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Demonstration of automated price response in large customers in New York City using Auto-DR and OpenADR

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Demonstration of automated price response in large customers in New York City using Auto-DR and OpenADR

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Disclaimer

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Abstract

Demand response (DR) – allowing customers to respond to reliability requests and market prices by changing electricity use from their normal consumption pattern – continues to be seen as an attractive means of demand-side management and a fundamental smart-grid improvement that links supply and demand. From October 2011 to December 2013, the Demand Response Research Center at Lawrence Berkeley National Laboratory, the New York State Energy Research and Development Authority, and partners Honeywell and Akuacom, have conducted a demonstration project enabling Automated Demand Response (Auto-DR) in large commercial buildings located in New York City using Open Automated Demand Response (OpenADR) communication protocols. In particular, this project focuses on demonstrating how the OpenADR platform, enabled by Akuacom, can automate and simplify interactions between buildings and various stakeholders in New York State and enable the automation of customers' price response to yield bill savings under dynamic pricing. In this paper, the cost control opportunities under day-ahead hourly pricing and Auto-DR control strategies are presented for four demonstration buildings; present the breakdown of Auto-DR enablement costs; summarize the field test results and their load impact; and show potential bill savings by enabling automated price response under Consolidated Edison's Mandatory Hourly Pricing (MHP) tariff. For one of the sites, the potential bill savings at the site's current retail rate are shown. Facility managers were given granular equipment-level opt-out capability to ensure full control of the sites during the Auto-DR implementation. The expected bill savings ranged from 1.1% to 8.0% of the total MHP bill. The automation and enablement costs ranged from $70 to $725 per kW shed. The results show that OpenADR can facilitate the automation of price response, deliver savings to the customers and opt-out capability of the implementation retains control of the sites by facility managers.

Keywords: price response, commercial building, demand response, dynamic pricing, mandatory hourly pricing, OpenADR, Open Automated Demand Response, smart grid

Table of Contents

List of Figures

List of Tables

Executive Summary

New York State's (NYS) electricity grid requires about 40% more generating capacity to meet summer-time peak demand as compared to other times of year. The top 100 hours of electricity demand cost NYS a disproportionate amount of the total system cost. Fossil fueled peaker plants that supply dispatchable generation during those hours have a greater environmental impact than other types of power generator. The expansion and maintenance of the transmission and distribution system to reliably meet system peak demand adds a significant cost. Similarly removing a portion of that peak load (either through energy efficiency or demand response) offers substantial cost and carbon reductions.

A 'smarter grid' is expected to more efficiently balance electricity supply and demand, minimizing costs and environmental impact, and can accommodate greater penetrations of intermittent renewable resources and plug-in electric vehicles (PEVs). ***Curtailment*** of customer load (decreasing immediate or future demand) can provide emergency relief, energy, capacity, reserve, or network relief benefits to a smart gird and electricity markets. Adding smart buildings to a smart grid requires a combination of technology and technique. The technology includes building automation, flexible loads, energy feedback, methods and standards for utility system integration and price signaling. The techniques include dynamic retail rate products, demand response program design, and aggregation of small loads.

Demand response (DR) – allowing customers to respond to reliability requests and market prices by changing electricity use from their normal consumption pattern – continues to be seen as an attractive means of demand-side management and a fundamental smart-grid application that links supply and demand. From October 2011 to December 2013, the Demand Response Research Center (DRRC) at Lawrence Berkeley National Laboratory (LBNL), The New York State Energy Research and Development Authority (NYSERDA), and partners Honeywell and Akuacom, conducted a demonstration project enabling price-responsive Auto-DR in large commercial buildings located in New York City (NYC).

The project focused on following:

- Demonstrating how the OpenADR platform, enabled by Akuacom, can automate and simplify interactions between buildings and various stakeholders in NYS including the NYISO, utilities, retail energy providers (REPs), and curtailment service providers (CSPs);
- Automating building control systems to provide event-driven demand response, price response, and demand management according to OpenADR signals;
- Providing cost-saving solutions to large customers by actively managing day-ahead hourly prices and demand charges; and
- Granting building management staff sub-system level granular control to remove any major piece of heating, ventilation, and air conditioning (HVAC) equipment from load-shed sequences, or opt a building out in its entirety.

Methodology

The methodology for this demonstration project included site recruitment, control strategy development, automation system deployment, evaluation of sites' participation in Automated Demand Response (Auto-DR) test events, and bill savings analysis under Mandatory Hourly Pricing (MHP). Each of the four facilities participating in the demonstration worked with LBNL to select and implement control strategies for demand response. LBNL worked with Honeywell and Akuacom to develop automation system designs for each facility based on existing Internet connectivity and the building control system.

Once automation systems were installed at each site, LBNL conducted communications tests to ensure that the Demand Response Automation Server (DRAS) correctly provided and logged the continuous communications of OpenADR signals with the energy management and control system (EMCS). LBNL also observed and evaluated shed strategies to ensure proper commissioning of controls. The communication system allowed the sites to receive day-ahead as well as day-of email notifications that included a price schedule and shed modes used for the test events. Facility managers were given granular equipment-level opt-out capability to ensure full control of the sites during the Auto-DR implementation.

To measure and estimate magnitude of load-shed, the team used three different baseline modeling techniques. The first model was NYISO's Customer Baseline Load (CBL) model, which used the average hourly demand of the five highest energy-consuming days during the 10 work days preceding the DR event of interest. CBL is not normalized for weather. The second model was the outside air temperature regression (OATR) baseline model, which employed load sensitivity to outside air temperature. The third model was LBNL's slope-based model, which used the average slope of historic demand curves to estimate the next time step based on a known starting point. Following the DR test period, the team interviewed facility managers regarding their overall experience, and any problems or issues that arose during the test events. Discussions covered occupant comfort, user interface, system controls, and overall user experience.

Following successful load-shed events, the team evaluated the costs of DR automation through a combination of invoices and quotes from enablement contractors. Costs included engineering time, installation costs, and direct hardware costs. The team found automation costs to range from $70 to $725 per kW shed. More than 70% of the total costs came from engineering costs (i.e., control logic programming). One building had a substantially higher automation costs ($725 per kW shed) than those observed in other projects conducted by LBNL with similar central plants and building management systems. Perhaps this was because Auto-DR was implemented first time in NYC by these vendors

Based on the load reductions demonstrated during test events, the team evaluated utility bill savings each site could expect by enabling Auto-DR under the utility's default rate for large customers – MHP. The team found expected savings to range from 1.1% to 8.0% of the total MHP bill. The potential bill savings were calculated based on a cost minimization algorithm developed by LBNL, which optimized electricity consumption under day-ahead hourly pricing and reduced peak demand of the billing period. For one of the sites, the team provided additional analysis that shows potential bill savings at the site's current retail rate.

Results

- **Four sites participated in the Auto-DR demonstration.** The participating sites were large commercial buildings located in New York City, primarily used for office space, and currently purchasing electricity through retail access.
- **All four sites were enabled to respond to DR events and day-ahead hourly prices using OpenADR protocols.** The team worked with the sites' curtailment service provider to trigger automated load shed for the ISO's and utilities' demand response events. Also, the receipt of day-ahead hourly prices and issuance of load shed events was automated based on the price level.

- **All four sites participated in test events during the summer of 2013.** There were 36 test events during the summer of 2013. The test events were used to evaluate Auto-DR and estimate load reductions at each site. On average, the sites were able to reduce 0.03 - 0.34 W/sqf of the electric load for *Moderate* mode and 0.08-0.47 W/sqft. for *High* mode.
- **Enablement costs for engineering, installation, and hardware ranged from $70-$725/kW.**
- **Auto-DR can reduce customers' electricity bills under day-ahead hourly pricing.** Using LBNL's cost minimization algorithm, potential bill savings were estimated for each site by automating price response. The analysis showed that the sites could save 1.1% – 8.0% of their total summer electricity bills under Con Edison's MHP.

  Building managers require equipment level opt-out control. All building managers requested granular opt-out control at the zone, sub-system, or equipment level. Primary drivers were the changing nature of critical operations over time, and the necessity to tailor load-shed to current building conditions or occupant requirements.

Recommendations and Future Directions

This project investigated a variety of issues during the field test. However, there is still confusion around the use and value of OpenADR, especially how it will stand the test of time in the face of developing trends on technology, markets and standards, and on its value to all the stakeholders.

One of the key values of automating DR is to automate once and reap the benefits of the initial investment many times over the life of the participation. The benefit to participating in DR with standard protocols is the choice of vendor and aggregator it provides to the customer. A next step to this project would be to demonstrate a variety of transactions these sites can participate in given the initial investment as well as the variety of values they can extract from these markets. In addition, a comparison of a building with interoperable communications versus another building with proprietary communication would inform the operators and policy makers of pros and cons of their choices. The new initiatives can benefit from the latest version of OpenADR, version 2.0 which includes two-way messaging capability between a DRAS, that publishes information, and a client that subscribes to the information. With OpenADR 2.0, utilities, grid operators, and CSPs will be able to manage peak demand and load shifting in an automated and scalable fashion, thus reducing the cost of DR technology enablement and customer adoption.

Introduction

Background

Demand response (DR) – allowing customers to respond to reliability requests and market prices by changing electricity use from their normal consumption pattern – continues to be seen as an attractive means of demand-side management and a fundamental smart-grid application that links supply and demand. Large customers are often the first and most cost effective target for DR because they are major contributors to peak demand for electricity, and are equipped with centralized building management system (BMS) that automate control. With increased adoption of smart meters, standards-based building control networking, and building automation systems, an enormous opportunity lies ahead for medium and large customers to exercise their full DR potential.

New York State's (NYS's) market electricity structure provides several mechanisms intended to encourage larger customers to reduce their impact on the grid through DR. Such mechanisms include dynamic pricing, load shifting incentives, and curtailment programs. To actively manage building load shapes, and fully take advantage of market efficiencies, building owners and operators must have granular control and automation to make adjustments to building operations sequences.

Today, however, most adjustments to building controls and operations are done manually, making response to more frequent reliability events, hourly prices, or daily peak shaving impractical. Furthermore, many building owners hedge against energy expenditure uncertainty by purchasing flat-priced forward contracts. The problem of this trend is that, by nature, flat price retail contracts hedge against price fluctuations and therefore do a poor job of reflecting wholesale near-term market prices (day-ahead, hour-ahead and real-time). Flat price contracts are also more expensive due to the inherent risk premium of offering a less variable rate [Goldman et al., 2002]. Of the current barriers to adopting a more cost-effective dynamic energy rate is the difficulty and rigidity of building controls operations. DR strategies may allow customers to benefit from market incentives, while providing a more reliable forecast of future energy expenditures.

Customers' ability to perform DR can significantly improve by enabling automated demand response (Auto-DR). By reducing the need for humans in the loop, Auto-DR can reduce the operational burden to provide real-time response and lower the costs associated with monitoring building energy consumption and responding to load-shed requirements. Auto-DR also helps customers leverage the flexibility of their buildings' load shapes by automating the reaction to price and reliability signals.

Although automation of demand responsive control strategies may provide financial benefits such as management of day-ahead hourly pricing and demand charge reduction, building owners and managers are often reluctant to adopt automation because they perceive it as relinquishing full control of their systems. Building management staff priorities lie in the delivery of service and comfort for tenants and, therefore, savings cannot be perceived to come at the cost of tenant satisfaction.

The rest of the report is organized as follows. The methodology section describes site information, the Auto-DR system architecture, and all details relating to site enablement and testing. The results section describes the load shed analysis results as well as Auto-DR implementation costs, and feedback from the participating sites. The utility-bill savings section describes results of the cost-minimization algorithms, and presents a case study for potential savings at a particular site. Finally, the report concludes with project findings summarized, and next steps for the research.

Goals and Objectives

From October 2011 to December 2013, the Demand Response Research Center (DRRC) at Lawrence Berkeley National Laboratory (LBNL), New York State Energy Research and Development Authority (NYSERDA) and partners Honeywell and Akuacom conducted a demonstration project enabling price-responsive Auto-DR in large commercial buildings located in New York City (NYC).

The project focused on following:

- Demonstrating how OpenADR can automate and simplify interactions between buildings and various stakeholders in NYS including the NYISO, utilities, retail energy providers (REPs), and curtailment service providers (CSPs);
- Automating building control systems to provide event-driven demand response, price response, and demand management according to OpenADR signals;
- Providing cost-saving solutions to large customers by actively managing day-ahead hourly prices and demand charges; and
- Granting building management staff more granular control to remove any major piece of heating, ventilation, and air conditioning (HVAC) equipment from load-shed sequences, or opt a building out in its entirety.

Project Partners

The project team was comprised of the New York State Energy Research and Development agency (NYSERDA), Lawrence Berkeley National Lab (LBNL), Honeywell Building Solutions (HBS), and Akuacom Inc. (a Honeywell company). LBNL managed all aspects of the project including site selection, demand management control strategy development, and analysis of results. HBS served as the installation coordinator and provided technical expertise for site enablement through hardware installation, control sequence programming, on-site support, system commissioning, and controls vendor management. Akuacom provided all demand response automation server (DRAS) support, software, and services.

Acronyms used in the following chapters

- Auto-DR	Automated Demand Response
- AMI	Advanced Metering Infrastructure
- BMS	Building Management System
- CBL	Customer Baseline Load
- CSP	Curtailment Service Provider
- DDC	direct digital control
- DPR	demand peak reduction
- DRAS	Demand Response Automation Server
- DR	Demand Response
- DRRC	Demand Response Research Center
- DRQAT	Demand Response Quick Assessment Tool (DRQAT)
- HBS	Honeywell Building Solutions
- HVAC	heating, ventilation and air conditioning
- ISO	Independent System Operator
- kW	kilowatt
- kWh	kW hour
- LBNL	Lawrence Berkeley National Laboratory
- MHP	Mandatory Hourly Pricing
- NYC	New York City
- NYS	New York State
- NYPA	New York Power Authority
- NYSERDA	New York State Energy Research and Development Agency
- OATR	Outside Air Temperature Regression
- REP	Retail Energy Provider
- TOD	Time Of Day
- TOU	Time Of Use

Methodology

Site Information

Three office buildings and one campus building located in NYC participated in Auto-DR tests during the summer of 2013. Table 1 provides brief information about the four participating sites. More detailed site descriptions are provided in the previous report of this project (Kim et al., 2013). The participating sites are anonymized to protect their privacy.

Table 1. Site Information

Facility	Business Type	Floor Area (ft^2)	Electricity Supplier & Rate
Office Building A	Office	1,400,000	NYPA – TOD
Office Building B	Office	1,700,000	Direct Energy – fixed rate
Office Building C	Office	1,400,000	NYPA – TOD
Campus Building	Campus	122,000	NYPA – TOD

All sites purchased electricity through retail access on different rate structures (i.e., New York Power Authority's Time-of-Day rate (NYPA – TOD), a fixed rate) and paid Consolidated Edison Company of New York (Con Edison) delivery charges that were calculated primarily based on the peak demand usage. Since the sites' electric demand and consumption were the highest in summer, the most tangible goal for them was to reduce peak demand and overall electric consumption during summer months.

Automated Demand Response System

Prior to this project, all sites provided manual DR and were not capable of responding to machine-readable price signals. During the site enablement process, an OpenADR client called JACE® (Java Application Control Engine) was installed at each site to receive the LBNL/Akuacom generated price and operation mode signals using OpenADR protocols. Upon receiving, JACE® translated these signals into BACnet® messages. Then, it sent the messages to Honeywell's ComfortPoint™ Open Plant Controller (CPO) to activate pre-programmed control strategies through the site's BMS. Building managers were allowed to modify pre-programmed control strategies by deselecting individual control strategies via the CPO's graphical user interface shown in Figure 1. They were also able to opt out of the entire Auto-DR event by switching the system button from 'On' to 'Off' via the CPO. The opt-out could be pre-scheduled via Akuacom's DRAS customer interface.

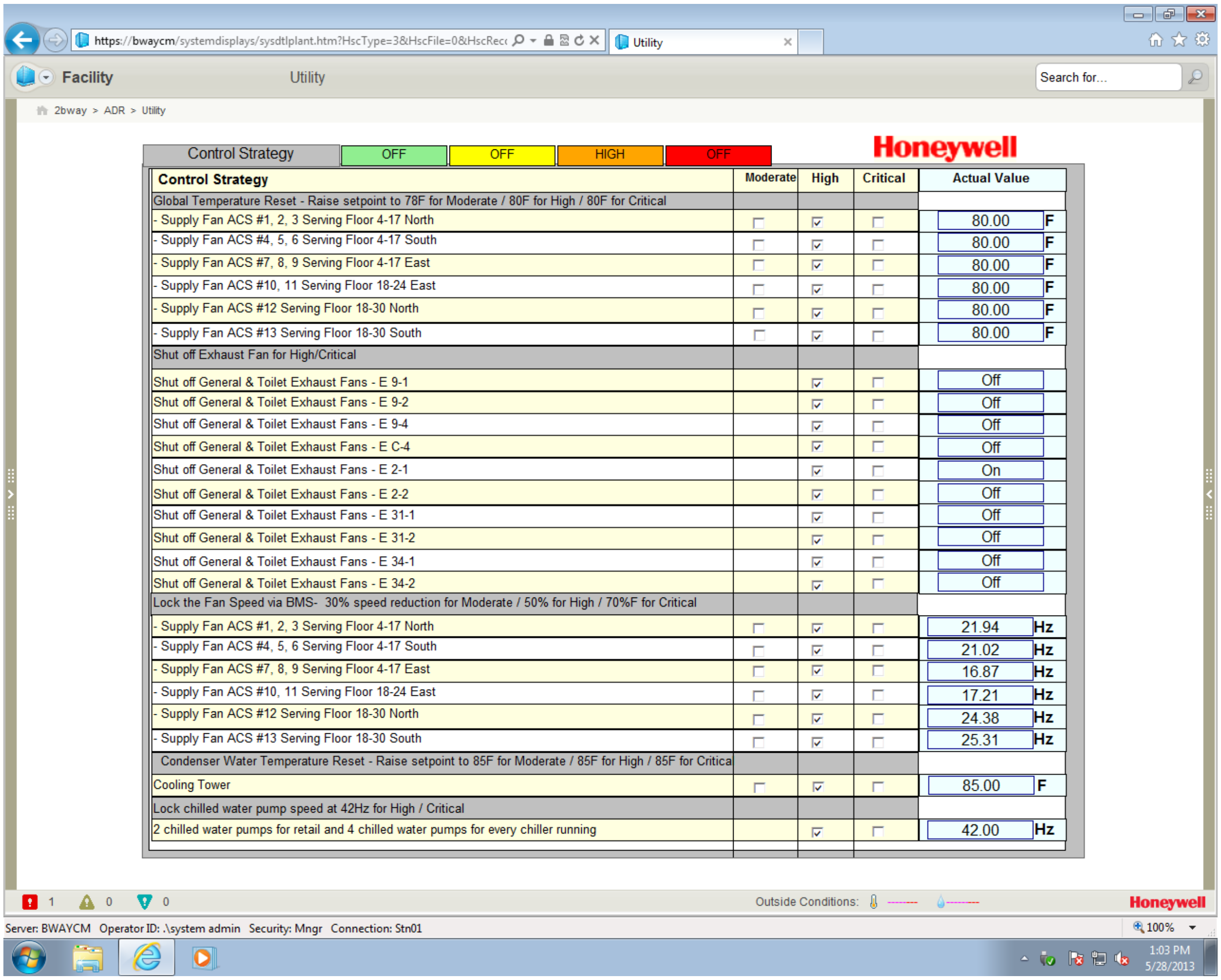

Figure 1. Honeywell's ComfortPoint™ Open Plant Controller User Interface

Control Strategies

Based on the sites' existing control strategies used for the utility's DR events, LBNL developed summer shed strategies that were appropriate for each site. Only the strategies that could be automated were chosen and grouped into three levels of shed response: *Moderate*, *High*, and *Critical*. Pre-cooling was considered as a load shifting strategy but could not be automated due to the NYC Fire Code requirements to have a licensed engineer on site to start chillers. To minimize the post-DR rebound effects, equipment was returned to the normal operation in a sequential manner.

Table 2 shows control strategies for the four participating sites. All of the control strategies were linked to HVAC systems due to the easy integration with the existing BMS. Centralized lighting control was not available through the existing BMS in these sites.

Table 2. Automated Control Strategies for Demonstration Sites

Facility	Operation Mode	Global temperature adjustment	Supply fan speed reduction	Exhaust fan quantity reduction	Chilled water temperature increase	Chilled water pump speed reduction	Shutting off chilled water pumps	Chiller quantity reduction	Condenser water temperature increase	Shutting off condenser water pumps	Slow recovery	Sequential equipment recovery
Office Building A	Critical	x	x	x	x	x	x	x	x	x	x	x
	High	x	x	x	x	x			x	x	x	x
	Moderate	x	x		x				x	x	x	x
Office Building B	Critical		x	x		x			x		x	x
	High		x	x		x			x		x	x
	Moderate		x			x			x		x	x
Office Building C	Critical		x	x			x				x	x
	High		x	x			x				x	x
	Moderate			x			x				x	x
Campus Building	Critical	x	x	x						x	x	x
	High	x	x	x						x	x	x
	Moderate	x	x							x	x	x

Site Programming and Trend-logging

For each site, a BMS vendor was hired to program proposed control strategies into the facility's BMS so that the strategies can be activated upon receiving OpenADR signals. Honeywell and LBNL oversaw this activity and coordinated logistics with the controls vendors. The controls vendors set up trend logs in the facilities to record affected control points for monitoring purposes. After each test event, trend logs were downloaded and checked against control points to confirm whether the BMS responded to OpenADR signals as programmed. LBNL also collected 15-minute interval whole building power data via the DRAS's client interface. A minimum of one month of data prior to the two-week test period was collected to develop a baseline model.

Commissioning

The Auto-DR enablement in each site was followed by a commissioning process that involved manually triggering of OpenADR signals to confirm the BMS response. The *Normal*, *Moderate*, and *High* operation modes were tested. Honeywell trained building managers how to use modification and opt-out functions available in the CPO manager. During the commissioning, the building managers practiced the use of these functions by manually opting out of the test event via the CPO manager. They were also trained to download trend logs from the BMS in a spreadsheet format for LBNL's review.

