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Findings from Seven Years of Field Performance Data for Automated Demand Response in Commercial Buildings

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Findings from Seven Years of Field Performance Data for Automated Demand Response in Commercial Buildings

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ABSTRACT

California is a leader in automating demand response (DR) to promote low-cost, consistent, and predictable electric grid management tools. Over 250 commercial and industrial facilities in California participate in fully-automated programs providing over 60 MW of peak DR savings. This paper presents a summary of Open Automated DR (OpenADR) implementation by each of the investor-owned utilities in California. It provides a summary of participation, DR strategies and incentives. Commercial buildings can reduce peak demand from 5 to 15% with an average of 13%. Industrial facilities shed much higher loads. For buildings with multi-year savings we evaluate their load variability and shed variability. We provide a summary of control strategies deployed, along with costs to install automation. We report on how the electric DR control strategies perform over many years of events. We benchmark the peak demand of this sample of buildings against their past baselines to understand the differences in building performance over the years. This is done with peak demand intensities and load factors. The paper also describes the importance of these data in helping to understand possible techniques to reach net zero energy using peak day dynamic control capabilities in commercial buildings. We present an example in which the electric load shape changed as a result of a lighting retrofit.

Introduction

California consumes about 60 GW of electricity on hot summer days. The commercial sector accounts for about one-third of this peak demand (Yin et al. 2010). Large buildings—those with peak electric demand greater than 200 kW demand—account for about 6 GW, or 10% percent of the summer peak demand, while small commercial buildings account for 10 to 12 GW, or 20 to 25% percent of the peak (Kiliccote et al. 2009a). California's peak demand has been increasing faster than total electricity use. Peak hours are expensive, and require more power plants, and a larger transmission and distribution system. The electric system is less reliable during peak hours because the system is more brittle when fully loaded.

Demand Response (DR) is a set of demand-side activities to reduce or shift electricity use to improve the electric grid reliability and manage customers' electricity costs. Fully-automated DR does not involve human intervention, but is initiated at a home, building, or facility through receipt of an external communications signal which triggers pre-programmed DR controls strategies. Automation helps improve the performance of DR programs by allowing the response to be more repeatable and reliable. The open and interoperable information exchange specification, which enables fully automated DR, was developed by the DR Research Center (DRRC) to reduce the costs of DR automation. This automated DR signaling system was named OpenADR (Open Automated Demand Response) to differentiate it from proprietary systems that are not interoperable (Piette et al. 2009). OpenADR uses utility-provided price, reliability, or event signals to automatically trigger customers' pre-programmed energy management strategies (Piette et al. 2006). OpenADR was developed between 2003 and 2006, using field tests and pilots, and commercialized in 2007 when it was adopted by California investor-owned utilities.

OpenADR consists of two parts, both built on an open interface standards model (Kiliccote et al. 2009b). First, a Demand Response Automation Server (DRAS) publishes signals that notify electricity customers of DR events. Second, a DRAS client located at the customer's site listens and provides automation signals to existing pre-programmed controls.

This paper reports on the status of OpenADR in California since its first field test implementation in 2003. First, we discuss the implementation of OpenADR and customer performance data in terms of load sheds and shed variability. On the one hand, we use the term "shed" to refer to the reduction in electricity use during a DR event compared to a standard baseline. On the other hand, in some cases the demand is "shifted", e.g., sites with pre-cooling. The majority of sites we automated "shed" load during DR events and do not make up that load within the same 24 hours. This paper also examines how the DR performs over time. We have explored the idea of DR shed erosion; do we see sustained, multi-year DR performance? We propose a set of metrics for evaluation of shed variability that can also be utilized for evaluating energy efficiency impacts on load in commercial and industrial facilities. We present a multi-year building analysis case study that illustrates the use of these metrics to identify the changes in the load shape due to energy efficiency measures and its effects on demand sheds. Finally, we summarize lessons learned and describe key issues related to the future of OpenADR.

Background

The automated DR data model development and field testing that began in 2003 involved five commercial buildings representing 500 kW of load shed. OpenADR implementations began in 2003 and 2004 as field test; continued in 2005 and 2006 as pilot studies to automate the Pacific Gas and Electric Company's critical peak pricing (CPP) program; and was offered in a third-party program in 2007. The number of DR participants increased throughout its seven-year history with current enrollment in automated DR (originally known as Auto-DR) programs in California providing over 60 MW of DR from over 250 commercial and industrial facilities. In 2006, the DRRC worked with San Diego Gas & Electric (SDG&E) on an Auto-DR pilot to demonstrate the performance of automation.

