Automated Price and Demand Response Demonstration for Large Customers in New York City using OpenADR

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***Abstract*— Open Automated Demand Response (OpenADR), an XML-based information exchange model, is used to facilitate continuous price-responsive operation and demand response participation for large commercial buildings in New York who are subject to the default day-ahead hourly pricing. We summarize the existing demand response programs in New York and discuss OpenADR communication, prioritization of demand response signals, and control methods. Building energy simulation models are developed and field tests are conducted to evaluate continuous energy management and demand response capabilities of two commercial buildings in New York City. Preliminary results reveal that providing machine-readable prices to commercial buildings can facilitate both demand response participation and continuous energy cost savings. Hence, efforts should be made to develop more sophisticated algorithms for building control systems to minimize customer's utility bill based on price and reliability information from the electricity grid.**

***Index Terms*—Price response, demand response, dynamic pricing, real-time pricing, automated control, energy management, load management, load shedding, load forecasting, dynamic response.**

I. Introduction

In order to ensure reliable and affordable electricity, the flexibility of demand-side resources to respond to the grid reliability requests and wholesale market conditions is required (Borenstein et al., 2002; Hirst et al., 2001). Large customers are often the immediate target for demand response (DR) because they are major contributors to peak demand for electricity and they are equipped with centralized building management system (BMS) to adjust electric loads. However, much of DR is still manual because most BMS do not have a built-in capability to support DR participation (i.e., pre-programmed DR strategies). Hence, providing frequent DR is a daunting task for many customers, which undermines the full potential of demand-side management among large customers. The customer's ability to perform DR can be significantly improved by enabling automated demand response (Auto-DR) (Piette et al., 2005). By eliminating the human in the loop, Auto-DR eases the operational burden to provide frequent DR and reduces the cost associated with monitoring and responding.

It has been argued that Auto-DR and enabling technologies would play a critical role in creating price-responsive load (Goldman et al., 2002). The application of Auto-DR to dynamic pricing has attracted attention since several states and utilities deployed full-scale dynamic pricing programs. To facilitate price and reliability information exchange among various stakeholders in the electric grid, Lawrence Berkeley National Laboratory (LBNL) developed Open Automated Demand Response (OpenADR) (Piette et al., 20009). OpenADR is an open and interoperable standard that uses an XML (eXtensible Markup Language) based information exchange model to send DR requests and pricing signals from a server (i.e., utility, system operator, aggregator) to a client (i.e., customer site). Ghatikar et al. (2010) discussed the use of OpenADR for price response presenting strategies to operationalize dynamic pricing signals into load control modes.

Understanding Auto-DR potential in commercial buildings requires examining the capabilities of existing control systems and communication protocols. A centralized BMS can integrate individual control systems/devices to provide greater controllability and efficiency to building managers. Open communication protocols allow interoperability between different vendors' systems/devices. Therefore, as more buildings adopt the centralized BMS and open communication protocols, the cost and time to enable Auto-DR will decrease. According to the Energy Information Administration's 2003 Commercial Buildings Energy Consumption Survey (CBECS), 7% of commercial buildings have BMS which represents 31% of the national floor space (Kiliccote and Piette, 2006). This percentage has probably increased by now since more buildings are built with a BMS or retrofitted with it. The recent revisions of building energy efficiency standards now include DR in their specifications. Examples are the Automated Demand Response section in California's Title 24-2013 and the pilot demand response credit in U.S. Green

Building Council's LEED (Kiliccote et al., 2012). Standards like these may encourage control vendors to install built-in DR capabilities in their BMS. In such case, the efforts to customize DR strategies will be significant reduced.

II. Objectives and Significance

This paper reports on the latest efforts to automate customer response to price and reliability signals for large commercial buildings in New York City (NYC). It is significant in two ways. First, the paper raises the awareness to key cost challenges for commercial customers who are subject to the default day-ahead hourly pricing in New York State (NYS) and provides a practical solution that the facility can adopt for continuous energy management. Second, it provides a framework to develop and test control algorithms that optimize energy use and cost in large commercial buildings.

A note on terminology: dynamic pricing is referred to energy prices that are available to customers in regular intervals no more than a day in advance. In NYS, wholesale electricity prices are set day-ahead, hour-ahead or in real-time by the New York Independent System Operator (NYISO) wholesale markets. In this paper, we focus on day-ahead hourly pricing, which is the default tariff for large customers in NYS.

The rest of this paper is organized as follows. In Section II, we summarize the existing demand response programs in NYS. In Section III, we discuss OpenADR communication architecture, prioritization of price and reliability signals, and control methods for large commercial buildings that participated in our demonstration project. In Section IV, the application of Auto-DR under MHP is explored through energy simulation and field tests of two demonstration buildings in NYC. Preliminary findings from the demonstration project are discussed in Section V. Lastly, in Section VI, we conclude with suggestions for future research directions.

