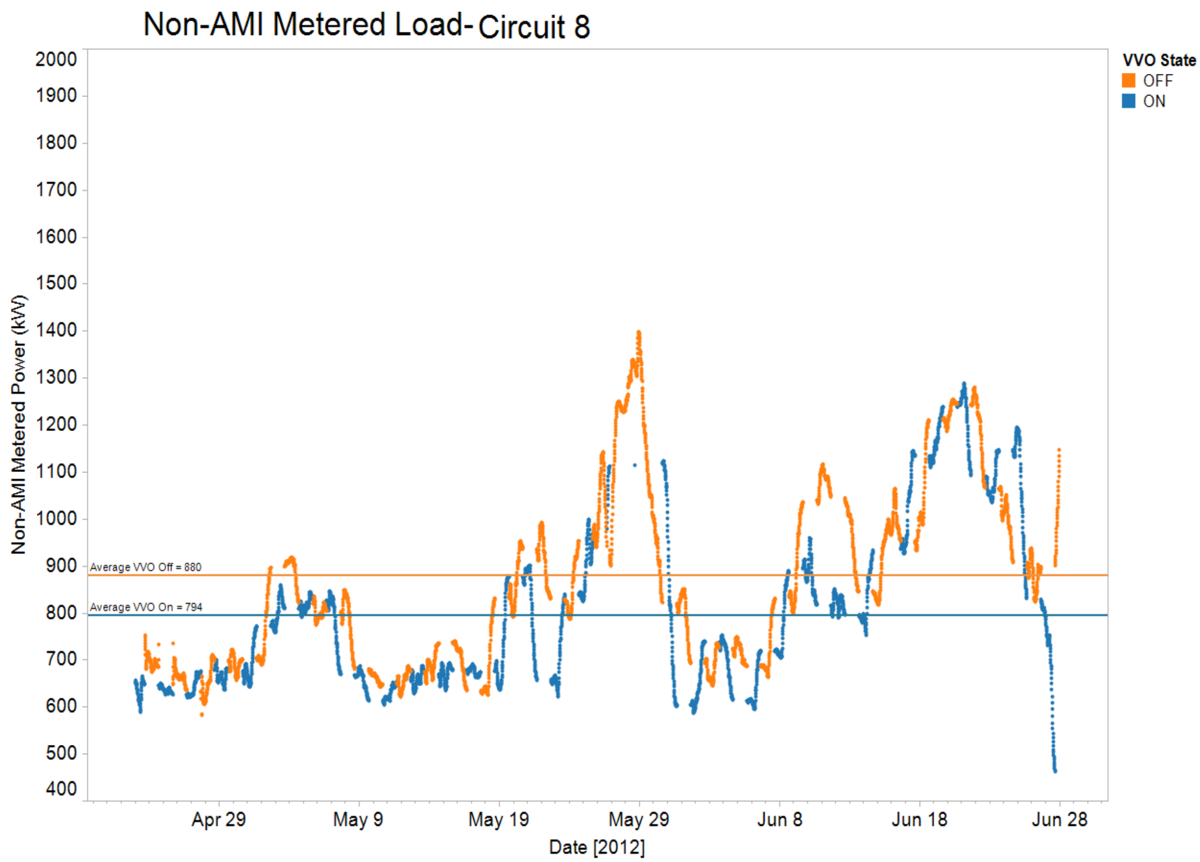

Figure 144. Circuit 8: Non-AMI Metered Power vs. Time

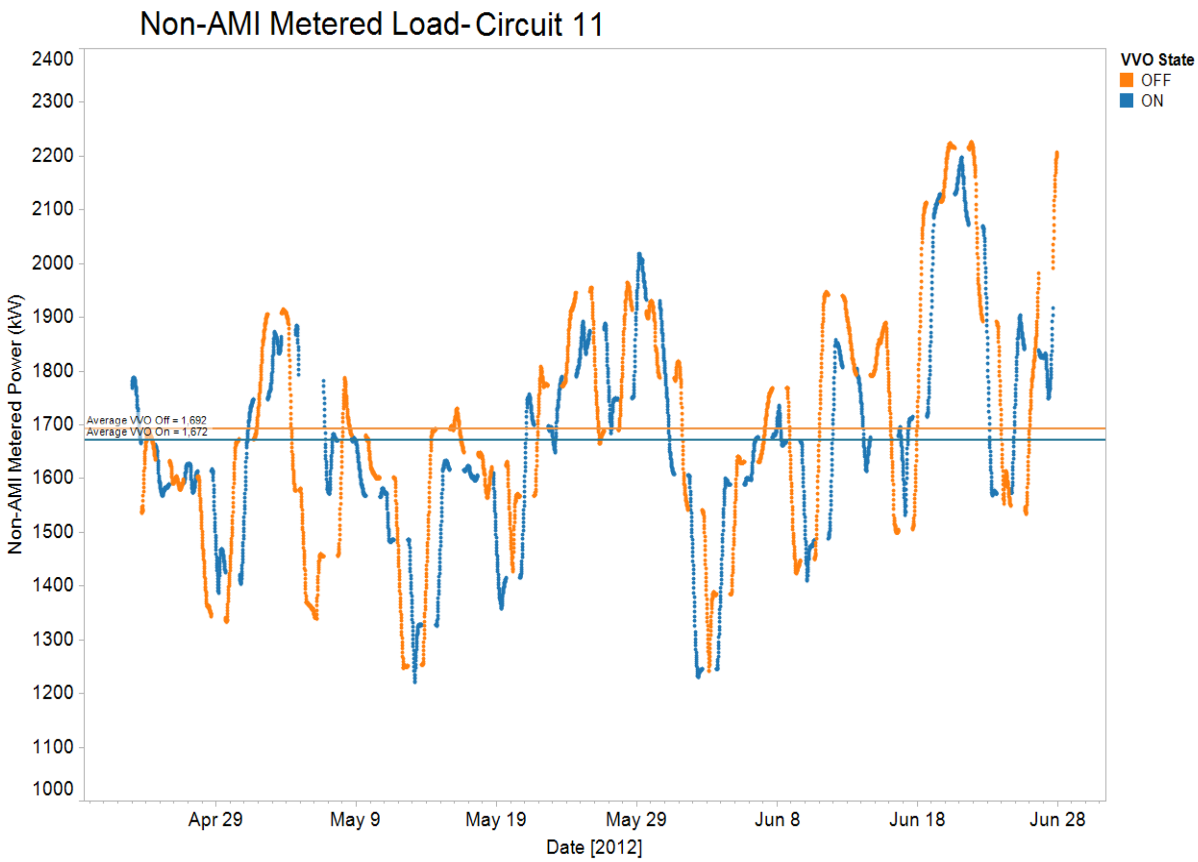

Figure 145. Circuit 11: Non-AMI Metered Power vs. Time

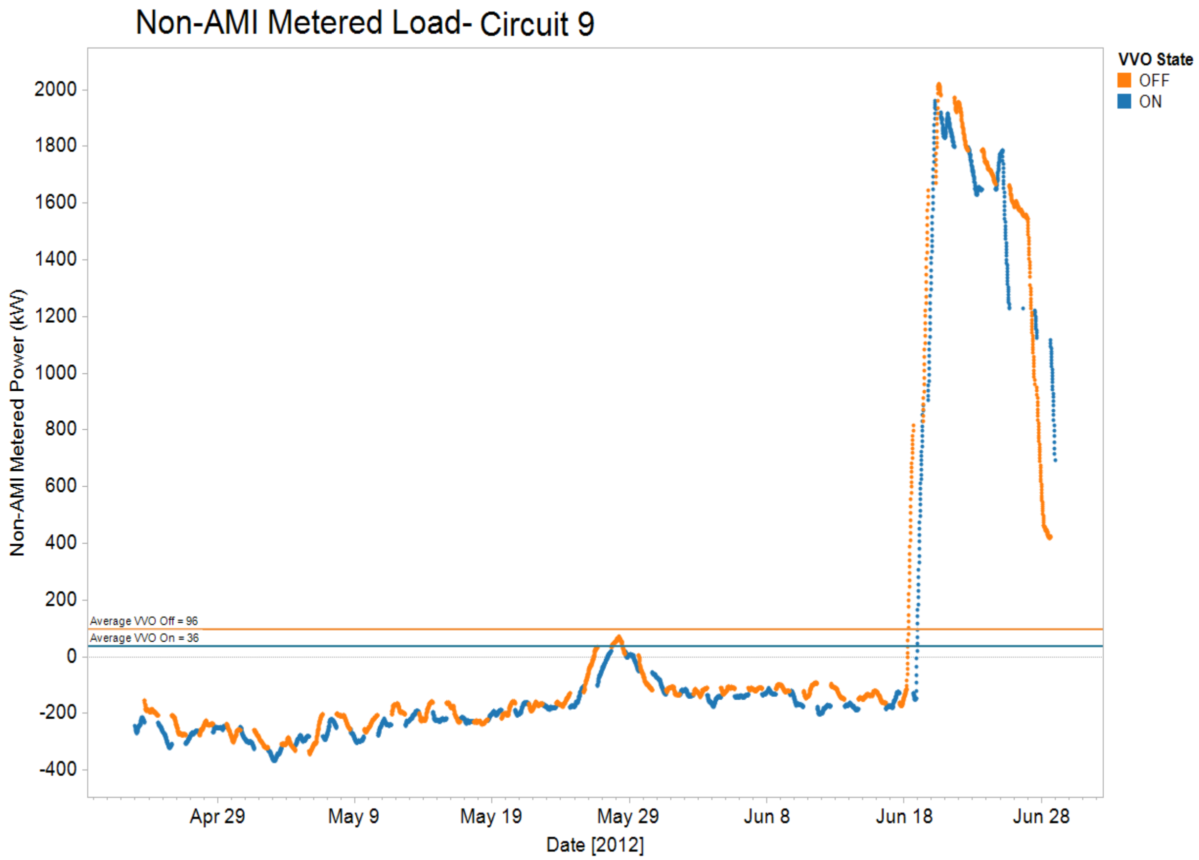

Figure 146. Circuit 9: Non-AMI Metered Power vs. Time

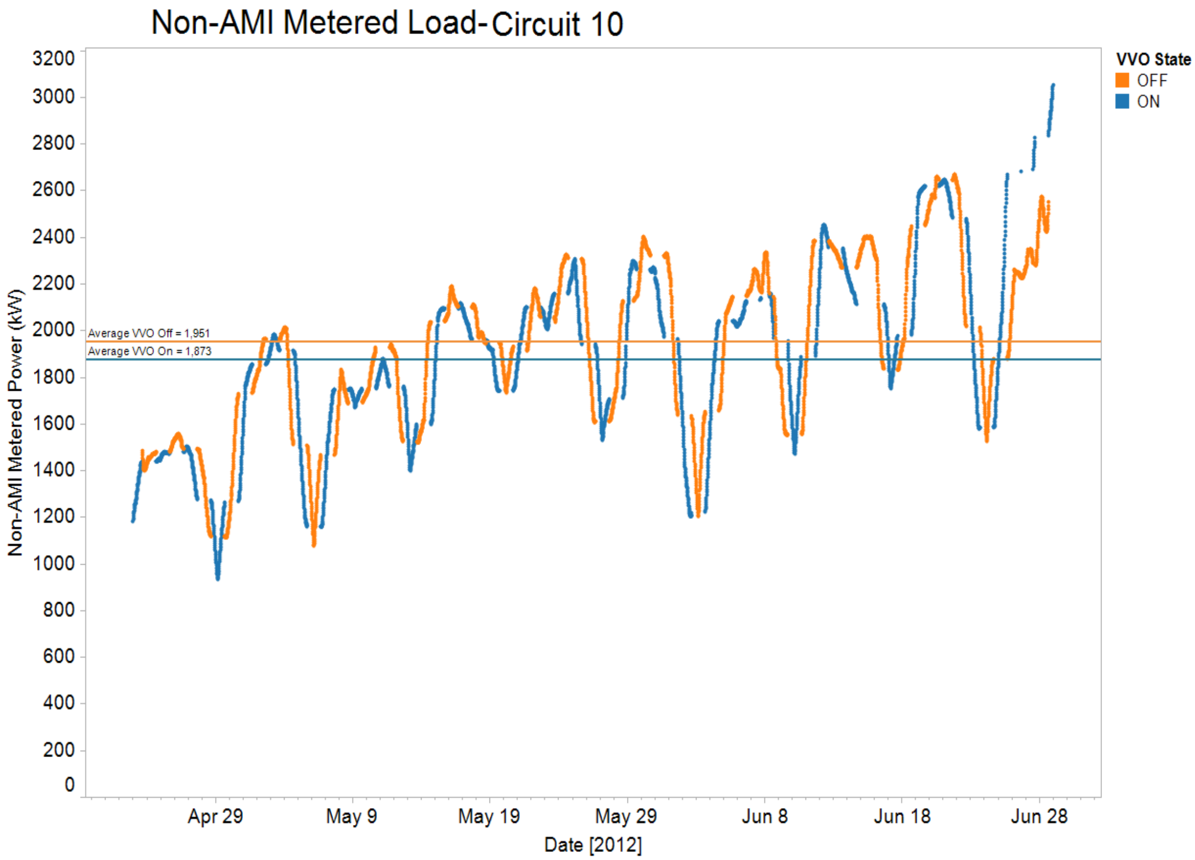

Figure 147. Circuit 10: Non-AMI Metered Power vs. Time

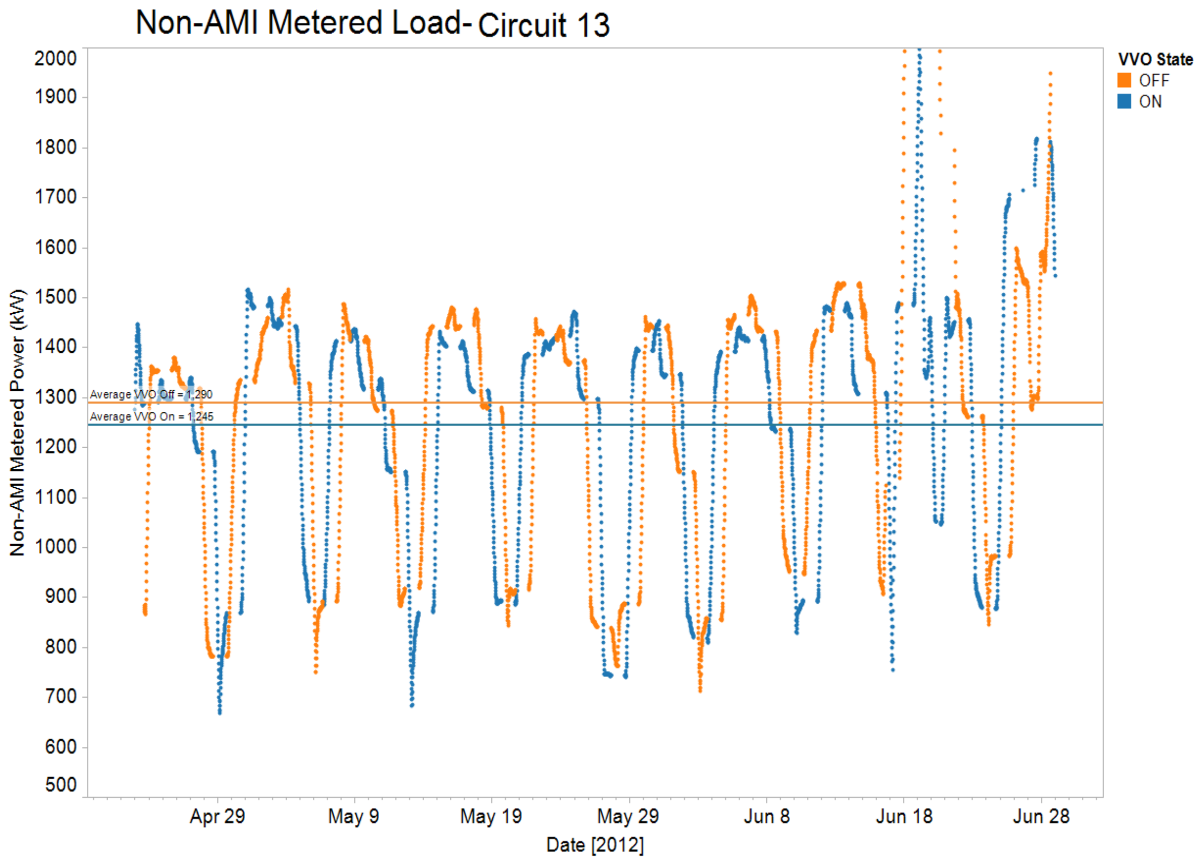

Figure 148. Circuit 13: Non-AMI Metered Power vs. Time

6.5.7.6 Summary

For the majority of circuits, non-AMI metered load was reduced during VVO On periods. This reduction was associated with both losses and reductions in other non-AMI metered loads, such as street lights). For Circuit 1, there was approximately a 4 percent reduction in non-metered load.

6.5.8 Distribution Power Factor (M23-VVO)

6.5.8.1 Objective

VVO reduces circuit demand by flattening and lowering circuit voltages, primarily by using voltage regulators. Simultaneously, VVO actively controls capacitor banks to maintain circuit power factors near unity. Power factor is an indication of how efficiently the distribution system is delivering power. A system operating at unity power factor delivers power more efficiently than one operating at either a leading or lagging power factor. This impact metric presents the reported power factor for circuits across various time ranges.

6.5.8.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

This measure has not been adjusted for any load, weather, or seasonal factors.

6.5.8.3 Calculation Approach

The following queries and methods were used to generate results:

- Power factors per circuit, VVO controller status, and time were calculated by dividing the real power on the circuit by the apparent power on the circuit.
- Hourly outdoor temperature in degrees Fahrenheit for Port Columbus International Airport was collected from the National Oceanic and Atmospheric Administration.

6.5.8.4 Organization of Results

The following section reports power factors achieved for VVO circuits when VVO was on versus off. Each plot shows circuit load, power factor when lagging, and power factor when leading color coded by VVO status.

6.5.8.5 Data Collection Results

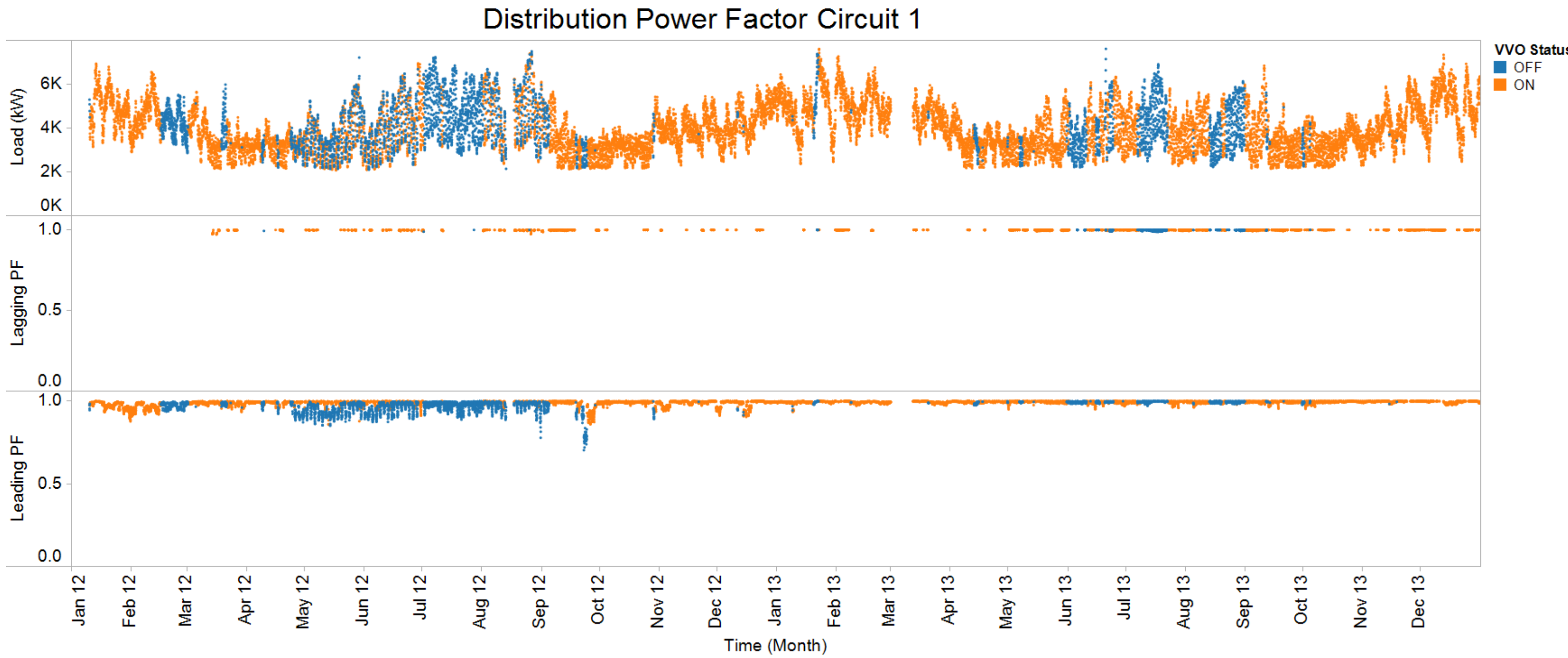

Figure 149. Circuit 1: Power Factor

Circuit	VVO On Average Power Factor	VVO Off Average Power Factor
Circuit 9	0.95316	0.93325
Circuit 13	0.96541	0.9783
Circuit 14	0.98753	0.99159
Circuit 15	0.98468	0.98457
Circuit 17	0.98188	0.98431
Circuit 16	0.99479	0.98604
Circuit 3	0.99087	0.97011
Circuit 4	0.97623	0.98803
Circuit 6	0.96716	0.98603
Circuit 7	0.94318	0.95313
Circuit 12	0.98488	0.99303
Circuit 5	0.97937	0.97898
Circuit 11	0.98253	0.98361
Circuit 8	0.96501	0.97264
Circuit 1	0.99171	0.9721
Circuit 2	0.9929	0.99286
Circuit 10	0.98371	0.97398

Table 25. Average Power Factor by Circuit -2012

6.5.8.6 Summary

VVO On shifted power factors from leading toward lagging compared to VVO Off cases. The VAR flows were more stable with VVO On. The overall power factor across all circuits did not significantly deviate from unity.

6.5.9 CO_2 Emissions - Project area (M32-VVO)

6.5.9.1 Objective

VVO has the potential to dynamically control voltage and power factor on circuits to reduce consumer energy consumption and losses. This reduced demand can result in energy conservation, reduced costs, deferred capital investments, extended equipment life, and reduced fuel consumption. The reduction in energy consumption from VVO is expected to have a direct impact on reduced CO_2 emissions through a reduction in emissions from power generation plants. This impact metric presents the CO_2 emissions reduction as a function of conserved energy in the Project area.

6.5.9.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The day/on day/off sequence operated over a subset of the Project. Load reductions for the remainder of the Project were consistent with those measured during the testing period.
- CO_2: 0.00068956 tons/kWh
  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West R*egion

6.5.9.3 Calculation Approach

The following queries and methods were used to generate results:
Energy reduction due to VVO was estimated for each VVO circuit during times when the system was operated in a day/on day/off sequence.

Because VVO was operated in a day/on day/off sequence over a subset of the year, up to 11 percent of circuit load readings produced load reduction estimates. In order to accurately convey the potential energy savings associated with VVO, these load reduction values were then extrapolated to the full number readings in a year in order to calculate what the load reduction would have been if the VVO systems operated continuously during the year.

CO_2 avoided due to VVO was then calculated by multiplying load reduction by a typical generation emissions factor of 0.68956 metric tons per MWh.

6.5.9.4 Organization of Results

The following section provides an estimate of CO_2 reduction due to the reduction in energy use associated with the VVO system. Positive numbers indicate a reduction in CO_2 emissions.

6.5.9.5 Data Collection Results

The results below quantify the impact metric for this section.
Presentation of CO_2 Avoided:

- Total energy usage avoided during VVO day/on day/off sequence: 3,912 MWh
- Total CO_2 emissions avoided during VVO day/on day/off sequence: 2,679 Metric Tons
- Energy avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 36,360 MWh
- CO_2 avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 25,072 metric tons

6.5.9.6 Summary

CO_2 emissions reduced due to VVO are a conversion of total energy conserved into equivalent CO_2 reductions. This assessment indicated that during the VVO day/on day/off sequence, 2,679 metric tons of CO_2 were avoided, and that if VVO had been on continuously throughout 2012 and 2013 for all 17 Project circuits, 25,072 metric tons of CO_2 would have been avoided.

6.5.10 Pollutant Emissions - Project area: SO_X, NO_X, and $PM_{2.5}$ (M33-VVO)

6.5.10.1 Objective

VVO has the potential to dynamically control voltage and power factor on circuits to reduce consumer energy consumption and losses. This reduced demand can result in energy conservation, reduced costs, deferred capital investments, extended equipment life, and reduced fuel consumption. The reduction in energy consumption from VVO is expected to have an impact on reduced pollutant emissions through a reduction in emissions from power generation plants. This impact metric presents the pollutant emissions reduction as a function of conserved energy in the Project area.

6.5.10.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The day/on day/off sequence operated over a subset of the Project. Load reductions for the remainder of the Project were consistent with those measured during the testing period.
- SO_x: 0.00263084 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- NO_x: 0.00117934 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- $PM_{2.5}$: 0.001 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*

6.5.10.3 Calculation Approach

The following queries and methods were used to generate results:
Energy reduction due to VVO was estimated for each VVO circuit during times when the system was operated in a day/on day/off sequence.

Because VVO was operated in a day/on day/off sequence over a subset of the year, up to 11 percent of circuit load readings produced load reduction estimates. In order to accurately convey the potential energy savings associated with VVO, these load reduction values were then extrapolated to the full number readings in a year in order to calculate what the load reduction would have been if the VVO systems operated continuously during the year.

NO_X avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 1.17934 kg per MWh.

$PM_{2.5}$ avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 1.0 kg per MWh.

SO_X avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 2.63084 kg per MWh.

6.5.10.4 Organization of Results

The following section provides an estimate of pollutant reductions due to the reduction in energy use associated with the VVO system. Positive numbers indicate a reduction in pollutant emissions.

6.5.10.5 Data Collection Results

The results below quantify the impact metric for this section:

- Total energy usage avoided during VVO day/on day/off sequence: 3,912 MWh
- Total NOx emissions avoided during VVO day/on day/off sequence: 4,613 kg
- Total $PM_{2.5}$ emissions avoided during VVO day/on day/off sequence: 3,912 kg
- Total SO_X emissions avoided during VVO day/on day/off sequence: 10,291 kg
- Energy avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 36,360 MWh
- NOx avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 42,881 kg
- $PM_{2.5}$ avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 36,360 kg
- SOx avoided if VVO had been on continuously for all 17 Project area circuits throughout 2012 and 2013: 95,657 kg

6.5.10.6 Summary

Pollutant emissions are a direct multiplier of energy reductions. This analysis indicated that operating VVO full time for the Project circuits would have resulted in annual reductions of 42,881 kg of NO_X, 36,360 kg of $PM_{2.5}$, and 95,657 kg of SO_X during 2012 and 2013.

6.5.11 CO_2 Emissions - System area (M34-VVO)

6.5.11.1 Objective

The previous two subsections examined the influence of VVO on pollutant emissions in the Project area. This impact metric extends that work by estimating the potential for reducing CO_2 emissions if VVO were deployed across the System area.

6.5.11.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The day/on day/off sequence operated over a subset of the Project. Load reductions for the remainder of the Project were consistent with those measured during the testing period.
- VVO would have a similar impact on circuit load for circuits in the non-Project area.
- CO_2: 0.00068956 tons/kWh

Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*

6.5.11.3 Calculation Approach

The following queries and methods were used to generate results:

Energy reduction due to VVO was estimated for each VVO circuit during times when the system was operated in a day on/day off sequence. This estimation is explained under M13, Distribution Circuit Load.

Because VVO was operated in a day on/day off sequence over a subset of the year, roughly 10.9 percent of circuit load readings produced load reduction estimates. In order to accurately convey the potential energy savings associated with VVO, these load reduction values were then extrapolated to the full number readings in a year and to the full number of circuits in the System area.

CO_2 avoided due to VVO was then calculated by multiplying extrapolated energy reduction by a typical generation emissions factor of 0.68956 metric tons per MWh. To determine the CO_2 reductions that would have been obtained if the entire System area had deployed VVO for all of 2012, the Project area reductions are multiplied by a factor of 25.159, which is the ratio of total energy in the system to energy in the VVO circuits.

6.5.11.4 Organization of Results

The following section provides an estimate of potential CO_2 reduction due to the reduction in energy use associated with the VVO system. These results are an extrapolation to the AEP Ohio System area based on energy reductions observed in the Project area. Positive numbers indicate a reduction in CO_2 emissions.

6.5.11.5 Data Collection Results

Presentation of CO_2 Avoided:
System extrapolation of VVO energy reduction for 2012 and 2013: 882,504 MWh
System extrapolation of VVO CO_2 emissions avoided: for 2012 and 2013: 608,539 metric tons

6.5.11.6 Summary

System CO_2 reductions projections indicated that 608,539 metric tons of CO_2 emissions would have been avoided if VVO operated continuously across the entire System area for all of 2012 and 2013.

6.5.12 Pollutant Emissions - System area: SO_X, NO_X, and $PM_{2.5}$ (M35-VVO)

6.5.12.1 Objective

The previous subsection estimated the potential for reducing CO_2 emissions if VVO were deployed across the System area. This impact metric provides similar estimates for additional pollutant emissions.

6.5.12.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data:

- The day/on day/off sequence operated over a subset of the Project. Load reductions for the remainder of the Project were consistent with those measured during the testing period.
- VVO would have a similar impact on circuit load for circuits in the non-Project area.
- SO_X: 0.00263084 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- NO_X: 0.00117934 kg/kWh

  Source: *U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region*
- $PM_{2.5}$: 0.001 kg/kWh
- Source: U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region

6.5.12.3 Calculation Approach

The following queries and methods were used to generate results.

Energy reduction due to VVO was estimated for each VVO circuit during times when the system was operated in a day/on /day/off sequence. This estimation is explained under M13, Distribution Circuit Load.

Because the AEP Ohio day/on day/off sequence only operated over a subset of the year, roughly 10.9 percent of circuit load readings produced load reduction estimates. In order to accurately convey the potential energy savings associated with VVO, these load reduction values were extrapolated to the full number of readings in a year and to the full number of circuits in the System area in order to calculate what the potential load reduction would be if VVO systems were installed System-wide and operated continuously.

NO_X avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 1.17934 kg per MWh.

$PM_{2.5}$ avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 1.0 kg per MWh.

SO_X avoided due to VVO was calculated by multiplying load reduction by a typical generation emissions factor of 2.63084 kg per MWh.

To determine the pollutant reductions that would have been obtained if the System area had deployed VVO for all of 2012, the Project area reductions are multiplied by a factor of 25.159, which is the ratio of total load in the system to load in the VVO circuits.

6.5.12.4 Organization of Results

The following section provides an estimate of potential pollutant reduction due to the reduction in energy use associated with the VVO system. These results are an extrapolation to the System area based on energy reductions observed in the Project area. Positive numbers indicate a reduction in pollutant emissions.

6.5.12.5 Data Collection Results

The results below quantify the impact metric for this section:

- System extrapolation of VVO energy reduction for 2012 and 2013: 882,504 MWh
- System extrapolation of VVO NO_X emissions avoided for 2012 and 2013: 1,041,000 kg
- System extrapolation of VVO $PM_{2.5}$ emissions avoided for 2012 and 2013: 883,000 kg
- System extrapolation of VVO SO_X emissions avoided for 2012 and 2013: 2,322,000 kg

6.5.12.6 Summary

System pollutant reductions projections indicated that using VVO continuously for all System circuits would have resulted in annual reductions of 2,322,000 kg of SO_X, 1,041,000 kg of NO_X, and 883,000 kg of $PM_{2.5}$ and during 2012 and 2013.

6.6 VVO Conclusions

Voltage standards exist in the electric utility industry, such as ANSI C84.1, that mandate an acceptable voltage range at the secondary of the distribution transformer. VVO enables a reduction of the average voltage that each consumer on the circuit receives, thereby reducing the annual energy consumption of the circuit while maintaining the quality of service to the consumer.

Based on Project results, AEP Ohio estimates that a 3 percent reduction in energy consumption and a 2 to 3 percent reduction in peak demand can be obtained on those circuits on which VVO technology is deployed.

6.7 Lessons Learned

During the Project, implementing VVO technology was new to AEP Ohio and there were lessons learned regarding implementation, operations, and the technology itself. This section shows those lessons learned. AEP Ohio addressed these issues during the Project and continues to use this experience to develop processes and guidelines for future VVO deployments. Lessons learned are provided for Technology, Implementation, and Operations.

6.7.1 Technology

- Systems engineering for new technology requires planning.
- Smart grid technologies require a high level of team coordination during commissioning and engineering phases. This includes system planners, circuit engineers, telecommunications, security dispatch centers, distribution control engineers.
- Work with vendors to ensure equipment interoperability. It is important for utilities and vendors to work together to enhance smart equipment so multiple devices become interoperable. Continuous updates to vendor equipment and specifications create challenges. Therefore, it is critical to ensure proper integration with existing systems.
- The use of three-phase regulators is not recommended. Some technical issues were encountered working with three-phase regulators and other legacy components.
- Turn data into action. The introduction of new smart grid devices and the ability to communicate information has created large amounts of data and log files. This includes system operation and equipment performance data. IT reporting and data mining applications need to be developed to turn this data into actionable knowledge.

6.7.2 Implementation

- Include performance specifications in all Requests for Proposal (RFP) to gauge market readiness.
- Testing, configuring and commissioning devices and automation schemes is more time consuming and complicated than stand-alone devices.
- Validate vendor system claims including acceptance testing, consumer support, and escalation procedures

- Establish compensation structures to better ensure that vendors achieve anticipated outcomes.

- Deploying DACR and VVO in the same area created unforeseen challenges:
  - VVO was designed and constructed first before circuit reconfiguration in sub-optimal footprint.
  - Initial VVO applications required stable topology.
  - Today interoperability between DACR/VVO means VVO is turned off prior to allowing DACR to change topology.

6.7.3 Operations

Establish interoperability between DACR and VVO to enable VVO to remain on even when DACR changes topology.

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7 DEMONSTRATED TECHNOLOGY – ELECTRIC VEHICLES

7.1 Purpose

The introduction of electric vehicles into the consumer market has raised questions around grid and load preparedness for mass market adoption. AEP Ohio set out to gain a better understanding of the charging behavior of drivers of plug-in electric vehicles (PEVs) and to explore how consumer programs, Electric Vehicle Supply Equipment (EVSE) locations, and supply level affect users' charging behavior. AEP Ohio also examined the impact that electric vehicles may have on the utility system.

7.2 Technology

AEP Ohio deployed PEVs - nine Chevrolet Volt plug-in hybrid electric vehicles (PHEVs), one CODA battery electric vehicle (BEV), two Mercedes Smart Electric Drive BEVs, and one Ford Escape modified to be a PHEV. The Ford Escape and Mercedes Smart Electric Drives were withdrawn from the program due to ongoing mechanical issues.

AEP Ohio deployed 36 charging stations. Level 1 (L1) EVSEs usually are provided by the vehicle manufacturer and use a standard 120V electrical outlet. L1 EVSEs typically charge at a rate of about 1.4 kW. Thirteen 120 V outlets were installed among four workplace locations for L1 charging. AEP Ohio selected Ecotality's Blink EVSE as the Level 2 (L2) charger. Level 2 chargers were available in both wall mount and pedestal models, required installation, and utilized a 240 volt AC input electrical outlet. The Blink EVSEs had communications built in and were able to collect charging data including event times and energy provided. Twenty-three L2 EVSEs were installed in a combination of residential, workplace, and public locations. L2 EVSEs typically charge at a rate of about 3.3 kW or 6.6 kW depending on the vehicle. On L2, the Volts charge at 3.3 kW while the CODA charges at 6.6 kW.

AEP Ohio collaborated with the Electric Power Research Institute (EPRI) to implement an on-board vehicle data acquisition system to gather vehicle performance information for both charging and driving events, which was used on the Chevrolet Volts.

7.3 Approach and Implementation

AEP Ohio reviewed various vehicle manufacturers to evaluate all technologies. However, due to market penetration and vehicle availability, vehicle options were limited. Ten vehicles were selected and deployed for the majority of the project, which included nine Chevrolet Volts and one CODA.

Participants were chosen from AEP employees who lived in the AEP Ohio gridSMART® Demonstration Project (Project) area. Each participant was assigned a vehicle to drive for at least one year. Some vehicles were then redistributed to a new set of participants. A total of sixteen employees were assigned vehicles during the Project.

AEP Ohio also explored the installation process of EVSE infrastructure. Participants with a range of demographics were chosen for the residential installations, including a residential apartment complex. AEP Ohio provided an Advanced Metering Infrastructure (AMI) meter for all installations to gather energy consumption data for charging the PEVs. Most of the residential installations were non-billing meters, but two participants received actual EVSE billing meters. One of the two participants had a second meter installed in parallel to the residential meter, while the other had the meter installed in an apartment complex.

Each participant was provided with an L2 EVSE at their residence. Participants were required to be on a variable rate tariff to examine the effect pricing might have on their charging behavior. Three tariffs were available to the participants including:

TOD2 – Two Tier	
Peak	1 p.m. – 7 p.m., M-F June 1 – September 30
Off Peak	All other time
TOD3 – Three Tier with Critical Peak Price	
High	1 p.m. – 7 p.m., M-F, June 1 – September 30
Medium	7 a.m. – 1 p.m. & 7 p.m. – 9 p.m., M-F, June 1 – September 30
Low	Midnight – 7 a.m. & 9 p.m. to Midnight, M-F, June 1 – September 30
Critical Peak Pricing (CPP)	Up to 15 events/year, up to 5 hours/event
RTP_{da} – Price calculated at 5-minute intervals	

Table 26. Variable Rate Tariffs

A combination of L1 and L2 locations were provided at four AEP work locations in central Ohio as follows:

- One Riverside Plaza (1RP): 2 L2s and 5 L1s
- 850 Tech Center Dr., Gahanna (GAH): 2 L2s and 3 L1s
- Ohio Operations Center (OOC): 2 L2s and 3 L1s
- Dolan Technology Center (DTC): 1L2 and 2 L1s

The participants were given the option to use workplace charging for a fee of $10 per month. If enrolled, they were assigned an L1 parking location with unlimited charging. The L2 EVSEs were not assigned but were available for use by any participant enrolled in workplace charging although they were requested to limit their L2 use to no more than 4 hours per day. A Blink Fleet card was required to use the L2 workplace EVSEs that enabled the project to track usage by participant.

Finally, five L2 EVSEs were installed for public use as follows:

- 2 units at a Walmart/Sam's Club location
- 2 units at Easton Town Center
- 1 unit at the GAH office

All participants were given a Blink Public card (an identification card designed to authenticate the user's charging session) that allowed them to charge at these locations and to track their charging events. Blink cards were provided to the proprietors allowing non-Project participants to use the EVSEs. Any Blink member with a card could also use these EVSEs, making the chargers open to the public. These public chargers allowed charging at no cost to the consumer.

In all cases (residential, workplace, and public), metering and EVSE data was captured providing a data set of charging behavior.

7.4 Analysis

7.4.1 Cost of Installation

The figure below shows the average installation cost for residential, workplace, and public locations.

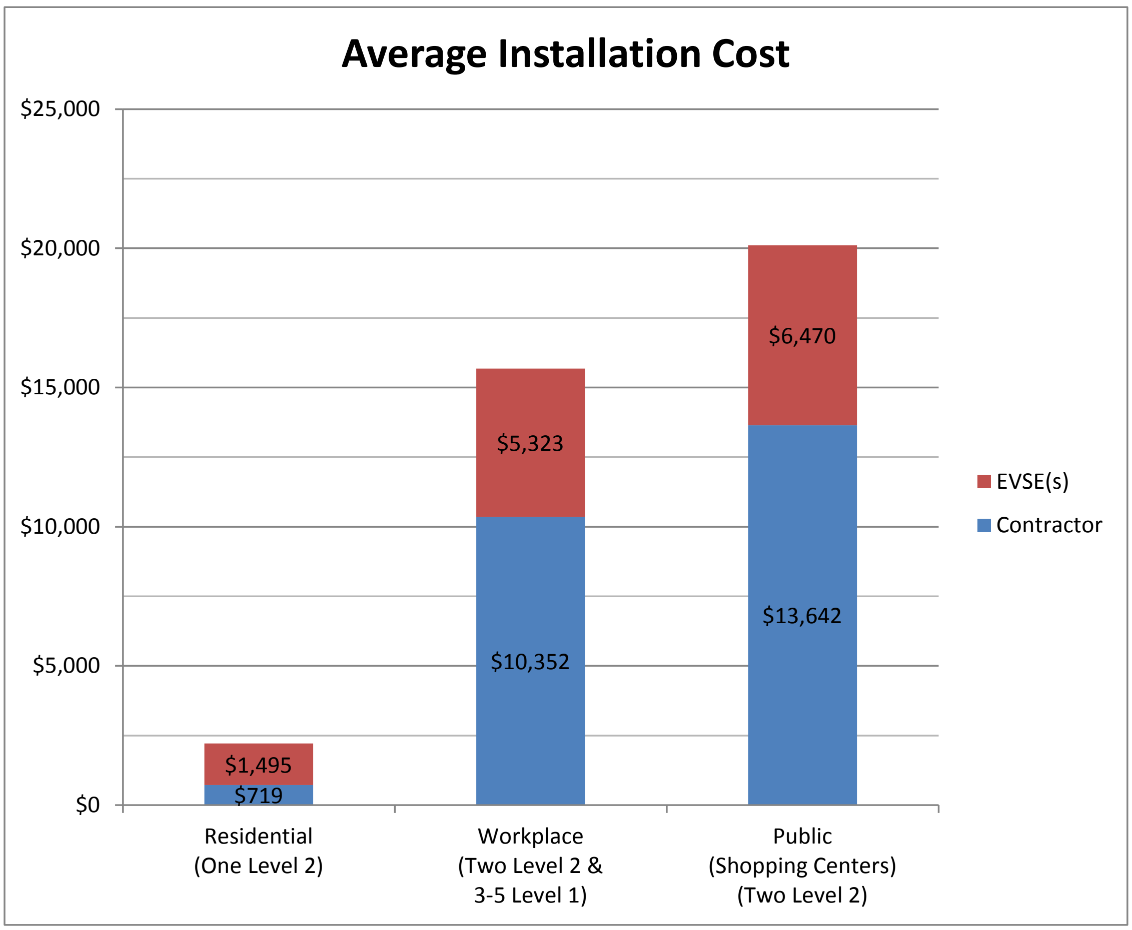


Figure 150. Average Installation Costs

The apartment location was not included because it was significantly different from a residential installation. Its cost was $3,675.00 ($2,180.00 contractor cost and $1,495.00 EVSE cost). The DTC workplace location was not included because the labor was performed by employees.

7.4.2 Grid Impact – Level 1 and Level 2 Charging

A concern an electric utility may have as PEVs are adopted is the effect charging will have on the distribution assets' ability to serve the increased demand.

7.4.2.1 Objective

AEP evaluated the impact that PEV charging may have on residential transformers. The participants were served from distribution transformers ranging in size from 25 kVA to 100 kVA.

7.4.2.2 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Transformer load was modeled using actual 15-minute load profiles from two one-year periods:

- Period 1 was October 1, 2011 to September 30, 2012 that included a summer with multiple extremely hot days.
- Period 2 was October 1, 2012 to September 30 2013 and included a mild summer.

The summer temperatures were of interest because peak summer loading could be a limiting factor for an asset's ability to carry load and to achieve its desired life expectancy.

7.4.2.3 Calculation Approach

An average annual vehicle profile at 15-minute intervals was calculated based on the residential charging profiles from Project vehicles.

The method used to determine a calculated transformer life in years was to add the average annual vehicle load profile to a given transformer's load profile for the designated period. This calculation was performed for zero to ten PEVs, simulating the effect of no PEVs on the transformer up to ten to determine if the transformer life would fall below AEP's guideline of 30 years. This was done for both periods and for each of the 16 transformers considered.

7.4.2.4 Results

According to the simulation, 14 of the transformers could accommodate at least 10 PEVs for both periods. One 25 kVA transformer was limited to 9 PEVs for Period 1. Another 25 kVA transformer was limited to 4 PEVs during Period 1 and 8 PEVs during Period 2. The table below shows the impact of PEV charging on transformer life expectancy. The red cells indicate life expectancy less than AEP's guideline of 30 years.

Xfmr #	kVA Rating	Period	Number of PEVs Simulated on the Transformer										
			0	1	2	3	4	5	6	7	8	9	10
1	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
2	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
3	25	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
4	100	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
5	37.5	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
6	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
7	25	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
8	25	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
9	37.5	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
10	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
11	75	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
12	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
13	25	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
14	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
15	50	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											
16	75	Year 1 (10/1/11-9/30/12)											
		Year 2 (10/1/12-9/30/13)											

Table 27. The Impact of PEV Charging on Transformer Life Expectancy

The participants had the option to enroll in workplace charging for a $10 monthly fee. Nine participants enrolled in workplace charging for the entire time they had a vehicle while three participants did so for part of the time they had a vehicle. Four participants chose not to enroll in workplace charging. Average charging profiles were created based on a participant's workplace charging enrollment status.

Figure 151 through Figure 156 represent average residential and workplace charging profiles for the groups of participants with and without workplace charging. The plots include bars showing the first standard deviation. The general shape of the demand profiles for both groups during weekday and weekend charging is similar. The group without workplace charging experienced an average peak demand of 1.0 kW at 8:00 p.m. while the group with workplace charging experienced an average peak demand of 0.7 kW at the same time.

A significant standard deviation during charging periods indicated a high variability of actual charging demand.

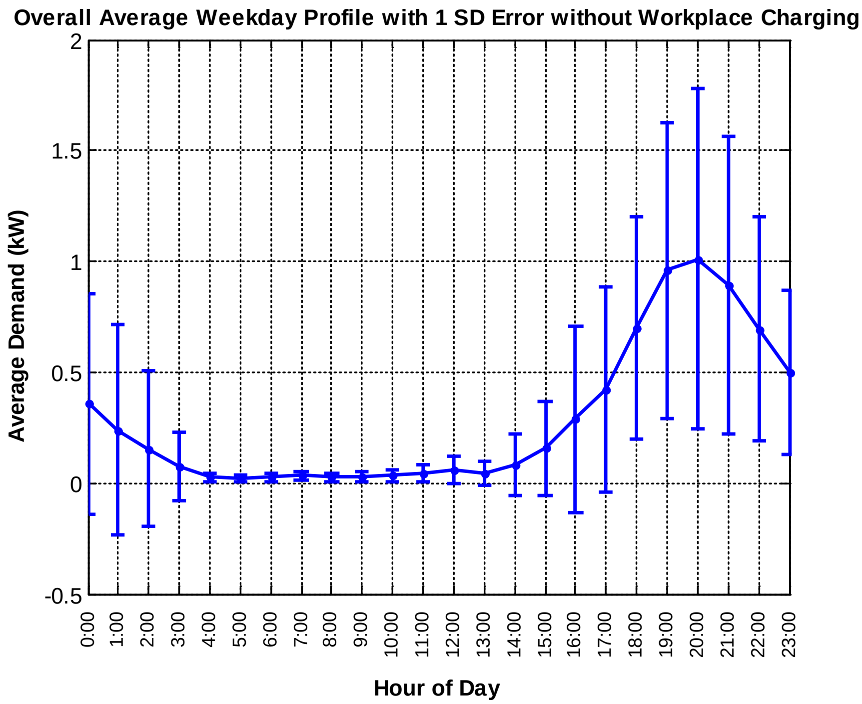


Figure 151. Average Residential Weekday Profile of Group without Workplace Charging

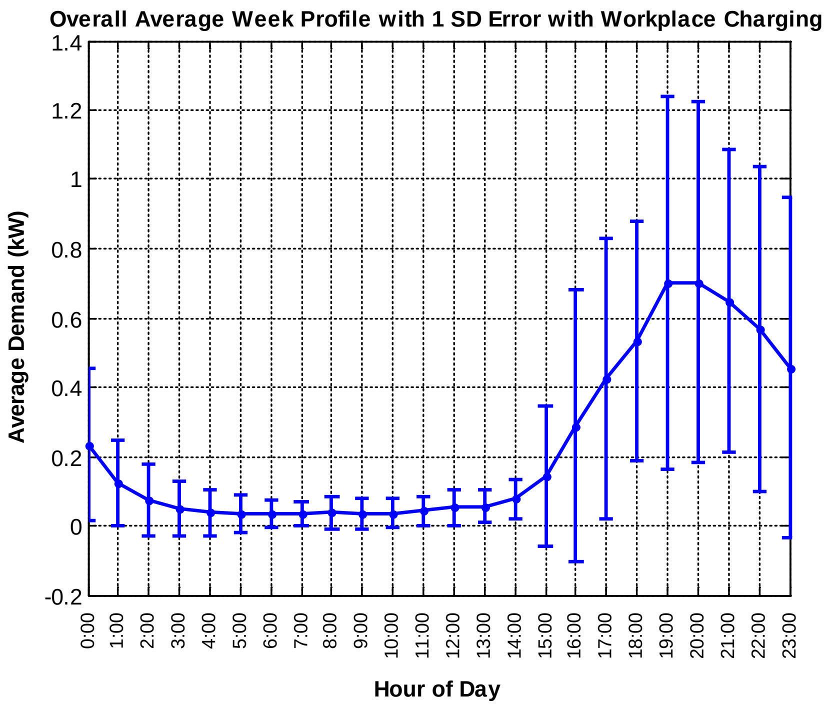


Figure 152. Average Residential Weekday Profile of Group with Workplace Charging

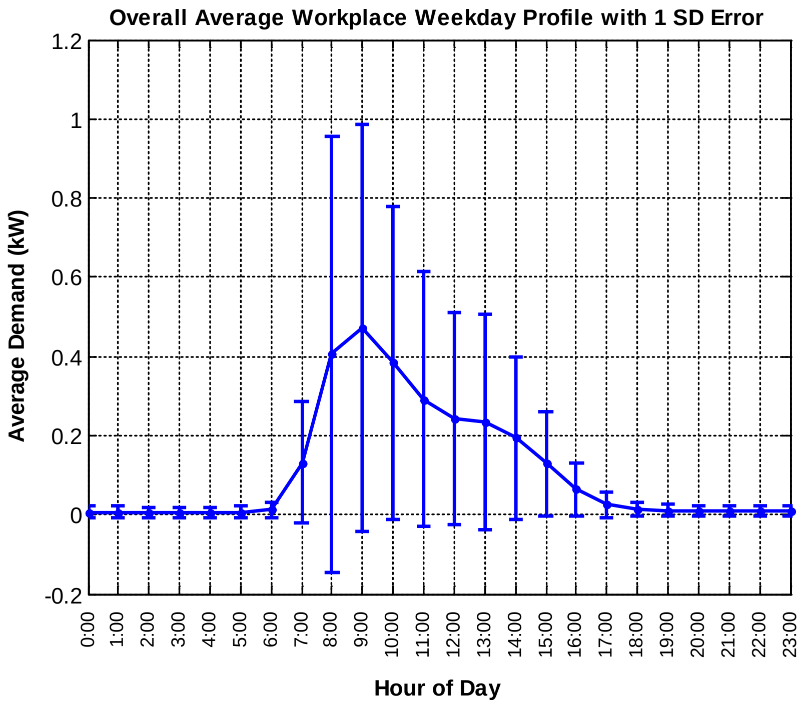


Figure 153. Average Workplace Weekday Profile of Group with Workplace Charging

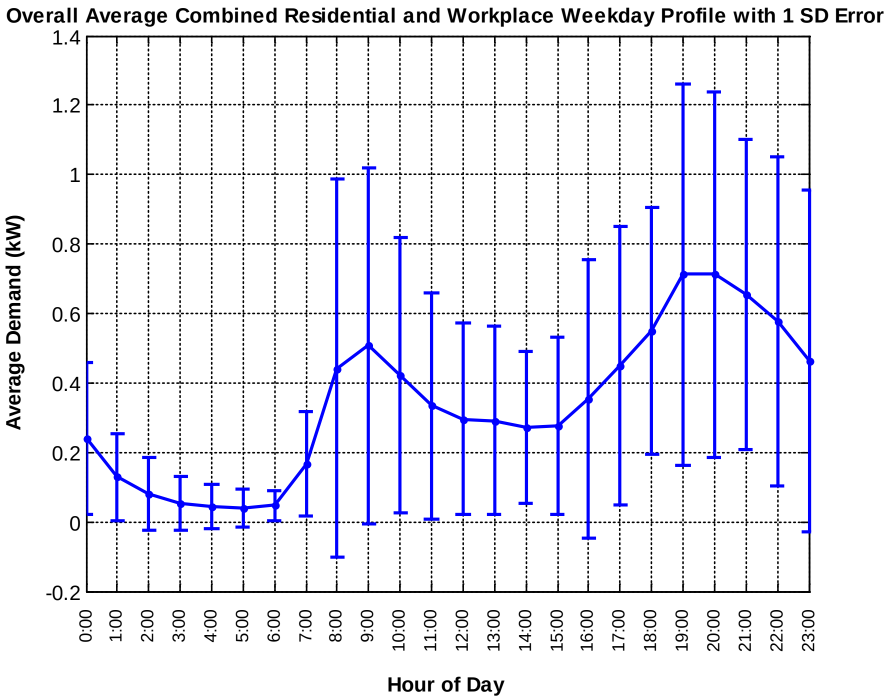


Figure 154. Average Combined Residential and Workplace Weekday Profile of Group with Workplace Charging

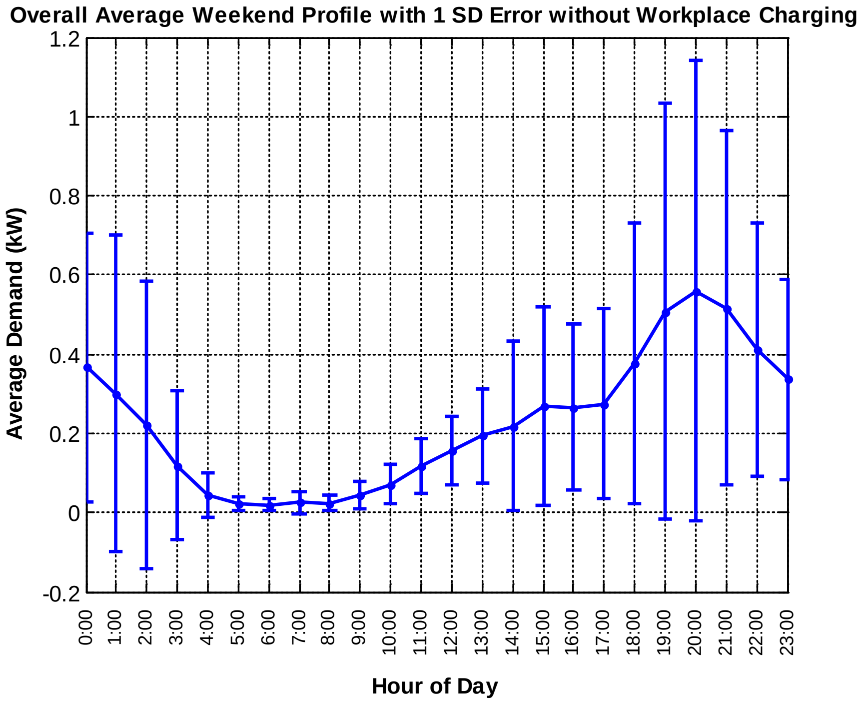


Figure 155. Average Residential Weekend Profile of Group without Workplace Charging

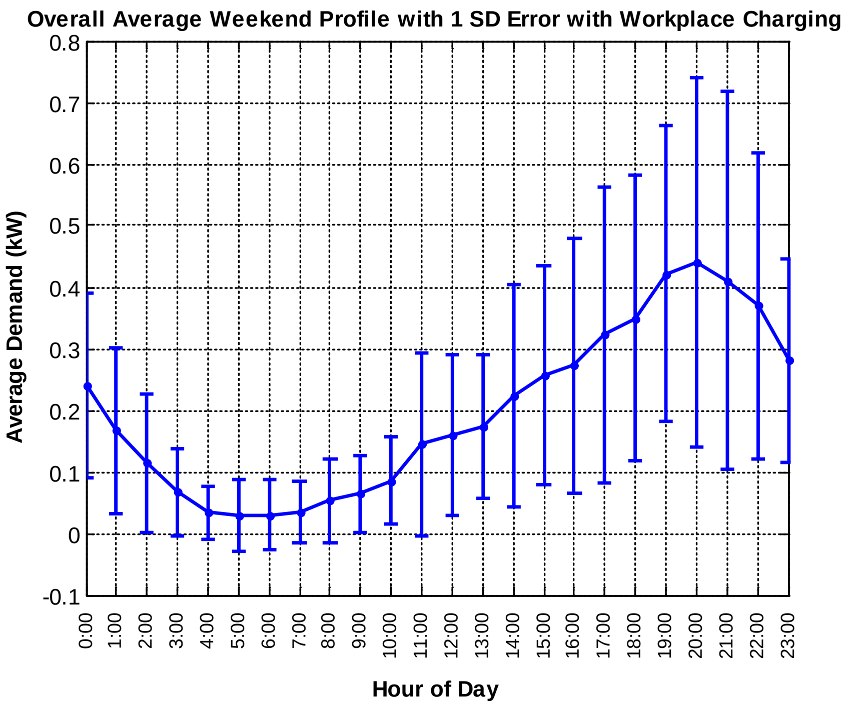


Figure 156. Average Residential Weekend Profile of Group with Workplace Charging

The figure below represents the average annual energy consumption by location type. The residential locations were divided into two groups of those with and without workplace charging. The group without workplace charging received more energy at home than the group with workplace charging. The Level 2 workplace units were used to deliver an average of 1161 kWh annually compared to 325 kWh for the Level 1 locations. The public Level 2 units delivered an average of 1497 kWh.

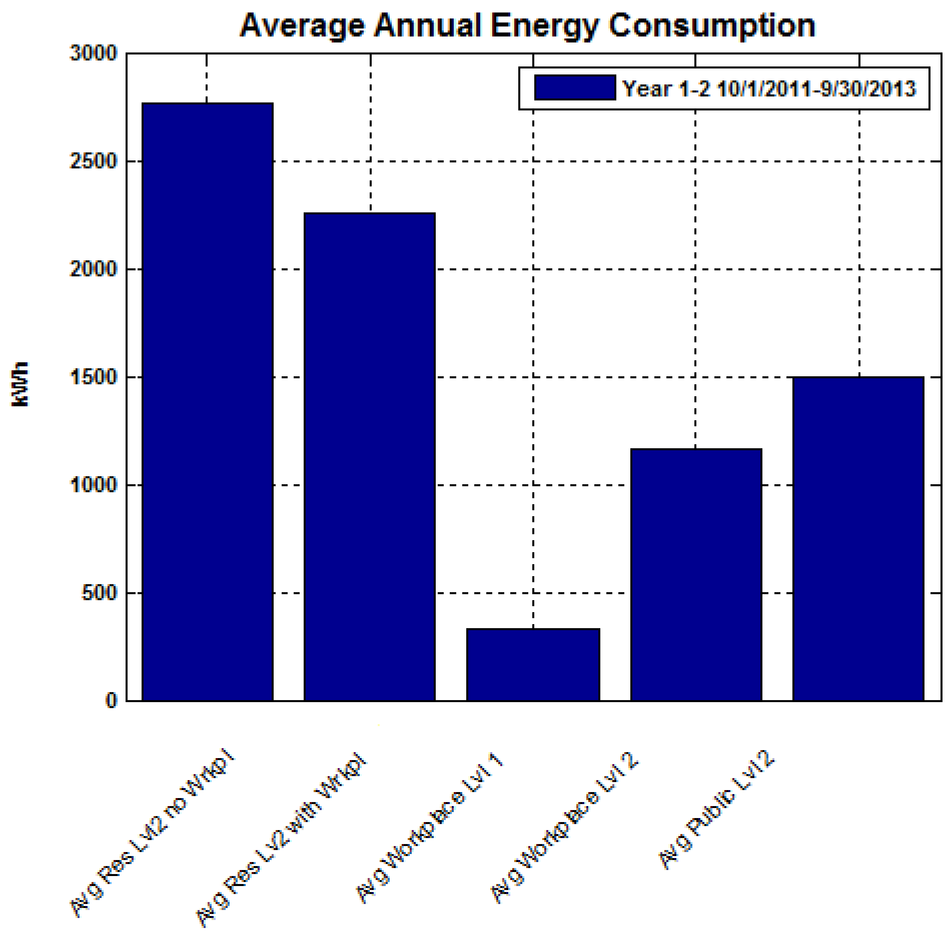


Figure 157. Average Annual Energy Consumption by Location

7.4.3 Grid Impact – Level 1 Only Charging

7.4.3.1 Objective

AEP Ohio evaluated the effect of replacing Level 2 with Level 1 charging based on the amount of energy delivered during a charge event.

7.4.3.2 Calculation Approach

The following queries and methods were used to generate results.
AEP Ohio determined how much energy was delivered for each Level 2 charging event and then how much energy would have been delivered during the same connection time using a Level 1 charging rate. The approximate Level 2 charge rate for the Volt is 3.3 kW and for the Coda was 6.6 kW, compared to an approximate Level 1 charge rate of 1.44 kW for the Volt and 1.47 kW for the Coda. This comparison was performed separately for the Coda and the Volt due to the different Level 2 charge rates. It was also performed separately for residential, workplace, and public charging since the typical connection times one might spend at each type of location may differ.

7.4.3.3 Results

The figures below represent the probability that a given percentage of a Level 2 charge could have been obtained using Level 1 charging at residential locations. For the Volt, 40 percent of an L2 charge would have been obtained about 18 percent of the time, while 100 percent of the L2 charge would have been obtained 70 percent of the time. For the Coda, 100 percent of the L2 charge would have been obtained 58 percent of the time.

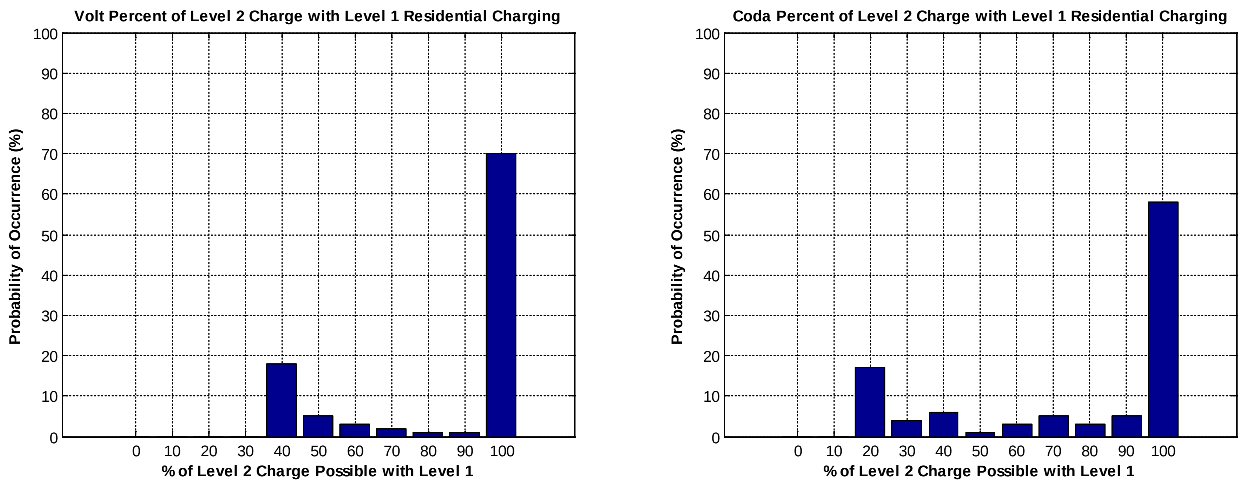


Figure 158. Residential Percent of Level 2 Charge Possible with Level 1 Charging on Two Vehicle Models

The following figures represent the probability that a given percentage of a Level 2 charge could have been obtained using Level 1 charging at a workplace location. For the Volt, 100 percent of an L2 charge would have been obtained about 54 percent. For the Coda, 100 percent of the L2 charge would have been obtained 66 percent of the time.