The California Public Utilities Commission's (CPUC) Assigned Commissioner's Ruling in August 2006 mandated all Investor-Owned Utilities (IOUs) in California offer Auto-DR programs to their customers starting in 2007. This marked the regulatory support for its commercialization. Since then, all three IOUs have developed their own ways of offering Auto-DR programs. Table 1 summarizes the automated DR programs in California today. California IOUs have offered automated DR programs since 2007 (Piette et al. 2006).

Table 1. Summary of Automated DR Programs since OpenADR Commercialization in 2007

Investor-Owned Utility	Year	Program	Market	Automated Signal Description	Number of DR events
Pacific Gas & Electric (Managed by 3rd Party)	2007 - present	Critical Peak Pricing (CPP)	Retail	Moderate price: noon -3pm High price: 3-6pm Normal price: All other times	Maximum 12
	2007 - present	Demand Bidding Program (DBP)	Retail	Standing bid with normal, moderate or high levels for each hour between noon and 8 pm	Varies by year (no minimum or maximum)
	2008	Business Energy Coalition (BEC)	Retail	High prices to indicate event	Varies by year (no minimum or maximum)
	2009 - present	Peak Choice (PC)	Retail	Similar to Demand Bidding but with more choices for customers	Varies by year and customer choice
	2009	Participating Load (PLP)	Wholesale	Normal, Moderate and High; Load Level.	Varies by year (no minimum or maximum)
	2010	Peak Day Pricing (PDP)	Retail	High Price between 2 pm and 6 pm.	Maximum 15
San Diego Gas & Electric (Managed In-House)	2007 - present	Capacity Bidding Program (CBP)	Retail	High Prices to indicate an event to aggregators	Varies by year (no minimum or maximum)
Southern California Edison (Managed In-House)	2007 - present	Critical Peak Pricing (CPP)	Retail	Similare to PG&E's CPP	Maximum 15
	2007 - present	Demand Bidding Program (DBP)	Retail	Standing bid with normal, moderate or high levels for each hour between noon and 8 pm	Varies by year (no minimum or maximum)

OpenADR Commercialization

LBNL's OpenADR commercialization in California began in the summer of 2005 when the DRRC and PG&E collaborated on a pilot project to automate price response. This section describes this pilot project including: 1) DRRC's research and development into DR deployment; 2) various facilities' DR strategies; and 3) utility incentives for OpenADR.

DR Deployment Activities During Commercialization

Transitioning OpenADR from field tests to pilots and initial commercialization was a major undertaking. The DRRC assisted each of the utilities in their deployment efforts. The goal in 2007 was to transfer the DRRC's knowledge to the utilities and develop a process to streamline automation by providing guidance on DR building control strategies, training on installation, and assistance on measurement and verification. Each utility developed a different method for recruiting and installation. PG&E continues to contract with a third party to run the Auto-DR programs with LBNL as a technical advisor. SCE integrated Auto-DR under their

Technical Audit/Technology Incentives (TA/TI) program, and SDG&E works with aggregators on automated CBP. SDG&E recently added automation of CPP to their DR portfolio.

DR Strategies

Throughout OpenADR commercialization, the DRRC continued research on DR strategies for commercial buildings and expanded research to industrial facilities (Motegi et al. 2007; McKane et al. 2008). While industrial customers participate in DR by reducing their process loads, commercial facilities typically modify their building services to detectable, but acceptable, levels (Newsham & Birt 2009). For hot summer afternoons, the most common reductions are from ventilating and air conditioning electric loads and lighting loads.

Utility Incentives

To encourage participation in OpenADR programs, the CPUC approved Technology Assistance and Technology Incentives (TA/TI) funding. This funding is available as a DR program participation incentive and is offered to cover the cost of automation enablement. The TA/TI funds have totaled $300/kW in the summer of 2007, 2008, and 2009. TA/TI funding is lowered to $250/kW for the 2009 to 2010 DR filing period. Kiliccote et al. (2008) review each of the incentives for PG&E's deployment. The recruitment fund was only available in 2007; in future years, those funds were redesigned to equipment installation incentives which were increased from $125/kW in 2007 to $180/kW in 2009. The equipment installation funds are available to offset the costs associated with the design, procurement, and installation of the OpenADR supportive technologies and measures. In nearly all cases, this incentive covered 100% of the customer's OpenADR project costs (Kiliccote et al. 2008). The customer participation incentive of up to $50/kW paid customers for their participation and validated performance during the DR-event period (May 1, 2007 through October 31, 2007). Finally, the technical coordinator incentive paid for the services of trained energy management control system vendors, who worked to ensure that the Auto-DR equipment was properly operating and that estimated load reductions were being realized. The change in allocation of the $300/kW shows the progress of Auto-DR programs in California. Equipment installation continues to be the largest allocation. Equipment installation incentives are used for pre-programming building controls and enabling secure communication. In cases where a building automation system is not available, installation of a building controls system is also funded by the incentive. The Customer Participation incentive is actually decreasing over time, suggesting that the program is attractive on its own. This may be attributable to Auto-DR's reduced cost of labor compared to manual response and its reduction in overall electricity costs for the facility. The incentive for the Technical Coordinator is also decreasing in proportion to the reduced level of engagement over time by the Technical Coordinators.