III. Demand Response in New York State

In NYS, DR is mainly promoted through reliability-based programs and dynamic pricing. There are a number of reliability-based programs offered to customers by NYISO and utilities, commonly referred to as DR programs. Since the initial offering in 2001, NYISO's DR program registration has grown steadily. In 2001, there were approximately 300 participants enrolled in reliability-based programs such as Special Case Resource/Emergency Demand Response Program (SCR/EDRP) with the total participating load of 750 MW. By 2011, NYISO had a total of 5,807 participants for the SCR/EDRP program providing 2,173 MW of curtailable load (Patton et al., 2012). Most customers in NYS are enrolled in DR programs through Curtailment Service Providers (CSPs). CSPs manage a portfolio of DR resources and aggregate demand reduction to maximize DR compensation. They help customers assess the DR potential and develop load curtailment strategies. Contracting a CSP typically means that customers meet the minimum shed requirements during the DR test/event and receive DR compensation in return.

Dynamic pricing is offered to induce price-responsive load, flattening system demand by applying high prices during peak periods and low prices during off-peak periods. Pacific Gas and Electric (PG&E) Critical Peak Pricing and Southern California Edison's (SCE) Real-Time Pricing are examples of dynamic pricing. In 2005, the State of New York Public Service Commission ordered utilities to provide day-ahead hourly pricing as the default tariff to non-residential customers whose demand is roughly over 500 kW (NYPSC, 2005). This tariff is also known as Mandatory Hourly Pricing (MHP). Although utilities offer MHP as the default service to large customers, NYS's retail access policy allow customers to purchase their energy from any retail third party supplier as an alternative to the utility. Hence, MHP is not strictly 'mandatory'. As of 2011, only 15% of the MHP-eligible customers were enrolled in MHP and the rest (85%) were retail access customers (Joskon, 2012). The problem of this is that flat price retail contracts that hedge against price fluctuations and therefore do a poor job of reflecting wholesale near-term market prices (day-ahead, hour-ahead and real-time) (Goldman et al., 2002). They also tend to be expensive due to the inherent risk of offering a less variable rate. When retail prices are not tied to wholesale market variations, they can "inefficiently increase the level of peak demand by underpricing" electricity and can also "discourage increased demand during off-peak hours by overpricing it" (Joskon et al., 2012). Therefore, switching from MHP to a retail rate can hamper the development of price-responsive load.

The primary barriers to the adoption of MHP are identified as the insufficient resources (both labor and equipment) to monitor hourly prices and inflexible labor schedule (KEMA, 2012). This is not surprising since most customers rely on manual approach to provide DR. Providing DR manually is a resource-intensive process. If customers are not capable of monitoring and responding to hourly price variations, they are likely to choose a more conventional rate such as a fixed rate. Moreover, customers have not yet found a compelling business case to stay with MHP. Many customers presume that the cost of monitoring and automation outweighs the potential savings. Even if the savings exist under day-ahead hourly prices, they are not as obvious and repeatable as the DR payments because the savings are a function of the market and are embedded in the total electricity bill. Therefore, in order to increase the adoption of MHP and dynamic-price retail contracts, we not only need to make the prices broadly available and automate customers' price response but also effectively communicate potential savings to customers and ways to achieve it.

In NYC, MHP is billed under Rider M: Day-Ahead Hourly Pricing from Con Edison where the cost of energy is calculated based on the customer's actual hourly energy usage multiplied by NYISO's day-ahead zonal locational based marginal price (LBMP) (Con Edison). In addition, customers pay demand charge imposed on the maximum demand of each

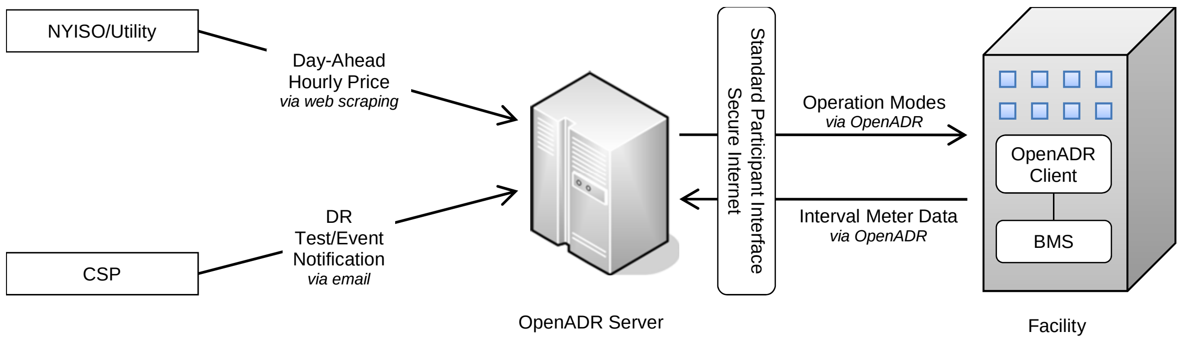

Figure 1. OpenADR communication architecture for the New York City demonstration project.

billing cycle. The demand charge varies depending on the Time-of-Day (TOD) and season (Con Edison). Based on our billing analysis, the demand charge accounts for 19% - 55% of the customer's electric bill depending on time of use. To reduce the total electric bill, customers need to control their electric consumption according to the hourly price variations and limit the building's peak demand during expensive hours.

