In Proc. 4th IEEE International Smart Cities Conference (ISC2 2018), September 16-19, 2018, Kansas City, Missouri, USA

Impact of HVAC Set Point Adjustment on Energy Savings and Peak Load Reductions in Buildings

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***Abstract*—Quantifying energy savings and peak demand reduction potentials in a building due to adjustment of HVAC set point during a demand response (DR) period is critical for active DR program participation and optimal demand-side resource allocations. This has been a topic of great challenge given the complex nature of physical characteristics and HVAC system thermal dynamics in commercial buildings. Based on the building model developed in eQUEST validated against measured power consumption data from a smart meter, this paper investigates how energy savings and peak demand reduction potentials of a building are impacted by HVAC set point changes during a DR period. Simulation results reveal that the days with high outdoor temperature are expected to achieve a predictable percentage of daily energy savings and peak load reductions when HVAC set points are raised in summer. However, the inevitable demand restrike, i.e., increase in building peak demand after a DR event, is a concern.**

Keywords— eQUEST; building simulation; demand response; energy savings; peak load reduction; demand restrike.

I. Introduction

As the fundamental component of modern cities, buildings contribute to about 40% of the total energy consumption in the U.S [1]. Due to variation in day-to-day occupant activities and outdoor weather conditions, building power consumption profiles tend to have irregular patterns across different days but with noticeable weekly and seasonal patterns, which results in peak loads typically on hot summer days. The existence of peak load has posed significant challenges to the economic and efficient operation of the power grid. The idea of demand response (DR) is therefore raised for mitigating power grid stress conditions [2]. DR serves as a financial incentive for customers, who compromise parts of their power usage need to reach the targeted energy savings or peak load reductions [3]. Buildings actively participated in DR programs can contribute to improving the reliability and efficiency of the smart grid, and serving as building blocks of functional smart cities. Among different building end-uses, space heating and cooling can be considered as the most energy-intensive load in buildings. Therefore, heating, ventilation and air conditioning (HVAC) is usually the most suitable load for participating in DR programs. However, there is no reasonable guideline for selecting the HVAC thermostatic control strategy due to the lack of knowledge that maps the set point change with the expected energy savings and peak demand reductions. This knowledge gap prevents electric utilities from effectively allocating DR resources, and at the same time spoils customers' enthusiasm to participate in DR programs.

Common HVAC system control strategies for DR include: fan control [4]–[5], rooftop units coordination [6] and thermostatic control [7]. Among them, thermostatic control requires no additional hardware investment and can be easily implemented. As thermostat set point directly decides energy consumption behaviors of HVAC system, it is intuitively understandable that its change will largely impact building electrical load profiles in summer. However, traditional load forecasting methods [8]–[12] can only respond to the outdoor temperature change but not the set point adjustment, as set point schedules are assumed to behave constantly on both training horizon and testing horizon. This brings the objective of this research: to study how a short-term HVAC set point change influences energy savings and peak demand reduction potentials in buildings under various outdoor weather conditions.

To achieve the above targets, an exhaustive exploration on set point variance is necessary. Experiments on set point adjustments are inefficient and practically infeasible in a real-world building. Hence, a DOE-2 engine first-principle software tool, eQUEST, is chosen to capture the detailed building thermal dynamics and simulate the interaction between set point changes and building load shift in this study. The feasibility of applying the first-principle building simulation tool to fit with real building physical characteristics and thermal dynamic are discussed in many literatures and the methodology is maturely developed [13]–[15]. Few studies have analyzed the relationship between set point adjustments and demand response potentials. Although the framework proposed in [16] can be applied to roughly estimate the DR potential (%) of a certain building, this framework relies on a large number of simulation runs on hundreds of prototype buildings by manipulating building's parameters, which is time-consuming and over-generalized. This work contributes to the idea of quantifying such a relationship relying only on the hourly power meter data gathered from the investigated building. The conclusion made in this paper can serve as a guideline to estimate energy savings/DR potentials tailored to a specific building. Such a methodology can be possibly extended to the distribution level to help construct more energy-efficient and self-aware smart grids and smart cities.