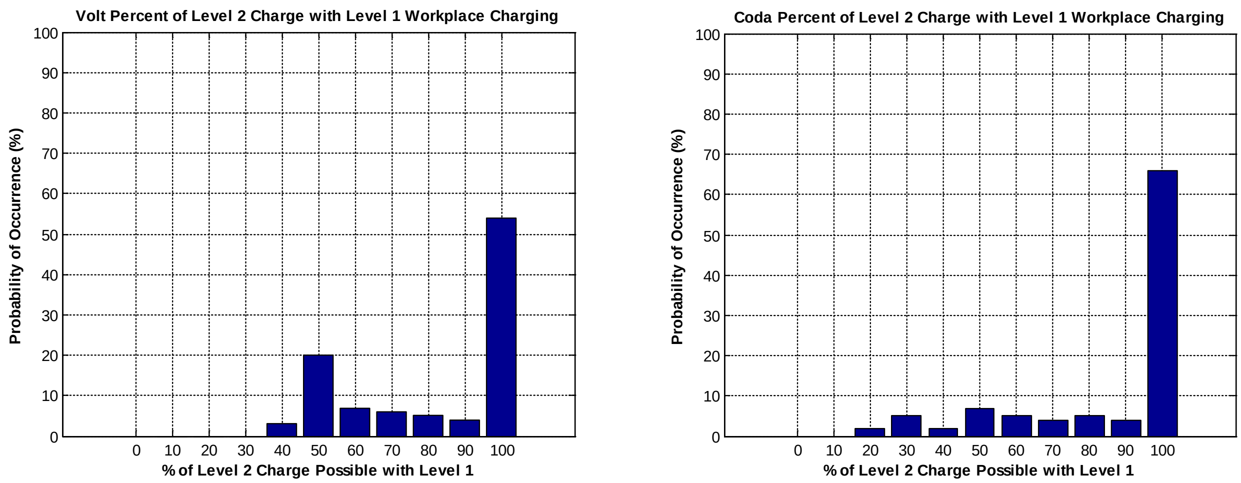


Figure 159. Workplace Percent of Level 2 Charge Possible with Level 1 Charging on Two Vehicle Models

The figures below represent the probability that a given percentage of a Level 2 charge could have been obtained using Level 1 charging at a public location. For the Volt, 50 percent of an L2 charge would have been obtained 60 percent of the time, while 100 percent of the L2 charge would have been obtained 23 percent of the time. For the Coda, 30 percent of the L2 charge would have been obtained 67 percent of the time.

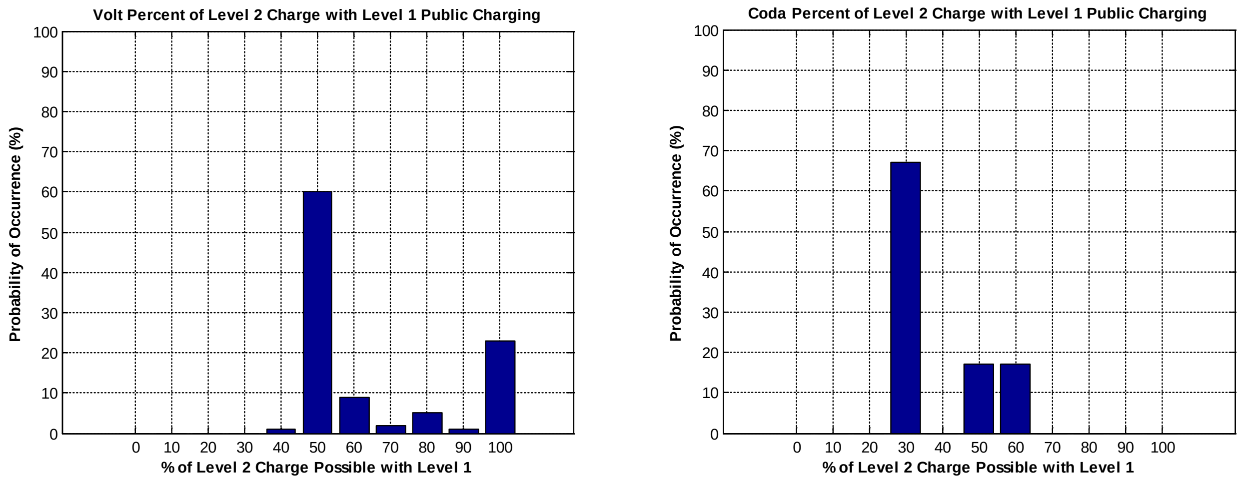


Figure 160. Public Percent of Level 2 Charge Possible with Level 1 Charging on Two Vehicle Models

7.4.4 Grid Impact – Public Locations

7.4.4.1 Assumptions

This section contains assumptions made when collecting, analyzing, and presenting the data.

Level 1 charging is sufficient for the home and workplace locations since the time generally spent there is long enough to obtain a full charge while locations of shorter stays, like those at public locations, would benefit from Level 2 charging.

7.4.4.2 Objectives

AEP looked at what impact the charging of PEVs might have on public Level 2 charger locations.

7.4.4.3 Results

The figure below represents the total energy used to charge vehicles by public locations by month in kWh. There was a significant difference in the amount of energy used between these two locations even though they were located in close proximity to one another. The location could be a key to EVSE usage especially during the early adoption period of PEVs.

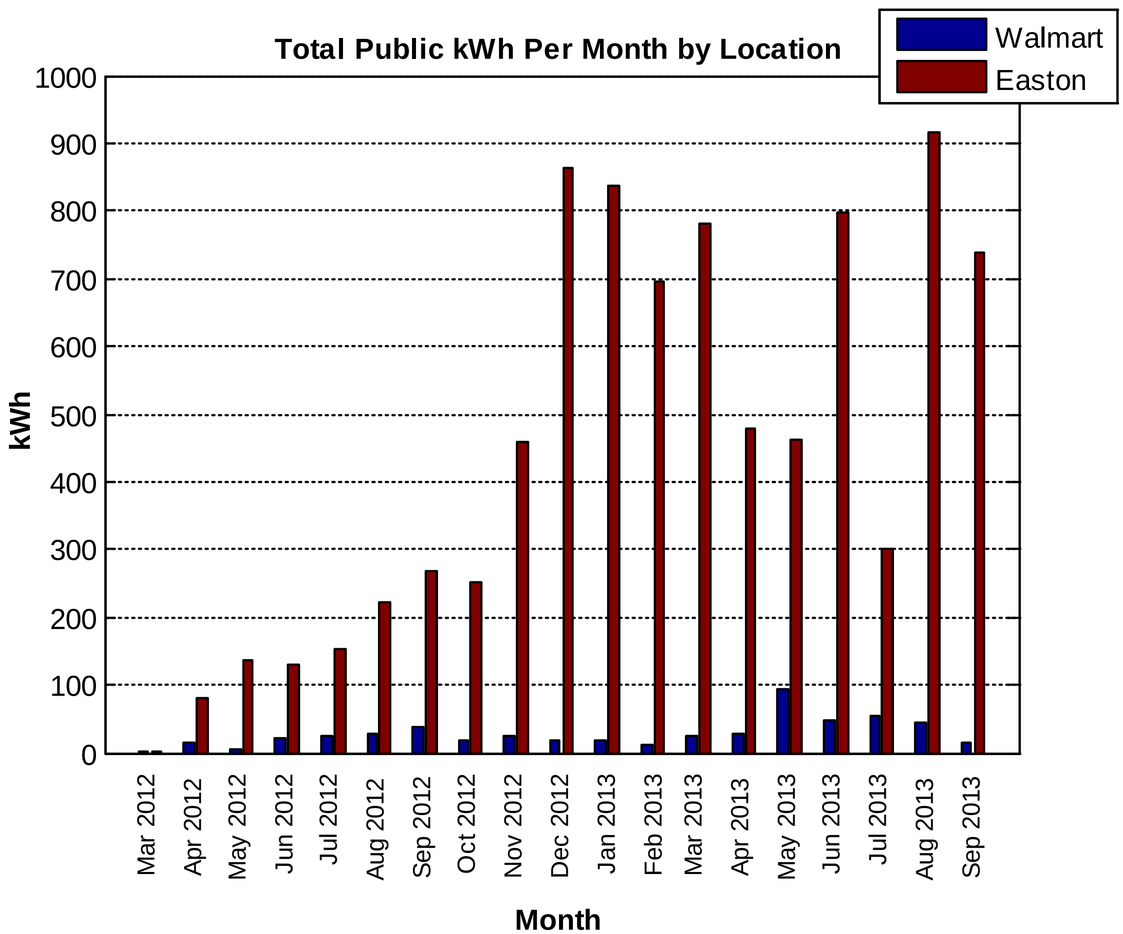


Figure 161. Energy Consumed by Month at Public EVSE Locations

The following figure shows the number of charging events at each of the public locations by month. There was a significant increase in the number of charge events per month over the course of the Project at the Easton location, while the Walmart location experienced a lower utilization.

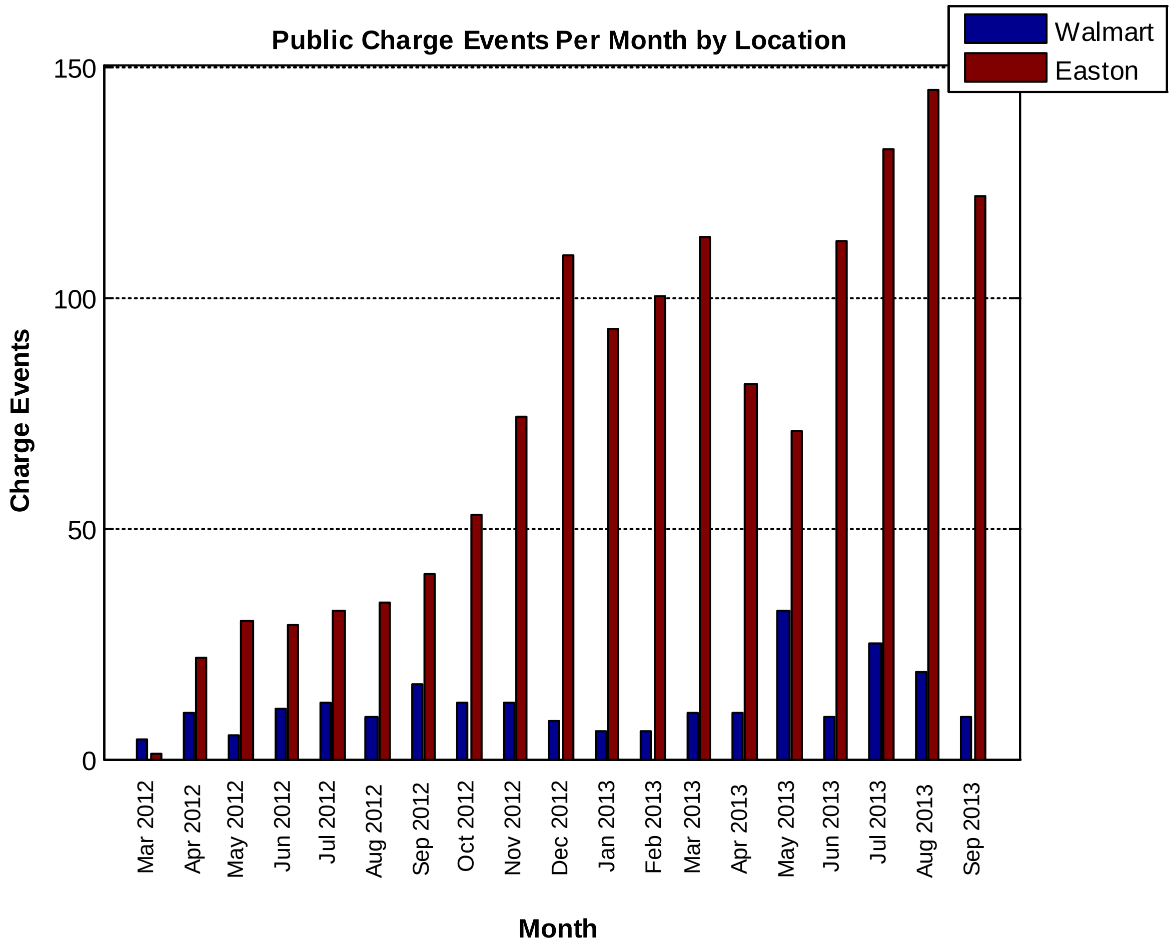


Figure 162. Number of Charging Events by Month at Public EVSE Locations

7.4.5 Consumer Behavior by Participant

7.4.5.1 Objective

To examine the effect pricing might have on charging behavior, each participant was required to be on one of three variable price tariffs: TOD2, TOD3, or RTP_{da} as described at the beginning of this section.

7.4.5.2 Calculation Approach

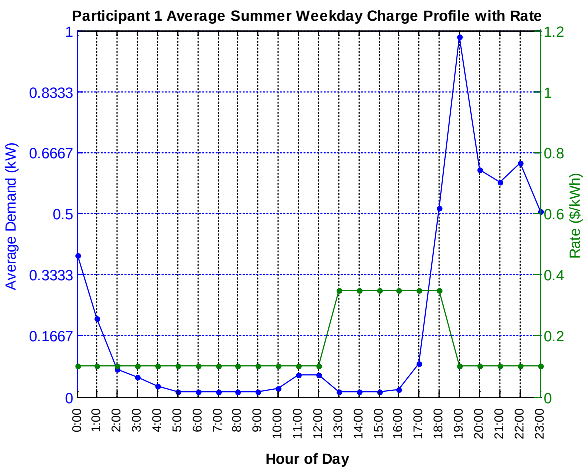
The peak demand during the elevated price time was compared to the peak demand of the entire profile to determine if the participant was predominantly charging the vehicle during the low cost period. This ratio (R) was used to classify the participant's tendency to charge during the low price times as follows:

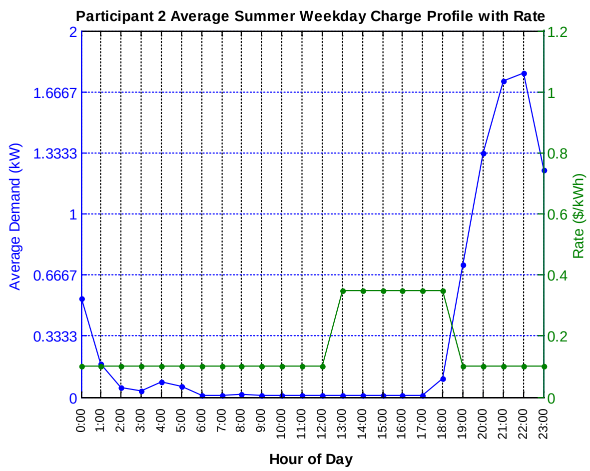
- Strong: R < 0.2 - Participant predominantly charged during low price times.
- Moderate: 0.2 <= R <= 0.4 - Participant generally charged during low price times.
- Mild: R > 0.4 - Participant would regularly charge during higher price times.
- None - If the peak demand occurred during a higher price time.

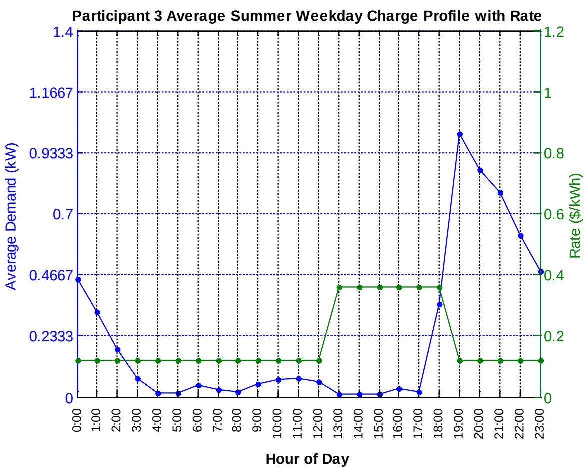
7.4.5.3 Results

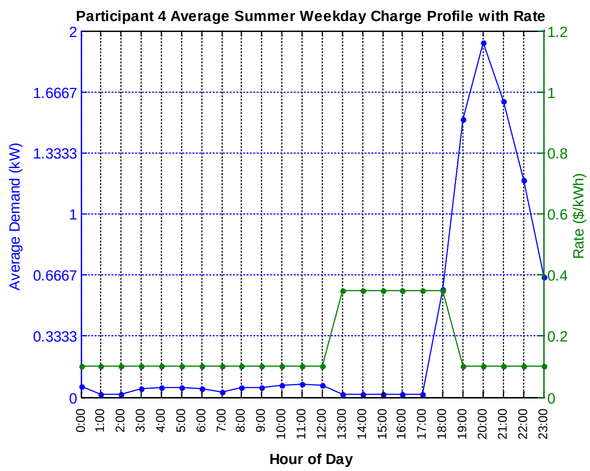
The 14 graphs in the following figure represent the average weekday load profile for each participant during the June 1 through September 30 2012 and June 1 through September 30 2013 periods when they had a vehicle and were on one of the time-of-day tariffs. Also plotted is the average weekday tariff during that period. This makes it easy to see if a participant was predominantly charging their vehicle during the low cost period.

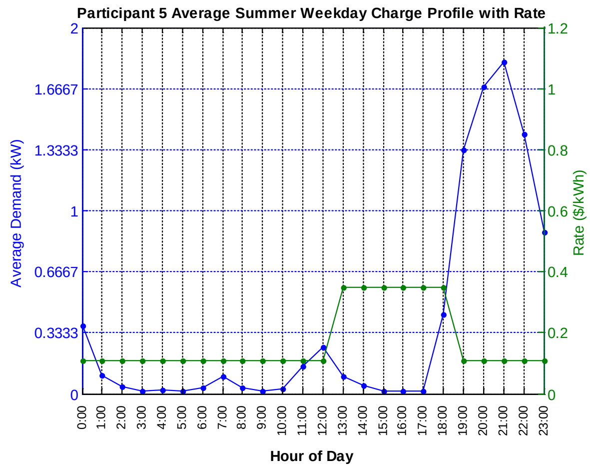
Of the 16 participants, one participated in the real time pricing tariff which wasn't quantified in the terms described above. Another participant did not have the vehicle during the June through September period and was not quantified as well.

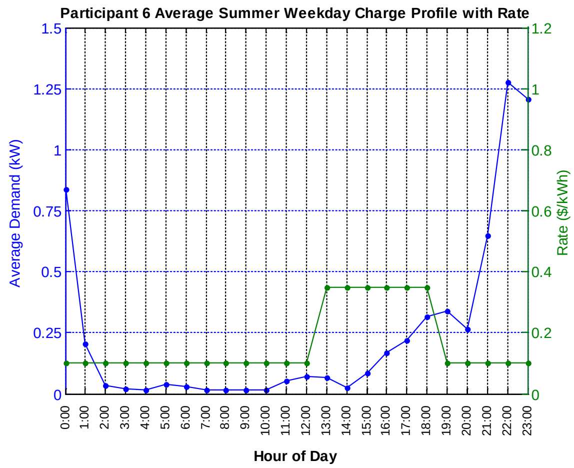


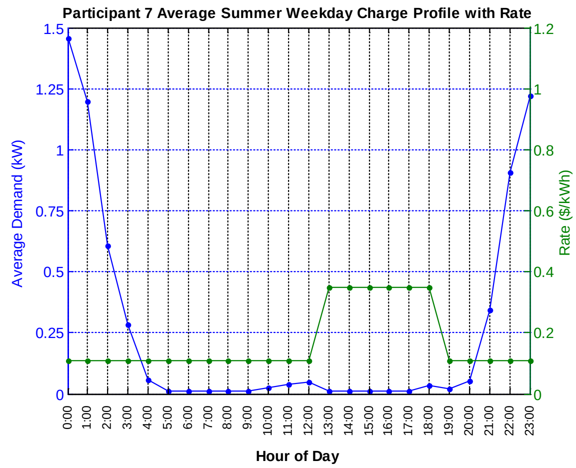


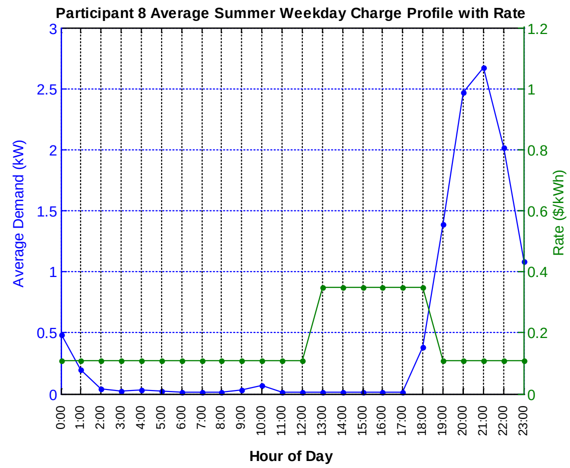


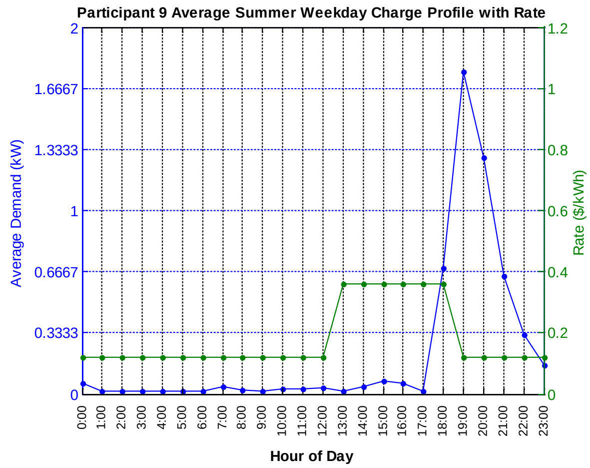


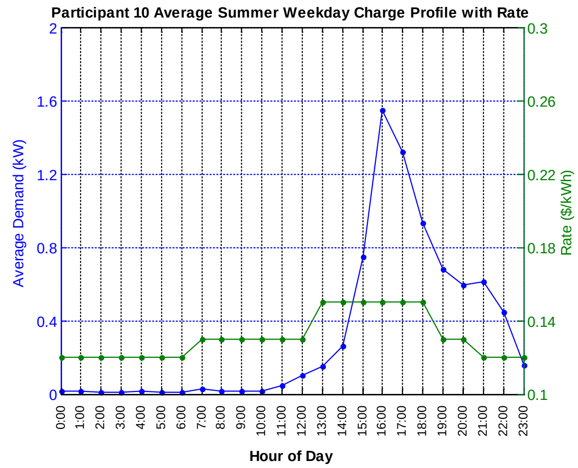

Participant 5 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day


Participant 6 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day


Participant 7 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day


Participant 8 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day


Participant 9 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day


Participant 10 Average Summer Weekday Charge Profile with Rate
Average Demand (kW)
Rate ($/kWh)
Hour of Day

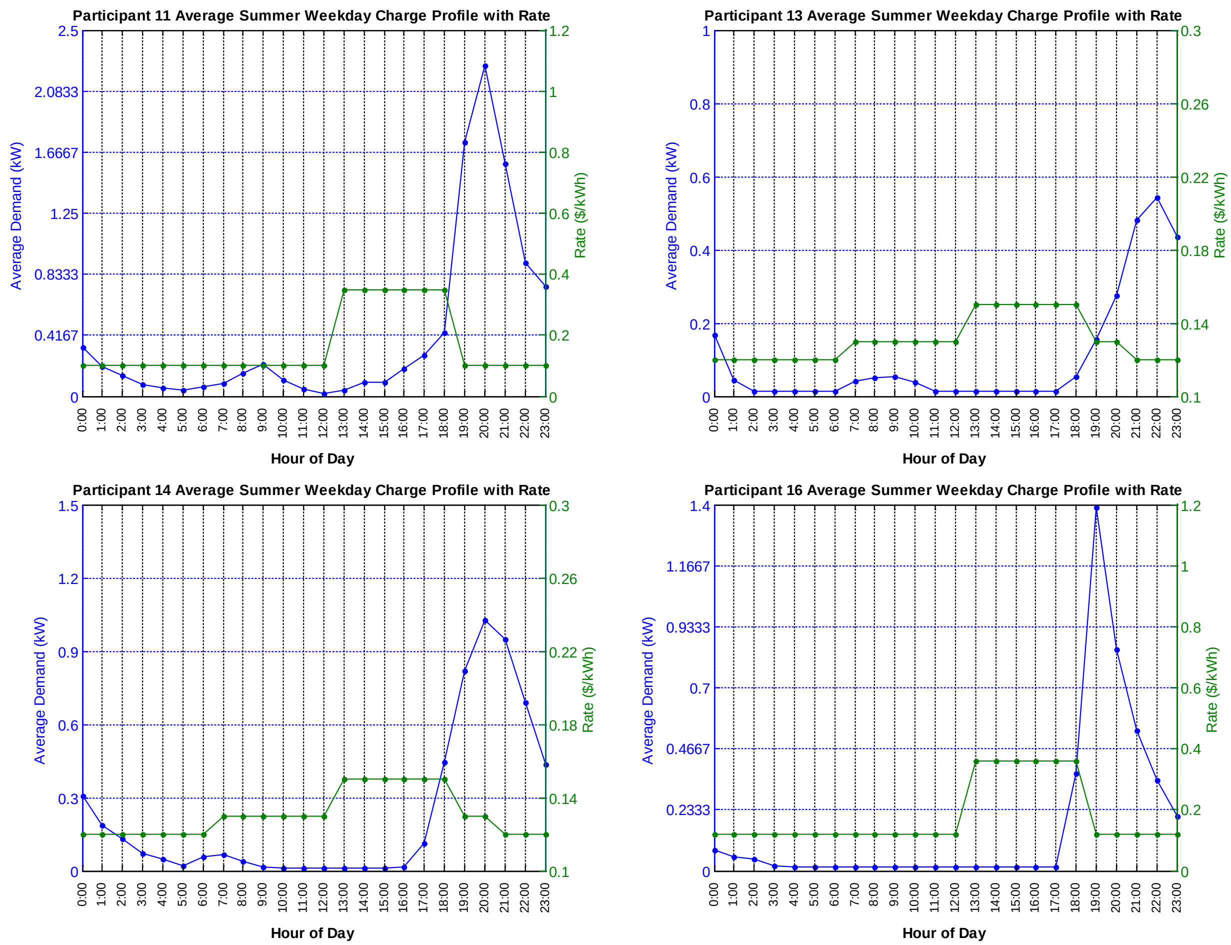


Figure 163. Participant Profiles During Time of Day Pricing

The following table shows the tendency of the participants to charge during the low price period. Overall 72 percent of participants demonstrated a Strong or Moderate tendency to charge during the low price period. Of those on the Two Tier tariff, 91 percent showed a Strong or Moderate tendency to charge during the low price period. None of the participants on the Three Tier tariff showed a Strong or Moderate tendency to charge during the low price period. This may be due to the fact that the price difference between low and higher periods is greater for the two tier-tariff than for the three-tier tariff.

	Overall		Two Tier Time of Day		Three Tier Time of Day	
Tendency to Charge at Low Price	Number of Participants	Percentage	Number of Participants	Percentage	Number of Participants	Percentage
Strong	4	29%	4	36%	0	0%
Moderate	6	43%	6	55%	0	0%
Mild	2	14%	1	9%	1	33%
None	2	14%	0	0%	2	67%
Total	14		11		3	

Table 28. Participants Tendency to Charge during Low Price Periods

7.4.6 Consumer Behavior by Location

Participants were given the option to use workplace charging for a fee of $10 per month. Participants' workplace charging was metered so that the total energy consumed by each participant is known.

7.4.6.1 Objective

AEP determined energy usage of each participant at home and at work.

7.4.6.2 Calculation Approach

The average cost of energy ($/kWh) for workplace charging by participant was calculated. Twelve of the participants used workplace charging.

7.4.6.3 Results

The following figure shows the average cost of energy for each participant to charge their vehicle at home and work. The average cost of all charging energy is also shown. Eight participants paid a higher effective rate for workplace charging than they did at home and seven of these were significantly higher. Four participants paid a lower effective rate to charge at work. Participant 15 was on the RTP_{da} tariff so their average rate was not calculated. In addition, they did not use workplace charging.

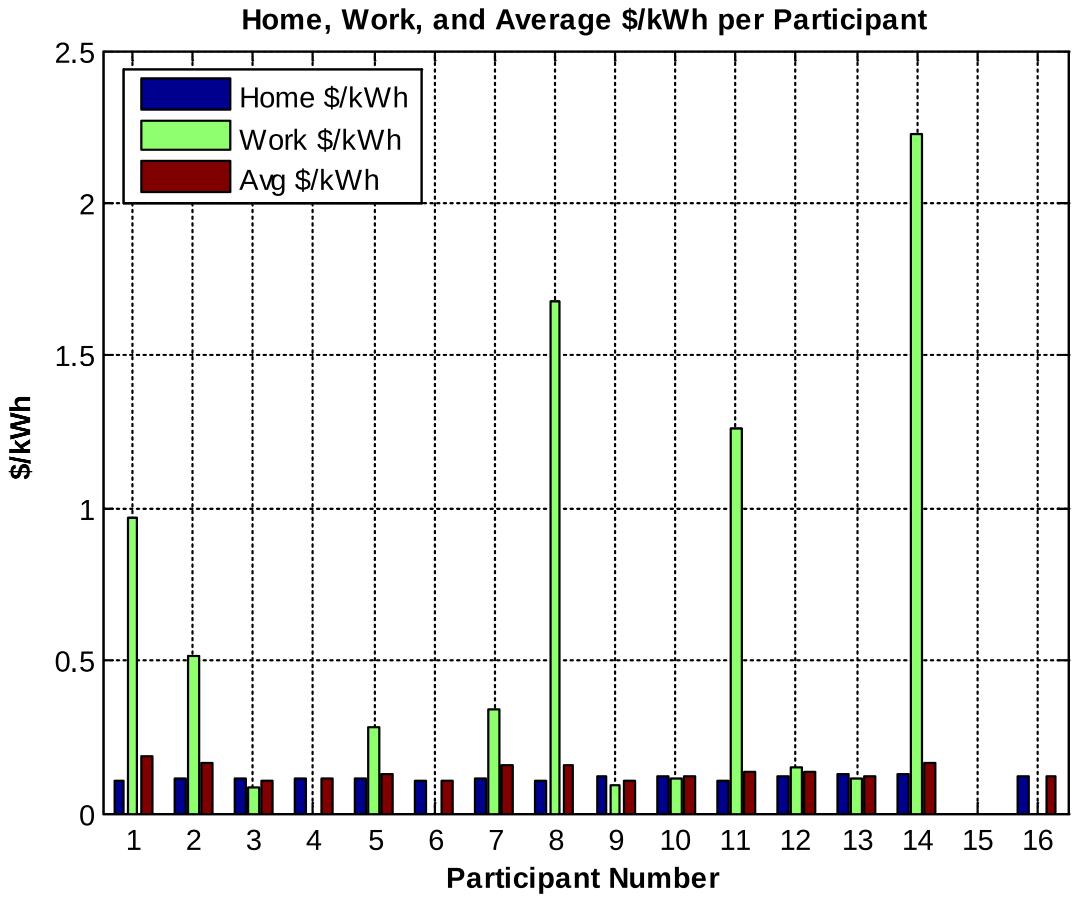


Figure 164. Average Cost of Energy to Charge PEVs at Home and Work by Participant

The figure below shows the average cost of energy to charge PEVs at home, work, and the overall average for participants who used workplace charging. On average, the group paid about $0.11/kWh to charge at home compared to $0.21/kWh to charge at work. If the PEV gets about 2.8 miles/kWh and that a similar gasoline vehicle would get 26.3 mpg, then $0.21/kWh works out to an equivalent $1.97/gallon of gasoline. An employee would need to consume approximately 91 kWh per month at work to achieve the same rate of $0.11/kWh at home. A driver would need to consume an average of 4.55 kWh/day at work, assuming 20 work days per month.

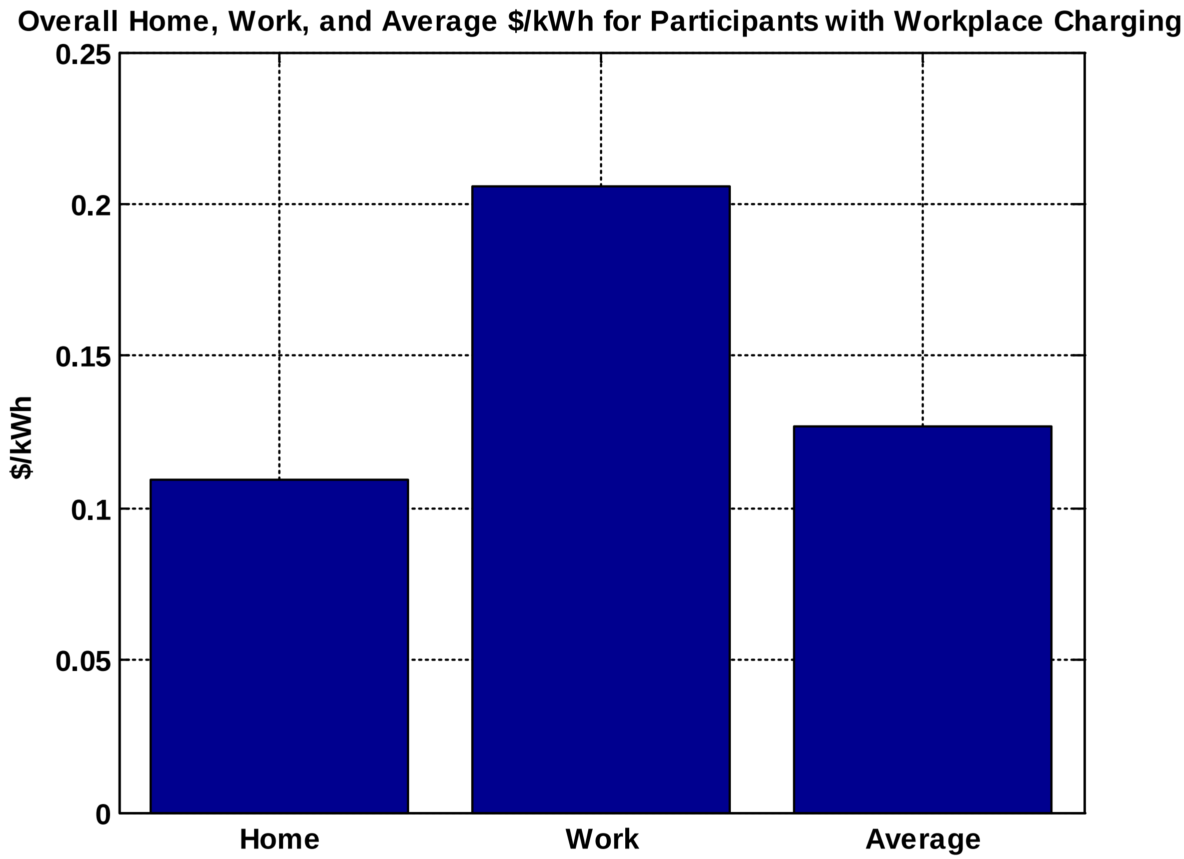


Figure 165. Average Cost of Energy to Charge PEVs at Home, Work, and Overall Average for Participants with Workplace Charging

The figure below represents the number of charging events by location (Residential, Workplace, and Public) for each participant.

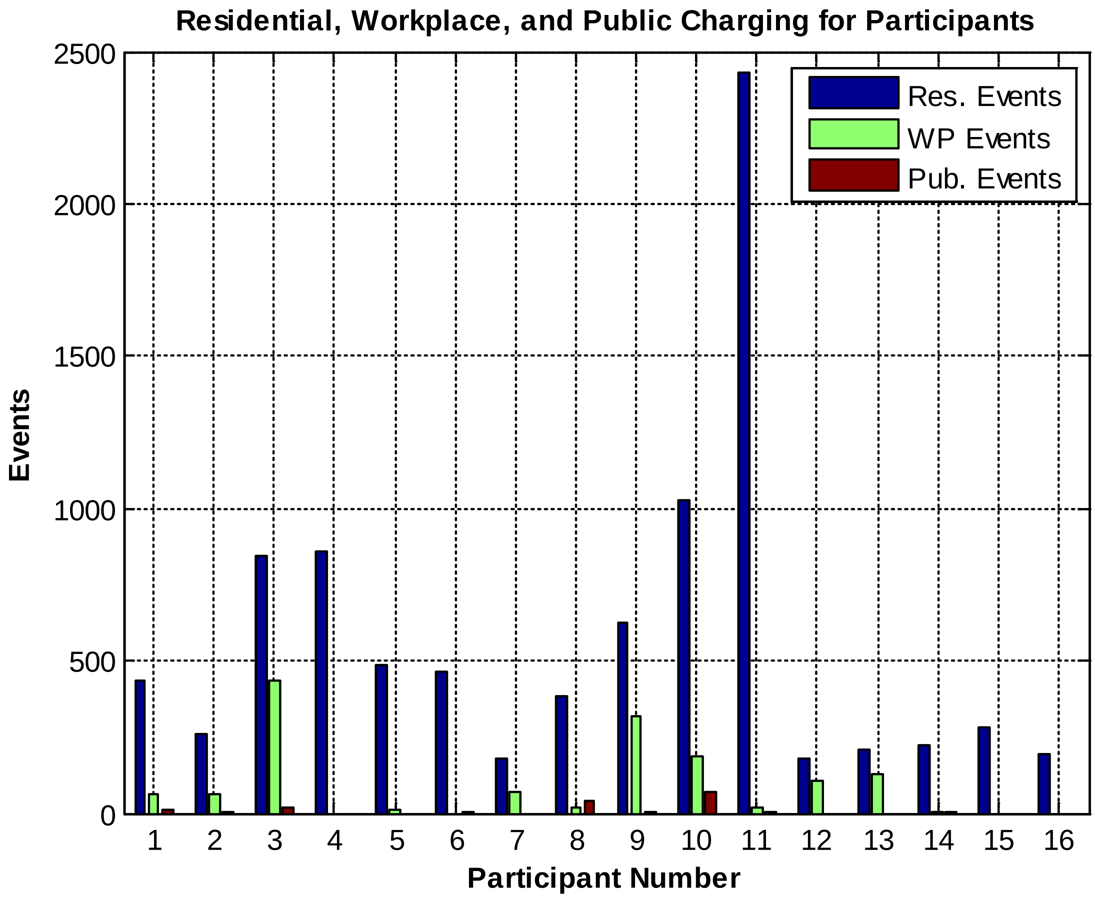


Figure 166. Number of Charging Events by Location for Each Participant

The figure below represents the total kWh consumed by location for each participant. The majority of events and energy consumed for every participant occurred at their residence.

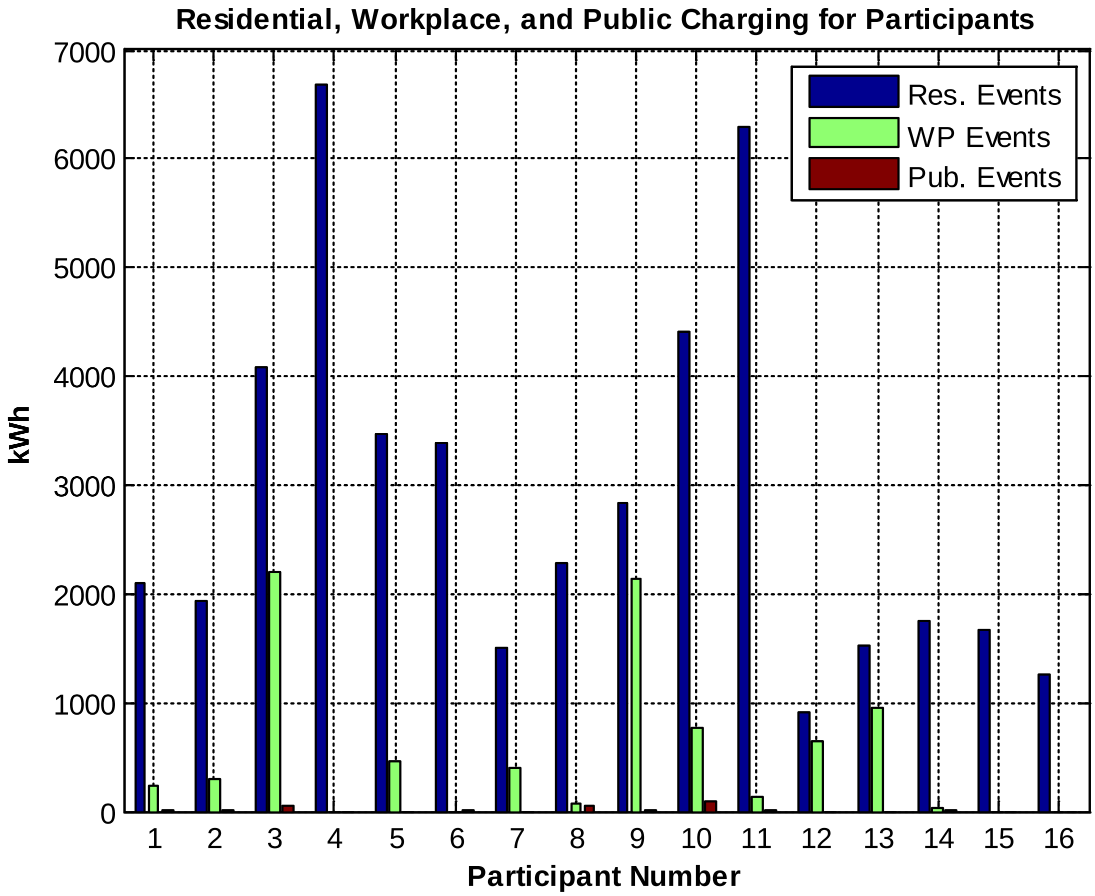


Figure 167. Amount of Energy Consumed by Location for Each Participant

7.4.7 Vehicle Statistics

7.4.7.1 Objective

AEP Ohio analyzed ten of the PEVs used in this Project.

7.4.7.2 Results

Ten vehicles were driven for a total of 271,415 miles of which 67 percent or 182,286 were electric miles and 33 percent or 89,129 were gasoline miles. These vehicles averaged 112 mpg. Driving on battery saved 7,781 gallons of gasoline. The following table provides a summary.

Vehicle Information Summary	
Total Miles	271,415
Electric Miles	182,286
Gas Miles	89,129
MPG (Average)	112
Gallons of Gas Consumed	2,434
Gallons of Gas Saved	7,781

Table 29. Vehicle Statistics Summary

The following figure shows the number of total, electric, and gas miles driven for each vehicle. In all cases the number of electric miles exceeded the number of gas miles.

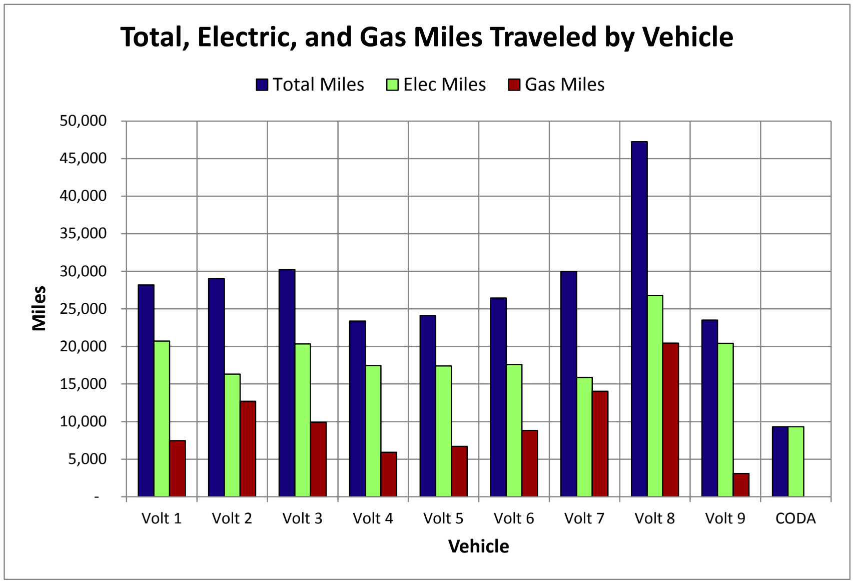


Figure 168. Total, Electric, and Gas Miles Traveled by Vehicle

This figure shows the average mpg for each vehicle excluding the Coda since it was all-electric. The vehicles ranged from an average of 76 mpg to over 250 mpg with the overall average for these vehicles being 112 mpg.

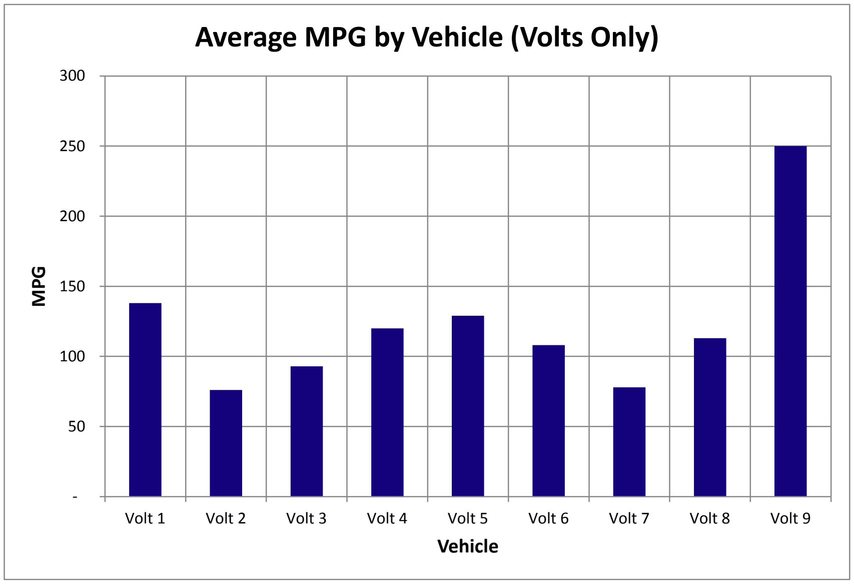


Figure 169. Average MPG by Vehicle

The figure below shows the number of gallons of gasoline consumed and saved by each vehicle. The number of gallons saved exceeded those consumed in all cases. The gasoline saved ranged from 352 gallons to 1379 gallons and averaged 778 gallons per vehicle.

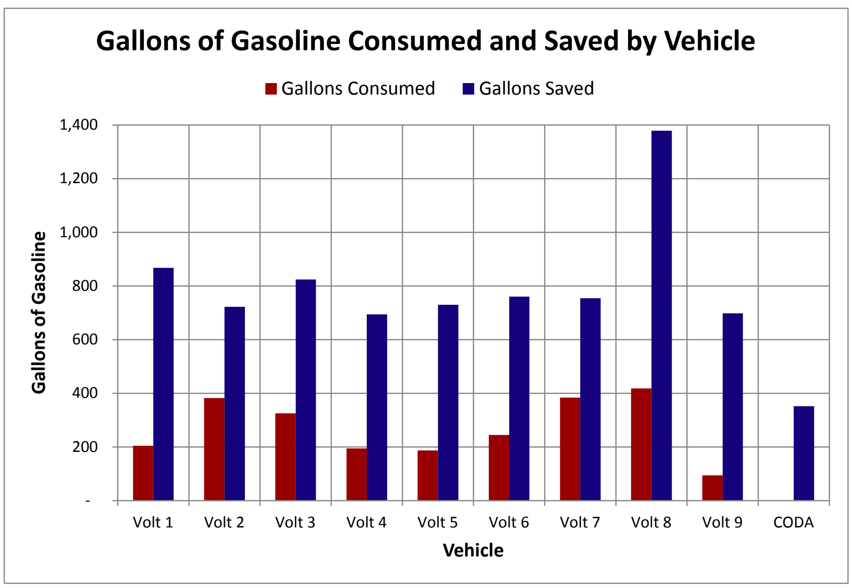


Figure 170. Gallons of Gasoline Consumed and Saved by Vehicle

7.4.8 Vehicle Performance

One of the Volts participated in an EPRI project whereby certain vehicle performance data was collected and shared on an aggregate basis. This vehicle was assigned to a single participant for the duration of the Project. The following figure shows the average miles driven per kWh by month for this vehicle, which ranged from a low of about 2 miles/kWh in February 2013 to a high of 3.7 miles/kWh in August 2013. The miles per kWh for the vehicle were generally lower during the winter and higher during moderate and warmer months.

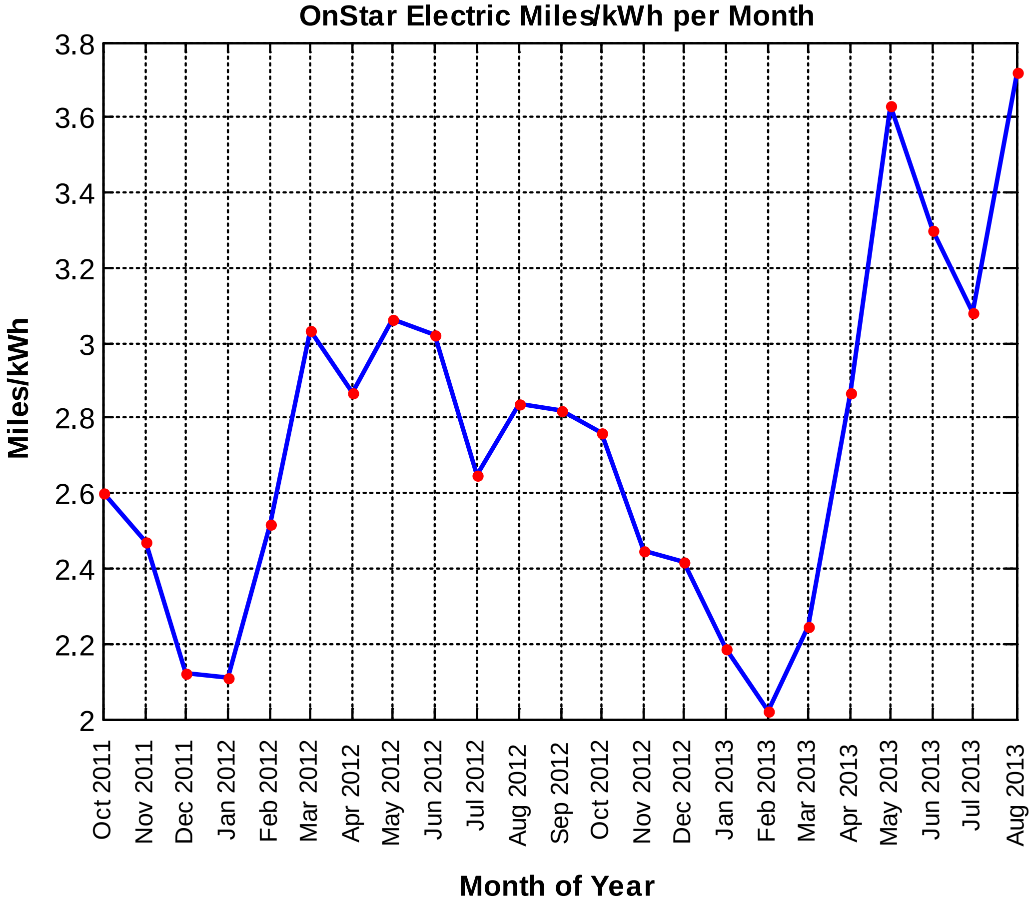


Figure 171. Average Miles Driven per kWh by Month

7.4.9 Consumer Experience

Each participant was asked to fill out a survey related to their overall experience with the vehicles and the project. The overall experience was positive. Four of the questions related to electric vehicles could be quantified and are shown in the following figures.

The figure below shows the majority of participants were more interested in the range of the vehicle than its affordability or comfort. Participants generally tried to drive on electric as much as possible to minimize their fuel expense.

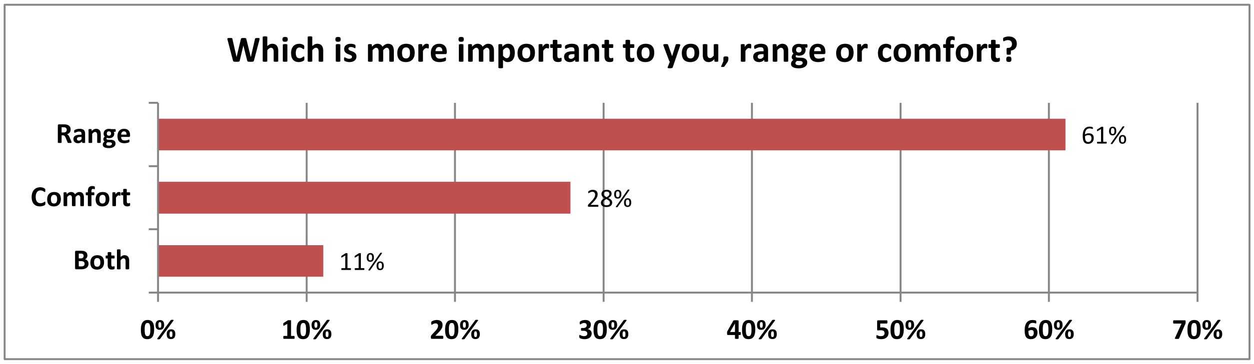


Figure 172. Range or Comfort Preference

The figure below shows the participants were willing to consider an electric vehicle for use as their personal vehicle. The majority of these participants cited the cost of electric vehicles as a barrier to their purchase.

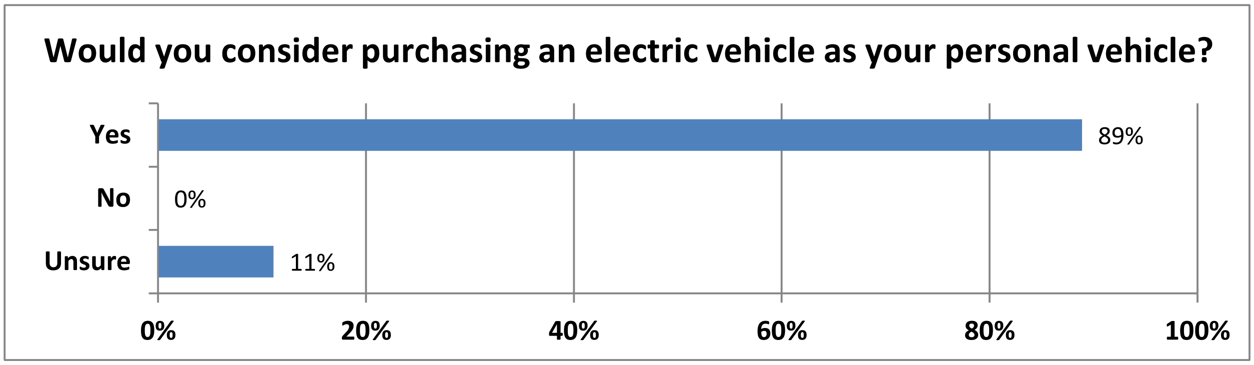


Figure 173. Consider Purchasing an EV

The following figure indicates that for 39 percent of the participants, the availability of Level 3 charging would have some influence on their decision to purchase an electric vehicle

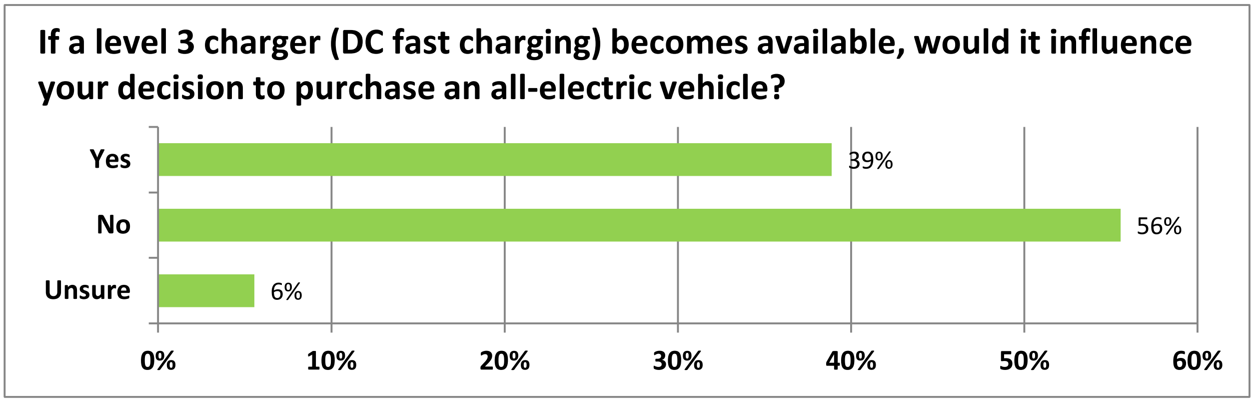


Figure 174. Level 3 Charging Effect on Purchasing an EV

The figure below indicates that the participants have a strong preference toward making their next vehicle purchase an electric vehicle of some sort. Sixty-four percent favor a PHEV and 14 percent a hybrid electric vehicle (HEV), resulting in 78 percent favoring an electric vehicle of some sort.

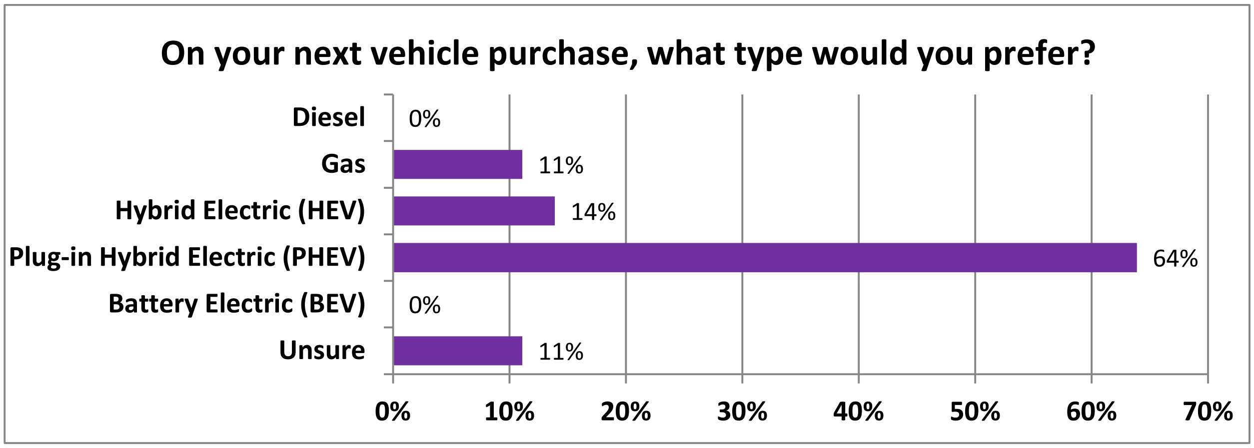


Figure 175. Next Vehicle Purchase Type Preference

7.5 Electric Vehicles Conclusions

Initial adoption of PEVs did not appear to have a significant impact on transformer loading. As adoption rates increase, the rate (kW demand) at which PEVs charge increases. Increased adoption rates as well as increased PEV charge rates (kW demand) are ongoing considerations for the utility.

The analysis showed that Level 1 charging may be sufficient for most adopters at home and the workplace, especially if the vehicle was a PHEV instead of a BEV. Level 2 charging would be more beneficial at locations where shorter charge times would be experienced, but this would only be necessary in some cases for a BEV.

There was a correlation between electric rates and charging behavior when the price difference was significant as was the case with the two-tier tariff. In this case, 91 percent of the participants demonstrated a strong or moderate tendency to charge during the low price time periods. In the three-tier tariff where the price difference was less significant between the electric rates, the participants showed little to no tendency to charge during low price periods.

Workplace charging was used by 12 of the 16 participants. Eight of these participants paid a higher rate at work than they did at home. Five participants paid rates for workplace charging that were higher than what they would have paid to use gasoline instead of the electricity they received at work. It was unclear to what extent participants might have been aware of the effective cost ($/kWh) they were paying for workplace charging, since they paid a flat monthly fee of $10. At least one participant would have preferred an option to pay per charge at work.

Ten vehicles were driven for a total of 271,415 miles of which 67 percent or 182,286 were electric miles and 33 percent or 89,129 were gasoline miles. These vehicles averaged 112 mpg. Driving on battery saved 7,781 gallons of gasoline.

The majority of the participants indicated that they would prefer their next vehicle purchase be an electric vehicle of some type.

7.6 Lessons Learned

This section describes lessons learned for PEV technology.

- Initial adoption of PEVs *did not* appear to have significant impact on residential transformer loading.
- A thorough analysis should be completed before public chargers are sited, as PEV usage tends to be location-specific.
- Level 1 charging may be sufficient in most cases (residential and workplace) as parking duration is long enough for full charge.

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8 Demonstrated Technology – Cyber Security

8.1 Purpose

AEP Ohio endeavored to build a secure, interoperable, and integrated smart grid infrastructure in northeast central Ohio. The deployed technologies required comprehensive cyber security capabilities for both new and legacy systems. The AEP Ohio gridSMART® Demonstration Project cyber security team integrated into all areas of the Project to ensure device and threat monitoring and sharing.

8.1.1 Device Security

The smart grid used various techniques and technologies to provide a more reliable and stable power grid. Many of the technologies used were new, redesigned, or re-provisioned from a previous purpose. Both types introduced new risks to critical infrastructure components. The role of the cyber security technology was to ensure the security of all new and existing devices and networks.

The Cyber Security plan, as approved by the U.S. Department of Energy (DOE), required each technology implementation to provide clear documentation demonstrating its proposed approach to cyber security. This approach would prevent broad-based systemic failures in the electric grid should a cyber security breach occur.

The cyber security team worked closely with the technology teams and vendor participants to meet the cyber security requirements by implementing security assessment processes, procedures, standards, and policies for all technology areas. Upon determining cyber security risk types and levels, AEP Ohio established acceptable risk levels for each technology area, and designed, tested, and implemented strategies and mitigations.

8.1.2 Cyber Threat Monitoring and Sharing

The interconnectedness of the smart grid opened opportunities for cyber security threats to utility networks, which could be difficult to pinpoint and address. Tools, processes, and concepts were used to deter and detect a variety of these threats, including:

- Location
- Investigation
- Minimization of impact
- Mitigation

Additionally the cyber security team was continually learning and adapting to attackers' techniques, tactics, and procedures.

8.2 Technology

8.2.1 Device Security

AEP is committed to ensuring a reduction of risk to the lowest acceptable level, not only for AEP, but also for its consumers and the grid. This required extensive testing of all technologies. The following commercially available technologies were subjected to intensive cyber security testing:

- **General Electric (GE) i210+c Meter –** Primary residential AMI meter deployed in the Project area.
- **GE KV2C –** Primary commercial AMI meter deployed in the Project area.
- **Silver Spring Networks (SSN) UtilityIQ®** – AMI head-end system for meter management and monitoring.
- **SSN Demand Response Manager (DRM) –** SSN's head-end software application in the UIQ application suite. DRM's web-based interface allowed utility operators to manage HAN devices, create, monitor and manage demand response events, and obtain analytics about load shed and customer participation.
- **Home Energy Manager (HEM) –** Provided an interface to consumers participating in the Real Time Pricing with Double Auction ($RTP_{da)}$ program. This device served as the communication agent among the Enhanced Programmable Communicating Thermostat (ePCT), the AMI meter, and the Smart Grid Dispatch system.

8.2.2 Cyber Threat Monitoring and Sharing

The Project acquired a suite of cyber security capabilities and services that provided advanced network protection and a multi-pronged approach to advance threat detection and management.