IV. Approach

Since October 2011, the Demand Response Research Center (DRRC) at LBNL and New York State Energy Research and Development Authority (NYSERDA) have conducted a demonstration project enabling automated DR and price response in large commercial buildings located in NYC using OpenADR. The recruitment efforts were focused on large commercial buildings in NYC. Preferences were given to the buildings that represented the typical construction of commercial buildings in NYC and previously participated in DR programs. Four facilities were recruited for the demonstration project. All of them previously participated in one or more DR programs through CSPs providing manual control of HVAC, lighting, and other systems during DR events. Some also provided manual peak load management. But because DR was manually performed, the buildings did it only on hot days or DR event days. They did not do any price response prior to the demonstration project. The customer's participation in this project was driven by the motivation to automate the control strategies that they used for DR events. Automation allows building operators to automatically respond to DR events without having to manually activate individual control strategies. All facilities are on a retail rate and are not enrolled in MHP. In this paper, we set out to investigate a hypothetical scenario wherein the demonstration buildings purchase electricity under the MHP tariff and therefore have to respond to the variability of day-ahead hourly prices.

A. OpenADR Communication Model

To automate price and demand response using OpenADR, three basic technologies are required: an OpenADR server to receive reliability and price signals; an OpenADR client at the facility to receive the reliability and price signals; and a BMS to program and activate control strategies (Wikler et al., 2008). We used OpenADR version 1.0 for the demonstration project. OpenADR version 2.0, available currently, was not released at the time of the project implementation. Figure 1 shows the OpenADR communication architecture for the demonstration project. Day-ahead hourly prices are obtained from NYISO's website and DR test/event notifications are received from the customer's CSP. Based on the price and reliability signals, an operation mode is determined for each hour of the following day. Once the signals are processed, the OpenADR server sends twenty-four hourly prices and corresponding operation modes to the facility to activate preprogrammed control strategies for next day. The OpenADR server also logs the building's 15-minute meter data via kyz pulses and monitors the electric demand throughout the day. All information exchange is accomplished through a secure Internet connection with 128-bit Secure Sockets Layer (SSL) encryption. The facilities can opt-out of Auto-DR at any time via the OpenADR server's client interface accessible over the Internet. The opt-out can be scheduled in advance for a specified period which can be a few hours or days depending on the facility's operational needs.

B. Prioritization of DR signals

Three types of DR signals are issued: 1) reliability, 2) demand limiting, and 3) day-ahead hourly price signals. These signals are prioritized differently depending on the next day's DR test/event status as described in Figure 2. For non-DR test/event days, the facilities respond to price signals until the building's electric demand exceeds a pre-set threshold, in which case, the OpenADR server would switch the signal type from price to demand limiting. When a DR test/event is issued, the facilities only respond to reliability signals during the DR test/event period. If the building's demand exceeds a pre-set threshold, demand limiting signals would be issued to reduce the demand. We decided to turn off price signals during DR test/event days to prevent curtailment activities affecting the customer baseline. This is applicable to customers who use morning adjustments to calculate their energy compensation (i.e., the NYISO's Weather-Sensitive Customer Baseline) (NYISO).

The reliability, demand limiting, and price signals are mapped into four levels of operation mode that are tied to preprogrammed DR strategies via the facility's BMS. OpenADR version 1.0 supports following operation modes:

Normal, *Moderate*, *High*, and *Special* (which we call *Critical* for the demonstration project).

- *Normal* indicates the normal operation triggered when the energy price is acceptable and there is no DR test/event issued.
- *Moderate* indicates the first level of load shed triggered when the energy price is moderately expensive.
- *High* indicates the intermediate level of load shed triggered when the energy price is highly expensive. *High* is also triggered when electric demand exceeds the pre-set threshold.
- *Critical* indicates the highest level of load shed triggered when the DR test/event is issued and electric loads need to be curtailed at the maximum reduction level.

C. Auto-DR Control Logic

Using OpenADR, the facilities can control electricity usage and cost by responding to both price and demand limiting signals. The Auto-DR intelligence can reside 1) within the facility or 2) in the cloud (i.e., the OpenADR server). While the first option has the advantage of unrestricted building data retrieval and direct control over the building systems/devices, it requires on-site development and operation of Auto-DR software. Locating the intelligence in the cloud has the advantage of flexible energy monitoring and DR management. Cloud computing also offers remote data storage and processing capabilities. However, the availability of building control and real-time feedback may be restricted if the building does not want to open their network firewall. Moreover, building managers may be opposed to the idea of their building being controlled by remote intelligence. For our demonstration project, we located the Auto-DR intelligence within the facilities to obtain full access to building data and avoid potential threats to the building network security.

If the building data retrieval and direct control over the building systems/devices are available, the customer's energy cost for a given day can be minimized through load optimization in response to NYISO's day-ahead zonal LBMP (C_t), as expressed in (1).

$$\min \sum_{t=1}^{k} C_t \cdot g(u_t, x_t, w_t) \tag{1}$$

Optimal electricity usage (kWh) is determined by the objective function (g) based on following variables: u is the input constraints for control strategies; x is the building system states (i.e., HVAC set points, operation schedules); and w is the weather (i.e., outside air temperature, relative humidity). t represents the time interval and k indicates the total number of time intervals in a day. The demand charge can be minimized by reducing the building's peak demand during a billing cycle, as expressed in (2).

$$\min\left(\max_{i \in 1,\ldots,N} h(u_i, x_i, w_i) \right) \tag{2}$$

h represents the electric load (kW) at a given time interval (i) and N indicates the total number of time intervals in a billing cycle.