Auto-DR Testing

A total of 36 test events were dispatched based on day-ahead hourly wholesale market prices during the summer of 2013. The purpose of the test events was to capture load shed response during high-priced periods in order to estimate the buildings' load shed capacity. In NYC, energy price typically reaches its highest point in the afternoon. Therefore, the test events were scheduled to coincide with the high-priced periods. Table 3 summarizes the test dates and time, duration, and opt-out details.

Table 3. Test Dates, Time, Duration, and Opt-Out Information

Facility	Date	Time	Moderate duration (hr)	High duration (hr)	Opt-out?
MTA	29-Jul-13	4pm - 5pm	1	0	No
	30-Jul-13	3pm - 5pm	1	1	No
	1-Aug-13	2pm - 3pm	0	1	No
	2-Aug-13	2pm - 4pm	2	0	No
	5-Aug-13	3pm - 5pm	2	0	No
	6-Aug-13	2pm - 4pm	1	1	No
	7-Aug-13	3pm - 5pm	0	2	No
	9-Aug-13	2pm - 5pm	2	1	No
WFC	8-Jul-13	3pm - 4pm	1	0	No
	9-Jul-13	3pm - 5pm	1	1	No
	10-Jul-13	3pm - 4pm	0	1	No
	12-Jul-13	3pm - 5pm	0	2	No
	22-Jul-13	3pm - 5pm	1	1	No
	23-Jul-13	2pm - 5pm	2	1	No
	24-Jul-13	3pm - 5pm	2	0	No
	25-Jul-13	2pm - 5pm	1	2	No
	26-Jul-13		2	0	Yes
Paramount	27-Jun-13	4pm - 6pm	2	0	No
	28-Jun-13	4pm - 5pm	0	1	No
	2-Jul-13	4pm - 5pm	0	1	Yes for Moderate
	3-Jul-13		0	0	Yes
	8-Jul-13	3:30pm - 4:30pm	1	0	No
	9-Jul-13	3pm - 5pm	1	1	No
	10-Jul-13	3pm - 5pm	0	2	No
	11-Jul-13		2	0	Yes
	12-Jul-13	3pm - 5pm	1	2	Yes for Moderate
	15-Aug-13		2	0	Yes
	16-Aug-13	3pm - 5pm	1	2	Yes for Moderate
	5-Sep-13	2pm - 4pm	2	0	No
	6-Sep-13	2pm - 4pm	1	1	No
NYU	24-Sep-13	2pm - 3pm	1	0	No
	25-Sep-13	3pm - 4pm	0	1	No
	2-Oct-13	1pm - 2pm	1	0	during 2nd hour
	4-Oct-13	3pm - 4pm	0	1	No
	15-Oct-13	3pm - 5pm	0	2	No
	22-Oct-13	1pm - 3pm	2	0	No

As test events were scheduled as soon as the sites were enabled and ready, test event dates vary among the participating sites. The sites were asked to participate in test events during a three-week period. The testing hours were limited to three at a time to minimize occupant discomfort.

Prior to each test event, LBNL set price thresholds to generate a combination of *Normal*, *Moderate*, and *High* operation modes for the following day. Akuacom's DRAS web interface was used to schedule the test event, observe server/client communications in real-time, and create a trend log. Figure 2 shows screenshots of Akuacom's DRAS web interface showing two different price scheduling methods.

1. Simple – set one threshold for the whole day
2. Advanced – set thresholds for each hour of the day

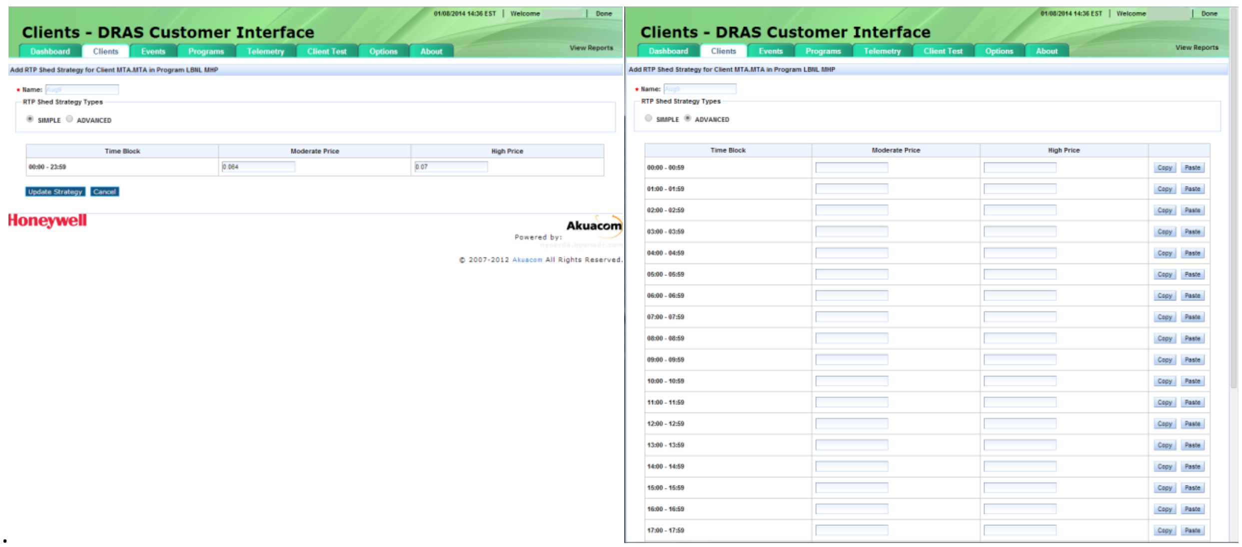

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Figure 2. Screenshots from Akuacom's DRAS Web Interface

During the testing period, participating sites received day-ahead notifications which included a price schedule and corresponding operation mode for each hour of the next day. They also received day-of notifications at the beginning and finish of each test event. The building managers were able to opt out of test events via the CPO manager or the DRAS customer interface.

Evaluation Techniques

To evaluate the test events, LBNL collected whole-building power data and equipment trend logs from each site. Three baseline models were used to quantify load shed during the test events.

1. NYISO's customer baseline load (CBL) with morning adjustment
2. Outside air temperature regression (OATR) model
3. LBNL's slope-based model

Appendix A describes the calculation methods of the above three baseline models.

NYISO's CBL with morning adjustment is the default baseline calculation method in NYS. CBL uses the average hourly demand of the five highest energy-consuming days during the 10 work days preceding the DR event of interest. It is the baseline used by utilities and ISO to calculate DR compensation. The OART baseline model is a regression-based baseline which employs load sensitivity to outside air temperature.

It works best for weather-sensitive buildings. However, collecting weather data from a site or a location close to a site can be cumbersome. The slope-based model is newly developed by LBNL to improve short-term load predictions. It uses the average slope of historic demand curves to estimate the next time step based on a known starting point. The strength of the slope-based model is that it provides a fairly accurate prediction of the next point as long as the building behaves as in the past. However, as the prediction period increases, subsequent points are estimated based on the predicted point and their accuracy may reduce. Hence, the slope-based model should only be used to predict the next few time steps instead of a whole-day trend.

Follow-up Interview and Survey

LBNL contacted each site to record reactions to the Auto-DR tests, DR strategies and any comfort complaints. Additional information about effectiveness of the shed strategies and issues that arose as a result of the tests were obtained by interviewing the responsible building engineer after the test was completed. Appendix B documents the raw data obtained from the post-test interviews.

Results

Load Shed Analysis

For all test events, baseline loads were calculated using three baseline models – NYISO's CBL, OATR, and the slope-based model. Load sheds were calculated by taking the difference between the building's actual and baseline loads. Appendix C shows the load shapes and load shed distributions from the test events for all four sites. Load sheds were also plotted against outside air temperature to check the weather sensitivity of load sheds.

NYISO's CBL model takes a straightforward approach to calculate a baseline for DR event days by averaging the highest load of 5 out of 10 workdays prior the DR event day. However, it assumes that the building has minimal load variability and it doesn't taken weather sensitivity into account. If the DR event day is warmer or colder than previous days, the calculated CBL would be underestimated or overestimated. While OATR baseline model can capture the relationship between the outside weather, and building cooling loads, this baseline model requires a valid weather data source, high weather sensitivity and minimal load variability (Coughlin et al., 2008; Mathieu et al., 2011]. The slope-based model provides a fairly accurate prediction over a short period as long as the building behaves as in the past (Motegi et al., 2004]. Based on the load analysis, two of the participating buildings indicated a medium (0.65-0.8) degree of correlation between load and temperature. The other two buildings had a low (<0.65) weather sensitivity in summer season. In terms of load variability, all four buildings had a relative low load variability (<0.15). When the DR test hour load shapes of the participating buildings were examined, the team found that most of load slopes were very similar over the previous days prior the DR event day. Since the shed period was kept short and there was negligible weather effect on the controlled equipment (e.g. fan speed reduction on constant air volume fans), the slope-based model was used to calculate load reductions and potential bill savings for each site.

To estimate the load shed capacity of each site, an average of load sheds for each operation mode was calculated. Table 4 summarizes the load sheds of all participating sites from the test events.

Table 4. A Summary of Load Shed

Facility	Avg. Load Shed (kW)		Avg. Load Shed (W/sqf)		Avg. Load Shed / Max. Demand	
	Moderate	High	Moderate	High	Moderate	High
Office Building A	480	652	0.34	0.47	7.7%	10.5%
Office Building B	56	137	0.03	0.08	1.2%	2.9%
Office Building C	52	151	0.04	0.11	0.9%	2.5%
Campus Building	30	57	0.24	0.47	6.5%	12.7%

During the averaging process, any load sheds that were one standard deviation away from the mean were removed in order to minimize the effects of outliers. An exception was made – if the team believed that the load shed was a good reflection of the intended control strategies based on the trend log and field verifications, it was included in the average even though it was considered an outlier.

Auto-DR Implementation Costs

The automation of DR strategies and sequences required a combination of control and communication hardware to be installed, as well as control logic programming to the existing Building Management

System (BMS). Costs were broken down into hardware costs and enablement engineering costs respectively.

Table 5. Enablement Hardware Costs

	Hardware Costs (total)	Hardware Costs ($/kW)
Building A	$11,485	$18
Building B	$14,420	$105
Building C	$13,230	$88
Campus Building	$8,855	$155

Table 6. Enablement Engineering Costs

	Engineering Costs (total)	Engineering Costs ($/kW)
Building A	$33,915	$52
Building B	$29,680	$217
Building C	$32,400	$215
Campus Building	$32,485	$570

Table 7. Total DR Automation Costs

Site	Hardware $/kW	Engineering $/kW	Total Enablement $/kW
Office Building A	18	52	**70**
Office Building B	105	261	**366**
Office Building C	88	215	**303**
Campus Building	155	570	**725**

The automation and enablement costs observed for this demonstration project ranged from $70 to $725 per kW shed. Campus Building had a substantially higher enablement cost ($725 per kW shed) than those observed in other projects with similarly complex central plants and building management systems. Perhaps this was because it was implemented first time in NYC by these vendors. Enablement costs observed across Pacific Gas and Electric, as well as Southern California Edison were approximately $225/kW (Ghatikar et al., 2014).

Customer Feedback

Following the completion of load-shed test events, the project team conducted a series of interviews with staff members from each of the participating sites. Feedback was relatively homogenous in the praise of simplicity of opt-out control, as well the requirement of allowing human-in-the-loop overrides when necessary. The 'exit' interviews conducted strongly supported the necessity for an intuitive interface that allows building management staff to customize their respective DR strategies to the operating conditions and tenant requirements on any given day of a DR event. The following list summarizes lessons learned from the participant interviews

- **Overcoming fear of discomfort is critical to adoption of automated load-shed strategies**. Although not always used, granular control allays fears of discomfort and backlash from occupants or tenants.
- **Portfolio managers have to offer building level management staff granular control beyond low, medium, high**. Intricacies of occupancy, staffing, and user requirements demand controls at the zonal or equipment level.
- **Building or portfolio managers don't consider DR automation strategies as opportunities to take advantage of MHP or demand management savings**. This is due to a combination of operator training, and inadequate technology.
- **As diversity in space usage and schedule increases, so does the granular control requirement**. Changes in occupancy schedules can change tolerance to service interruption, thus easily configurable control is required.
- **Building managers tended to prefer automatic enrollment with options to 'opt-out' as opposed to 'opt-in' controls**. This was typically due to the fact that most thought they would forget to opt-in, and would then be penalized.
- **On larger campuses, building engineers often travel between buildings, so a web-accessible portal for opt-out control is important**. Only one of the buildings was part of a 'campus' environment, but the participating site stressed the importance due to the geographically scattered nature of building management staff.
- **Cost savings can be viewed as equally important as energy savings, but priority can depend on institutional mandates**.

Utility Bill Savings Potential of Automated Price Response

In NYS, MHP is the default tariff for large customers. Under MHP, customers' electricity cost is calculated based on day-ahead hourly wholesale market prices, also known as Locational Based Marginal Price (LBMP). However, many customers opt for a more conventional rate such as time-of-use or fixed rate purchased from a retail supplier to avoid the inherent volatility in the wholesale markets. However, if the customers are equipped to perform automated price response, they could easily manage price fluctuations in the wholesale markets. Through the project, the team demonstrated that automated price response could remove the burden of manually monitoring hourly prices and allow customers to respond to price signals.

To understand the potential cost savings of automated price response, four scenarios were developed to look at the participating sites' electric utility bill over a billing period (e.g., a month), shown in Table 8.

Table 8. Customers' Utility Bill Savings Scenarios

	MHP	Current Retail Rate
Normal Operation	Scenario A	Scenario C
Automated Price Response	Scenario B	Scenario D

In Scenario A, a shadow MHP bill was developed for a select month in 2013 to understand how much the sites would have paid if they purchased electricity from Con Edison under MHP. Then, the cost minimization algorithm, described in Figure 3, was applied to Scenario A to estimate how much the sites would have saved if they enabled automated price response. This is shown in Scenario B. For Office Building A, additional analysis was provided to show how much the site would have saved had it enabled automated price response at its current NYPA rate (Scenario D) compared to the scenario with normal operation (Scenario C). The MHP and NYPA bills were calculated based on the tables described in Appendix D. Only the charges that are publicly available on Con Edison's website were used to calculate MHP bills. Taxes were not included in the final bill amount.

Cost Minimization

The objective of automated price response is to reduce the customer's electric cost, J, by minimizing energy and demand costs under the MHP tariff within user-specified constraints. It can be mathematically described as follows.

$$J = \sum_{k=1}^{N} \{EC_k P_k t\} + Max_{1 \le j \le N'} \{DC_j P_j\} \qquad (1)$$

The energy cost is calculated by multiplying average hourly demand (kW), P_k, with day-ahead hourly LBMP ($/kWh), EC for the corresponding time interval, k. Therefore, t is an hour and N is the number of hours in the billing period. The demand cost is calculated by multiplying demand charge ($/kW), DC, to the highest 30-minute average demand, P_j, in a billing period. Hence, the time interval, j, is a half-an-hour and N' is the number of 30-minute time intervals in the billing period.

Based on Equation 1, a cost minimization algorithm was developed to compute the participating sites' one-month electricity bill using three modules: demand limiting, price response – level I, and price response – level II. Figure 3 shows the process of cost minimization.

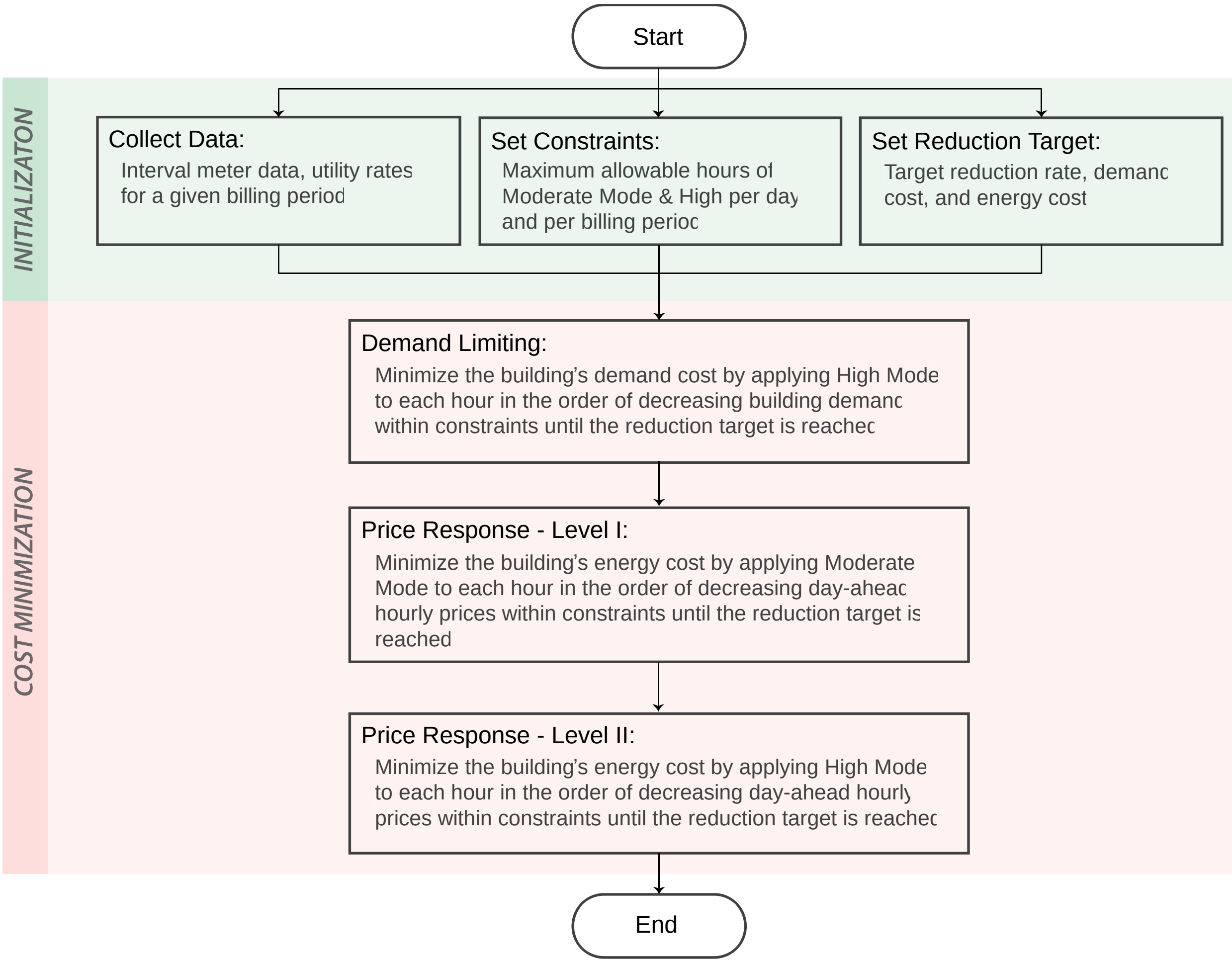

Figure 3. Cost Minimization Flow Chart

The purpose of the demand limiting module is to minimize the building's demand cost by reducing its peak demand during the billing period. The purpose of the two-level price response modules is to minimize the building's energy cost by reducing its electric usage during high-priced periods. *High* mode was applied to the demand limiting module to maximize the peak demand reduction. Both *Moderate* and *High* modes were used for the price response modules to have more granular responses to different price levels. *Moderate* and *High* modes were scheduled only for the weekdays since the participating sites were mainly occupied during weekdays.

The control strategies included load shedding and not load shifting. Load shifting refers to a part of the loads that can be shifted from peak hours to off-peaks. An example is Office Building A and Campus Building which performed regular precooling during summer months as a load shifting strategy. However, precooling could not be automated due to the NYC Fire Code requiring a licensed engineer to be on site for chiller operations. Hence, it was not included in the control strategies tested in this project.

The potential for cost savings was calculated based on the average load shed calculated from the project's summer test events. In order to simplify the analysis, it was assumed that *Moderate* and *High* mode would yield the same amount of load shed under similar outside weather conditions and building operation schedules. Based on this assumption, the month that had the most test events was chosen to construct a shadow bill and applied the average load shed of the test events to estimate potential utility bill savings. For this study, the effects of solar radiation, humidity, internal heat gains, and wind speed were regarded negligible since the electric load of the participating sites did not show significant correlation with these parameters. This assumption was reasonable since most of the control strategies (e.g., fan speed reduction on constant air volume fans) were not affected by outside weather conditions.

To calculate how much the sites would have saved by enabling automated price response, a series of computer simulations were run using R following the logic described in Figure 3. The pseudo-code used for the computer simulation is provided in Appendix E. For each simulation, a target reduction rate for energy and demand cost was set and limited the number of hours of *Moderate* and *High* modes per day and per billing period as described in Table 9.

Table 9. Daily and Monthly Constraints on Price Response

ID	Description	Daily Limit (hr)		Monthly Limit (hr)	
		Moderate	High	Moderate	High
Case 0:	No price response	0	0	0	0
Case 1:	Price response w/ month limits - low impact	2	1	40	20
Case 2:	Price response w/ month limits - med impact	3	2	40	20
Case 3:	Price response w/ month limits - high impact	4	3	40	20
Case 4:	Price response w/o month limits - med impact	3	2	Unlimited	Unlimited

Once the optimal price response schedule was obtained from the simulations, it was used to calculate a shadow bill. The billing analysis used a retroactive data structure to modify building energy usage of the past according to the cost minimization algorithm. However, the same algorithm can be applied to future events if the building is capable of forecasting its electric loads.

Case Studies

This section presents the results of the customer billing analysis. Three of the four participating sites in the project purchased electricity at a time-of-use rate and one site purchased at a fixed rate. To show potential bill savings under Con Edison's MHP tariff, a shadow MHP bills was constructed based on the cost scenarios described in Table 8. Then, a series of simulations were run using the cost minimization algorithm to calculate potential bill savings with automated price response. The following sub sections summarize the results of the cost scenarios for each participating site.

1) Office Building A – MHP Case Studies for August 2013

Office Building A had a fairly consistent and repeatable weekly load profile in August 2013. During weekdays, the building's electric demand gradually increased in the morning until it reached a daily peak around 6,000 kW. Then, it quickly dropped at the end of operation as shown in Figure 4. The site managed its peak demand with frequent precooling and night flushing. As a result, the site did not have any unusual spikes that could contribute to unexpectedly high demand charges. A smooth slope on the building's duration curve shown in Appendix F is another evidence of well managed peak demand. However, the building can still benefit from automated price response by reducing energy consumption during high-priced periods. In August 2013, LBMP in NYC mostly stayed below $75/MWh but during the last two weeks, it increased to $102/MWh. Therefore, a case that assigned the most amount of price response events during the last two weeks could help the building minimize the most amount of energy costs.