OpenADR has proven a successful means of implementing DR strategies developed by the DRRC and reducing the peak demand on hot summer days in California. DRRC's OpenADR field tests in the Pacific Northwest in both the winter and summer with the same sites showed that similar DR strategies can be developed for winter and the facilities' energy management and control systems can deliver year round DR (Kiliccote et al. 2010).

OpenADR Deployment in California

This section describes OpenADR deployments in California, between 2007 and 2009. It also presents a longitudinal analysis of OpenADR performance at a retail store.

OpenADR Programs: 2007 to Present

Commercialization and large-scale implementation of OpenADR programs began in 2007 and continue to date. Figure 1 displays DR programs automated each year from each of three California IOUs. The majority of the OpenADR programs are price-responsive DR programs, in which customers adjust their loads to avoid higher electricity charges or sell their energy back to the utility. DR events are announced a day ahead or on the day of the DR event. Figure 1 also summarizes the number of accounts in each program and load shed they deliver as an aggregate.

In California, customers in DR programs extend beyond individual commercial and industrial customers to DR aggregators, who deliver DR through managing a portfolio of retail customers. In San Diego, Auto-DR customers participate in the Capacity Bidding Program which is aggregator-dominated. Aggregators bid their customers' demand five days prior to the start of a month and receive capacity payments each month and energy payments on DR events.

Figure 1. Automated DR Programs in California by Utility

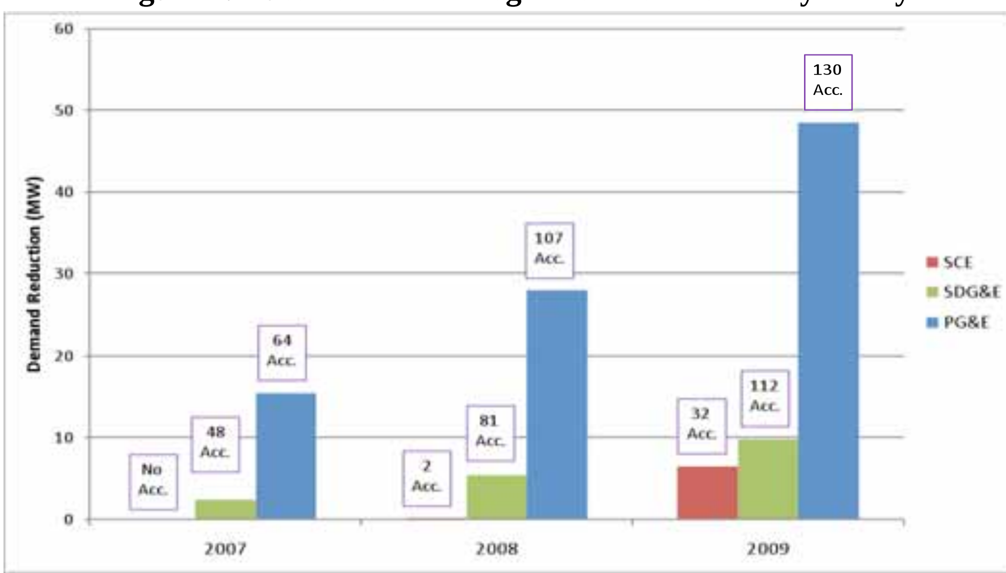
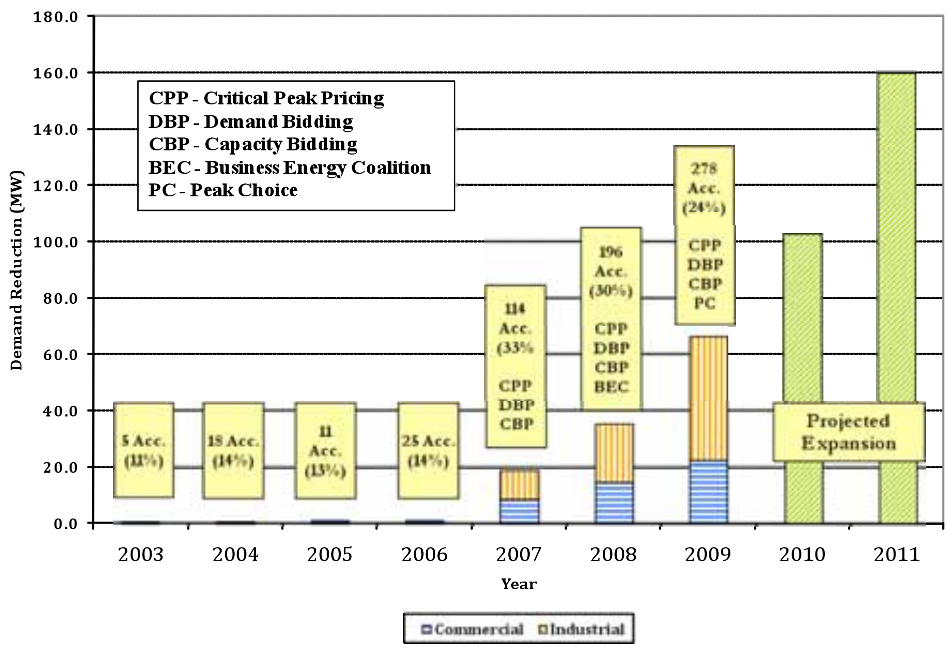