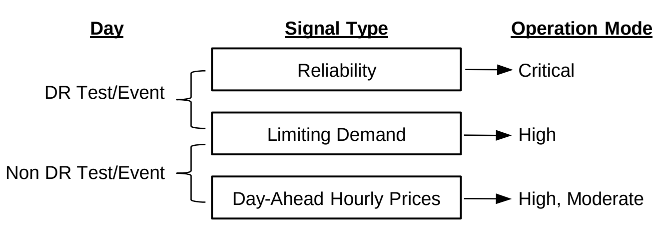

Figure 2. OpenADR signal prioritization.

D. Open-Loop and Closed-Loop Control

There are two types of controls that can be used for Auto-DR: open-loop and closed-loop (Kiliccote et al., 2006). In open-loop control, the OpenADR server sends DR signals to the facility but does not use real-time feedback to track the performance target determined by the objective functions in (1) and (2). Closed-loop control, on the other hand, uses the real-time feedback to reach the performance target. As such, it is more advantageous if the DR performance has to be guaranteed. However, it requires more granularity of control over the building systems/devices and real-time decision making capabilities. For the demonstration project, open-loop control is used to respond to price and reliability signals and closed-loop control is used to provide demand limiting. The feedback is provided via electric meter readings to generate demand limiting signals and calculate load prediction. To estimate DR performance under different operation mode, we simulated whole building energy usage using EnergyPlus. EnergyPlus is an energy analysis and thermal load simulation software which allows calculating heating and cooling loads based on building geometry, building envelope, internal loads, HVAC systems, and weather (EnergyPlus, DOE). Based on the energy simulation results, we selected control strategies and inputs for each operation mode that would produce the target load reduction and thermal comfort level.

V. Application

Implementing Auto-DR is a multi-step process. First, we need to understand the building's current and historic electric use patterns and evaluate building systems, DR capabilities, and operational constraints (Mathieu et al., 2011). Then, we identify DR opportunities and develop control strategies for each facility. Finally, proposed control strategies need to be tested and modified to improve the DR outcome. In this section, we explain the process of developing control strategies for two of the participating buildings from our demonstration project.

A. Site Description

The first building, located in NYC, is a 32-storey office building with a glass curtain-wall extending the full height of the building (here in called "office building"). The office building has a total conditioned floor area of 130,000 m^2 (1.4 Million ft^2). The building's HVAC consists of multiple-zone reheat systems with constant air volume and air-handling units (AHUs) controlled by variable frequency drive (VFD). There

TABLE I
LOAD SUMMARY*

Facility	Peak Load (kW)	Peak Load Intensity (W/m²)	Load Factor	Annual Consumption (kWh)
Office Bldg	6,200	48.0	0.51	27,612,000
Campus Bldg	600	53.0	0.40	2,150,000

*Computed for Sep 2011 - Aug 2012, with 15-minute interval data.

are three 1,350-ton centrifugal chillers with constant speed and one 900-ton centrifugal chiller with variable speed that supplies chilled water to AHUs. Each zone temperature is controlled via direct digital control (DDC). Currently, the office building does not have the Global Temperature Adjustment (GTA) capabilities to change zone temperature setpoints for the entire facility (Motegi et al., 2007). The facility is heated via Con Edison steam. The building is equipped with Honeywell's Enterprise Buildings Integrator™ for HVAC control. Multi-zone control is available for lighting through relays but it is not connected to the BMS. The facility is in operation from 6am to 6pm during weekdays and closes during weekends.

The second building is a 14-storey university building also located in NYC (herein called "campus building"). The campus building recently went through a complete renovation and system upgrades and was recently occupied in September 2011. The newly renovated building has the total floor space of 11,330 m^2 (122,000 ft^2) containing classrooms, computer labs, offices, and conference rooms. There are eleven AHUs, each equipped with VFDs. The building is equipped with a 400-ton chiller supplying chilled water to AHUs. Heating is provided with steam, which is used for AHU reheat, unit heaters, and stairwell heating. The campus building has an Automated Logic Corporation's WebCTRL® system used for HVAC control. The indoor space is largely lit by T5 fluorescent fixtures located within hallways, offices, and the lobby. Office lighting is on motion sensors. The campus building is equipped with the NexLight two-way digital lighting control system but this system was not used for DR in the past. There are three elevators in the campus building: two passenger elevator and one passenger/freight elevator. Previously, one of the three elevators was shut off during DR events. The facility is open from 7am to 11pm for seven days a week.