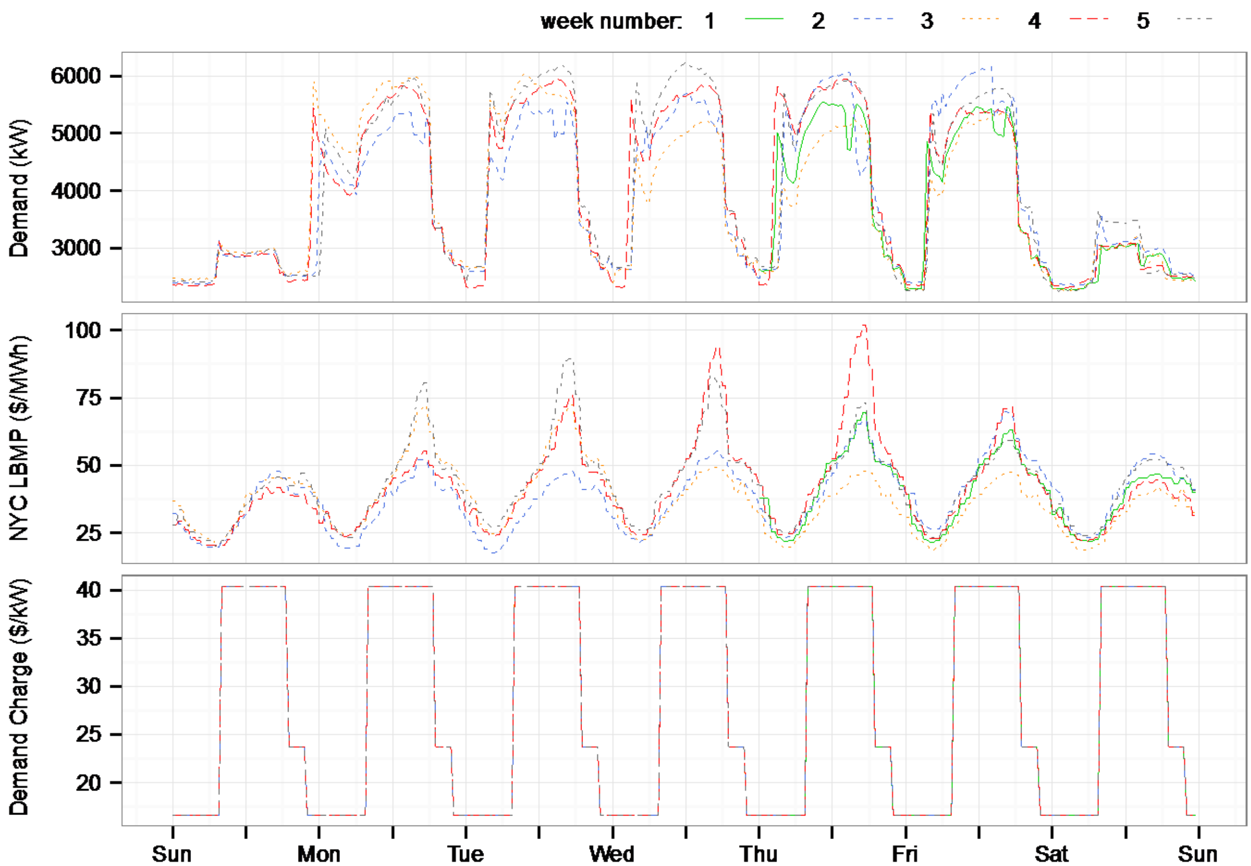

Figure 4. Office Building A – Weekly Profile of Demand, LBMP, and Demand Charge

Figure 5 shows the total MHP bill savings of the five cases described in Table 9. Appendix G shows a breakdown of the MHP bill in terms of target reduction rates. If Office Building A purchased electricity under Con Edison's MHP tariff and enabled automated price response, it could have saved up to $10,710 (1.9 % of the total bill) in August 2013.

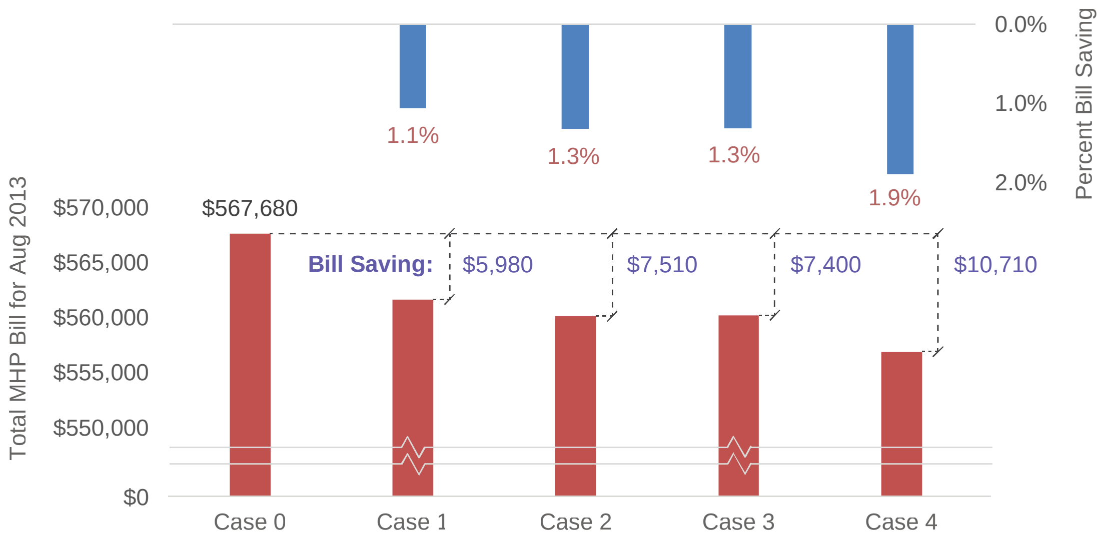

Figure 5. Office Building A – Potential Bill Savings Summary under MHP

Case 4 produced the highest saving among the four cases. It did not require any monthly restrictions but had daily restrictions (two hours of *High* mode and three hours of *Moderate* mode per day). Without monthly restrictions, price response was scheduled every day during weekdays to reduce electricity consumption when LBMP and demand charges were high (between 2pm and 7pm). For Case 1, Case 2, and Case 3, monthly restrictions were applied. Hence, price response had to be strategically scheduled to maximize the bill savings without exceeding monthly limits. Varying degrees of daily limits on *Moderate* and *High* modes among the three cases differentiated their cost savings. Case 1 allowed only one hour of *High* mode and two hours of *Moderate* mode. Hence, price response was focused on reducing energy usage during the most expensive few hours of each day. Case 2 added one more hour and Case 3 added two more hours of price response to both *Moderate* and *High* modes than Case 1.

Case 1 yielded the smallest saving of $5,980 (1.1% of the total bill). Case 2 had a saving of $7,510 (1.3% of the total bill) and Case 3 had a saving of $7,400 (1.3% of the total bill). Although the difference in savings between Case 2 and Case 3 was very small, Case 2 yielded a slightly higher saving than Case 3 despite the fact that it had fewer allowable hours for price response per day than Case 3. This can be explained by the way a MHP bill is calculated. While a large portion of the energy cost in MHP is calculated based on LBMP, there are other charges applied to customers based on the total electric consumption of their buildings. When there was no change in the monthly restrictions, Case 3 ended up using more of its available *High* and *Moderate* modes on high-priced hours in a billing period than Case 2. The high-priced hours were mostly concentrated on the last two weeks of August 2013 and some of them were not the typical high-energy consuming hours of the building. As such, the overall consumption (kWh) of Case 3 increased, resulting in a higher MHP bill compared to Case 2. When the monthly restrictions were removed in Case 4, price response was scheduled to reduce daily consumption and peak demand. Hence, the savings increased to $10,710 (1.9% of the total bill). The monthly schedule for automated price response for all cases is shown in Figure 6.

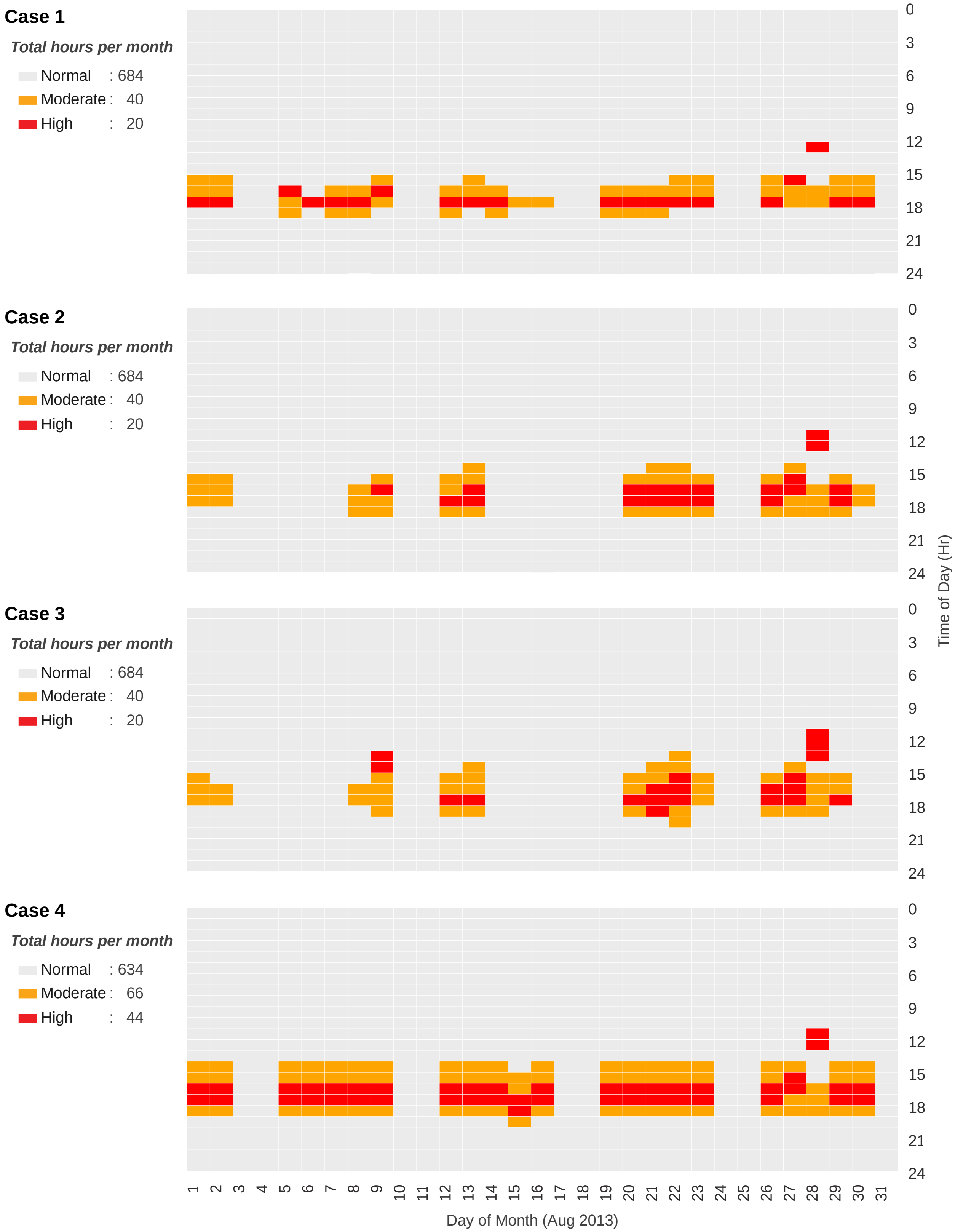

Figure 6. Office Building A - Automated Price Response Schedule for August 2013

Office Building A purchased its electricity from NYPA under the Time-of-Day rate for Service Classification No. 69: General Large. To understand how much Office Building A would have saved by automating price response at its current retail rate, shadow bills were developed based on the charges applied to Office Building A in August 2013 by NYPA, as described in Appendix D. The same operation schedule and load data obtained from the MHP billing analysis was used to calculate the NYPA shadow bills. The summary of the NYPA billing analysis is shown in Figure 7.

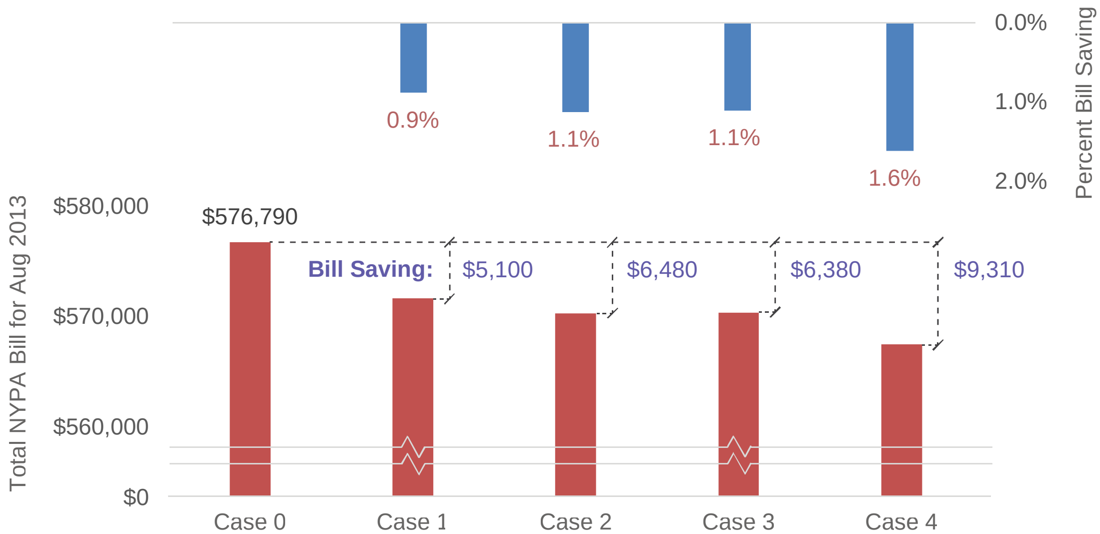

Figure 7. Office Building A – Potential Bill Savings Summary under NYPA Tariff

NYPA's bills are calculated based on the peak demand and on- and off-peak consumption. Hence, Case 4, which had the lowest peak demand and the smallest on-peak consumption, produced the highest saving among the four cases. While Case 2 yielded the second highest saving, the difference in savings between Case 2 and Case 3 were minimal. It is worth mentioning that the cost minimization algorithm was developed to respond to hourly price fluctuations. When it comes to on- and off-peak pricing, the algorithm can be simplified to reduce the highest demands of each day. For a building like Office Building A which has a fairly predictable demand profile, the automated price response schedule would then assign *High* and *Moderate* modes to the afternoon hours during weekdays.

2) Office Building B – July 2013

Office Building B had a fairly irregular load profile in July 2013. The daily demand peaked around 4,000 kW most of the month except for the fourth week during which the demand peaked close to 6,000 kW. Such difference in daily peaks was due to the increased air conditioning loads as the outside air temperature warmed up. The energy price also rose during the fourth week as shown in Figure 8. LBMP in NYC mostly stayed below $100/MWh in July 2013, but it escalated all the way up to $318/MWh during the fourth week. Therefore, to minimize energy and demand costs, the building would have to lower both daily peaks and consumption during the fourth week.

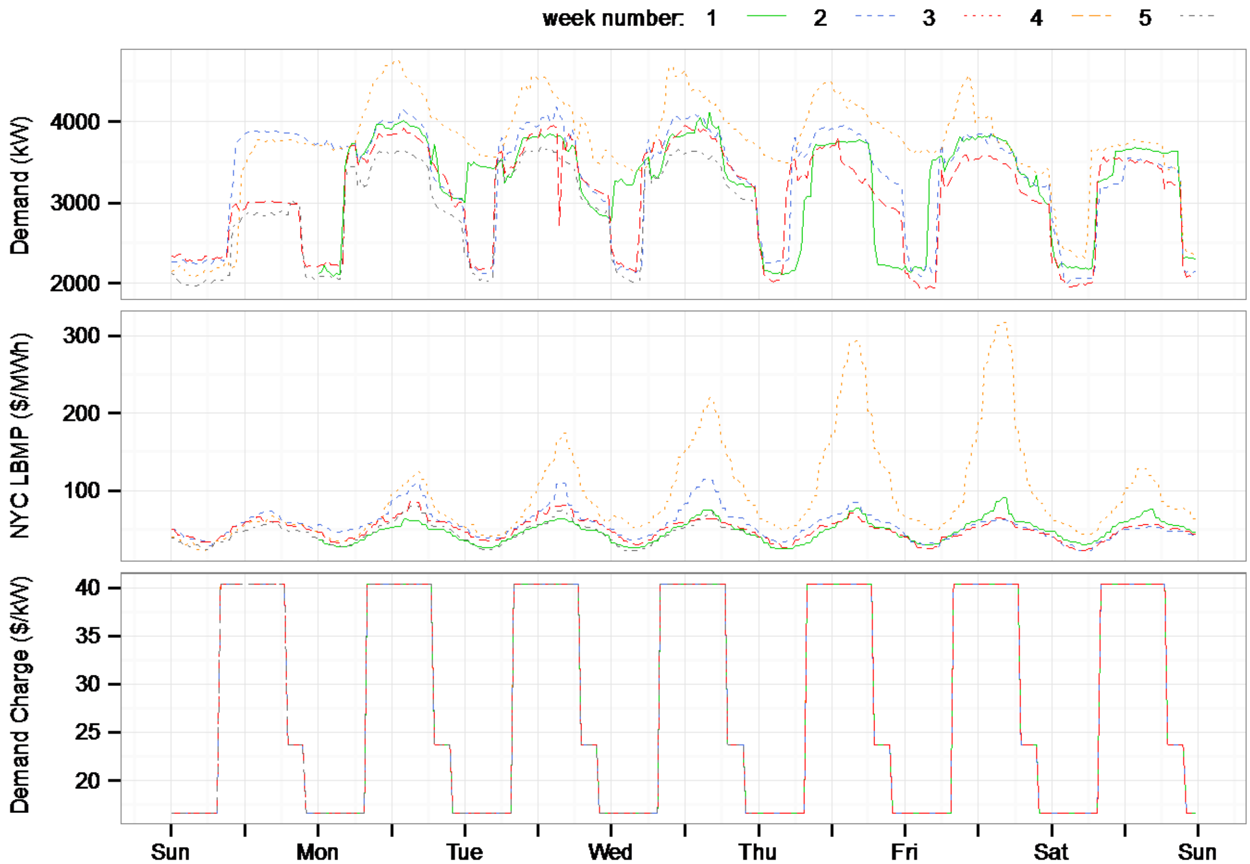

Figure 8. Office Building B – Weekly Profile of Demand, LBMP, and Demand Charge

Figure 9 shows the total MHP bill savings of the five cases described in Table 9. Appendix G shows a breakdown of the MHP bill in terms of target reduction rates. If Office Building B purchased electricity under Con Edison's MHP tariff and enabled automated price response, it could have saved up to $5,290 (1.1 % of the total bill) in July 2013.

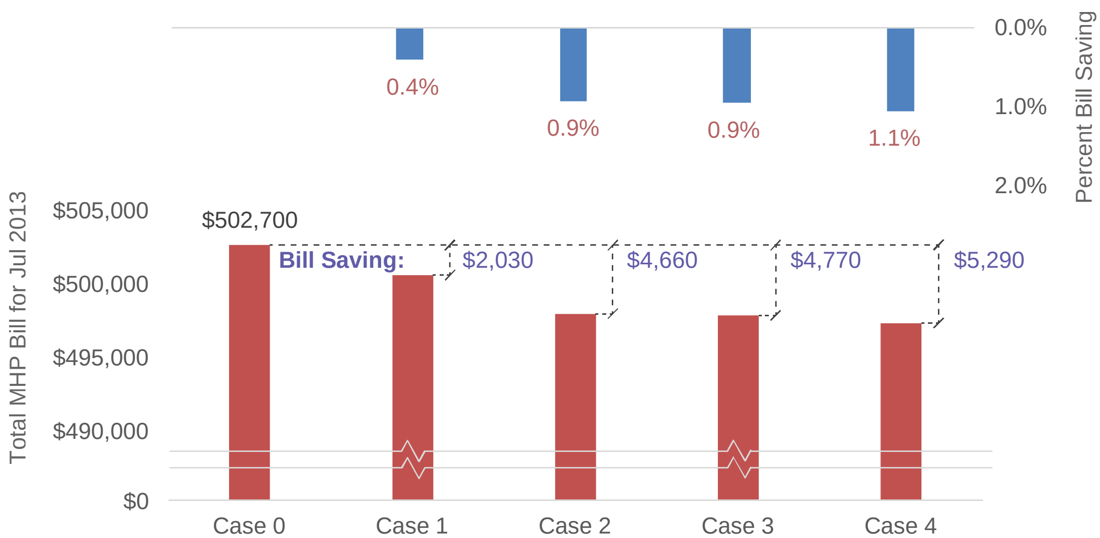

Figure 9. Office Building B – Potential Bill Savings Summary under MHP

Case 4, which had no monthly restrictions, produced the highest saving among the four cases. Case 3 yielded the second highest savings by assigning more price response events during the fourth week in order to reduce the daily peaks and energy consumption. There was not much difference in cost savings between Case 2 and Case 3 because allowing more hours for daily price response beyond certain level did not make much difference in the overall savings. The monthly schedule for automated price response for all cases is shown in Figure 10.

Office Building B has a unique opportunity that other buildings do not have which is the onsite generation capabilities. Utilizing onsite generation for price response can not only increase the site's bill saving potential but also alleviate the concern for reduced occupant discomfort during warm days. However, onsite generation is not free since there is a cost associated with its operation. Therefore, a billing analysis should include the operating costs of onsite generation in its calculation if the onsite generation is used as a price response strategy. This will allow building managers to weigh the benefits and costs of running onsite generation for price response.