8.3 Approach and Implementation

8.3.1 Device Security

The Project implemented a comprehensive cyber security plan that included a complete battery of vulnerability and penetration tests starting with the meter, through the network, to the head-end system. The comprehensive testing strategy for the Project involved a series of steps strategically placed throughout the development and deployment cycle of the Project. The steps were as follows:

Step 1 – Technology Review
Step 2 – Risk Assessment
Step 3 – Vulnerability Assessment
Step 4 – Penetration Testing

In Step 1, the review entailed researching all of the capabilities of the product and identifying the potential points of attack.

In Step 2, AEP conducted formal risk assessments on all technology components.

In Step 3, AEP evaluated applications and hardware to determine if there were potential vulnerabilities in the product.

Step 4 consisted of penetration testing for all technology areas.

During Steps 3 and 4, AEP developed final reports that outlined the severity of the vulnerabilities identified and the recommended actions for remediation. If the determined risk was greater than the acceptable level, a remediation plan was developed and implemented.

AEP Ohio subjected all technology components of the Project to this complete battery of tests, including penetration testing.

8.3.2 Cyber Threat Monitoring and Sharing

Lockheed Martin collaborated with AEP Ohio to develop the Palisade™ suite of tools based on the intelligence management approach. Palisade enabled cyber security analysts to manage alerts, detections, mitigations, and courses of action in a single application. This centralization of investigative activities greatly reduced the amount of time analysts needed to filter through noise. These tools allowed analysts to focus their time on extracting actionable intelligence and using this intelligence to detect active threats on the network.

The threat and information sharing portal was launched to foster a secure environment allowing cyber threat intelligence to be shared among the utility industry, and included approximately 15 large utility adopters as of summer 2013. Building an extensive cyber security threat database was extremely important to utilities seeking advanced computer network defense capabilities. Other industries, including oil and gas and healthcare, have also adopted the collaboration and intelligence sharing benefits of the Threat and Information Sharing portal.

Advanced Persistent Threats (APT) Sensors integrated into existing corporate security environments to provide ongoing and focused network visibility. The sensors provided detection and alerts on covert malicious command and control challenges, network anomalies, and detection of advanced file exploits.

8.4 Cyber Security Conclusions

8.4.1 Device Security

Several vulnerabilities were discovered in Step 1 shown in paragraph 8.3.1. The first vulnerability was fixed with a change in physical production of a device while the second one required updated software

Step 2 issuers of data being transferred from AEP systems to third-party systems in an unsecure manner were resolved by changing to Secure File Transfer Protocol (FTP). Secure FTP has now been made the standard method of data transfer between AEP systems and third-party systems.

Step 4 penetration test issues were resolved through the reconfiguration of network security devices.

Further issues were resolved with updated meter management software. The cyber security team determined that there was a need for a recurring assessment of network security due to the continually evolving environment with the addition of new devices, updated firmware, and updated software.

8.4.2 Cyber Threat Monitoring and Sharing

Through Palisade and in collaboration with sources including the Department of Homeland Security (DHC), the threat and information sharing portal, and the North American Electric Reliability Corporation (NERC), the cyber security team reviewed and discussed intelligence reports of known issues that affected the electric industry and those potentially aimed at AEP. The gridSMART cyber security team is now a member of several threat information sharing teams networks, products, and devices.

AEP developed the Cyber Security Operations Center (CSOC). It was designed to provide highly customizable threat management and response that was implemented on top of AEP's existing security framework. The CSOC included:

- The Palisade suite of tools that provided single-source threat detection management.
- Advanced Persistent Threat (APT) sensors that delivered a wide visibility of IT assets and critical network infrastructure.
- Threat and information sharing that included a secure portal to share vital threat information practices among participating utility partners.

9 DEMONSTRATED TECHNOLOGY – INTEROPERABILITY

9.1 Purpose

Interoperability (IOP) is the ability of systems and/or components to provide and receive services and information in a predictable way without significant user intervention. The exchange of information and interfaces was based on openly available standards and integrated, commercially available products, new technologies, and new consumer products and services within a single, secure, two-way communication network between the utility and consumers. The primary focus of IOP was to identify gaps in the current and proposed standards.

9.2 Technology

Interoperability is not a technology to be implemented, but rather a goal to be accomplished. The Interoperability Plan was outlined to accomplish two goals. The first goal was to develop a plan to use to ensure interoperability among all systems, devices, and data sources. The second goal was to document the extent to which the first goal was accomplished.

For the interoperability of the back office, the primary goal was to implement systems in such a way to protect against cascading failures. To accomplish this, the team implemented a communication standard and drove compliance to that standard. AEP Ohio engaged Electric Power Research Institute (EPRI) to assist in creating the Interoperability Plan. For this exercise, the team defined an interface as a pairing of systems or actors. This resulted in the creation of multiple use cases and multiple interfaces.

9.3 Approach and Implementation

The IOP test plan was organized by topic, such as Demand Response, Distribution Grid Management, and AMI. Each topic contained a set of use cases analyzed to discover the number and purpose of interfaces involved with each topic. Each interface was assessed to determine whether a relevant standard existed, with particular emphasis being placed on the standards enumerated in National Institute of Standards and Technology (NIST) Special Publication 1108, *NIST Framework and Roadmap for Smart Grid Interoperability Standards*. The interfaces were then assessed to determine if relevant standards were implemented by AEP Ohio and/or by its vendors in a manner that could be tested for standards compliance.

Interoperability's two-phase testing approach combined lab and field testing to obtain a complete Project evaluation. The first phase involved extensive lab testing of technologies by exercising their full range of functions. The second phase involved field tests with a limited base of consumers. This approach determined the functionality, reliability, security and overall system interoperability.

Because IOP affected several different technologies, there was not a single approach for the cumulative group. Each Project technology area had a unique approach for implementing interoperability. However, some common themes prevailed through most of the Project area, such as Common Information Model (CIM) messaging.

9.3.1 Common Information Model Compliant Messaging

Common Information Model compliant messages were implemented across several topic areas as a means of communication between systems. By implementing CIM-compliant messaging, a standard message format was created to exchange information between new and legacy systems, allowing for interoperability beyond AEP systems. This was part of the back-office strategy for interoperability.

9.3.2 IntelliGrid

EPRI's IntelliGrid methodology provided a conceptual architecture that was implemented within platform-independent solutions. This methodology promoted open, interoperable systems and standards; provided tracking and analysis of smart grid technologies; and captured best practices. The Project Interoperability Plan was derived from the IntelliGrid methodology with specific roadmaps for smart grid development and deployment.

The IOP test plan started with a conceptual architecture and then moved to development of a platform-independent architecture that provided a basis for integrating applications. The primary goal was to develop an architecture with vendor-specific aspects, but with the ability to plug in many different vendor applications as a result of industry interface standards. Legacy systems and technology were integrated using appropriate gateways and translators.

9.4 Use Cases

Twenty-seven use cases were developed, in cooperation with EPRI, to test the interoperability of the Project components. These components included: back-office systems, communication network, Home Area Network (HAN), and AMI. These use cases were grouped in five categories:

- Demand Response – nine use cases
- Distribution Grid Management – two use cases
- Electric Transport – one use case
- Advanced Metering Infrastructure – twelve use cases
- Work Management System – three use cases

9.5 Use Case Analysis

There were eight interface types:

- CIM or ANSI standards
- Future CIM or ANSI standards
- Vendor Proprietary
- AEP Proprietary
- Open – applying for CIM or ANSI standard
- None – no standard applies
- Proprietary LAN
- Custom

AEP identified these standards within the five categories of use cases:

Demand Response had nine use cases using twenty-eight interfaces

- Standard – seventeen
- Vendor Proprietary – two
- Open – five
- None – four

Distribution Grid Management had two use cases using thirteen interfaces

- Vendor Proprietary – three
- AEP Proprietary – three
- Proprietary LAN – seven

Electric Transport had one use cases using five interfaces

- Standard – one
- Vendor Proprietary – three
- None – one

AMI had twelve use cases using nineteen interfaces

- Standard – thirteen
- Vendor Proprietary – four
- None – two

Work Management System had three use cases using twenty-one interfaces

- Standard – seven
- Future Standard – five
- Vendor Proprietary – two
- Custom – seven

9.6 Interoperability Conclusions

The barriers to interoperable implementation of smart grid technologies consisted of the varying maturity of vendor products. The majority of Project interfaces were CIM and ANSI standards compliant. Application for CIM standardization for some interfaces was submitted.

Overall, the integration of devices into AEP Ohio systems proved to be interoperable. Although the integration processes were manual and required significant effort and end-to-end verification of every data point from the field to the back office, they were successfully implemented. AEP Ohio mitigated resource requirements by using a single communications protocol, limiting device types, and creating internal data exchange standards.

10 DEMONSTRATED TECHNOLOGY – MODELING AND SIMULATION

10.1 Purpose

In the AEP Ohio gridSMART® Demonstration Project (Project) area smart grid technologies were deployed to 80 distribution circuits. It was important to assess potential impact if the technology deployments were extended to the remaining 1,700 distribution circuits in AEP Ohio's service territory. The Modeling and Simulation (M&S) project developed a simulation engine and applied it to evaluate the effects of new technologies in a variety of circuit configurations. In addition to simulating the types of technologies that were field deployed as part of the Project, photovoltaic, sodium sulfur batteries, and community energy storage were also simulated. The technologies that were studied to determine their effects on circuit behavior included:

- 25kW Community Energy Storage (CES)
- 1MW Sodium Sulfur Battery (NaS)
- Photovoltaic (PV)
- Plug-in Hybrid Electric Vehicle (PHEV) and Plug-in Electric Vehicle (PEV) charger
- Volt VAR Optimization (VVO)
- Fixed Price Tariff
- Load Control Switch (LCS) used for Direct Load Control (DLC)
- Time of Day (TOD) Tariff
- TOD Critical Peak Pricing (TOD/CPP) Tariff
- Real Time Pricing Double Auction (RTPda) Tariff

M&S modeled a representative subset of the 1,700 distribution circuits in AEP Ohio. Modeling a representative subset of circuits could allow technology impacts to be scaled up to all circuits in AEP Ohio. Models were representative of AEP circuits and indicate what may happen in practice. There are multiple variables that may impact simulations as well as field deployment results.

All results provided in this section are from simulations incorporating the above technologies.

10.2 Technology

The M&S team used GridLAB-D™, an open source code developed by Pacific Northwest National Laboratory (PNNL) to model the circuits. Additional proprietary modifications were made to GridLAB-D to simulate the new technologies for the Project. GridLAB-D simulated the distribution circuit from the substation to the individual premises along with their appliances, outlet and lighting loads, air conditioning, water heater, and the home insulation characteristics. Voltage, power, switch operations, and other dynamic variables at any location on the circuit model were provided at discrete time intervals for conditions specified by a simulation. Performance metrics such as maximum peak power demand and energy consumption were estimated by analysis of the GridLAB-D outputs.

Building each circuit model required the following data:

- Graphical Information System (GIS) information describing the circuit configuration
- County Auditor information describing the premises' age, size, and location
- Premises and the associated distribution transformer
- Conductor information describing the house to distribution transformer connection
- Premises' characteristics
  - Number of occupants
  - Gas versus electric heat
  - AC versus no AC
  - Existing demand response model
  - Additional technologies
- Climate data
- Consumer electrical usage behavior based on their demand response

Information was gathered from existing AEP databases and other sources. The Project identified data sources and provided a centralized location to store the data.

A software tool was developed to facilitate the frequent building and modification of circuit models and assist in manipulating and analyzing GridLAB-D models. The new tool, GridCommand™ Distribution (GCD), is now commercially available. Highlighted features of GCD include the ability to:

- Create GridLAB-D model file from CymDist model files
- Import existing GridLAB-D files
- Export to GridLAB-D file format
- Display the circuit graphically based on latitude/longitude
- Add or delete new items from the circuit model using the console or graphical interfaces
- Support user scripts to modify the circuit model
- Display a tree view of every object in the model organized by type
- Support parametric analysis

10.3 Approach and Implementation

M&S was implemented using a sequence of four interrelated tasks:

- Stakeholder question analysis
- Baseline circuit model development
- Parametric analysis
- Reporting

Stakeholder question analysis defined project goals, identified questions that needed to be asked to achieve these goals, and developed metrics for the modeling process. As a result of this task, a set of goals, questions, and metrics (GQMs) was derived. A matrix of circuit simulations and experimental design was created using this set of GQMs.

Baseline circuit model development required identifying which circuits would be modeled and then developing accurate GridLAB-D models for each circuit. To select representative circuits, data regarding characteristics of all 1,700 circuits in the AEP Ohio distribution territory was collected. Circuits were then grouped into clusters based on these characteristics. This cluster analysis categorized the 1,700 circuits into 25 circuit types and identified 12 circuits that represented 94 percent of AEP Ohio distribution circuits. A total of 32 circuits were modeled that incorporated these 12 circuit types.

Baseline circuit models were developed and validated against Supervisory Control and Data Acquisition (SCADA) data for each circuit using GridLAB-D. A year-long GridLAB-D simulation was created for each of the circuits using a typical meteorological year (TMY) as the reference weather data. These models were validated against SCADA data from 2010 by comparing the simulated outputs against the SCADA records.

Parametric analysis included 1,247 year-long simulations, counting both baseline configurations and the technologies that were modeled. This task considered variations on technology penetration levels within a single circuit along with combinations of technologies within the same circuit.

10.4 Technology Model Descriptions

Modules for many of these technologies existed in GridLAB-D prior to starting the project, including PV, PHEV/PEV, DLC, ToD, ToD/CPP, VVO, and RTP_{da}. However, the CES, and NaS modules did not exist and were added to GridLAB-D as part of this Project. Technology specification documents were generated for each of the technologies, and the existing modules were evaluated to determine if they were sufficient to support the proposed numerical analysis. Additionally, a proprietary VVO module was used for circuits that had at least one line regulator. A short description of each technology follows.

Community Energy Storage (CES) units were evaluated on a set of 12 baseline circuit models. CES was evaluated in three major modes of operation: islanding, peak shaving, and VAR support. In islanding mode, CES was examined to determine its ability to island customers during an outage. The effects of CES islanding support on System Average Interruption Duration Index (SAIDI) were reviewed. In peak shaving mode, CES was operated using both scheduled and load following charge/discharge methods. Finally, CES's ability to provide VAR support was also considered. The effects of CES were evaluated as a function of penetration density for each circuit, where penetration density was computed as the fraction of total connected kVA for a given circuit. CES units were then added to each circuit model for a range of densities, and with varied control parameters at each density. In each model, all of the CES units were operated as a fleet using a central control with all units operating identically.

Sodium Sulfur batteries (NaS) were evaluated on a set of 12 baseline circuit models. NaS was evaluated in three major modes of operation: islanding, peak shaving, and VAR support. In islanding mode, NaS was examined to determine its ability to island customers during an outage. The effects of NaS islanding support on SAIDI were reviewed. In peak shaving mode, NaS operated using scheduled and load following charge/discharge methods. Finally, NaS's ability to provide VAR support was also considered. The effects of NaS were evaluated as a function of penetration density (battery size) for each circuit, where penetration density was computed as the fraction of total connected kVA for a given circuit. A single NaS unit of the appropriate size was then added to each circuit model for a range of densities with varied control parameters at each density.

Photovoltaics (PV) were evaluated on a set of 12 baseline circuit models. The ability of PV arrays to reduce circuit demand and energy was evaluated. This included an examination of how well PV complements peak shaving when a CES fleet is added to the circuit. Circuit voltage profile with PV arrays was examined including the arrays' effect on voltage regulation when transient events occur (i.e., cloud cover). Circuit demand and energy were evaluated under several PV array configurations. Each PV array configuration specified both total PV generation capacity and PV array locations along the circuit. Total PV generation capacity was specified as a fraction of total circuit connected kVA, calculated as the sum over transformer nameplate ratings. Location of PV arrays along the circuits included both evenly distributed and intentionally clustered cases.

Plugin Hybrid Electric Vehicle/Plugin Electric Vehicle (PHEV/PEV) was evaluated on a set of 12 baseline circuit models. The impact of PHEV/PEV on circuit behavior was evaluated in three major areas: equipment, overloads, circuit demand, and energy usage. Additional models evaluated the interaction of PHEV/PEV with CES batteries. In the combined technology (CES and PHEV/PEV) simulations, CES was operated using load following peak shaving method. The effects of the combined technologies were examined for individual distribution transformers. The effect of the PHEV/PEV on circuit demand and energy usage was evaluated, along with the possibility of equipment overloads. This included an examination of how circuit demand could be affected by the combination of PHEV/PEV demand and CES peak shaving and charging demands. PHEV/PEV was added to each circuit using a range of densities.

Volt VAR Optimization (VVO) technology was evaluated on a set of 32 baseline circuit models. The impact of VVO on circuit behavior was evaluated in three major areas – real and reactive circuit demand, real and reactive energy, and voltage profile management. The ability of VVO to reduce circuit demand and energy consumption was evaluated as well as its influence on circuit voltage profiles. For VVO operating alone, different combinations of end-of-line voltage and circuit power factor target settings were used. Additionally, VVO combined with PV, and VVO combined with fleets of CES batteries were evaluated. The combination of these technologies was evaluated to determine whether or not they operated synergistically together. Density level of other circuit components such as capacitors and regulators was examined.

The five tariff programs were evaluated on three baseline circuit models. Simulating consumer response to tariffs required trying to predict human response to pricing changes. Unlike other technologies such as PV or EV, there was no simulation object that can predict exactly how humans will respond. Because of this consumer response uncertainty, the tariff results in this simulation were meant to show a range of potential responses. This is why the tariff analysis was limited to three circuits. The ability of tariffs to reduce peak circuit demand and energy consumption was evaluated. Circuit demand and energy were evaluated under each tariff at varying consumer response levels. When possible, consumer responses to tariffs were based on available data from existing tariff programs. If no data was available, high and low response levels were simulated to demonstrate a range of potential consumer responses.

10.5 Summary of Simulation Results

Results from the simulations for each of the technologies are summarized in the following paragraphs.

10.5.1 CES

Community Energy Storage was analyzed as a fleet of CES units across 12 different circuits. Each of these circuits represents a single cluster of circuit types. Each CES unit includes a battery with a 23.4 kilowatt (kW) rated power output, 23.4 kVAR reactive power support, and 23.4 kilowatt-hours (kWh) of energy available when fully charged. The CES control managed the activities of the individual CES units in the fleet. CES was evaluated for its islanding, peak shaving, and reactive power support capabilities. For each of these operating modes a Goals, Questions and Metrics (GQM) was identified to determine the effectiveness of that mode.

CES Islanding

The ability for CES to provide islanding support was evaluated by reviewing the average fleet state charge using both the load following and scheduled peak shaving methods. The 12 circuits modeled in this analysis experienced an average of approximately 1.7 outages per year, with an average outage duration of approximately 2.3 hours. The results showed that on average there was sufficient battery capacity to sustain consumers for the 2.3 hour outage average. Islanding provided by CES was found to improve SAIDI. The percent change in SAIDI from the baseline was shown to be directly proportional to the number of houses on the circuit connected to CES.

CES Peak Shaving

The CES was operated using two peak shaving control methods, load following and scheduled. For the load following control method, discharge and charge set-points were chosen based on circuit load to determine when CES should start discharging and start charging. In the scheduled control method, a set discharge and charge daily time schedule was determined for each circuit.

The first figure that follows shows CES peak shaving using scheduled discharge for one of the 12 circuits during a two-day period, The second figure that follows shows the same result using load following Peak Demand Reduction.

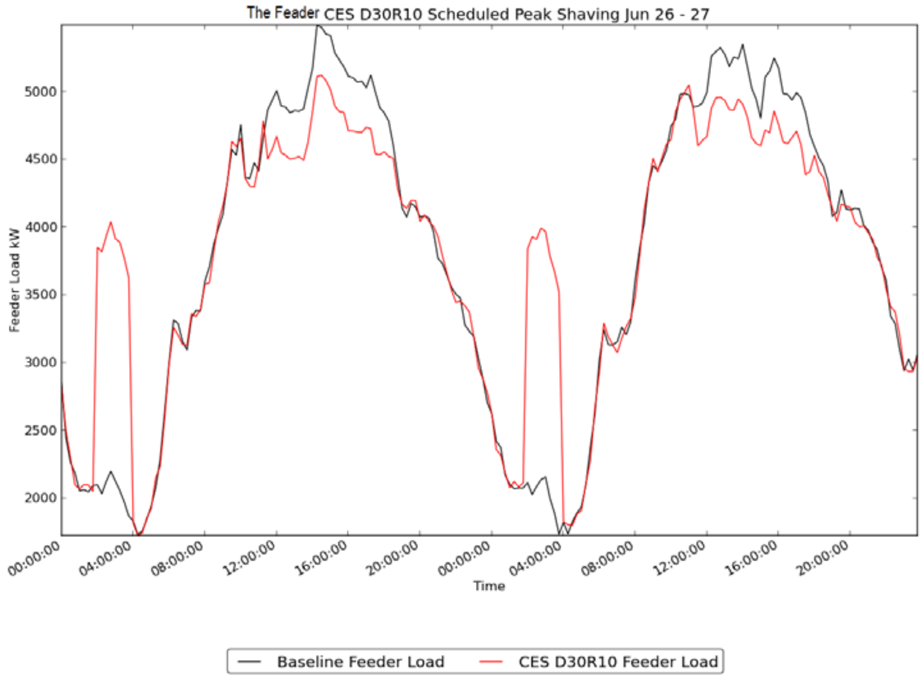

Figure 176. The Circuit Scheduled Peak Demand Reduction -- June 26 -27

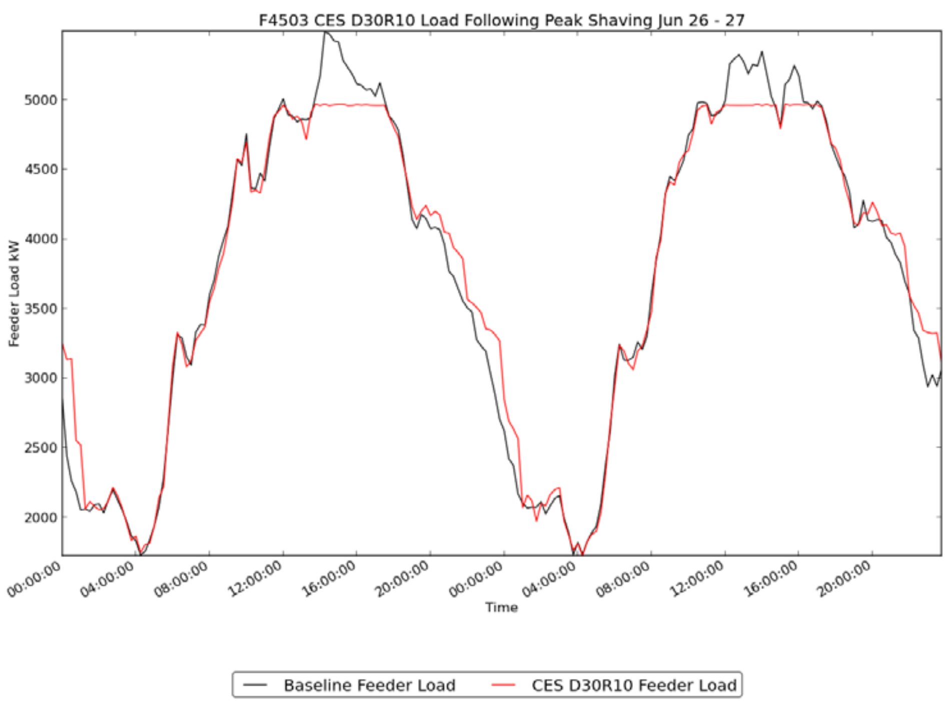

Figure 177. The Circuit Load Following Peak Demand Reduction -- June 26 - 27

For each of these control methods, the amount of peak demand shaved, energy reduction, and the number of active versus successful peak shaving days were evaluated. The results showed, on average, scheduled shaved less peak demand than the load following control method. The average over all circuits and densities was 1.75 percent for scheduled and 3.27 percent for load following. Often the scheduled discharge missed the peak event and produced a much smaller difference between the circuit peak and the CES peak.

The load following analysis also showed that CES peak shaving worked best on circuits that had a high level of residential consumers, low commercial, and low levels of industrial consumers. These circuits had a large connected kVA, which resulted in more CES units being deployed on those circuits (simulation based on residential connected kVA). On average, the load following peak shaving events had both a larger peak reduction and larger percentage peak reduction compared to the scheduled events.

The ratio of successful to unsuccessful peak shaving days was higher in load following method compared to the scheduled method because the load following method had better set-points compared to the scheduled peak shaving method. Increasing CES density and reducing the reserve island capacity gives the greatest peak shaving and overall energy reduction. The results also show that for the load following case, it was extremely important to have load balanced among the phases on the circuit. Despite careful analysis to determine the best discharge and charge set-points, it could result in models that do not discharge/charge correctly. This implies that using static settings for the entire year may not work. These settings may need to be periodically reviewed and adjusted to better meet the objectives.

CES VAR Support

CES was evaluated in reactive power support mode. For the circuits modeled in this analysis, CES was effective at driving the average power factor to unity for most of the circuits. Those circuits that did not reach unity achieved an average power factor of 0.98. In general CES was able to reduce the yearly average in each circuit. There were a few exceptions to this in the load following peak shaving control method. Despite these exceptions, load following performed much better in general compared to scheduled discharge.

However, considering all circuits and all densities together, on average the kVARh reduction was 3.45×106 for scheduled and 3.26×106 for load following. This was due to several cases in the load following method where the kVARh savings were negative, compared to the scheduled results, which only had one instance. These negative values occur for the higher densities in one circuit and for lower densities in another. Negative values also occur for one circuit, but only at the highest density level for the load following control method. Load following, unlike scheduled, only discharged on a few days of the year for most circuits, and it only did so during a peak event.

Thus, any reactive power support that occurred during these events was subject to available battery capacity not used for real power peak shaving. The scheduled results showed that on average, the amount of reactive power was always reduced. This was because scheduled discharges occurred every day, even on days when demand was small, so there was more power available for reactive power support. For some circuits, the power factor of the baseline model was very close to unity, which indicated that they had sufficient VAR support from capacitor banks. This meant that when CES was actively providing VAR support, an excess number of VARs was generated. Increasing the CES density was more effective at reducing kVARh. However, for most of the circuits, the kVARh reduction saturated because the power factor reached unity.

Overall, CES for both load following and scheduled methods provided significant reactive power support. No direct correlation was found between the CES reactive power support capability and the circuit characteristics.

CES Control Strategy

The simulated control strategy analysis indicated that load following control resulted in the best method to support peak shaving and reactive power support based on the circuits modeled. Load following also provided the most benefit to islanding because the low number of active peak shaving days resulted in an average annual battery state of charge that was close to 100 percent. Given the size of the CES deployed in the models, there was sufficient battery capacity to eliminate the average service interruptions for consumers connected to CES on the circuits that were studied.

10.5.2 NaS

A single NaS battery was deployed on each of the 12 baseline circuits. The NaS battery size varied based on the density being modeled for a given circuit. The battery could provide both real and reactive power support. Like CES, the NaS control managed the activities of the NaS battery. NaS was evaluated for its islanding, peak shaving, and reactive power support capabilities. For each of these operating modes, a GQM was identified to determine the effectiveness of that mode.

NaS Peak Shaving

The NaS battery was operated with two peak shaving methods – load following and scheduled. For the load following control method, discharge and charge set-points were chosen to determine when the battery should start discharging and start charging. In the scheduled control method, a set discharge and charge schedule was determined for each circuit.

The following figure shows NaS peak shaving using scheduled discharge for one of the 12 circuits during a two-day period. The next figure shows the same result using load following.

NaS Islanding

The simulated control strategy analysis indicated that load following control was the best method to support peak shaving and reactive power support based on the circuits modeled. Load following also provided the most benefit to islanding because the low number of active peak shaving days resulted in an average annual battery state of charge (SOC) that is close to 100 percent. The results also showed that in the types of outage events where NaS islanding would be effective (outages affecting the entire circuit), the NaS batteries were capable of providing islanding support to a limited number of consumers on the circuit, positively affecting the system reliability indices for these circuits. These gains were limited by the fact that NaS islanding applied to only a small subset of the outages experienced on a circuit, and that in most cases, only a fraction of the consumers on a circuit could be supported during an outage due to the location of high demand consumers. For this reason, circuit layout and battery placement should be considered in order to optimize islanding benefits.

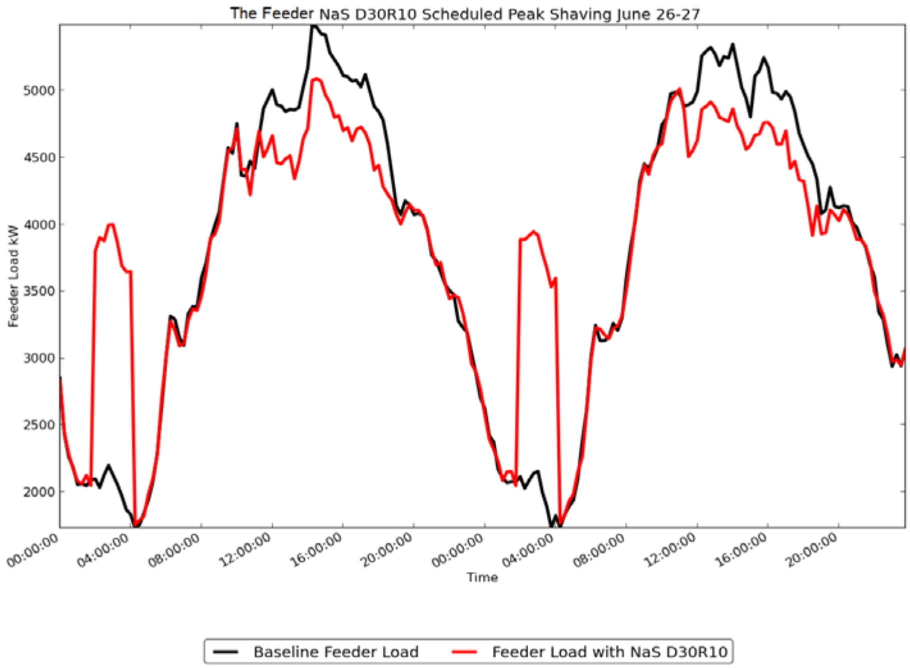

Figure 178. The Circuit Scheduled NAS Peak Demand Reduction -- June 26 -27

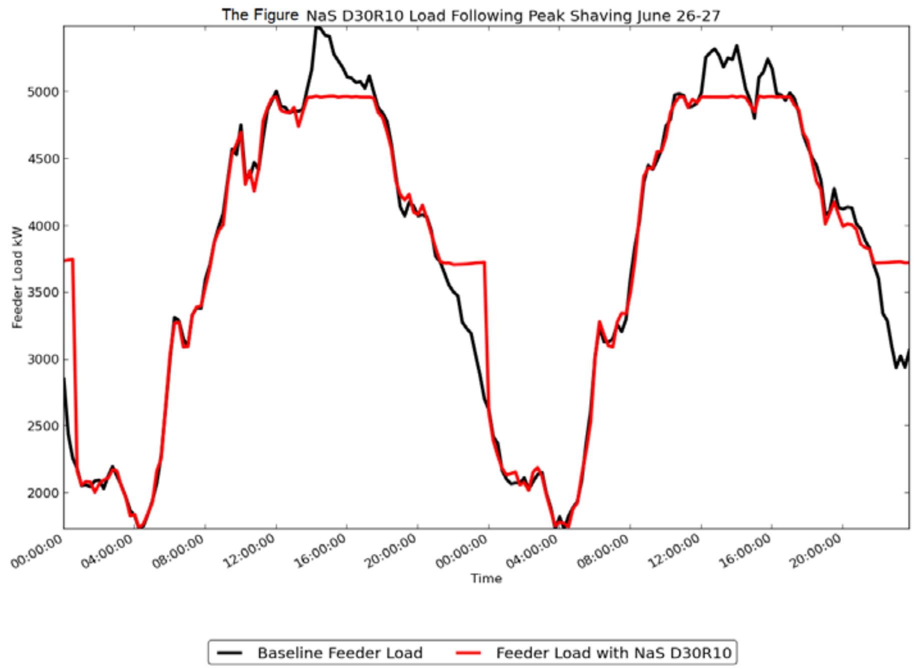

Figure 179. The Circuit Load Following NAS Peak Demand Reduction -- June 26 - 27

For each of these control methods, the amount of peak shaved, energy reduction, and the number of active versus successful peak shaving days were evaluated. The results showed the scheduled method shaved more peak energy than the load following control method. Scheduled was active every day of the year, and load following was active a fewer number of days. This was due to the fact that load following charges/discharges were based on set-points and was independent of the time of day when the peak occurred. Scheduled was directly dependent on the time of day when the peak occurred. Often the scheduled discharge missed the peak event and produced a much smaller difference between the circuit peak and the NaS peak. The load following analysis also showed that NaS peak shaving worked best on circuits that had a high level of residential consumers, low commercial, and low levels of industrial consumers. These circuits had a large connected kVA, which resulted in a larger NaS battery being deployed on those circuits.

On average, the load following peak shaving events had both a larger peak reduction and percentage peak reduction compared to the scheduled events. The ratio of successful to unsuccessful peak shaving days was higher in the load following method compared to the scheduled method. This was because the load following method had better set-points compared to the scheduled peak shaving method. This was due to the fact that load following charges/discharges based on set-points and thus was independent of the time of day when the peak occurred. The scheduled method was directly dependent on the time of day when the peak occurred. In many cases the annual peak was reduced with the addition of NaS. This showed how NaS peak shaving could be used as an alternative to traditional capacity improvement technologies to mitigate distribution system overloads.

NaS VAR Support

NaS was evaluated in reactive power support mode as well. For the circuits modeled in this analysis, NaS was effective at driving the average power factor to unity for all of the circuits. In general, NaS was able to reduce the yearly average kVARh in each circuit. Increasing the NaS density was more effective at reducing kVARh; however, for most of the circuits, the kVARh reduction saturated because the power factor reached unity. Overall, the NaS battery using both load following and scheduled methods provided significant reactive power support. No direct correlation was found between the battery's reactive power support capability and the circuit characteristics.

10.5.3 PV

PV was analyzed across the same 12 representative circuits used for CES and NaS. Each PV array had a 5 kilowatt (kW) rated power output. The impact of PV arrays on circuit behavior was evaluated in three major areas – circuit demand, energy usage, and the voltage profile of the circuit. Effects caused by sudden cloud cover were also studied. For each of these effects, a GQM was identified to determine the effectiveness of PV in each area.

PV Impact Evaluation

One of the potential benefits of PV was its ability to shave peak demand. PV output could provide energy during peak times to effectively offset circuit demand. Since PV output relied solely on the amount of sunlight, optimum peak shaving occurred when the solar irradiance level was high at the time of peak loading.

The following figure shows the demand reduction generated using PV for one of the 12 circuits.

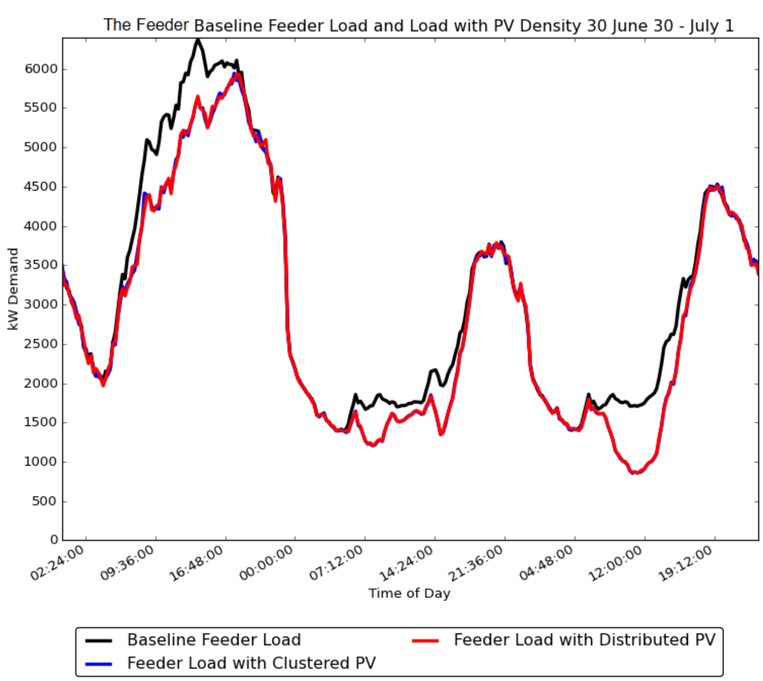

Figure 180. The Circuit PV Peak Demand Reduction -- June 30 - July 1

The examination of the effectiveness of PV peak shaving for the 12 circuits showed there was good synchronization between PV output and the annual maximum peak load. On nine of the twelve circuits, the annual maximum circuit peak load was effectively shaved. Higher PV penetration densities achieved larger amounts of peak shaving on the highest annual peaks. The amount of load shaved ranged from less than 1 percent to just below 12 percent of the maximum peaks. In only three simulation cases, the maximum annual peak circuit load was not shaved by the PV output. These three circuits were night peaking and did not benefit from PV during the highest peak times. The analysis showed that at least 40 percent of the time PV would shave some of the daily baseline peak. Based on annual averages, daily peak shaving was not strongly influenced by PV deployment density.

The amount of energy produced by the simulated PV deployments and its effect on circuit energy consumption was also examined. The annual energy produced by a single PV array was 7,887 kWH. The peak output in the winter months was approximately 50 percent of the peak output during the period from late spring through early fall. The highest power output of a single array during the year was 4.78 kW. PV deployed on a circuit provided substantial savings in annual circuit energy. For PV with penetration density of 30 percent, the reduction in average annual energy ranged from 1.14 percent to 8.65 percent. For PV with density of 10 percent, the average annual reduction ranged from 0.484 percent to 3.08 percent. Increasing the PV density increased the amount of peak shaved and energy reduction for the circuits modeled. The results showed that circuits with larger PV densities installed had the most peak reduction.

Reduced energy consumption resulting from PV was significant for all circuit types and the amount of energy saved was linearly dependent upon PV penetration density with higher densities providing increased energy savings. The largest energy savings occurred from late spring through early fall when the PV output was greatest. Distributed and clustered PV deployments had essentially the same amount of annual energy savings.

The impact of PV deployment on circuit voltage was examined. Deployment of PV could improve system voltage, but it also had the potential to create voltage problems. The impact on the voltage profile from clustering groups of PV arrays on the circuit and the impact from distributing PV arrays more uniformly along the circuit were compared.

The deployment of PV on the 12 circuits did not create voltage problems on the circuits even when PV arrays were clustered and the PV density was 30 percent. The PV deployment did not appreciably change the average voltage profile of the circuit. On some circuits there was a slight increase (0.1 to 0.2 volts) in average voltage with the PV deployed. Voltage regulators did not experience a substantial increase in the number of tap changes over the course of the year. The investigation into the impact of PV on the voltage profile revealed no significant issues from increased voltage excursions outside the prescribed limits of 117 to 126 volts at end-of-line (EOL) monitoring points or circuit regulators, and regulator tap changes were nearly unaffected.

The impact of a large and rapid change in PV output was examined. Rapid changes in the solar irradiance that may occur during cloud cover events translate into rapid changes in PV output, and hence, the circuit load, potentially affecting voltage on the circuit. An extreme cloud event was simulated on each of the 12 circuits. Large and rapid changes in the circuit load caused by

PV output power swings from the simulated cloud cover event did not create issues with voltage-level excursions at the circuit regulator. At EOL locations, voltage could potentially swing up to 4 volts during cloud cover events on long circuits with large PV installations. In 11 out of 12 cases, the cloud event did not create any voltage issues at the EOL locations. The longest circuit modeled saw the largest voltage swing, but even its EOL voltage excursions remained within established flicker limits.

Combination of PV with CES
In addition to deploying PV arrays, simulations were conducted that combined PV and CES. The CES control managed the activities of the individual CES units in the fleet. The combination of CES and PV was examined to quantify the peak shaving benefits. Both technologies were deployed at a density of 20 percent for this analysis. A probability analysis previously mentioned above to quantify the effectiveness of PV peak shaving for daily demand was repeated for the CES and PV combination. This showed that at least 60 percent of the time CES and PV would have shaved some of the daily peak compared to baseline, an improvement over the 40 percent result found for PV alone. Results for individual circuits based on maximum annual peaks were varied depending on whether comparisons were done using synchronized or unsynchronized peaks. The discrete nature of the simulation results, with results recorded on 15-minute intervals, may indicate the need to average the annual maximum results, such as occurred in the probability analysis. Median synchronized annual peak reduction for the 12 circuits was 4.5 percent for CES and PV, and 2.5 percent for PV alone. Using unsynchronized annual peaks, the median reduction was 2.1 percent for CES and PV, and for PV alone. By adding CES to the circuits with PV both the maximum annual and daily peak shaves are likely to improve.

The simulation results show that PV provided benefits in all three major areas – circuit demand, energy, and the voltage profile of the circuit. Daily demand peaks were shaved at least 40 percent of the time, and the highest daily peak during the year was shaved on all daytime peaking circuits. PV also significantly reduced energy consumption for all circuit types with higher PV densities giving increased reductions. The deployment of PV did not create voltage problems on the circuits.

10.5.4 PHEV/PEV

The deployment of PHEV/PEV charging stations was analyzed across the same 12 representative circuits. The impact of PHEV/PEV charging stations on circuit behavior was evaluated in four major areas – circuit demand, voltage excursions, density effects and energy consumption. For each of these effects, a GQM was identified to determine the effects of PHEV/PEV charging stations in each area.

PHEV/PEV Charger Impact Evaluation
On a circuit level, PHEV/PEV chargers could shift the circuit peak demand if the additional load created was large enough relative to the overall circuit load, and the PHEV/PEV charging time frame occurred later than the peak time without PHEV/PEV installed. The following figure illustrates this shift for one of the 12 circuits.

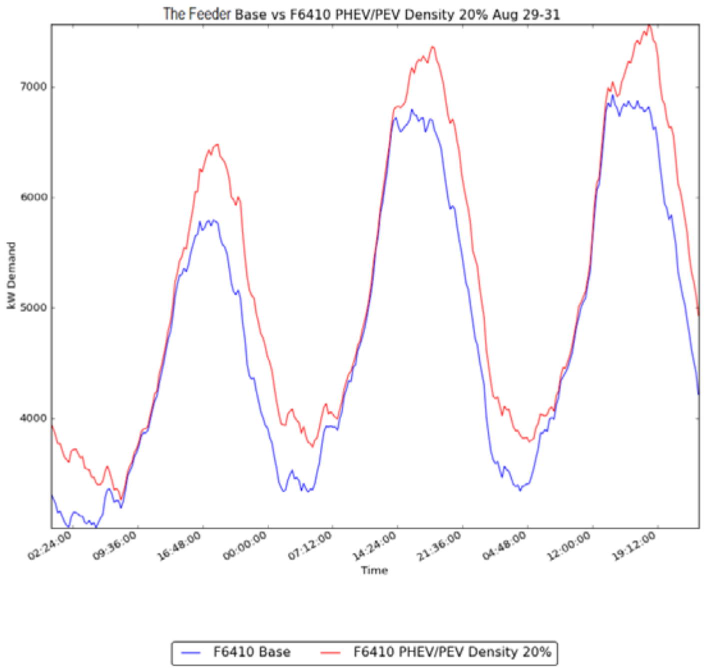

Figure 181. The Circuit Peak Demand Shift Due to PHEV/PEV -- August 29 - 31

This shift in peak demand was highly dependent on the circuit characteristics and loading profile.

The load from the PHEV/PEV chargers increased the daily circuit peak almost every day of the year on each circuit. The maximum daily circuit peak load increase due to the PHEV/PEV charger load as a percentage of the daily peak ranged from:

- 3.2 percent to 19.5 percent for PHEV density at 10 percent (average 10.3 percent)
- 5.1 percent to 29.8 percent for PHEV density at 20 percent (average 15.8 percent)
- 9.3 percent to 44.9 percent for PHEV density at 30 percent (average 23.0 percent)

The maximum increase in the daily circuit peak from the PHEV/PEV chargers did not occur on the same day that the maximum circuit peak for the year occurred. These were often shifted to completely different days of the year. The peak demand from PHEV/PEV chargers was not influenced by weather conditions like the annual peak day. With PHEV/PEV chargers, the daily peak often did not occur at the same time as the base case. The peak typically shifted to a later time in the day.

The PHEV charger load made up a larger portion of the daily peak load in the off peak seasons, such as the months of January and October, than in the peak season of June. For PHEV/PEV densities of 10 percent, 20 percent, and 30 percent, the average annual energy increase per circuit was 4.72 percent, 9.51 percent, and 14.7 percent respectively. Because consumption varied linearly with PHEV/PEV density, the data could be used to extrapolate the effects of a higher or lower density of PHEV/PEV chargers on the circuit.

Considering the total number of PHEV/PEV chargers installed on each circuit, very few line transformers over 25 kVA in size were overloaded with the addition of charger load even at the highest density. On some rural circuits with predominantly smaller (less than 25 kVA) transformers installed, the addition of one to two larger PHEV/PEV chargers could be enough to create overload conditions.

Regarding low voltage conditions, as more PHEV/PEV chargers were installed; more voltage drops below the acceptable 115v were observed. Because 114v must be maintained at the consumer's service entrance, 115v was chosen as the voltage excursion point to allow for a 1-volt drop on the secondary service equipment between the transformer and the consumer meter. Due to low service voltage, more line transformer, secondary conductor and service lateral upgrades will be required as additional PHEV/PEV chargers are added.

Based on results from the voltage excursion and transformer overload analysis, maintaining secondary service voltage within acceptable limits is more likely to be an issue than the overloading of line transformers.

Combination of PHEV/PEV with CES

In addition to deploying PHEV/PEV charging stations, simulations were conducted that combined PHEV/PEV charging stations and CES. The CES control managed the activities of the individual units in the CES fleet. For this analysis, the combination of CES and PHEV/PEV load profile was evaluated. CES was previously shown to be an effective technology for reducing daily peak load on circuits. The addition of PHEV/PEV chargers largely did not disrupt the ability of CES to shave loads. Generally, there was little evidence of synergy between the CES and PHEV/PEV charging schedules, and CES may temper the peak loads caused by PHEV/PEV chargers.

Simulation demonstrated that widespread deployment of PHEV/PEV charging stations can have substantial impacts on circuit behavior. These impacts could result in equipment upgrades of service transformers as well as secondary side service laterals. PHEV/PEV charging stations not only resulted in overload situations, they also affected the time of day when the peak demand occurred. This shift in peak is potentially harmful to service equipment because the power consumption remains high for longer periods during the day, which increases wear on equipment. This data shows that PHEV/PEV charging station effects scale linearly with density, which gives greater ability to assess the impact of these technologies on a circuit.

10.5.5 VVO

This section describes results from a parametric study of Volt VAR Optimization (VVO) on a set of 32 baseline circuit models. The impact of VVO on circuit behavior was evaluated in three major areas – circuit demand, energy usage, and the voltage profile of the circuit. The impact of VVO on circuit behavior was also evaluated for each of the 32 circuits with three modifications – added circuit components (voltage regulators and capacitors), added CES, and added PV. For each of these effects a GQM was identified to determine the effectiveness of VVO in each area.

In the original experimental design, 32 circuits were planned to be simulated with VVO. However, circuits with multiple regulators could not be simulated using the built-in GridLAB-D VVO module. A proprietary module was used for these circuits which had mixed results. There are 6 circuits out of the 32 that have multiple regulators. As a result for the VVO only sections, results are shown for 26 circuits.

VVO Technology Impact

VVO was effective in reducing synchronized and absolute annual demand peaks and in reducing energy consumption. With VVO targeted for 117V EOL voltage and 0.98 leading power factor (PF), the median annual peak kW demand reduction for the 26 circuits studied was 2.43 percent for synchronized peaks and absolute peaks. The median daily average peak demand reduction was 3.68 percent with VVO set for 117V EOL voltage and 0.98 leading PF. With the same VVO target settings, the annual energy savings averaged 4.05 percent (median = 4.24 percent) relative to the baseline cases.

On average EOL target voltage played a more significant role than did target PF in determining the amount of peak demand reduction and energy savings. Based on the median percentage annual energy reduction, the 117V target setting provided the best energy savings compared to 118V and 119V settings at a target PF of 0.98 leading. Four of the five circuits that benefited most from VVO for daily peak demand reduction also benefited most for reducing energy consumption. Defining circuit characteristics such as miles, line number of residential consumers, or primary circuit voltage were not common among these high performing circuits.

The VVO results were affected by the use of two different VVO modules. An open source VVO controller was used for simulations if the circuit did not have a line voltage regulator. A proprietary VVO controller was used for simulations of circuits that had line voltage regulators. The open source controller was unbiased and treated the voltage set point as its target allowing the EOL voltage to be below the target at times. The proprietary controller treated the voltage set point target as a minimum and biased the EOL voltage to be above this target most of the time. Because of the differences in the way each controller responded to the EOL voltage target, the results produced by these different controllers were significantly different.

These differences affected comparisons between the results for circuits with a line regulator and the results for circuits without a line regulator. Regardless of the target voltage and power factor, the median VVO annual peak demand reduction percentage was significantly lower than the median VVO daily average peak demand reduction percentage. This difference was indicative of the inability of the circuit voltage regulators and line voltage regulators to lower the voltage profile on most circuits as much during peak demand periods as they could during periods of lighter load. During peak periods, the higher load on the circuit caused increased voltage drop, and the voltage regulators had to maintain a higher voltage level in order to keep the EOL voltages within acceptable limits. The following two figures illustrate the voltage profiles for one of the modeled circuits during off peak and peak demand respectively.

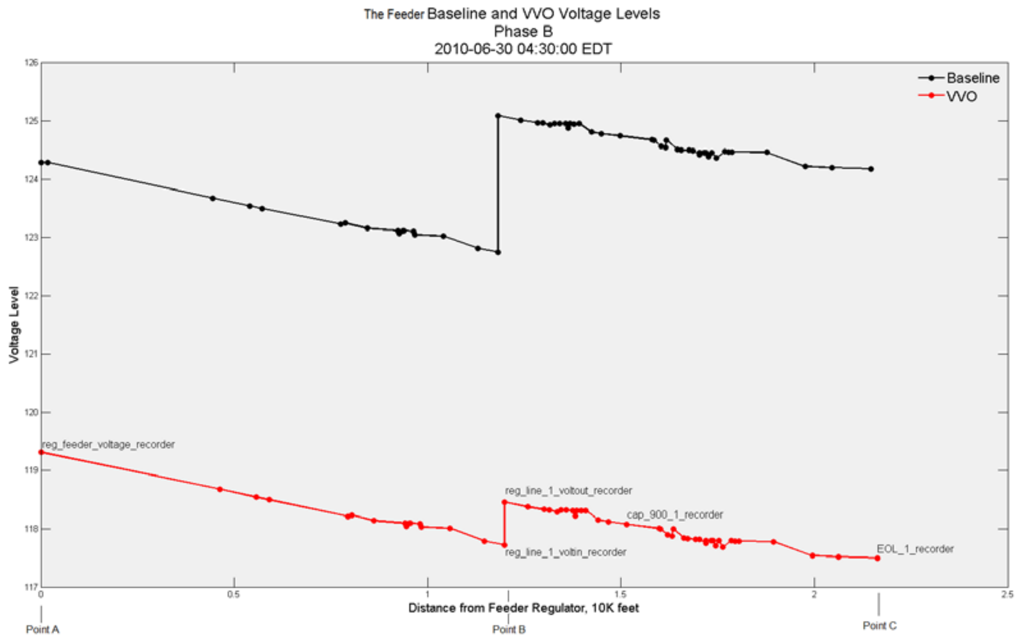

Figure 182. The Circuit Off Peak Voltage Profile Drop Due to VVO

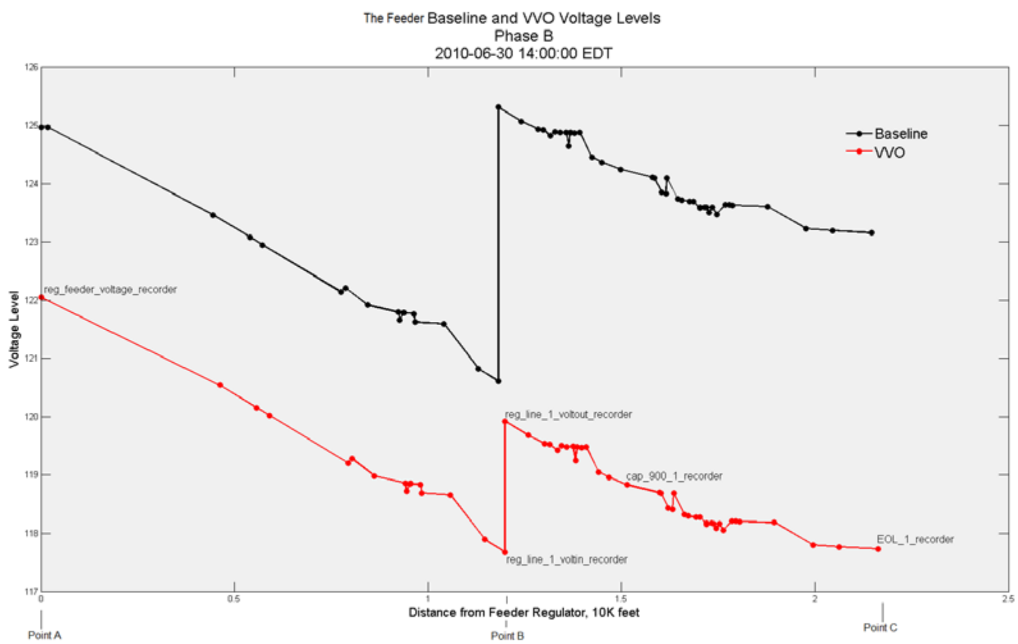

Figure 183. The Peak Voltage Profile Drop Due to VVO

VVO was less effective in reducing reactive demand peaks than it was in reducing kW demand peaks. Individual circuit results were highly variable, but median annual reactive demand reductions ranged from 0.92 percent to 1.79 percent for both synchronized and absolute peaks.

For 117V, 118V and 119V target EOL voltage, VVO improved the annual average PF on 15, 15, and 16 of the 26 circuits respectively. For the remaining circuits the same target EOL and PF values produced a slight decrease in annual average PF. For target PF values of 0.98 leading, 0.98 lagging, and 0.96 leading with a 117V target EOL voltage, VVO improved the annual average PF on 14, 15, and 15 of 26 circuits, respectively. Changes in target power factor settings had more effect on reactive demand peak reduction than the changes in EOL target voltage.

For reactive energy consumption, VVO provided mixed results with large variations in reduction from circuit to circuit. With varying EOL voltage target and a constant target PF of 0.98 leading, the annual reactive energy savings ranged from a savings of 81.26 percent to an increase in consumption of 181.47 percent. Changes in target power factor settings had more effect on reactive energy reduction than did changes in EOL target voltage. The varying results in reduction may be due to:

- Constant power loads dominating peak conditions
- Different control logic, control points and control measures used to control the capacitors[2]

Adding a line regulator, a capacitor or both a line regulator and a capacitor on circuits with VVO did not consistently improve VVO peak demand reduction performance. This lack of consistent peak demand reduction was because added components were not able to flatten circuit voltage profiles much better than the flattening provided by the VVO before additional components were added. Additionally, the proprietary VVO object used in the simulations maintained higher voltage profiles compared to the open source GridLAB-D VVO object, which was also used.

The small improvement in annual and average daily energy savings and demand reduction from circuit components added to a circuit with VVO could be attributed primarily to the fact that the implementation of VVO without added circuit components harvests most of the potential energy savings and demand reduction from lowering the circuit voltage. Because the circuit demand was near its peak for only a small percentage of time during the year, the implementation of VVO allowed the existing regulators and capacitors on the circuit to lower the voltage profile significantly for most of the year.

The addition of a supplemental line voltage regulator or capacitor may allow the voltage on portions of the circuit to be lowered further, but the amount of further reduction would be very limited. The VVO had already greatly flattened the circuit voltage profile using the existing voltage regulators and capacitors on the circuit. Also, the voltage reduction from the added regulator or capacitor would have affected a small portion of the load on the circuit further limiting the amount of reduction. Because the circuit voltage profile was higher during times when the circuit load was high, an added voltage regulator or capacitor would be most effective

[2] In the baseline case, each capacitor was switched using kVAR on and kVAR off set-points to switch the capacitor on and off using kVAR measurements from only one of the three phases at the capacitor location. In the VVO case, the capacitors were switched based upon the total three phase kVAR measured at the circuit regulator.

at reducing the voltage during those times. However, the amount of time the demand was high was relatively short, and the amount of further voltage reduction was still very limited. The addition of a capacitor provides less potential for an improvement in VVO demand reduction and energy.

Compared to the baseline, VVO set for 117V EOL target voltage and 0.98 leading PF decreased the median number of annual regulator tap operations by 0.2 percent. However, individual circuit results varied widely. For target voltage of 117V, 118V, and 119V simulated with a target power factor of 0.98 leading, 13, 13, and 12 of 26 circuits respectively showed a decrease in the annual number of regulator tap operations, and the remaining circuits showed an increase. Similarly for all three target power factors simulated with a target EOL voltage of 117V, 13 of 26 circuits showed a decrease in the annual number of regulator tap operations and the remaining circuits showed an increase.

Voltage excursions outside the 116.5V - 126.5V range were examined as indicators of potential voltage issues from VVO operation. With EOL target voltages of 117V, 118V and 119V and a target PF of 0.98 leading, the number of annual voltage excursions above 126.5V either stayed the same or decreased on 23 of the 26 circuits. However, the number of voltage excursions above 126.5V increased on 3 of the 26 circuits.

With VVO set for 117V and the three target PF (0.98 leading, 0.96 leading, and 0.98 lagging), the 0.96 leading PF setting produced the best results with only 5 of the 26 circuits experiencing an increase in the number of voltage excursions above 126.5V.

With VVO target settings of 117V and 0.98 leading PF, 23 of 26 circuits experienced an increase in the number of voltage excursions below 116.5V. With target voltage settings of 118V and 119V with 0.98 leading PF, fewer circuits experienced an increase in the number of voltage excursions below 116.5V and the amount of increase was generally smaller than the amount of increase with the 117V setting.

For voltage excursions below 116.5V, with VVO set for 117V and the three target PFs simulated, the 0.96 leading PF setting produced the best results with only 5 of the 26 circuits experiencing an increase in the number of voltage excursions. With VVO set for 117V the majority of circuits experienced a large increase in the number of voltage excursions below 116.5V at each of the three VVO PF settings.

If a VVO target voltage setting of 117V is selected, the circuit may need to be monitored to insure voltage levels remain above the lower limit. Improved voltage excursion results may be possible by modifying VVO control settings such as time delays and dead band settings.

Evaluate Combination of VVO with PV

In general the addition of PV did not have a significant impact on the number of voltage excursions experienced on the 26 circuits. Based on this result, the addition of PV should not create out-of-limits voltage conditions.

For many circuits either clustered or distributed, PV combined with VVO improved the annual maximum kW peak shaving performance compared to the performance of VVO operating alone. On several circuits the maximum PV output on the day of the maximum annual peak demand did not coincide with the annual maximum peak demand. For these circuits, this difference in timing resulted in little or no peak shaving contribution from the PV.

Because most of the 25 circuits were summer peaking and the daily maximum PV output coincided more closely with the summer peak than at other times of the year, VVO combined with PV was more effective in reducing the annual maximum peak demand than reducing the daily average peak demand.

A comparison was made between the annual peak shaving results for VVO combined with PV to the sum of the annual peak shaving results for VVO operating alone and the annual peak shaving results for PV operating alone. The objective was to see if the interaction of VVO and PV operating together produced a greater sum than the sum of their individual effects when operating alone. The result of this comparison suggests that very little synergy existed between the two technologies.

At the circuit level the addition of PV to VVO universally improved the savings in annual energy usage over the savings provided by VVO operating alone. The energy consumption reduction results of VVO plus PV compared to the sum of PV and VVO reduction results revealed very little synergy between the technologies when VVO was combined with PV.

Based upon median results, VVO combined with PV did a better job of reducing synchronous reactive peak demand than VVO operating alone. This result reflects the reduced PF caused by the real power output of the PV and by the limitations placed upon the VVO by the number and size of switched capacitors on the circuit.

Some circuits were not affected by the PV because their reactive demand peak occurred while there was no PV output. For circuits that were affected by the PV output, the VVO did not fully compensate for the circuit reactive demand peak on some of them. For other circuits affected by the PV, the VVO overcompensated as it tried to maintain the target power factor. As a result, some circuits decreased peak reactive demand and some circuits increased peak reactive demand when VVO was combined with PV compared to VVO alone.

In addition, negative values in peak reactive demand reduction may be attributable to slight timing effects. The circuit load composition on some circuits being predominated by loads with ZIP fractions model increased reactive loading when the circuit voltage was lowered by the VVO. In addition, the average PF under baseline conditions was higher than the VVO target PF of 0.98. Under these conditions, the reactive demand with VVO or with VVO combined with PV would be expected to be somewhat greater at times than the baseline reactive demand.

Even though PV did not provide VAR support, VVO combined with PV produced additional reduction in annual reactive consumption for many circuits compared to the baseline case. The median improvement in annual reactive consumption reduction considering all 25 circuits was only 0.01 percent for all PV densities for both distributed and clustered configurations, comparing the annual reactive energy consumption reduction for VVO combined with PV compared to the annual reactive energy consumption reduction for VVO operating alone. The combination of VVO with PV significantly increased the number of voltage excursions above 126.5V on most of the 25 circuits as compared to the number of excursions on circuits with VVO only. Compared to the baseline case, VVO operating alone with target EOL voltage at 117V and target PF of 0.98 leading generally increased the number of voltage excursions below 116.5V. For nearly all of the circuits, PV deployment with the VVO operational increased the number of excursions below 116.5V. The number of voltage excursions was independent of the PV density for both clustered and distributed configurations.

Circuits with VVO and clustered PV had more voltage excursions below 116.5V than circuits with VVO and distributed PV. On some circuits, the power output from clustered PV and higher density PV appears to have raised the EOL voltage at some locations causing the VVO to lower voltage regulator output voltage too much at times. Customizing VVO control settings such as time delay and voltage bandwidth to reflect the unique conditions on a particular circuit may be advisable to reduce the number of voltage excursions.

When PV density or clustering of PV concentrates in one area on a circuit with VVO, relocation of an existing EOL monitoring point or the placement of a new EOL monitoring point may be necessary to maintain voltage within the acceptable voltage range. On circuits with higher concentrations of PV where VVO implementation is being planned, studies should be made that take PV into account when locating the VVO EOL voltage monitoring points.

Evaluate Combination of VVO and CES

VVO and CES produced poor results in terms of additional annual peak demand reduction compared to VVO operating alone. Just over half the circuits with data showed some additional annual demand reduction with CES added. However, the amount of reduction was less than 1 percent on most of the circuits which had additional demand reduction. Slightly better results were produced for additional daily peak demand reduction, but the VVO and CES improved the median average daily peak demand reduction by less than 1 percent considering both clustered and distributed CES configurations. Adjustment of the CES control set-point would have improved peak demand reduction performance.

With the addition of CES, the charging energy for the CES units decreased the annual and daily energy savings compared to VVO operating alone. However, the average daily energy savings for VVO and CES was positive for all circuits with available data.

The additional VAR support provided by CES resulted in an additional reduction in reactive demand on most circuits compared to VVO operating alone. VVO and CES clustered improved the annual reactive demand reduction on twenty-four of the twenty-four circuits and improved the daily average reactive demand reduction on twenty-four of the twenty-four circuits.

The VAR support from CES complemented the VAR support provided by the VVO by further reducing the reactive energy requirements on the circuits. The VVO and CES significantly reduced the annual reactive energy usage compared to the VVO operating alone. Compared to VVO operating alone, VVO and CES (distributed and clustered) reduced the annual reactive energy usage on all circuits with available data. The average daily reactive energy results did not reflect significant VAR contribution from CES.