Figure 2 shows trends in Auto-DR implementation in California from 2003 to 2009 with projected expansion in 2010 and 2011. The projected expansion numbers are derived from 2009 to 2011 utility filings and the Department of Energy Smart Grid Investment Grant to deliver 80 MW of DR in California using OpenADR. The number of participants in OpenADR programs increased steadily from 2003 to 2009. The graph shows the total demand reduction (from all of the facilities) achieved each year. The percentage values are the average percent peak demand reduction for all facilities in the given year. The average percent peak demand reduction is calculated by dividing the average actual load shed by the baseline peak load for each DR event. The boxes above the bars list the number of accounts that participated.

The graph shows an increase throughout the years in number of accounts as well as demand reduction enabled with automation. This increase in participation can be attributed to: 1) the goals that the utilities set forth in their 2006 and 2009 DR filing; 2) the incentives that are offered to customers that cover the cost of automating DR program participation; and 3) industrial facilities that participate in auto DR programs tend to be larger and tend to reduce a higher percentage of their load during DR period. The increase in the average percent peak demand reduction from 14% to 33% between 2006 and 2007 is due to industrial facilities participating in Auto-DR programs. Industrial peak load reduction dominates the demand savings in OpenADR programs and made up 55%, 58%, and 70% of customers' demand in 2007, 2008, and 2009, respectively. These customers are targeted for recruitment since they deliver a large demand shed that can often fulfill utility goals.

Figure 2. Demand Reduction Summary for Automated Demand Response, 2003 to 2009 with Projected Expansion through 2011



While the trend over the past years displays an increase in aggregate demand reduction, a close look at individual buildings shows that there is high variability in demand shed over each DR event in the same year as well as variations in different years. Automation guarantees that each building is operated in the exact same way at each DR event. Some buildings, however, increase their demand reduction during the DR periods, while others yield reduced demand savings over time. Figure 3 displays average shed of 36 DR events between 2006 and 2008 and the estimated demand reduction, or shed, for 22 of the initial CPP participants using an outside air temperature regression baseline (Piette et al. 2006). The error bars on the average shed indicate minimum and maximum demand reduction. There is no general trend, up or down, in the shed variation of all the sites.