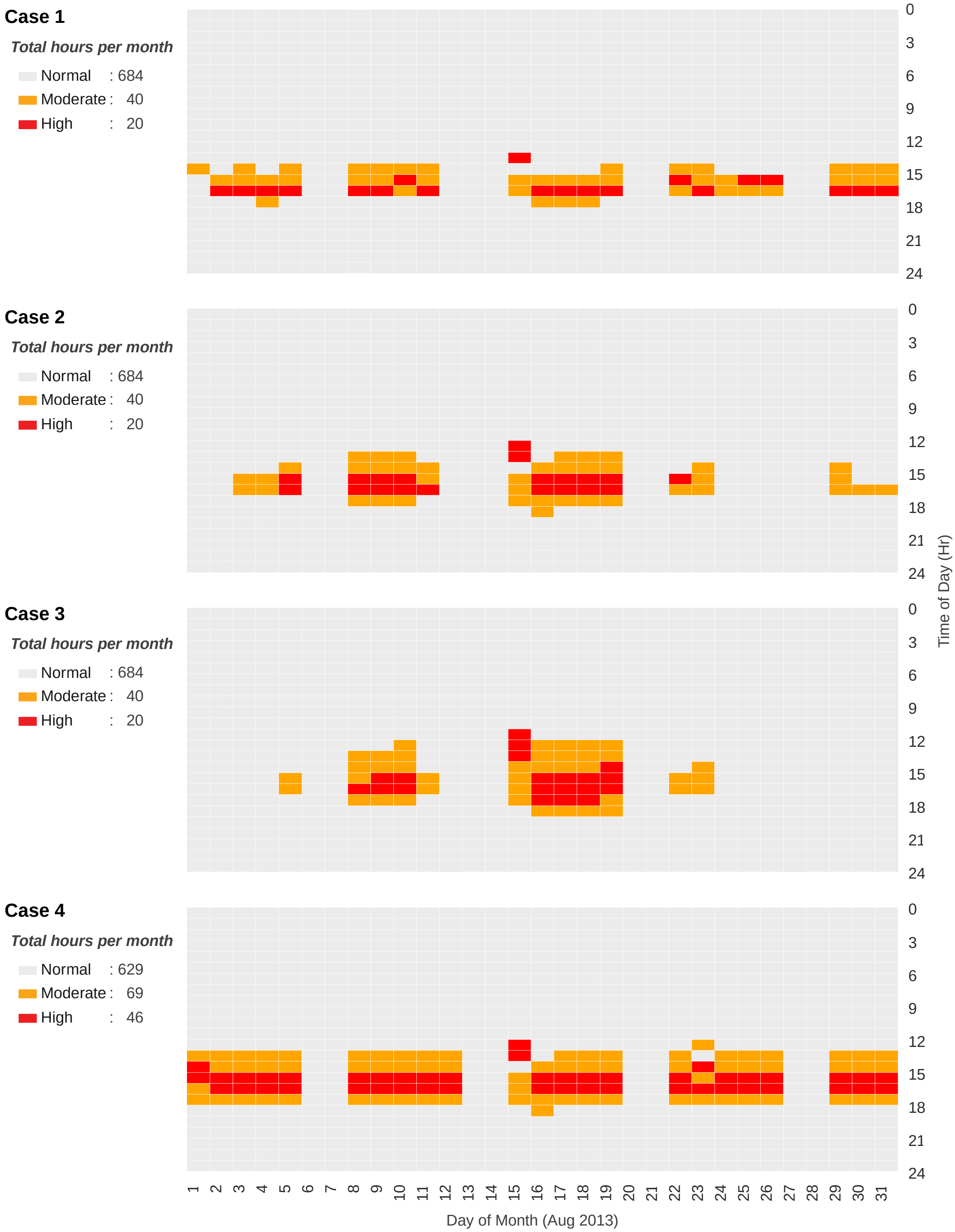

Figure 10. Office Building B - Automated Price Response Schedule for July 2013

3) Office Building C – July 2013

Office Building C had a very consistent and repeatable load profile in July 2013. During weekdays, the building's demand gradually increased in the morning until it reached a daily peak around 4,000 kW. Then, it slowly declined after building operation hours (8 am to 6 pm) and stayed low until the next day as shown in Figure 11. The energy consumption on July 4 and July 5 was low due to holiday effects.

The month's highest demand was marked by an unusual spike at 1 pm on July 2, 2013. This spike caused a very steep slope in the building's duration curve included in Appendix F. In July 2013, LBMP mostly stayed below $100/MWh except for the fourth week when the price escalated up to $318/MWh. Hence, bill saving strategies for this building would be to limit the building's electric demand below a preferred threshold and minimize its consumption during expensive hours.

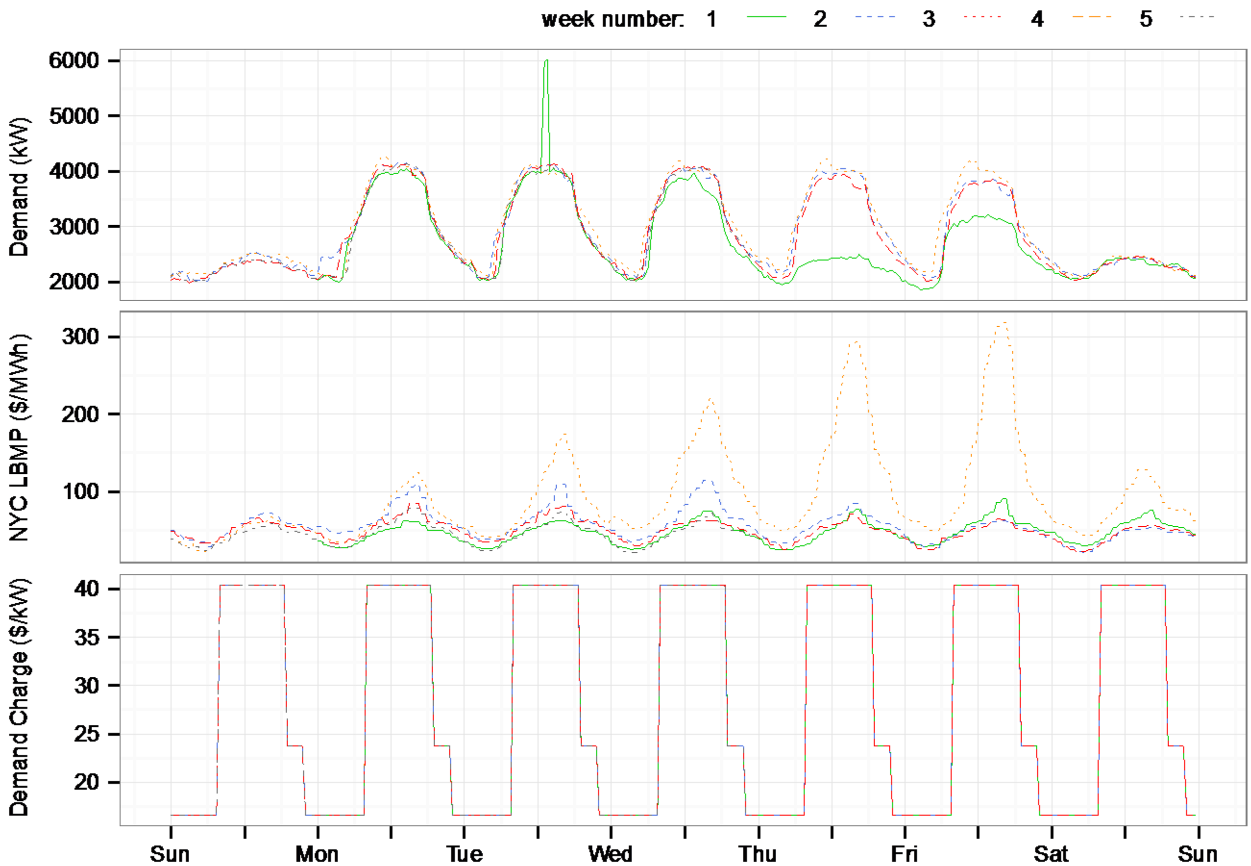

Figure 11. Office Building C – Weekly Profile of Demand, LBMP, and Demand Charge

Figure 12 shows the total MHP bill savings of the five cases described in Table 9. Appendix G shows a breakdown of the MHP bill in terms of target reduction rates. If Office Building C purchased electricity under Con Edison's MHP tariff and enabled automated price response, it could have saved up to $10,530 (1.9 % of the total bill) in July 2013.

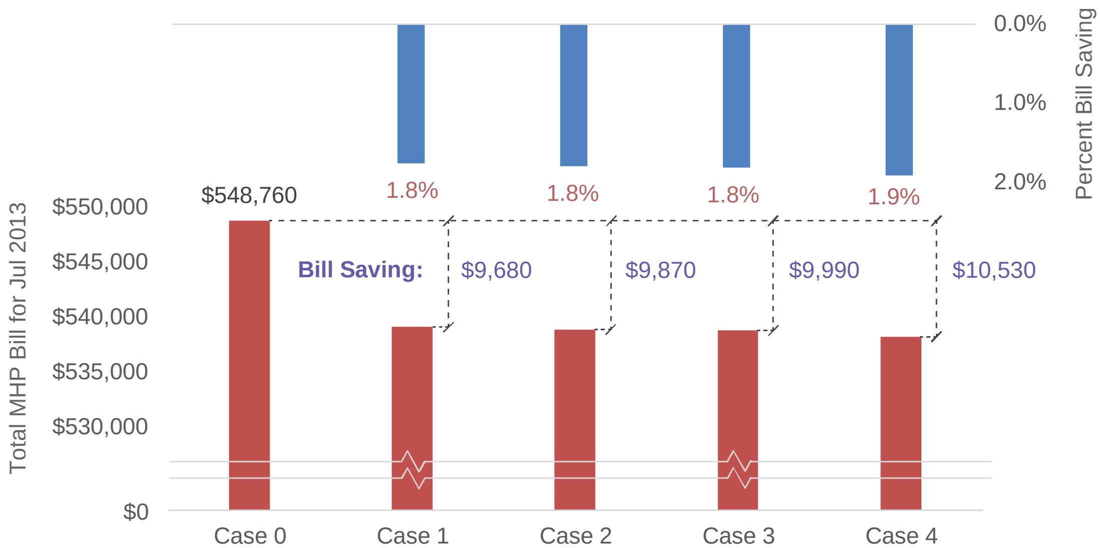

Figure 12. Office Building C – Potential Bill Savings Summary under MHP

Case 4 produced the highest saving among the four cases. It did not require any monthly restrictions but had daily restrictions (two hour of *High* mode and three hours of *Moderate* mode per day). Without monthly restrictions, price response was scheduled every day during weekdays to reduce electric consumption when LBMP and demand charges were high (between 1pm and 6pm).

For Case 1, Case 2, and Case 3, monthly restrictions were applied. Hence, price response had to be strategically scheduled to maximize the bill savings without exceeding monthly limits. Varying degrees of daily limits on *Moderate* and *High* modes among the three cases differentiated their cost savings. However, incremental savings after Case 1 were small since the largest saving was already achieved in Case 1 by reducing the building's highest demand of the month. Adding more hours to daily price response did not make much difference in the total savings because the building had a relatively flat load profile and small load shed capacity (52 kW for *Moderate* mode and 151 kW for *High* mode). The monthly schedule for automated price response for all cases is shown in Figure 13.

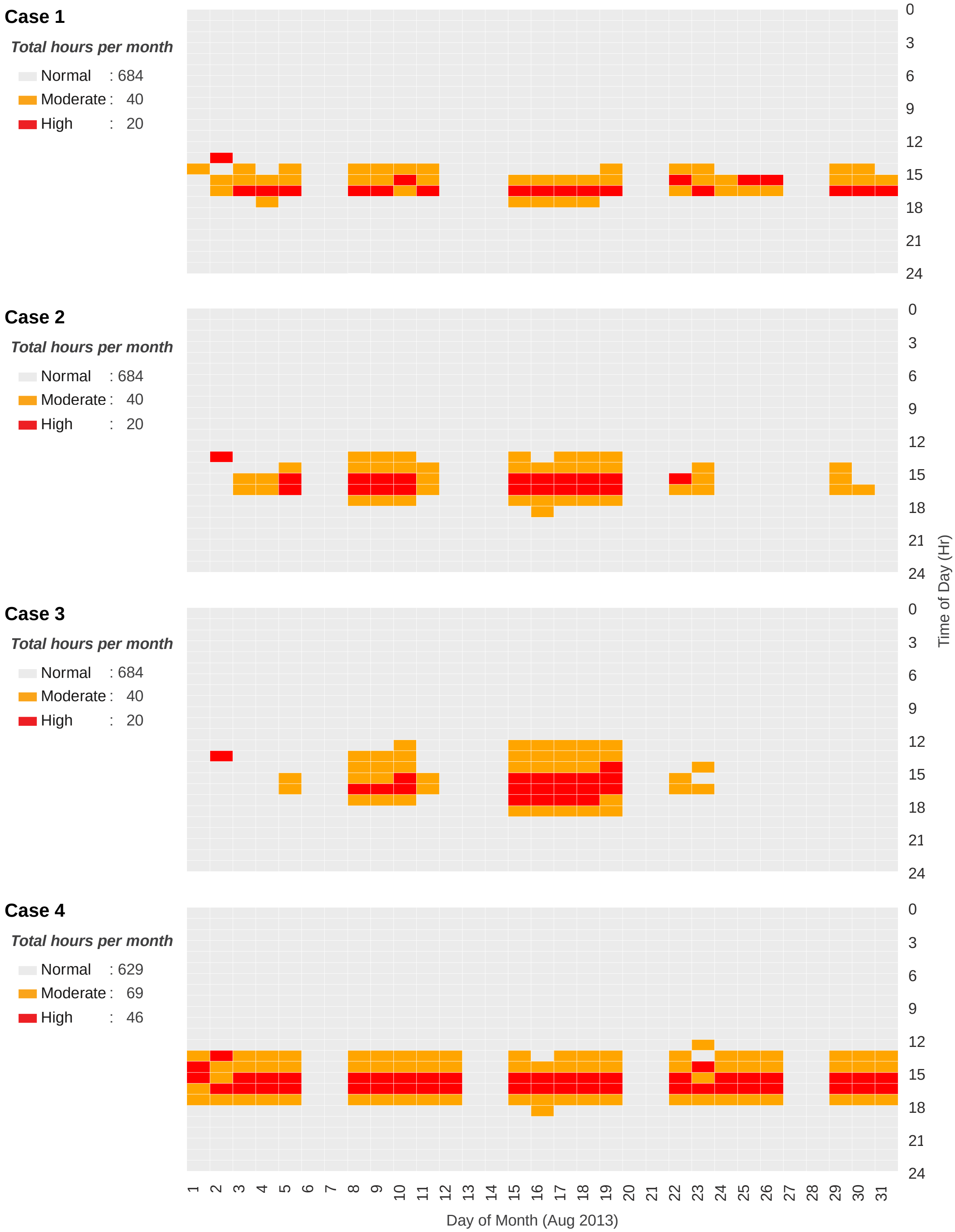

Figure 13. Office Building C - Automated Price Response Schedule for July 2013

4) Campus Building – August 2013

Campus Building's weekly load profile showed a fairly consistent pattern of building operation (from 7 am to 11 pm for seven days a week). In August 2013, the building had a number of spikes that could contribute to high demand costs as shown in Figure 14. These spikes created a very steep slope in the building's duration curve during the top one percent of the time, as shown in Appendix F. Most of these spikes were caused by precooling and morning ramp-up concurrently starting at 7 am. As a result, the building experienced an electric surge during the first hour of the building operation which often marked the highest demand of the day. Some of the spikes were caused by the classroom schedule. LBMP mostly stayed below $75/MWh except for the last two weeks of August 2013. Strategies to save energy costs and demand charges included limiting the building's electric demand below a preferred threshold and reducing its consumption during expensive hours. The issue of morning electric surge could be resolved by starting precooling earlier and/or dividing the morning ramp-up into multiple stages.

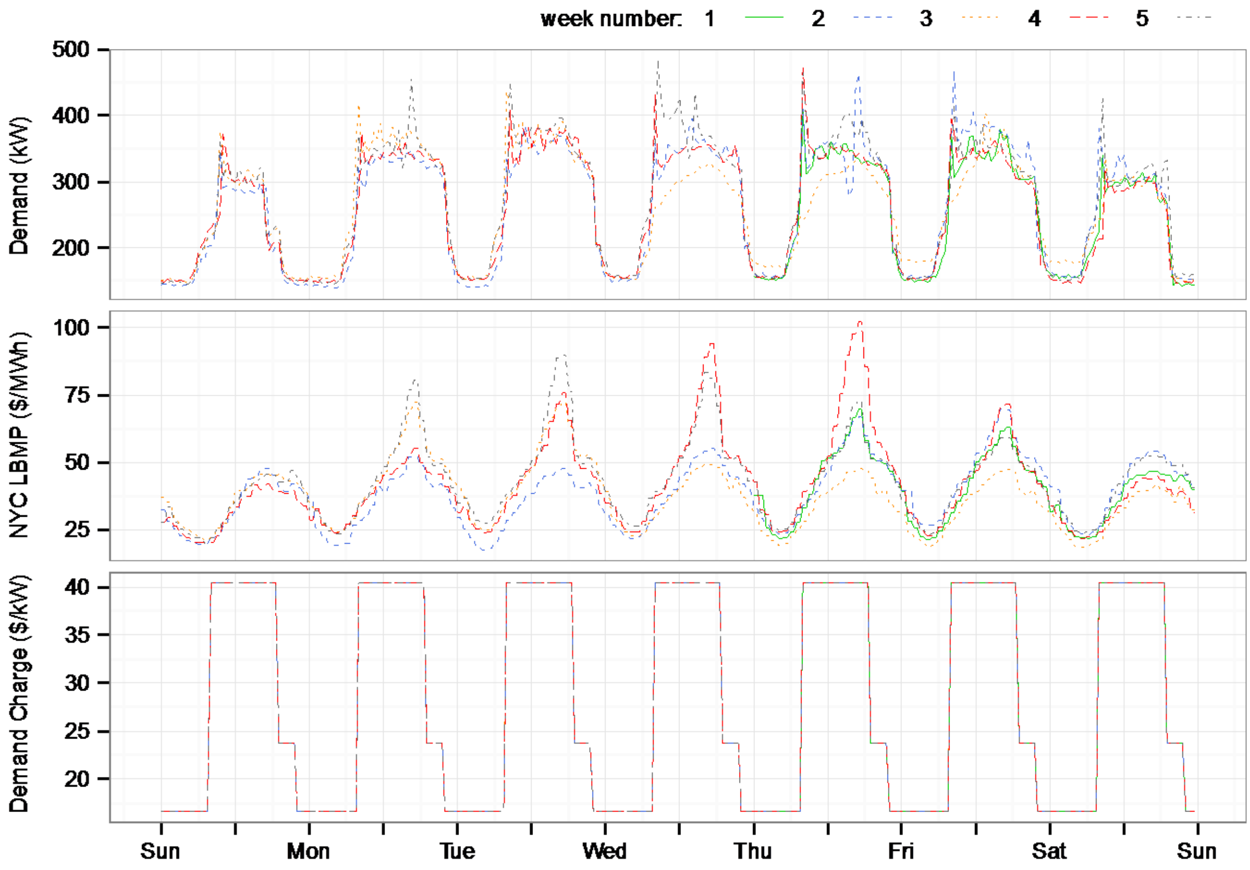

Figure 14. Campus Building – Weekly Profile of Demand, LBMP, and Demand Charge

Figure 15 shows the total MHP bill savings of the five cases described in Table 9. Appendix G shows a breakdown of the MHP bill in terms of target reduction rates. If Campus Building purchased electricity under Con Edison's MHP tariff and enabled automated price response, it could have saved up to $3,370 (8.0 % of the total bill) in August 2013.

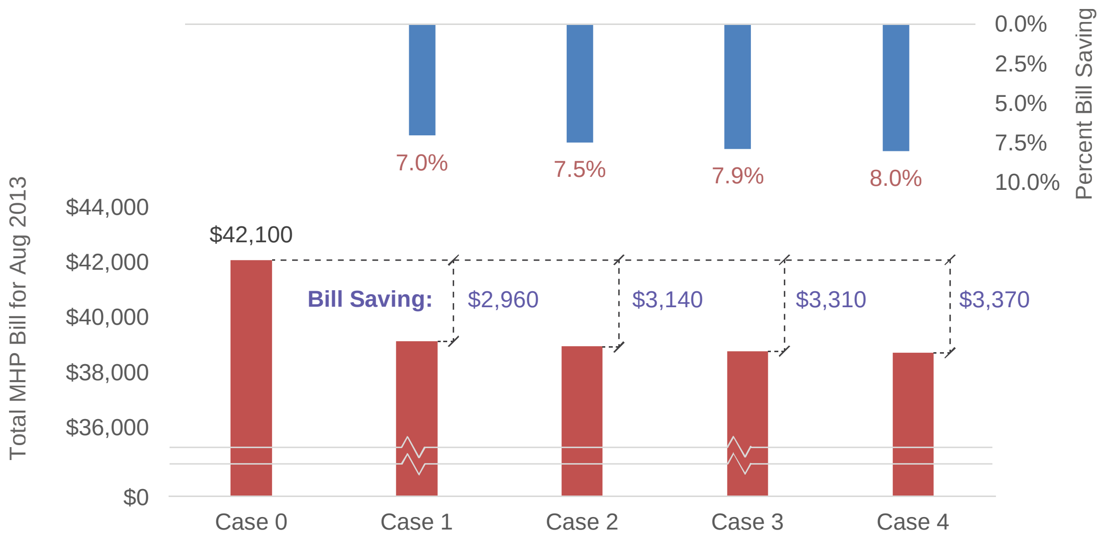

Figure 15. Campus Building – Potential Bill Savings Summary under MHP

The maximum saving was produced by Case 4 which had no monthly restrictions. For Case 1, Case 2, and Case 3, monthly restrictions were applied. Hence, price response had to be strategically scheduled to maximize the bill savings without exceeding monthly limits. Varying degrees of daily limits on *Moderate* and *High* modes among the three cases differentiated their cost savings. However, incremental savings after Case 1 were small since the largest saving was already achieved in Case 1 by reducing the building's highest demand of the month. The monthly schedule for automated price response for all cases is shown in Figure 16.