All circuits with available data except four experienced an increased number of tap operations with VVO and CES compared to VVO acting alone. For several circuits, the increase was significant with the number of tap operations more than doubled by adding a large density of CES. Overall the combination of VVO and CES had a beneficial effect by reducing voltage excursions compared to VVO operating alone on most circuits, but VVO significantly increased the number of regulator tap operations. For 21 of the 24 circuits, the number of annual voltage excursions below 116.5V either stayed the same or decreased for VVO and CES clustered compared to VVO operating alone. The results for distributed CES showed the number of voltage excursions above 126.5V were similar to the results for clustered CES. However, distributed CES had fewer excursions.

For voltage excursions below 116.5V, the number of voltage excursions either stayed the same or decreased for 21 of the 24 circuits comparing VVO and CES clustered with VVO operating alone. For VVO and CES distributed, the annual number of excursions below 116.5V was slightly better than VVO with clustered CES.

$CVRf_{Energy}$ is a metric used to measure the average responsiveness of a circuit's energy consumption to voltage reductions. $CVRf_{Energy}$ factors for 25 circuits with VVO were calculated. The $CVRf_{Energy}$ varied from circuit to circuit and ranged from a high of 2.52 to a low of 0.51. $CVRf_{Energy}$ closely correlated to the Average $CVRf_{Demand}$. For a given circuit the $CVRf_{Energy}$ varied over a very small range as the VVO voltage and PF settings were changed. The median of the $CVRf_{Energy}$ factors for these circuits varied slightly from a low of 0.76 to a high of 0.77 for the five VVO settings simulated. The relationship between the circuit energy consumption and voltage level was nonlinear, that is a given percentage voltage change at a higher voltage level produced more energy consumption change than the same percentage voltage change at a lower voltage level. None of the defining circuit characteristics had significant correlation with $CVRf_{Energy}$.

The simulation results show that VVO provided benefits in all three major areas: circuit demand, energy usage, and the voltage profile of the circuit. Adding conventional circuit components such as voltage regulators or capacitor banks was compatible with VVO operation and marginally improved VVO performance. Adding more recently introduced technologies such as photovoltaic arrays or CES was compatible and complementary to VVO performance.

10.5.6 Project Tariffs and Riders

This section analyzes the deployment of multiple types of Project tariffs and riders (Tariff) on three circuits from AEP Ohio. Only three circuits were chosen because consumer response to Tariffs is not dependent on circuit characteristics. Each Tariff was deployed at 100 percent penetration for the simulations. The results of the simulation should therefore be scaled to expected penetration levels. Circuit demand and energy were evaluated under each Tariff at varying consumer response levels. When possible, the range of consumer responses to Tariffs

were based on available data from existing Tariff programs. This data was used to set high and low response levels.
If no data was available, high and low response levels were estimated to demonstrate a range of potential consumer responses. For each of these effects, a GQM was identified to determine the effectiveness of Tariffs in each area.

Tariff Impact
One of the potential benefits of Tariffs is the ability to shave peak demand. Tariffs offer an incentive for consumers to reduce electricity usage during peak demand times. For DLC, some circuits showed peak reductions ranging from 0.2 percent to 0.3 percent for both high and low response cases. Sample circuit A showed a 33.9 percent peak reduction for the low response case, and 39.4 percent for the high response case. The success of the peak demand reduction depended largely on whether or not the maximum 4-hour load control event was timed correctly with the circuit peak. The load control event was timed correctly for sample circuit A, but missed the peak time on sample circuits B and C. The DLC event time periods were chosen by selecting the typical peak hours on the hottest days of the year. Given the 4-hour event time limit, initiating the event too early may result in an absolute peak that occurs after the event has ended. Initiating the event too late may mean that the opportunity to reduce the absolute peak has passed.

Simulation results show the ideal time period for a DLC event, but it is more difficult to set the ideal event time period without knowing exactly when the absolute peak will occur. In an actual DLC event, there obviously would not be a way to know exactly when the absolute peak will occur. The TOD tariff reduced peak demand in the range of 23.26 percent to 34.83 percent for the low-response cases across all three circuits. The peak was reduced in the range of 24.93 percent to 35.79 percent for the high-response circuits. TOD/CPP peak reduction ranged from 31.03 percent to 44.88 percent for low-response cases, and 37.61 percent to 69.06 percent for high-response cases, with critical peak events proving to be very effective at reducing demand. RTP_{da} peak demand reduction ranged from 2.51 percent to 10.17 percent for low-response cases and 1.53 percent to 9.89 percent for high-response cases. These results should be scaled to expected penetration levels. For each tariff, a common byproduct of the peak reduction was a sharp increase in demand immediately after the peak pricing period. This demand rebound often went higher than the original peak. Because the demand rebound is expected to scale linearly with penetration levels, this effect would be significantly lessened at penetration levels less than 100 percent.

Another potential benefit of Tariffs is a reduction in energy consumption. Each Tariff showed a net energy reduction despite the high demand rebound after peak periods. The DLC had average daily energy savings ranging from 0.39 percent to 0.67 percent for low-response cases, and 0.46 percent to 0.79 percent for high-response cases. The TOD tariff had an average daily energy reduction ranging from 4.79 percent to 9.17 percent for low-response cases, and 4.73 percent to 9.35 percent for high-response cases. The TOD/CPP tariff low-response cases ranged from 8.62 percent to15.69 percent and 8.78 percent to 15.73 percent for high response cases. For the RTP_{da} tariff, average daily energy reduction ranged from 5.60 percent to 9.53 percent for low-response cases and 6.96 percent to 12.00 percent for high-response cases. Like the peak demand reduction results, these results should be scaled to expected Tariff penetration levels.

Tariff simulations for DLC, TOD, TOD/CPP, and RTP_{da} showed that each Tariff can be effective at reducing peak demand and energy usage. Each Tariff also showed a demand rebound immediately after the peak pricing period. Because these simulations were run at 100 percent Tariff penetration, the peak demand reductions should be scaled to expected Tariff penetration levels. The demand rebound effect would also be significantly lessened at penetration levels less than 100 percent.

10.6 Modeling and Simulation Conclusions

The overarching conclusions of the Modeling and Simulation effort show the effects of adding smart technologies to the grid. A benefit of using modeling for this type of analysis is that it provides the ability to predict the effects of smart grid technologies before capital investments are incurred. Synergies among multiple smart technologies and potential negative combinations of others can be identified. Modeling and Simulation provides beneficial analysis to invest in a stronger, more robust electric grid for the future.

Details and conclusions regarding the simulation results of individual technologies as well as combinations of technologies are more fully described in the section labeled *Summary of Simulation Results*.

10.7 Lessons Learned

- Open source distribution circuit simulation tools allow sophisticated and detailed simulations for many aspects of the distribution circuit from the substation down to the individual houses and their appliances, outlet and lighting loads, air conditioning, water heater, and the home insulation characteristics.
- User interfaces and analysis tools such as GridCommand Distribution provide speed and efficiency for developing and evaluating GridLAB-D models and simulations.
- Smart Grid Technologies are developing, and due to the interplay between simulation and implementation, the technology simulation tools are also developing.
- Open source modules for several distributed generation technologies are currently full-featured and provide valuable tools for simulations of both individual and combined technologies.
- Open source simulation modules for VVO are adequate for many simulations, but their current versions have limited ability to deal with complex circuits containing multiple line regulators connected in series configurations.
- The section labeled *Summary of Simulation Results* provides information regarding how combinations of technologies might work together. These combinations include PV and CES, PEV and CES, VVO and CES, and VVO and PV.

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11 COMMERCIALIZATION

11.1 Background

AEP Ohio and Battelle partnered on the AEP Ohio gridSMART® Demonstration Project to build a secure, interoperable, and integrated smart grid that demonstrates the ability to improve grid reliability, efficiency, and cost through the effective evaluation, integration, and deployment of innovative energy technologies in central Ohio. Part of the overall project involved actively attracting, educating, enlisting, and retaining consumers using innovative business models that provide tools and information to reduce costs, consumption, and peak demand, as well as providing the Department of Energy (DOE) with optimal information to evaluate technology and preferred business models. In addition, the project assessed the commercialization opportunities for a number of technologies that were demonstrated in partnership with participating companies, including the market readiness of emerging technologies and the economic impact of these commercial activities.

As part of the Project, commercialization opportunities were assessed for a number of technologies demonstrated in partnership with participating companies, which included the market readiness of emerging technologies, the economic impact of such commercial activities, and lessons learned. A wide variety of commercial partners committed to collaborate and assist AEP Ohio in evaluating and advancing promising technologies. The Commercialization Working Group (CWG) included AEP Service Corporation, AEP Ohio, Battelle, and The Ohio State University's (OSU) Fisher College of Business. The CWG provided a forum for sharing information necessary to complete outcome-oriented business plans that create and evolve market-ready, smart grid products by considering existing markets, manufacturing capabilities, and distribution channels.

The CWG's goal was to track commercial progress of smart grid technologies, report to the DOE how the AEP Ohio gridSMART Demonstration Project accelerated commercialization of smart grid technologies, and develop a comprehensive collection of market intelligence, tactical guidance, and cost-benefit analyses for commercial partners.

During the course of the Project, the utility market in Ohio moved from a regulated utility market to a competitive retail electric service (CRES) market. As of March 1, 2012, there were 14 CRES providers actively serving consumers in AEP Ohio's service territory, which meant they were potentially within the project area as well.

The Project was designed to successfully accelerate the commercialization of smart grid technologies through multiple stages of testing and guidance from the commercial partners. A wide variety of commercial partners committed to help in evaluating and advancing promising technologies. The proposed process included three segments:

- Extensive equipment laboratory testing
- Equipment field deployments
- Assessment by the AEP Ohio gridSMART® Demonstration Project CWG

The overall structure is shown in the figure below.

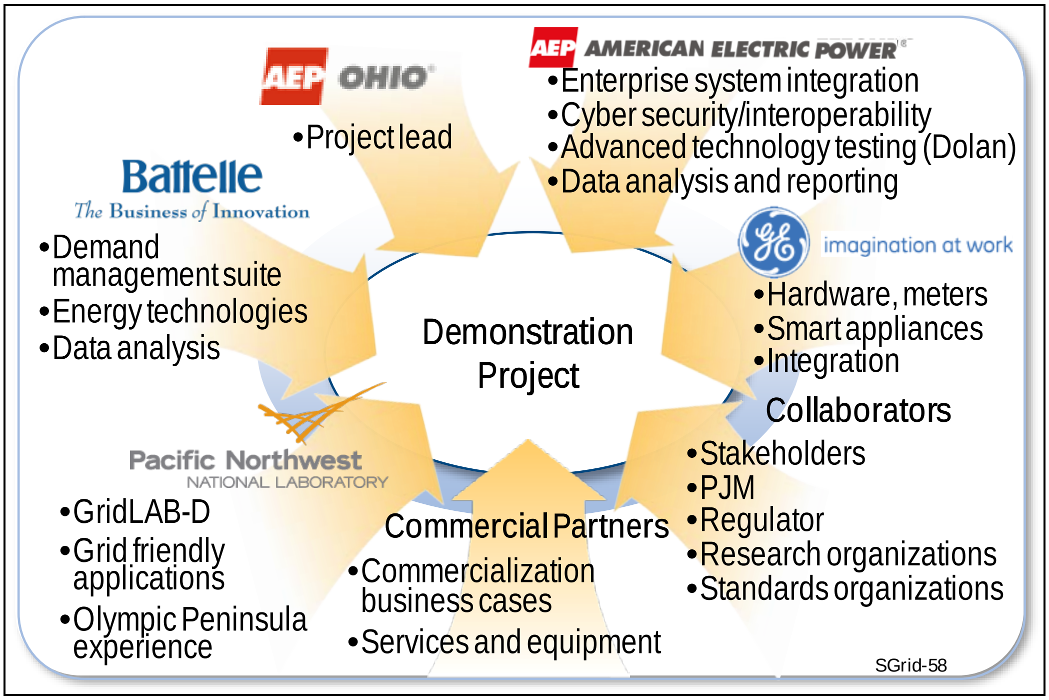

Figure 184. Integrated Project Team

Equipment testing was conducted by the commercial partners, Battelle, and AEP Ohio at AEP's Dolan Technology Center (DTC). Equipment field deployments provided performance data for both the individual products as well as integrated, optimized solutions. AEP Ohio used GridLAB-D, a simulation software package, to appropriately identify the best scenarios for component integration without costly trial-and-error approaches. The CWG provided a forum for sharing information necessary to complete outcome-oriented business plans that evolve and create market-ready smart grid products.

Vendor risk was reduced through rigorous testing, and key commercialization insight was provided by the CWG's processes. This strategy included field deployment experience through a commercialization process agreed upon by the CWG and the commercial partners. It considered existing markets, distribution channels, and manufacturing capabilities.

AEP Ohio and Battelle agreed to engage OSU's Fisher College of Business Technology and Entrepreneurship Center (TEC) to provide an evaluation framework for use by the CWG.

11.2 Purpose

This document details AEP Ohio's gridSMART® Commercialization Plan that contains a process and framework developed by TEC and the CWG. This plan enabled AEP Ohio and Battelle to track commercial progress of smart grid technologies and report to the DOE how the Project has accelerated commercialization of smart grid technologies.

TEC and the CWG evaluated the commercial progress of selected technologies being developed within the Project and summarized key results and successes achieved by those commercial partners' technologies. In addition to technical and commercial progress, TEC and the CWG considered important societal benefits, including economic impact, job creation, and local benefits. TEC and the CWG provided an overview of the acceleration of commercialization achieved through the Project.

The CWG also created reports containing lessons learned, including best practices for commercialization, and elaborated on how lessons learned in the Project can benefit future technology development and energy product vendors. The aggregated evaluations from the various technologies developed a comprehensive set of market intelligence, tactical guidance, and a cost-benefit analysis for commercial partners based on a regulated utility market.

11.3 Roles and Responsibilities

This project was performed by three key groups: AEP Ohio, CWG, TEC, and the individual commercial partners.

The role of the CWG was to provide critical industry-wide insight into utility industry needs, trends, and other industry attributes to support the commercial evaluations and reporting. The CWG was ultimately responsible for gaining commercial partner approval to provide demonstration data to be delivered to the DOE as well as partner-specific insights into the technical and commercial opportunity for each commercial partner. They also shared market and technical data as well as conclusions based on laboratory and field testing to assess the commercialization progress. AEP provided resources to the CWG and made initial contacts to potential commercial partners to gain their support and involvement in the commercialization plan. Battelle provided data and resources to the CWG as required.

Technology Entrepreneurship and Commercialization Center (TEC) provided expertise in early-stage commercial evaluations as well as in evaluating a breadth of technologies and products in the context of a customized commercial framework. This evaluation was designed to fit the specific stage of product development or technologies of each commercial partner. Evaluations were used to assist in developing reports demonstrating progress of commercial partners related to the Project. TEC was responsible for gathering data from the CWG and commercial partners as well as performing secondary market research to support these efforts. TEC used multiple data sources to support preparation of reports describing the progress of the commercial partners and to communicate TEC's findings to the three key groups and the individual commercial partners.

The role of each commercial partner was to provide data necessary for the Project's reporting and the commercial progress evaluations. Individual commercial partners were responsible for providing data on the start-of-project, end-of-project, and periodic status updates describing technical and market development.

11.4 Methodology

The broad objective underlying commercialization was to drive innovation and technology-based economic development through advanced grid technologies. TEC worked closely with the CWG to develop a customized commercialization framework to assess and accelerate the commercial advancement of each commercial partners' technologies and products. This framework was used in parallel with the commercialization framework supported by the CWG to provide valuable market intelligence to commercial partners and establish and measure the societal benefits of the Project.

11.5 Commercialization Framework

The State of Ohio adopted a comprehensive framework for assessing the stage of commercial development for new technologies. Because of its relevance to economic development in Ohio and the degree to which the broader economic development community was familiar with this framework, TEC and the CWG decided to use the Commercialization Framework (see figure below) for the following purposes:

- To assess the progress of the overall Project for moving energy technologies closer to commercialization.
- To understand the specific opportunities and challenges each commercial partner faced along the commercialization path.
- To identify the key transitional resources that have enabled the commercial partners to have an economic impact.

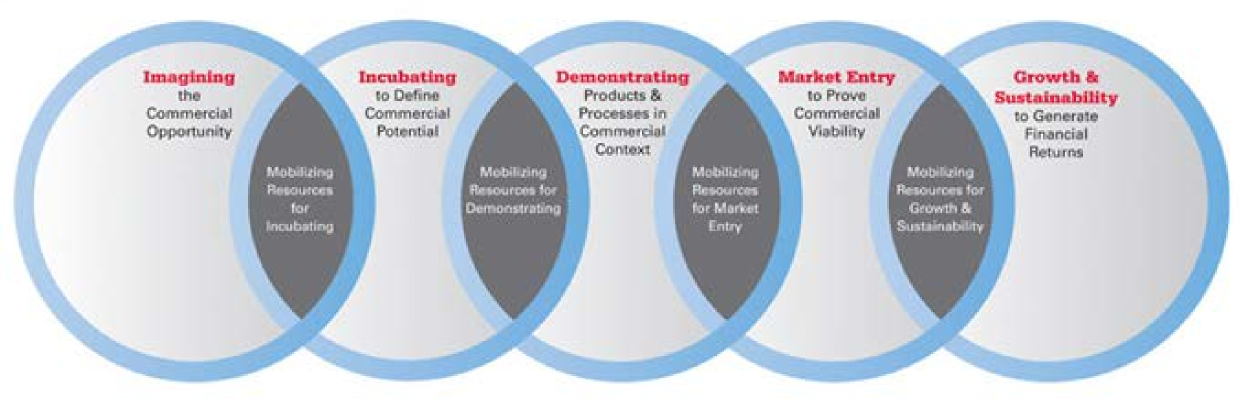

Figure 185. Commercialization Framework

An important benefit was the ability to track the progress of individual technologies and products as well as the overall evolution of the collection of technologies and products over time. The framework accommodated the layers of resources, activities, and engagements to capture the progression through various stages of commercialization.

The innovation process for the market introduction of new products and services involved a great deal of uncertainty. In order to understand how the participating companies progressed under these conditions, TEC and the CWG used the *Inside Innovation* framework to assess the unique factors, opportunities, and challenges each company managed during the Project. The Inside Innovation framework tracked progress on and iteration between three factors critical to innovation: Technology, Market, and Implementation[3] as defined below.

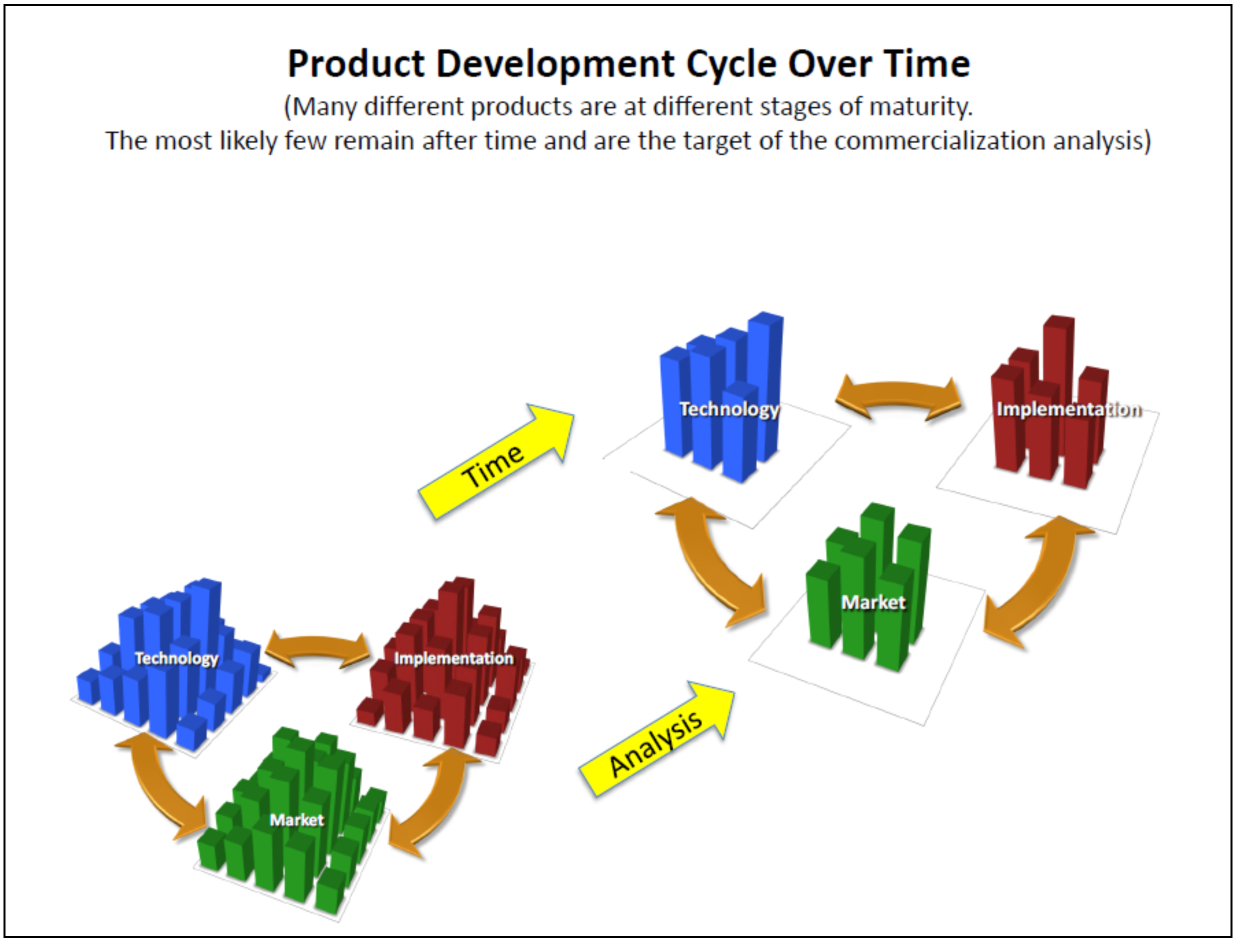

Figure 186. Inside Innovation Framework

Technology:	Technical factors that are objectively verifiable by scientific methods.
Market:	Individuals and organizations that actually use the proposed innovation, what value they perceive in the innovation, and what specific benefits they realize from its use.
Implementation:	The processes and transactional experiences that must occur to make the innovation functional in the designated market.

[3] Fitzgerald, E., Wankerl, A. and Schramm, C., Inside Real Innovation, World Scientific Publishing Co., Singapore, 2011.

TEC integrated and modified these models so that:

- They were uniquely effective at assessing the degree of innovation traction and economic impact in the gridSMART® Demonstration Project.
- They were useful for communicating the position and progress of each commercial partner and for the Project as a whole to the DOE.

11.6 Segments

Technical validation was performed through a three-segment process supported by AEP Ohio, Battelle, and utility industry members. The three segments included the following.

- Extensive laboratory testing
- Equipment field deployments
- Assessment by the commercial partner and the CWG

Equipment testing was performed by the commercial partners as well as at AEP's DTC facility. Field deployments and software simulation and modeling provided critical data for integration. Finally, the CWG met with commercial partners to review testing and field evaluation, to review performance against expected metrics, and to develop / refine business cases.

11.7 Factors

The CWG developed business cases that included a review of the core intellectual property and its readiness for commercialization, the viability of the commercial partner, estimated utility and/or consumer adoption of each technology, and the estimated market potential for the technology. The overall business case included the following.

- Potential revenues
- Utility, consumer, and societal costs and benefits
- Full consideration of the regulatory framework for recovery of costs and sharing of benefits

11.8 Impact on Technology Commercialization

TEC and the CWG performed detailed characterization of the commercialization progress for technologies and products listed in the *Commercialization Opportunities* table in this section. When necessitated by the gridSMART products budget, the technologies and products were selected and prioritized based on factors such as business alignment, stage of commercialization, probability for success, magnitude of projected benefit, and the commercial partner's willingness to engage in the process.

- For selected technologies at the imagining and incubation stages, TEC evaluated each technology according to TEC's Capabilities, Methods, Outcomes (CMO) methodology. CMOs provide a structure by which competitors' complementary technologies can be identified and compared. In addition, TEC provided basic market information such as market size or trends predicted for each selected technology, as well as an estimated break-even price to achieve market entry success.

- For innovations at the incubation and demonstration stages, TEC made available its Structured Concept Testing process, by which key features were articulated, key market targets were identified, features were validated with relevant market players, and an estimated breakdown price to achieve market entry success was determined.
- For products in the demonstration and market entry stages, TEC developed and assessed innovative business models, including assessing the industry value system, supply chain, pricing strategy, decisions about partnering/outsourcing, a cost-benefit model, core assets, and infrastructure costs.

For the selected technologies, three common dimensions of benefit were considered:

- **Benefit to Utility –** For all technologies, TEC assessed the market impact or prospective market impact of the innovation. The core of this assessment is a cost-benefit analysis that may be used to address regulatory considerations. Together, these considerations were aggregated into overall industry value drivers. In addition, TEC assessed the impact innovations have on competition, competitive behavior, and how markets operate.
- **Benefit to Consumer –** In addition to directly quantifiable benefits related to energy savings as a result of controlling time of use or direct rate impacts, TEC considered non-utility consumer benefits such as the impact of improved efficiency or reliability as identified by commercial partners or the CWG.
- **Broader Societal Impacts –** Beyond direct benefits to the utilities and consumers, TEC also considered the broader societal impacts of AEP Ohio's gridSMART Project with a specific focus on the efforts of its technologies and commercial products, such as educational benefits, workforce development, economic development, and diversity.

Suite/Product	Technology/ Product	Start-of-Project Status	End-of-Project Status
Distribution Automation	Distribution Management System and SSI Interface	Incubating	Market Entry
	Volt VAR Optimization	Incubating	Market Entry
	Volt VAR Optimization	Incubating	Market Entry
	Circuit Reconfiguration	Demonstrating	Growth & Sustainability
Cyber Security and Operations Center		Imagining	Demonstrating
Smart Appliances		Demonstrating	Growth and Sustainability
AMI Meters	Smart Meter	Demonstrating	Growth & Sustainability
AMI Communications	Communication to meter	Demonstrating	Growth & Sustainability
	Utility IQ	Demonstrating	Growth & Sustainability
Automobile	Electric Vehicles	Demonstrating	Growth and Sustainability
	Charging Stations	Incubating	Market Entry
Demand Reduction and Management	Grid Router / Home Energy Manager (HEM)	Imagining	Demonstrating
	enhanced Programmable Control Thermostat (ePCT) (COTS)	Market Entry	Market Entry
	Centralized Distribution Management System Control	Imagining	Incubating
	enhanced Programmable Control Thermostat (ePCT) (AEP Standard)	Imagining	Demonstrating
	enhanced Programmable Control Thermostat (ePCT) (Real-time Pricing - Battelle)	Imagining	Demonstrating
	SmartGrid Dispatch Engine	Imagining	Demonstrating
	In-Home Energy Display (Standard)	Imagining	Demonstrating
	In-Home Energy Display (real-time pricing)	Imagining	Incubating
Modeling, Analytical, and Simulation Tools	Grid Lab-D	Incubating	Demonstrating
	Integration of Grid Lab-D Open DSS and Near-real-time Power flow modeling	Imagining	Imagining
Consumer Programs	AEP Billing Engine (ABE)		
	Customer Engagement/ Characterization	N/A	Incubation
	Consumer Web Portals	Incubating	Demonstrating

Table 30. Commercialization Opportunities

11.9 Engaging Commercial Partners

Initially, AEP reached out to each commercial partner to introduce the technology Commercialization Plan and communicate the high-level benefits to the partners. The CWG then interviewed selected commercial partners in order to understand the specific inventions, products, business models, and other technical and commercial information.

TEC also worked closely with AEP Ohio to understand AEP Ohio's requirements and objectives. The CWG shared its perspective on market features, trends, and regulatory considerations. TEC performed primary and secondary market research and combined this data with the insights provided by the commercial partners and the internal gridSMART assessment team data. The value of TEC's evaluations depended directly on the engagement with the commercial partners and the quality of information shared. Participation by the commercial partners in the Project was voluntary, and TEC and the CWG appropriately safeguarded any confidential information.

11.10 Benefits to Commercial Partners

The selected commercial partners received valuable market intelligence, including opportunity size, industry trends, and value system analyses that augmented existing market intelligence. This information can be prohibitively expensive when purchased from traditional research organizations. In particular, commercial partners were able to improve product features and refine development plans based on customized assessments of competing technologies produced from public sources and insights into emerging technologies.

The market intelligence developed was tailored for the stage of development of each commercial partner. The independent economic and competitive analysis performed on behalf of the commercial partners could be used to confirm and validate internal business plans. However, the extent to which these analyses were performed was dependent on the amount of information obtained from public marketing materials.

The CWG also performed an economic assessment of the technology/product that was developed in the Project. In addition to topline market size, penetration estimates, and revenue potential, the CWG considered costs and benefits to the utility, consumer, and society as related to the subject innovation. These benefits were considered within a regulatory framework for recovery of costs and sharing of benefits.

Cooperation from each commercial partner ensured that the CWG and TEC were able to bring the highest quality data and analysis to bear on accelerating and guiding commercialization of each commercial partners' product or technology.

11.11 Commercial Partner Reports

Progress/status reports were provided to the Project team at regular intervals. These reports characterized the partner's stage of commercialization, their partners, resources, cost-benefit analysis, and other factors that governed the characterization and were the basis for commercial adoption. These reports also described the work performed and the results of that work to characterize the commercial partners as detailed in the Methodology section above.

Based on the interests of the commercial partners, alignment with Project goals, and budgets, commercial partner projects were selected and prioritized as necessary. Aggregating individual status reports helped to capture the path to commercialization taken by the commercial partner.

11.12 Project Report

The status reports and summary reports for commercial partners were used to prepare Project status reports that tracked the overall evolution of the portfolio of technologies and commercial products. The report highlighted commercialization trends, lessons learned, and best practices based on the evolution of the individual participants and a summary of overall Project effectiveness.

11.13 Commercialization Conclusions

Engaging vendor participants in the Commercialization effort allowed for assessment of commercialization opportunities including the market readiness of the emerging technologies and the economic impact of these commercial activities. While AEP provided the utility perspective, Battelle and TEC provided valuable analysis and insights regarding the product development. The Project successfully accelerated the commercialization of smart grid technologies through multiple stages of testing and guidance from the commercial partners.

11.13.1 Overarching Observations

The primary lesson learned from the Project was that external DOE funding was particularly effective at advancing technologies over regulatory or technical demonstration barriers. Products and technologies where DOE funding was especially meaningful include:

- Those that faced regulatory considerations, including rate structure limitations;
- Technologies that were in an early stage of technical development; and
- Products that addressed a need where the solution benefits from close collaboration among utilities.

In contrast, those technologies facing consumer adoption barriers benefited less substantially from DOE funding. Technologies which commercial advancement was more significantly supported by the DOE funding are Cyber Security, GridLAB-D, and Smart Grid Dispatch Engine (SGDE).

- Cyber Security was recognized by utilities as a priority prior to the Project. The Project adopted the Palisade suite of tools. More importantly, cyber security collaboration among utilities was a direct outcome of DOE funding. The collaboration between AEP Ohio and Lockheed Martin supported by the DOE funding has led to a more secure utility grid.
- Development of the Grid Command™ Distribution tool, used with GridLAB-D, accelerated development of the simulation environment up to the critical point of becoming practical to use by utility engineers and not solely by researchers. Enhanced simulation environments are enabling more rapid development and deployment of new grid capabilities. DOE funding was able to kick-start creation of this capability to a point where industry and academia is able to continue its refinement.
- For SGDE, the dearth of utility markets that allow demand-based residential pricing clearly discourages commercial enterprises from developing such a system. With DOE funding, the demonstration system was developed and possible. Policy makers can now use this information to evaluate if free-market pricing for residential electricity is desirable. Without DOE funding for this demonstration project, such decision would lack market pricing efficacy data in the electric utility domain.

End-user focused technologies that were not significantly impacted include the ePCT and GE Smart Appliances.

- In the case of ePCT, the initial product form was a thermostat with a programmable interface. While this feature was valuable for demonstration projects, the ePCT technology itself was already commercially viable, and so did not advance in the framework during the Project. The fact that the ePCT could be adapted to the real-time-pricing application was a strong endorsement of the flexibility of this device in the marketplace.
- The GE Smart Appliances also did not significantly advance in the framework. Because no national standard for communications between residences and utilities is imminent, this product was a weak fit for the Program. GE has since modified its approach with this technology toward a more appropriate business model focused on consumer connectivity and convenience.

The most significant impact of DOE funding can be seen in areas where DOE investment broadly impacted the industry, as opposed to a single utility or commercial partner. Cyber Security is the clearest example of such an impact as it is a pervasive concern throughout the utility industry. Cyber Security centers are now at each utility where DOE funding had a large impact.

Demonstration of the Home Energy Manager (HEM) had comparatively less impact given the level of investment. Each demonstration involved individual consumers, education, and buy-in. While long-term impact may be substantial, the impact-to-cost ratio for a technology like HEM was less than that for Cyber Security.

Another successful technology demonstration is Volt VAR Optimization (VVO). Because of the technical nature of the system and investment in engineering and sensors, the cost was significant. The potential improvement in grid performance and long term return clearly supported this demonstration.

11.13.2 Other Observations

11.13.2.1 Need for Technology-Stimulating Policy Considerations

Due to the dynamics of the regulatory environment, the Smart Grid Dispatch Engine (SGDE) faced a “chicken and egg” challenge. The current regulatory landscape does not widely support variable pricing and, therefore companies are unwilling to fund projects to develop technology that enables or streamlines variable (market-based) pricing. Potential vendors of technologies like SGDE seek clear signs from regulators that tariff structures might change.

The regulators are cautious in advancing variable pricing models absent clear demonstration that this type of system is viable. The developer of SGDE, Battelle, believes that the DOE funding helped move the technology ahead of the market. The Project demonstrated the viability of market-based pricing for residential utility consumers, and in a sense is “pushing the market” toward being able to consider such pricing schemes.

Recognizing a general societal preference for market choice, and a move toward choice in the electrical utility industry, it is reasonable to conclude that technology that enables true supply-demand market pricing fits with a broad underlying trend within the society.

11.13.2.2 Financing/Accounting/Investment Considerations

Traditionally, amortization periods for utility equipment are controlled in accordance with investments that must remain in place for many years. However, today’s smart grid technologies often have lifecycle dynamics more similar to computer and information technology than transmission infrastructure.

This resulted in recognition that even if a new technology proved to be effective in today’s environment, required amortization schedules would require carrying the asset on a utility’s books long beyond the end of its useful life. This accounting dynamic has direct implications on the adoption of emerging smart grid technologies.

The accounting practices of the utility industry were not a specific focus of the Project. The topic was recognized during discussions with commercial partners and utility professionals.

11.13.2.3 Results

DOE funding for the Project provided impetus and risk management for critical smart grid technologies. The complex nature of the smart grid is impacted by:

- Ratepayer preferences and preconceptions
- Current Electric utility practices and installed infrastructure
- Regulatory precedence and political considerations

DOE funding for the Project helped reduce hesitation in exploring new technologies and allowed participants to experiment with approaches and technologies that might have otherwise been considered too risky. This increased innovation accelerated learning and encouraged collaborations and, for some technologies, advanced their commercialization potential.

The technologies that advanced most with DOE funding were those that are more utility-centric, such as, Cyber Security, VVO, and GridLab-D. Those technologies that focused on ratepayers saw progress, but the greater number of individuals involved with ratepayer decision-making dampened the impact of DOE funding for those technologies.

A clear exception to this observation is SGDE, which bridges utility and ratepayer. For SGDE, DOE funding was essential, since a working model of a market-driven pricing for electric power is unlikely to be developed and implemented without external support. SGDE is important also because it provides early evidence supporting free-market based pricing for electricity, supporting general trends toward markets, and choice in the utility industry today.

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12 WORKFORCE PLANNING

12.1 Purpose

The purpose of the workforce plan is to provide a summary outlining the composition of the workforce required to support the AEP Ohio gridSMART® Demonstration Project implementation.

The workforce plan enables AEP Ohio to understand what workforce requirements are needed to successfully design, operate, and maintain the technologies and provides valuable information for future smart grid deployments.

12.2 Background

The emerging technologies of the Project required specialized skill sets to carry out their deployment. The legacy organizational structure and job descriptions did not easily accommodate the needed skill sets. As the Project progressed, the roles and responsibilities necessary to be effective were established. Resources were identified across the company, and those resources stepped up to contribute their talents to the Project. This staffing exercise further provided insight to workforce planning requirements for future smart grid implementations across the industry.

12.3 Challenges

It was critical to identify the resource requirements and existing gaps as part of the planning, implementation, and operation of gridSMART technologies. Challenges that affected the resource identification were:

- The traditional organizational structure is vertical in nature with the various functional areas established in silos. This structure posed a challenge for communication across impacted functional areas
- New technologies required skills from multiple resources across the organization.
- The project goals eliminated the need for certain positions, so it was necessary to identify ways to re-train and re-deploy existing resources.

12.4 Cross Functionality

The technologies implemented for the Project were more sophisticated than existing technologies and included multiple organizational disciplines. For example, Information Technology (IT) was a key resource for each of the technologies. IT's role included the need for such proficiencies as software support/ monitoring and data management/ analysis. These skills were needed to effectively implement and operate all facets of the Project technologies – engineering, equipment, operations, and consumer support. Existing job descriptions did not accommodate any single job that had a combination of the needed attributes.

Impacted functional areas identified as a result of the Project were:

- Information Technology (IT)
- Cyber Security
- Interoperability
- Information Privacy
- Telecommunications and Network Services
- Engineering
- Equipment Installation and Maintenance
- Operations
- Customer Service/ Call Center

Resources were identified for the purposes of the Project; however, future implementations of the technologies will require:

- Job descriptions/roles that blend proficiencies from multiple functional areas to achieve effective results.
- Re-training resources that are displaced due to the implementation of smart grid technologies. For example, meter readers that are displaced with AMI technology could be re-trained to support the technology in place of the previously required physical meter readings.
- Cross training of skill sets enables the transfer of knowledge and effective support across functional areas. This approach ensures day-to-day coverage and manages employee attrition more seamlessly.

12.5 Customer Service

A critical goal of the Project was managing customer satisfaction as they were introduced to new technologies and programs. More advanced skills in customer support were needed to be able to respond to inquiries and resolve issues because of the complexity of the technologies.

For future deployments of smart technologies, customer service representatives (CSR) will need to be trained in depth on all facets of a technology – the equipment, the technology system, the back office systems, and IT troubleshooting. This approach equips the CSRs with a comprehensive understanding of the technologies to be able to effectively troubleshoot and resolve issues.

12.6 Observations

The following information is the result of the experience and feedback from the different technology teams that participated in the Project as it pertains to workforce concerns.

- Provide additional employee resources to manage data as a result of the implementation of new software applications and the resulting data influx.
- Include sufficient time and resources to perform employee training. Identify key resources to train and cross train in specialized areas when implementing new and complex technology and processes. Keep up-to-date documentation and a knowledge database for specific roles to ensure continuity and ease of learning to mitigate employee turnover during the Project.
- Train customer service groups and representatives to support consumer inquiries immediately upon installation of new equipment and programs.
- Co-locate IT resources from both the utility/operations area and the research/development entity for better communication, more effective collaboration, and more efficient decision making.
- Leverage existing talent from within the company before bringing in external consultants. Provide specialized training to enhance the internal resources' value to the project.
- Build the technology team with key resources from both the utility and the R&D provider and co-locate them for better collaboration and a more efficient development process.
- Gain efficiencies with the expertise throughout the organization. Currently the expertise is within organizational silos.
- Provide the opportunity for employees to acquire new skill sets such as data analysis and network expertise. AEP's workforce developed knowledge of alarms and systems monitoring, which resulted in actionable work for field personnel.
- Ensure that experienced testers are available for system testing.
- Improve project manager continuity and technical support.
- Clarify and document essential roles and responsibilities.
- Implement a tiered technical support staff to install and maintain grid management systems.
- Create opportunities for existing engineers to add new competencies and expertise.

12.7 Industry Changes

As smart grid technologies become more prevalent across the industry and job descriptions change, it will be important to prepare the incoming work force:

- Redefine college curriculum to accommodate the new smart grid technologies associated with their power and telecommunications courses.
- Mentor and train incoming resources, so they are equipped to take on the new and blended roles as the currently aging work force retires.

- Utility companies will need to upgrade existing job descriptions and redefine new roles that include the blended skill sets.
- The organizational structure will need to adapt to support cross-cutting technologies.

12.8 Workforce Planning Conclusions

As a result of the Project, AEP Ohio recognized the inherent challenges associated with the existing workforce as effective resources for the Project and for smart grid technologies in general. As smart grid technologies emerge, one of the most critical concerns for effective implementation and ongoing operations will be newly defined job skills and the necessary training. Utilities must become more nimble to adjust workforce management policies and develop cross-functional work processes and training programs to facilitate the implementation of smart grid technology and ensure qualified personnel are retained.

13 LESSONS LEARNED

This section describes lessons learned for all demonstrated technologies. Others may find benefit from issues and solutions that AEP encountered, mitigated or resolved. Lessons Learned are provided for Technology, Implementation, and Operations.

13.1 Technology

- Smart grid technologies require a high level of interdepartmental coordination.
- Ensure communication network is designed and operational before field equipment is installed. Network optimization is essential to facilitate efficient operations.
- Develop robust test cases to ensure functionality of the systems.
- Monitor network equipment and components for performance and downtime.
- Perform a gap analysis on reporting tools and systems. Develop or purchase new tools where in-house technology does not exist.
- Align software development goals with ongoing operational systems.
- Identify project key personnel and conduct thorough training that includes hands-on access to the equipment they will be supporting.
- Allow sufficient time in the project plan to ensure the technology and processes are tested and ready for implementation to save time and costs and preserve positive consumer perceptions.
- Maintain a consumer-centric focus to help socialize new technologies and processes, grow positive consumer perception of the utility, and successfully participate in a competitive market.
- When developing and implementing smart grid technology, provide in-depth communication and training to regulators providing a better understanding of the tariffs and riders being requested.
- Perform thorough testing of all equipment and software in collaboration with vendor suppliers to ensure its readiness for implementation with consumers.
- Assess data management based on system and equipment potential for data volume. Estimate data storage requirements and plan/build data warehouse accordingly. Ensure all data is available for complete analysis and reporting.
- IT reporting and data mining applications need to be developed to turn the large amount of data into knowledge and identify which items the utility needs to take proactive action on.
- Work with vendors to ensure equipment interoperability. It is important for utilities and vendors to work together to enhance smart grid equipment resulting in interoperable devices, ensuring successful integration with existing systems.

13.2 Implementation

- When deploying multiple technologies, synchronize deployment to maximize efficiencies and reduce rework.
- Stringent processes are needed to gauge and mitigate interdependencies when new technologies are implemented.
- Vendor-managed and vendor- hosted technology implementation is the most cost effective strategy.
- Clarification and documentation of roles and responsibilities are essential in project planning.
- When technological issues arise, a root cause analysis must be performed to gain understanding and make improvements.
- Engage other utilities and industry experience to develop best practices in consumer outreach and education.
- A phased rollout approach allows for effective consumer communications. Consumers were engaged through letters, phone calls, door hangers, and mail communications pieces, emphasizing consumer benefits of the technology.
- Contract terms with vendors and service providers must address:
  - Documentation and key deliverables
  - Enumeration of roles and responsibilities
  - Service level expectations
  - User acceptance testing requirements
  - System acceptance testing requirements
  - Software/firmware licensing and support
- Customer service groups and representatives must be fully trained and ready to support consumer inquiries immediately upon installation of new equipment and implementation of programs.
- Allow sufficient implementation time to manage potential technology issues that may be identified following installation.
- Conduct focus groups and use surveys to gain a better understanding of the consumers' perceived benefits, enabling the team to better direct both the consumer education and the technology to the targeted consumers.
- Schedule time-sensitive pieces of the proposed tariffs and riders to ensure coordinated timing with the actual rollout of technology and equipment to consumers.
- Develop an integrated marketing and consumer outreach strategy for more effective coordination of schedules and operational controls to ensure cost and time savings.

- Testing, configuring and commissioning devices and automation schemes is more time consuming and complicated than stand-alone devices.

13.3 Operations

- Keep consumer messages simple, concise, and benefit-driven.
- Provide an education process for internal resources to enable them to act as ambassadors of the technology that strengthen consumer acceptance.
- Leverage internal resources and expertise whenever possible to ensure more control and involvement in decision making, development, and implementation.
- When selecting vendors, service providers, or partners, have more closely aligned goals that accommodate effective collaboration and consistent outcomes and deliverables.
- When a vendor performs updates to a user interface, application, or device, the documentation must also be updated accordingly. This documentation enhances consumer support as well as back office operations.
- Integrate AMI ping/poll functionality into major storm restoration efforts to reduce time and effort and maximize employee efficiency.
- Implement a sleep timer for meter power up messages to reduce communication losses for distribution automation operations. These messages will transmit at a predetermined time (set at five minutes). The five-minute delay would allow the DA commands and status indications to pass without competing with meter messages for communication resources.
- Align regulatory requirements to maximize impact of technology capabilities to operations.For example, eliminate connect/disconnect site visit requirements to efficiently use remote capabilities.

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14 PROJECT CONCLUSIONS

14.1 Introduction

The AEP Ohio gridSMART® Demonstration Project was designed to evaluate a broad scope of potential smart grid technologies in order to guide subsequent deployment plans. AEP Ohio has not only gained valuable experience in the performance of these technologies, but also in the operation of communication interfaces and how to optimize the processes to deliver the benefits envisioned. This experience prepares AEP Ohio for a more efficient and effective implementation as it deploys select technology and process improvements across the AEP Ohio service territory.

The following benefits have been achieved as a result of the Project:

- Improved safety for AEP Ohio employees
- Operational efficiencies through real-time information and remote operations
- Improved access to meter reading data
- Fewer number of consumer outage events
- Reduced number of consumers experiencing sustained (>5 minutes) outages
- Faster restoration times for sustained outages (>5 minutes)
- Demand reduction through new tariff offerings and the education of consumers regarding energy costs and use of technology
- Improved energy efficiency and demand reduction
- Improved customer satisfaction

The DOE funding was instrumental in advancing smart grid technologies and ensuring Project success. DOE funding was especially meaningful for the following areas:

- Regulatory considerations, including rate structure limitations
- Technologies that were in an early stage of commercial development
- Products that addressed a need where the solution benefits from close collaboration among utilities
- Best technologies for moving from an integrated utility to one functioning in a deregulated market
- Information sharing to promote a secure and interoperable system

14.2 AMI

The Project demonstrated several operational benefits. For instance, by installing AMI meters, AEP Ohio eliminated 100 percent of the meter reading routes (187 routes) in the area where AMI was deployed. AMI also enabled AEP Ohio to reduce costs associated with meter operations activities.

For example, through the use of remote service switch capabilities that enable secure connection and disconnection of electric service to customer premises from the utility back office, AEP Ohio reduced field visits associated with standard move in/move out orders. The combined meter reading and meter operations savings totaled approximately $859,100 ($7.81 per meter per year).

Category	Project area result
AMI Meters	110,000
Meter Reading and Meter Operations Savings (annual)	$859,100 ($7.81/meter)

Table 31. AMI Meter Benefits

Credit, collections and revenue enhancements through earlier theft detection, lowered consumption on inactive meters and greater billing accuracy led to additional savings and benefits.

AMI offered a host of important benefits, including:

- Improved data for billing
- Better customer service and satisfaction
- Reduced outages
- Improved crew and meter reader safety
- Reduced environmental impact

Note: The above benefits have not been monetarily quantified.

With automated meter reads, AMI nearly eliminated estimated bills, improving billing accuracy. AMI yielded a typical monthly read rate of 99.9 percent, leading to greater billing accuracy and improved customer satisfaction.

AMI led to better customer service. For instance, when a consumer wanted to terminate service, the AMI meter could be read remotely and a final bill sent without delays caused by manual reads. Similarly, AMI meters equipped with a remote service switch enable power to be turned on or off remotely. As a result, a consumer moving in could have service turned on in minutes, rather than waiting days.

AMI provided consumers with the ability to view their energy consumption on a more granular level; typically multiple data points per day were provided. This data provided consumers a better understanding of their consumption behavior. The availability of this data also enabled consumers to participate in consumer programs. These programs were designed to reduce peak demand, thereby allowing consumers to benefit through savings.

AMI also provided billing and customer service efficiencies that enabled AEP Ohio to quickly address inquiries. Consumers experienced fewer billing issues from continual meter reads and the elimination of estimated meter reads through AMI. Company representatives had near real-time access to meter data that helped them discuss actual usage information with consumers.

When a consumer called about power loss, the near real-time access also enabled the company to determine whether the power loss was due to an outage or to an issue on the consumer side of the meter, such as a blown house breaker fuse.

From a reliability perspective, when an AMI meter detected a loss of voltage, a message was sent indicating the consumer had lost power. Messages that successfully reached AEP Ohio's internal systems were used in conjunction with consumer telephone calls to predict the extent of the outage. Also, meters were queried (pinged/polled) to get an indication of whether a consumer had power. This indication was useful to troubleshoot consumer issues and to verify restoration following an outage.

From a safety perspective, because crews could remotely determine whether a meter had power, crew exposure and safety were improved. Also, due to AMI, fewer meter readers were required in the field, which reduced physical meter reading efforts and, thus, reduced safety issues.

With remote capabilities, the number of miles driven by metering and service personnel was reduced. In addition, there were environmental benefits associated with reduced vehicle emissions as a result of reduced vehicle miles traveled.

14.3 Consumer Programs

AEP Ohio offered consumer programs as part of the AEP Ohio gridSMART Demonstration Project. AMI provided consumers with the ability to view their energy consumption on a more granular level, which provided a better understanding of consumption behavior. Consumer programs were designed to reduce peak demand, thereby allowing consumers to benefit through savings.

Consumer programs provided significant net benefit to consumers. These programs were:

- SMART Shift^{SM} two-tier time-of-day tariff
- SMART Shift Plus^{SM} three-tier Time-of-Day with Critical Peak Pricing
- SMART Cooling^{SM} direct load control (DLC) program
- SMART Cooling Plus^{SM} DLC program
- SMART Choice^{SM} real time pricing with double auction
- eView^{SM} consumer usage feedback device

Additionally, Home Area Network (HAN) devices were used by consumers to better use data and pricing signals to control their consumption activity.

The consumer programs proved to be a technical success and were accepted by consumers. Consumers who participated in AMI-enabled consumer programs rated their overall satisfaction with AEP Ohio higher than did AEP Ohio consumers overall.

The Project engaged in a public outreach and education plan which played a key role in the successful implementation of consumer programs. A multi-pronged communications approach engaged key community thought leaders, consumers, and other targeted audiences by providing timely and thorough information regarding the overall Project, timeline, rollout and benefits of the technologies. The plan clearly communicated with communities and consumers to ensure acceptance, which ultimately led to higher customer satisfaction and retention rates.

The proposed AEP Ohio gridSMART Phase 2 will deploy AMI meters with communication modules to enable in-home communication from the meter. This communication facilitates consumer program offerings. AEP Ohio views its role as a provider of the metering infrastructure that enables the offering of these programs by market participants. AEP Ohio envisions that Competitive Retail Electric Service (CRES) providers will take the lead role in these enhanced customer program offerings.

14.4 Real Time Pricing with Double Auction

AEP Ohio was able to successfully demonstrate an experimental tariff that allowed consumers to take advantage of fluctuating energy pricing. The Project demonstrated that the approximately 250 participating consumers were able to shift their energy consumption and paid less for energy by using RTP_{da} technology. The experimental program worked as designed resulting in net benefits to the consumers and the utility.

Challenges would need to be addressed before considering future deployments. AEP Ohio was often required to make multiple trips to consumers' homes to install, commission, and ensure functionality of RTP_{da} equipment. Once installed, there were reliability issues; some with the equipment itself as well as with the communications between the various devices and the back-office systems. Cellular service was not available in all parts of the Project area, which did not allow those consumers to participate in the program. The combined cost of equipment and communications was significant and, when compared to other consumer programs, the RTP_{da} program provided less financial value to consumer and utility.

14.5 DACR

The Project, through the deployment of DACR on 70 circuits, was able to reduce Customer Minutes of Interruption (CMI), improving reliability. While weather conditions are the primary driver for changes in SAIFI and CAIDI, AEP Ohio attributed some improvements of these indices from the DACR deployment. All consumers on the 70 DACR circuits experienced improved SAIFI and SAIDI.

In addition to the reliability benefits described above, the systems also enabled crew labor savings, up to 2 hours per event, and in some instances avoided service calls entirely. Both of these situations provided opportunities for AEP Ohio to perform additional proactive work on circuits in need of service, further enhancing reliability.

Improved system reliability has significant impact on economic output too. Based on the *Cost of Power Interruptions to Electricity Consumers in the United States, Ernest Orlando Lawrence Berkeley National Laboratory* (2006), AEP Ohio, if expanded to an additional 250 circuits, estimates that DACR could reduce societal costs by approximately $71 million per year through the reduction of outages experienced by consumers.

14.6 VVO

The Project VVO demonstration was designed to realize a reduction in energy consumption and a reduction in peak demand on circuits where VVO was deployed.

Voltage standards exist in the electric utility industry, such as ANSI C84.1, that mandate an acceptable voltage range at the secondary of the distribution transformer. VVO enabled a reduction of the average voltage that each customer on the circuit received, thereby reducing the annual energy consumption of the circuit while maintaining the quality of service to the end-use consumer. Based on results obtained through field demonstrations, AEP Ohio estimates that a 3 percent reduction in energy consumption and a 2 to 3 percent reduction in peak demand can be obtained on those circuits on which the technology is deployed.

Along with the efficiency benefits, the technology associated with VVO also provided VAR support, offsetting the need for Generation and Transmission resources to provide VARs. The technology required for VVO augmented other technologies to improve visibility into system performance and circuit automation.

14.7 Security and Interoperability

The Project implemented innovative advancements in the cyber security and interoperability arena. The Project was able to validate secure two-way communications from AEP systems through consumer premises. The Project engaged in penetration and interface testing to facilitate this validation.

The Project developed and implemented a state of the art Cyber Security Operations Center (CSOC). The CSOC continuously provided advanced security checks, monitored the network, and identified vulnerabilities and threats to ensure grid security. The CSOC, with its industry threat sharing integration functionality, continuously gathered and shared threat information with peer utilities and government agencies.

AEP Ohio treated consumer consumption data collected through the smart grid with a high level of protection. Consumers were assured that the safety and security of their information were protected by extensive and dedicated resources.

The Project cyber security and interoperability efforts have led the development of industry standards. AEP Ohio will continue to strive to improve interoperability, security, and consumer protection. AEP Ohio will continue to use the CSOC and dedicated security and privacy experts to review smart grid technologies and equipment to ensure strict standards are met. AEP Ohio will continue to place emphasis on building interoperability, security, and privacy into future deployments.

14.8 Next Steps

The AEP Ohio gridSMART Demonstration Project successfully demonstrated the deployed technologies. AEP Ohio submits that a gridSMART expansion enables a fundamental change in the way the company operates, serving as the necessary foundation upon which AEP Ohio will provide more reliable service and greater efficiency opportunities for consumers. AEP Ohio has filed the AEP Ohio gridSMART Phase 2 (Phase 2) plan with the Public Utilities Commission of Ohio to extend elements of gridSMART throughout AEP Ohio's service territory.

Phase 2 builds upon the Project's success. It includes Advanced Metering Infrastructure (AMI) for approximately 894,000 customers across urban and suburban areas; Distribution Automation Circuit Reconfiguration (DACR) for approximately 250 circuits; and Volt VAR Optimization (VVO) for approximately 80 circuits. AEP Ohio is targeting a deployment timeline of approximately four years for all three technologies as proposed. In addition to extending the benefits of AMI, DACR, and VVO achieved by the Project to a larger base of consumers, it is envisioned that Phase 2 also will provide the following benefits:

- Support for a more robust consumer choice market by enabling consumer access to information, improved data for market settlement, and potential for time-differentiated rate design offerings.
- Reduced uncollectible revenue, theft and consumption on inactive meters through automated remote disconnect and continuous usage data availability.
- Enhanced customer service and satisfaction (for example, through faster, remote service connection).
- Better information to consumers concerning their electricity usage, enabling them to conserve energy, save money, and help to protect the environment.

Phase 2 is built upon proven technologies and solutions that have been implemented in the Project and broadly deployed in the market. Phase 2 will extend the benefits demonstrated in the Project and deliver additional benefits to a broader set of consumers. Through Phase 2, the company expects to:

- Drive significant financial benefits.
- Positively impact customer service and customer satisfaction.
- Improve safety performance.
- Improve regional economic output.
- Reduce environmental impacts.
- Enable CRES providers to offer valuable consumer programs.
- Improve CMI where DACR is deployed.
- Avoid millions of dollars of potential lost economic productivity annually.
- Generate significant efficiencies that translate to consumer savings.

GLOSSARY OF TERMS

Word/Phrase	Definition
Access Points	Access Points – Devices that connect the radio frequency mesh network linking all intelligent endpoints to the utility's backhaul or wide area network links.
Active Load	In the RTP_{da} program, the amount of responsive load that cleared to run in the market period – participation in an auction.
American Electric Power	American Electric Power is one of the largest electric utilities in the United States, delivering electricity to more than 5 million customers in 11 states. AEP ranks among the nation's largest generators of electricity, owning nearly 38,000 megawatts of generating capacity in the U.S. AEP also owns the nation's largest electricity transmission system, a nearly 39,000-mile network that includes more 765 kilovolt extra-high voltage transmission lines than all other U.S. transmission systems combined. AEP's transmission system directly or indirectly serves about 10 percent of the electricity demand in the Eastern Interconnection, the interconnected transmission system that covers 38 eastern and central U.S. states and eastern Canada, and approximately 11 percent of the electricity demand in ERCOT, the transmission system that covers much of Texas. AEP's utility units operate as AEP Ohio, AEP Texas, Appalachian Power (in Virginia and West Virginia), AEP Appalachian Power (in Tennessee), Indiana Michigan Power, Kentucky Power, Public Service Company of Oklahoma, and Southwestern Electric Power Company (in Arkansas, Louisiana and east and north Texas). AEP's headquarters are in Columbus, Ohio.
AEP Ohio	Ohio Power Company is a unit of the American Electric Power System and does business as AEP Ohio. It is the surviving entity of the merger with Columbus Southern Power Company. It is the electric utility distributing electricity to portions of Ohio and West Virginia and is the award recipient.
AEP Ohio gridSMART® Demonstration Project	One of the sixteen (16) ARRA- funded Smart Grid Demonstration Projects (SGDP) awarded by DOE to AEP Ohio.
Bridge	Device used to create a connection between two separate computer networks or to divide one network into two.

Word/Phrase	Definition
Customer Average Interruption Duration Index (CAIDI)	The average outage duration that any given customer would experience in a sustained outage. This index is calculated by dividing the total consumer minutes of interruption by the number customers interrupted.
Circuit	The wired power grid infrastructure distributing electricity from an electric utility
Check Read	An on-demand meter reading
Columbus Southern Power (CSP)	Columbus Southern Power is the original award recipient, and was merged out of existence with Ohio Power Company.
Distribution Automation Circuit Reconfiguration (DACR)	Automatic circuit configuration for recovery from electric faults.
Direct Load Control (DLC) Event	To respond to a period of high energy demand, the utility sends signals to Home Area Network (HAN) devices in the consumer residence to reduce usage.
Direct Load Control (DLC) Rider	The mechanism by which participation in the DLC program is reimbursed for participation. A credit is applied to the monthly bill.
Double Auction	A process of buying and selling where competitive buyer bids (demand bids) are matched with competitive seller offers (supply bids). Potential consumers submit their bids for energy based on the smart appliances' needs and the electric utility simultaneously compiles an asking price related to the quantity of energy supplied. The system combines the received consumer bids for energy and compares this cumulative bid curve with the electric utility's cumulative generation and purchase cost curve to determine the market cost for energy to be consumed. The intersection of the cumulative demand bid curve with the energy supply cost curve is the resulting market value or the clearing price of energy for the present time increment. The clearing price is the actual price paid for energy by the consumer but limits and adjustments, such as cost correction factors, may be applied before the clearing price is determined.
Circuit	The wired power grid infrastructure distributing electricity from an electric utility.
Feeder	See Circuit.
Grid	The wired infrastructure, above and below ground, which distributes electricity from the electric utility to the consumer.
gridSMART®	The AEP registered trademark for implementation of smart grid technology.

Word/Phrase	Definition
Inactive Load	In the RTP_{da} program, the amount of responsive load that did not clear to run in the market period – nonparticipation in an auction.
Last Gasp (outage) message	The alarm message sent by the AMI meter that power has gone out. A capacitor in the meter discharges to send a signal over the communications network prior to losing power.
Momentary Average Interruption Frequency Index (MAIFI)	The average number of momentary interruptions that a consumer would experience. This is calculated as the total number of consumer momentary (<=five minutes) interruptions divided by the total number of consumers served.
Must-Run State	During an RTP_{da} auction when the observed temperature exceeds the offset set temperature, the HEM increases the bid price to the maximum and no further temperature adjustments to the ePCT are made.
Ohio Power Company	The unit of the American Electric Power System that distributes and sells electricity in Ohio and West Virginia, the surviving company of the merger with Columbus Southern Power Company. It is also known as AEP Ohio, the name used throughout this report.
Outage Response Time	In this report, the time between notification of an outage and when AEP Ohio declares an outage and dispatches a crew.
Peak Load	The maximum amount of power that is used or produced by consumers over a defined period of time.
Peak Load and Mix	The analysis of peak load at a point in time and the different types of consumers contributing to that peak (residential, commercial, and industrial). Consumers are on different tariffs and in different demographics.
Ping/Poll	A process that determines the availability of a network devices or interfaces by using an echo request.
PJM Interconnection LLC (PJM)	A Regional Transmission Organization (RTO) in the United States.
Project	AEP Ohio gridSMART Demonstration Project, awarded to Ohio Power Company by U.S. DOE (award number DE-OE0000193).
Project area	The Project area is located in the northeast quadrant of Central Ohio.
Rate	The cost of electricity per unit of measure.
Residential Peak Day	The peak load consumed by residential consumers on a week day.
Rebate	A credit applied to consumers' electricity bill for their participation in certain types of programs.

Word/Phrase	Definition
Relay	A device that extends the radio frequency signal in places where meters are not located and an Access Point is out of reach. A relay can be deployed on pole tops or building floors and can efficiently augment and retransmit the radio frequency signal.
Responsive Load	The sum of all the RTP_{da} HVAC loads on the circuit.
Rider	A rate mechanism that collects or refunds costs for specific projects or services.
System Average Interruption Duration Index (SAIDI)	The average outage duration that any given customer would experience in a sustained outage. This index is calculated by dividing the total customer minutes of interruption by the number of customers served.
System Average Interruption Frequency Index (SAIFI)	The average number of sustained interruptions that a customer would experience. This index is calculated as the total number of consumer sustained interruptions (>five minutes) divided by the total number of consumers served.
Smart Grid	A suite of existing and emerging concepts, technologies, tools, techniques, and system configurations that can be innovatively applied and integrated to improve technical, operational, efficiency, reliability, safety, and environmental impact of electricity consumption.
Smart Grid Demonstration Program (SGDP)	The 16 U.S. Department of Energy projects demonstrating new and more cost-effective smart grid technologies can be applied and integrated to significantly improve technical, operational, and business-model feasibility. See www.smartgrid.gov.
eView℠ SMART Shift℠ SMART Shift Plus℠ SMART Cooling℠ SMART Cooling Plus℠ SMART Choice℠	The AEP Ohio branded Consumer Programs demonstrated by this Project.
Smart Meter	A utility meter capable of two-way communication with the utility company.
System area	The System area is the area served by Columbus Southern Power in 2009; approximately 750,000 electricity consumers. This was established at the beginning of the Project. CSP merged with Ohio Power Company and is known as AEP Ohio.
System Peak Day	The peak load of a combination of circuits that constitute the utility company footprint on a given day.
Tariff	A Public Utilities Commission of Ohio (PUCO) approved algorithm for the electricity utility to use in charging and billing consumers for the use of electricity.