B. Load Characteristics

Approximately two years of 15-minute whole building electric load data was made available to the project team for the office building and the campus building. Table 1 summarizes the data over one year period (Sep 2011 - Aug 2012). To characterize the behavior of building energy use, we plotted the load profile against different time scales. First, weekly electric demand and consumption was plotted from January 2011 to August 2012 in Figure 3. Examining these plots revealed following findings: 1) both the office and campus buildings had relatively constant minimum demand throughout the year; 2) the maximum demand was higher in summer than in winter for both buildings; and 3) maximum demand (kW) varied more significantly from season to season than electric consumption (kWh). Next, the buildings' interval load was plotted over a one-week period for summer months (May to Aug 2012) in Figure 4 and for winter months (Nov 2011 to Feb 2012) in Figure 5. The scatter plots reveal following things. 1) The office building was in use during weekdays while the campus building was in use for seven days a week, confirming the operation schedule of the two buildings provided to the project team. 2) In both facilities, the spikes shown at the beginning of each weekday during summer months indicated precooling activities and the system overload. For the office building, precooling typically started at midnight and for the campus building, it started at 7am. The campus building had a start-up electric surge during the first hour of the building operation which marked the highest

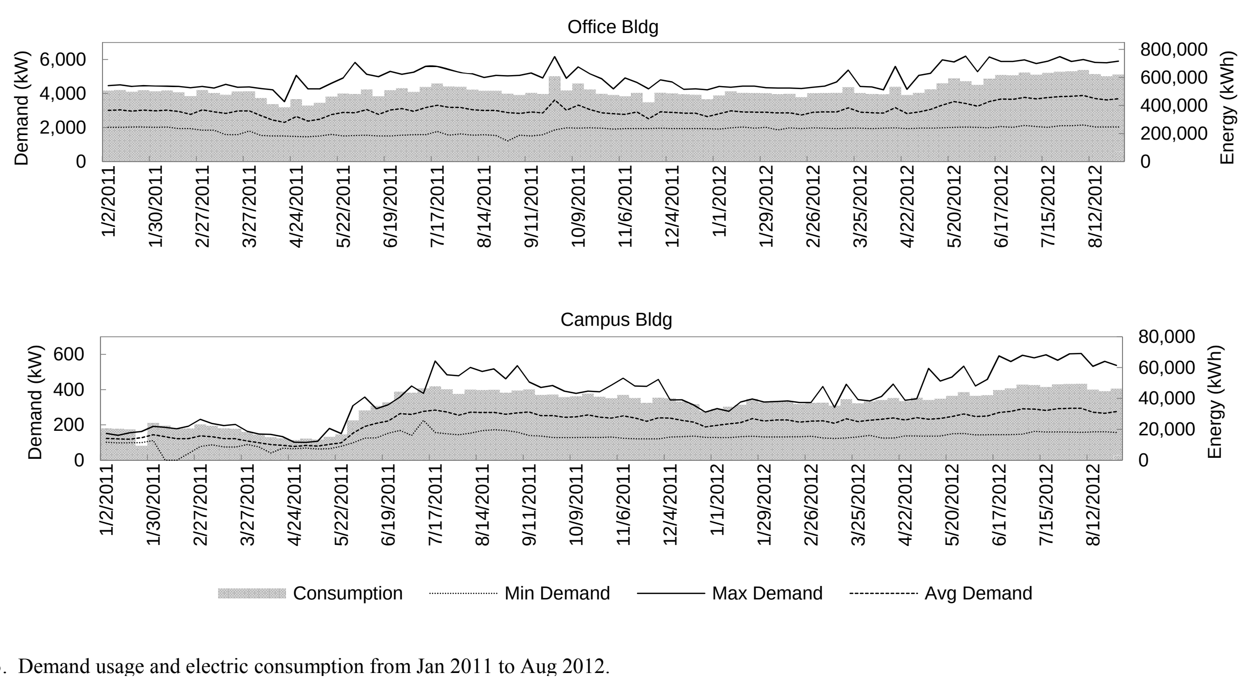

Figure 3. Demand usage and electric consumption from Jan 2011 to Aug 2012.

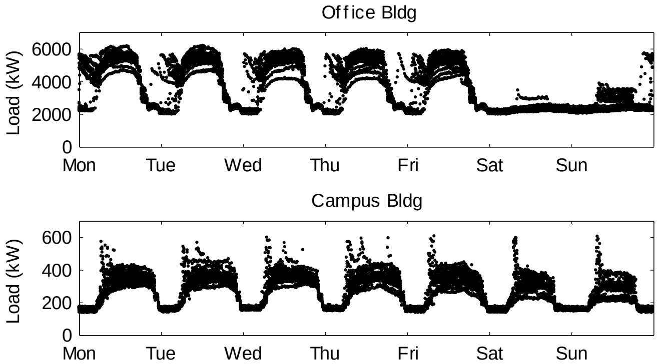

Figure 4. Scatter plot: time-of-week from May to Aug 2012 excluding holidays (Memorial Day and Independence Day).