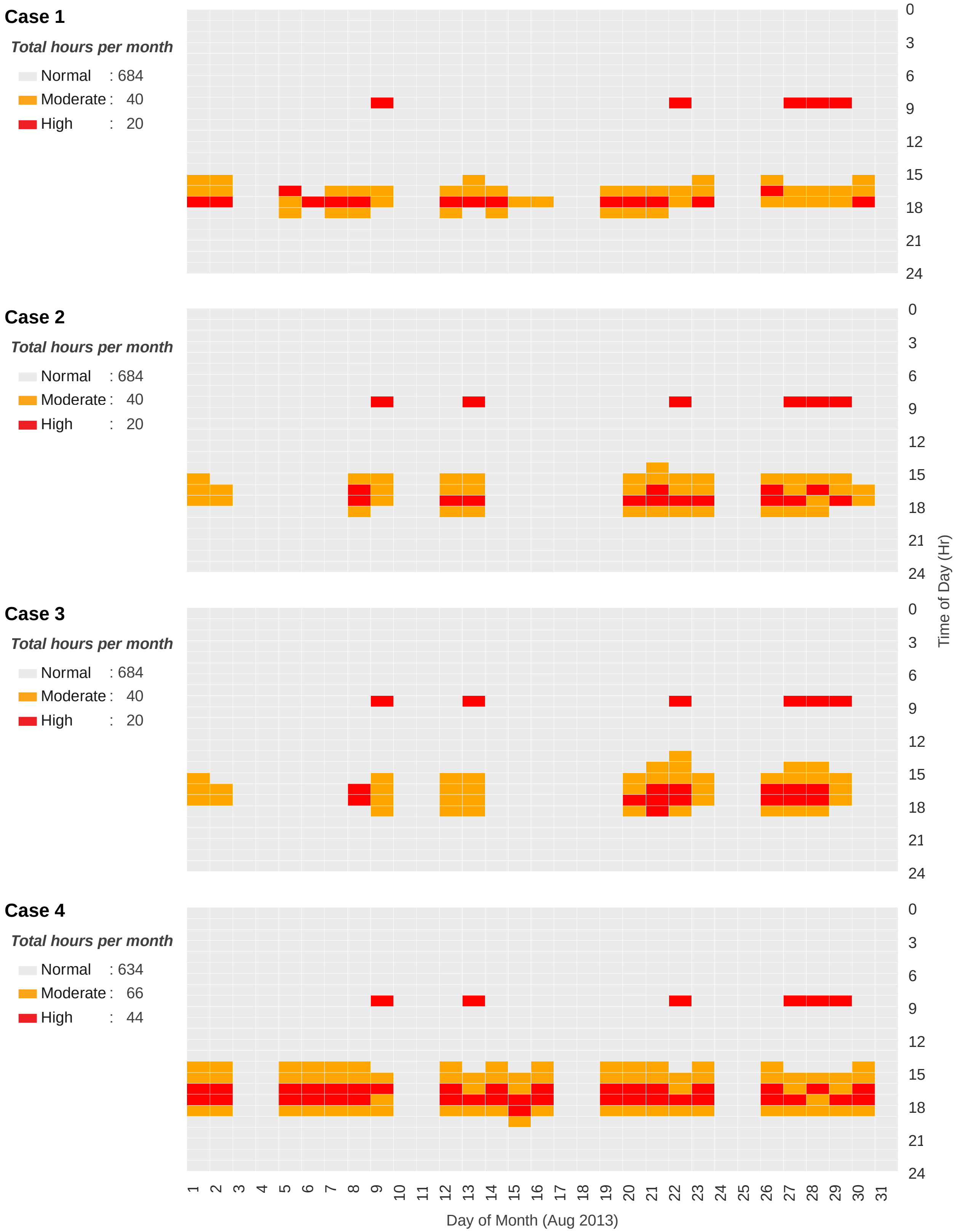

Figure 16. Campus Building - Automated Price Response Schedule for August 2013

Conclusions and Recommendations

NYS's grid requires about 40% more generating capacity to meet summer-time peak demand as compared to other typical periods. The top 100 hours of electricity demand cost NYS a disproportionate amount of the total system cost. Fossil fueled peaker plants that supply dispatchable generation during those hours have a greater environmental impact than other types of power generator. The expansion and maintenance of the transmission and distribution system to reliably meet system peak demand adds a significant cost. Similarly removing a portion of that peak load (either through energy efficiency or demand response) offers substantial cost and carbon reductions.

A 'smarter grid' is expected to more efficiently balance electricity supply and demand, minimizing costs and environmental impact, and can accommodate greater penetrations of intermittent renewable resources and PEV's. <u>*Curtailment*</u> of customer load (decreasing immediate or future demand) can provide emergency relief, energy, capacity, reserve, or network relief benefits to a smart gird and markets. Adding smart buildings to a smart grid requires a combination of technology and technique. The technology includes building automation, flexible loads, energy feedback, methods and standards for utility system integration and price signaling. The techniques include dynamic retail rate products, demand response program design, and aggregation of small loads.

The initial goal of this project was to evaluate the use of EMCS and EIS in commercial buildings to fully automate DR participation in response to dynamic prices in NYS. Through the process, following areas were explored:

- Use of EMCS and EIS by the facility operators for decision making
- Use of forecasting and simulation to facilitate flexibility and automation of DR strategies
- DR strategies in humid climates.

Over the years, in addition to the original focus of the project, which were reported on various meetings, papers and reports, the team focused on following:

- Demonstrating how OpenADR can automate and simplify interactions between buildings and various stakeholders in NYS including the NYISO, utilities, retail energy providers (REPs), and curtailment service providers (CSPs);
- Automating building control systems to provide event-driven demand response, price response, and demand management according to OpenADR signals;
- Providing cost-saving solutions to large customers by actively managing day-ahead hourly prices and demand charges; and
- Granting building management staff more granular control to remove any major piece of heating, ventilation, and air conditioning (HVAC) equipment out of load-shed sequences, or opt a building out in its entirety.

Over the duration of this project, the project team realized that NYS buildings can take manual measures to occasionally participate DR, but also demonstrated how large buildings in NYS/NYC can use the same flexible loads to respond to hourly price signals. The buildings in the study all had elasticity in their operations and automation provided easy access to this flexibility to be used on a regular basis. There is economic value in using the elasticity to respond to day-ahead hourly prices as described in this report. Hourly operations and flexible load can be optimized (shifting/precooling/curtailing) without significant reductions in comfort and performance on hot days. However, there is a need to dynamically integrate comfort in closed-loop building controls and co-optimization of savings and comfort. Currently, this is determined on a case by cases basis and thresholds for comfort. In the future, there may be systems that capture these interactions dynamically and use in real-time.

DR automation requires detectable and acceptable strategy implementation at the sites and an interoperable communications infrastructure to trigger these strategies. The team observed that there are five or six common curtailment strategies that are widely understood and accepted by facility operators and can likely be automated in large NYC buildings. These include global temperature adjustment, duct static pressure decrease, fan variable frequency drive limit, supply air temperature increase, chilled water temperature and rebound avoidance strategies. Implementing automated DR for each individual building requires skilled people who are knowledgeable about the site under consideration to spend hours developing strategies, coding these into the system, installing, testing and maintaining communication devices. Buildings that are already doing manual DR (running around activating switches, chiller settings and BMS sequences) are good candidates to automated their DR since they developed a set of strategies and had experience implementing them. However, enablement of DR in new buildings with no DR experience may be costly. To lower the costs of DR enablement, the team suggests working with building codes and standards bodies and also working with open standards for communication with the various grid stakeholders. Interoperable automation of DR allows the consumers to participate in grid transactions with variety of stakeholders, at a lower cost and seamlessly while also allowing them to take advantage of a variety of market transactions.

A next step to this project would be to demonstrate a variety of transactions these sites can participate in given the initial investment as well as the variety of values they can extract from these markets. In addition, a comparison of a building with interoperable communications versus another building with proprietary communication would inform the operators and policy makers of pros and cons of their choices. The new initiatives can benefit from the latest version of OpenADR, version 2.0 which includes two-way messaging capability between a DRAS, that publishes information, and a client that subscribes to the information. With OpenADR 2.0, utilities, grid operators, and CSPs will be able to manage peak demand and load shifting in an automated and scalable fashion, thus reducing the cost of DR technology enablement and customer adoption.

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Appendix A. Baseline Calculation Methods

Five-in-ten (5/10) CBL (Customer Base Load) baseline

New York utilities use the 5/10 baseline to estimate the baseline against which DR savings are calculated. The 5/10 baseline is the average hourly load shape of five hottest days during the most recent 10 work days (excluding holidays, any days declared by Con Edison and NYISO as SCR or EDRP events, low usage days). A disadvantage of the 5/10 averaging baseline method is that it may calculate a baseline that is lower than actual demand if the site's demand is weather sensitive and the weather temperatures were mild during the period prior to the DR event day. This can occur if a DR event is called on a day with more extreme outside temperatures than during the previous 10 days. When cooling loads are shed for DR (typically done in warm climates), baseline demand curves can be biased low if the previous 10 working days were cooler than the DR event day. The (low) bias problem can also occur for estimates related to winter tests when heating loads are shed for DR as was done for this test because the previous 10 days were likely to be warmer than the day of the DR event. For commercial buildings, the OATR baseline is a more accurate and less biased baseline than the 5/10 baseline (Coughlin et al., 2008).

Outside air temperature regression model baseline (OATR)

For the OATR baseline model, a whole building power baseline was estimated first, using a regression model that assumes that whole building power is linearly correlated with outside air temperature. The model is computed as shown in equation.

$$L_i = a_i + b_i T_i$$

Where L_i is the predicted 15-minute interval electricity demand from time i from the previous non-DR event workdays. In this study, T_i is the 15-minute interval outside air temperature for time i. The parameters L_i and L_i are generated from a linear regression of the input data for time i. Individual regression models are developed for each 15-minute interval, resulting in 96 regressions for the entire day (24 hours/day, with four 15-minute periods per hour). Selected baseline days were non-weekend, non-holiday and Monday through Friday workdays. The source of the weather data was located at Center Park in New York City. Meter data were 15-minute interval whole building electricity demand.

Electricity consumption data for each site were collected either through meter data monitoring and logging equipment installed at each facility or through Con Edison. The actual metered electric consumption was subtracted from the baseline-modeled demand to derive an estimate of demand savings for each 15-minute period. Previous research recommends a weather-sensitive baseline model with adjustments for morning load variations for accuracy (Goldberg and Agnew 2003).

Weather regression baseline model

Correlation analysis: In this study, weather data was downloaded from National Climatic Data Center (NCDC) and was interpolated into 15-minute interval data including outside air temperature (OAT), relative humidity (RH), dew point temperature (DP), wind direction (WD), wind speed (WS) and other available weather variables. Correlation analysis is used to measure strength of the association (linear relationship) between the weather variables and the whole building demand power and determine the significant weather variables to be considered into the linear regression. The sample correlation coefficient is computed as shown in equation.

$$R = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{[\sum(X - \bar{X})^2][\sum(Y - \bar{Y})^2]}}$$

Where:

R = sample correlation coefficient

X = value of independent variable

Y = value of dependent variable

After the correlation analysis of New York climate weather data, three significant weather variables are identified as follows: outside air temperature (OAT), Dew Point (DP) and Wind Speed (WS). As the result, the OATR baseline model was modified as shown in equation.

$$L_i = a_i + \ b_i(OAT_i) + \ c_i(DP_i) + \ b_i(WS_i)$$

For each DR event day, a weather regression baseline model was developed base on previous 20 workdays exclude holidays, DR test days and other event days issued by NYISO. In general, the weather regression baseline provides a more accurate prediction of weather sensitive loads than NYISO's CBL, while the condition is that the building power demand is weather sensitive and the weather data source is credible.

Slope-based baseline model

In this study, another slope-based baseline model is proposed to estimate the demand power in a short-term period. The reason for developing a baseline model is to quantify the demand reduction performance during Auto-DR test hours. It is clearly seen that the demand power of the start hour and the end hour is known, while the load pattern is unclear. Therefore, it could be less complex with a focus on the prediction of the load curve between the DR test's start hour and end hour, which is called slope-based baseline model. In observed the load patterns during DR test hours for each building, it was found that most of load slopes are very close. Each time step's predicted slope coefficient is taken at 75th percentile of previous non-DR days' each time step from 1 PM to 6 PM.

References:

Goldberg, Miriam L. and G. Kennedy Agnew 2003. Protocol Development for Demand Response calculations: Findings and Recommendations. Prepared for the California Energy Commission by KEMA-Xenergy. CEC 400-02-017F

Appendix B. Customer Interview Questions

1. **Perception/attitude towards Auto-DR**

- Before the project: did you or your team any misunderstanding or predisposed ideas about Auto-DR? Is your perception different now, after the project has concluded?
- During the project: did you or your team experience any institutional or technical barriers to implement the Demand Response automation and control?
- Now that the project has concluded, has your understanding of Auto-DR, and the associated opportunities, changed? In a positive way or negative way? What caused the change?

2. **Granular control & opt-out capability**

- Our team did not record any changes to the the default control strategies throughout the testing phase. In your case, was this because you didn't need to or, or because you didn't know how to make changes?
- Independent of the default control strategies, did having granular control help you feel more in control during Auto-DR tests? What was your comfort level with Auto-DR more broadly?

3. **Auto-DR user interface**

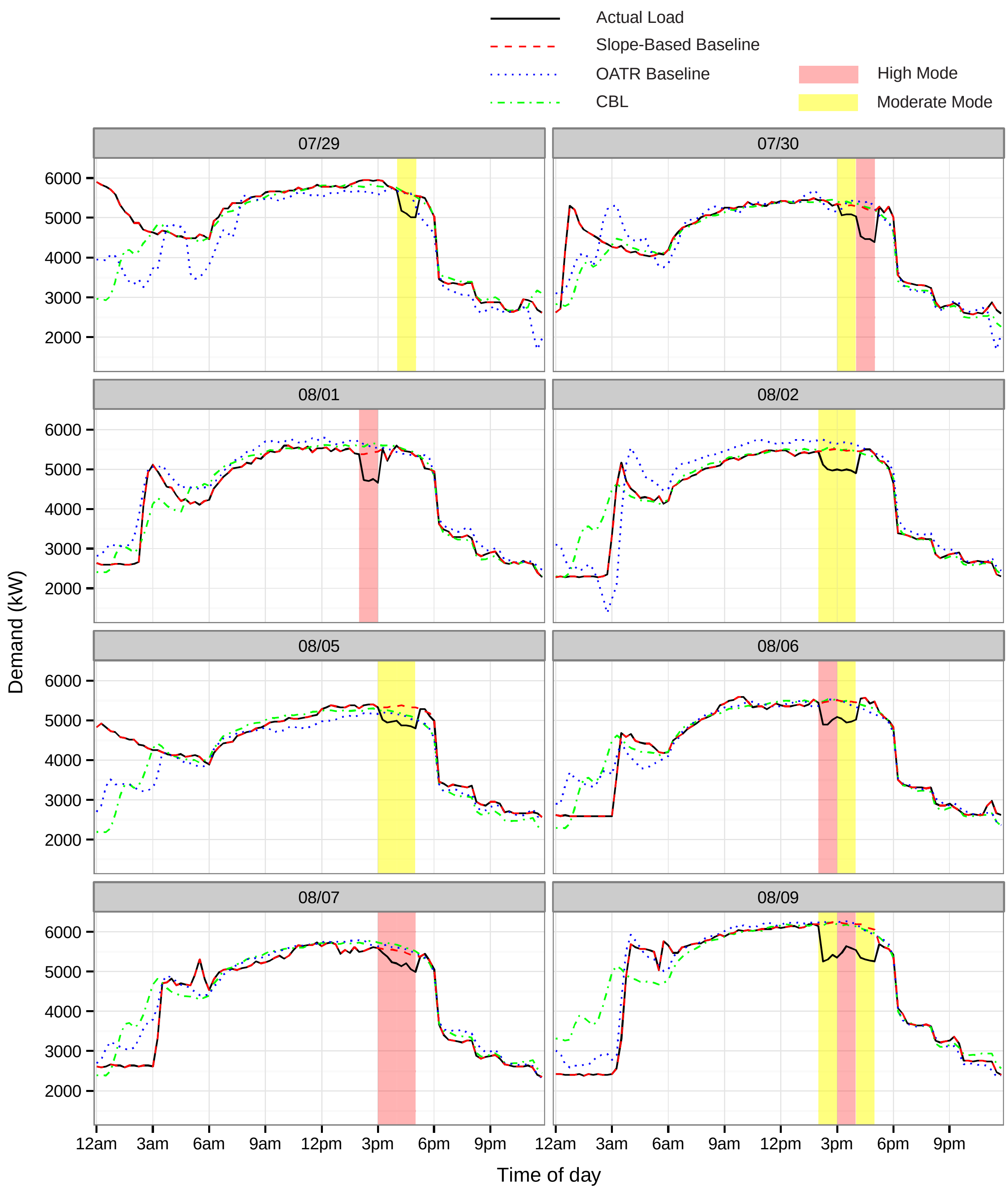
- Was there any particular feature or function that you liked or disliked? (functions, look, usability, etc.)
- Were there any particular features or functions that did not work?
- Can you provide suggestions for improvements to the interface?

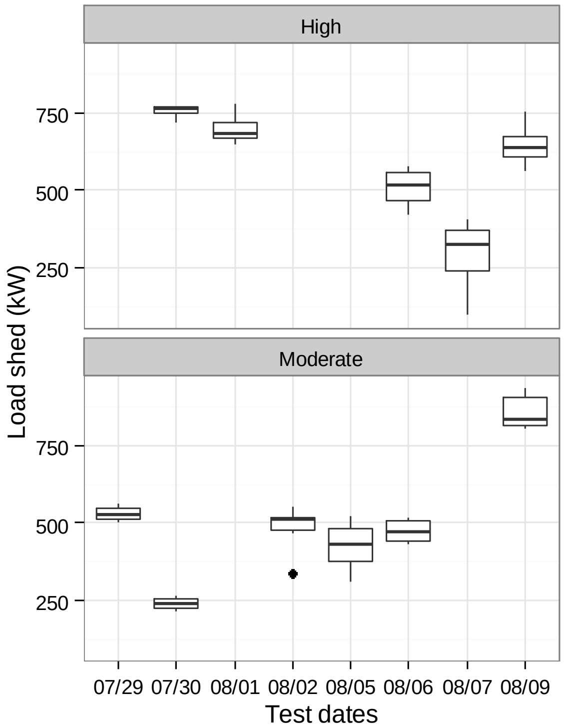
4. **The use cases for Auto-DR**

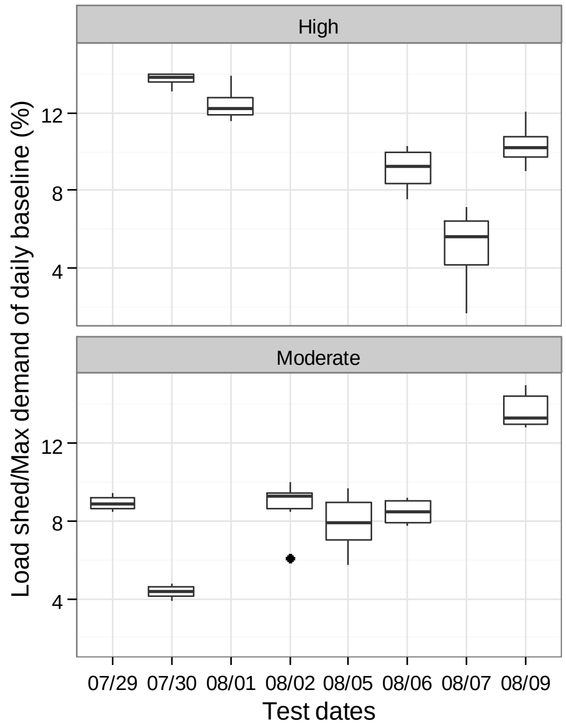
- If you were to adopt the Auto-DR technology for ongoing operation, what would be the use of it?