Figure 3. Shed Variation of 22 Auto-CPP Customers between 2006 and 2008

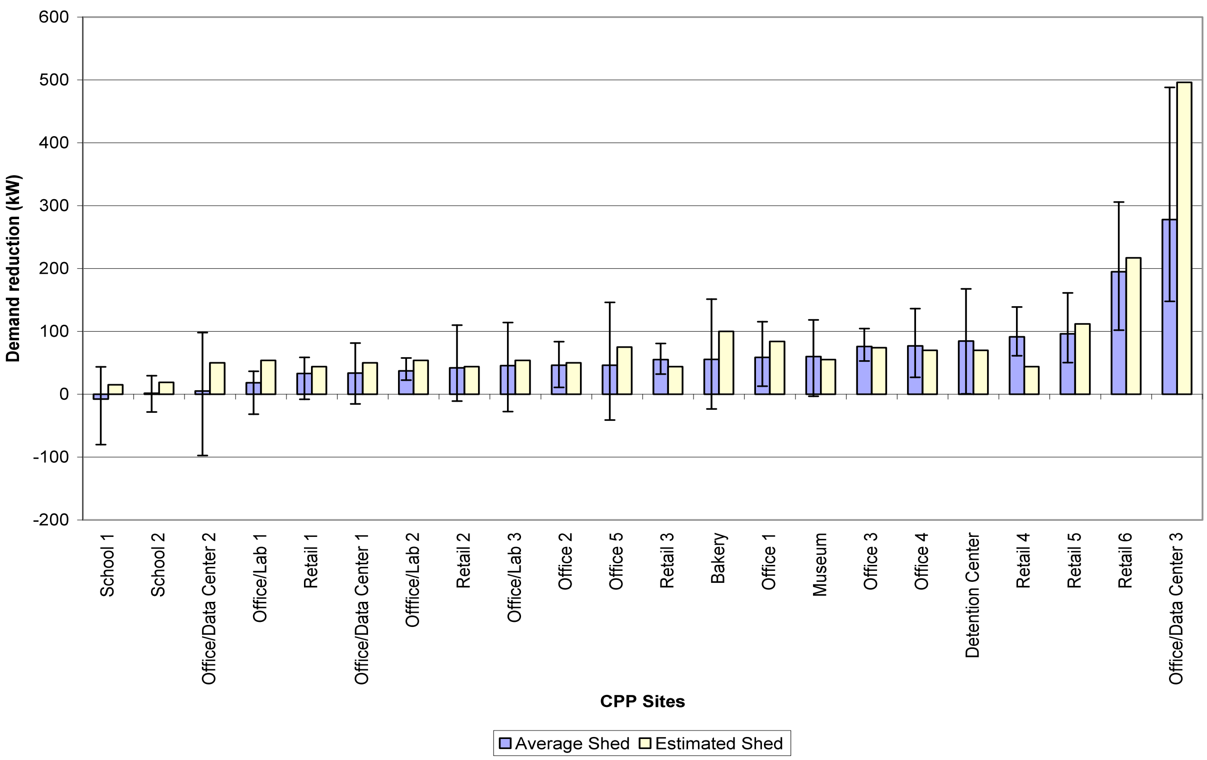


Figure 3 underscores the following research questions:

1. Although each site is implementing the same DR control strategy each time a DR event is called, why do the sheds vary?
2. What are the factors that effect shed variability?
3. How do actual performances over time measure against initial estimates?

In the next section we concentrate on the first question and state our hypothesis on the remaining questions. We develop a framework and metrics and apply these to an existing building.

Methodology

DR sheds are estimated by subtracting the actual load on a DR day from a baseline that predicts loads if there was no demand response. Accuracy of the baseline is an important and complex issue (Coughlin et al. 2009). Over time, sheds may increase, decrease or fluctuate. Since up to 12 CPP events are called each year, the availability of multi-year historical interval meter data are available for some of the facilities. As we examine shed variability, we have developed methods to account for variations in weather. Weather normalization is done by computing temperature-based baseline regression models for each year. We use one year's hourly temperature data to predict demand for other years. To evaluate the shed variability of a facility, we suggest the following metrics:

- **Energy Use Intensity (EUI):** EUI is a measure of total energy use, typically over a year, normalized for floor area (kWh/ft^2-yr^2). EUI may be reduced by many site-specific factors such as increased efficiency or reduced operational hours.

- **Load Factor:** Load factor is a measure of the uniformity of electrical energy use calculated by dividing the kilowatt-hours consumed during a period by the peak demand for the same period times the hours during the period.
- **Load Statistical Summary**: This is a summary of hourly loads where the average, minimum and maximum monthly loads are calculated. Other metrics that are useful include "near-peak load" and "near-base load" which represent 97.5 and 2.5 percentile loads.
- **Load Variability and Weather Sensitivity**: We calculate the variance of load divided by the average load to get a percentage that represents load variability. For weather sensitivity calculations, we use rank-order correlation to temperature and load values from highest to lowest, replace these with ranks and calculate the correlation of ranks for each hour.
- **Peak Electric Demand Intensity**: This metric is the annual maximum peak electrical demand per unit of gross building area (W/ft^2).