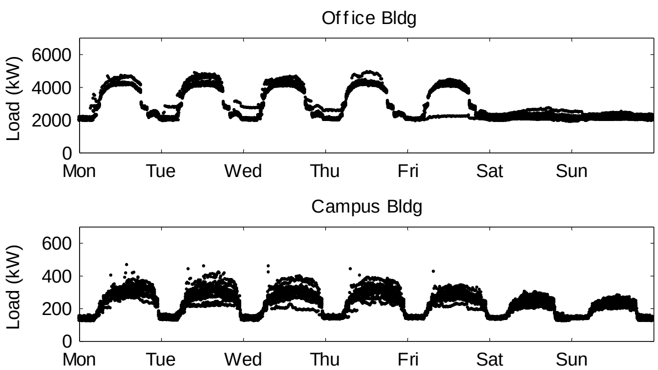

Figure 5. Scatter plot: time-of-week from Nov 2011 to Feb 2012 excluding holidays (Veterans Day, Thanksgiving Day, Christmas Day, New Year's Day, Birthday of Martin Luther King, Jr., and Washington's Birthday).

demand of the day. In summer, starting precooling at 7am would add more loads to the morning ramp-up and increase the demand even higher. 3) Both buildings showed a wide range of daily demand during summer months versus winter months while the base load stayed relatively constant throughout the year. This was more prevalent in the office building than the campus building. Since both buildings were heated with steam, the difference in summer and winter demand was likely to be influenced by the amount of cooling loads. To understand the dependence of the building demand on outside weather, we plotted the electric load for occupied hours during weekdays against outdoor air temperature and relative humidity as shown in Figure 6. From the National Climatic Data Center, we acquired hourly outdoor air temperature data for each facility from the nearest weather station (NOAA). Some of the missing data were filled in by linear interpolation. As seen in Figure 6, both the office and campus buildings' electric loads were highly sensitive to the outside air temperature. However, some of the peak loads shown in the campus building's scatter plot were more influenced by the classroom schedule than outside weather. Both buildings did not show a significant relationship between building load and relative humidity.

C. Demand Limiting and Price Thresholds

In order to determine operation mode for each hour of the day, customers need to establish the demand and price thresholds to which the selection of a particular operation mode can be based upon. These thresholds can be updated as frequently as required (i.e., weekly, quarterly, or yearly). To help customers choose the appropriate demand and price thresholds for their facility, we first evaluated the buildings' load duration curves to look for demand reduction opportunities. Figure 7 shows the one-year load data (from September 2011 to August 2012) plotted in descending order over the proportion of time. For the office building, the weekday load duration curve descended at a gradual slope and there was no unusual peaks observed in the plot. The weekend/holiday curve was much lower than the weekday's since the office building was not in service during weekend/holidays. However, the weekend/holiday load during the top one percent was "peakier" than the rest. This was probably caused by night flushing and precooling of thermal mass performed during Sunday evenings in preparation for the next business day or occasional use of the facility over the weekends. For the campus building, the difference between

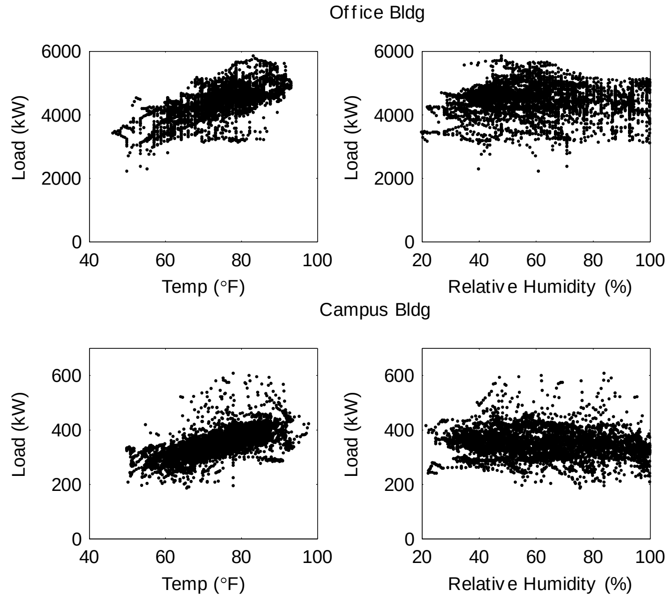

Figure 6. Scatter plot of load versus temperature and humidity. Data shown are from May to Aug 2012.

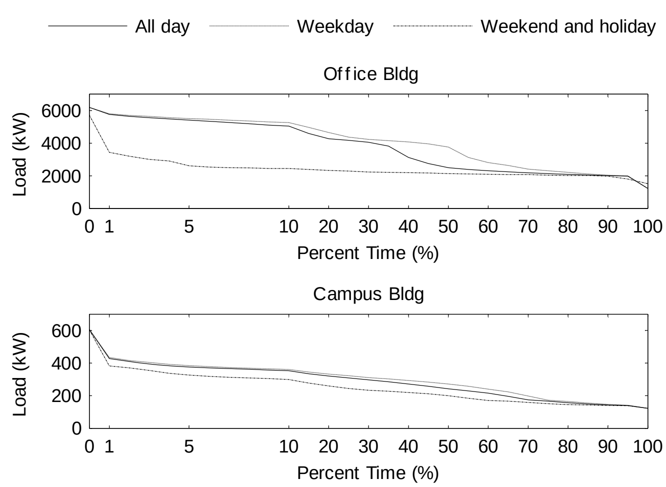

Figure 7. Load duration curves. Data shown are from Sep 2011 to Aug 2012.

the weekday and the weekend/holiday load duration curves was small since the building was in operation for seven days a week. Both curves showed a significant increase in load during the top one percent of the time. This behavior was probably caused by the system overload experienced during the first hour of the building operation. This issue can be resolved by shifting some loads to earlier times in the morning or later during the day and limiting demand below the level corresponding to the top one-percent of the time.