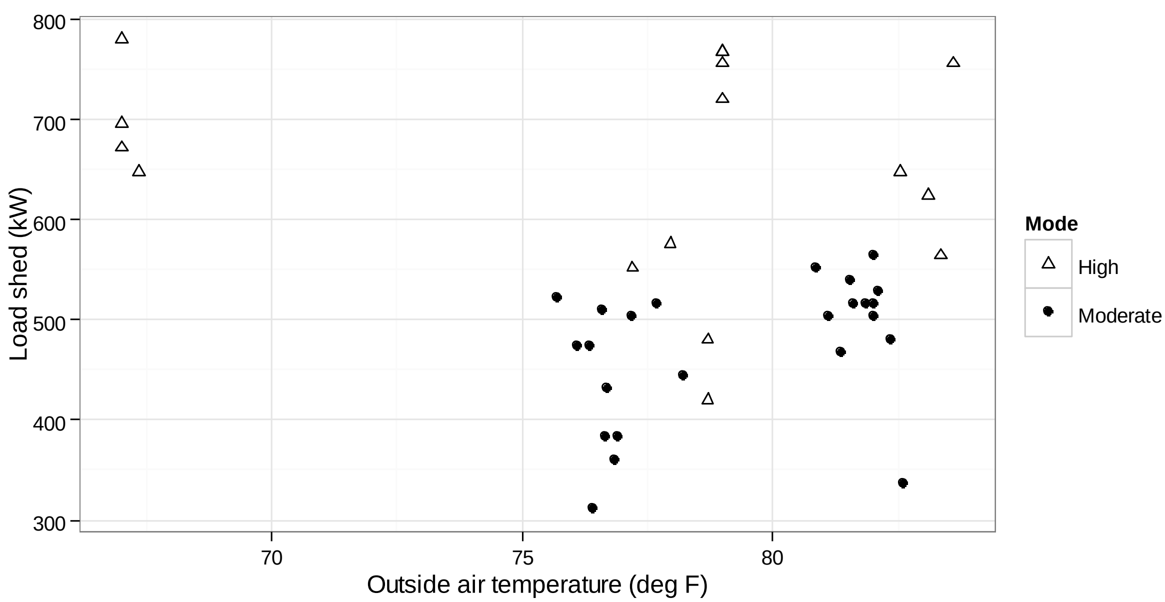
Appendix C. Auto-DR Test Results

Office Building A

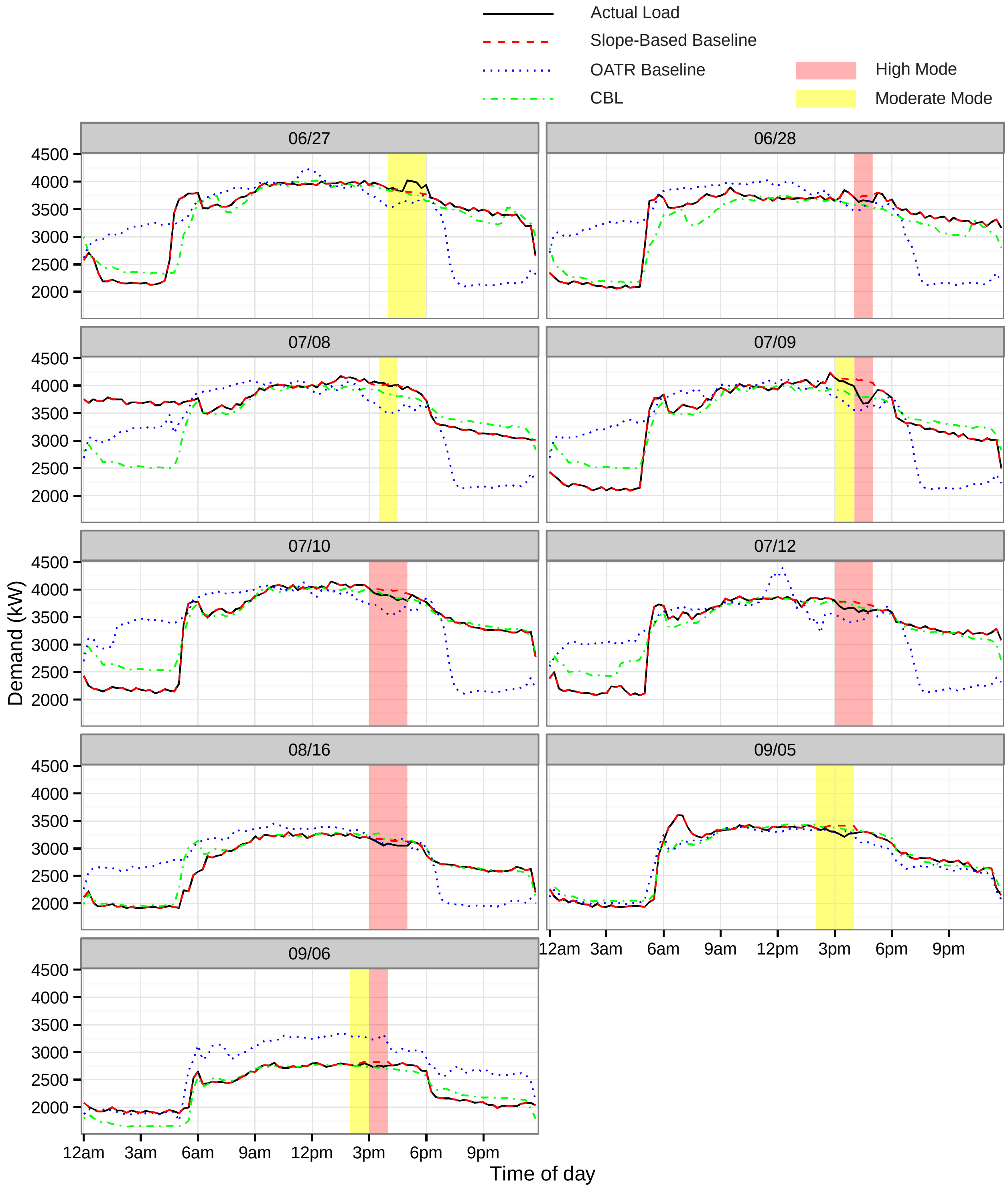


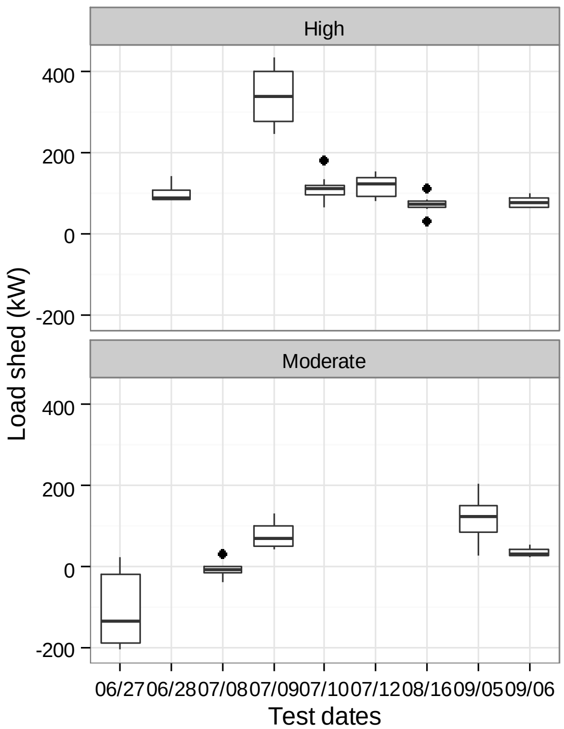

High
Moderate
750
500
250
Load shed (kW)
07/29 07/30 08/01 08/02 08/05 08/06 08/07 08/09
Test dates

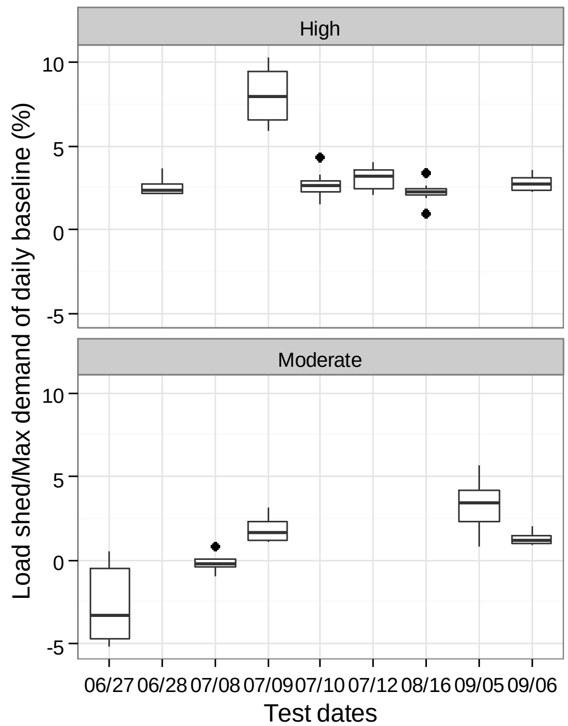

High
Moderate
12
8
4
Load shed/Max demand of daily baseline (%)
07/29 07/30 08/01 08/02 08/05 08/06 08/07 08/09
Test dates

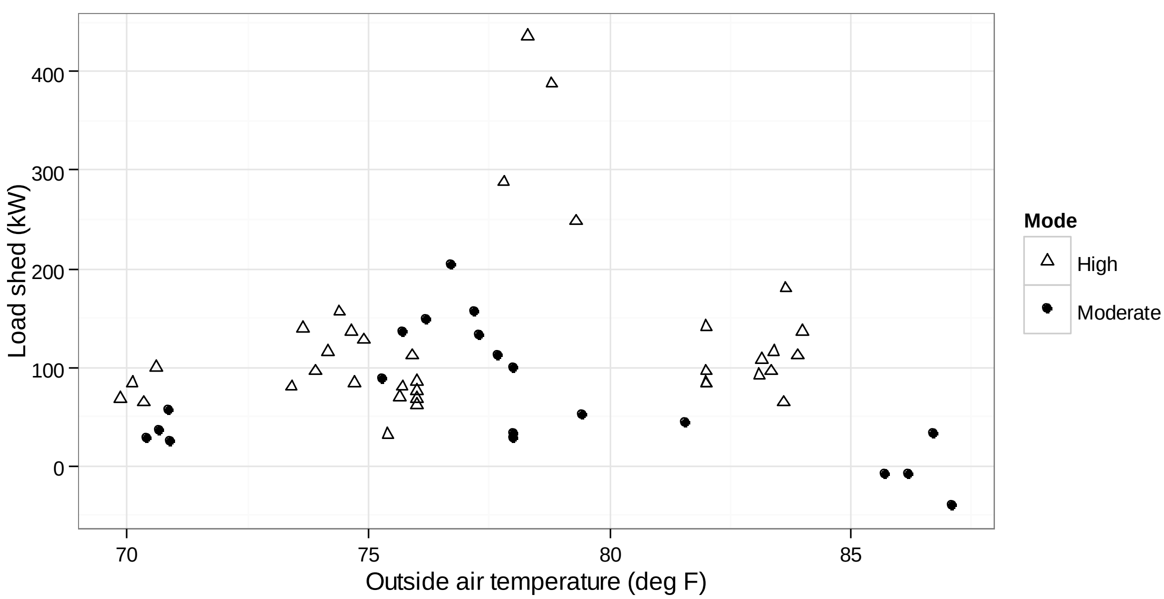

800
700
600
500
400
300
Load shed (kW)
70
75
80
Outside air temperature (deg F)
Mode
High
Moderate

Office Building B

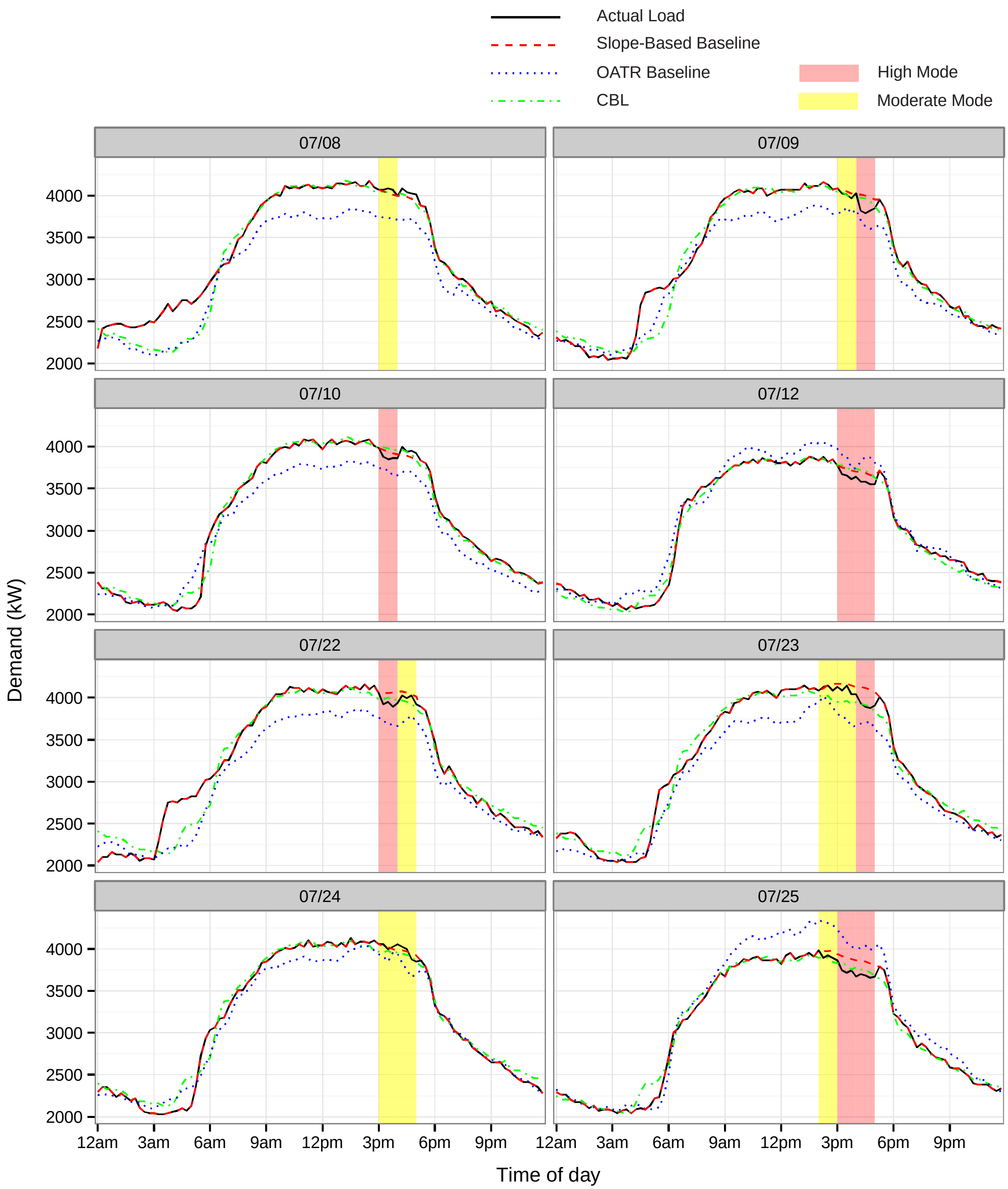


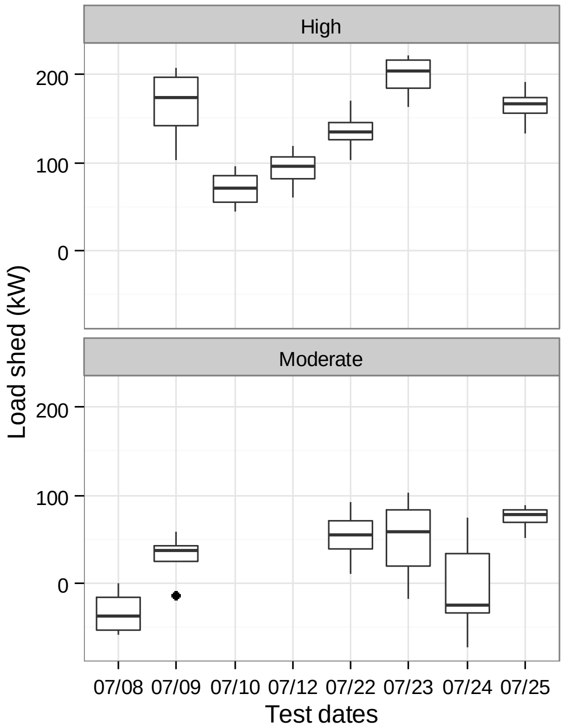

High
Moderate
Load shed (kW)
400
200
0
-200
06/27 06/28 07/08 07/09 07/10 07/12 08/16 09/05 09/06
Test dates

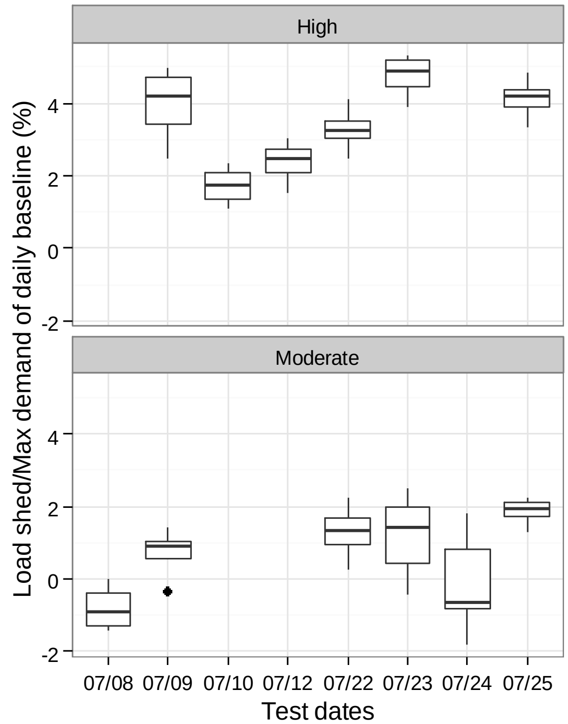

High
Moderate
Load shed/Max demand of daily baseline (%)
10
5
0
-5
06/27 06/28 07/08 07/09 07/10 07/12 08/16 09/05 09/06
Test dates

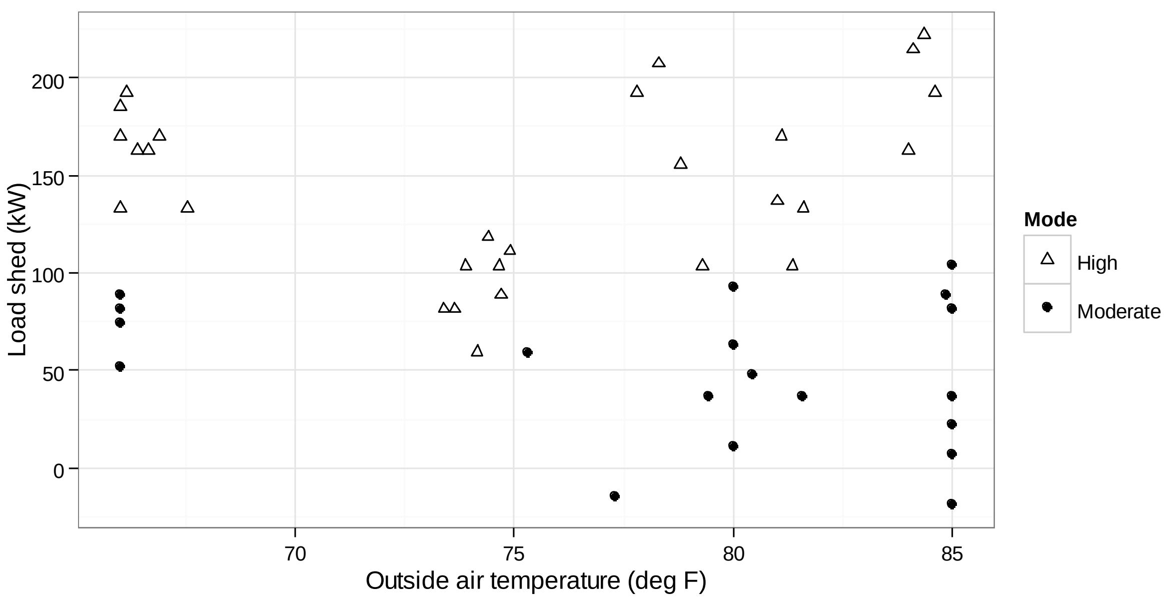

Load shed (kW)
400
300
200
100
0
70
75
80
85
Outside air temperature (deg F)
Mode
High
Moderate

Office Building C

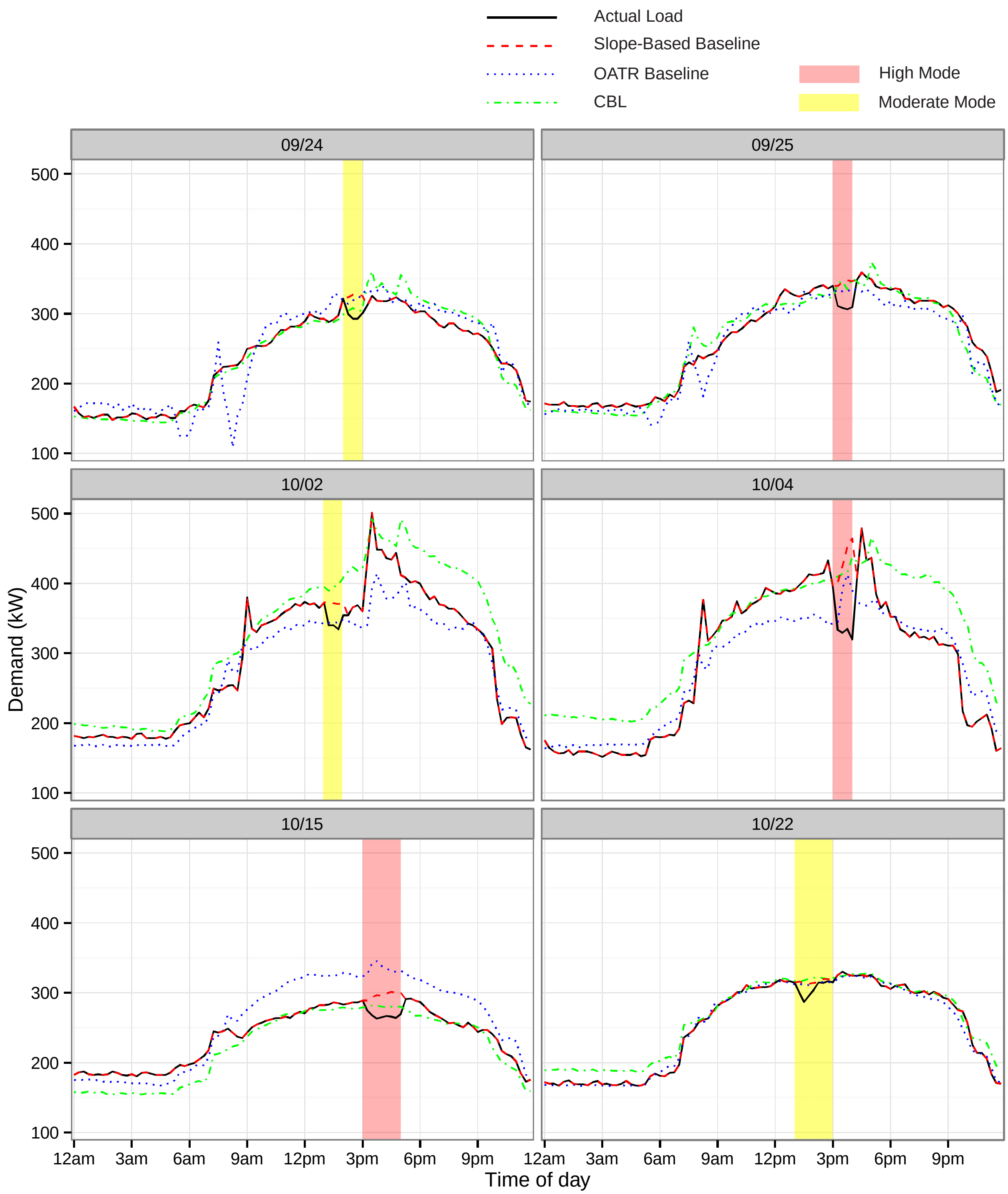


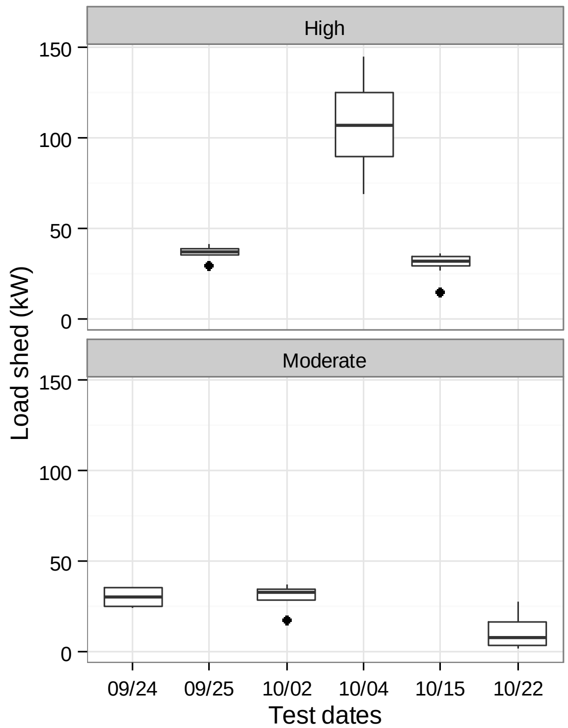

High
Moderate
Load shed (kW)
200
100
0
07/08 07/09 07/10 07/12 07/22 07/23 07/24 07/25
Test dates