The next section is a case study applying these metrics to evaluate how DR varies over time.

IKEA East Palo Alto Study

This section provides an analysis of multi-year DR at IKEA East Palo Alto (EPA), which has used OpenADR since 2006. IKEA EPA is a two-story, 300,000 ft^2 facility with 43 rooftop packaged units. In 2009, maximum demand for this facility occurs during the weekend at 1.4 MW. Weekday maximum demand is 1.2 MW. Over the last three years, this site has participated in an energy efficiency retrofit as well as automated CPP. The site has low load variability (0.08 or 8%) and high weather sensitivity (0.77). The EUI for 2009 is 17.5 kWh/ft^2-yr with a load factor of 44%. Table 2 presents summary statistics for this facility in 2007 and 2009 for the entire year. These values are not weather normalized. To compare energy usage at IKEA EPA year-to-year, we weather-normalized IKEA EPA's 15-minute interval demand data by computing temperature-based regression baseline models for each year (2006 to 2009) and then used summer (May 1 through Sept 30) 2006 interpolated temperature data from nearby NOAA weather stations to predict demand for each summer.

Daytime and nighttime demand were computed separately since the building operates in different modes (and therefore has a different temperature dependence) in day and night. Daytime demand was computed, assuming a piecewise linear and continuous temperature dependence, as:

$$D_d(i) = \alpha(i) + \sum_{j=1}^{6} \delta_j T_c(i,j)$$

where i is a 15-minute time interval, $\alpha(i)$ is a parameter that characterizes temperature-independent load at interval i, δ_j's are six temperature parameters each assigned to a different outdoor air temperature interval (e.g., <40° F, 50 to 60° F, etc.), and $T_c(i,j)$'s are components of the outdoor air temperature at interval i, T(i), that are assigned to each temperature interval. Nighttime demand was computed, assuming linear temperature dependence, as:

$$D_n(i) = \alpha(i) + \delta_n T(i)$$

where δ_n is a nighttime temperature parameter. More details about the baseline model can be found in Mathieu et al. (2010).

Using the weather-normalized models, we computed total energy consumption and peak power usage for each summer. Peak power was computed as the average of the three highest 15-minute interval demands throughout the summer. Results are given in Table 3. The weather-normalized results show that IKEA EPA has become more energy efficient each year. Peak power savings were inconsistent, though this is likely, in part, a result of our methodology.

Table 2. Summary Statistics for Retail Store for 2007 and 2009 (Not weather normalized).

Summary Statistics	2007	2009
Load Factor (%)	55	44
Weekday Load Factor (%)	57	50
Weekend Load Factor (%)	56	46
Maximum Demand (kW)	1,295	1,417
Weekday Maximum Demand (kW)	1,248	1,244
Weekend Maximum Demand (kW)	1,295	1,417
Average Demand (kW)	712	630
Minimum Demand (kW)	0	0

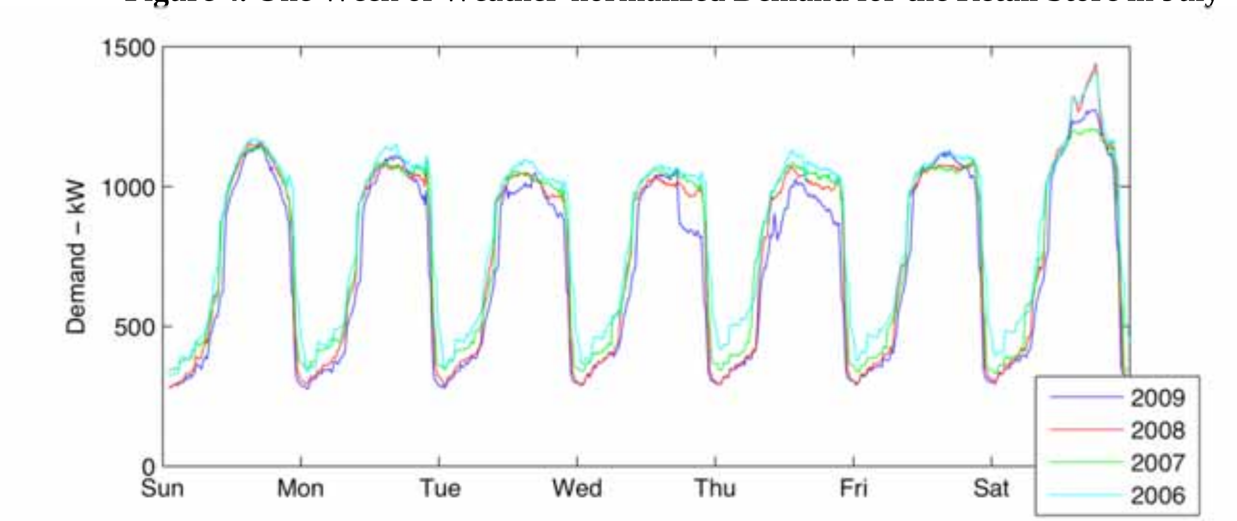
Table 3. Summer (May 1 to Sept. 30) Percent Energy and Peak Power Savings as Compared to 2006