Similarly, price thresholds can be established by analyzing hourly price distribution over time. Figure 8 displays a price duration curves over the time period of September 2011 - August 2012. We used NYISO's day-ahead LBMP for Zone J: NYC since both the office building and the campus building were located in NYC (NYISO). Day-ahead LBMP did not vary significantly between weekdays and weekend/holiday and most of the time the price stayed below $100 per MWh. Only significant deviation was seen during the top one percent of the time where the price increased up to $363 per MWh. The loads corresponding to the top one percent of the time are concentrated in summer and winter months. When plotted against the time of day, it was clear that the expensive hours were either cooling hours (mid-day) or heating hours (morning and evening). Therefore, limiting the building's demand during the top one percent of the time via Auto-DR can help customers reduce energy cost.

D. DR strategies

Both the office and campus buildings currently participate in NYISO's SCR/EDRP through separate CSPs. For the NYISO initiated DR test/event, the office building have a minimum shed requirement of 2,000 kW. The shed requirement of the campus building has not yet been established. To help the facilities meet their DR targets, CSPs developed DR strategies for their clients that were used for previous DR test/events. Based on the customers' existing DR strategies, we selected the ones that could be automated and grouped them into *Critical*, *High*, and *Moderate* operation mode, as shown in Table 2. The project team added GTA capabilities to the office building to enhance DR control. Automating lighting control in auxiliary space such as hallways and lobby was discussed but was put on hold due to budget constraints. As for elevators, we recommended that the facilities maintain manual control over their elevators for both DR and non-DR days. To minimize the post-DR rebound effects, *Normal* operation mode returns slowly with sequential equipment recovery. If there is less than one hour left until the end of occupancy period, DR is extended to the end of the occupancy period and then the building returns to *Normal* operation mode.

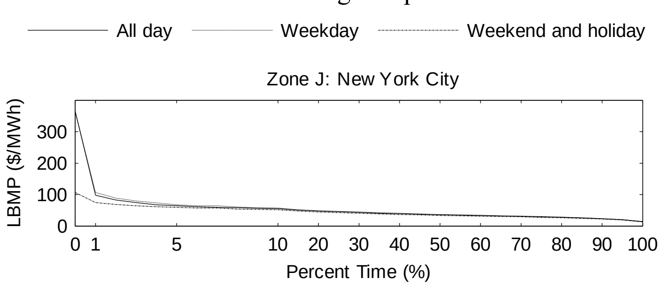

Figure 8. Price duration curves. Data shown are from Sep 2011 to Aug 2012.

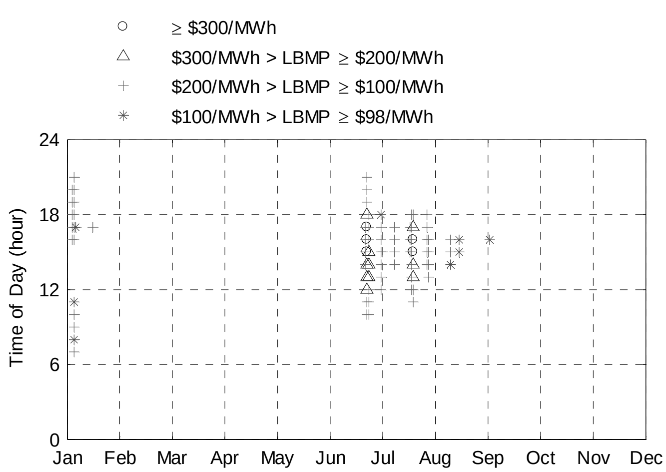

Figure 9. LBMP distribution against month and time-of-day during the top one percent of the time from Sep 2011 to Aug 2012.

TABLE II
DR STRATEGIES AND OPERATION MODES

Facility	Operation Mode	Global temperature adjustment	Precooling	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	Turning off lighting in auxiliary space	Slow recovery	Sequential equipment recovery	Extended DR control Period
Office Bldg	Critical	x	x	x	x	x	x	x	x	x	x		x	x	x
	High	x	x	x	x	x	x			x	x		x	x	x
	Moderate	x		x		x				x	x		x	x	x
Campus Bldg	Critical	x	x	x	x						x		x	x	x
	High	x	x	x	x						x		x	x	x
	Moderate	x		x							x		x	x	x

VI. EVALUATING DR PERFORMANCE

In this section, we show how Auto-DR can be performed on a non-DR event day and on a DR event day through field-test results and energy simulation. First, we examined the load data taken from the actual DR event day on June 20, 2012 that the office building participated, as illustrated in Figure 10. The DR event was called between 2pm and 6pm, during which the minimum 2,000 kW reduction was expected in reference to NYISO's Average Coincident Load (ACL) baseline (NYISO).[1] The office building achieved the reduction target only during the last two hours of the event period by activating all DR strategies listed under *Critical* operation mode. It experienced a post-DR rebound effect with an average spike of 12% from the baseline load over a one hour period. The maximum

[1] NYISO's ACL baseline averages customer's 20 highest loads of 40 highest system load hours excluding hours in which DR events were previously activated.