In order to enable energy savings/peak demand reduction analysis using the case of a specific real-world building, the

work performed in this study is divided into three steps: (1) building model development & validation; (2) set point exploration; and (3) pattern recognition. The first step is to develop the building model in eQUEST and validate the simulation output against smart meter data (kWh). The second step is to collect enough energy savings and peak demand reduction response of the developed building models under different thermostatic control strategies. The third step is to explore hidden energy savings/peak demand reduction patterns under different outdoor temperature conditions based on the data collected from the second step.

The paper is organized as follows: Section II introduces the building model development process and validation results, using one commercial building as an example. Results obtained from the set point exploration and pattern recognition steps for the same building are discussed in Section III. Conclusion and suggestion of future work is presented in Section IV.

II. Building Model Development & Validation

A. Building Description

The selected building for demonstrating the building modeling & validation work is a three-story building with the building area of 17,340 square feet. This building has an H-shape footprint, comprising one rectangular and one square buildings connected with each other. The outer wall is made of brick and concrete materials with two glass doors on the West side of the building. There are 122, 35 and 60 windows installed on the West, South and North, respectively. Building operation starts from 8AM to 6PM on weekdays and it is closed on weekends. Fig. 1 depicts the 3D model of this building developed in eQUEST. Anonymized metered electricity data (kWh) from August 1, 2016 to July 31, 2017 are used for eQUEST model validation at one-hour intervals as shown in Fig. 2.

B. Building Model Development

The building model development was performed using the Wizard mode and the Detailed Data Edit mode in eQUEST.

In the Wizard mode, building envelope, construction materials, floor plan, office equipment/lighting/computer server intensity, HVAC system type, HVAC capacity, activity area distribution and seasonality were defined based on the anonymized building information provided by Commonwealth Edison Company, electric utility in Chicago area, USA. The seasonality, non-HVAC load (office equipment/lighting/computer server intensity) and HVAC capacity were assumed by observing the building hourly electricity load profile throughout a year based on smart meter data (kWh).

The next step is to fine-tune the outputs from the Wizard mode in the Detailed Data Edit mode. To accomplish this, the building load profile was analyzed by breaking it down into three categories: fixed load, flexible load and weather-dependent load portions.

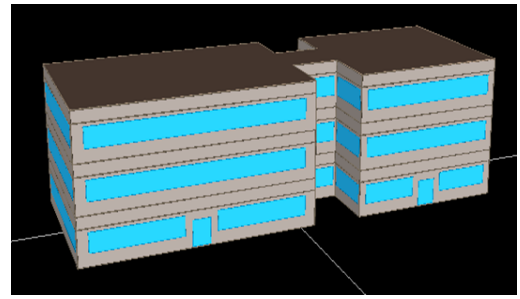

Fig. 1. 3D building envelop developed in eQUEST.

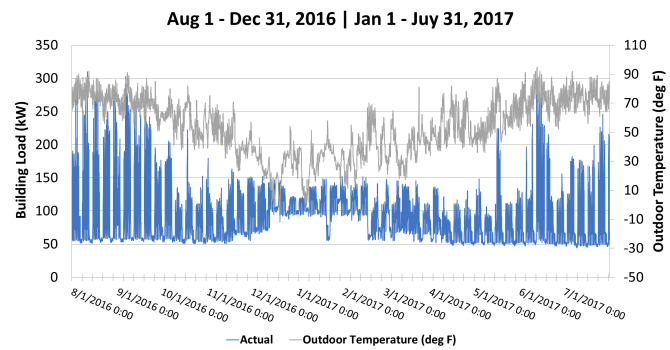

Fig. 2. Hourly building load (kW) from Aug 1, 2016 to July 31, 2017 from a smart meter.

- The fixed load portion represents the lower boundary of the building load that varies every season. This information was used to define the base load density (W/sqft) in eQUEST.
- The flexible load portion represents daily load usage patterns that are relatively constant across weekdays or weekends for a season. This information was used to define the hourly usage schedules of office equipment and lighting loads on weekdays/weekends.
- Lastly, the weather-dependent load portion is sensitive to outdoor temperature conditions and contributed fully by HVAC systems. Based on this weather-dependent load, the size and efficiency of HVAC systems were defined, together with their schedule set points.