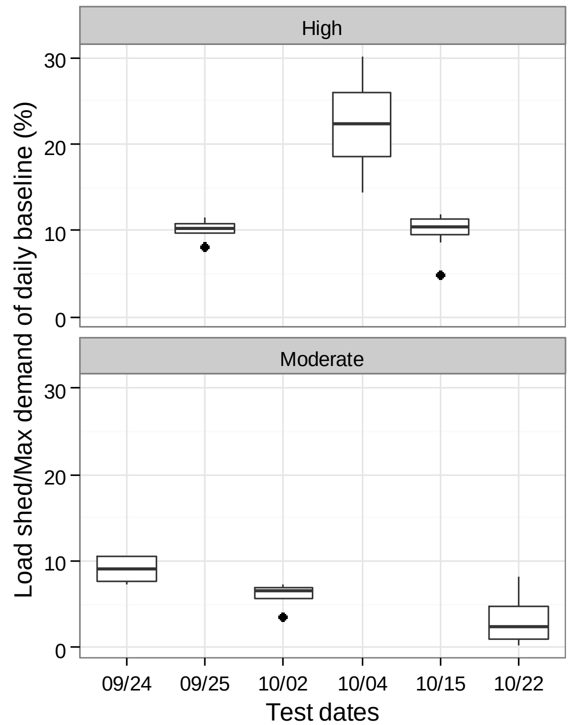

High
Moderate
Load shed/Max demand of daily baseline (%)
4
2
0
-2
07/08 07/09 07/10 07/12 07/22 07/23 07/24 07/25
Test dates

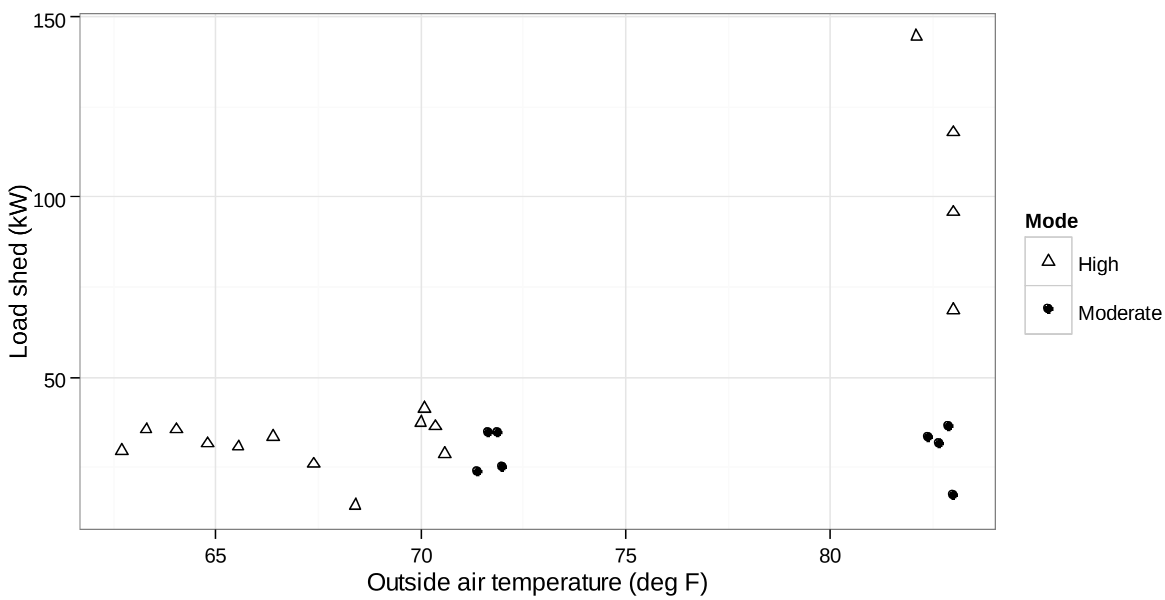

Load shed (kW)
200
150
100
50
0
70
75
80
85
Outside air temperature (deg F)
Mode
High
Moderate

Campus Building




High
Moderate
150
100
50
0
Load shed (kW)
09/24
09/25
10/02
10/04
10/15
10/22
Test dates


High
Moderate
30
20
10
0
Load shed/Max demand of daily baseline (%)
09/24
09/25
10/02
10/04
10/15
10/22
Test dates


150
100
50
Load shed (kW)
65
70
75
80
Outside air temperature (deg F)
Mode
High
Moderate

Appendix D. Customer Bill Calculation Tables

	Con Edison SC-9, Rate II: TOD - Rider M, Mandatory Hourly Pricing			All Participating Buildings	
Types of Chargers	Bill Component	Unit	Determinant	Jul-13	Aug-13
Supply/Production	Market Supply Charge (MSC)				
	Cost of energy based on NYISO market prices	$/MWh	kWh per hour	Market price	Market price
	Cost of capacity based on NYISO market prices	$/kW-month	kW	17.8	17.8
	Ancillary Service Charges	¢/kWh	kWh	0.3601	0.5125
	NYPA Transmission Adjustment Charges (NTAC)	¢/kWh	kWh	0.0994	0.0778
	Certain other transmission-related charges and credits				
	Merchant Function Charge (MFC)				
	Supply-related Charge	¢/kWh	kWh	0.0899	0.0899
	Credit and Collection-related Charge	¢/kWh	kWh	0.0515	0.0515
	Uncollectible-bill Expense - MSC	¢/kWh	kWh	0.0265	0.0589
	Transition Adjustment	¢/kWh	kWh	-0.0075	-0.0075
Delivery	Demand				
	Summer, weekday, 8am-6pm (additive)	$/kW-month	kW	8.28	8.28
	Summer, weekday, 8am-10pm (additive)	$/kW-month	kW	15.49	15.49
	Summer, all days, all hours	$/kW-month	kW	16.62	16.62
	Winter, weekday, 8am-10pm (additive)	$/kW-month	kW		
	Winter, all days, all hours	$/kW-month	kW		
	Energy				
	All hours	¢/kWh	kWh	0.82	0.82
	Metering Services			75.66	75.66
	Meter ownership charge	$-month	n/a		
	Meter service provider charge	$-month	n/a		
	Meter data service provider charge	$-month	n/a		
	Reactive Power Demand Charge				
	Monthly Adjustment Clause (MAC)				
	Customer Charge MAC	¢/kWh	kWh	0.832	0.94
	MAC Reconciliation	¢/kWh	kWh	0.2475	-0.1385
	Uncollectible-bill Expense - MAC	¢/kWh	kWh	0.0094	0.0093
	Transition Adjustment	¢/kWh	kWh	-0.003	-0.003
	Revenue Decoupling Mechanism	¢/kWh	kWh	-0.365	-0.365
	Billing and Payment Processing	$-month	n/a	1.04	1.04
	System Benefit Charge (SBC)	¢/kWh	kWh	0.34	0.34
	Renewable Portfolio Standard (RPS)	¢/kWh	kWh	0.23	0.23
	Con Ed 18-a Assessment Charge	¢/kWh	kWh	0.1656	0.1656
	Taxes	% or percent	on pre-tax bill	Not included	Not included

	NYPA SC-69: TOD - General Large			Office Building A
Types of Chargers	Bill Component	Unit	Determinant	Aug-13
Production	Summer Charges			
	Energy On-Peak, 8am - 10pm weekdays	¢/kWh	kWh	6.935
	Energy Off-Peak, all other times	¢/kWh	kWh	4.887
	Energy Charge Adjustment	¢/kWh	kWh	0.212
	Time of Day Demand	$/kW-month	kW	13.23
Delivery	Summer Charges			
	Time of Day Demand Low Tension	$/kW-month	kW	45.72
	Taxes	% or percent	on pre-tax bill	Not included
Other	Revenue Decoupling Mechanism	various	n/a	7560
	Con Ed 18-a Assessment Charge	various	n/a	3050
	Smart Grid Charge	various	n/a	291
	Demand Management Charge	various	n/a	387

Appendix E. Cost Minimization Algorithm

Cost Minimization Algorithm

Start

P = average building electrical demand (kW)
t = time interval (hr)
k = hourly time step
N = number of k in a given billing period
J = 30-min time step
N' = number of j in a given billing period
EC = day-ahead hourly energy price ($/kWh)
DC = demand charge ($/kW)
High_shed = load shed estimate for *High Mode*
Mod_shed = load shed estimate for *Moderate Mode*
num_High_day = number of *High Mode* per day
num_Mod_day = number of *Moderate Mode* per day
num_High_month = number of *High Mode* per billing period
num_Mod_month = number of *Moderate Mode* per billing period

Set constraints:
max_High_day = maximum allowable number of *High Mode* per day
max_Mod_day = maximum allowable number of *Moderate Mode* per day
max_High_month = maximum allowable number of *High Mode* per billing period
max_Mod_month = maximum allowable number of *Moderate Mode* per billing period

Compute target demand cost and target energy cost:
r = reduction rate
TDC = $(1\text{-}r) \times \mathrm{Max}_{1 \le j \le N}\{DC_j P_j\}$
TEC = $(1\text{-}r) \times \sum\{EC_k P_k t\}$

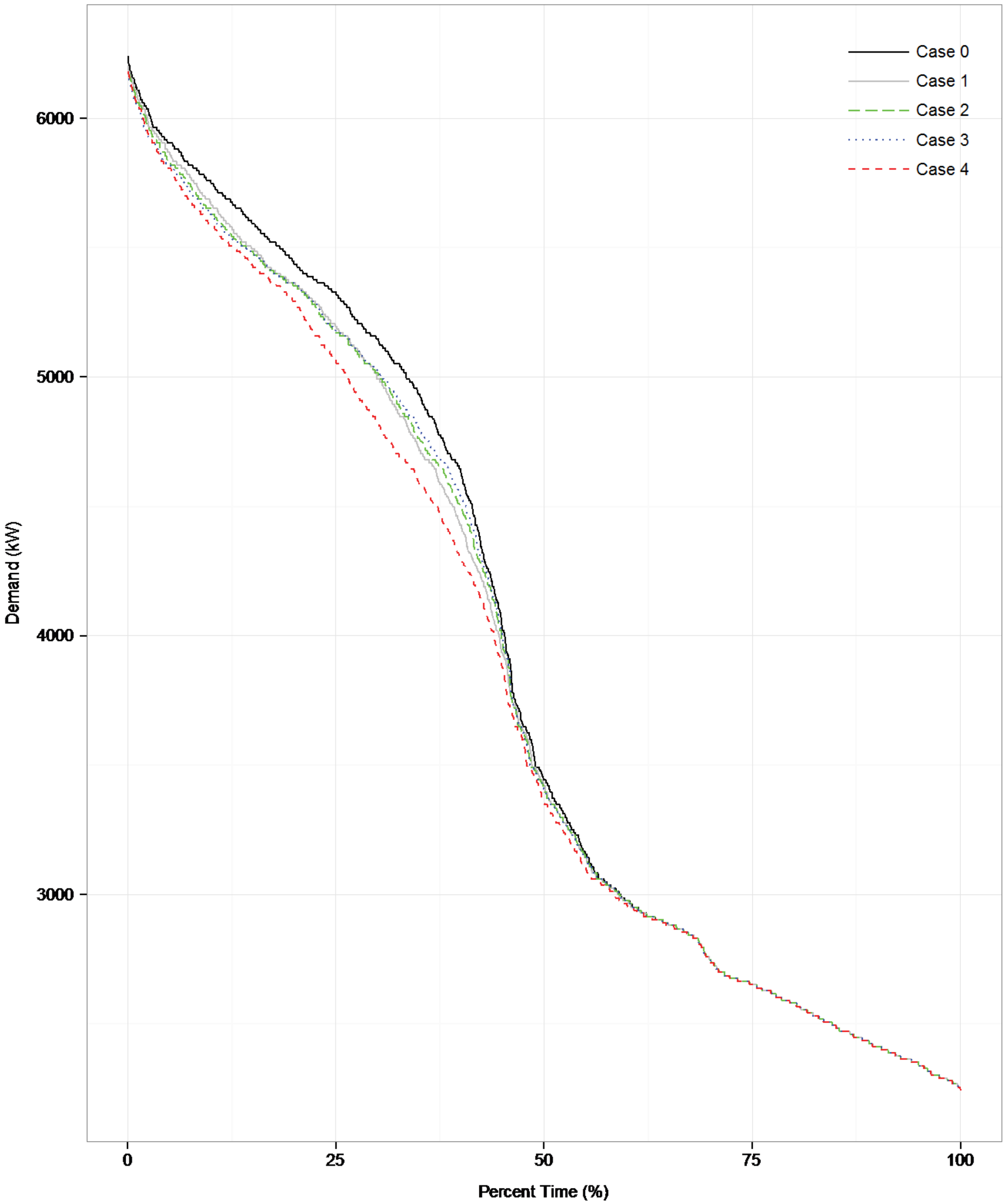
For Demand Limiting:
Sort P_j in the order of $DC_j P_j$
for each j,
If TDC $\geq \mathrm{Max}_{1 \le j \le N}\{DC_j P_j\}$ and
num_High_day ≤ max_High_day and
num_High_month ≤ max_High_day, **then**
apply *High Mode* to j and update $P_j = P_j$ - High_shed
else
End Demand Limiting

For Price Response I:
Sort P_k in the order of EC_k
for each k,
If TEC $\geq \sum\{EC_k P_k t\}$ and
num_Mod_day ≤ max_Mod_day and
num_Mod_month ≤ max_Mod_day, **then**
apply *Moderate Mode* to k and update $P_k = P_k$ - Mod_shed
else
End Price Response I

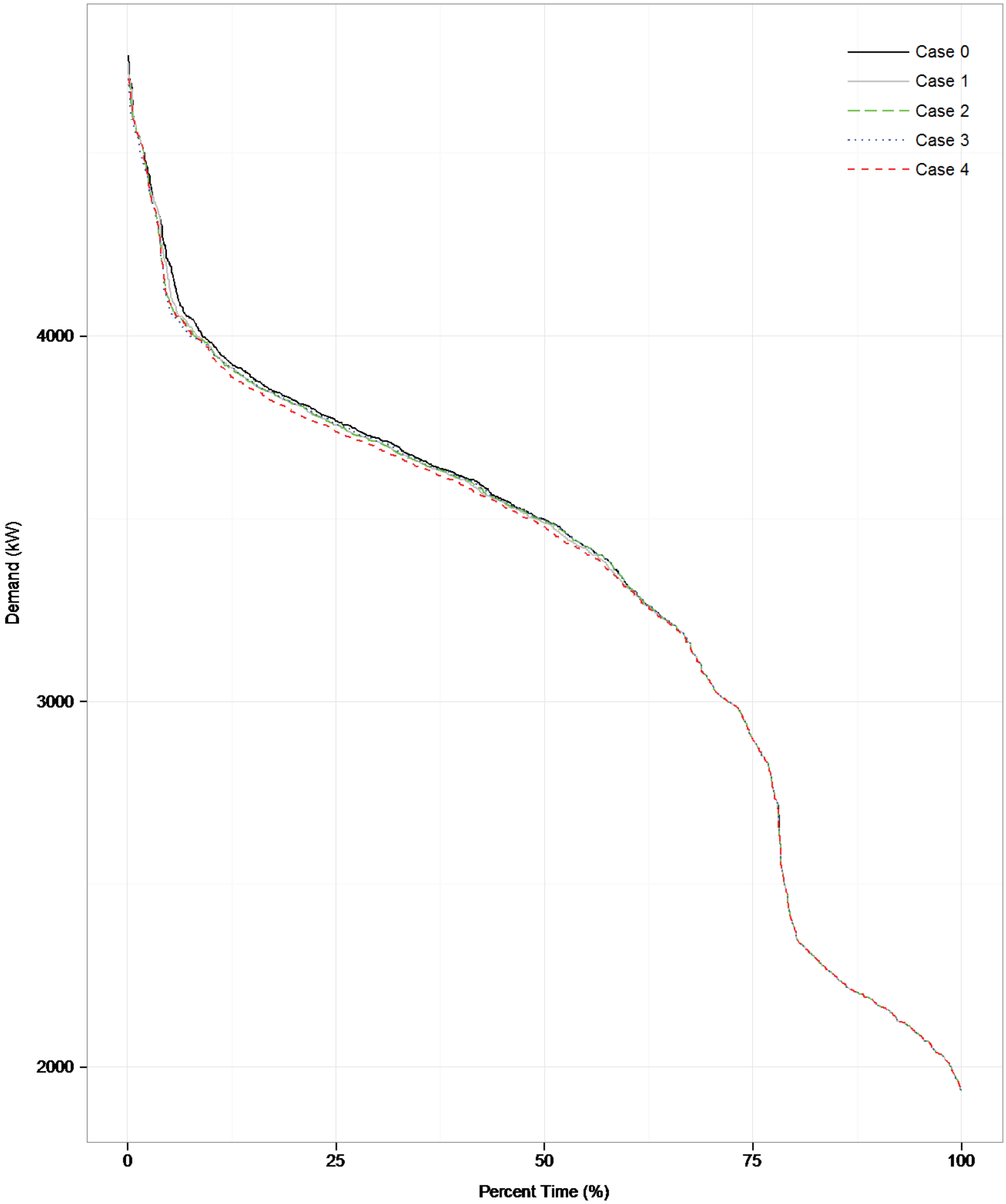
For Price Response II:
Sort P_k in the order of EC_k
for each k,
If TEC $\geq \sum\{EC_k P_k t\}$ and
num_High_day ≤ max_High_day and
num_High_month ≤ max_High_day, **then**
apply *High Mode* to k and update $P_k = P_k$ - High_shed
else
End Price Response II