	Weather Normalized			Not Weather Normalized		
	2007	2008	2009	2007	2008	2009
% Energy Savings	4%	10%	15%	4%	10%	15%
% Peak Savings	14%	-3%	11%	12%	9%	5%

We used outdoor air temperature data from the third week in July 2006 to generate plots of weather-normalized demand (Figure 4). The plot shows a reduction in energy use from year-to-year which is especially visible in the facility's night-time loads.

IKEA EPA participated in automated CPP program from 2006 to 2008 (in 2009 they participated in an wholesale DR pilot). In addition to reducing energy use, IKEA EPA's DR parameters changed over time. To demonstrate this change, we used a baseline model (described above) to predict what IKEA EPA's demand would have been without DR, subtracted the predictions from the actual demand data to produce DR residuals, and then analyzed the residuals.

Figure 4. One Week of Weather-normalized Demand for the Retail Store in July

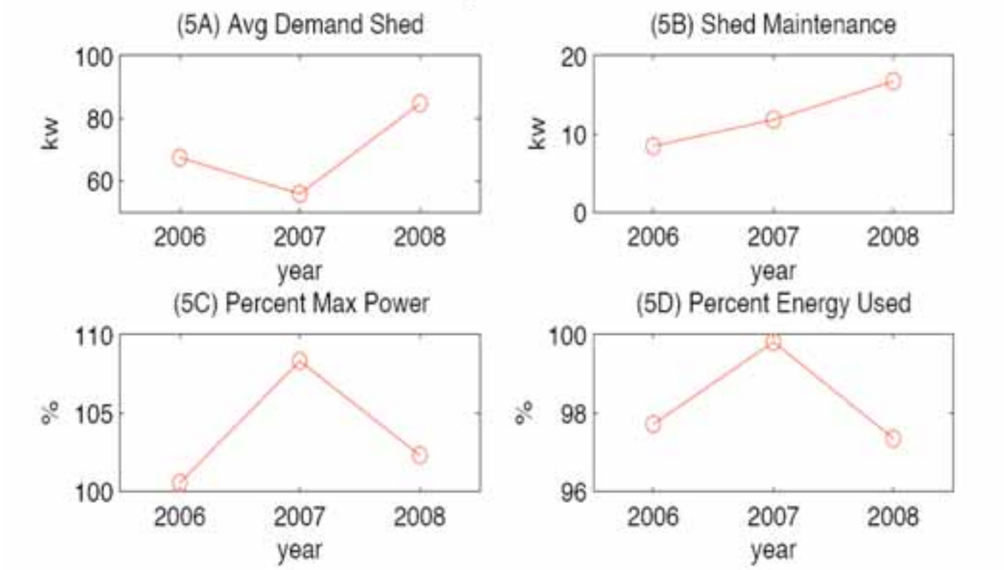


Details on this methodology are in Mathieu et al. (2010). Specifically, we looked at the following DR parameters computed for an average CPP event day for each year (Figure 5):

- *Average Demand Shed (kW):* the average power shed during the CPP event, calculated for the high price period.
- *Shed Maintenance (standard deviation of demand shed) (kW):* the standard deviation of power shed during the CPP event, calculated for the 3 pm to 6 pm (high price) period.
- *Percent Maximum Power (%):* the actual maximum daily demand divided by the baseline-predicted maximum daily demand.
- *Percent Energy Used (%):* the actual daily energy use divided by the baseline-predicted daily energy use.

As can be seen in Figure 5, the average demand shed (5A) decreased slightly between 2006 and 2007 and then increased in 2008. During the same period, shed maintenance (5B) grew showing that IKEA EPA became less able to maintain a steady shed throughout the three-hour period Percent average energy (5D) is consistently less than 100% indicating that on CPP event days IKEA used less energy than on normal days. However, percent maximum power (5C) is greater than 100% indicating that IKEA EPA's load shape is 'peakier' on CPP event days. This is because IKEA EPA's exhibits post-event rebound peaks. Figure 5A shows that DR capabilities do not necessarily decrease as facilities use less energy, though demand shed erosion has been seen in other cases. Energy efficiency and DR have a complex relationship that will be the subject of a future paper. The findings from this case study, and indeed, from the Auto-DR data presented in Table 3, inform our future research directions and our discussion of the future of Auto-DR in California and nationwide.