With the initial knowledge of a building electrical load density (based on industry standards and actual building load profiles), as well as initial assumptions on hourly usage profiles of building loads and HVAC system sizes and schedule, these parameters were adjusted in the eQUEST model. Simulated hourly electricity consumption (kWh) data from eQUEST were compared against the smart meter data. In the case of differences between the simulated and measured data, these parameters were adjusted to capture the information regarding daily usage patterns across different periods.

C. Model Validation

Fig. 3 shows the comparison between the actual and simulated monthly building electricity consumption (MWh) for 12 months between August 2016 and July 2017. The

simulated monthly electricity consumption closely fits the actual consumption with the average monthly error of 2.21%.

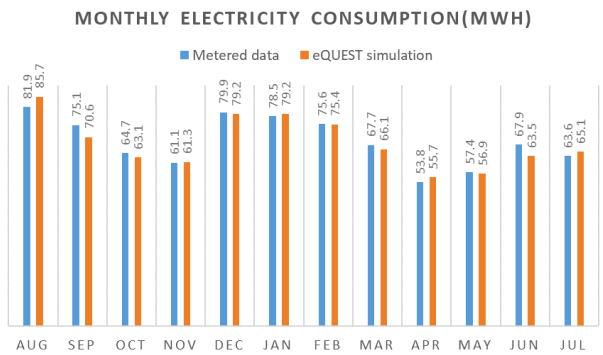

Fig. 3. Actual and simulated monthly building electricity consumption (MWh).

Fig. 4 and Fig. 5 show the detailed comparison between actual hourly building load with simulated hourly building load (kW), for the periods of one year and one week, respectively. Fig. 4 demonstrates that the annual load pattern can be modeled quite satisfactory; and the building load model is able to respond to the outdoor temperature variance. Fig. 5 illustrates that the simulated hourly load also closely follows the actual load.

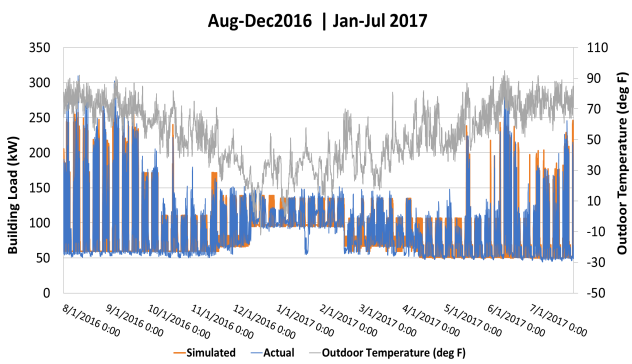

Fig. 4. Actual and simulated hourly building load (kW) from August 1, 2016 to July 31, 2017.

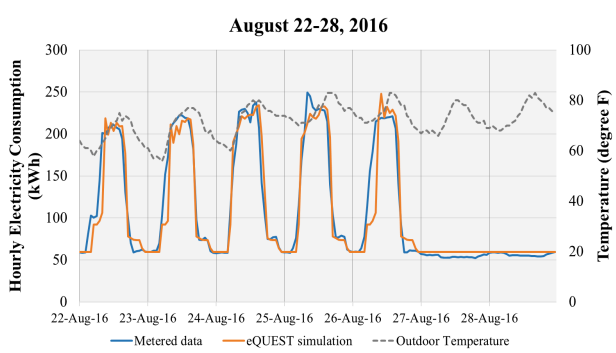

Fig. 5. Actual and simulated hourly building load (kW) for one week.

Fig. 4 and Fig. 5 demonstrate that building load schedules and load distribution can be adjusted in the developed eQUEST building simulation model to effectively reflect operating characteristics in the actual building, thus validating the model.

III. Set point Exploration and Pattern Recognition

Intuitively, outdoor temperature profiles have considerable influence on power consumption of HVAC load in buildings. Significant differences on energy savings and peak load reductions are expected for same thermostatic control on two days with different outdoor weather conditions.