Appendix F. Duration Curves

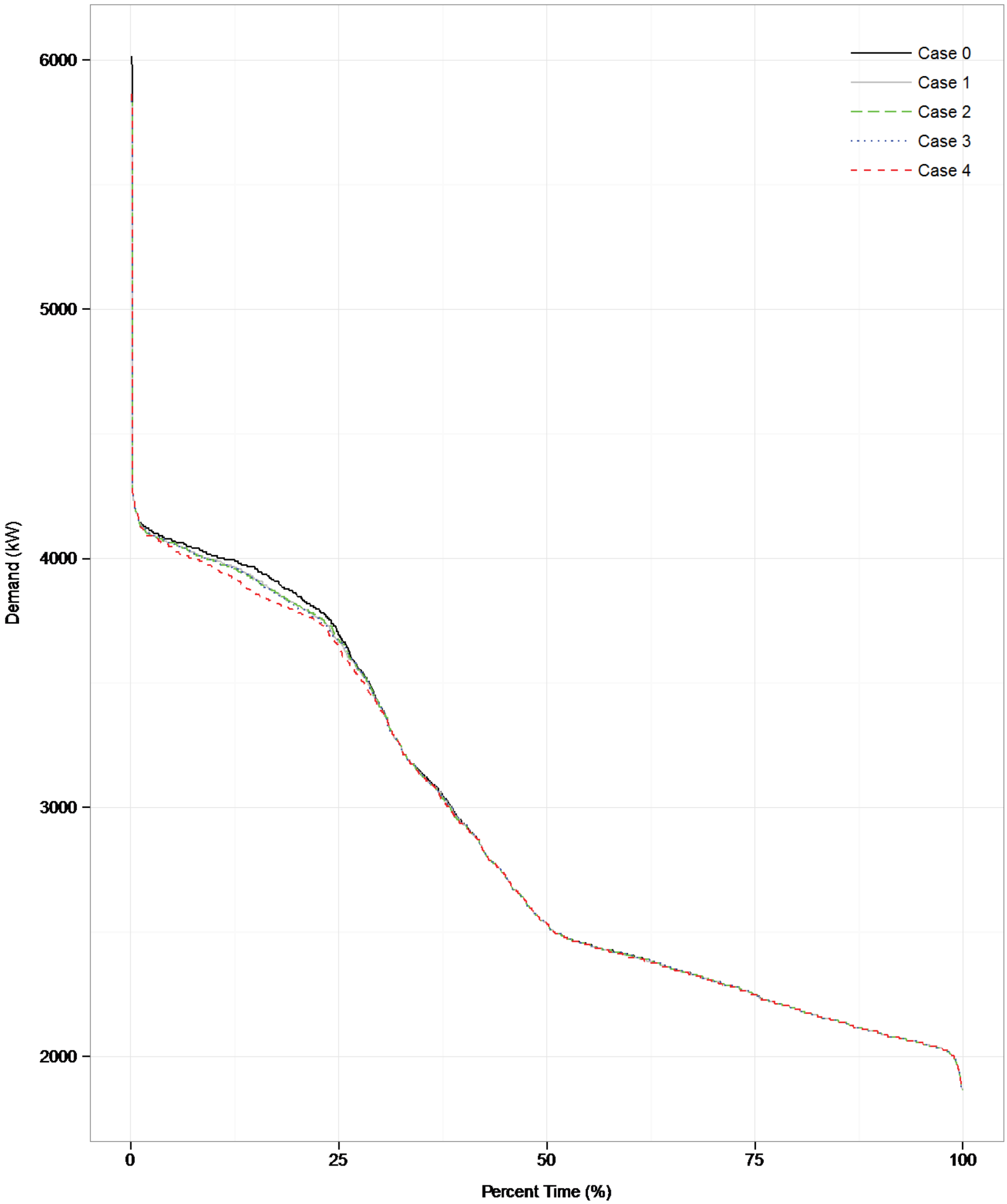
Office Building A



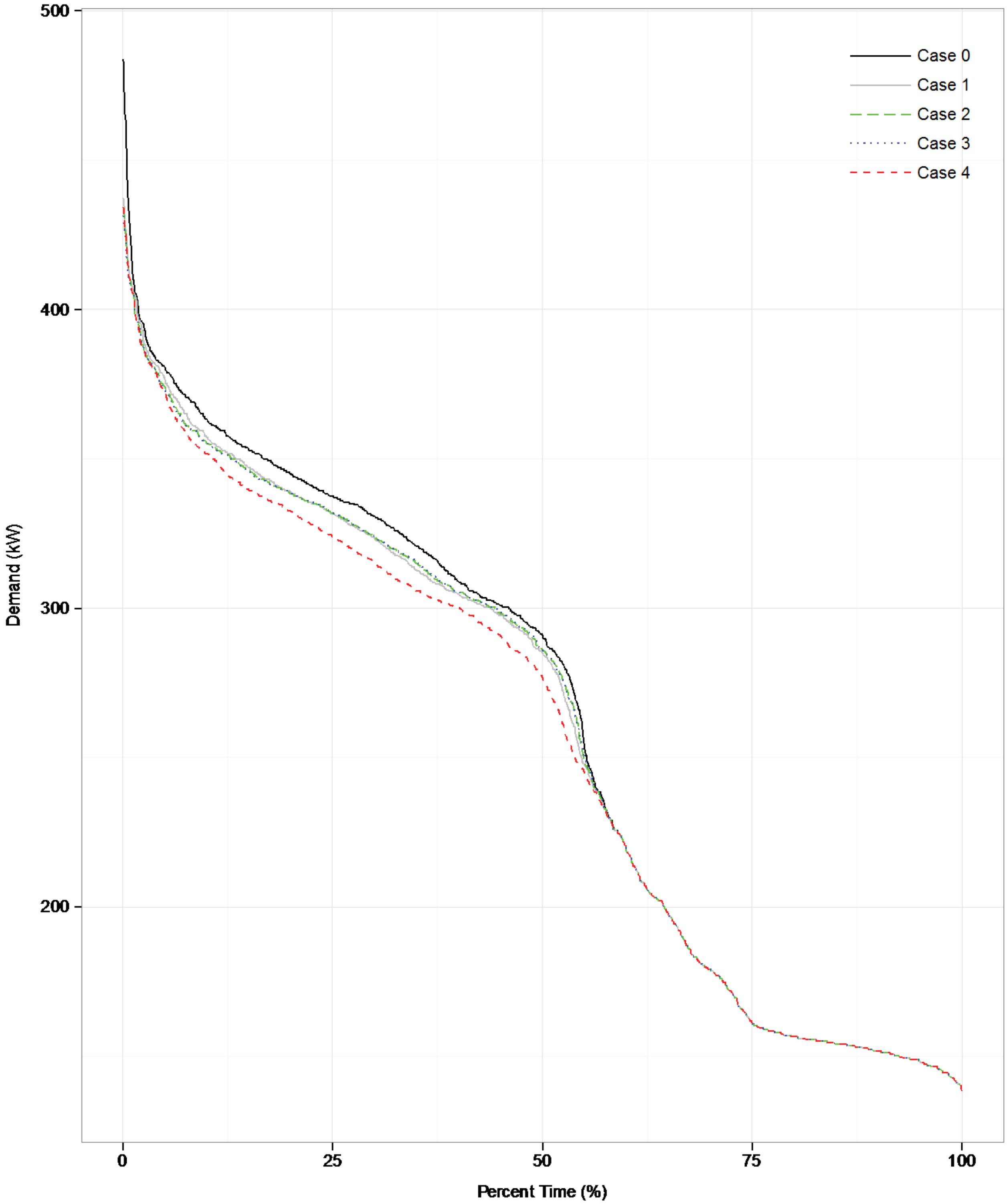
Office Building B



Office Building C



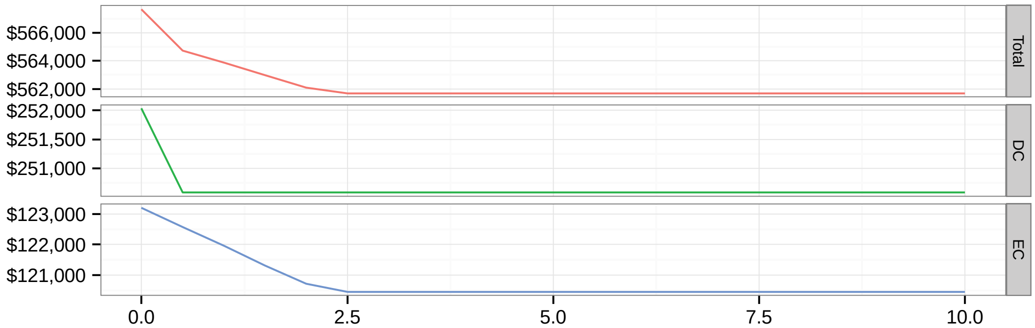
Campus Building



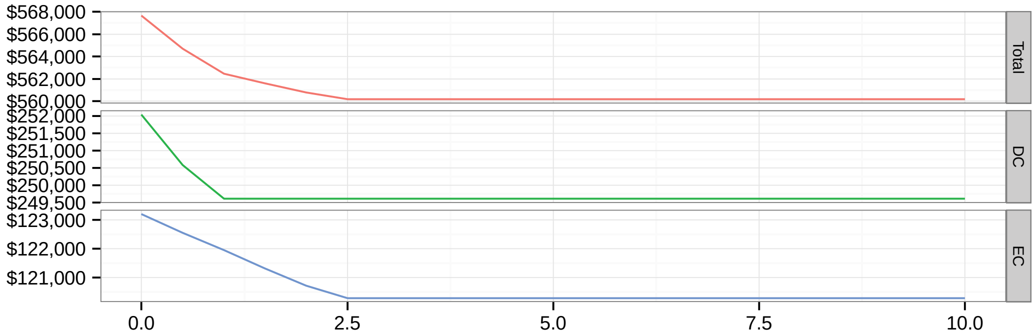
Appendix G. Bill Savings Breakdown

Office Building A

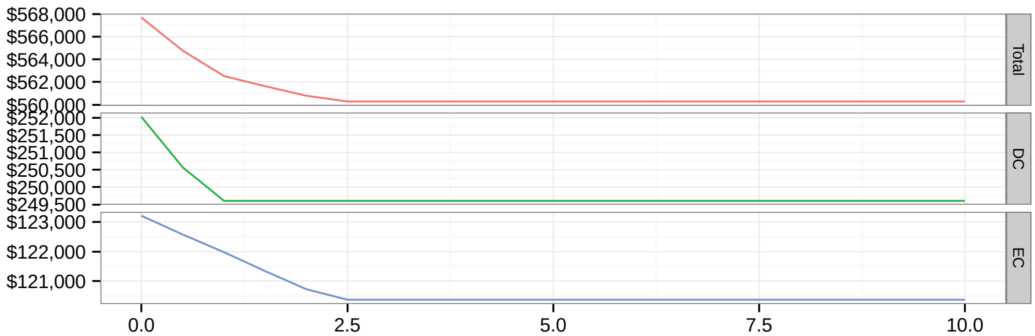
Case 1



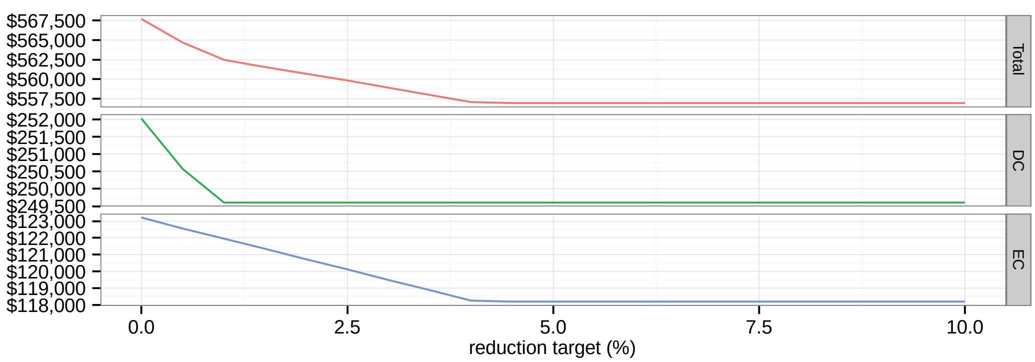
Case 2



Case 3

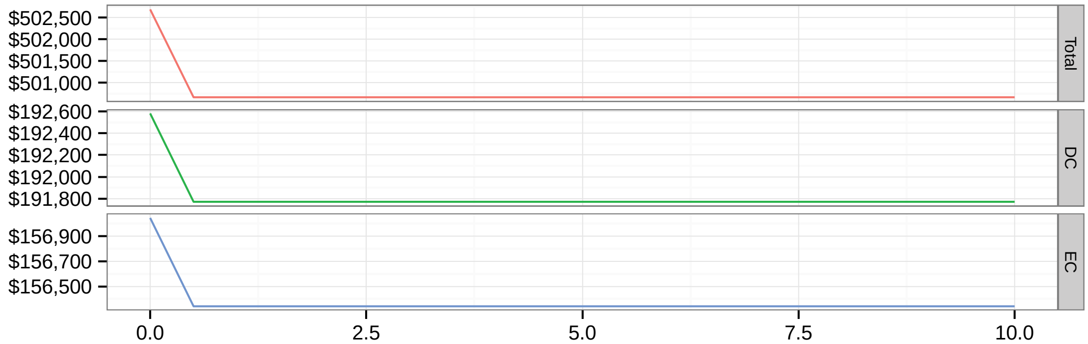


Case 4

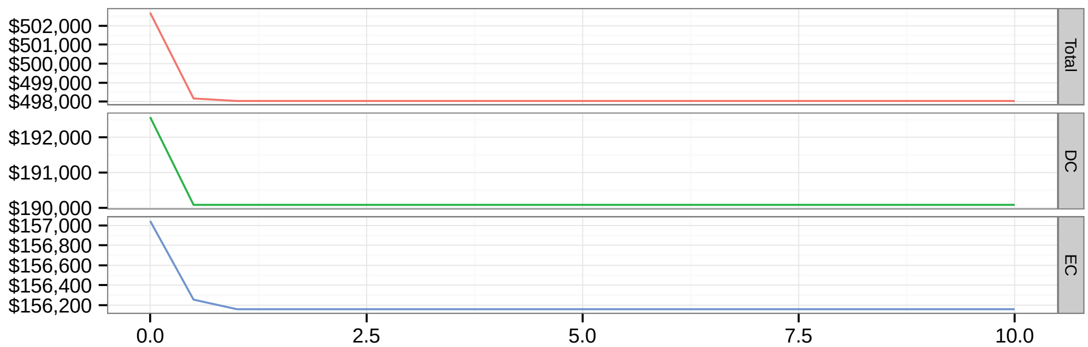


Office Building B

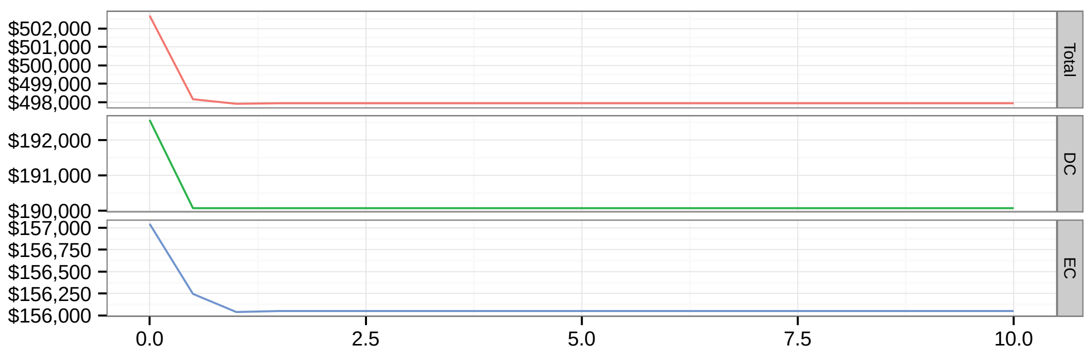
Case 1



Case 2



Case 3



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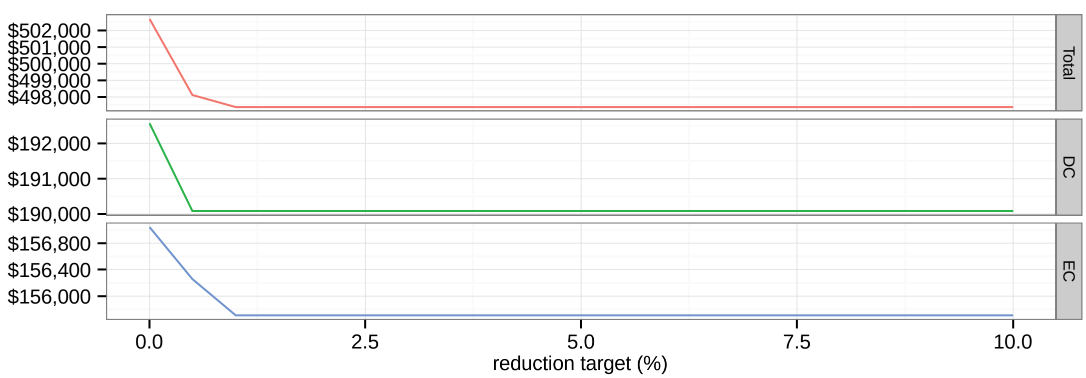
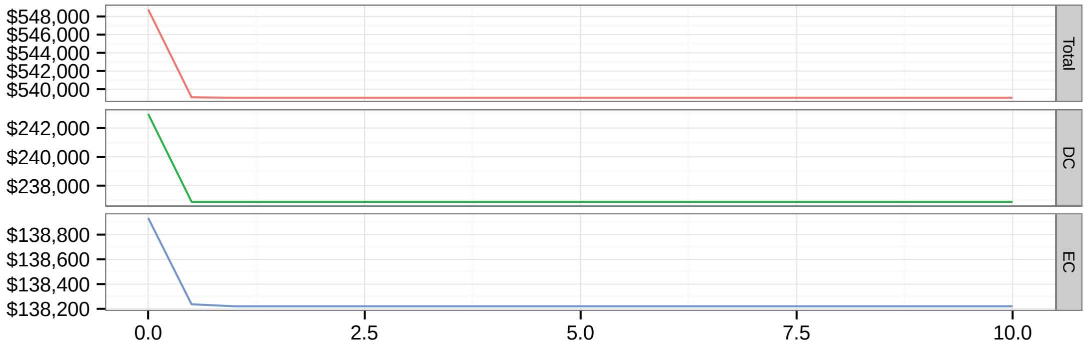
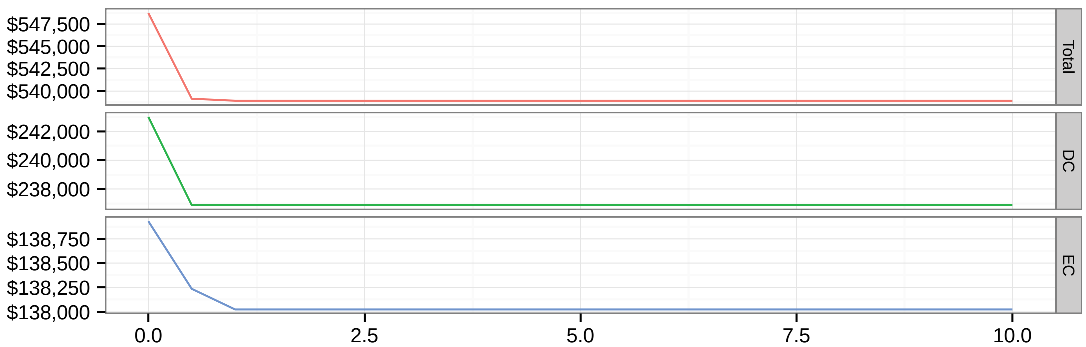


Office Building C

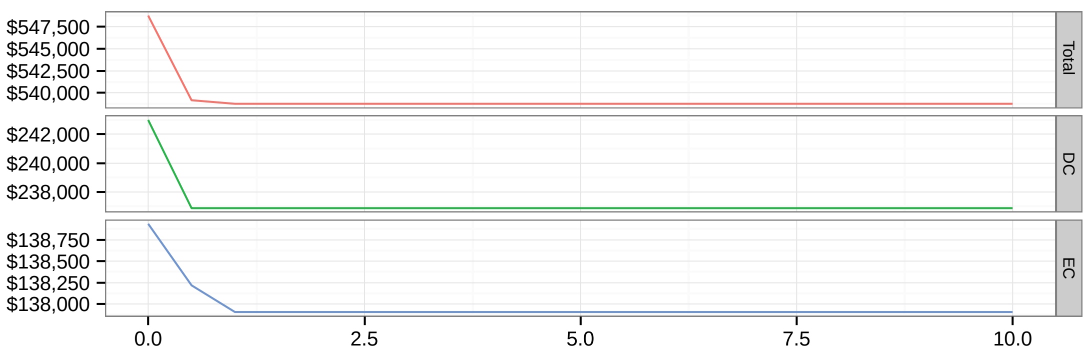
Case 1



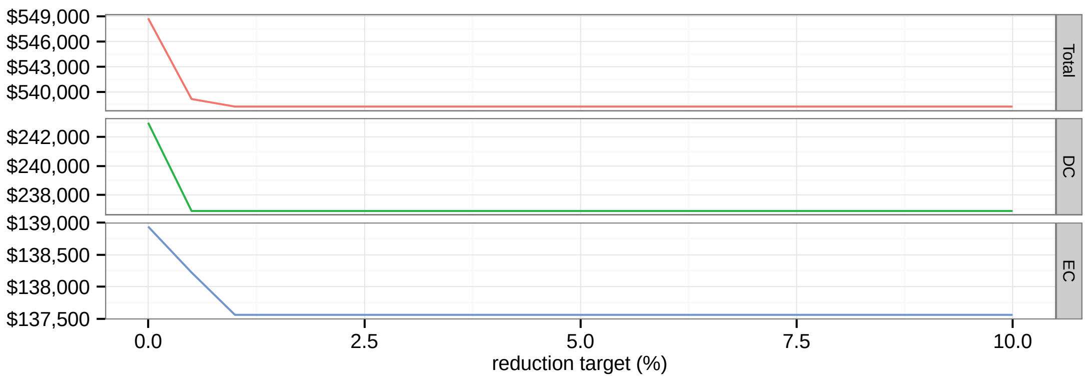
Case 2



Case 3

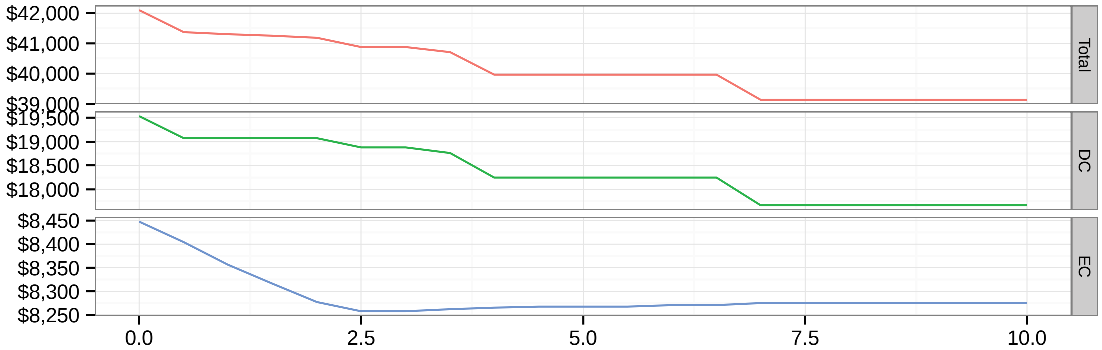


Case 4

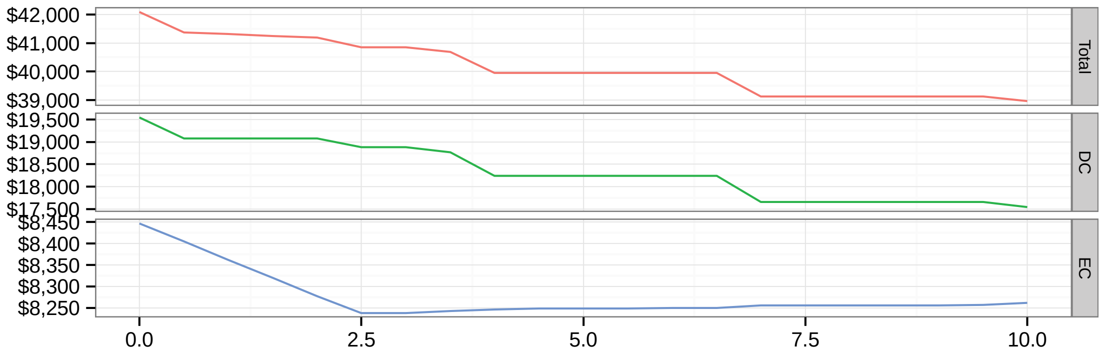


Campus Building

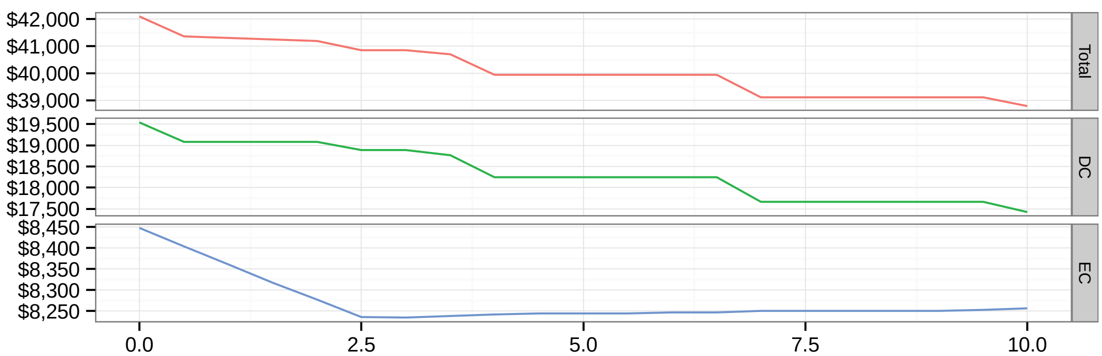
Case 1



Case 2



Case 3



Case 4