Word/Phrase	Definition
Unity	Refers to a power factor of 1.0 that is obtained when current and voltage are in phase.
Unresponsive Load	In the RTP_{da} program, the total circuit load minus the responsive load during the market period on the circuit.
VAR	Volt-ampere reactive, a component of electricity on the grid.
Volt VAR Optimization (VVO)	A demand-side management program that reduces energy consumption and demand without consumer interaction or participation

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LIST OF ACRONYMS/ABBREVIATIONS

Acronym	Definition
AC	Alternating Current
ACE	AEP Cost Engine
AMI	Advanced Metering Infrastructure
ANSI	American National Standards Institute
ARRA	American Recovery and Reinvestment Act of 2009
BEV	Battery Electric Vehicle
CARB	California Air Resources Board
CAIDI	Customer Average Interruption Duration Index
CES	Community Energy Storage
CIM	Common Information Model
CMI	Customer Minutes Interrupted
CO_2	Carbon Dioxide
CP	Consumer Programs
CPP	Critical Peak Pricing/Price
CRES	Competitive Retail Electric Service
CSOC	Cyber Security Operations Center
CVVC	Coordinated Volt VAR Control
CWG	Commercialization Working Group
DA	Distribution Automation
DAC	Distribution Automation Controller
DACR	Distribution Automation Circuit Reconfiguration
DLC	Direct Load Control
DMS	Distribution Management System
DNP	Distributed Network Protocol/Disconnection for Nonpayment
DOE	U. S. Department of Energy
EOL	End-of-line
EPA	Environmental Protection Agency
ePCT	Enhanced Programmable Communicating Thermostat
EVSE	Electric Vehicle Supply Equipment
FRO	Field Revenue Operations
FTP	File Transfer Protocol
GQM	Goals, Questions, and Metrics
GridLAB-D	Smart Grid Simulator Utility
HAN	Home Area Network
HEM	Home Energy Manager
HVAC	Heating, Ventilation, and Air Conditioning
ID	Identifier
IEC	International Electrotechnical Commission
IHD	In-home Display
IMU	Interface Management Unit
IT	Information Technology

Acronym	Definition
kVARh	kiloVolt-Amp-reactive-hour
LCS	Load Control Switch
LMP	Locational Marginal Price
MAIFI	Momentary Average Interruption Frequency Index
MDM	Meter Data Management
MFR	Multi-Feeder Reconnection
MRO	Meter Revenue Operations
NIST	National Institute of Standards and Technology
NO_X	Nitrogen Oxides
OMS	Outage Management System
PCT	Programmable Communicating Thermostat
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PJM	PJM Interconnection LLC
PUCO	Public Utilities Commission of Ohio
PV	Photovoltaics
RF	Radio Frequency
RTP_{da}	Real Time Pricing with Double Auction
RTPi	Real Time Pricing Integration Layer
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	Supervisory Control and Data Acquisition
SGD	Smart Grid Dispatch
SO_2	Sulfur Dioxide
SO_X	Sulfur Oxides
TERS	Trouble Entry Reporting System
TOD	Time-of-Day
TOD/CPP	Time-of-Day with Critical Peak Price
UIQ	UtilityIQ®
VAR	Volt-Ampere Reactive
VOT	Virtual Operations Test
VVO	Volt VAR Optimization

APPENDIX A – ENVIRONMENTAL REFERENCES

This Appendix contains a list of conversion constants used in the calculations associated with the Impact Metric analysis. These factors were either provided by AEP to Battelle when they were specific to utility operations or by Battelle for standardized engineering calculations.

AEP-Authored Conversion Factors

[CF-AEP-01] Meter event labor cost for truck roll avoided $20.00

This factor provides a dollar value representing the amount of labor saved for each truck roll avoided due to AMI.

[CF-AEP-02] Meter event labor cost truck roll added $50.00

This factor provides a dollar value representing the amount of additional labor required for each new truck roll required due to AMI.

[CF-AEP-03] Short truck roll avoided vehicle cost - switching event $7.50

This factor provides a dollar value representing the vehicle related savings for each short truck roll avoided due to circuit reconfiguration DA.

[CF-AEP-04] Standard truck roll avoided Vehicle Cost - switching event................ $45.25

This factor provides a dollar value representing the vehicle related savings for each standard truck roll avoided due to circuit reconfiguration DA.

[CF-AEP-05] Short truck roll avoided Labor Cost - switching Event $15.75

This factor provides a dollar value representing the labor savings for each short truck roll avoided due to circuit reconfiguration Distribution Automation.

[CF-AEP-06] Standard truck roll avoided Labor Cost - switching Event................... $94.00

This factor provides a dollar value representing the labor savings for each standard truck roll avoided due to circuit reconfiguration Distribution Automation.

[CF-AEP-08] $/CMI $0.052

This factor provides a dollar value representing the savings associated with avoiding one customer minute of interruption.

Battelle-Authored Conversion Factors

AMI

CO_2: 8.8kg/gal gasoline; 10.1 kg/gal diesel

Source: United States EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-05-001)

SO_x: 0.165 g/gal gasoline; 0.0963 g/gal diesel

Calculated from: sulfur content of gasoline = 30 ppm

Source: U.S. EPA 40 CFR parts 80, 85, and 86 AMS–FRL–6516–2

Sulfur content of ULSD diesel fuel = 15 ppm

Source: U.S. EPA Office of Transportation and Air Quality Emissions Facts (EPA420-F-00-057)

Molecular weight of SO_2 = 64 g/mole

Density of gasoline = 2.75 kg/gallon

Density of diesel fuel = 3.21 kg/gallon

NO_x: 0.05 g/mi

Source: United States EPA 40 CFR part 86 Subpart S Tier 2 Bin 5 Emissions limits at 50,000 mi

$PM_{2.5}$: 0.01 g/mi

Source: United States EPA 40 CFR part 86 Subpart S Tier 2 Bin 5 Emissions limits at 100,000 mi

Consumer Programs

CO_2: 0.00068956 tons/kWh

Source: U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region

SO_x: 0.00263084 kg/kWh

Source: U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region

NO_x: 0.00117934 kg/kWh

Source: U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region

$PM_{2.5}$: 0.001 kg/kWh

Source: U.S. EPA eGRID2012 Version 1.0 Year 2009 Summary Tables for RFC West Region

DACR and VVO

Note that DACR conversion factors are the same as that for AMI and that VVO conversion factors are the same as that for CP.

APPENDIX B – PACIFIC NORTHWEST NATIONAL LABORATORY REPORT WITH REAL TIME PRICING

U.S. DEPARTMENT OF ENERGY

PNNL-23192

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

AEP Ohio gridSMART® Demonstration Project Real-Time Pricing Demonstration Analysis

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February 2014

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PNNL-23192

AEP Ohio gridSMART® Demonstration Project Real-time Pricing Demonstration Analysis

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February 2014

Prepared for
the U.S. Department of Energy
under Contract DE-AC05-76RL01830

Pacific Northwest National Laboratory
Richland, Washington 99352

Summary

This report contributes initial findings from an analysis of significant aspects of the American Electric Power, Ohio (AEP Ohio) gridSMART® Real-Time Pricing – Double Auction (RTP_{da}) demonstration project (the Project). Over the course of four years, Pacific Northwest National Laboratory (PNNL) worked with Ohio Power Company (the surviving company of a merger with Columbus Southern Power Company), doing business as AEP Ohio, and Battelle Memorial Institute to design, build, and operate an innovative system to engage residential consumers and their end-use resources in a participatory approach to electric system operations, an incentive-based approach that has the promise of providing greater efficiency under normal operating conditions and greater flexibility to react under situations of system stress. The material contained in this report supplements the findings documented by AEP Ohio in the main body of the gridSMART report. It delves into three main areas: impacts on system operations, impacts on households, and observations about the sensitivity of load to price changes.

The RTP_{da} system operated from December 2011 through the fall of 2013. An adequate population of households for system experiments was achieved in the late spring of 2013. As air conditioning equipment was the only type of load under RTP_{da} control, and as the great majority of this equipment only operated in cooling mode, the period of analysis was set from June 1 to September 30, 2013. The system was designed to collect a large amount of operational data, including the status of the enhanced programmable communicating thermostat (ePCT) parameters, indoor temperature, household energy consumption, and the RTP_{da} market data (such as household and supply price and quantity bids, market cleared price, and total distribution feeder[1] load). This was supplemented by data from the meter data management system, the billing system, weather data, and demographic data about the households (such as square footage and type of construction).

As with any operating system, the data are incomplete and testing behavior can pose challenges. Gaps in data from communications errors, equipment failures, and the like offered challenges to the analysis and add a level of uncertainty to the findings. In addition, the investigation found that the Project's plans to frequently exercise the RTP_{da} system with congestion events imposed on the households to observe their response under different circumstances (for example, days of week, times of day, and temperature conditions). A congestion event occurs when the load level of a distribution circuit (otherwise known as a feeder) exceeds the capacity limit of the feeder. Operators can impose a congestion event by setting the capacity limit below the present load level. This causes the market clearing process to drive prices higher. The investigation found that by frequently imposing congestion events, the resulting high prices desensitized the response of the equipment to normal market fluctuations when not in a congestion event. Once problems such as these were uncovered, the analysis attempted to compensate for their impacts, and thus come closer to a more accurate picture for addressing the questions under investigation. Simulations of the RTP_{da} system were also performed to help address some of these challenges and to scale the household resources to a size that allows for the investigation of system impacts.

[1] The term "distribution feeder" refers to the electric line that feeds a community of houses and terminates in a distribution substation. This is also known as a distribution circuit, as used elsewhere in the AEP Ohio gridSMART Demonstration Project Report. For the sake of brevity it is referred to simply as a feeder in this document.

The findings confirm the basic premise correlating reduction of short-term energy use with price increases and conversely, increase in energy use with price decreases. From a system impact point of view, simulations show that with a 35% penetration of RTP_{da} households, a load reduction of about 5% can be obtained for a 3.5-hour system peak event. For a 2-hour local, feeder peak event, a nearly 8% load reduction can be obtained. Regarding the impact on 5-minute wholesale energy purchases, the field data analysis indicates that, if there were no congestion events, overall energy consumption by the average RTP_{da} household could be reduced by over 5% and wholesale costs could similarly be reduced by 5% compared with the average non-responsive control group household. Simulations of the same wholesale impacts report an average of 1.2% reduction in energy consumption per household and 2.5% reduction in wholesale energy costs.

Consumer impacts studied include household bills, their thermostat statistics, and the actual energy use of the air conditioning equipment. When the RTP_{da} households' bills are computed using the RTP_{da} tariff versus the standard tariff, the study shows that there is good dispersion of relatively minor increases and decreases across all household energy use levels. Average monthly bills decrease slightly using the RTP_{da} tariff, thanks largely to the incentive savings. When investigating the average RTP_{da} bill compared to a calculation of the average bill of the non-responsive control group on the standard tariff, the analysis indicates about 5% reduction in the average RTP_{da} household bill, with a slight increase in overall energy usage. The components that appear to contribute to the average bill reduction are the incentive payments from the frequent congestion events and the flexibility to alter energy use in response to market price fluctuations. The energy usage is not reduced as reported in the wholesale energy purchases above because the congestion events are not excluded in this analysis as they were for the wholesale purchases analysis. Simulations indicate a roughly 4% savings in RTP_{da} bills versus the same households on the standard tariff that are not responding to price signals and incentives.

A study of thermostat settings shows a wide variety of settings by consumers with some indications of clusters, such as those who prefer more comfort and those who balanced comfort and economy more. To study consumer learning patterns, their behavior would need to be monitored for a longer period of time that included multiple seasons. The congestion events indicate that only 4% of the consumers overrode their thermostat setting at some point during the 2-hour events, whereas 10% of the consumers overrode their thermostat setting at some point during the 4-hour events. This provides some verification of consumer fatigue that would need careful attention in operating such programs. Lastly, the amount of energy bid in the market for the air conditioning units appears to have been underestimated from the observed energy draw on these units. The amount of energy bid into the real-time market should be more accurate in a full-scale deployment.

To analyze the sensitivity of load to price changes, the energy data measured at 5-minute intervals for each household was correlated with the corresponding 5-minute wholesale market information. Though the distribution of individual household responses is quite scattered, a filtering of the information corroborates the expectation that energy use decreases when price increases. This is particularly pronounced during hot periods when there is a great deal of air conditioning load operating in the presence of high, but fluctuating, energy prices. In addition, an analysis of the RTP_{da} household response to congestion events (resulting in high market prices) shows a strong dependence on outside temperature and the timing of the events (for example, peak versus off-peak periods). These factors affect the amount of energy curtailment initially available from the population of RTP_{da} resources, as well as the subsequent response of these resources to maintain, degrade, or enhance curtailment levels over the duration of the event. The findings contained in this report are termed *initial* because they only begin to address some of the questions about the operation of the RTP_{da} system. Due to the complex nature of interactions between consumers and the electricity system, and the complexity of electric system operations in general, many more questions arise about the performance and potential benefits of this approach. The data gathered as a result of this project will be of significant value for further research.

Acronyms and Abbreviations

AEP Ohio	American Electric Power, Ohio
CAISO	California Independent System Operator
CPP	critical peak pricing
DOE	U.S. Department of Energy
ePCT	enhanced programmable communicating thermostat
ERCOT	Electric Reliability Council of Texas
HEM	home energy manager
HVAC	heating, ventilation, and air conditioning
kW	kilowatt(s)
kWh	kilowatt-hour(s)
LMP	locational marginal price
MDM	meter data management
MSE	mean-squared error
MWH	megawatt-hours
P_{base}	base price of the supply curve
P_{cap}	price cap
P_{clear}	cleared price
PDF	probability distribution function
PJM	PJM Interconnection, LLC, AEP Ohio's Regional Transmission Organization
PNNL	Pacific Northwest National Laboratory
Q_{clear}	cleared load/quantity
RTP	real-time pricing, also used as a shortened version of $\mathrm{RTP}_{\mathrm{da}}$
$\mathrm{RTP}_{\mathrm{da}}$	real-time pricing, double auction
SMART Shift Plus$^{\mathrm{SM}}$	a form of critical peak pricing implemented in the GridSMART Project
SRMCP	synchronized reserve market cleared price
$T_{desired}$	desired temperature
T_{max}	maximum temperature
T_{min}	minimum temperature

Contents

Figures

Tables

1.0 Introduction

The gridSMART® Real-Time Pricing– Double Auction (RTP_{da}) Demonstration Project (the Project) is a part of the consumer-oriented projects within the overall American Electric Power, Ohio (AEP Ohio) gridSMART program. This project engages residential households to adapt their electricity use in response to a fluctuating 5-minute price signal. In particular, heating, ventilation, and air conditioning (HVAC) units are managed by intelligent software in the home that interacts with a real-time electricity market. The electricity supply price is function of the PJM wholesale market price of electricity as described in the real-time tariff approved by the Public Utility Commission of Ohio (Schedule RS-RTP, 2012).

Significant effort went into the specification, design, development, and deployment of the RTP_{da} demonstration so that AEP Ohio, the U.S. Department of Energy (DOE), and the Project partners could learn from the experience of this innovative approach to engaging end-use systems to the benefit of the consumer and the service provider. The analysis of the RTP_{da} demonstration addresses the question, "What did we learn from the RTP_{da} experiment?" The topics for analysis were developed by the AEP Ohio and Pacific Northwest National Laboratory (PNNL) Project team and each organization was given responsibility for a portion of the topics. This report covers analysis topics assigned to PNNL. Other analysis topics related to the RTP_{da} demonstration, such as customer satisfaction, are covered elsewhere in the gridSMART Project report.

While this analysis report provides insights into the behavior of the RTP_{da} system and its implications for service providers and consumers, it represents only a step on a path to discovering the characteristics and capabilities of end-use systems to participate in system operations and how to best engage them for consumer, local, and regional system objectives. Where appropriate, the report provides perspective for the results and lists additional issues that still need to be addressed.

1.1 Analysis Objectives

The RTP_{da} demonstration represents the first time that a real-time electricity market with an approved regulatory tariff has operated in a realistic situation of approximately 200 households. These households are supplied by four distribution feeders and represent a small fraction of the roughly 2000 total number of households on these feeders. While the measurements on the HVAC systems in these households provide good data to help quantify their price-responsive behavior, the penetration level is too low to address other analysis questions that require significant penetration levels of RTP_{da} households. For this reason, simulations of a higher penetration of RTP_{da} households are needed. Once calibrated to behave similarly to actual household loads, simulations can be configured to provide insights into questions that would be difficult and costly to address in the demonstration.

This analysis report investigates the following areas:

- the potential benefits of RTP_{da} for system-capacity and feeder-capacity issues
- the potential benefits of improving wholesale purchases in the real-time (5-minute) market and participation in a spinning reserve market

- the impacts of RTP_{da} from the consumer's perspective, including consumer bills and consumer configuration of the thermostat set point and adjustments of it over time
- a characterization of the sensitivity of the RTP_{da} loads to price fluctuations and their behavior when called upon for system events.

This analysis report explains the approach taken for the investigation, the source of the information, and the results obtained. Other areas of analysis, such as the implications of RTP_{da} in overall energy consumption or customer satisfaction with the program offering, were done by AEP Ohio. This document supplements that other analysis.

The analysis also includes the results of simulations of RTP_{da} households. While the measurements on these HVAC systems in these households provide good data to help quantify their price-responsive behavior, the penetration level is too low to address other analysis questions that require significant penetration levels of RTP_{da} households. For this reason, simulations of a higher penetration of RTP_{da} households are needed. Once calibrated to behave similarly to actual household loads, simulations were used to provide insights into questions that would be difficult and costly to address in the demonstration.

1.2 RTP_{da} Theory of Operations

The following sections describe the way in which the RTP_{da} system operates. This provides a context for better understanding the analysis results described in this report. The theory of operations starts with a description of how the distribution feeder market works. This is followed by a high-level description of the RTP_{da} dispatch system and how the end-use devices interact with this this system.

1.2.1 Market Operations

The RTP_{da} system follows a transactive-control approach to coordinate household equipment participation in system operations. The term "transactive control" refers to a distributed decision-making approach that allows suppliers and consumers of energy to arrive at a coordinated solution for how each participant will operate based upon a trade-off of the value they place on electricity for a specified time. In this case, an energy market is used to resolve which HVAC loads will run in the next operating interval. The design combines

- a 5-minute retail RTP_{da} reflecting PJM wholesale locational marginal price (LMP) and capacity values
- an RTP_{da} tariff designed to be revenue neutral for the average consumer prior to any load shifting induced by the rate, and with the intent to robustly protect the consumer and the utility from long-term fluctuations in market prices
- a retail double-auction market design that directly manages congestion (that is, limits that constrain the amount of load served) at the distribution feeder level
- a retail market design capable of managing a share of congestion occurring at levels in the grid above a distribution feeder (for example, transmission), allocated to responsive load served by that feeder

- an economically rational heating/cooling thermostat design that balances a consumer's desire to save on their electric bill in exchange for their willingness to be flexible, and that bids the price at which the load it controls will operate (or not), plus the quantity of that load
- a price-normalization scheme that eliminates the need for a consumer to understand or specify price levels as (for example) high, medium, and low, and that adapts to both short-term (days) and long-term (years) changes in price.

The following sections present the operational objectives driving the Project and the design incorporating the elements listed above.

1.2.1.1 $\mathrm{RTP_{da}}$ Market – Uncongested Conditions

A double-auction market implements a mechanism to determine the price at which supply and demand match at a given time. Bids are collected for a specified period of time from market opening to market closing, after which the market is cleared. The market clears every 5 minutes, a period that approximately matches the typical air conditioning load cycle.

After the market clears, the cleared price (P_{clear}) becomes the new prevailing retail $\mathrm{RTP_{da}}$ and the cleared load (Q_{clear}) varies with the demand curve. When the cleared price is published, devices can respond appropriately based on internal price-response logic. The auction itself does not provide any bookkeeping or enforcement of the price-response logic. It simply provides a central facility for buyers and sellers to deliver their price and quantity response information and obtain the prevailing RTP. The following figure shows the feeder supply curve, the ordered demand curve of bids for energy from the $\mathrm{RTP_{da}}$ households, and the market clearing at the intersection of these two curves.

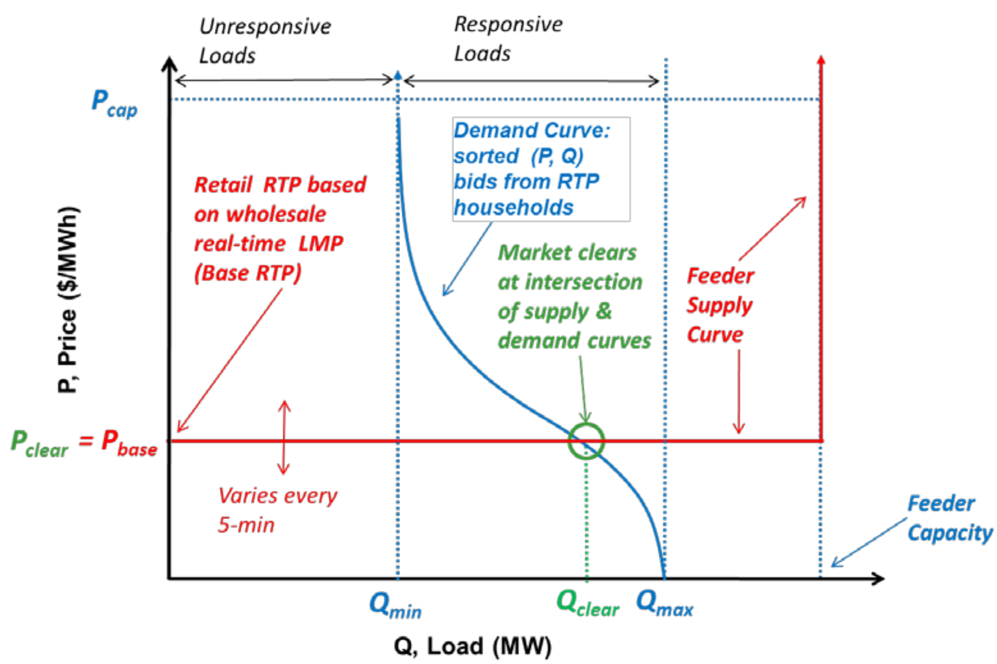

Figure 1.1. $\mathrm{RTP_{da}}$ Market Clearing – Uncongested Condition

1.2.1.2 RTP_{da} Market – Distribution Congestion

Congestion reflects feeder capacity limit constraints or system-wide operational constraints whose resolution could benefit from load reduction. Congestion can be addressed by allocating load reduction at the distribution feeder level in proportion to household bids on that feeder. By participating in a reoccurring market mechanism to negotiate energy need by willingness to pay, participants' actions can dynamically mitigate congestion limits.

During congestion, the cleared price (P_{clear}) is greater than the 5-minute, price of supply (P_{base}), and the cleared quantity (Q_{clear}) equals the feeder capacity, as shown in the Figure 1.2. Every time period (5 minutes), P_{clear} varies in order to try to keep load at the feeder capacity. The market auction proceeds as follows:

- The cleared price (P_{clear}) is set to clear the total load (Q_{clear}) at feeder capacity.
- When congested, $P_{clear} > P_{base}$.
- P_{clear} varies every 5 minutes to try to keep load at feeder capacity.
- If there is an inadequate amount of responsive load to hold the feeder capacity, the market will clear at its limit, that is, the price cap, P_{cap}.
- As shown in Figure 1.2, the total load on the feeder can theoretically vary between a minimum (Q_{min}) and maximum (Q_{max}).

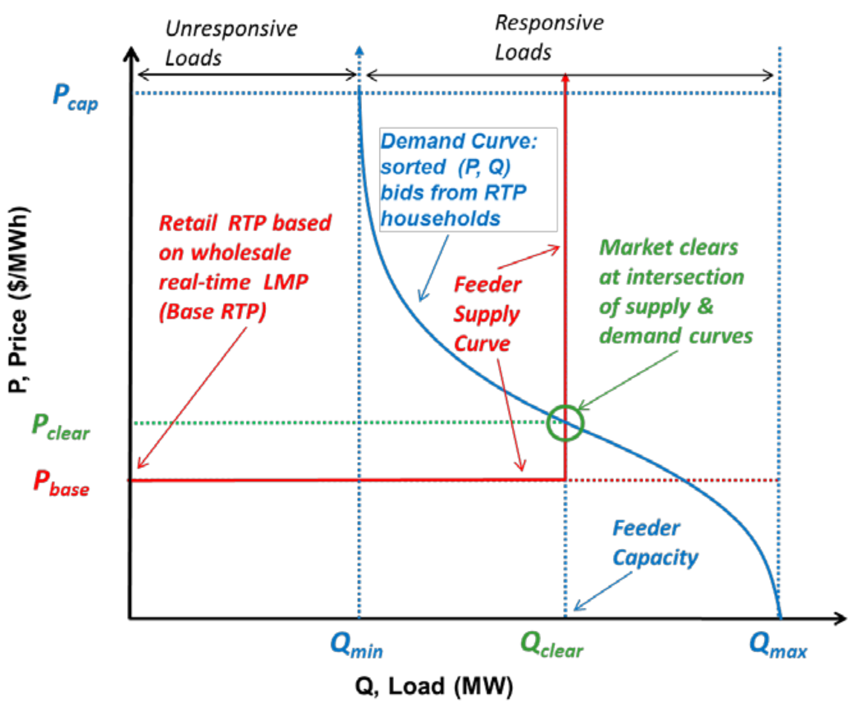

Figure 1.2. RTP_{da} Market Clearing – Congested Condition

The RTP_{da}mechanism can also be used to address system congestion issues, that is, issues that the service provider may have with system capacity constraints. In that case, an overall system load reduction target is desired. To accomplish this, a share of the system-wide load reduction target can be allocated to each distribution feeder's households in proportion to their price and quantity bids. The number of RTP_{da} households per feeder and the feeder load itself play important roles in keeping Q_{clear} below the feeder capacity.

1.2.1.3 RTP_{da} Market – Rebate and Incentive Mechanisms

The market clearing at a higher price during congestion events encourages the bidding equipment to curtail operations. This allows consumers to avoid paying a high market price for energy; however, their exposure to higher prices was done to benefit the system, not to make the price-responsive consumer pay more for energy than a flat-rate consumer. The excess payment of the RTP_{da} consumers due to the higher cleared price than the base supply price (P_{base}) is indicated in Figure 1.3 as the congestion surplus (in the figure, only the households in the RTP_{da} program are represented). This surplus is either rebated back to the consumers at the end of the month, or equivalently, the consumers are only charged the P_{base} price even though the market cleared above this price. As the service provider did not experience added costs from associated wholesale price increases, and was able to avoid other, higher priced solutions (such as purchasing generation), the congestion surplus represents revenue for the service provider. Returning the congestion surplus back to the consumer removes the unfair burden of charging price-responsive consumers more, when in fact they are helping the service provider to avoid more costly alternatives.

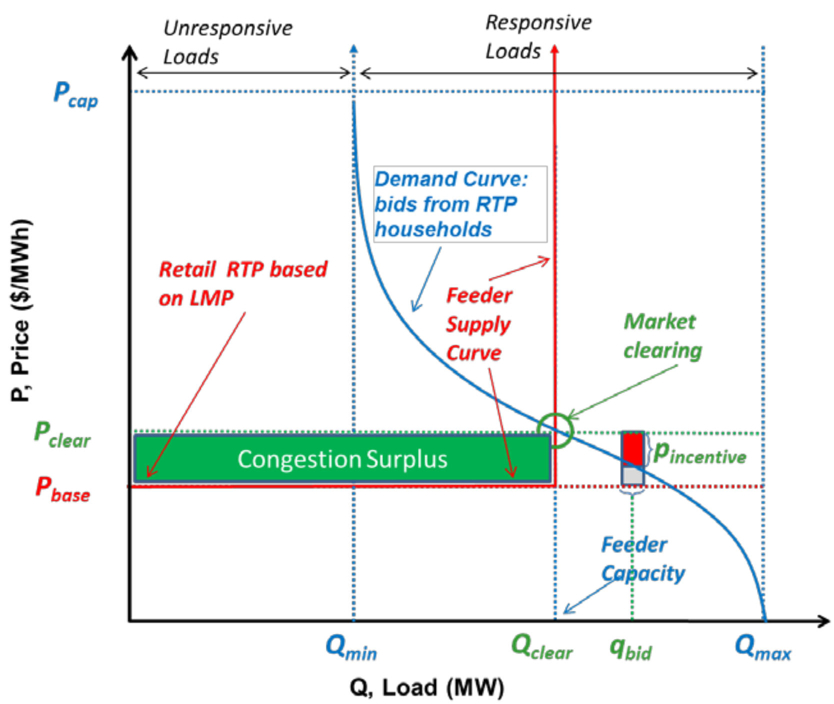

Figure 1.3. RTP_{da} Congested Condition – Congestion Surplus Rebate and Incentive

In fact, the rebate of the congestion surplus does not include any percentage of the added, long-term benefit that system operation achieves by reducing or moving a peak load condition (for example, deferring distribution system infrastructure upgrades). The value of this long-term benefit can be shared with the RTP_{da} households that actually reduced their load by using an incentive mechanism. Several alternatives were reviewed by the Project team as to how an incentive could be calculated. The team chose an algorithm meant to reward consumers who are the most flexible to price changes. Figure 1.3 shows an example of the incentive provided to a consumer with the bid (p_{bid}, q_{bid}). The incentive is computed as the quantity of energy consumed (that is, the product of the bid and the 5-minute time interval) times a function of the difference between cleared price and RTP$_{da}$ base price.

If $P_{base} \le p_{bid} \le P_{clear}$,

then $p_{incentive} = q_{bid} \times \mathrm{F}(P_{clear} - P_{base})$.

If not, then no incentive is applied.

1.2.2 Dispatch System

The RTP$_{da}$ system runs an electricity market on a distribution feeder-by-feeder basis. For the demonstration, four markets are running simultaneously, one for each of four feeders that supply the participating households. A simplified drawing of one of the markets is depicted in Figure 1.4.

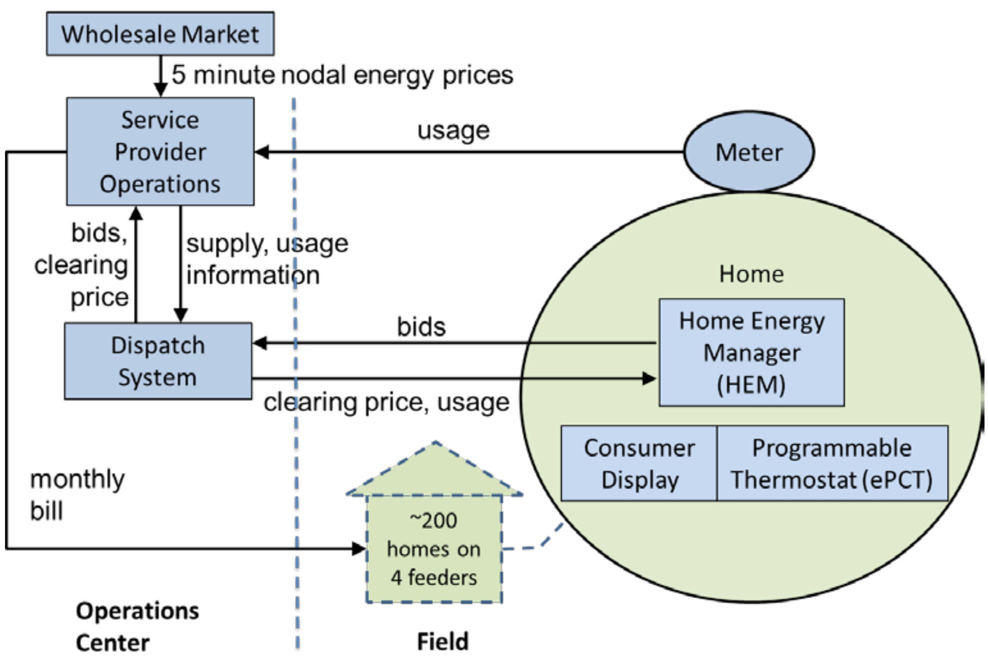

Figure 1.4. RTP$_{da}$ System Overview

Within the home is an electronic program-controlled thermostat (ePCT) communicating with an HVAC unit and a home energy manager (HEM). The HEM hosts a software agent that monitors the market price of electricity and converts the residents' desired temperature set point, the current deviation from that set point, and their preference setting for relative comfort and savings into an amount it is willing to bid for the next 5 minutes of electricity. The HEM takes this price, along with the amount of electricity needed to run the HVAC unit, and assembles all bids in the home (in this case there is only one, representing the HVAC ePCT) and communicates the bid information via a cellular connection to the dispatch system located in the operations center.

The dispatch system assembles the bids from all households on the feeder along with the market price for supplying electricity as determined by the RTP_{da} tariff and based on the LMP for electricity in the feeder's service area. The dispatch system clears the market of supply and demand bids where the two curves intersect, creating a cleared price (as shown in Figure 1.1). The cleared price is broadcast to all homes' HEMs and sent to the service provider's operations system for billing. The billing system exchanges information with the advanced metering infrastructure smart meter at the home to obtain the energy used during the 5-minute interval so the bill can be calculated. The HEM communicates the results of the auction to the ePCT, which sends the appropriate operating signal to HVAC unit. A consumer display is built into the ePCT; it displays the estimated billing price for energy so the consumer can participate with other energy saving actions, should they be monitoring the system.

This transactive-control approach results in very simple message exchange. In general, the approach is sensitive to data-exchange privacy concerns because the transacting parties only need to share what they are willing to pay for a quantity of electricity. What is returned to all participants on the feeder is the market cleared price. For experimental purposes, additional information is collected to understand the performance of the RTP_{da} system. For example, the observed temperature in the home is recorded, as is the deviation of the temperature from the desired set point. In addition, the configuration of the ePCT is monitored, including the residents' preference for savings or comfort and any system overrides, so that consumer behavior can be studied.

1.2.2.1 Thermostat Agent

The smart thermostat agent is configured by the consumer to address their preference for comfort versus economy. For each daily period of operation (for example, "Home," "Away," or "Night"), the homeowner specifies their desired temperature ($T_{desired}$), and influences their minimum and maximum temperatures (T_{min}, T_{max}), through a five-level setting for their preference for more comfort (tighter temperature control) or more savings (more flexible temperature control), as represented by the slope (k) in Figure 1.5. To simplify the discussion, only cooling mode is described below.

The thermostat agent's price-responsive controller is programmed to account for two market phenomena: price trends and price variability. In the case of price trends, the agent needs to determine whether a price is expensive or inexpensive. What may seem like a high price today may seem like a low price tomorrow, and vice versa. We see this in the fluctuation of the price of gasoline, where today's price may seem low compared with the price paid several months ago. In the case of price variability, we look at the volatility of short-term changes in price. Although the average price over a period may be relatively constant, the variability of the actual price above and below the average can change.

The volatility (standard deviation divided by mean) of wholesale and retail prices varies over time. Because the price-responsive controllers are designed to attenuate their response in the presence of more volatile prices, the determination of volatility is essential to the operation of the overall RTP_{da} system. In the case of this demonstration, the time window for the calculation of price volatility is the most recent 24 hours. The effect of this implementation is to attenuate the responses of the thermostat agents during the 24 hours that follow a period of significantly increased price volatility. The longer the duration of increased volatility, or the greater the volatility, the more the thermostat agents' responses are attenuated. For this reason it is typical to see diminished response to LMP fluctuations during the 24 hours that follow a feeder constraint event.

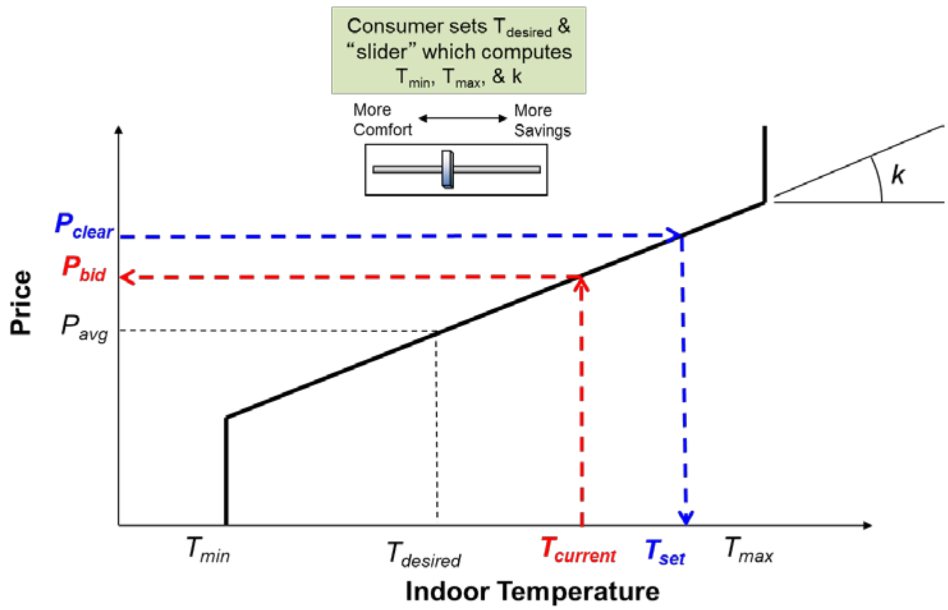

Figure 1.5. HVAC Thermostat Agent Price-Response Curve in Cooling Mode[1]

Bids are submitted every 5 minutes up until 60 seconds before the market is cleared. The bid price P_{bid} in the figure above is computed by each thermostat agent as follows:

$$P_{bid} = P_{avg} + \frac{(T_{current} - T_{desired}) \times k \times P_{dev}}{T_{max} - T_{min}} \tag{1.1}$$

where P_{avg} = the average price over the last 24 hours
P_{dev} = the standard deviation of the price over the last 24 hours
$T_{current}$ = the current indoor air temperature
$T_{desired}$ = the desired indoor air temperature
k = the responsiveness desired by the consumer
T_{max} = the maximum temperature limit
T_{min} = the minimum temperature limit.

P_{bid} and q_{bid} are sent by the HEM to the market system, where they are assembled with the other bids and the market is cleared. The cleared price (P_{clear}) is then published to all the RTP_{da} HEMs on the feeder, which pass it on to the thermostat agents where the price-response curve is used to define the temperature set point for the next 5 minutes of operation (T_{set}, see Figure 1.5). In the cooling mode case in Figure 1.5, the fact that $P_{clear} > P_{bid}$ results in T_{set} being set higher than $T_{current}$ and less than T_{max} so the HVAC unit will not run. A higher comfort setting would result in higher prices bid as the indoor temperature deviates from $T_{desired}$.

[1] Hammerstrom, D. J., et al, "Pacific Northwest GridWise® Testbed Demonstration Projects, Part I. Olympic Peninsula Project," Pacific Northwest National Laboratory, PNNL-17167, October 2007.

In cooling mode, if the current temperature is above the maximum temperature ($T_{current} > T_{max}$), then a bid at the price cap with zero quantity is submitted (that is, the consumer is fully unsatisfied). If the current temperature is below the minimum temperature ($T_{current} < T_{min}$) then a bid of zero price and zero quantity is submitted as a programming convention to represent that the consumer is fully satisfied.

The bid quantity is provided by the RTP_{da} equipment installer based on the estimated nominal power demand of the heating/air-conditioning unit. The bid state is determined by the operating mode of the heating/air-conditioning unit—for example, "Off," "Cool," or "Heat."

If a previously submitted bid is invalidated by a change in ePCT state (for example, "Off" to "Cool"), or if there was a disruption of service, then a new bid is computed and submitted to replace the previous bid. All bids received are recorded in the system database, but only the last bid received is used to clear the market.

1.2.2.2 HVAC Operating States

To better understand the operating status of the HVAC equipment and its interplay with the market bidding system, the following states are considered in the summer cooling scenario of the analysis. A diagram of the HVAC states and their possible transitions over time is depicted in Figure 1.6. The flag, "Included in Market," indicates that the HEM successfully communicated with the RTP_{da} dispatch system so that its bid can be included in the next auction.

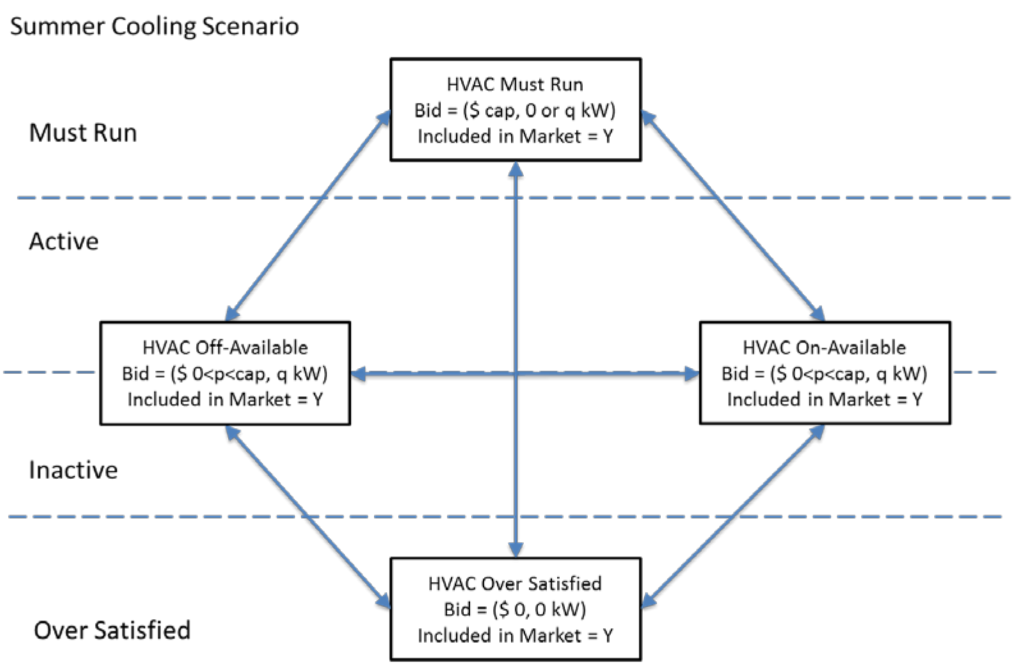

Figure 1.6. HVAC State Diagram

- Must Run: This state is reached in two situations. First, if the household temperature and comfort settings in the ePCT result in a bid at the highest price allowed in the market, P_{cap}, then the unit will automatically clear the market and will be expected to be in the "On" state during the next 5-minute period. Second, in the case where $T_{current} > T_{max}$ (that is, the household temperature is over the maximum temperature set point), then the thermostat agent is programmed to bid price = \$0 and quantity = q_{bid}, and it is expected to be in the "On" state no matter what the cleared market price. This distinction is made so that the HVAC unit is counted as unresponsive load. This convention allows the dispatch system to more easily recognize it as unresponsive.

- Over-Satisfied: If $T_{current} < T_{min}$ (that is, the household temperature is below the minimum temperature set point), then the HVAC unit is in the Over-Satisfied state and will bid price = \$0 and quantity = 0.
- Active: Represents the state where the HVAC bid was cleared (p_{bid} higher than P_{clear}) to run in the market period. The HVAC unit can either be Off and available to remain Off or turn On, or On and available to remain On or turn Off.
- Inactive: Represents the state where the HVAC bid was not cleared (p_{bid} lower than P_{clear}) to run in the market period. As with the Active state, the HVAC unit can either be On or Off and available to switch states.

In moving from one auction to the next, it is possible that an HVAC unit may stay in the same state or move to any other state. As the internal temperature is increasing in conditions of steady market supply price, one would expect an HVAC unit to move from Inactive to Active, and possibly to Must Run, if it could not keep up with the temperature increases. However, under volatile market conditions and congestion events, state changes could be more dramatic.

Considering the entire RTP_{da} household load under control (RTP_{da} Load), a more detailed market clearing illustration is presented in Figure 1.7 to reflect the different states of the HVAC units in a

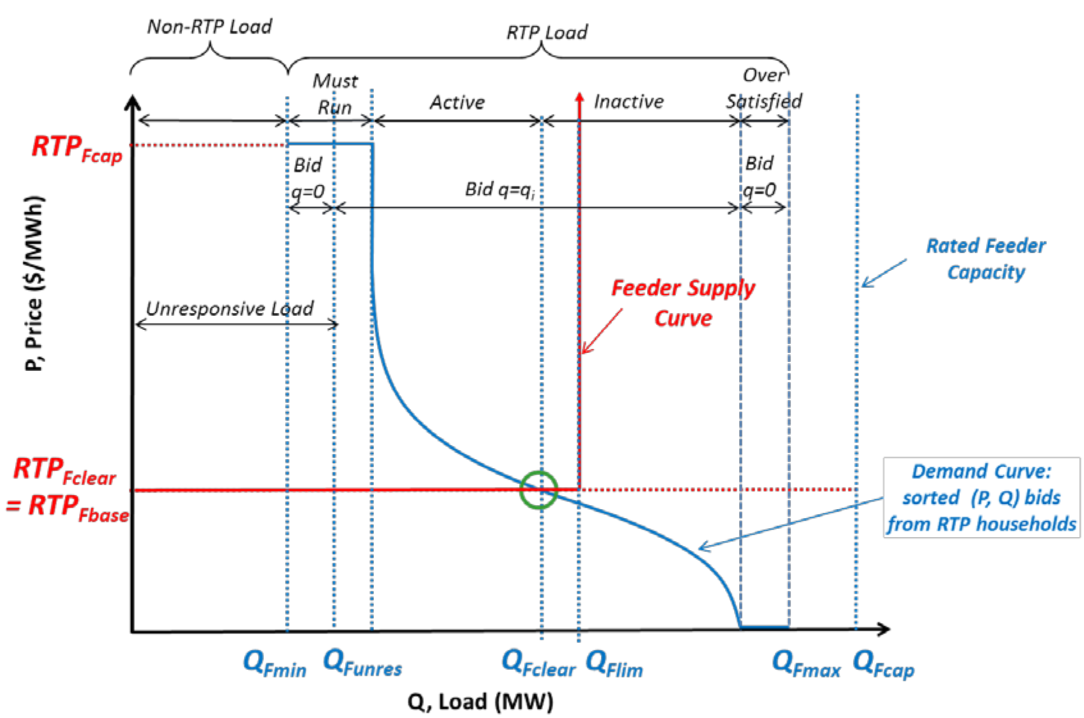

Figure 1.7. RTP_{da} Load Bidding Classifications – Non-Congested Case

particular 5-minute auction. The HVAC units to the left in the figure are in the Must Run state, followed by the Active units, then the Inactive units, and lastly the Over-Satisfied units. The remaining load on the feeder is referred to as Non-RTP_{da} Load. This is slightly different from the definition of the Unresponsive Load, which also includes the Must Run devices that submit a zero bid. The subscript F in the figure refers to feeder-based variables, with new variable Q_{Funres} being the quantity of unresponsive load on the feeder, Q_{Flim} being the congestion limit placed on the feeder, and Q_{Fcap} being the rated capacity of the feeder.

1.3 RTP_{da} Experiment Setup

To run the RTP_{da} demonstration, households were recruited to participate under the RTP_{da} tariff and they were outfitted with the ePCTs and HEMs. The RTP_{da} dispatch system was commissioned and communication was enabled between the various components of the system. An operations experiment plan was developed for testing the RTP_{da} system and performing congestion experiments.

1.3.1 RTP_{da} Households

The RTP_{da} households were selected from a pool that already had smart meters installed. These meters provided data to the meter data management (MDM) system and were also read by the HEMs, which returned metered data with their market bids, the status of the ePCT, and the indoor temperature. Based on consumer recruitment into the RTP_{da} program, changes that occurred with the households, and the eventual decommissioning, the number of participants grew over the spring and summer of 2013 and diminished in the fall months as their equipment was removed. The household equipment was configured at the time of installation, and the consumer was trained on how to enter their desired thermostat settings and change them to reflect their preferences over time. Any changes were recorded and sent back to the RTP_{da} dispatch system from the HEM.

The RTP_{da} dispatch system and the HEMs were designed to handle problems with communications. For example, default values were used for the PJM LMP price if there were delays in getting that from PJM. If a HEM's bid came in too late for the 5-minute market auction, then it did not participate in that auction, but it could participate in the next auction in which a successful bid was submitted and received. To properly analyze the behavior of the system, missing or bad data need to be detected and removed. An understanding of the default or backup settings is needed, as their appearance in the data collection can become regular, potentially skewing analysis results and observations.

The RTP_{da} system operated from December 2011 through the fall of 2013, but a sufficient population of households for conducting the experiments was not installed and operational until June, 2013. As most of the HVAC resources only operated in cooling mode, there was little heating HVAC market interaction after the beginning of October. For this reason, we limit the bulk of RTP_{da} analysis to the period from 1 June 2013 through 30 September 2013.

1.3.2 Operations Experiments and Data Collection

To identify and quantify various value streams, and to fully characterize the behavior of RTP_{da} resources, various operating scenarios were designed for the congestion experiments. The operating scenarios involved changing feeder congestion limits for varying durations to engage the RTP_{da} resources.

The RTP_{da} experiments were conducted to test the response of RTP_{da} resources based on parameters such as time of day (peak/off-peak), day of week, and weather conditions (temperature, wind, etc.). Operating scenarios were also designed to test the response of RTP_{da} resources during the critical peak pricing (CPP) events called by AEP Ohio. Finally, fatigue experiments were designed to test the extent to which the RTP_{da} households continued responding to high clearing prices, by letting the indoor temperature rise, before manually overriding the thermostat settings.

Feeder Limit Setting for RTP_{da} Congestion Experiments

First, the process of inducing feeder congestion to conduct an RTP_{da} experiment will be described. Figure 1.8 presents a conceptual view of how congestion limits were set to engage RTP_{da} resources during experiments. The dispatch system allows the operator to enter a percentage ($C_{\%}$) of the feeder's rated capacity (Q_{FCap}) to define the feeder congestion limit (Q_{Flim}). The initial plan was to conduct the congestion experiments by setting the feeder congestion limit in a manner that would engage 10–25% (α) of the total RTP_{da} responsive load on the feeder, using the following formula:

$$C_{\%} = Q_{Flim} / Q_{Fcap} \times 100\% \tag{1.2}$$

$$C_{\%} = (Q_{Ftotal} - \alpha Q_{res}) / Q_{Fcap} \times 100\% \tag{1.3}$$

where
$\alpha < 1$ = portion of Q_{res} to engage
Q_{Flim} = feeder congestion limit
Q_{FCap} = feeder rated capacity
Q_{Ftotal} = total feeder load
Q_{res} = responsive feeder load
$C_{\%}$ = percent of the feeder rated capacity.

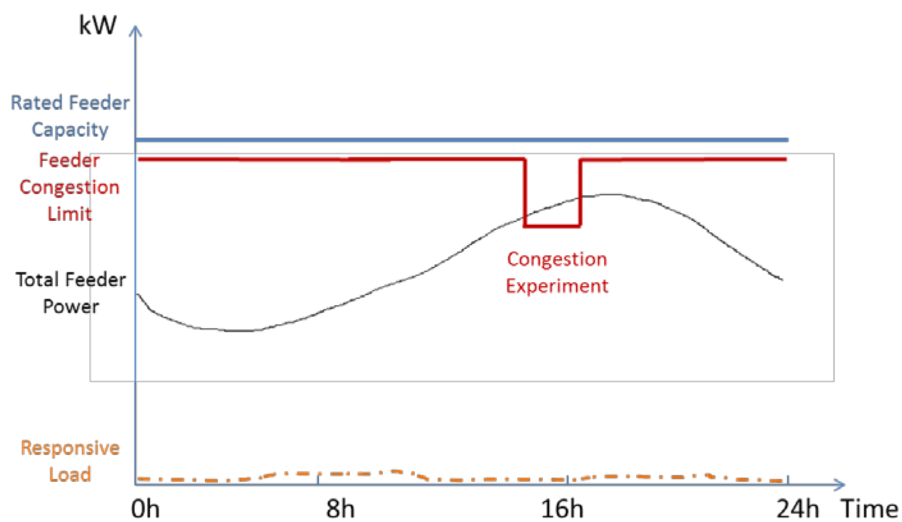

Figure 1.8. Engaging Responsive Load on a Feeder by Varying the Congestion Limit

However, the responsive loads were low compared to the total feeder load levels to the extent that the normal unresponsive load variations were greater than the total responsive load; thus, the reduction of the feeder capacity limit as a percentage of the responsive load did not always lead to congestion on the feeder. To be sure that the RTP_{da} resources would be engaged, the feeder congestion limit (Q_{Flim}) in the congestion experiments was set at 10% below the total (responsive plus unresponsive) prevailing feeder load, instead of the total responsive load. As an example of setting the feeder congestion limit, consider a total load level of 3 MW on a 10 MW feeder with only 100 kW of total responsive load. To impose congestion during an experiment, the feeder limit would be set at 10% below 3 MW, i.e., 2.7 MW (Q_{Flim}) or at 27% ($C_{\%}$) of the rated feeder capacity of 10 MW (Q_{FCap}).

Period of Study

The initial two-week period in the beginning of June was deemed a practice period. Congestion experiments were scheduled during this period on a limited basis to help shed light on the systemic behavior of RTP_{da} resources under different operating conditions. The information gathered during this period was instructive in setting up more extensive experiments later.

Practice Period

RTP_{da} resources were initially engaged for 60 minutes by setting the feeder capacity limit at 10% below the prevailing feeder load. If the RTP_{da} resources were not exhausted during the test period, the length of time to impose congestion was increased by 30 minutes during the experiment, while keeping the same congestion limit. Congestion experiments during the practice period were conducted under constant supervision of staff members at both PNNL and AEP Ohio.

Normal Operation

After the initial practice period, congestion experiments were scheduled daily during the last two weeks of June. The experiments were initially conducted under constant supervision of PNNL and AEP Ohio staff members. However, the experiments were later scheduled to run without constant supervision, once it was determined that market conditions were not being violated and that the RTP_{da} resources were not being exhausted during the course of the experiment. Table 1.1 and Table 1.2 present a breakdown of congestion experiments scheduled over different hours of a day, as well as weekend versus weekday experiments. As can be seen in Table 1.1 and Table 1.2, respectively, majority of the congestion experiments were conducted during peak periods on weekdays. The feeder capacity limits were set at 10% below the prevailing feeder load at the start of the experiment to ensure that the RTP_{da} resources were engaged.

Table 1.1. Breakdown of Congestion Experiments by Hour of Day

5:00–10:00	10	10.42%
10:00–14:00	25	26.04%
14:00–22:00	61	63.54%
Total	**96**	100.00%

Table 1.2. Breakdown of Congestion Experiments by Day of Week

Weekend	25	26.04%
Weekday	71	73.96%
Total	**96**	**100.00%**

Table 1.3 presents the breakdown of congestion experiments based on the experiment durations. As mentioned earlier, 4-hour and 6-hour experiments were conducted to test consumer fatigue, as measured by the number of manual adjustments to thermostat controls.

Table 1.3. Breakdown of Congestion Experiments by Experiment Duration

2 Hours	70	72.94%
4 Hours	25	26.04%
6 Hours	1	1.04%
Total	**96**	**100.00%**

SMART Shift Plus Events and Feeder Constraints

To study the response of RTP_{da} resources during SMART Shift Plus^{SM} events called by AEP Ohio, experiments were scheduled to coincide with and span the duration of the SMART Shift Plus events. SMART Shift Plus events were typically called for 4 hours; these also served as consumer fatigue tests. Table 1.4 below shows the experiments scheduled on the SMART Shift Plus event days, when congestion experiments were scheduled to coincide with the SMART Shift Plus events.

Table 1.4. Congestion Experiments Scheduled during SMART Shift Plus Events

SMART Shift Plus Day	SMART Shift Plus Date	Start Time (Eastern)	Duration (Hours)
Tue	7/16/2013	13:00	4
Wed	7/17/2013	15:00	4
Thu	7/18/2013	15:00	4
Thu	8/22/2013	15:00	4
Tue	8/27/2013	14:00	4
Thu	8/29/2013	14:00	4
Fri	8/30/2013	15:00	4
Tue	9/10/2013	15:00	4
Wed	9/11/2013	15:00	4

1.4 Control Groups

A number of control households were selected that were expected to have characteristics similar to the RTP_{da} households, but that remained under the standard residential tariff. Changes in behavior of the RTP_{da} group can be estimated by comparing RTP_{da} results against those of the control group. A pool of thousands of households who did not participate in the customer-oriented projects was established from which control group households could be chosen. From this pool, PNNL developed a control group of 272 households for comparison in several of the analyses in this report. Note that this RTP_{da} control group is different from other control groups used in other parts of the gridSMART report.

This section describes the way in which the control group was selected from 2010 metered data and how the control group data from 2013 were corrected for use in comparisons with RTP_{da}2013 metered data. A set of definitions for the groups of households used for the analyses follows.

1. RTP13: This group represents the 192 households who were technology-enabled and participated in the RTP_{da} market some or all the time in 2013. Often their energy use in an interval such as 5 minutes will also be referred to as RTP13.
2. RTP10: This is a group of 272 households who were recruited in 2013 as potential RTP_{da} participants and were in the RTP_{da} system database. The 15-minute energy use data for 2010 was obtained for these households. This group includes the 192 RTP13 households that participated in the RTP_{da} market during the demonstration period; however, the selection was done prior to the analysis of how many RTP_{da} households actually participated in the market.
3. Ctrl10: From the pool of households who did not participate in the gridSMART program, a set of 272 households were identified as close to RTP10 in their 15-minute energy use profiles. These are referred to as Ctrl10.
4. Ctrl13: The energy use by the same set of households as Ctrl10 in 2013 is referred to as Ctrl13.
5. RTPnr10: The average energy used by a household in Ctrl10 was then adjusted to improve the comparison with the RTP_{da} households in 2010 (RTP10). This adjusted control group is referred to as RTPnr10 ("nr" meaning non-responsive).
6. RTPnr13: The average energy used by a household in Ctrl13 was then adjusted to improve the comparison with the RTP_{da} households in 2013 (RTP13). This adjusted control group is referred to as RTPnr13.

1.4.1 Control Group Member Selection Process

The following describes how the control group was initially selected to create a set similar to RTP_{da} households, but not in the program. This involved acquiring data for candidate households to be in the control group, processing the data, (including handling bad or missing values in the acquired data), and employing data filtering mechanisms to help match load shapes to select control group members from the candidates that could represent non-responsive RTP_{da} households.

Data Acquisition: The 2010 15-minute MDM data for approximately 11,800 homes were used to identify the control group. The analysis interval was from June 1, 2010 through September 30, 2010.

Bad and Missing Values: 15-minute values that exceeded 40 kWh (an unusually high and suspect value) were treated as bad data and removed by setting the large value to zero so that they would be handled as missing data during subsequent processing. Missing values in the household meter data were replaced using a zero-order hold before any selection filter was applied. Note that the missing values were reset to zero after the filter (see below) was applied to avoid affecting the match with an RTP_{da} household itself.

Filtering: Load data collected at sub-hourly intervals can exhibit large fluctuations in the average energy (that is, power) measurement due to the cycling behavior of large loads. The quantity of interest is the duty cycle, but this quantity cannot be directly observed from interval energy data. However, for time intervals longer than the cycling time of the loads the average load, P_{avg}, is related to the duty cycle, *D*, as

$$D = \frac{P_{average}}{P_{on}} \tag{1.4}$$

where P_{on} is power measured when the equipment is On.

This property is used to estimate the total load at various time intervals by filtering the load data using a sliding-window filter based on the $1/p$-state binomial probability distribution function (PDF). The binomial PDF is defined as

$$\text{Prob}\{t|n,p\} = \binom{n}{t} p^t (1-p)^{(n-t)} \tag{1.5}$$

where $p = 2$ and describes the probability that the true state (On or Off) at the time $t = n/2$ is described by the observed state at the time t. The choice of the window size n was based on the load cycling time relative to the sampling time Δt_{sample}; for example,

$$n = \frac{\Delta t_{on} + \Delta t_{off}}{\Delta t_{sample}} \tag{1.6}$$

Note that the filtered data has zero lag (it is shifted back by a half window). In addition, the last sample is held for an additional half window to provide a smooth end to the filtered data. The result of applying such a filter with window size of 8 15-minute periods is shown in Figure 1.9.

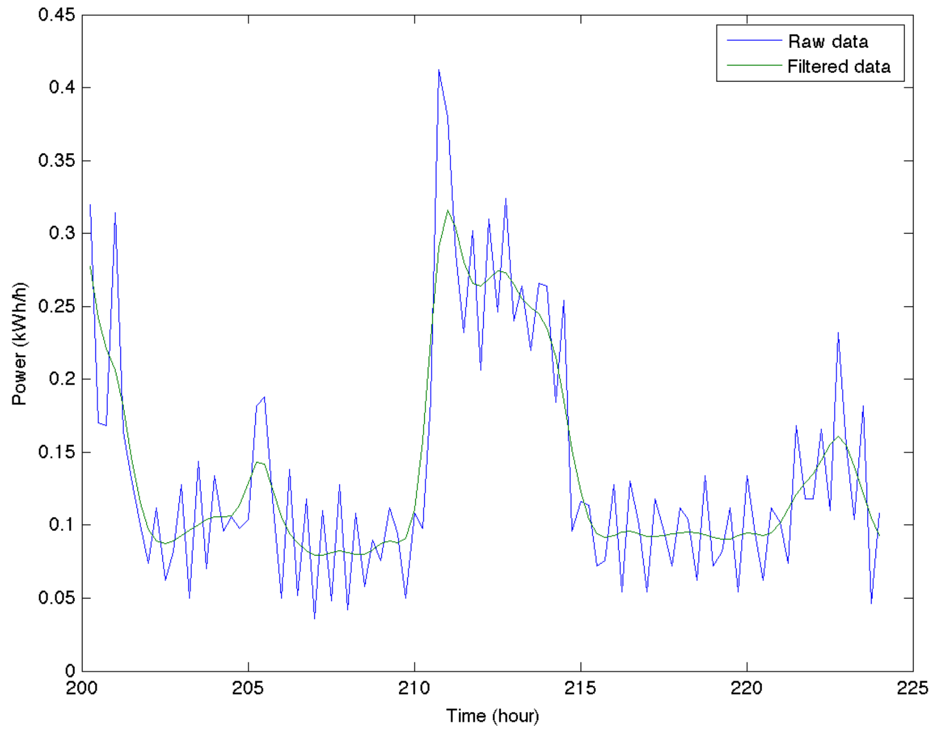

Figure 1.9. Raw and Filtered 15-Minute Electric Meter Data with a 2-Hour Binomial Window Size

Load Shape Matching: The simplest method for load shape matching is based on minimizing the total mean-squared error (MSE) between candidate load shapes

$$MSE = \sum_{t=1}^{N} (x_t^+ - y_t^+)^2 \quad (1.7)$$

where N is the number of samples in the time series, and x^+ and y^+ are the non-zero values from the load shape time-series vectors. An example of a match is shown in Figure 1.10. The corresponding figures, known as heat maps because they show the high (hot) and low (cold) areas, are shown in Figure 1.11. Each RTP_{da} home was assigned a single control home. However, some control home choices were matched to more than one RTP_{da} home. In such cases, the next-best match that was not already selected for the control group was chosen.