A. Energy Savings and Peak Demand Reduction Analysis

To generalize how outdoor temperature profiles impact energy savings and peak demand reduction potentials of a building, HVAC set point adjustment exploration and pattern analysis were conducted using the validated eQUEST building model discussed in Section II. Set point adjustment exploration is necessary for collecting enough raw data to be analyzed. This was done by deploying HVAC temperature set point adjustments (i.e., +1, 2, 3, 4 and 5°F) from the base-case set point (70°F) between 12noon-3PM (i.e., DR period) every day during mid-April to mid-October.

On each day during this period, the following information was collected and plotted against the average outdoor temperature between 12noon and 3PM:

- *Daily energy savings (%)*, which was calculated as the ratio of daily electricity savings (kWh) from the base case when the set point was raised by 1-5°F during the DR period to the baseline daily electricity consumption (kWh) when the set point was at 70°F. See Fig. 6.

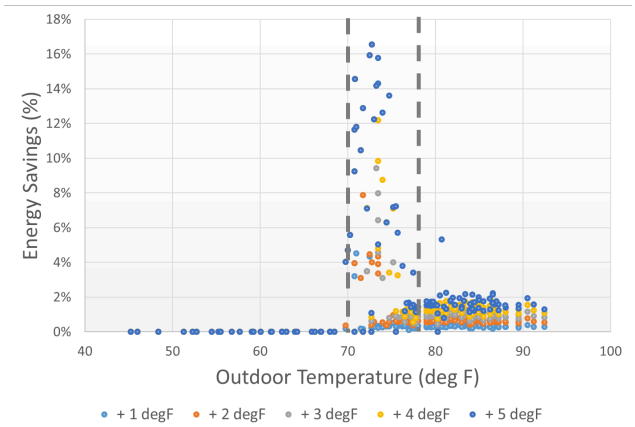

Fig. 6. Relationship between energy saving potential (%) and the average outdoor temperature (℉) during DR hours (12noon-3PM).

- *Peak demand reduction during DR period (%)*, which was calculated as the ratio of peak load kW reductions during the DR period when the set point was raised by 1-5°F from the base case to the baseline peak load (kW) during the DR period when the set point was at 70°F. See Fig. 7.

- *24-hr peak demand reduction (%)*, which was calculated as the ratio of peak load kW reductions when the set point was raised by 1-5°F from the base case for the entire day to the baseline peak load (kW) when the set point was at 70°F. See Fig. 8.

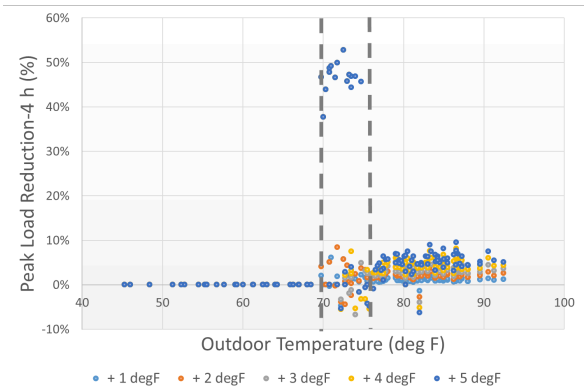

Fig. 7. Relationship between peak demand reductions during DR period (%) and the average outdoor temperature (℉) during DR hours (12noon-3PM).

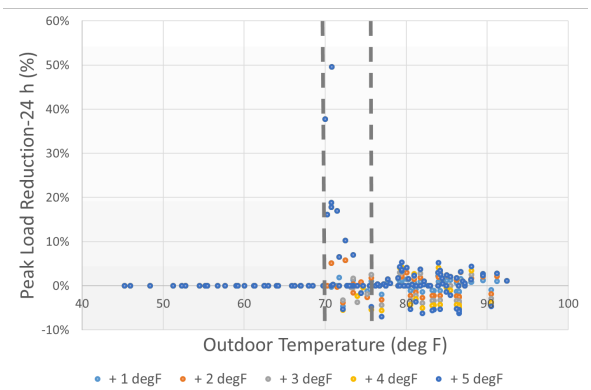

Fig. 8. Relationship between 24-hr peak demand reductions (%) and the average outdoor temperature (℉) during DR hours (12noon-3PM).

Note that while the peak demand reduction percentage during DR (%) measures the ability of thermostatic control for shaving the distribution system peak, the 24-hour peak demand reduction percentage (%) evaluates the performance of building peak load shifting.