Figure 5. Change in DR Parameters for 2006 to 2008, Computed for an Average CPP Event Day for Each Year



The Future: Key Implementation Issues

There is a number of important issues that utilities and regulatory agencies must address if OpenADR is to have wider adoption. We describe four key issues:

Better Linkage of Energy Efficiency and Demand Response

As shown in Figure 3, peak loads can change over time as customers conduct retrofits or implement DR strategies such as precooling as standard practice or running at warmer indoor temperatures. More research is needed to better understand the effects of energy retrofits (e.g., lighting retrofits) and DR participation by examining whole building load profiles and customer economics. Some customers who participate in DR are also likely to implement permanent energy efficiency measures, thus reducing their peak load permanently and making it more difficult to achieve the same load shed in DR events.

Market Transformation

As energy prices rise, we expect commercial and industrial customers to focus more on energy management resulting in commercial buildings being equipped with energy management and control systems as well as new codes that govern the performance of these systems. In the past, global temperature adjustment strategy, the most commonly used strategy for DR in commercial buildings, was adopted by Title 24 making each new building less costly to participate in DR manually. Similarly, any language developed and developed into codes that facilitate Auto-DR can reduce the cost of DR automation and increase participation.

Dynamic Rates and Renewables

Currently, all of the IOUs in California are moving their large customers from time of use rates to default dynamic rates. These rates are complex with many exceptions and some with reservation capacity options. If the complexity of the rates does not daunt the customers and cause them to opt-out of these rates, OpenADR can provide the peak day information to the customers and can be used to automate their response to high price periods. In addition automation is the key to fast DR where customers have to respond to grid signals within minutes and sometimes within seconds. The DRRC is conducting a study to evaluate how DR can mitigate the effects of intermittency of renewable generation on the electric grid.

Mainstreaming OpenADR

OpenADR is an open and interoperable information exchange model that has been facilitating the automation of DR programs in California. In 2008, DRRC published OpenADR as a draft specification and through the involvement of key stakeholders and current Smart Grid leaders, it was further developed and published in May of 2009. OpenADR was among the first 16 standards that the U.S. Department of Labor and U.S. Department of Energy identified as the key standards for Smart Grid. The OpenADR specification will be the basis for ongoing DR and distributed energy resource communications standards development efforts within both the Organization for the Advancement of Structured Information Standards (OASIS)[1] and the UCA International Users Group (UCAIug)[2]. With ongoing efforts of OASIS and UCAIug organizations, both of which are active in the emerging "Smart Grid" domain, OpenADR is on a path to become a formal standard within organizations such as the International Electrotechnical Commission (IEC).[3] With support from Smart Grid investment and demonstration grants, and other Smart Grid initiatives, OpenADR is under consideration to be deployed in Florida, Nevada, Hawaii, Oregon and Washington. Outside of the United States, OpenADR is currently under discussion for deployments in Canada, India, Korea and Australia.

Conclusion and Future Research

We summarized the OpenADR deployment and discussed the DR variability over time. We described a case study evaluating multi-year building energy use, comparing total electricity use and DR in 2006 through 2008. While the metrics allow us to quantify shed variability, understanding root causes of shed variation requires deeper understanding of trends in operational issues and contributing factors such as occupancy and other loads. A larger sample size and additional data are required to better understand these trends. As OpenADR expands, and more data are available from a larger sample of buildings, we plan to benchmark the peak demand of OpenADR buildings against other commercial buildings data. As outlined in the preceding pages, implementing OpenADR reduced peak demand by 14% on average in commercial buildings throughout California. Going forward, we anticipate expanding our research to dynamically identify and reduce loads in response to prices year round where prices are used to represent generation, transmission and distribution issues with the grid. As OpenADR gains adoption in California and beyond, more research is needed to better understand the issues outlined above and to understand how OpenADR can be implemented in other sectors, climates and market structures. Of particular interest are refrigerated warehouses, data centers, DR strategies for humid climates and automation of DR for dynamic prices.

[1] www.oasis-open.org/home/
[2] www.ucaiug.org/
[3] www.iec.ch

Acknowledgments

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