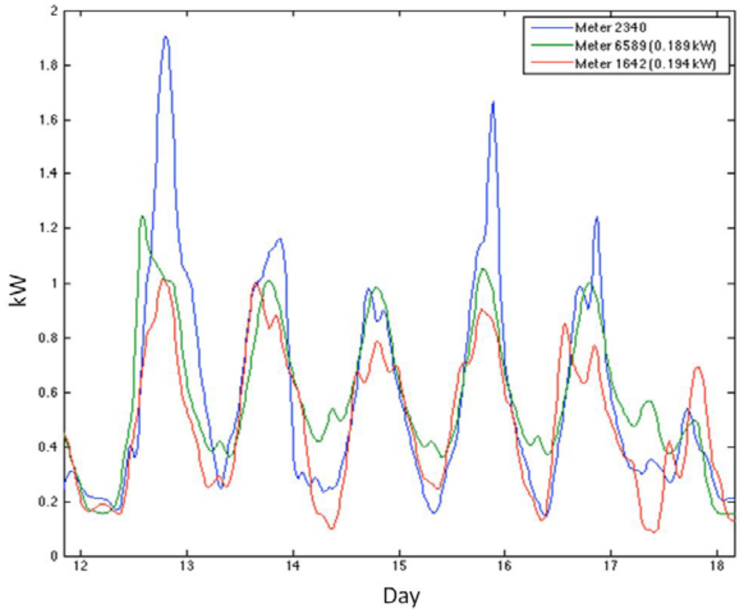

Figure 1.10. Illustration of Match of Reference Load (blue) to Best Fit (green) and Second-Best Fit (red)

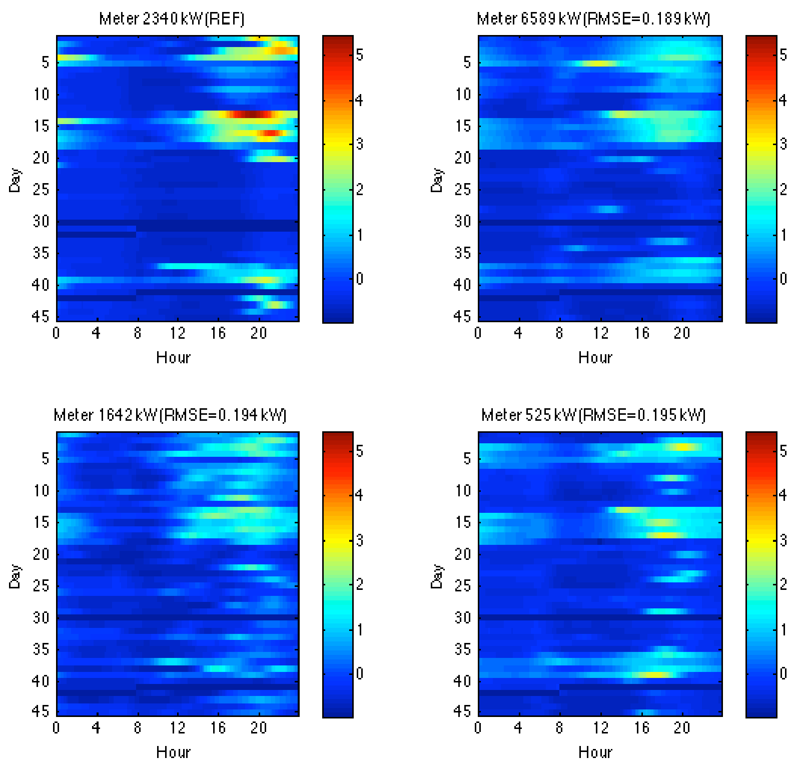

Figure 1.11. Load Shape Maps for Reference (upper left), Best Match (upper right), Second-Best Match (lower left), and Third-Best Match (lower right)

1.4.2 Control Group Adjustment for RTP_{da} Group Comparison

Recall that the RTP_{da} load data from the 2010 data are referred to as RTP10 and the RTP_{da} data measured during the course of the demonstration period in 2013 are referred to as RTP13. Similarly, the control group data for 2010 and 2013 are referred to as Ctrl10 and Ctrl13, respectively. If Ctrl13 accurately represents the behavior of RTP13 had they not been price responsive, then it is a simple matter to subtract the interval data for the average of the two groups to determine price response. Despite the optimal search for a best fit of Ctrl10 with RTP10, there were substantial differences. A typical 7-day profile of energy use by the two groups in 2010 is shown in Figure 1.12. The variations, especially of peak loads, are of concern. While the selection process emphasized load shape matching, it did not match peak energy use. An adjustment was made to make Ctrl10 closer to RTP10. The correction procedure is explained below, and the resulting group is RTPnr10.

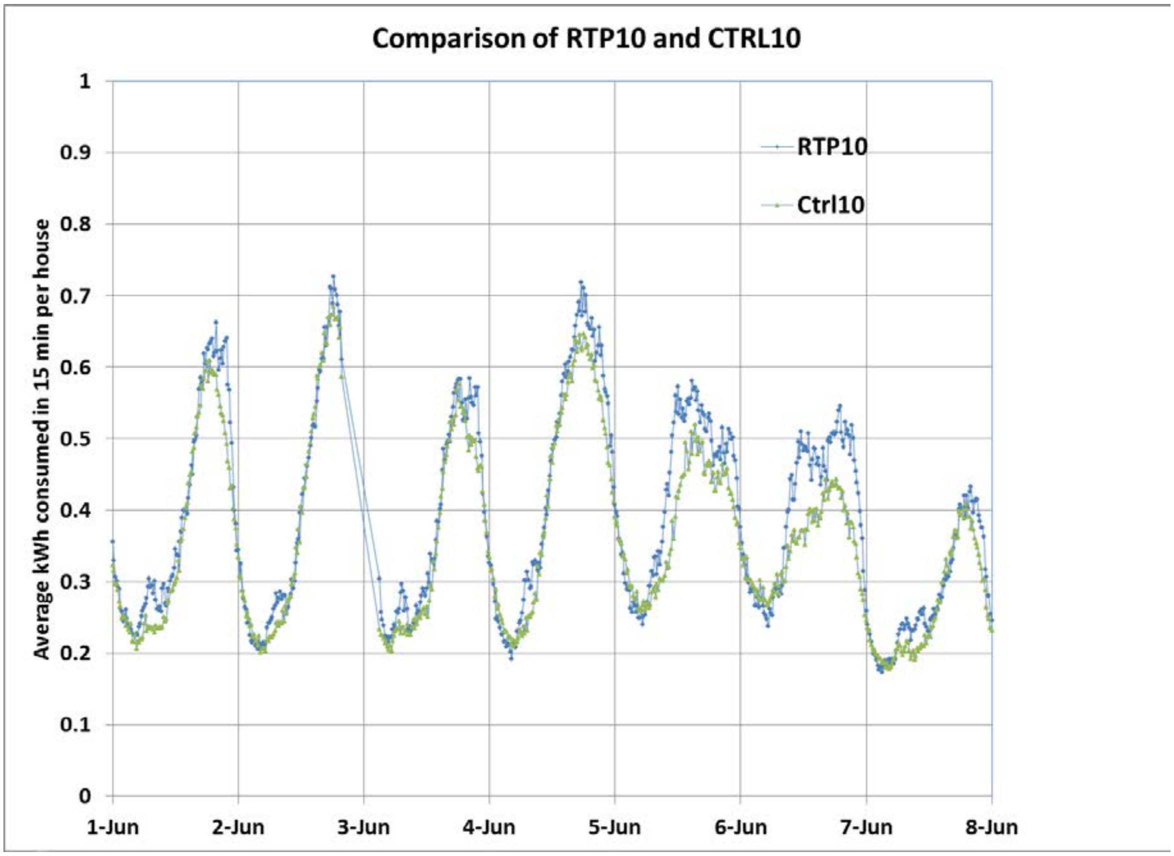

Figure 1.12. Comparison of RTP10 and Ctrl10 Profiles for a Typical 7-Day Period

Consider a relationship between RTP10(t) at time t and Ctrl10(t) of the form

$$RTP10(t) \sim f(Ctrl10(t), Time\ of\ day) \tag{1.8}$$

As RTP10 and Ctrl10 are experiencing the same outdoor temperature, the time of day (actual date is not relevant) turned out to be a good proxy for many of the un-modeled variables, including outdoor temperature. Another approach is to consider the difference between RTP10 and Ctrl10 as a function of Ctrl10 and time-of-day. A Ctrl10 value of 0.6 at 3 pm on a day in July (this would happen on a relatively cool July day) gets the same correction as a Ctrl10 value of 0.6 at 3 pm on a day in September (this would happen on a relatively warm September day). Thus, the Ctrl10 value and time-of-day act as proxies for temperature. So *RTP10 - Ctrl10 ~ f(Ctrl10, time-of-day)* is our non-parametric model. And *RTP10 ~ Ctrl10 + f(Ctrl10, time-of-day)* is just another *f(Ctrl10, time-of-day*). If the function *f* is parameterized in some fashion, the parameters can be estimated by a method such as the least-squares method. However, because the functional form as well as the parameters and their interpretation are not of much interest, a non-parametric method was used. The method of choice was LOcal regrESSion (LOESS).[2] This was implemented in MATLAB®.

The time series

$$RTPnr10(t) = f(Ctrl10(t), Time\ of\ day) \tag{1.9}$$

is a significantly better approximation of RTP10 than Ctrl10. Weekdays and weekends were treated separately. The resulting fit for the same 7-day period as in Figure 1.12 is shown in Figure 1.13.

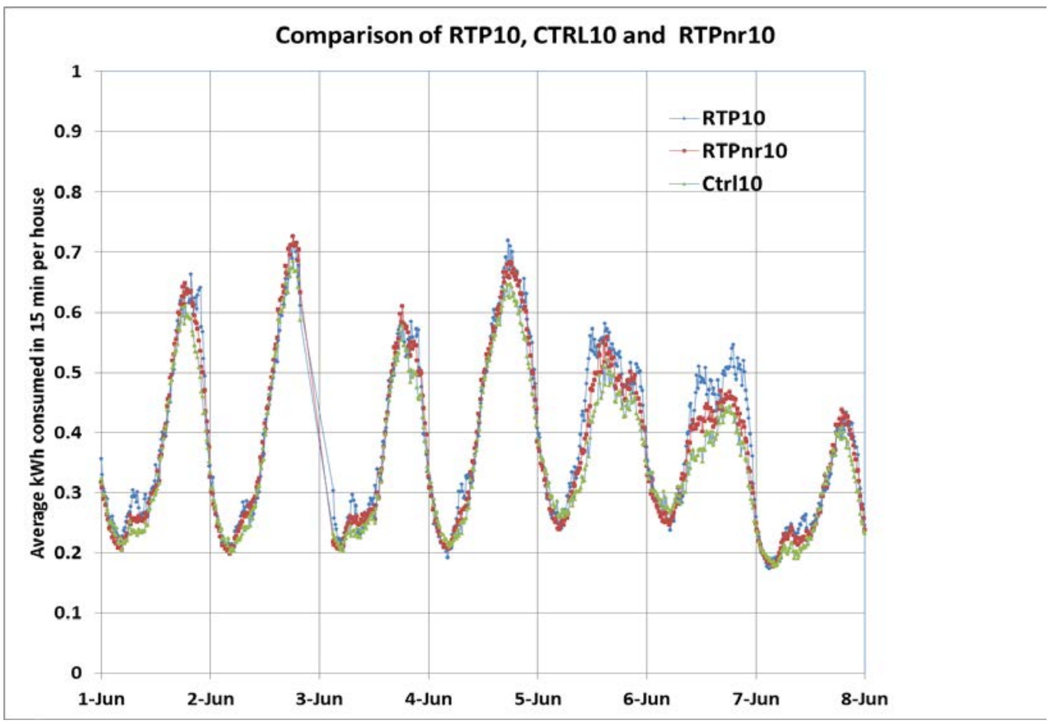

Figure 1.13. Comparison of RTP10, RTPnr10, and Ctrl10 Profiles for the Same 7-day Period as in Figure 1.12

The fit for the entire 122-day period is shown in Figure 1.14.

[2] http://www.mathworks.com/products/datasheets/pdf/curve-fitting-toolbox.pdf

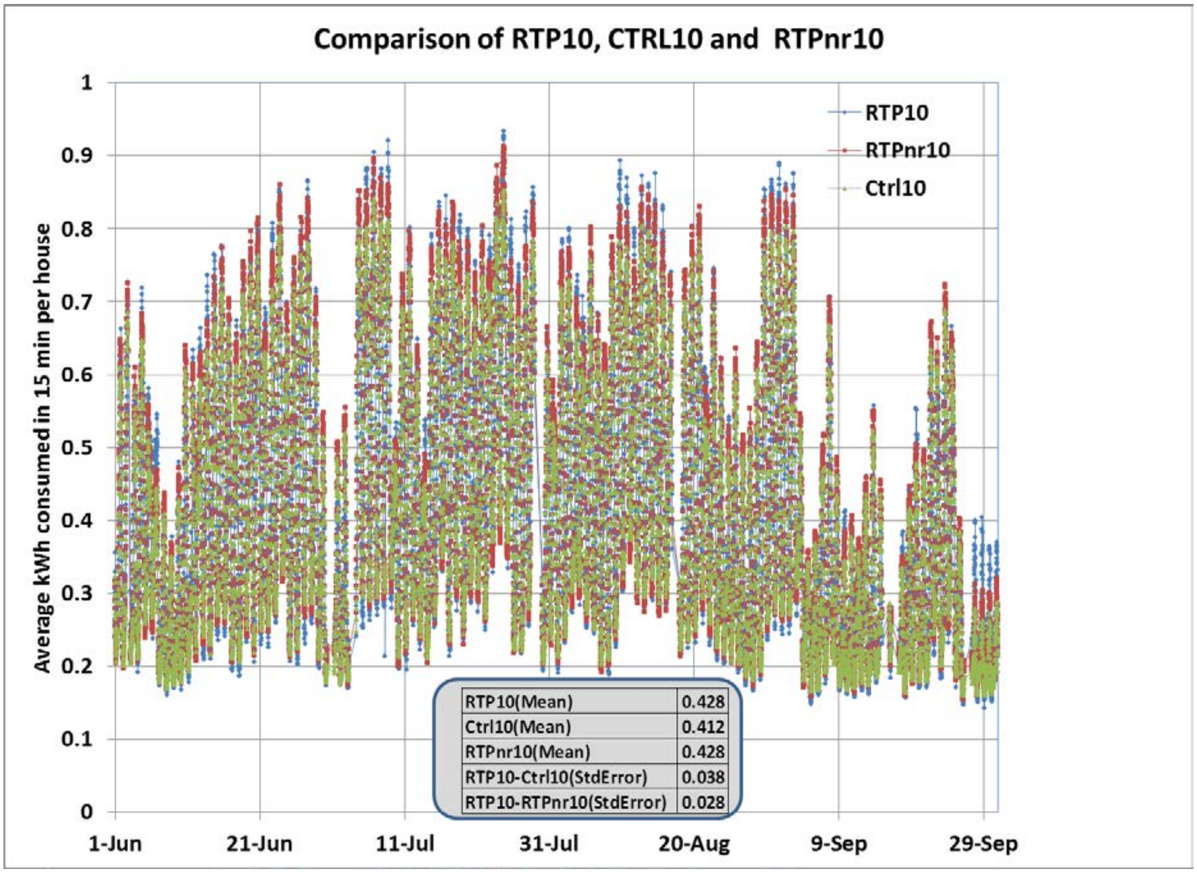

Figure 1.14. Comparison of RTP10, RTPnr10, and Ctrl10 Profiles for the Period June to September 2010

Although Figure 1.14 is crowded, one can discern that RTPnr10 is closer to RTP10 than Ctrl10 is. This is quantified by the comparison of means and standard errors in the inset in Figure 1.14. The performance of LOESS in matching peak loads can be assessed by comparing the top 5% of RTP10 loads with the coincident Ctrl10 and RTPnr loads. This is shown in Figure 1.15. It is clear that, for our purposes, RTPnr is a much more accurate representation of RTP_{da} than Ctrl.

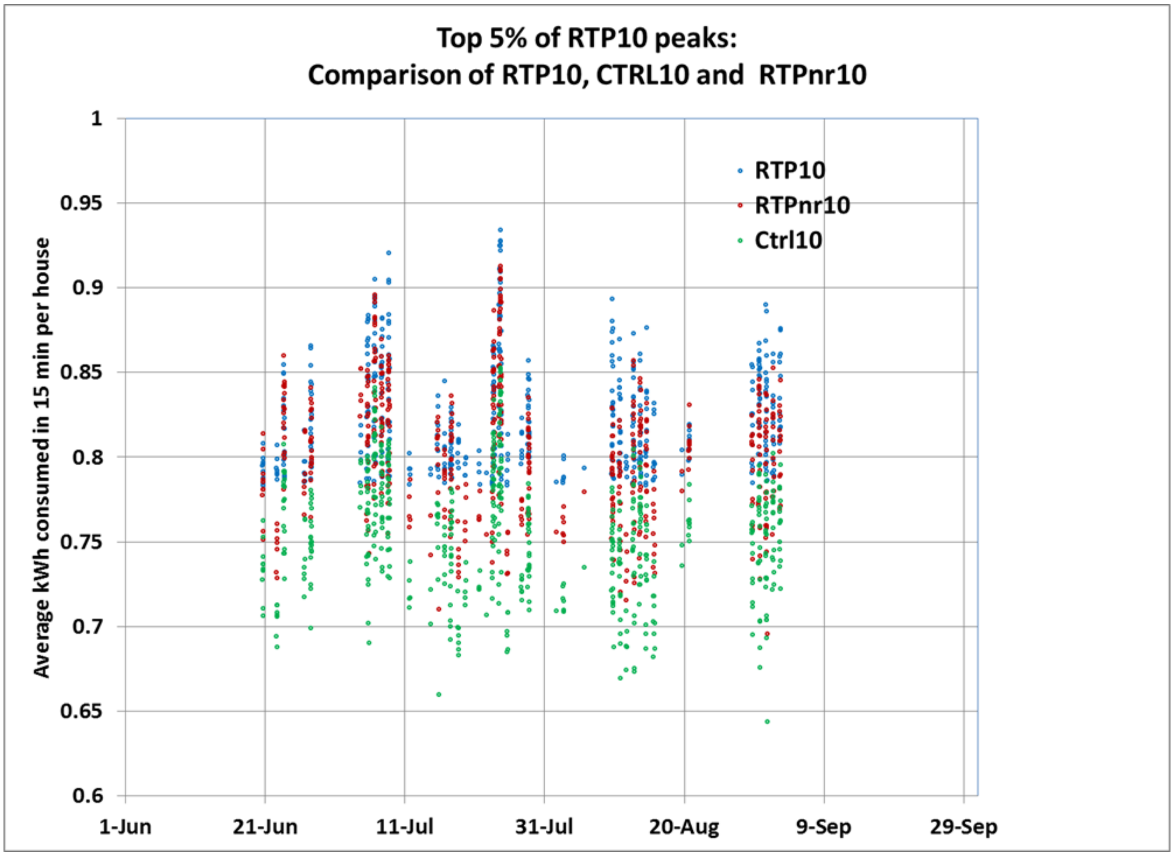

Figure 1.15. Comparison of the Top 5% of RTP10 Loads with the Coincident Ctrl10 and RTPnr Loads

We can now use the LOESS model to generate RTPnr13 from Ctrl13. From this point on, we will use RTPnr13 as the corrected control group with which RTP13 is to be compared. RTP13 is available in 5-minute intervals, whereas RTPnr13 (generated from 15-minute Ctrl13) is in 15-minute intervals. A linear interpolation method was used to generate 5-minute data from the 15-minute data. (This process is much cleaner than rolling up 5-minute RTP13 data into 15-minute data, for which missing data creates a number of special issues.)

Consistent handling of missing data is essential. Although Ctrl10 is an aggregate over a maximum of 272 households, there are many periods with fewer households. For obtaining statistically good aggregate data, only data to which >80% of the 272 contributed were retained. Similar processing was done for RTP10. The missing data time stamps for the two need not be the same. Only time stamps for which both RTP10 and Ctrl10 data are present are retained. Similar processing was done for RTP13 and RTPnr13.

1.5 Document Structure

This report supplements the RTP_{da} system analysis done by AEP Ohio in the main body of the gridSMART Project report. It covers three major areas:

- an analysis of the impacts of the RTP_{da} approach to engage end-use resources for system operations, including its application to address system capacity concerns, wholesale purchases, and spinning reserves,
- an analysis of impacts related to the consumer, including household bills, the consumers' interactions with the thermostats, and a comparison of the amount of energy bid into the market for running the HVAC units and the actual consumption of those units,
- and an analysis of the sensitivity of the of the RTP_{da} load to the fluctuating price of energy, including the observed response of the RTP_{da} resources to the congestion experiments.

2.0 System Impacts

The following sections describe the results of an analysis of impacts that affect system operations of the service provider. These include system- and feeder-capacity issues, wholesale power purchases, and the potential of applying RTP_{da} resources to spinning reserve markets.

2.1 Capacity

This analysis measures the reduction in capacity expansion requirements due to a price-induced shift in household peak load. The benefit of this analysis will be presented in terms of kW/household reduction in peak load.

Evaluating the capacity reduction is a complex problem that can be difficult to observe and characterize under real-world conditions, especially when the penetration level of RTP_{da} households is relatively low compared to other groups. A series of experiments were developed on the end-use resources to characterize their behavior and limitations. The results of these experiments were used to better calibrate the parameters of the simulation models. The simulation models were then used to quantify the potential for capacity reduction at various penetration levels.

2.1.1 Results of Analysis

The simulation models of the RTP_{da} system were evaluated on three peak days in July to determine the greatest sustainable capacity reduction that was achievable. On these days (July 16–18), the temperature was greater than 90^{o} F on five successive days. The evaluation was performed by (1) lowering the capacity limit until the cleared price reached the price cap during peak system load hours and (2) lowering the capacity limit until the price cap was reached during the projected peak feeder hours. The simulations in (2) were also run over the four-month test period to verify that the capacity could be maintained at a lower level throughout the four-month period. The simulations were performed at 15%, 25%, 35%, and 50% RTP_{da} penetration levels. The models were "tuned" to be responsive only to peak conditions, and not wholesale price fluctuations; this is similar to a day following a high-price event, when the controllers are desensitized to small fluctuations in the wholesale price.

Figure 2.1 shows a representative simulation during a 3.5-hour peak system load event. Figure 2.2 shows a representative simulation on the same day, but focusing on feeder peak reduction. All measurements are 15-minute average demand and are translated into a kW/household basis. Notice that the feeder peak is near the end of the event, highlighting that system and feeder peak demands do not necessarily align; hence the need to look at the availability of the resource in different periods. In Figure 2.1, notice that after the event is triggered, the two lines approach each other after approximately 2.5 hours, indicating that the resource is no longer able to hold a load reduction and the households begin to become less responsive, while in Figure 2.2 the resource begins to reduce sooner (approximately 2 hours into the event). The time the reduction is called for this peak load event affects the overall availability of the resource.

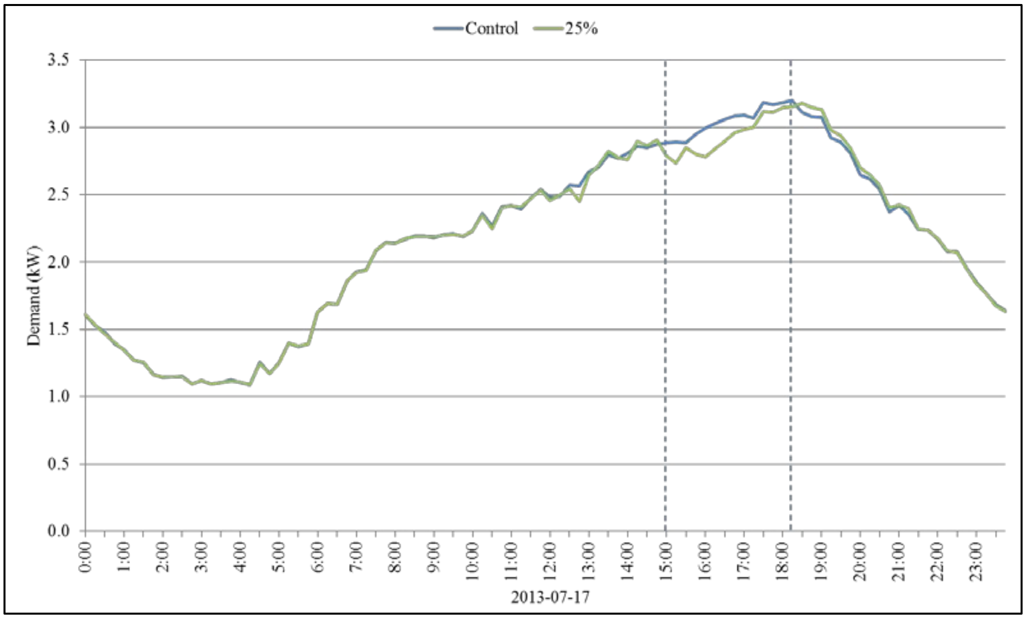

Figure 2.1. Time-Series Simulation during Peak System Load Event with 25% Penetration of RTP_{da} Households

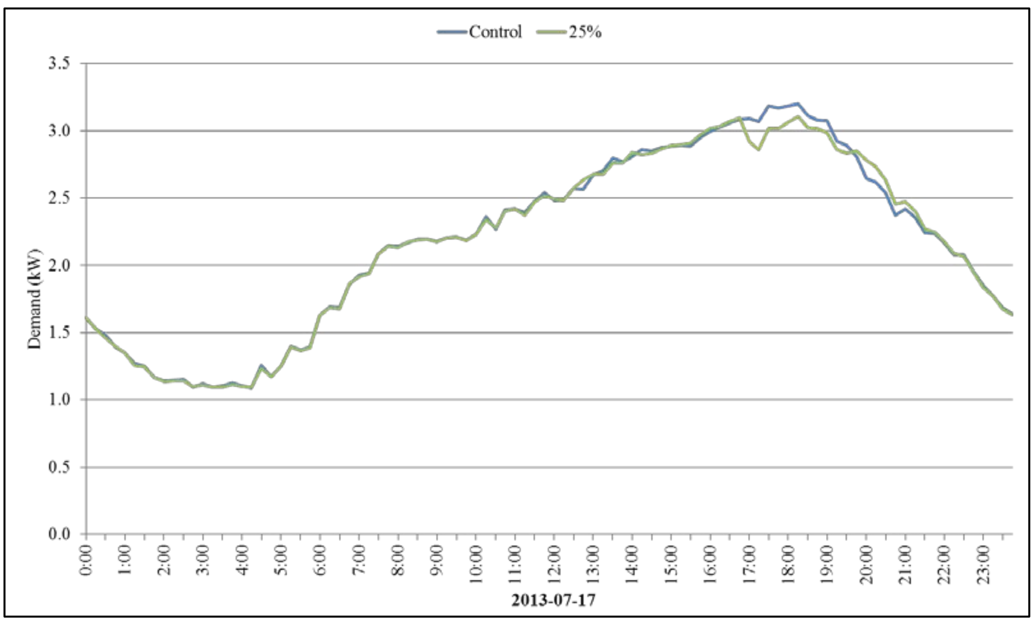

Figure 2.2. Time-Series Simulation of Feeder Peak Reduction with 25% Penetration of RTP_{da} Households

Figure 2.3 and Figure 2.4 show the peak demand reduction (i.e., the difference between the greatest demand before the capacity constraint was applied and the greatest demand after it was applied) as a function of RTP_{da} penetration levels for peak load events and feeder peak reduction, respectively. Additionally, a linear trend line has been added to the figures for clarification. Notice that the ability to reduce the peak during the feeder peak situation is much greater than during a peak system load event. This is for a number of reasons. The first is that the peak system load event lasted longer than the feeder peak event, meaning the resources are spread out over a longer period. The second is that the availability of resources for reduction is lower in non-feeder peak periods. If the values are extrapolated to 100% penetration (or the average response of an RTP_{da} household), it is seen that the RTP_{da} households provide a 13% load reduction during a peak system load event and a 22% reduction during feeder peak events.

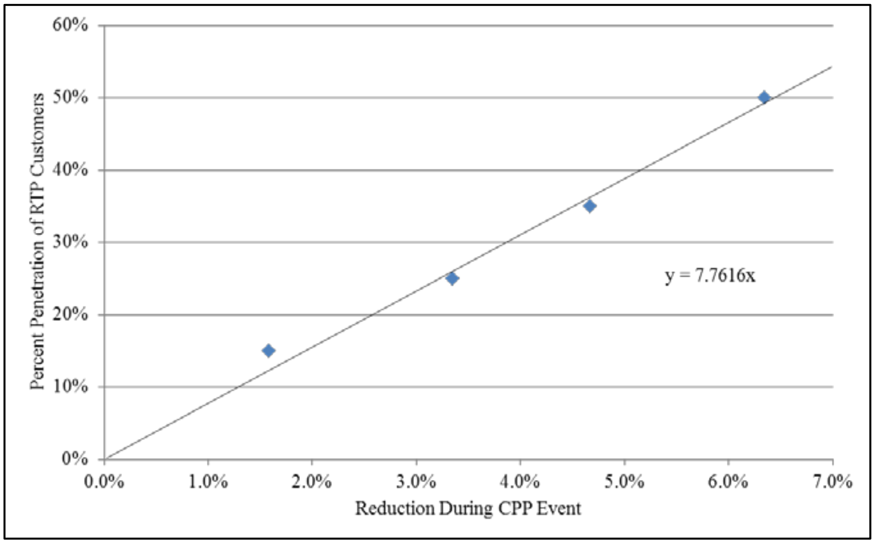

Figure 2.3. Comparison of Peak Reduction during a Peak System Load Event at Different RTP_{da} Penetration Levels

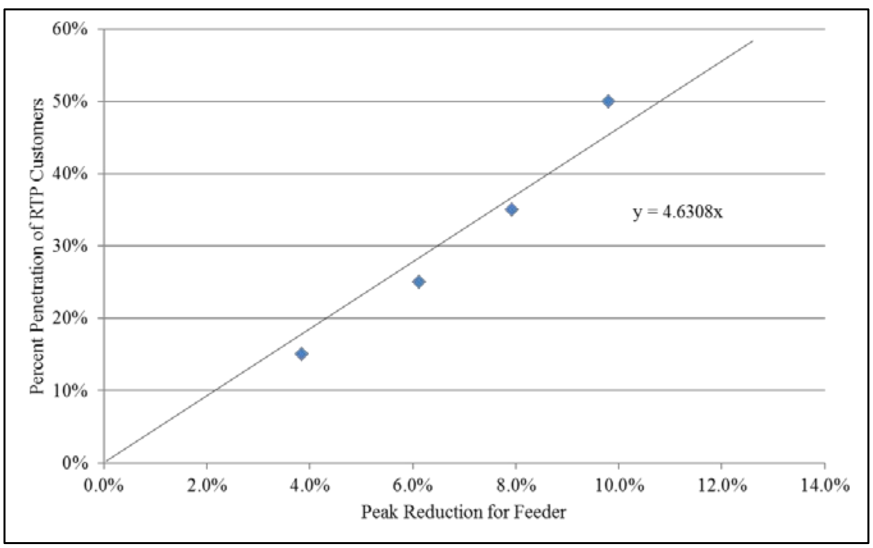

Figure 2.4. Comparison of Feeder Peak Reduction at Different RTP_{da} Penetration Levels

Note that these values represent a specific case for RTP_{da} household response, and in some ways, the "best case." In all simulations, it was known ahead of time when system peak events would occur and for how long, and what the load would be during a peak system load event. In an actual system, this will not be well known and the determination of the capacity limit may overuse resources (leading to early decay of the response) or underuse resources (leaving unused capacity from this resource). Even in simulation, the reduction did not provide a perfectly flat load (see Figure 2.2), as the market lags behind the changing load of the non-RTP$_{da}$ households. Incorporation of short-term load prediction may improve this aspect of RTP$_{da}$ system performance.

Additionally, the length of the time the resource is needed affects the amount of reduction available. For example, a 1-hour peak system load event is able to sustain deeper reductions than a 6-hour peak system load event. Figure 2.5 shows the reduction of demand as a function of the length of a peak system load event using the same simulation and day shown previously. This is shown with 100% penetration of RTP$_{da}$ households. Notice that after 4 hours, the load has effectively returned to a new baseline state, with a minor reduction coming from the thermostat setback. Also, note the magnitude of the rebound after releasing the peak system load event. While significant rebounds occur in the peak periods, if the end of the event is timed correctly after the control peak, the rebound is relatively minor and much lower than during the peak period. The recovery period for all events is such that most devices do not return to normal operation until 22:00 hours, seven hours after the start of the event.

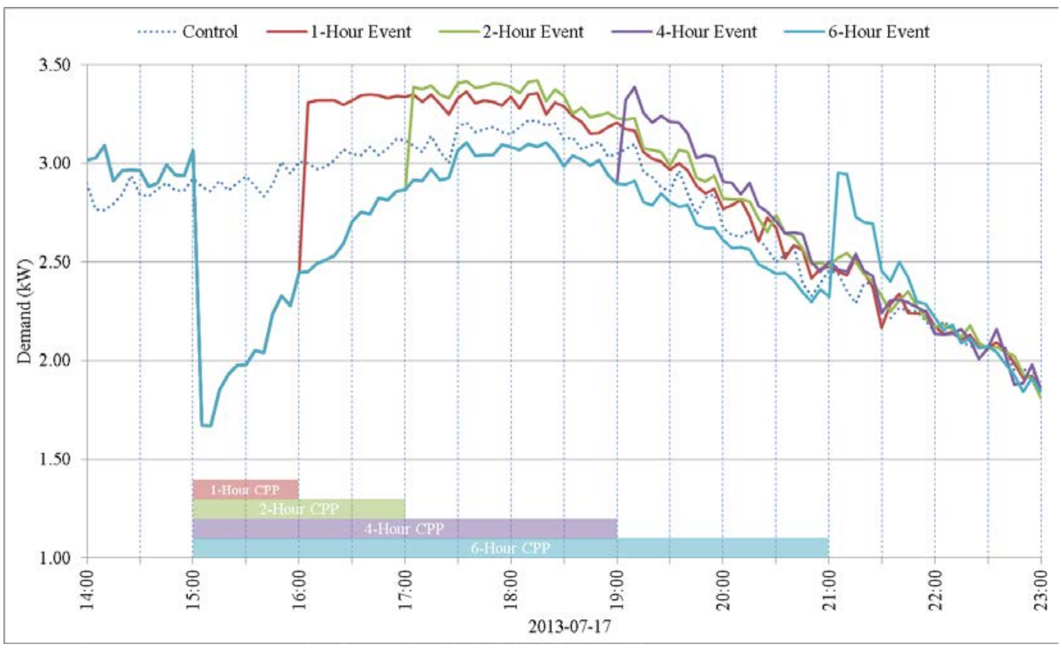

Figure 2.5. Comparison of Average Household Demand during a 1- to 6-Hour Peak System Load Event

2.2 Wholesale Purchases

Price-responsive loads alter their load shape in response to the retail energy prices. If the retail prices are determined in real time by wholesale market LMPs, then demand response to prices should result in decreased cost of wholesale energy purchases. The purpose of this analysis is to examine the impact on wholesale purchases using the data captured related to energy use by the HVAC systems in response to the market signal.

The approach is to compare the energy use in response to RTP$_{da}$ every 5 minutes by the RTP$_{da}$ households against the energy use by the control group. The difference is attributed to price response. Knowing the LMP, the difference in wholesale purchase costs can be calculated.

In this section, only the aggregate response by the participants is considered. That is, data from individual participants were aggregated. The way missing data were handled was considered in Section 1.4.2. The definitions of the household groups were listed in Section 1.4.

2.2.1 Response to Prices

It is instructive to examine RTP13 and RTPnr13 for typical periods. In addition, LMP data also were acquired. Figure 2.6 shows a comparison between RTP13 and RTPnr13 in the top panel and the difference between RTP13 and RTPnr13 and LMP in the bottom panel, which uses the same x-axis day intervals.

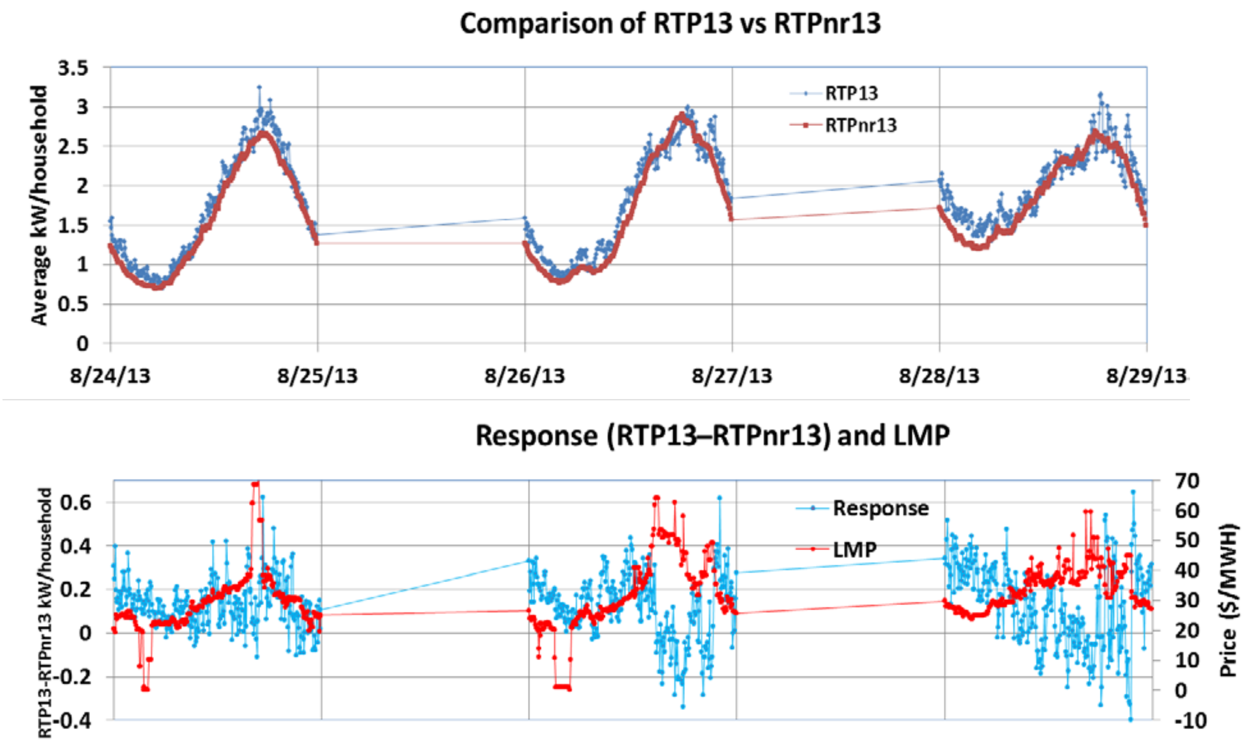

Figure 2.6. A Comparison between RTP13 and RTPnr13 (top), and between RTP13-RTPnr13 and LMP (bottom)

No data are plotted for August 25 and August 27. On those days, feeder congestion experiments were done, so on those days, the system is responding to real-time prices generated by simulated feeder congestion and not to wholesale LMP-generated prices. For this reason, feeder congestion experiment days were excluded from the wholesale purchase analysis. August 26 shows a very discernable load response to prices.

2.2.2 Totals for the 4-Month Period

The aggregation of RTP13 and RTPnr13 will now be examined to compare total loads with and without price response, and RTP13 × LMP and RTPnr13 × LMP will be examined to compare wholesale purchase costs with and without price response. Out of the 122 days in June, July, August, and September, all days when congestion experiments were performed were excluded. Furthermore, only aggregate data that received contributions from >80% of the maximum number of contributors was included. This resulted in 50 days of usable data—31 weekdays and 19 weekend days. Not all 50 days had data for every one of the 288 5-minute periods. Because this affected both RTP13 and RTPnr13 similarly, this was not considered sufficient reason to exclude a day. Table 2.1 shows a summary for the 50 days.

Table 2.1. Summary of Energy and Wholesale Costs for July–September Before Adjustments

Energy		
RTP13 (kWh/day/house)	36.21	
RTPnr13 (kWh/day/house)	35.55	
RTP13 is	1.9%	higher than RTPnr13
Wholesale cost		
RTP13 ($/day/house)	$1.432	
RTPnr13 ($/day/house)	$1.42	
RTP13 is	0.7%	higher than RTPnr13

Feeder congestion days were excluded, but they affected the behavior of the HVAC units the following day. The high prices (~$1000/MWH) experienced during the congestion period made the prices expected by HEMs high for 24 hours following the conclusion of the feeder congestion experiment. This resulted in the normal prices appearing low, and the HEMs responded by lowering the house temperatures. This can be seen in Figure 2.7, which shows that the daily average observed temperature for the non-congestion days was generally substantially lower than the desired set points. The moving average in the figure is computed over 5 points.

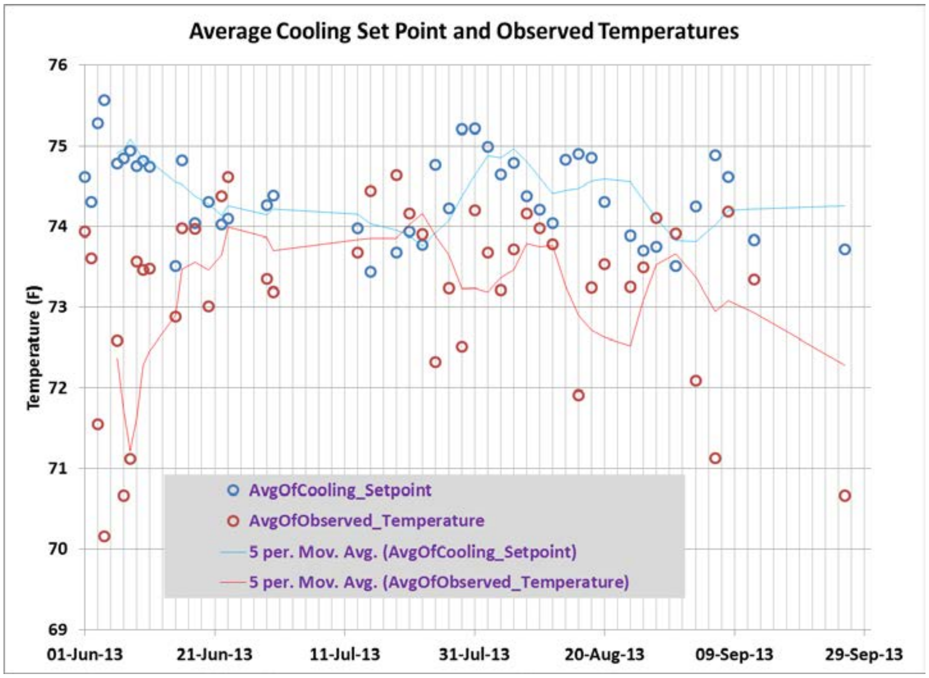

Figure 2.7. Daily Average Cooling Set Points and Observed Temperatures during Non-Congestion Days

The undesirable situation of temperatures below desired set points necessitated adjustments for the additional cooling energy use. This was done as follows. From a plot of daily average outside temperature obtained for the Columbus, Ohio, weather station, a regression of daily energy use versus daily average outside temperature was performed. Separate regressions were performed for weekdays and weekends. The results are shown in Figure 2.8 and Figure 2.9.

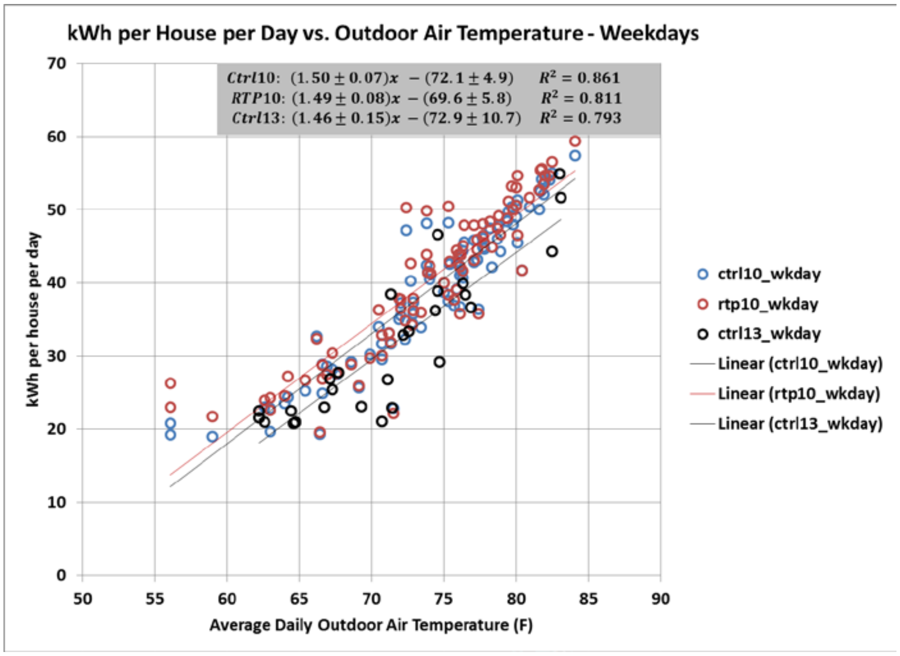

Figure 2.8. Plot of Daily Average Energy Use per House versus Average Outdoor Temperature for Weekdays

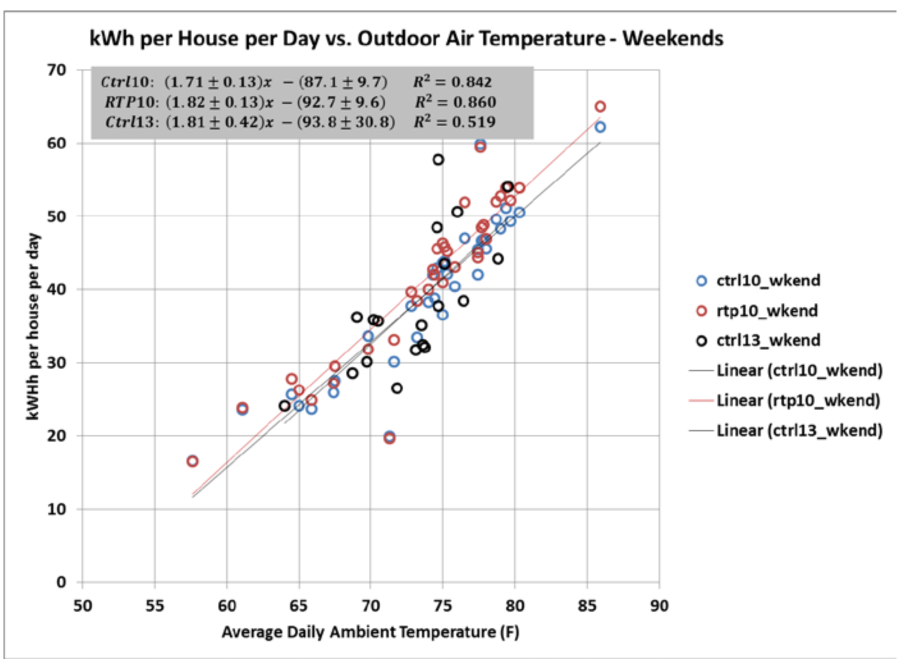

Figure 2.9. Plot of Daily Average Energy Use per House versus Average Outdoor Temperature for Weekend Days

From the above regressions, a value of 1.5 kWh/day/house/°F was derived for weekdays and 1.8 kWh/day/house/°F for weekend days. The behavior of Ctrl13 is statistically indistinguishable from that of Ctrl10. This means that on a weekday, if the average outdoor temperature increases by 1°F, the energy use for the day increases by 1.5 kWh/house. Similar considerations apply for the weekend days. Increasing the outside temperature by 1°F is, to a very good approximation for energy use, equivalent to decreasing the inside temperature by 1°F. If it is now assumed that, in the absence of feeder experiments, the average observed temperature would have been equal to the average desired temperature set point (rather than the observed temperature resulting from the RTP_{da}-driven set point), a compensation term for the daily energy use and the resulting impact to wholesale cost can be applied. The compensation term for the wholesale cost can be calculated as the average LMP for the day times the change in kWh per household for the day. The results of applying such compensation are shown in Table 2.2.

Table 2.2. Summary of Energy and Costs for July–September after Compensating for Congestion Experiments

After compensating for the impact of congestion experiments on non-congestion days		
Energy		
RTP13_Compensated (kWh/day/house)	33.66	
RTPnr13 (kWh/day/house)	35.55	
RTP13_Compensated is	5.3%	lower than RTPnr13
Wholesale cost		
RTP13_Compensated ($/day/house)	$1.351	
RTPnr13 ($/day/house)	$1.423	
RTP13_Compensated is	5.0%	lower than RTPnr13

The kWh usage is reduced by 5.3% and the wholesale costs by 5.0%. Comparing this table with Table 2.1, it can be seen that the effect of the temperature compensation on cost reduction was not commensurate with the effect of temperature compensation on kWh reduction. This is due to the fact that the compensation was effective largely during periods of low prices, as seen in Figure 2.10.

Some sources of error and their impacts follow. These include:

- There is a difference in the demographics of RTP_{da} households over the years 2010 to 2013, and similarly in the control group.
- The RTP10 group had 272 households, whereas RTP13 had 192 households. This is not necessarily a problem, but further review that the pool characteristics match would add confidence.
- The compensation method for the excessive cooling due to congestion experiments in the preceding day deserves further investigation.
- Good data representing only 50 days of operation survived the various filters.
- Even on these 50 days of good data, the number of houses contributing was variable.

No attempt was made to quantify the errors arising from these sources in this report; however, it remains a good topic for future investigation.

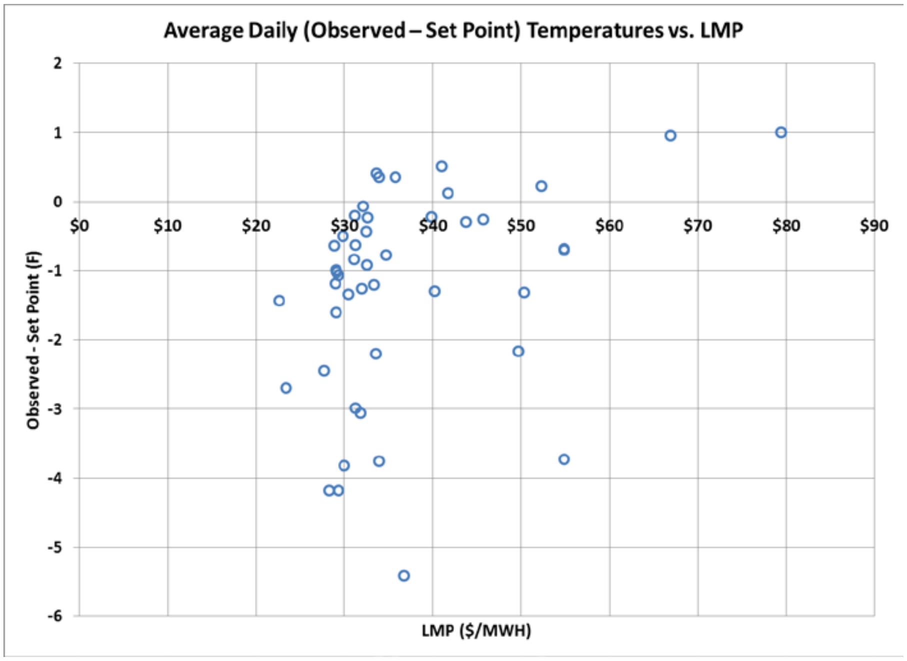

Figure 2.10. The Depression of Observed Temperature Below Set Point versus Average LMP for the Day

2.2.3 Simulated Results

The RTP_{da} household information was used to calibrate GridLAB-D[1] simulated models. These household models were used within GridLAB-D to represent 25% penetration of RTP_{da} households; 300 households were "experimental" while 900 were operated similarly in each simulation and did not respond to variations in price. The experimental households were modeled using three different scenarios:

1. Control – the households were simulated using the standard pricing tariff.
2. RTP_{da} – the households were simulated using the residential RTP_{da} service tariff and responded to wholesale price fluctuations in a manner similar to those observed in the pricing experiments (for example, thermostat slider and temperature settings, internal air temperature decay rates, etc.).
3. RTP_{da} Congested – the households were simulated using the residential RTP_{da} service tariff, responded to wholesale price fluctuations, and responded to capacity limits placed on the feeder aligned with the actual experiments (96 experiments in four months).

The simulations were run for four months, collecting energy consumed at 5-minute intervals by each of the 300 RTP_{da} households. An "average" RTP_{da} household was constructed from the resulting information by summing all 300 loads and dividing by 300 in each interval. The total wholesale energy cost for the average household is shown in Table 2.3. Table 2.4 shows these same values in terms of percent of total energy costs, showing an average RTP_{da} household savings of 2.5% for wholesale energy costs on a per RTP_{da} household basis. When accounting for the effects of the congestion experiments,

[1] www.gridlabd.org

this number is reduced to 1.5%. This is expected, as the effect of the congestion experiments is to reduce sensitivity to wholesale price fluctuations. Note that the energy costs per day match closely with the experiment results shown in Table 2.1 above.

Table 2.3. Comparison of Monthly Wholesale Energy Costs for an Average Household ($)

	Monthly Wholesale Energy Cost Per Household ($)					
	June	July	August	September	Average	Per Day
Control	$43.93	$57.57	$42.58	$37.92	$45.50	$1.492
RTP_{da}	$42.80	$55.68	$41.69	$37.17	$44.34	$1.454
RTP_{da} Congested	$43.10	$56.55	$42.05	$37.44	$44.79	$1.470

Table 2.4. Reduction of Wholesale Energy Costs for an Average Household (%)

	Change in Consumer Wholesale Energy Cost (% Savings)				
	June	July	August	September	Average
RTP_{da}	2.6%	3.3%	2.1%	2.0%	2.5%
RTP_{da} Congested	1.9%	1.8%	1.2%	1.3%	1.5%

Looking at the impact on energy consumption, Table 2.5 shows the average energy reduction for each of the cases (a positive number indicates reduced energy consumption). The average reduction in energy consumption is 1.2%, decreasing to 0.9% during the congestion experiments due to the effects of precooling.

Table 2.5. Reduction of Energy Consumption for an Average Household (%)

	Change in Consumer Energy (% Reduced)				
	June	July	August	September	Average
RTP_{da}	1.3%	1.3%	1.4%	0.7%	1.2%
RTP_{da} Congested	1.1%	0.9%	1.0%	0.7%	0.9%

While these values do not perfectly align with the estimated results in Table 2.2 above, they are very similar, and provide additional veracity to the method described in Section 2.2.2 for adjusting the load shapes.

2.3 Spinning Reserves

This analysis investigates the spinning reserve capacity that can be achieved at any given time due to the demand response capability of the loads in the demonstrations. “Spinning reserve” is the extra generating or demand response capacity that is available to the system operator within a short interval of time to meet demand in case a generator goes down or there is another disruption to the supply. Most system operators require the spinning reserve capacity to be available to compensate for the loss of the largest power plant (plus a fraction of the peak load) within a preset amount of time (typically 10 minutes), and be available to respond continuously for a preset amount of time (typically 30 minutes). The spinning reserve capacity is a short-term capability and can therefore be measured in kW/household/hour or kWh/household/hour. It can also be measured in annual monetary terms as the $/household earned in the spinning reserve market. This analysis evaluates the capability of RTP_{da} households to participate in spinning reserve markets. While this analysis is not comprehensive, it is used to determine a "best case" for RTP_{da} households participating in spinning reserve markets, using average market prices from various independent system operators.

2.3.1 Results of Analysis

Spinning reserve is an ancillary service that can be bid into the ancillary services market. Within PJM, the Synchronized Reserve and Regulation Market decides the Synchronized Reserve market cleared price (SRMCP). As load becomes price responsive, like the HVAC loads in the RTP_{da} demonstration, the load can be considered as a spinning reserve for specific durations in the day and can be bid into ancillary services markets. Knowing the amount of load that can be safely bid into the spinning reserve market is important not only to make a bid, but to also be assured that the required reserve requirement can be successfully satisfied if called upon to provide the service. The auction collects all RTP_{da} customer resource availability and the bid curve can be used to determine the amount of resource available at any given market period, as shown in Figure 2.11. The highlighted area represents the households that are willing to reduce their demand given the proper incentive (via the RTP). The service provider may engage only a fraction of the total available resource to participate in the spinning reserves market by setting the congestion limit, and hence the cleared price, appropriately. The utility would weigh the cost of acquiring the resource (incentive payment to displaced consumers) against the benefit from provision of spinning reserve capacity (revenue from spinning- reserve markets, or avoidance of self-scheduling cost).

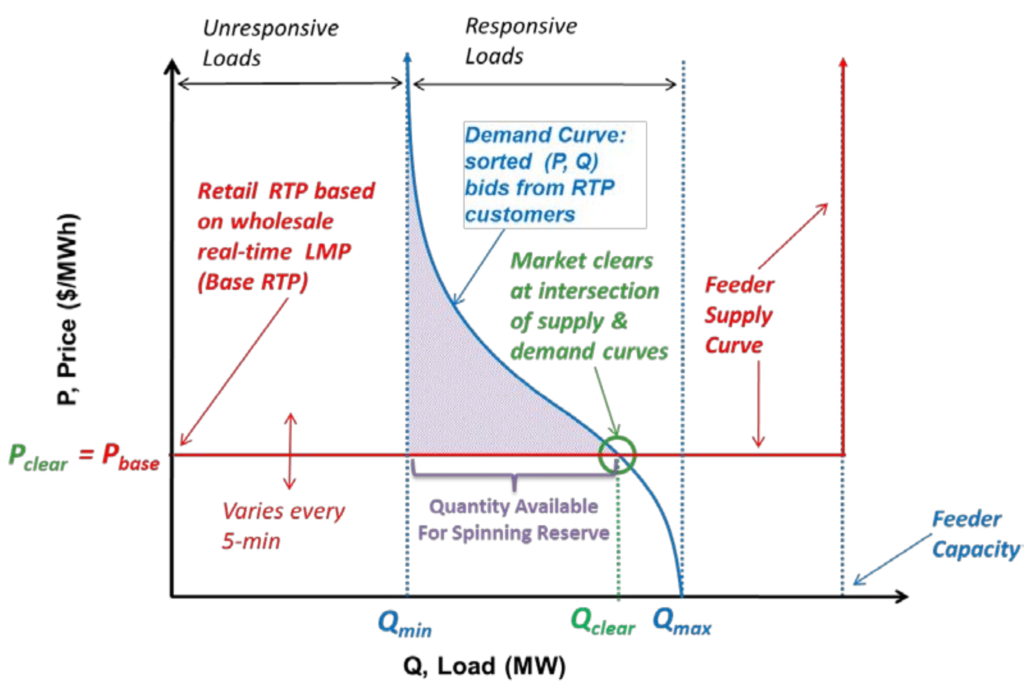

Figure 2.11. Resource Available for Spinning Reserve During Each Market Period

In each market period, the total quantity (kW) of responsive load less than the load at the cleared price is available for participation in the spinning reserve call. In this study, the quantity is calculated for each 5-minute interval, then averaged over the hour to determine the amount of load available for a one-hour spinning reserve call (although most spinning reserve calls last for periods much shorter than one hour).

The overall spinning reserve capabilities of the system during the study period are difficult to determine because the frequent congestion experiments held over the operational period distort a more natural behavior of the bidding system. To better estimate the benefits, PNNL instead used the simulated models to determine the average amount of resource available at every hour of the summer. By then comparing that value to the average PJM market price at each hour, the maximum amount of possible revenue generation in the spinning reserve market can be estimated. Note that this includes every hour in the summer and assumes that no spinning reserve calls were made to affect future household behavior. It also assumes that there is enough resource in the RTP_{da} system to participate in the market. These assumptions are used to determine the "best case" scenario for capturing spinning reserve revenue.

Table 2.6 shows the results of this study in the form of total revenue generated per RTP_{da} household per month. This is calculated by determining the total amount available (as shown in Figure 2.11), then dividing by the total number of RTP_{da} households. The spinning reserve prices were exceptionally low in the PJM market for the summer evaluated, averaging \$0.49/MWh between June and October of 2013. A number of additional historical spinning reserve markets were evaluated for comparison. While the potential in PJM's market is extremely small, in other markets, where spinning reserve resources are in higher demand, differing amounts of revenue can be generated with relatively little impact on the consumer (assuming the resource is called relatively infrequently). The results of three other markets are shown for comparison. This analysis does not address the impact on the spinning reserve market itself or the reduction of overall prices as additional demand- response resources participate, but rather highlights the potential uses of this system.

Table 2.6. Spinning Reserve Markets and the Maximum Amount of Revenue Available to RTP_{da}

	PJM 2013[a]	CAISO 2013[b]	ERCOT 2013[b]	ERCOT 2008[a]
Total Revenue Per Household Per Month	\$0.08	\$1.78	\$5.79	\$13.64

(a) Based on average hourly prices
(b) Based on average monthly prices

3.0 Household Impacts

This chapter analyzes the impacts of the RTP_{da} approach on consumers and their residential equipment. These include household electricity bills, consumer interactions with their thermostats, and the quantity of HVAC energy bid into the market versus the amount observed from the metering data.

3.1 Household Bill Impacts

This section analyzes the impact on RTP_{da} household bills (per tariff Schedule RS-RTP, 2012) for the months of June through September 2013. The RTP_{da} bills are divided into the following components:

$$B_{RTPtot} = B_{RTPeng} - B_{RTPinc} + B_{RTPfixed} \tag{3.1}$$

where B_{RTPtot} = RTP_{da} household total bill per period of interest
B_{RTPeng} = RTP_{da} household energy-sensitive component of the bill per period of interest
B_{RTPinc} = RTP_{da} household incentive savings component of the bill per period of interest
$B_{RTPfixed}$ = RTP_{da} household fixed, non-energy-sensitive component of the bill per period of interest.

The incentive savings is calculated as explained in Section 1.2.1.3. In any one month, the incentive savings (B_{RTPinc}) is not allowed to exceed the RTP_{da} market-based energy component (a portion of B_{RTPeng}) of the RTP_{da} bill; however, it is possible that $B_{RTPinc} > B_{RTPeng}$ on a daily or hourly basis. As the monthly billing periods for the households are staggered throughout a month, and 5-minute energy usage information is available from the meters, the non-energy portion of the monthly bill is spread evenly over 5-minute intervals to obtain $B_{RTPfixed}$ and the 5-minute energy data are used with the RTP_{da} tariff to obtain 5-minute portions of B_{RTPeng}. The 5-minute household market bidding data are used to calculate a 5-minute B_{RTPinc} component, and Equation (3.1) is used to calculate B_{RTPtot}. This 5-minute data forms the basis for calculating average hourly bills. The average bill for any one hour is calculated based on the population of households that are participating during that hour. This is done for every hour (for which good data exist) over the four-month period. These hours are also analyzed in subsets of peak and off-peak, and hot and mild temperature periods.

Because the bills in this analysis are calculated based on the energy use data captured by the RTP_{da} system about and the RTP_{da} tariff, there will be discrepancies with the actual bills calculated by the AEP Ohio billing system. That system must handle various complicating situations with regard to metering and household changes, and make appropriate adjustments to the final bill that are not replicated here.

The average \$/hr billing information over the months of June through September for all households in the RTP_{da} group is presented in Table 3.1 below. The total bill and the contributions to it are represented according to averages of the totals as well as the averages for the top and bottom 25% of households by bill component area. In addition, the average \$/hr of the bills for households in off-peak (22:00–14:00) and peak (14:00–22:00) periods is also listed. Both off-peak and peak periods are further filtered for mild (outdoor temperature ≤ 80°F) and hot (outdoor temperature > 80°F) weather. These same quantities are repeated in Table 3.2, but reflect percentages based on the average total RTP13 bill.

One can see from the tables that the incentive savings were dispersed to households of all levels of energy usage by amounts on the order of 3–4%. When looking at all the households according to incentive savings component, the average of the top 25% bills of the households received a savings of 12% of the average total bill of all households. This counteracts a 2.5% increase in the energy-sensitive portion of the bill, for a total bill savings of about 5% from the average $/hr over the entire population of households. Those in the bottom 25% have no incentive savings contribution and show a higher average total bill of about 10.5% compared with the average of all households.