It can be seen from Fig. 6-8 that the average outdoor temperature during 12noon-3PM varies between 45°F and 93°F between mid-April and mid-October. Two dashed lines in Fig. 6-8 differentiate how the outdoor temperature influences energy savings/peak demand reduction potentials of this building. The dashed line on the left of each graph corresponds to the "base-case set point" of the building, which is 70°F. The dashed line on the right of each graph indicates the "threshold outdoor temperature value", i.e., the average outdoor temperature above which results in predictable energy savings/peak demand reduction values. Notice that the left dashed line locates at the same position on all figures as the baseline set point is always the same; but the right dashed line is placed on a different location on each of the figures, indicating different threshold values.

Based on Fig. 6-8, three distinct patterns were recognized:

1) When the average outdoor temperature during the DR period is lower than the base-case set point, which is 70°F for the selected building, this building appears to have neither energy savings nor peak demand reduction potentials by increasing HVAC set point. This is because AC does not operate on those days. Very few points lying on the left side of the left dashed line show non-zero values due to high internal heat gain before DR begins.

2) When the average outdoor temperature is above a certain threshold value (i.e., 76-78°F in this case), daily energy savings and peak demand reduction potentials during the DR period are relatively constant and somewhat predictable. This is because raising the set point is equivalent to making HVAC operates less often. Note that if the outdoor temperature is extremely high, increasing the HVAC set point might not be able to provide any savings as HVAC will always be required to operate. Meanwhile, demand restrike events are observed in peak load reductions during 24-hour periods.

3) When the average outdoor temperature falls into the band between the base case set point and the threshold value, there appears random and unpredictable energy savings and peak demand reduction potentials of the building. This implies that there are other weather-related and perhaps non weather-related factors influencing the ability of a building to save energy and reduce peak demand. This can be further investigated by looking at building hourly load profiles of individual days.

Based on the above observations, building owners can wisely select a thermostat control strategy that can achieve an energy savings/peak demand reduction target (e.g., 4%) in response to a DR signal without unnecessarily scarifying the user comfort.

B. *Influence of Outdoor Temperature*

Fig. 9 and Fig. 10 compare hourly load profiles of two days (June 19th and June 20th) that have similar outdoor temperature profiles between 12noon and 3PM. However, when the HVAC set point is raised by 5°F, energy savings on June 20th is 0.7%, while energy savings of 5% is achieved on June 19th.

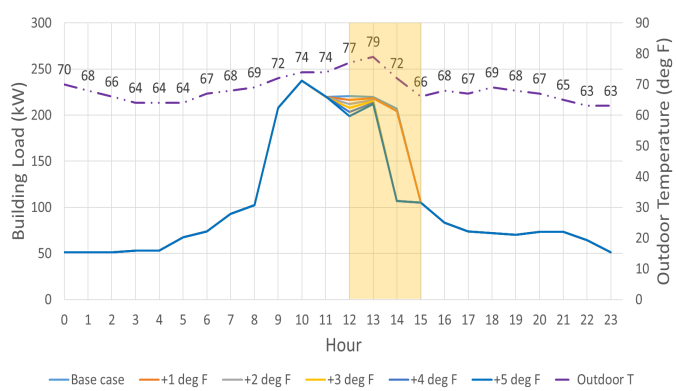

Fig. 9. Hourly building load and outdoor temperature profiles on June 19th, 2017, when raising the set point by 1-5°F between 12noon-3PM.

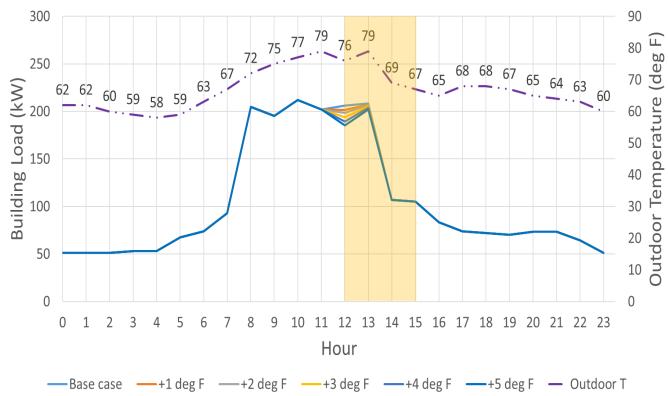

Fig. 10. Hourly building load and outdoor temperature profiles on June 20th, 2017, when raising the set point by 1-5°F between 12noon-3PM.