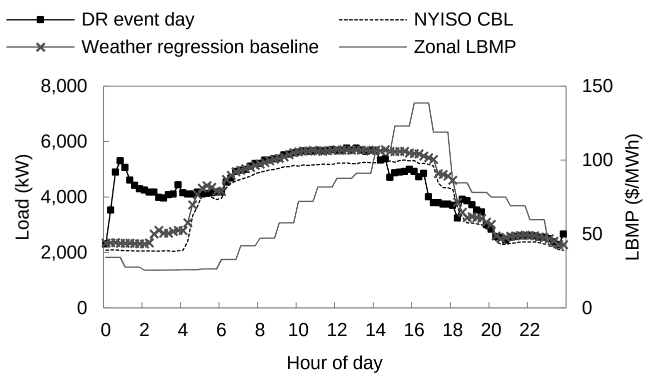

Figure 10. Load and price data of the sample DR event day.

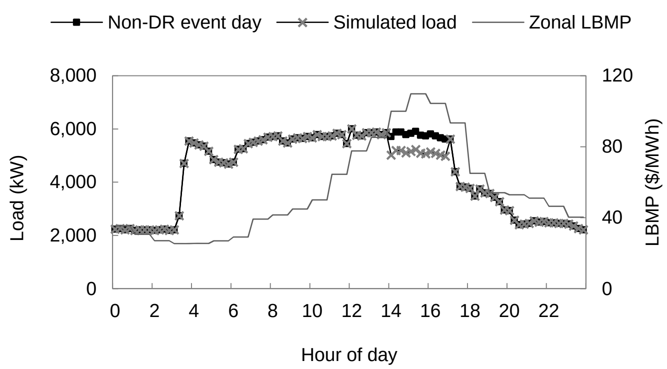

Figure 11. Load and price data of the sample non-DR event day.

rebound was recorded as 19% higher than the baseline load. To avoid the post-DR rebound effects, we recommended the development of DR recovery strategies for participating buildings. Next, we compared the load reduction with two different baselines to evaluate customer's DR performance: 1) NYISO's Average Customer Baseline (CBL) and 2) the weather regression baseline developed by LBNL (Coughlin et al., 2009).[2] NYISO's CBL has a tendency to underestimate or overestimate the building's power usage for the days with unusual weather conditions. In general, the weather regression baseline provides a more accurate prediction of weather-sensitive loads than NYISO's CBL. As seen in Figure 10, NYISO's CBL underestimated the baseline load because the DR event day was warmer than previous days. As such, DR payments would have been smaller if the compensation was calculated based on NYISO's CBL instead of the weather regression baseline.

Figure 11 illustrates the office building's response to price signals on a non-DR event day. The load data were taken from August 9, 2012, representing a typical weekday. The building underwent three hours of *Moderate* operation mode from 2pm to 5pm based on the price thresholds set at LBMP ≥ $98 for *Moderate* operation mode and LBMP ≥ $200 for *High* operation mode. We used EnergyPlus simulation to predict the effects of DR strategies for *Moderate* operation mode and compared the simulated load to the actual load which was unaffected by Auto-DR. According to the simulation results, the office building can reduce demand up to 700 kWh by implementing DR strategies listed under *Moderate* operation mode for this day.

It is noted that continuous energy management in response to hourly prices can impact the customer's DR baseline, potentially reducing DR payments due to lowered baseline usage. This can make DR programs less attractive to energy efficient customers under the day-ahead hourly pricing. However, DR program events are called only a few days a year and the incentives collected from DR programs are likely to be small compared to the utility savings achieved under day-ahead hourly pricing due to continuous energy management. Hence, as the commercial buildings move towards more dynamic response to prices, the applicability of baseline-based DR payments should be re-evaluated.

VII. Conclusions and Future Studies

We presented the process of automating continuous energy management with day-ahead hourly prices and demand response for large commercial buildings in New York who were subject to the default MHP tariff. OpenADR version 1.0 was used to facilitate the communication of price and reliability signals. Based on the preliminary findings from the New York demonstration project, we concluded that: 1) price response to day-ahead hourly pricing can be made easier through Auto-DR; 2) understanding customer's financial goals, such as reduction in utility bills including demand charges, and curtailment requirements by CSPs was critical in establishing Auto-DR goals and performance targets; and 3) price and demand response opportunities were unique to customer's electric load characteristics, control capabilities, and operational constraints.

Future studies include: 1) creating dynamic optimization capabilities in buildings given the availability of price and DR signals; 2) monitoring and evaluating the effects of control strategies on load and occupant comfort during operations; 3) increasing the customer's ability to modify and change individual control strategies within the facility; and 4) evaluating benefits and drawbacks of having Auto-DR intelligence in the cloud versus inside the facility. Finally, we recommend a comparative study on customer economics between MHP and retail rates to be conducted and the role of Auto-DR in cost savings to be further explored.

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[2] NYISO's CBL averages customer's five highest of the previous ten weekdays excluding holidays and previous DR event days.

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