Table 3.1. RTP$_{da}$ Bill $/hr Averages for All Households

Metric		RTP13				
		Total Bill	kWh	Energy	Incentive	Fixed
Average $/hr Total Bill		0.1916	1.4812	0.1909	0.0081	0.0087
	Top 25%	0.2563	1.9742	0.2539	0.0064	0.0087
	Bottom 25%	0.1289	0.9987	0.1277	0.0076	0.0087
Average $/hr Energy Bill						
	Top 25%	0.2531	1.9706	0.2529	0.0084	0.0087
	Bottom 25%	0.1290	0.9805	0.1253	0.0050	0.0087
Average $/hr Incentives						
	Top 25%	0.1820	1.5486	0.1963	0.0230	0.0087
	Bottom 25%	0.2116	1.5643	0.2029	0.0000	0.0087
Average $/hr Off-Peak		0.1506	1.2089	0.1457	0.0039	0.0087
	Off-Peak Mild	0.1204	1.0101	0.1148	0.0031	0.0087
	Off-Peak Hot	0.1754	1.3727	0.1712	0.0045	0.0087
Average $/hr Peak		0.2736	2.0257	0.2812	0.0164	0.0087
	Peak Mild	0.1891	1.5225	0.1884	0.0081	0.0087
	Peak Hot	0.3405	2.4247	0.3547	0.0230	0.0087

Table 3.2. RTP$_{da}$ Bill $/hr Averages: Percent of Average Total Bill for All Households

Metric		RTP13				
		Total Bill	kWh	Energy	Incentive	Fixed
Average $/hr Total Bill		100.0%	100.0%	99.7%	4.2%	4.6%
	Top 25%	133.8%	133.3%	132.6%	3.3%	4.6%
	Bottom 25%	67.3%	67.4%	66.7%	3.9%	4.6%
Average $/hr Energy Bill						
	Top 25%	132.1%	133.0%	132.0%	4.4%	4.6%
	Bottom 25%	67.3%	66.2%	65.4%	2.6%	4.6%
Average $/hr Incentives						
	Top 25%	95.0%	104.6%	102.5%	12.0%	4.6%
	Bottom 25%	110.5%	105.6%	105.9%	0.0%	4.6%
Average $/hr Off-Peak		78.6%	81.6%	76.1%	2.0%	4.6%
	Off-Peak Mild	62.8%	68.2%	59.9%	1.6%	4.6%
	Off-Peak Hot	91.6%	92.7%	89.4%	2.4%	4.6%
Average $/hr Peak		142.8%	136.8%	146.8%	8.5%	4.6%
	Peak Mild	98.7%	102.8%	98.4%	4.2%	4.6%
	Peak Hot	177.8%	163.7%	185.2%	12.0%	4.6%

The bill components can also be viewed across the peak and off-peak periods with hot and mild weather. This ranges from off-peak+mild incentive savings of 1.6% of the average \$/hr total bill to peak+hot incentive savings of 12%. The impact on the hourly rate of the bills over these periods is about 63% for off-peak+mild to about 180% for peak+hot periods when compared to the average \$/hr for all time periods. This range is more dramatic than for the kWh consumed in those periods because energy prices for the RTP_{da} households are generally greater during peak+hot periods than during off-peak+mild periods.

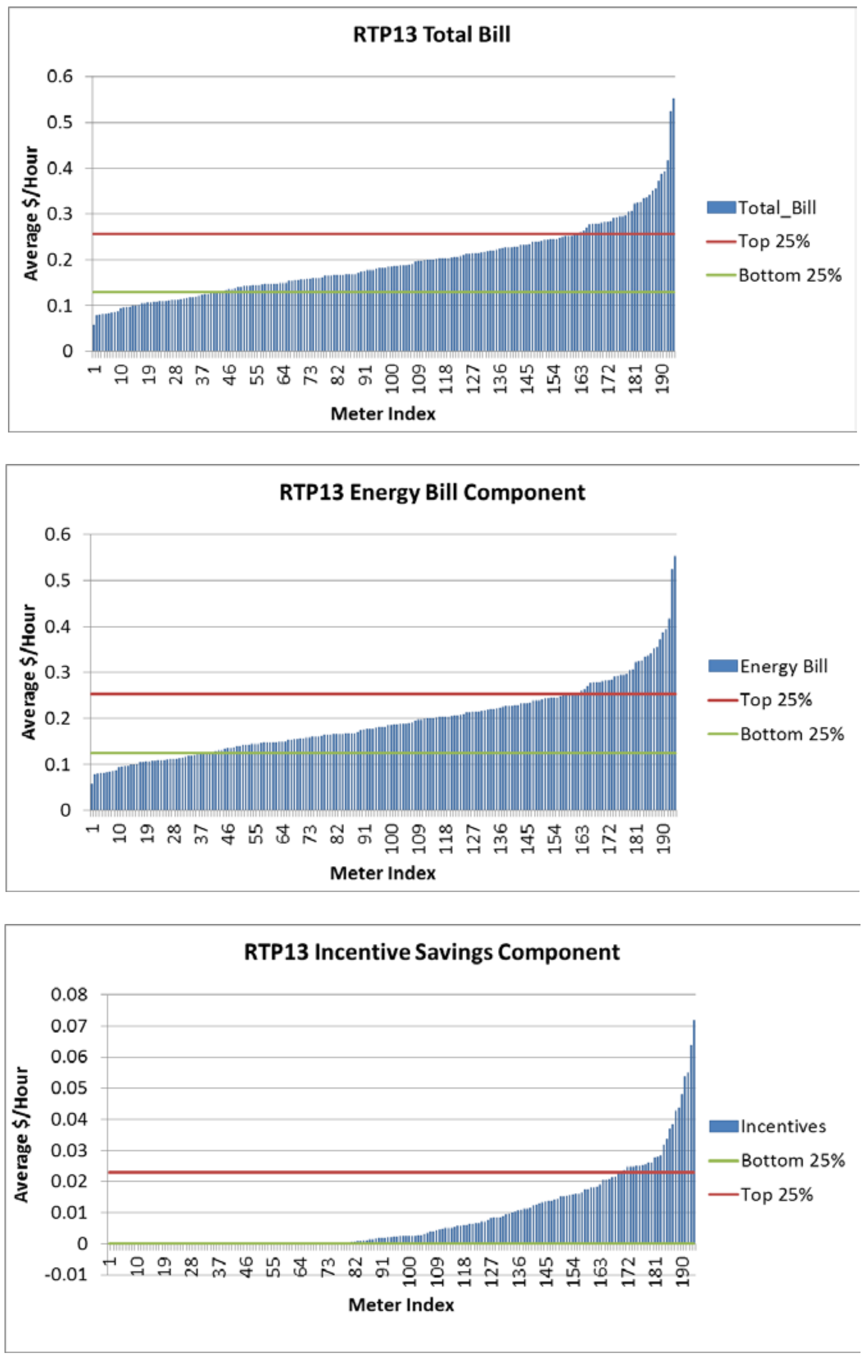

Figure 3.1. RTP_{da} Average Hourly Household Bills with Total, Energy, and Incentive Savings Components

The graphs in Figure 3.1 show the distribution of the hourly rates for the population of households as ordered from lowest to highest household for each bill component; the households (indicated by meter index in the graphs) are reordered in each graph from lowest to highest household contribution. Each figure includes the average of the top and bottom 25% for the population being displayed.

One can see from these figures that there are a few households with relatively high total average hourly energy bills, with the remainder distributed with a relatively flat slope. When one looks at the incentive savings component, about 40% of the households received little or no incentive savings, while about 10% of households had significant average $/hr incentive savings. Note that the incentive saving is allowed to exceed the RTP_{da} market-based contribution to the energy portion of the bill on an hourly basis, but not on a monthly basis.

The graphs in Figure 3.2 depict the distribution of the average $/hr energy-sensitive components of the bills for households in off-peak and peak periods. Both off-peak and peak periods are further filtered for mild and hot weather as defined above. For each graph, the households are reordered from lowest to highest contribution for the population displayed.

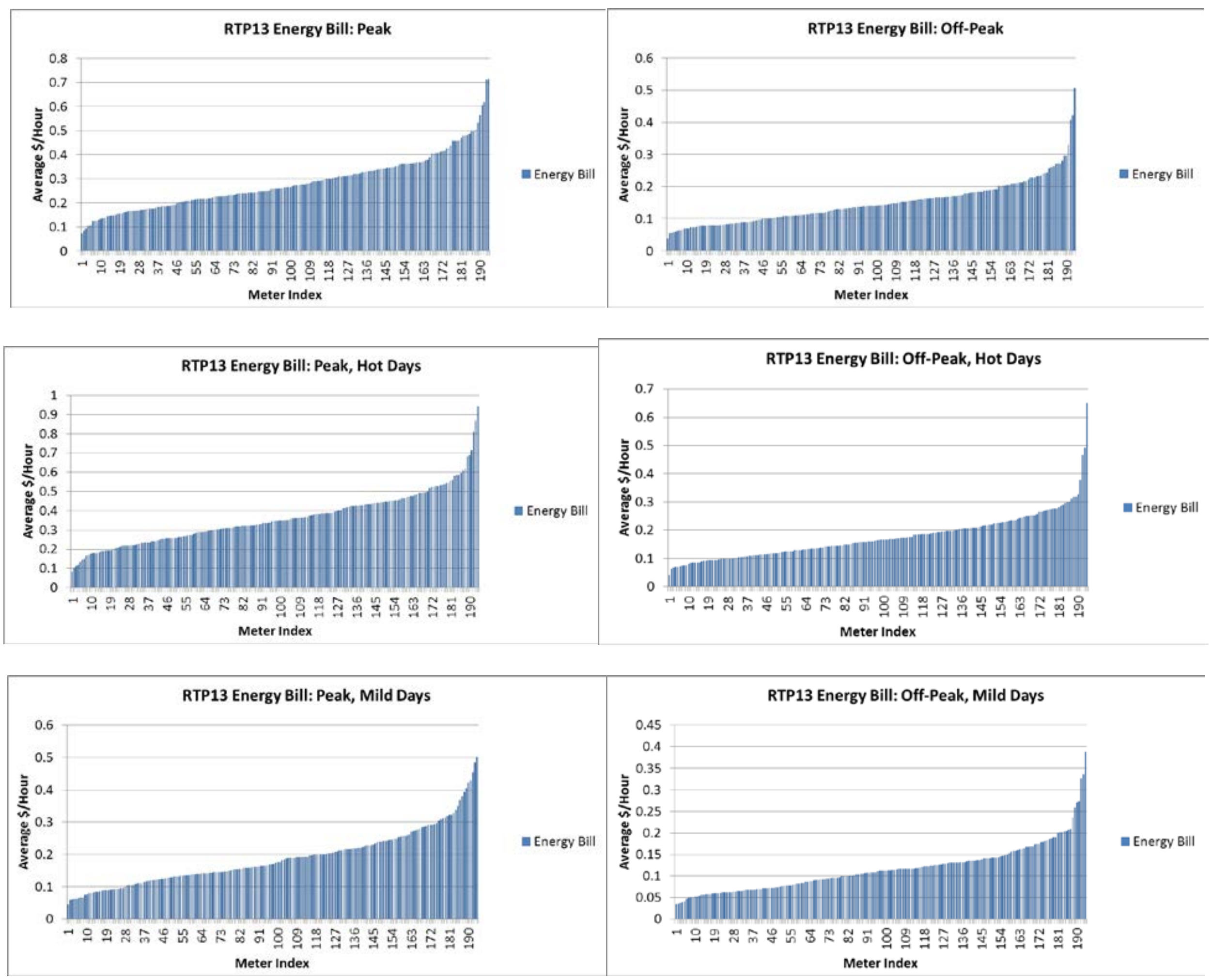

Figure 3.2. RTP_{da} Average Hourly Household Energy-Sensitive Bill Component for Peak and Off-Peak Periods

From these graphs one can see the relatively small number of households at the extremes of the billing range and the significant differences in peak+hot and peak+mild versus off-peak conditions. Similarly, the incentive savings contributions to the RTP$_{da}$ bills are shown in Figure 3.3.

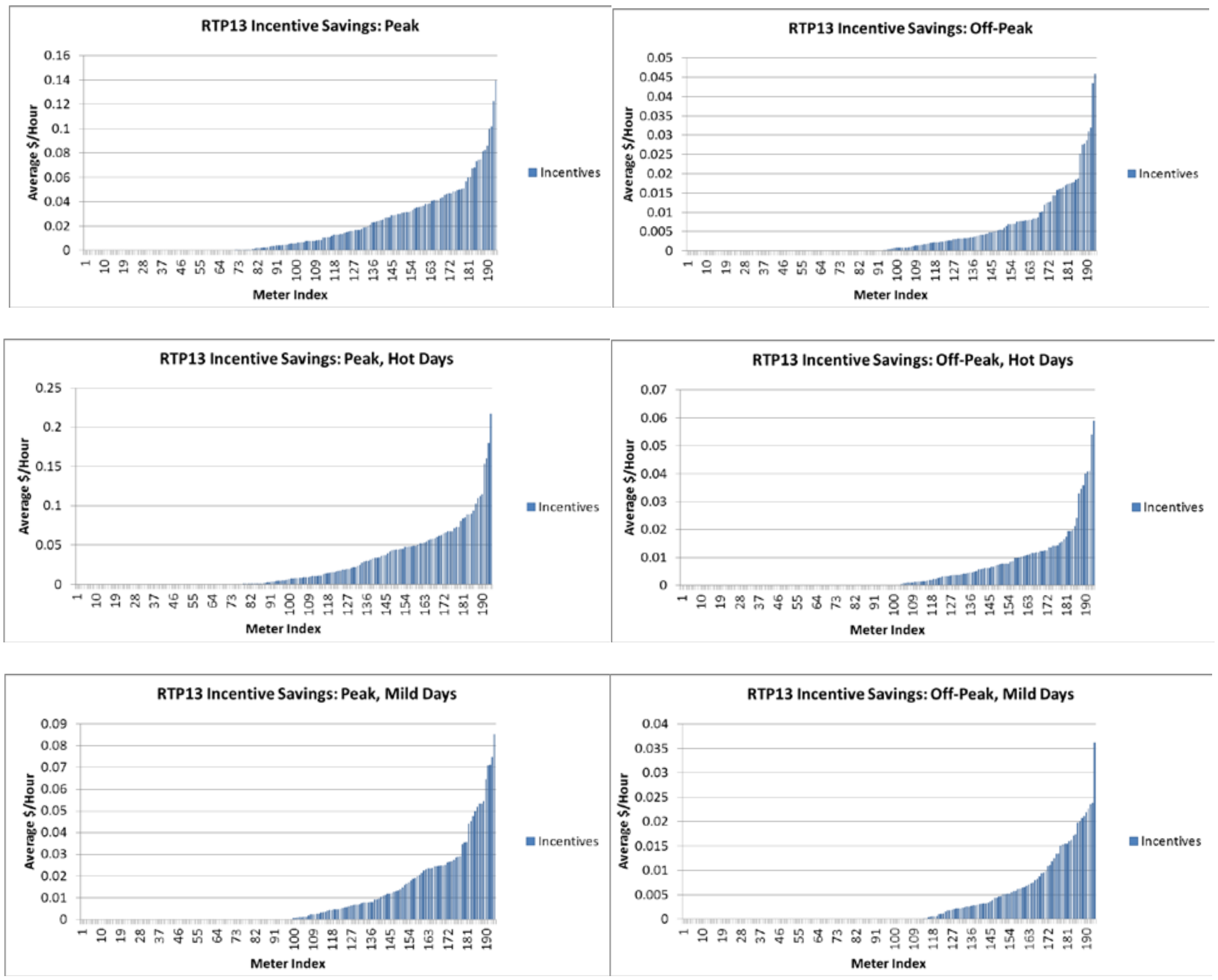

Figure 3.3. RTP$_{da}$ Average Hourly Household Incentive Savings for Peak and Off-Peak Periods

A review of the incentive savings indicates that the peak periods have significantly more savings than the off-peak periods. This is to be expected, as there is more HVAC resource available for market-based curtailment in the peak periods. The difference is also likely increased because more congestion experiments were run during peak periods (see Section 1.3.2). The hot days also have significantly more incentive savings than the mild days, again likely because there is more HVAC resource available to participate in the market.

The following subsections describe comparisons of the RTP$_{da}$ bill with bills for the same households subjected to the standard tariff (RTPstd). Since the RTP$_{da}$ congestion experiments called upon the households more frequently than would be expected in typical operations, an additional section is provided that compares the bills of RTP$_{da}$ to non-RTP$_{da}$ households.

3.1.1 RTP$_{da}$ Household Bills Compared with Standard Tariff

Figure 3.4 presents the total RTP$_{da}$ bill with the total standard tariff bill. Each "index number" is one household in one month (which may be June, July, August, or September); some households will be listed four times (June-September), while others may only appear once. Household bills that had less than 80% data acquisition through the RTP$_{da}$ dispatch system were removed from this analysis, due to large variability and errors in the bill calculation. Figure 3.4 orders the household bills by kWh consumed over the four-month period and compares the households' RTP$_{da}$ bills against the same households' bills as if they had been charged the standard tariff. One can see that there is a wide spread of relatively small bill increases and decreases at all levels of consumption; this is more clearly shown in Figure 3.5.

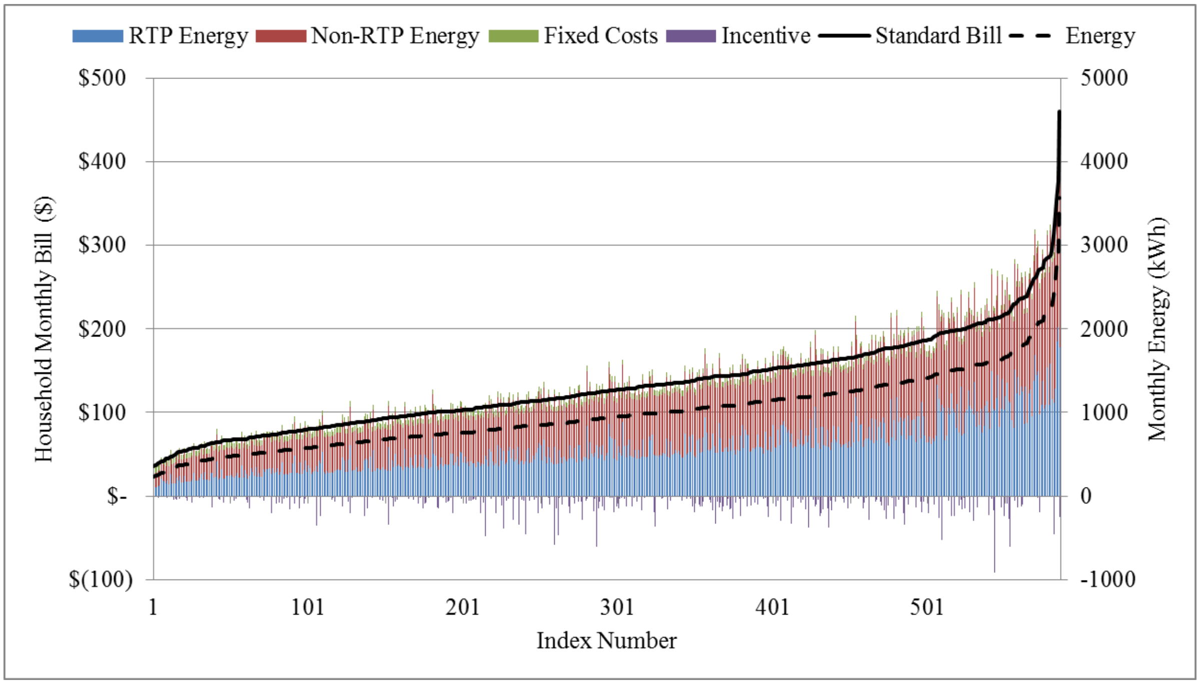

Figure 3.4. RTP$_{da}$ Bill Comparisons with Standard Tariff Applied to the Same Households

The distribution of the difference between the RTP$_{da}$ bills' without incentive savings compared to the same energy consumption calculated with the standard tariff is plotted in Figure 3.5. Again, this is sorted by monthly energy consumption. Figure 3.6 re-sorts the data by the change in overall bill. The two figures indicate that slightly more than half of the households were paying less under the new tariff; however, the households paying more did so by a greater amount, and on average, household bills were increased by $3.68, evenly spread across all household sizes. However, Figure 3.7 and Figure 3.8, in which the incentive is included in the bill calculation, show that many of the households were saving by switching to the new tariff; on average, household bills were decreased by $1.99, again spread across the sizes of the households. This indicates that the large number of congestion experiments may have made the prices appear lower (causing precooling) and disrupted the revenue neutrality calculations. However, when including the incentive, a majority of households were saving, indicating that by responding to the congestion events households are able to see savings.

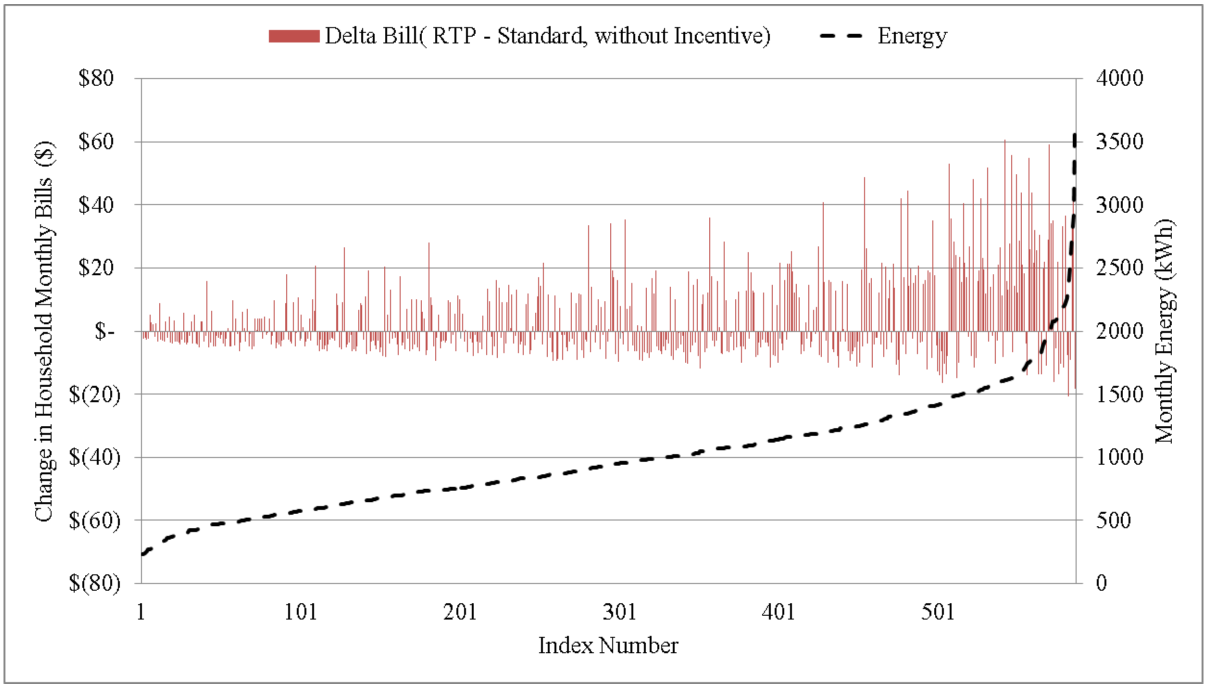

Figure 3.5. RTP$_{da}$ Bill (Without Incentive Component) Minus Standard Tariff Bill

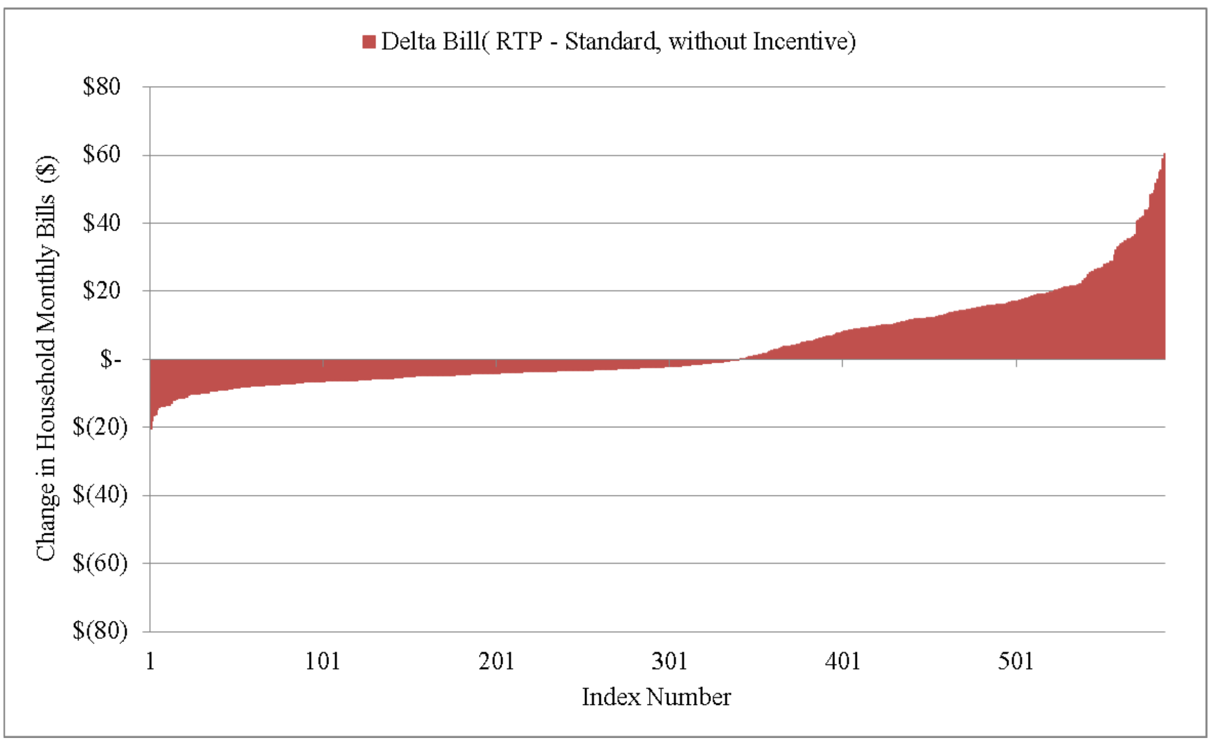

Figure 3.6. RTP$_{da}$ Bill (Without Incentive Component) Minus Standard Tariff Bill, Sorted by Change in Bill

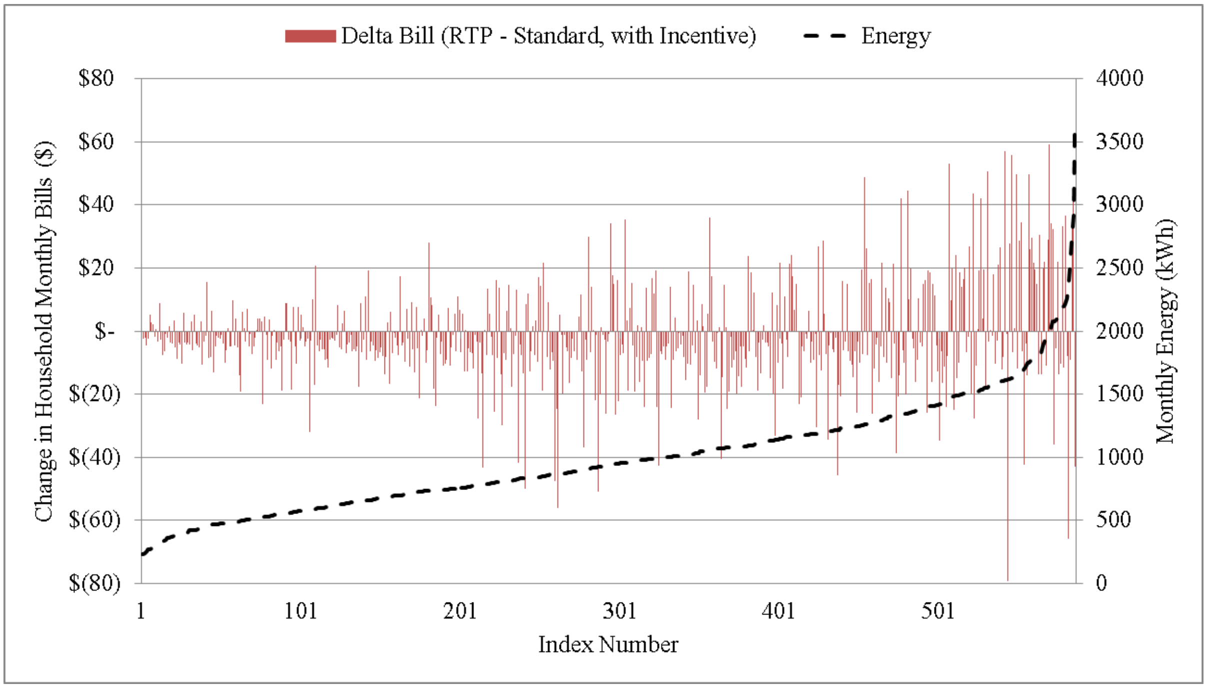

Figure 3.7. RTP$_{da}$ Bill (With Incentive Component) Minus Standard Tariff Bill

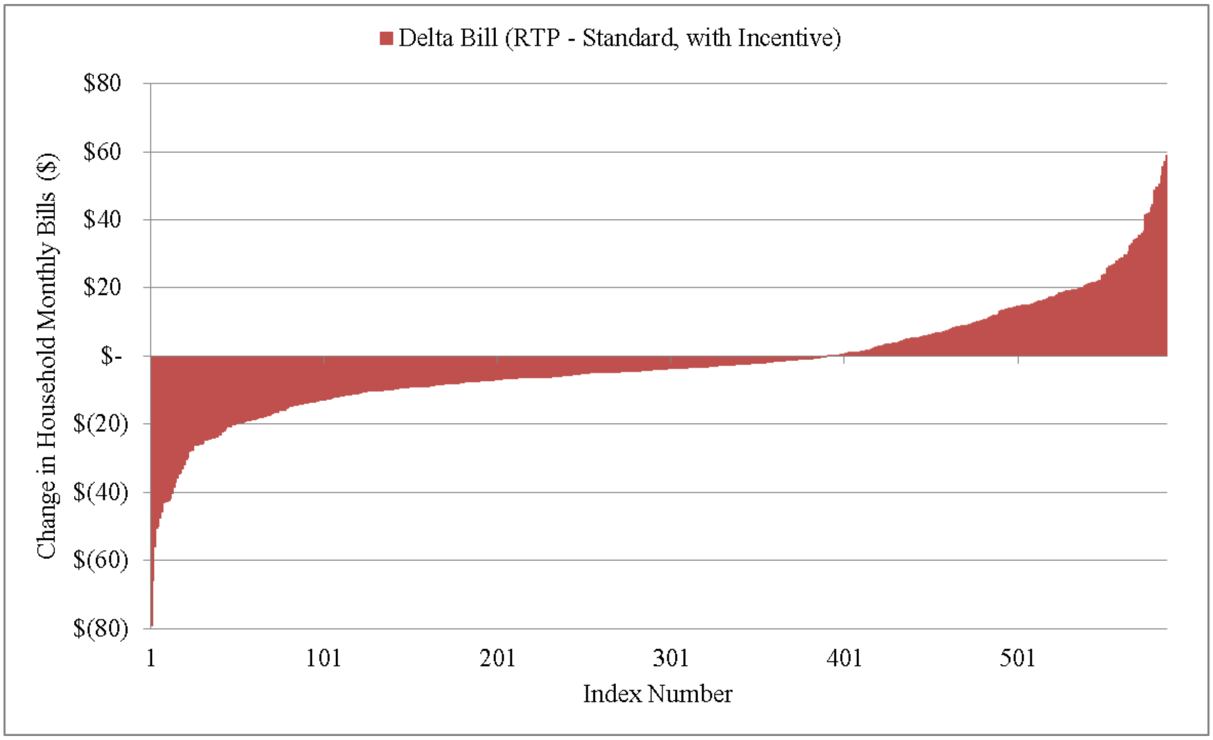

Figure 3.8. RTP$_{da}$ Bill (With Incentive Component) Minus Standard Tariff Bill, Sorted by Change in Bill

3.1.2 RTP_{da} Bills Compared to Control Group

The average $/hr billing information over the months of June through September for all households in the RTP_{da} group and the RTPnr control group, and their percentages with respect to the average of all households' RTP_{da} bills, are presented in Table 3.3 and Table 3.4. The fixed-cost portion of the bills is the same for both RTP_{da} and RTPnr bills; it is listed in Table 3.1 and not shown here, so the bill components will not sum precisely to the total bill. The difference represented in the Delta Energy column only shows the energy component and does not include the incentive savings component of the bills.

The RTP_{da} billing information is calculated as reported in Section 3.1. The RTPnr billing information is calculated from the 15-minute metered data obtained for the households in the control group, then averaged and adjusted as explained in Section 1.4.2 to create an average RTPnr household energy use for each hour. The standard tariff is then applied to this average energy use to calculate the total bill and the energy component. As with the RTP_{da} bill calculation, discrepancies may exist between the RTPnr average billing calculation and the actual bills for the control group.

Table 3.3. $/hr Averages for RTP_{da} Bill Households Compared with Control Group (RTPnr)

	RTP13				RTPnr13			Delta		
Metric	Total Bill	kWh	Energy	Incentive	Total Bill	kWh	Energy	Total Bill	kWh	Energy
Average $/hr Total	0.1916	1.4812	0.1909	0.0081	0.2016	1.4516	0.1928	-0.0101	0.0296	-0.0019
Average $/hr Off-Peak	0.1506	1.2089	0.1457	0.0039	0.1666	1.1878	0.1578	-0.0160	0.0211	-0.0120
Off-Peak Mild	0.1204	1.0101	0.1148	0.0031	0.1381	0.9736	0.1293	-0.0178	0.0365	-0.0145
Off-Peak Hot	0.1754	1.3727	0.1712	0.0045	0.1939	1.3934	0.1851	-0.0185	-0.0207	-0.0139
Average $/hr Peak	0.2736	2.0257	0.2812	0.0164	0.2717	1.9792	0.2629	0.0019	0.0465	0.0183
Peak Mild	0.1891	1.5225	0.1884	0.0081	0.2056	1.4817	0.1968	-0.0165	0.0408	-0.0084
Peak Hot	0.3405	2.4247	0.3547	0.0230	0.3283	2.4055	0.3195	0.0122	0.0192	0.0352

Table 3.4. $/hr Average Percentages of Average Total RTP_{da} Household Bill Compared with Control Group (RTPnr)

	RTP13				RTPnr13			Delta		
Metric	Total Bill	kWh	Energy	Incentive	Total Bill	kWh	Energy	Total Bill	kWh	Energy
Average $/hr Total	100.0%	100.0%	99.7%	4.2%	105.3%	98.0%	100.7%	-5.3%	2.0%	-1.0%
Average $/hr Off-Peak	78.6%	81.6%	76.1%	2.0%	87.0%	80.2%	82.4%	-8.4%	1.4%	-6.3%
Off-Peak Mild	62.8%	68.2%	59.9%	1.6%	72.1%	65.7%	67.5%	-9.3%	2.5%	-7.6%
Off-Peak Hot	91.6%	92.7%	89.4%	2.4%	101.2%	94.1%	96.6%	-9.6%	-1.4%	-7.2%
Average $/hr Peak	142.8%	136.8%	146.8%	8.5%	141.8%	133.6%	137.2%	1.0%	3.1%	9.6%
Peak Mild	98.7%	102.8%	98.4%	4.2%	107.3%	100.0%	102.7%	-8.6%	2.8%	-4.4%
Peak Hot	177.8%	163.7%	185.2%	12.0%	171.4%	162.4%	166.8%	6.4%	1.3%	18.4%

Overall, the average $/hr savings in the bills of all households in this analysis is about 5% in RTP_{da} versus the RTPnr control group; however, the overall energy consumption is about 2% higher. When one looks at the sensitivity of the bills to the different types of operating periods, further insights can be gained. For the off-peak periods, the RTP_{da} bills show a slightly greater savings compared to the control group even though their energy usage is slightly higher.

A potential reason for this is the ability of the RTP_{da} households' HVAC units to respond to market price fluctuations in the off-peak periods. As explained in Section 2.2, the many congestion experiments performed had the effect of desensitizing the thermostat controllers to high prices. This had the effect of making prices that were not near the market cap appear to be bargains for a significant period of time after a congestion experiment. This could have resulted in overcooling. When market prices remained high after the congestion experiment, the effect was to use more energy during a normally high-price period. This phenomenon appeared to be emphasized when looking at the average $/hr during the peak+hot period. In this case, the energy consumption was 1.3% higher for the RTP_{da} group than for the control group; however, the energy component of the bill was 18.4% higher and the total bill was 6.4% higher. This is likely because, on average, the additional energy was being purchased at high market prices relative to the standard tariff. The effect of the incentive savings during these periods was to significantly reduce the impact of the large energy component on the overall average total bills.

When looking at peak+mild days, a greater amount of energy was used by the RTP_{da} group on average; however, the total bills were reduced by 8.6% compared to the control group, likely because the mild weather suppressed the market prices. Similar savings were seen in all off-peak figures, likely due to the lower market prices during the off-peak periods.

To summarize, the bill comparison between the RTP_{da} households and the RTPnr control group indicated bill savings in the summer months. More-detailed examination of the behavior of the RTP_{da} group in different periods of operation and the changes in the bill components revealed a variety of differences between the two bills. The low penetration of RTP_{da} households on each feeder and the frequent congestion experiments had a large impact on the behavior of the RTP_{da} resources and their interaction with the market. In addition, the accuracy of the representation of the control group as a "non-responsive" reflection of the RTP_{da} households deserves further scrutiny. More investigation is needed to fully understand these impacts.

One approach to isolate the impact of the congestion experiments as well as to compare results with a "perfect" control group is to model the RTP_{da} system using the GridLAB-D simulator. Section 3.1.3 reports the results of the use of simulation to both increase the penetration of RTP_{da} households and independently look at the performance of the RTP_{da} system with and without congestion experiments.

3.1.3 RTP_{da} versus Non-RTP_{da} Bill Comparison – Simulation

Simulations of the RTP_{da} group with controls and the same households without controls have been executed in GridLAB-D. The simulated households have been configured to represent the sizes and types of housing in the RTP_{da} group. The observed RTP_{da} household thermostat statistics and energy usage information have been used to calibrate the simulated households. This section reports the comparison of their bills. Bill comparisons include the summer months without congestion events and with congestion events to better understand the impacts.

Households were simulated within GridLAB-D to represent 25% penetration of RTP_{da} households; 300 households were "experimental" while 900 were operated similarly in each simulation and did not respond to variations in price. The experimental households were run using four different scenarios:

1. Control – The households were simulated using the standard pricing tariff (Schedule R-R, 2012).
2. RTP_{da} Without Response – The households were simulated using the experimental residential real-time pricing service tariff (Schedule RS-RTP, 2012), but did not respond to price fluctuations (these households could be considered to serve a purpose equivalent to the RTPnr households described in the previous section, but with the advantage that in the simulator, they are precisely the same household models).
3. RTP_{da} – The households were simulated using the residential RTP_{da} service tariff and responded to wholesale price fluctuations in a manner similar to those observed in the pricing experiments (for example, thermostat slider and temperature settings, internal air temperature decay rates, etc.).
4. RTP_{da} Congested – The households were simulated using the residential RTP_{da} service tariff, responded to wholesale price fluctuations, and responded to capacity limits placed on the feeder aligned with the actual experiments.

The bills are calculated using all components of the tariffs, including all fixed, rider, and energy charges. The bills are presented as the average of all four months and the impact on that average monthly bill. Figure 3.9 shows the monthly billing impact when switching from the standard tariff to the RTP_{da} tariff, without changing load behavior. The left-hand axis (red bars) indicates the percentage by which the household's bill changes when switching from the standard tariff to the RTP_{da} tariff, where a negative number indicates a savings when moving from the standard tariff to the RTPda tariff. The right-hand axis (blue line) indicates the monthly energy consumption of the household, ranked from low to high (left to right). The percent differences are consistent across most household sizes with an average reduction of

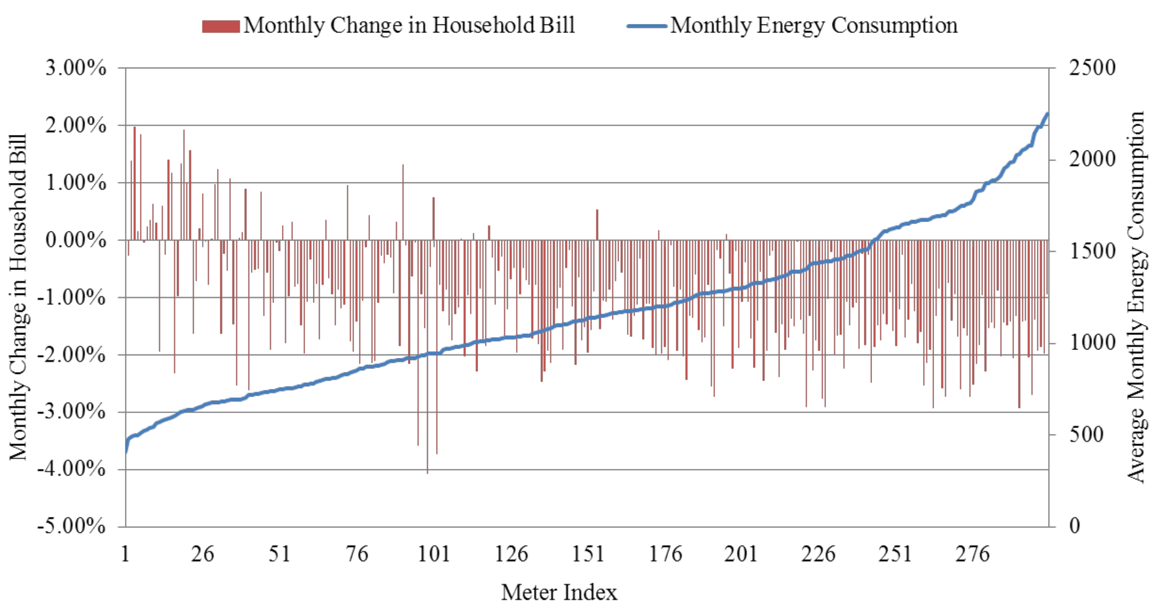

Figure 3.9. Change in Monthly Household Bills When Switching from Standard Tariffs to RTP_{da} (No Response), Without Responding to Price Fluctuations

1.1% in the bill. This indicates that during the four-month period, the RTP_{da} rate was nearly revenue neutral but slightly skewed toward decreasing the households' bills. The rate was designed to be revenue neutral over an entire year, but may show variance within any given period. The energy consumption is identical in these two cases.

Figure 3.10 shows a similar plot for households responding to wholesale price fluctuations. In this case, the difference in bills reflects moving from RTP_{da} Without Response to RTP_{da} (with response). The households are still stacked from left to right according to their energy consumption using the standard tariff (that is, Household 10 is the same Household 10 in each graph). This indicates the amount of savings seen by each household in responding to the price, with the effects of whether the rate is revenue neutral removed—in other words, the amount the household saves by allowing their thermostat to be adjusted in response to price fluctuations. The average reduction in the bill is 2.1%, with an average decrease in energy consumption of 1.2%.

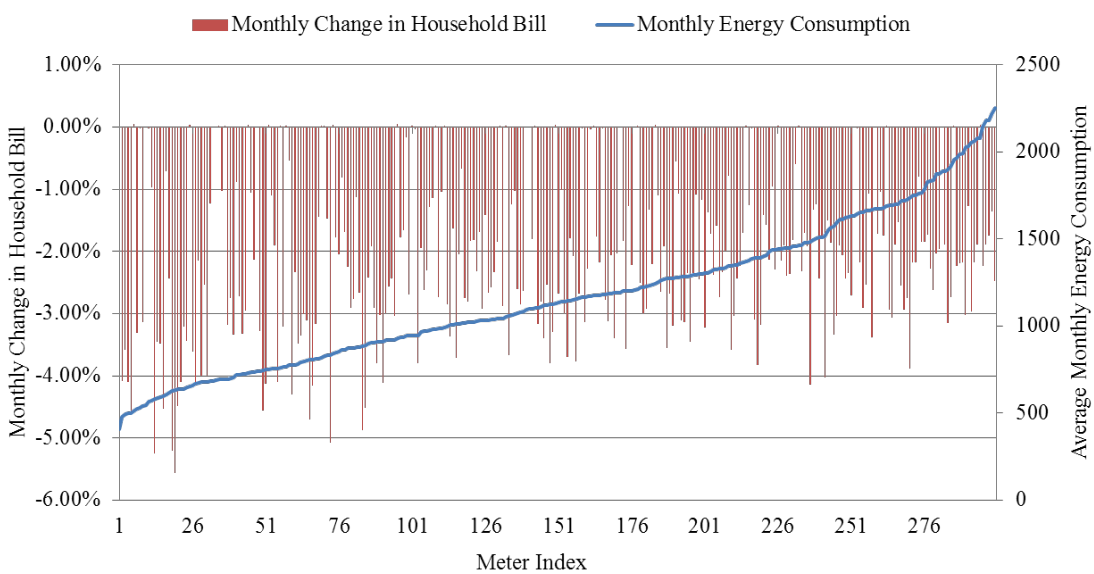

Figure 3.10. Change in Monthly Household Bills When Responding to Price Fluctuations (changing from RTP_{da} Without Response to RTP_{da} With Response)

Figure 3.11 is a combination of Figure 3.9 and Figure 3.10, moving from the standard tariff to RTP_{da} (with response). The average household reduces their bill by 3.2% and reduces energy consumption by 1.2%. Figure 3.12 shows the same information, but in terms of actual dollars saved (rather than percentage of bill). The average bill reduction is $5.11 with a maximum (average) reduction of $12.43 (one household was able to see a $22.52 reduction for the month of July). The reduction of the bill is consistent across household sizes in terms of percent reduction, with larger energy users seeing a larger decrease in proportion to their energy use.

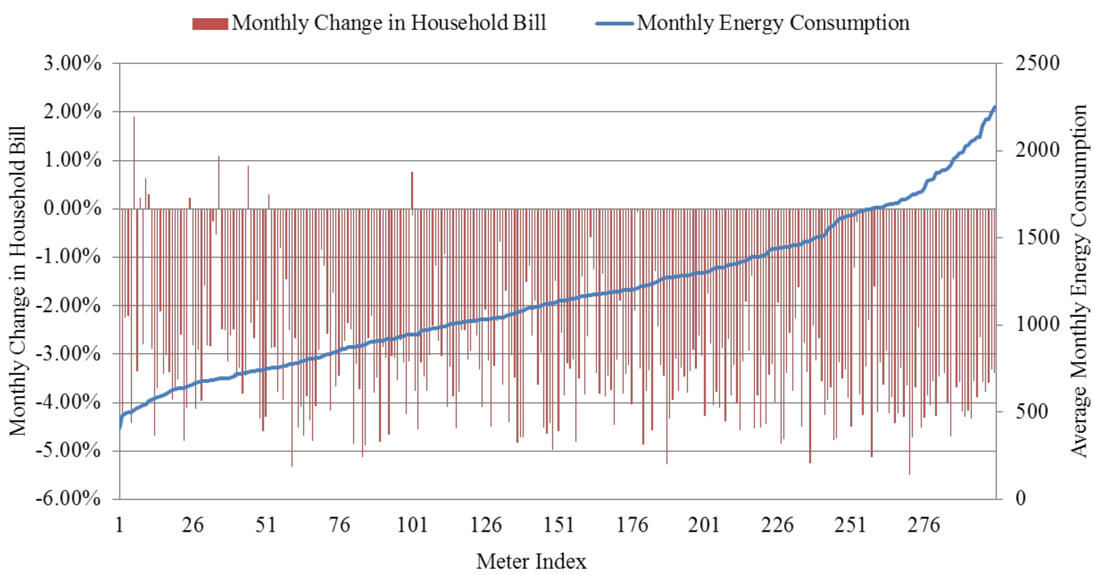

Figure 3.11. Percentage Change in Monthly Household Bills When Switching from Standard Pricing to RTP_{da} With Response

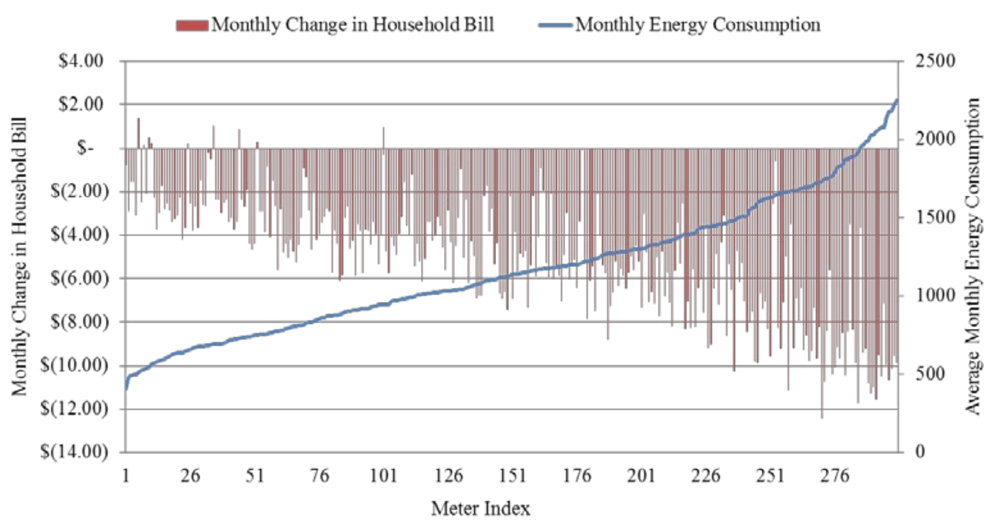

Figure 3.12. Change in Monthly Household Bills ($) When Switching from Standard Pricing to RTP_{da} With Response to Price Fluctuations

Figure 3.13 shows the impacts on the household monthly bill when moving from RTP_{da} with response to RTP_{da} Without Response with the 66 congestion experiments during the June-to-September period (out of 96 total congestion experiments done in all of 2013). The experiments caused prices to rise very high for a few hours and reduce demand, then "appear" very low for the following 24 hours as the average price was increased. This caused a number of units to lower their thermostat cooling set points and increase energy consumption (by 0.27% on average over the four-month period). For households that frequently responded to the congestion event by decreasing demand during the period, significant savings were seen (the maximum reduction was $31.16) driven by the incentive payment. Households that were not overly responsive saw a slight increase in their bills (between $0 and $3), driven by the increased demand caused by precooling. Ideally, the system would not be operated that often, so it is assumed that the level of impact and savings would be decreased.

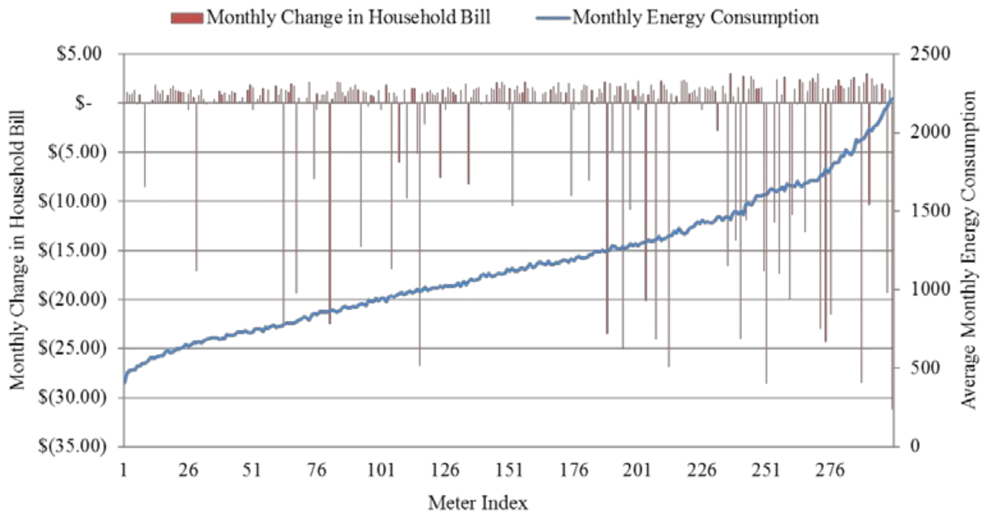

Figure 3.13. Change in Monthly Household Bills When Switching from RTP_{da} With Response to RTP_{da} Without Response, Taking into Account the Congestion Experiments Used in the Actual System

Table 3.5 through Table 3.8 show the average household bills by month for each of the cases discussed above. RTP_{da} cases include a breakdown into the base bill, rebate payments, and incentive payments. Note that the rebate payments approximately nullify the effects of increased prices due to the congestion experiments, but not quite (as indicated by the slight rise in most household bills during the experiments).

Table 3.5. Average Monthly Bill with Standard Tariff

	Average Household Bill Control Group (Standard Tariff)				
	June	July	August	September	Average
Total	**$153.14**	**$164.96**	**$161.19**	**$139.92**	**$154.80**

Table 3.6. Average Monthly Bill with RTP_{da} Tariff and No Response

	Average Household Bill RTP_{da} Without Response				
	June	July	August	September	Average
Base Bill	$148.25	$178.30	$152.40	$132.42	$152.84
Rebate	$–	$–	$–	$–	$–
Incentive	$–	$–	$–	$–	$–
Total	**$148.25**	**$178.30**	**$152.40**	**$132.42**	**$152.84**

Table 3.7. Average Monthly Bill with RTP_{da} Tariff and Response

	Average Household Bill RTP_{da} Wholesale Response				
	June	July	August	September	Average
Base Bill	$145.53	$172.97	$149.55	$130.71	$149.69
Rebate	$–	$–	$–	$–	$–
Incentive	$–	$–	$–	$–	$–
Total	**$145.53**	**$172.97**	**$149.55**	**$130.71**	**$149.69**

Table 3.8. Average Monthly Bill with RTP_{da} Tariff and 66 Congestion Experiments

	Average Household Bill RTP_{da} with Congestion Experiments				
	June	July	August	September	Average
Base Bill	$167.53	$232.78	$231.56	$199.80	$207.92
Rebate	$(21.38)	$(57.75)	$(80.80)	$(68.46)	$(57.09)
Incentive	$(1.08)	$(3.05)	$(3.35)	$(2.63)	$(2.53)
Total	**$145.08**	**$171.97**	**$147.42**	**$128.72**	**$148.30**

Table 3.9 summarizes the changes in household bills by month from the standard tariff to each of the three RTP_{da} experiments. Negative values (in parentheses) indicate a reduction in the bill. Notice the increase in July bills, even in the RTP_{da} Without Response case, indicating that wholesale prices were higher than expected in July.

Table 3.9. Comparison of Bill Reductions from Standard to RTP_{da} Tariff

	Delta Average Household Bill Control to RTP_{da}				
	June	July	August	September	Average
RTP_{da} Without Response	$(4.89)	$13.34	$(8.79)	$(7.50)	$(1.96)
RTP_{da} With Response	$(7.61)	$8.01	$(11.64)	$(9.21)	$(5.11)
RTP_{da} With Congestion	$(8.06)	$7.01	$(13.77)	$(11.20)	$(6.51)

3.2 Thermostat Statistics

This section explores the RTP_{da} consumers' interactions with their thermostat. A statistical characterization of the population of thermostat settings is presented, followed by an investigation of the thermostat override changes that occurred during congestion event periods.

3.2.1 Thermostat Settings

In the course of the Project, the consumers exercised their choice of setting the cooling and heating set points, as well as the comfort slider settings. In addition, they had the choice of overriding the system until the next scheduled period or indefinitely. A number of aspects of these choices can be studied, but the overall features will be considered first.

The period of analysis was the four-month period June 1–September 30, 2013. The occupancy status had four possibilities: "Home," "Night," "Away," and "Vacation." The day was divided into six parts of 4 hours each. Weekday and weekend differences are implicit in the occupancy status (that is, generally more hours of the day are in occupied status during the weekend), so no distinction was made for this study. The comfort setting has six possibilities: 0, 20, 40, 60, 80, and 100, with 0 being most comfort oriented and 100 being most economically oriented. The cooling set points covered a wide range: 55°F to 95°F. So the total number of bins will be (4 occupancy statuses) × (6 day periods) × (6 slider settings) × (41 cooling set points in 1°F increments), or 5904 bins. The amount of data available from a household was dependent on recruitment date, communication issues, and other matters. To normalize for this variability, each household was given one vote that could be distributed among the 5904 bins. Imagine each household receiving a sheet of paper of unit area. It can be torn into a maximum of 5904 pieces (often far fewer) in proportion to the fraction of time the house was in the state represented by a bin and placed in that bin. The areas of the pieces of paper in each bin were summed. These sums are shown in the graphs below, where a separate graph is drawn for each of the four occupancy statuses and six day periods, resulting in a possible 24 graphs. Each graph is further normalized so that the probabilities for each bin add up to 100%. "Away" status in the period midnight to 4 a.m. did not occur, so no graph is shown for that combination. The 23 graphs are shown in Figure 3.14, Figure 3.15, Figure 3.16, and Figure 3.17.

The trends seen in these graphs are generally self-explanatory. Additional studies exploring the changes during the course of the Project are possible but have not been performed. For example, a study of the default and initial comfort settings selected as part of the ePCT installation and training process could shed light on how these statistics evolved over time. As one demographic study, the impact of the size of the house on the settings was explored. Figure 3.18 shows the distribution of aggregated (overall occupancy modes and hours of day) overall occupancy statuses and day periods for the smallest 25% and the largest 25% of the houses as well as for all the households.

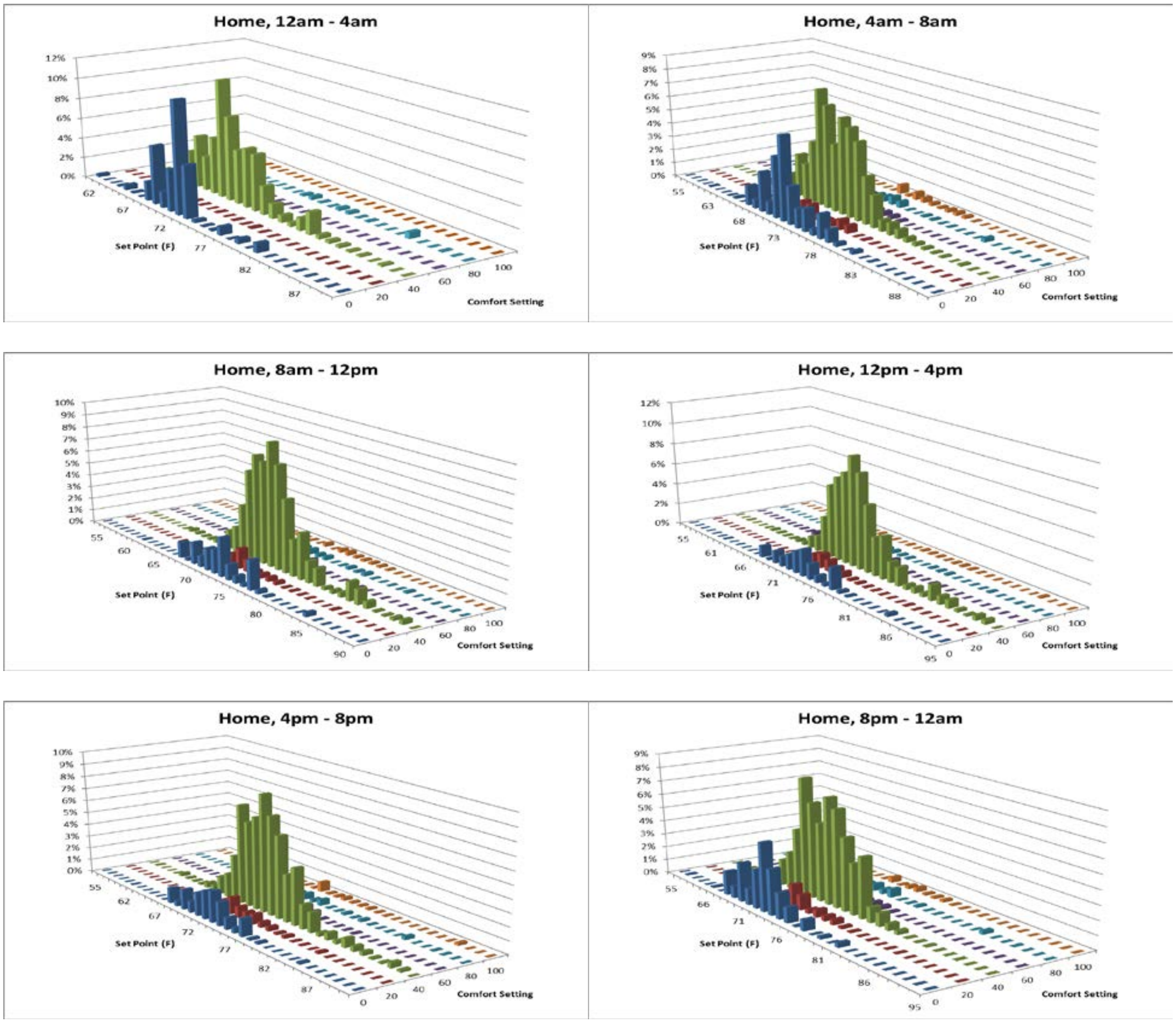

Figure 3.14. Cooling Set Point and Slider Distribution for Occupancy Status “Home”

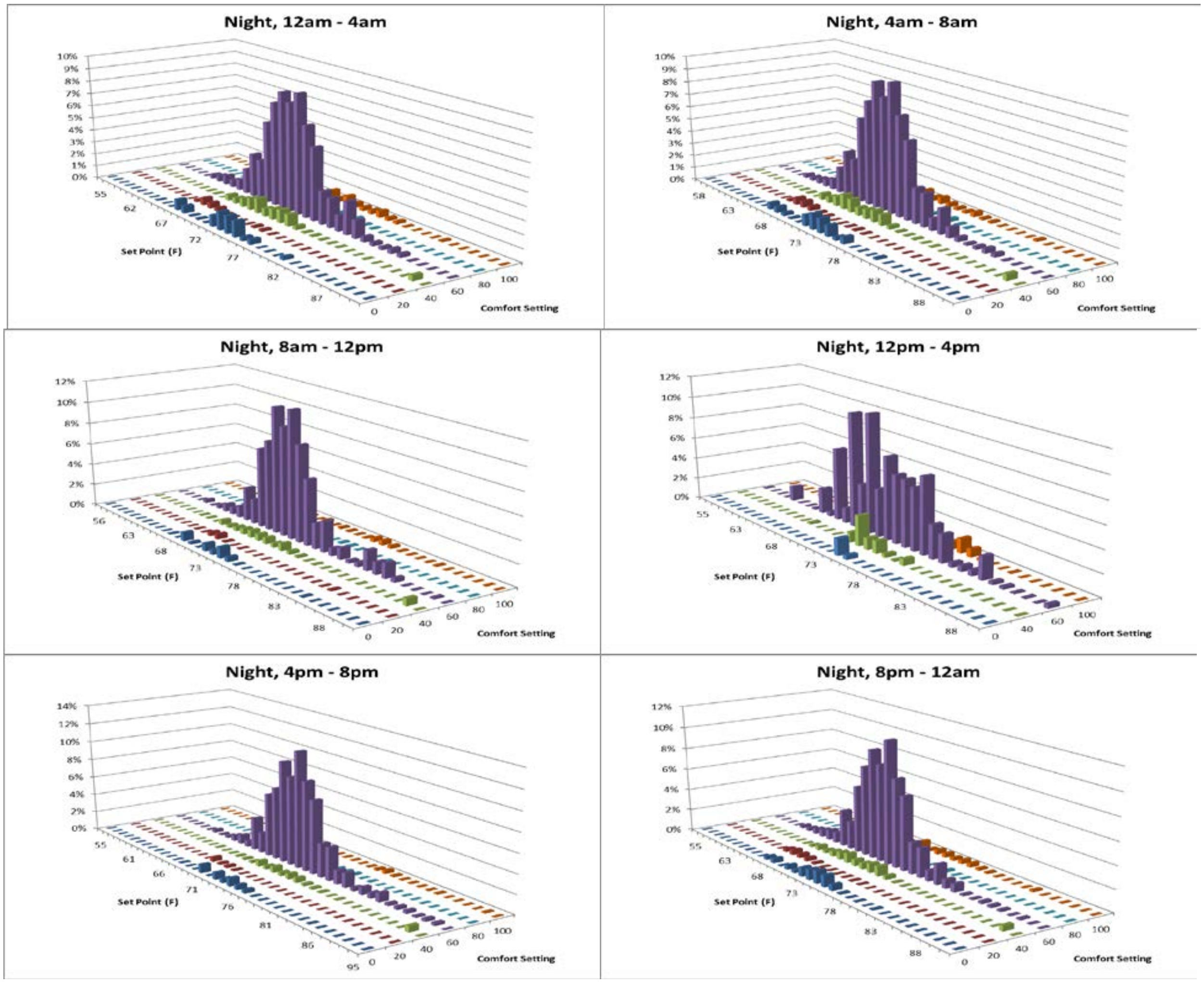

Figure 3.15. Cooling Set Point and Slider Distribution for Occupancy Status "Night"

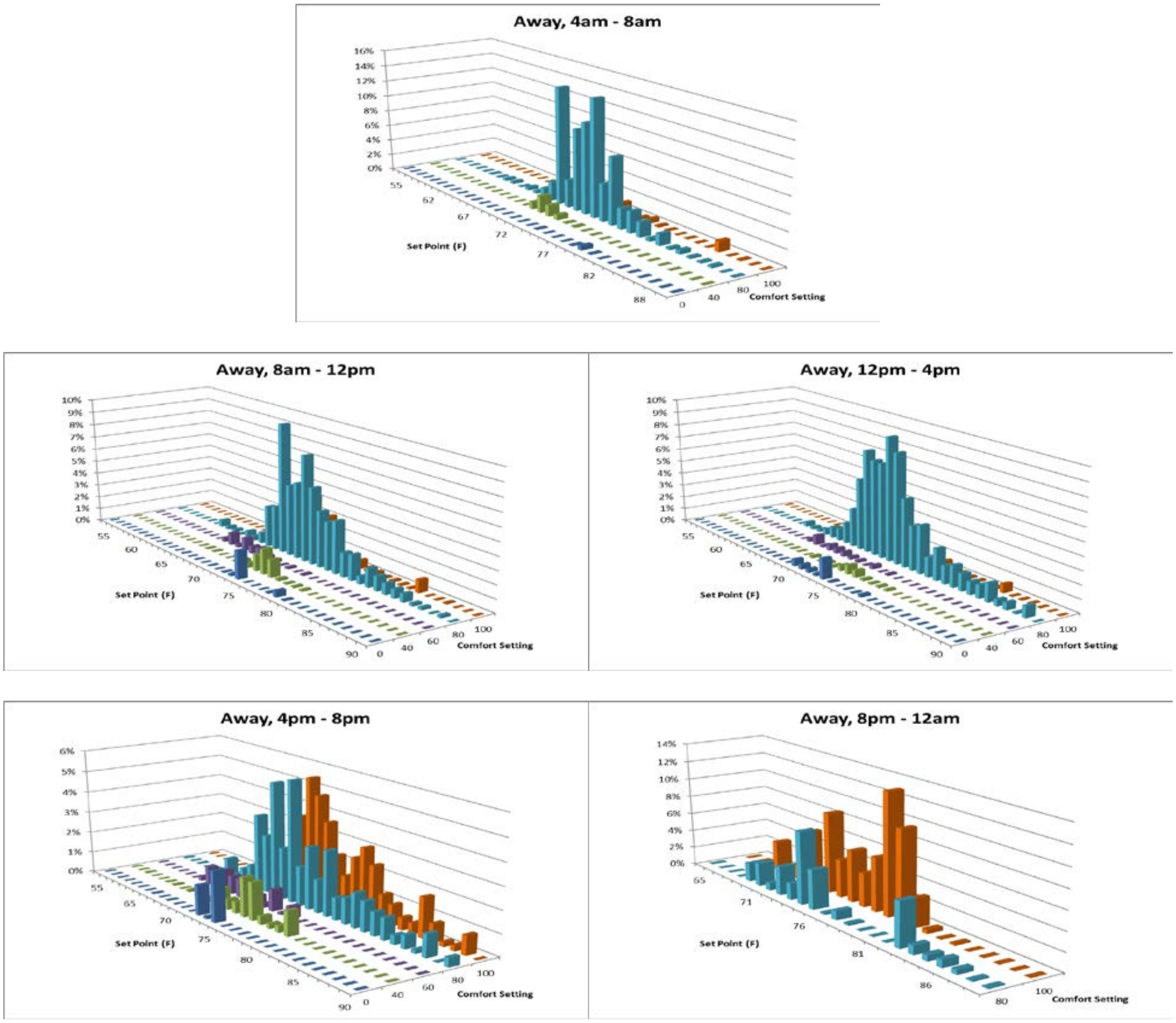

Figure 3.16. Cooling Set Point and Slider Distribution for Occupancy Status “Away”

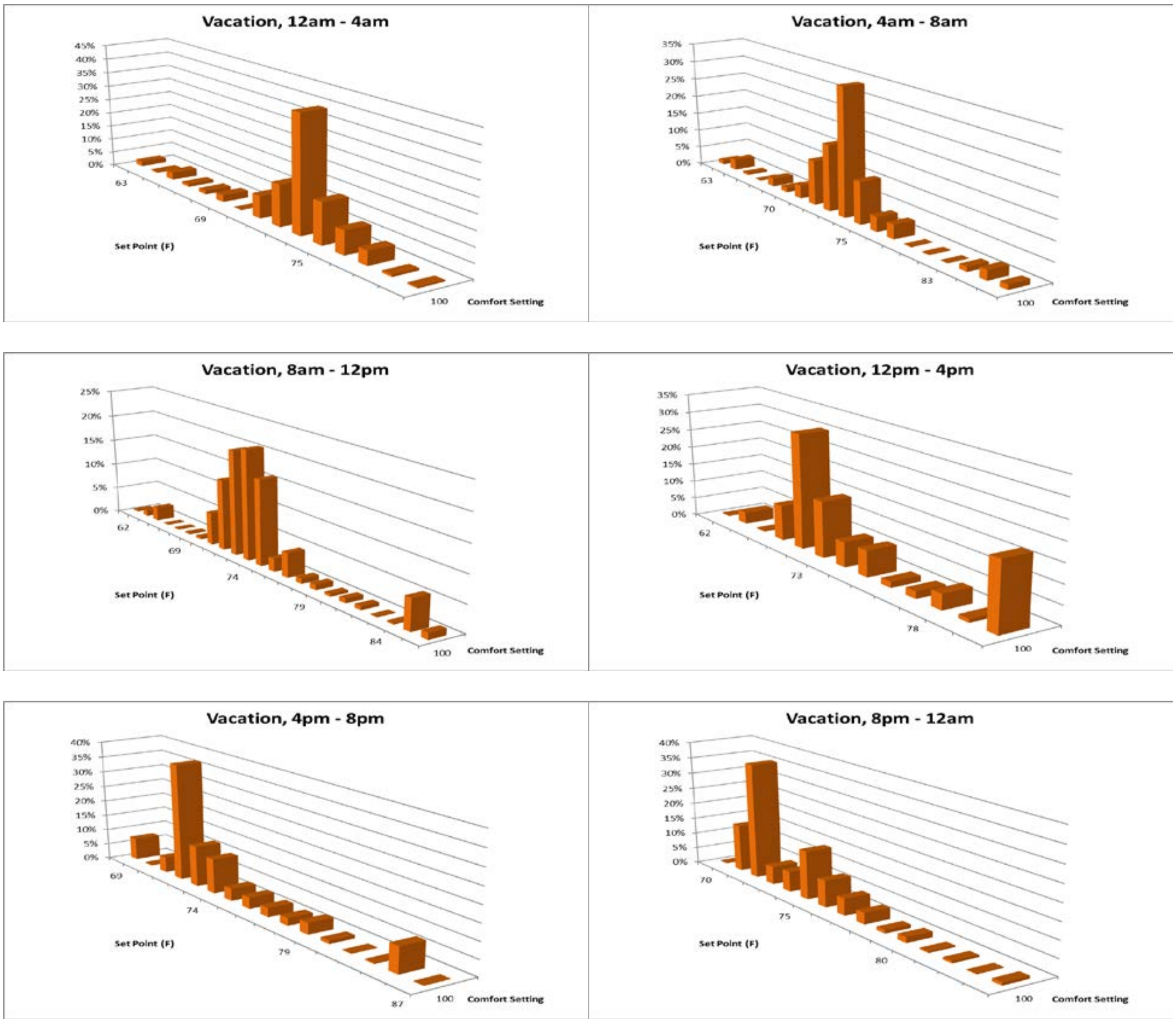

Figure 3.17. Cooling Set Point and Slider Distribution for Occupancy Status “Vacation”

Figure 3.18. Effect of House Size on Cooling Set Points and Slider Settings Aggregated over All Occupancy Settings and Hours of Day

3.2.2 Thermostat Override Statistics

Table 3.10 shows the percentage of households that overrode their programmed thermostat settings during 2-hour and 4-hour congestion experiments. The override status was calculated as being positive for only those thermostats that were not in the override mode at the start of the experiment (that is, they were participating in the market), but at some point during the experiment were manually overridden. In 14 out of the total 69 2-hour experiments no thermostats were overridden, while only three 4-hour experiments recorded no overridden thermostats.

Table 3.10. Thermostat Override Statistics for 2-hour and 4-hour Congestion Experiments

2-Hour Experiments			4-Hour Experiments		
% Households that Overrode	Frequency	Probability	% Households that Overrode	Frequency	Probability
0%	14	20.00%	0%	3	11.54%
0–1%	13	18.57%	0–1%	3	11.54%
1–2%	25	35.71%	1–2%	4	15.38%
2–3%	10	14.29%	2–3%	3	11.54%
3–4%	5	7.14%	3–4%	2	7.69%
4–5%	3	4.29%	4–5%	3	11.54%
5–6%	0	0.00%	5–6%	3	11.54%
6–7%	0	0.00%	6–7%	3	11.54%
7–8%	0	0.00%	7–8%	0	0.00%
8–9%	0	0.00%	8–9%	1	3.85%
9–10%	0	0.00%	9–10%	1	3.85%
Total	**70**	**100%**		**26**	**100%**

Figure 3.19 compares the numbers of households that overrode their programmed thermostat settings during on-peak and off-peak 2-hour congestion experiments. It is evident that more households in override status were recorded during on-peak periods (14:00 – 22:00), as compared to off-peak period (22:00 – 14:00) experiments.

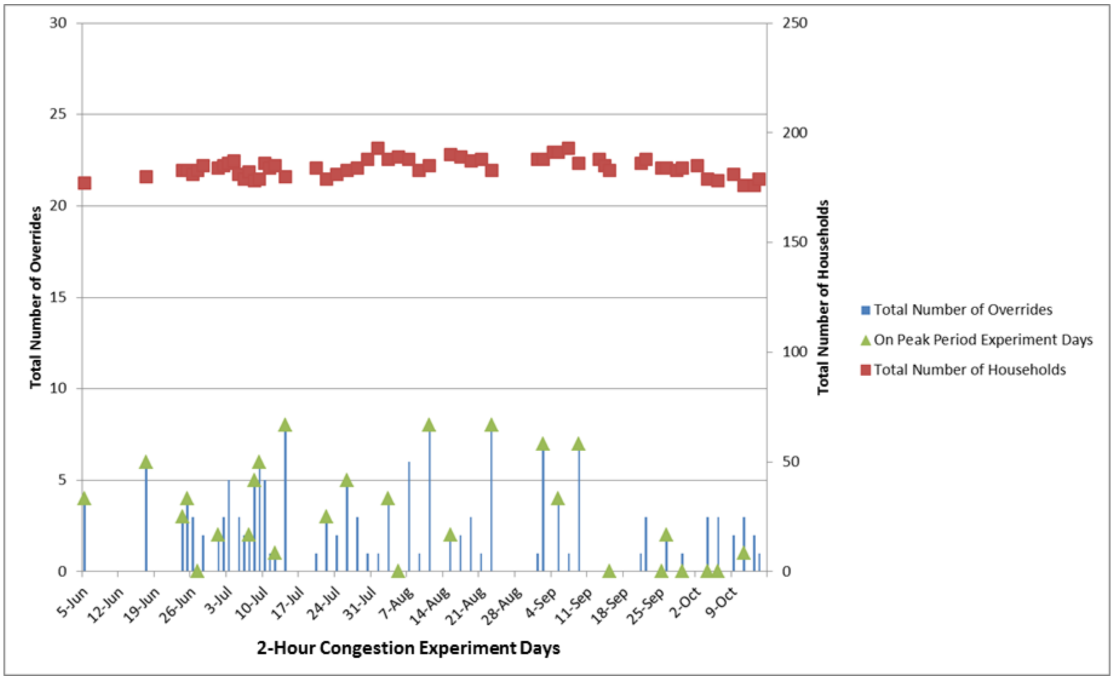

Figure 3.19. Thermostat Override Statistics during 2-hour Congestion Experiments

Figure 3.20 presents the override statistics recorded during 4-hour congestion experiments, which were conducted over the on-peak periods of the day. The figure also presents a comparison of the override statistics when the experiment was called during a SMART Shift Plus (critical peak pricing) event versus, along with the other 4-hour experiments. It is evident that a greater number of households overrode their programmed thermostat settings during SMART Shift Plus events.

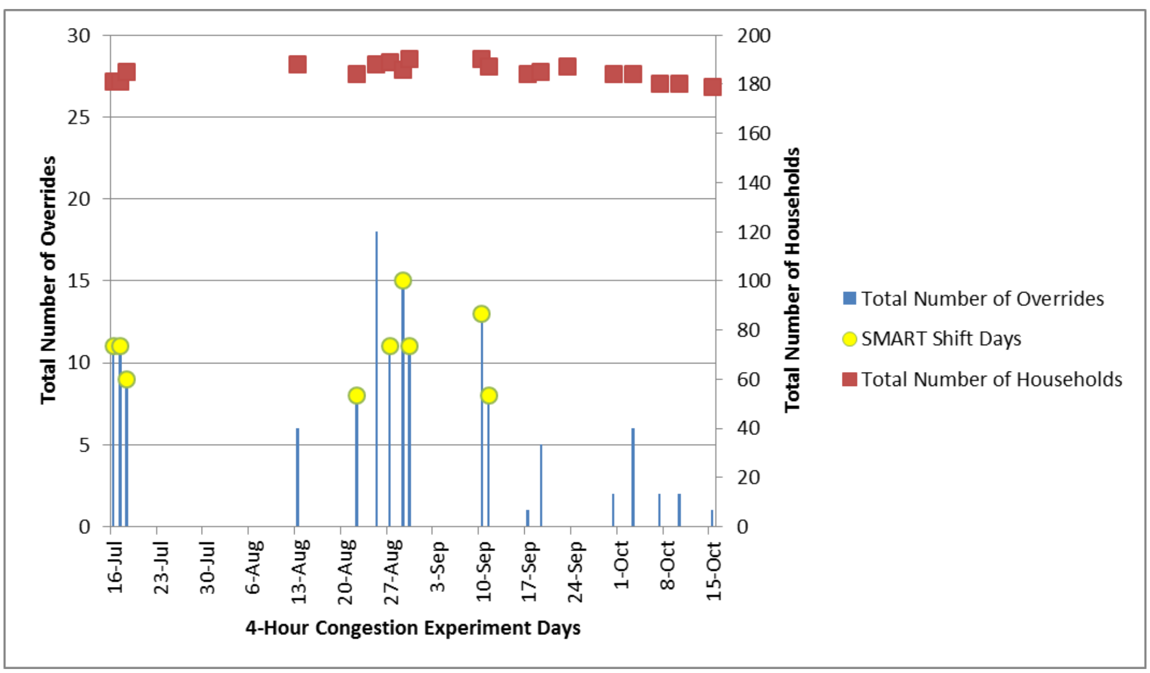

Figure 3.20. Thermostat Override Statistics during 4-hour Congestion Experiments

Figure 3.21 and Figure 3.22 present comparisons of the total numbers and the percentages of households that overrode their programmed thermostat settings during 2-hour versus 4-hour congestion experiments. The figures may be interpreted as override “duration” curves, presenting the numbers and percentages, respectively, of households in override status during 2-hour and 4-hour experiment periods. From both the figures, it is evident that a greater number of households overrode their programmed thermostat settings during 4-hour experiments than during 2-hour experiments. This may be attributed to greater discomfort due to the rising house temperatures during 4-hour experiments when HVACs stayed off for a considerably longer duration.

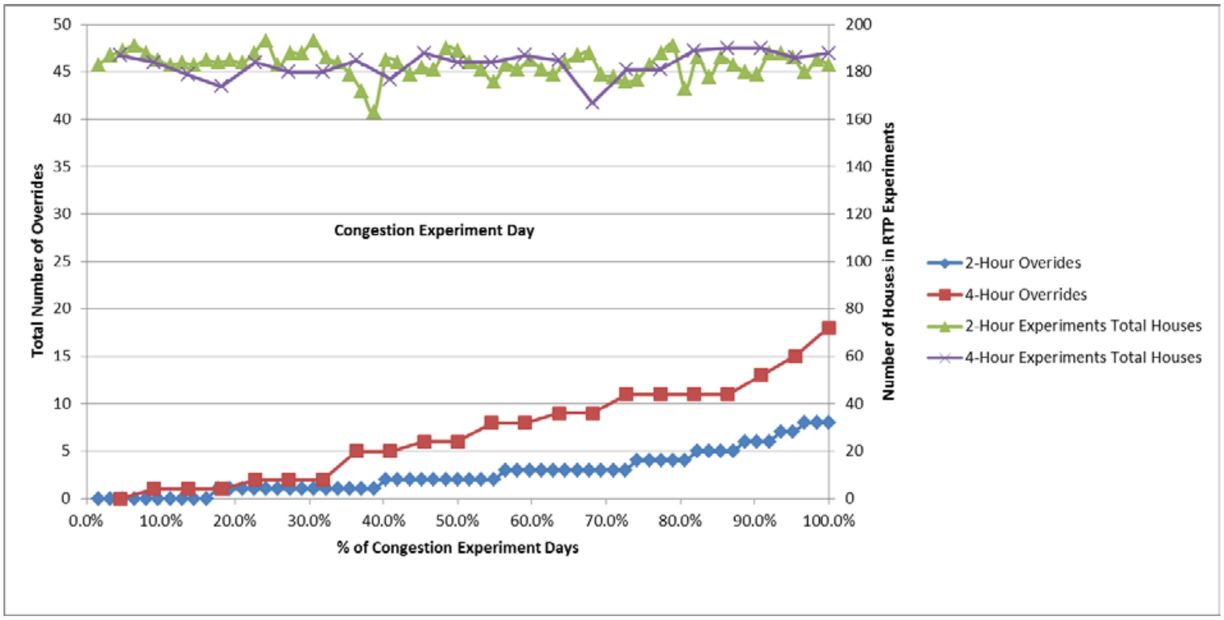

Figure 3.21. Override Duration Curves for 2-Hour and 4-Hour Congestion Experiments

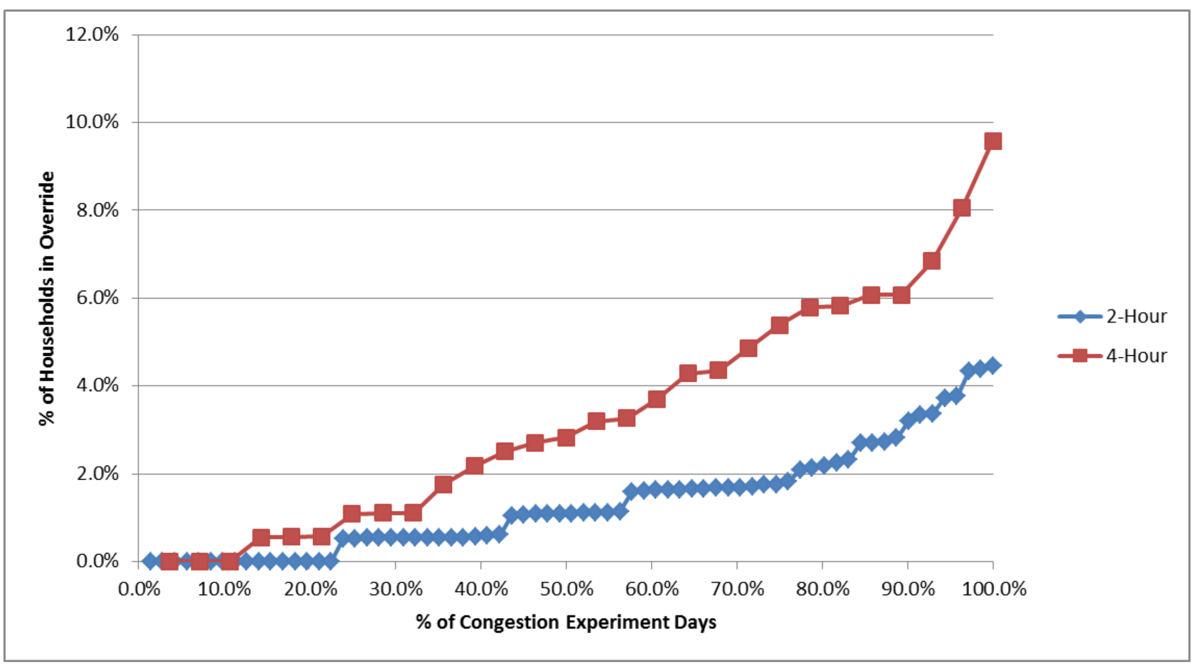

Figure 3.22. Override (% of total) Duration Curves for 2-Hour and 4-Hour Congestion Experiments

3.3 HVAC Bid Quantity versus Actual Load

When ePCT equipment was installed in a home, it was configured to store the estimate for the amount of power that the HVAC unit would draw when operating. The Project assumed that the compressors are fixed speed, which appears reasonable today, but will likely change in the future as HVAC units become more efficient. The installer estimated the power draw based on the nameplate rating and/or size of the compressor. A look-up table was provided to help convert HVAC heating/cooling size to the power draw. The estimated power draw was stored in the HEM equipment for use as the HVAC bid quantity (q_{bid}). The accuracy of this estimate when compared to the actual power draw could be important to the performance and stability of the RTP_{da} system under wide-scale deployment.

Analysis of the metered data for the RTP_{da} households was undertaken to determine the actual power drawn for each unit. The results of this analysis are presented below. Details of the methodology are left for a future publication.

3.3.1 Results of Analysis

Figure 3.23 plots the meter analysis value for each household as compared with the nominal value (q_{bid}) used in the RTP_{da} auction. If the values corresponded well, then the points in the graph would be expected to cluster closely around the dotted diagonal. Instead we see that, in general, the HVAC equipment is drawing more power than the household is bidding into the market. The distributions for 99 households of their bid power quantities and estimated power quantities are shown in Figure 3.24, indicating a significant deviation from the quantities bid.

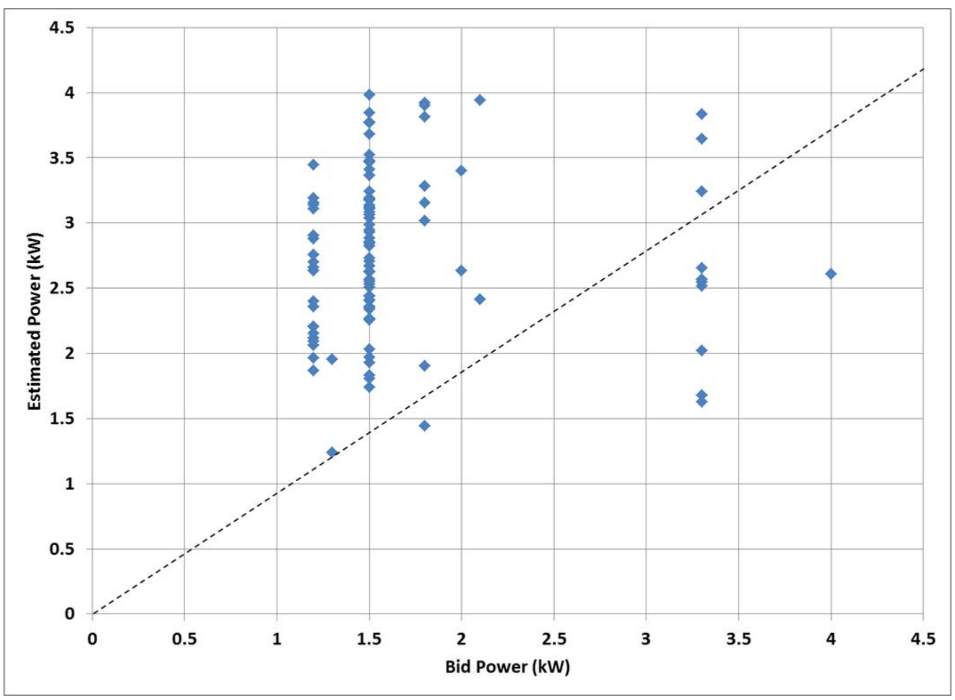

Figure 3.23. Estimated HVAC Power from Metered Data versus Bid Power for the Same Household

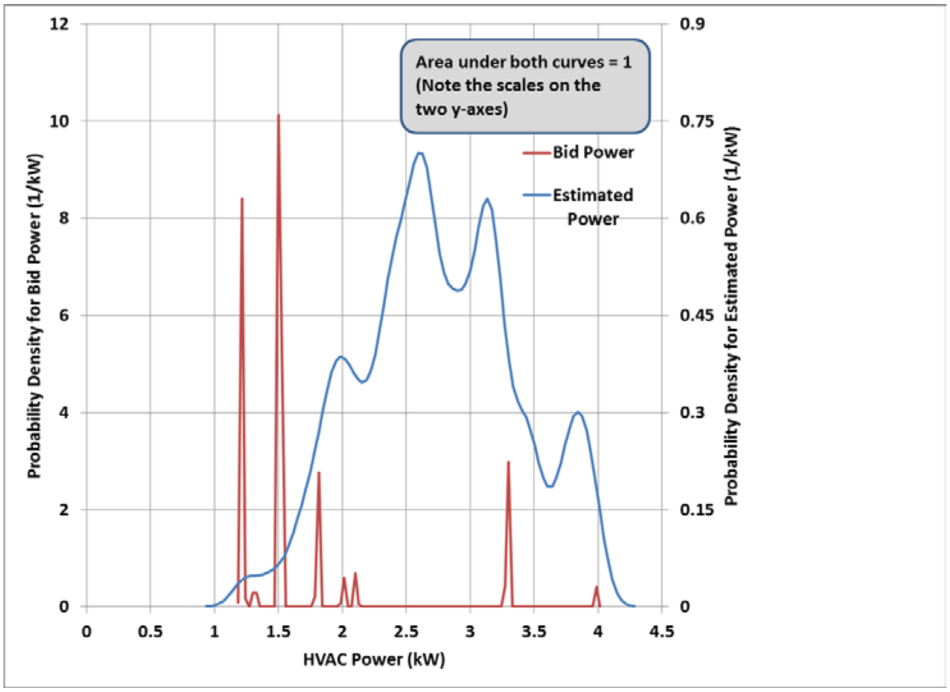

Figure 3.24. Distributions of HVAC Bid Power and Estimated Power

The linear vertical groupings of points in Figure 3.23 likely occurred because the look-up table listed a few key values: 1.2, 1.5, 1.8, 2.1, and 3.3. These values are also clearly apparent in the red line in Figure 3.24.

If the system becomes constrained either due to limited supply or due to congestion, the market cleared price is determined by price, energy bids. These bids should be accurate for proper operation. However, in this project, the responsive load was so small that the market either cleared at the feeder base price (non-congested situation) or at the feeder market cap (congested situation). In either case, the inaccuracy of the bid quantities did not affect the market clearing. As the energy-sensitive portion of the household bills were calculated from the metered quantity, this portion of the bill was not affected. However, the incentive saving calculation is dependent on the bid quantity, so inaccuracies can have an effect here.

Bid power inaccuracy would also have an impact on the analysis of load sensitivity to price when there is a high penetration of RTP_{da} resources on the feeder. In this case, a congestion situation can occur where the market clears between P_{base} and P_{cap}. The bid power inaccuracy may cause the market to clear at different energy quantity and price points (see Figure 3.25).

This situation is a topic for future analysis. A simulation of the RTP_{da} system could be set up to run two sets of scenarios using the PJM real-time market pricing information and the congestion event periods. One set of scenarios would run the households that bid q_{bid}, but size the HVAC models to match the distribution seen from the meter data analysis as in the demonstration. The other set of scenarios would adjust q_{bid} to accurately reflect the meter data analysis values. The scenarios would be scaled to show different penetrations of RTP_{da} households on the feeders. Comparisons of these runs would provide insight regarding the impact of bid power errors on the performance of the RTP_{da} system.

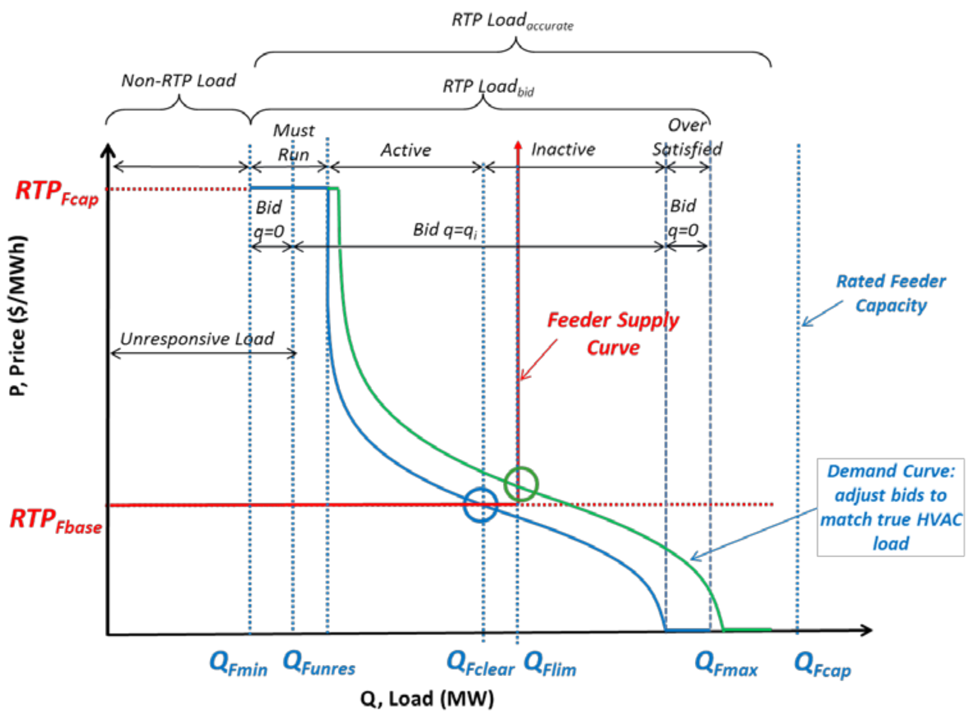

Figure 3.25. Conceptual Bid Curve Comparison of Bid versus Accurate HVAC Draw

4.0 RTP$_{da}$ Load Sensitivity to Price

This chapter investigates the price-responsive nature of the RTP$_{da}$ resources over the course of the summer. The first section analyzes data collected for each household to explore the population of RTP$_{da}$ resources' sensitivity to the 5-minute, LMP-based market price fluctuations experienced during the experiment. It is followed by a similar investigation done using the GridLAB-D simulator. The final section investigates the response of the RTP$_{da}$ resources to the imposed congestion events, where the market cleared at the price cap for the duration of the event.

4.1 Results from Measured Data

The responses of the thermostat agents are not really to energy prices but to variations in the prices around the "expected" price, the expected price being the average price experienced during the previous 24 hours. Consider the relationship between response defined as (RTP13 − RTPnr13) and LMP. The LMPs are used as proxies for the real-time prices that are used for the bids. An LMP of, for example, $40/MWH may be perceived as high at some times and as low at other times. If perceived as high, the result is a tendency for reduction of energy use compared to the control houses. If it is perceived as a low price, the tendency is toward increased energy use. Therefore for a given LMP, the response at different times can vary over a range of values. This is seen in Figure 4.1. In this figure, the 5-minute average change in energy between RTP13 and RTPnr13 households for non-congestion experiment days is plotted against the corresponding time period's 5 minute LMP. A heavily smoothed response is shown as the blue points. Also shown is a histogram of the LMPs in the data points. The series of vertical streaks

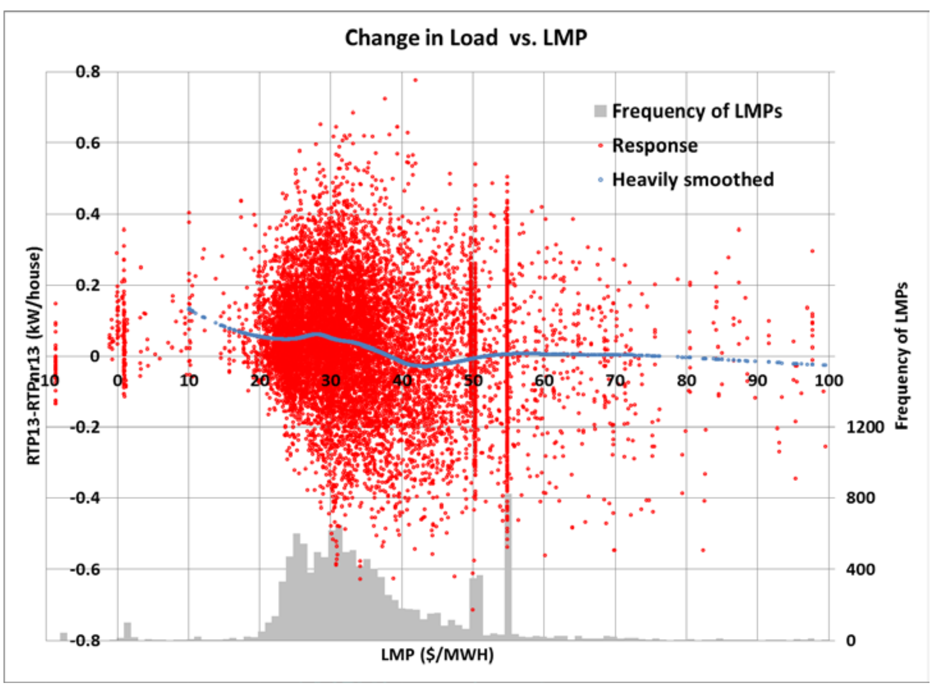

Figure 4.1. Response versus LMP for About 12,000 5-Minute Data Points Covering the Period June–September 2013

correspond to some default prices used when no LMP was transmitted. The LMPs are truncated at 100 \$/MWH because points beyond that are sparse. A histogram of the full range of LMPs from \$−8.67 to \$659.09 is shown in Figure 4.2.

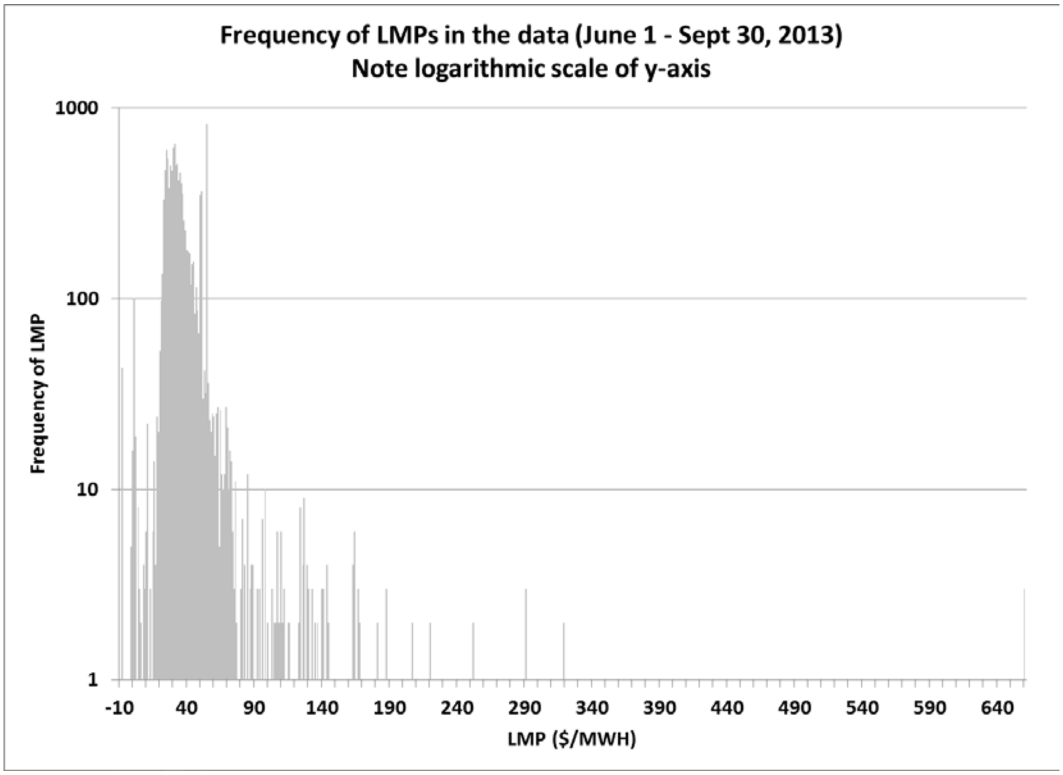

Figure 4.2. A Histogram of the Full Range of LMPs (from −\$8.67 to \$659.09) Seen During the Analysis Period

Even though the response is to variations in LMP and not to LMP itself, a heuristic expectation is that higher prices should generally result in a negative response. It is therefore of interest to determine the correlation coefficient between the response and LMP. This coefficient is −0.17, confirming heuristic expectations of the design of the RTP_{da} system.

4.2 Simulated Results

Similar to previous sections, households were simulated within GridLAB-D to represent 25% penetration of RTP_{da} households; 300 households were "experimental" while 900 were operated similarly in each simulation and did not respond to variations in price. The experimental households were modeled using three different scenarios:

1. Control – the households were simulated using the standard pricing tariff.
2. RTP_{da} – the households were simulated using the residential RTP_{da} service tariff and responded to wholesale price fluctuations in a manner similar to those observed in the pricing experiments (for example, thermostat slider and temperature settings, internal air temperature decay rates, and such).

3. RTP$_{da}$ Congested – the households were simulated using the residential RTP$_{da}$ service tariff, responded to wholesale price fluctuations, and responded to capacity limits placed on the feeder aligned with the actual experiments (96 experiments in four months).

The simulation results offer an additional comparison against the actual data, without the necessity of using filtering and regression techniques, as simulation provides a "perfect" control group. The graph in Figure 4.3 is similar to Figure 4.1, but uses the simulated response data (RTP$_{da}$ minus Control) and includes every day within the four-month period (rather than a subset in the field data case where congestion days were removed). The graph is truncated as before and does not show some periods of very high price and high load response. The figure is presented to show the similarities between the simulated and actual responsive loads; particularly the area around LMPs of 30 to 60 \$/MWh. A negative value on the y-axis indicates a reduction in demand when moving to the RTP$_{da}$ group. It can be seen that when the LMP is relatively low (less than \$30/MWh), there is almost no change in demand when moving to the RTP$_{da}$ rate. Further research is needed, though this may be indicative of having very little resource available for reduction during relatively low LMP periods (e.g., early morning periods). However, as LMP becomes higher, there is a significant trend toward reduced demand. It should be noted that data points higher than \$60/MWh are of much lower density and the trend line is less certain.

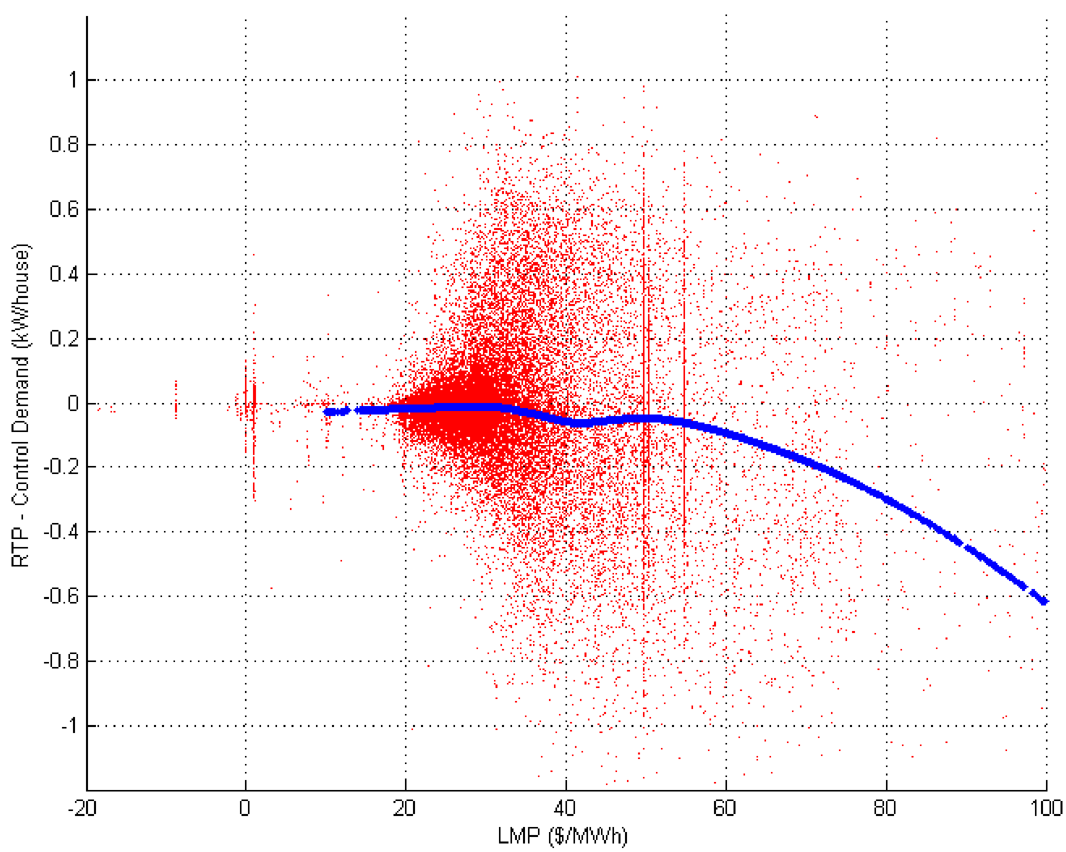

Figure 4.3. Change in Load versus LMP between the Control and RTP$_{da}$ Groups (positive value indicates increased load)

To replicate what was seen in the deployed system, the 96 congestion events were applied to the population of devices. Figure 4.4 shows the relationship between LMP (that is, not the price directly seen by the consumer) and the change in load behavior. The application of the congestion events tended to increase demand during periods of high prices and negate some of the decreases seen during low to medium price periods. This is most likely driven by the congestion event raising the average price and making the LMP look like a better deal in the hours following the events. This may have a significant impact immediately after a congestion event, when units are trying to recover, especially if high LMPs are coincident with the congestion event. The absolute LMP is indifferent to whether the congestion event occurred; however, the thermostat agents will perceive this price as relatively lower following a congestion event, and will increase their consumption following the event. While this is greatly exaggerated by using 96 congestion events, it does suggest that for 24 hours after a high-price or congestion event, households will tend to "over consume" relative to high LMP values, as this price will appear to be a relatively low price. More investigation is warranted to better understand and quantify the simulation results and calibrate simulation models with further information that can be gleaned from the field data.

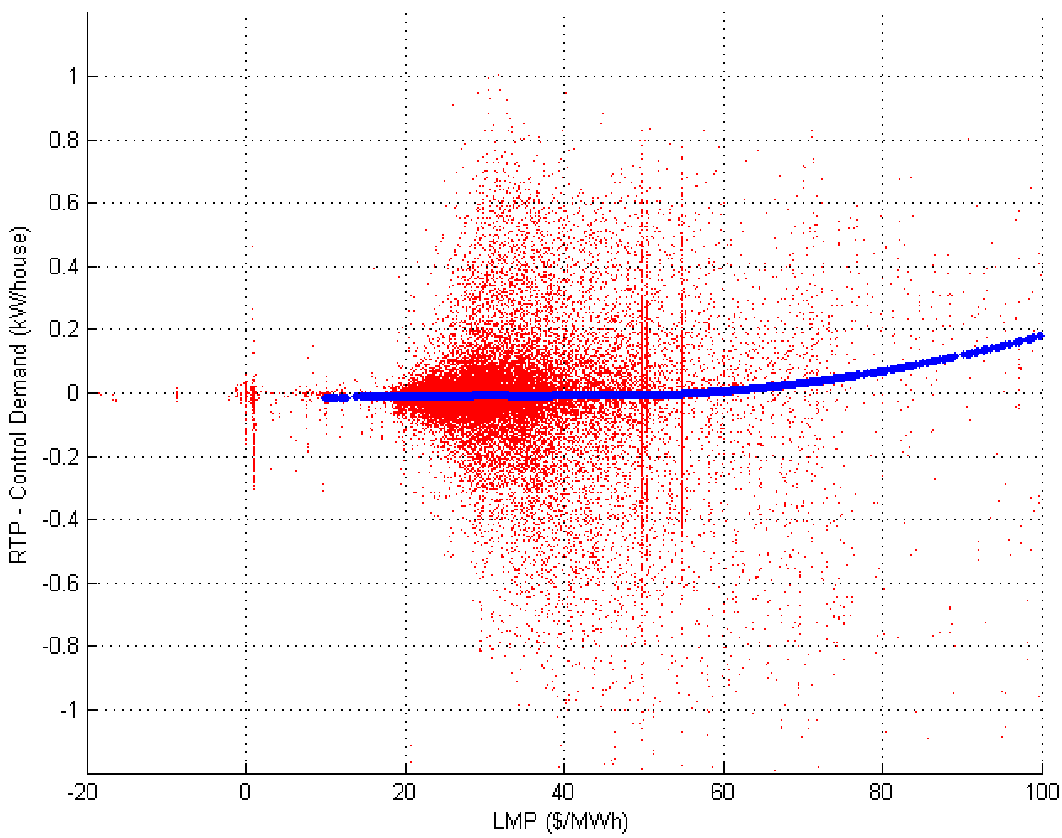

Figure 4.4. Change in Load versus LMP between the Control and RTP_{da} Groups Including Congestion Experiments

To look at this effect, Figure 4.3 and Figure 4.4 were adapted to look at the response to the supply price in terms of standard deviations from the average price. This effectively translates the price into how the thermostat controller views it; the current price is always relative to the average price from the previous 24 hours. So, the price is calculated and displayed as

$$P_\sigma = \frac{P_{supply\ bid} - P_{avgerage\ 24\ hours}}{P_{standard\ deviation\ 24\ hours}} \tag{4.1}$$

Figure 4.5 shows the same (non-congested) case as Figure 4.3, but with the price translated into relative prices. The patterns can be difficult to discern. In general, one would expect that as relative price increases, the amount of reduction in demand should increase. However, during any given market period, the response to price is dependent on what happened in previous markets. For example, after an extended period of +2.5 standard deviation prices, in which loads were continuously deferring, a price of +1.5 standard deviations might be a relatively attractive price due to the deferral of operation. So, at any given 5-minute period, the RTP_{da} load may increase with higher prices, but the overall trend should be strongly toward decreased demand during relatively high-price periods.

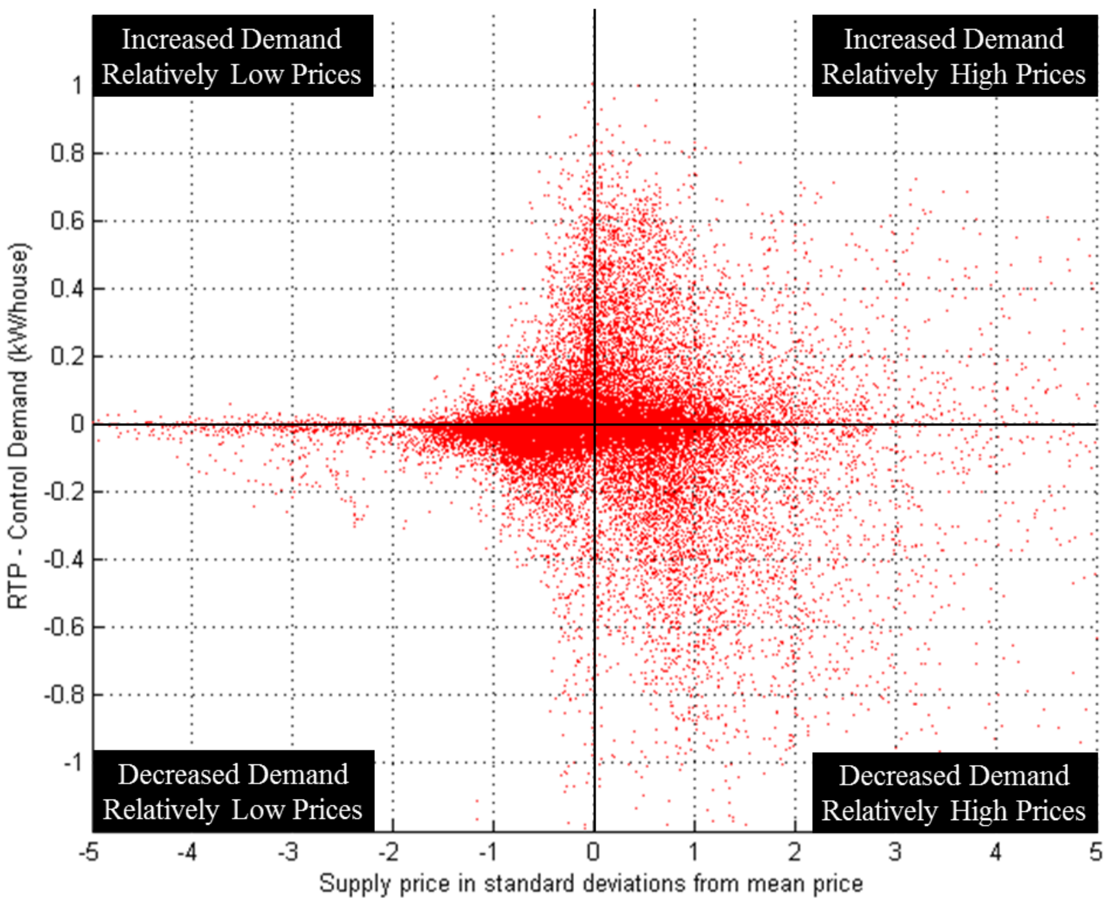

Figure 4.5. Change in Load versus Relative Price between Control and RTP_{da} Groups

Figure 4.6 breaks the same data into three temperature "bins," where the temperature bin represents the current outdoor temperature during that 5-minute market interval. Blue represents temperatures less than 70°F, green between 70 and 80°F, and red over 80°F. The black lines are trend lines determined using the same technique as in Figure 4.1. When presented this way, a number of trends are quickly identifiable. Again, the trends are important and not the individual points. In any given individual market clearing, depending on what occurred in previous market clearings, the RTP_{da} load may increase or decrease relative to the control group no matter the relative price. For example, if the RTP_{da} load has been deferred for 30 minutes, a relative price of +1 may appear quite reasonable (recovery from the deferral may cause an increase in load). However, if the price has been relatively low for the past 30 minutes, a price of +1 is too high for the current resource status (and decreases the load). Looking at the trend lines reduces this noise and determines whether the system in aggregate is behaving as designed, or in other words, decreasing demand during relatively high-price periods.

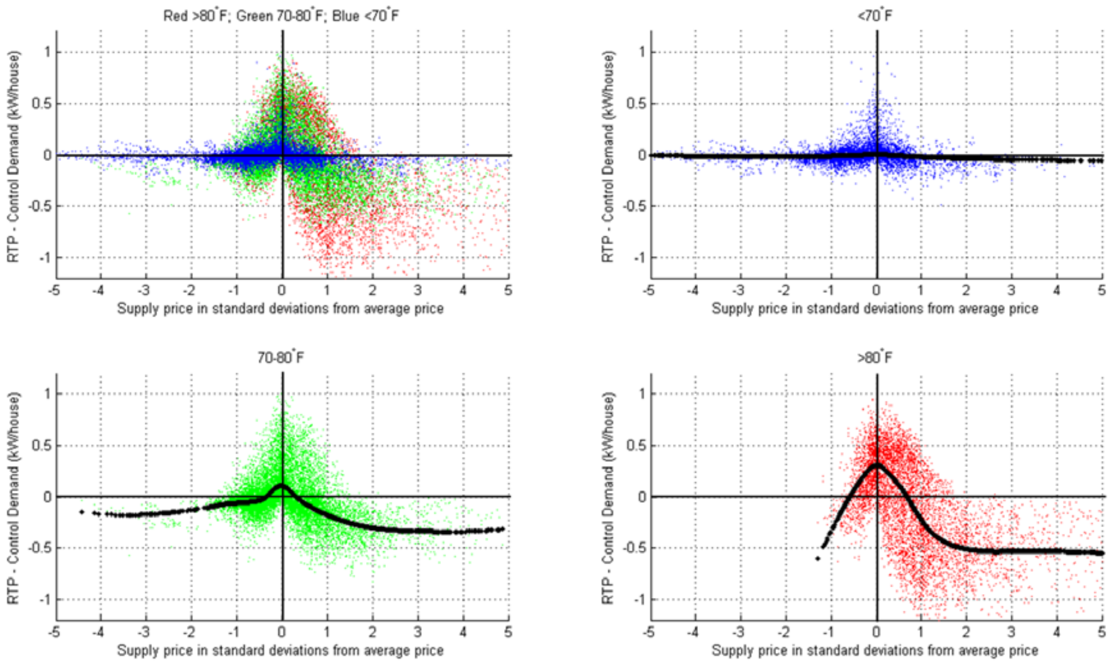

Figure 4.6. Change in Load versus Relative Price between Control and RTP_{da} Groups Broken into Outdoor Air Temperature Bins

In the "less than 70 degrees" bins (the simulations were for summer periods only), when there is minimal air conditioning, the trend is very flat with a very slight trend toward reducing demand as price increases. This is expected, as there is minimal resource during these periods (albeit some resources still available). Also, while there are some individual cases where demand increases or decreases, the overall trend is to minimally decrease load as a function of price. When temperatures are greater than 80 degrees (red), it is clear that as relative price increases, load decreases to a plateau value of approximately 0.5 kW/household. This is as expected (and desired). Of note, however, is that when price is between −0.5 and 0.5 standard deviations, the trend is actually to increase load. Most likely, this is caused by the devices "recovering" during slightly higher prices after very high-price periods that tend to occur more often during hot periods of the day. Data for the 70–80 degree time periods (green) are in between data for the other two graphs. Additionally, as temperature climbs, the relative price also climbs, indicating that a higher temperature day after a cooler temperature day tends to experience higher LMPs. In future applications, this observation could be used to better predict upcoming prices and better tune the controllers to respond to high and low price excursions, which would allow for a rough prediction of demand reduction available during any given market cycle as a function of outdoor air temperature.

In conclusion, this analysis of field and simulated data is but a start to understand and provide insight to the complex interactions at play in the RTP_{da} system. The basic trend observed of reducing load as LMPs rise is directional evidence of the desired behavior with the system; however, many more questions are raised about the strength of this correlation and its behavior under different market, weather, and temporal-related conditions. Further investigation is needed to address these questions and gain greater insight.

4.3 RTP_{da} Load Event Response

Due to the relatively low penetration of RTP_{da} households on each feeder, the impact of each congestion experiment was to engage all of the resources and drive the cleared market price to the price cap. A benefit of these experiments is that they demonstrated the maximum amount of response that could be obtained under various operating conditions. This section investigates the magnitude of the responses from the resources to the congestion events and how well the resources responded over the duration of the event.

4.3.1 Events Response Magnitude

The magnitude of the response is estimated by evaluating the difference between the fractional change in the control group load and the RTP_{da} group load relative to their averages for the 4 hours prior to the beginning of the event. The 4 hour period is chosen as it strikes a balance between prior conditions sample size and variance. The fractional response of response group x relative to control group y is defined as

$$r_t(x,y) = \frac{\sum_{n=1}^{N_x} x_{n,t}}{\sum_{n=1}^{N_y} y_{n,t}} - 1 \tag{4.2}$$

The mean response for the 4 hours prior to the start of the event at $t = 0$, where the time interval is 5 minutes and t is in hours, is evaluated as

$$\bar{r}(x,y) = \frac{1}{16} \sum_{-4<t\leq 0} r_t(x,y) \tag{4.3}$$

and is used to normalize all the responses thereafter. The percent response is evaluated relative to this 4-hour mean prior to the event.

The magnitude of the response after the start of the event relative to the response prior to the event is thus

$$R(x,y) = r_t(x,y) - \bar{r}(x,y) \tag{4.4}$$

This result is shown for 2-hour and 4-hour duration events by the solid lines in Figure 4.7.

4.3.2 Event Response Uncertainty

The uncertainty of the response is estimated by first evaluating the variance of the control group and the RTP_{da} response group for various response types (for example, 2-hour event, 4-hour event, mild day, hot day, off-peak period, on-peak period). All the responses for the selected response types were grouped after being normalized with respect to the conditions prior to the event. The variance of a group load x^N (N is the number of active meters) at the time t is given by

$$v_t(x) = \frac{1}{N^2}\sum_{n=1}^{N}\left(x_{n,t} - \bar{x}_t\right)^2 \tag{4.5}$$

To compute the uncertainty of the difference between response group x and the control group y, we must compute the covariance

$$c_t(x,y) = \frac{1}{N^2}\sum_{n=1}^{N}\left(x_{n,t} - \bar{x}_t\right)\left(y_{n,t} - \bar{y}_t\right) \tag{4.6}$$

The 63% confidence interval for the response of the response group x relative to the control group y is

$$\sigma_t = \sqrt{v_t(x) + v_t(y) - 2c_t(x,y)} \tag{4.7}$$

This result for 2- and 4-hour events is shown by the dotted lines in Figure 4.7.

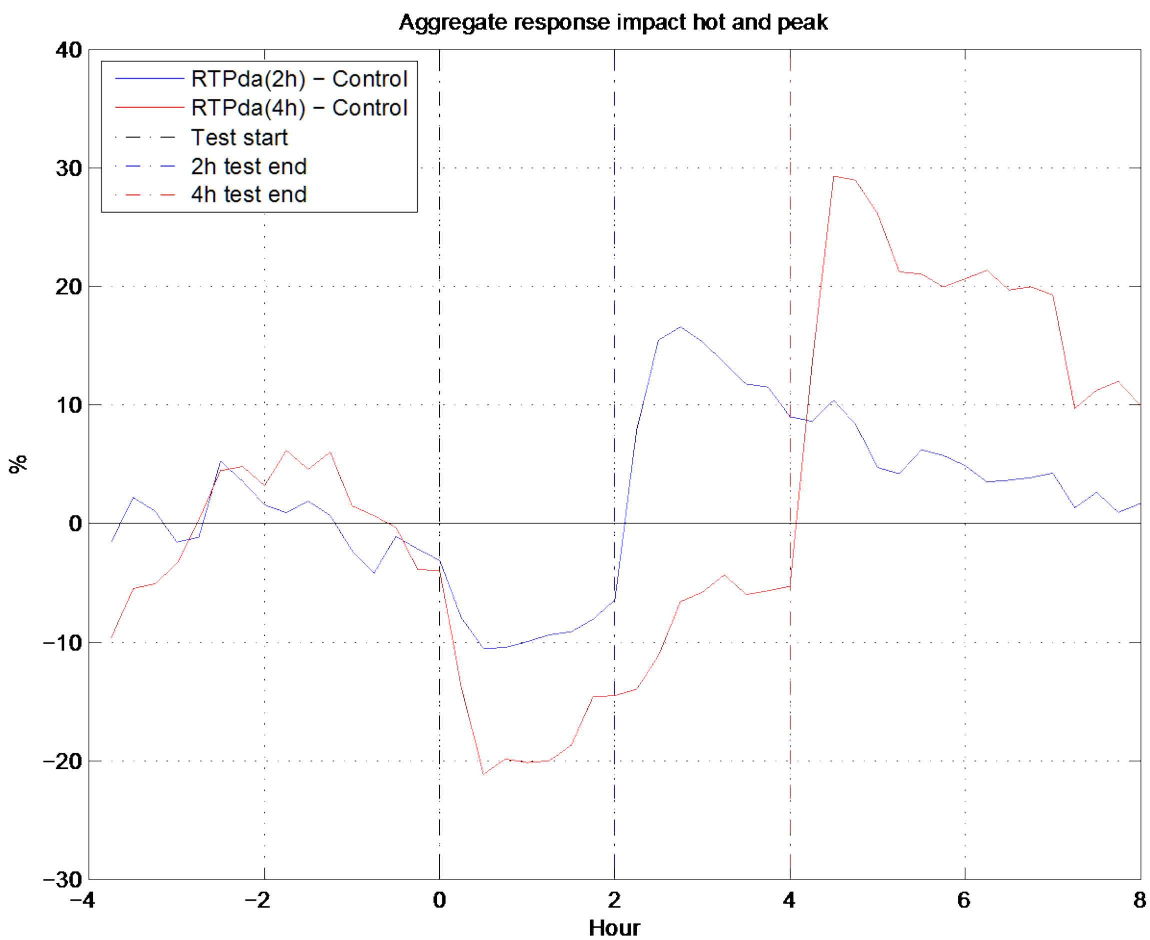

Figure 4.7. Aggregate Response to 2- and 4-hour Congestion Events

The results for the various event and day types are summarized in Table 4.1. The initial response is evaluated 15 minutes after the start the event. The response trend refers to the general trajectory of the response after the initial response to the event. It is evaluated for the duration of the event as a linear fit to the data in percent per hour with the same percent scale as initial response. The initial uncertainty is given for the 63% confidence interval on the same scale as the initial response. The uncertainty trend refers to the general trajectory of the uncertainty after the initial response to the event. It is evaluated in %/h on the same scale as the initial response for the duration of the event.

Table 4.1. Summary of Group Responses by Event and Day Type

Event Type	Initial Response (%)	Response Trend (%/h)	Initial Uncertainty (%)	Uncertainty Trend (%/h)
All events	−8.6	1.0	4.2	−0.2
All 2 h	−6.4	−0.3	5.9	−0.3
Hot+peak 2 h	−10.5	1.3	11.4	−0.6
Mild+peak 2 h	−1.4	−3.1	16.4	−0.8
All 4 h	−17.9	4.1	17.2	−0.6
Hot+peak 4 h	−22.5	4.7	23.1	−0.7
Mild+peak 4 h	−9.3	3.0	63.4	−2.0

The 2-hour events have a much shallower initial response than the 4-hour events (10.5% versus 22.5%). This is mostly driven by the timing of the events. Many of the 4-hour events occurred during high peak periods in the late afternoon on successive hot days, while the 2-hour events occurred over a greater variety of situations in both time of day and daily temperatures. Also, on mild days 4-hour events tended to start later in the day relative to 2-hour events. Thus the 2-hour events tended to start with very few RTP_{da} HVAC resources available and as more unconstrained HVAC resources began operating, the system became more responsive (hence the negative percent response trend). In contrast, 4-hour events started with more RTP_{da} resources already in operation and moved into times of the day where RTP_{da} resources became more constrained in their ability to respond. Therefore, the trend was for decreasing RTP_{da} resource response (positive response percent trend). On peak days, events usually began with more RTP_{da} resources available and the trend was generally toward fewer RTP_{da} resources as time passed. As the resources were depleted, it became harder to distinguish the experiment response from the control group.

Further analysis of the data, such as segmenting the graphs according to time of day, weekday versus weekend, and temperature can help in more fully characterizing the response of the RTP_{da} resources to these events.

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