This energy savings variation is contributed by outdoor temperature profiles before and during the DR event. That is, the outdoor temperature in early morning on June 20th is lower but climbs above 72°F sooner than that on June 19th. This results in sooner AC operation on June 20th (at 8AM) than that on June 19th (at 9AM). This sets different initial conditions of the building when the DR event starts in the afternoon.

During the DR event, on the other hand, the hour when the outdoor temperature drops below 70°F on June 20th starts earlier (at 2PM) than that on June 19th (at 3PM). Hence, with the base case set point, the AC operates longer on June 19th (until 3PM) as opposed to June 20th, which AC stops at 2PM. This is the reason for higher savings on June 19th as the savings comes from the reduced AC load after 2PM when the set point is raised by 2°F or more.

Similar observations can be made when comparing Fig. 11 and Fig. 12 where energy savings is 6.1% on June 27th as opposed to the savings of 13.3% on June 7th with the 5°F set point raise.

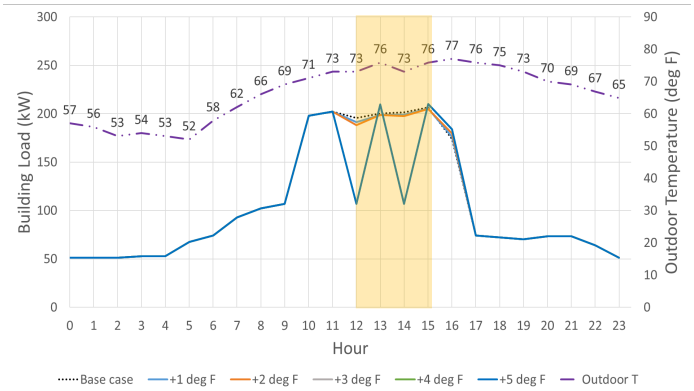

Fig. 11. Hourly building load and temperature profiles on June 27th, 2017, when raising the set point by 1-5°F between 12noon-3PM.

Fig. 11 and Fig. 12 depict hourly load profiles of the other two days (i.e., June 27th and June 7th, respectively) that have the same average outdoor temperature during the DR period, but with slightly different characteristics. That is, the outdoor temperature on June 27th at 1PM (76°F) goes above the raised set point (+5°F). However, on June 7th, the highest daily outdoor temperature remains at 75°F, which is at the raised set point (+5°F). Hence, when the set point is raised by 5°F, the reduced AC load can be expected on June 7th (while AC still needs to operate on June 27th).

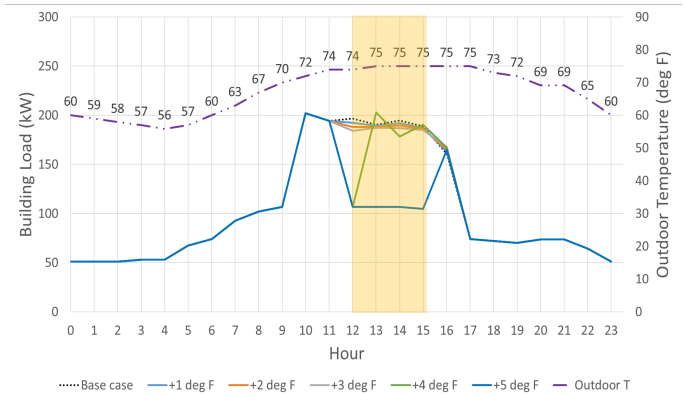

Fig. 12. Hourly building load and temperature profiles on June 7th, 2017, when raising the set point by 1-5°F between 12noon-3PM.

In summary, the trend of outdoor temperature profiles before and during the DR period influences the daily energy savings and peak load reduction potential of a building.

C. *Additional Findings on Energy Savings and Peak Demand Reductions*

Table I summarizes important findings regarding the energy savings and peak demand reduction potentials in the selected building, that can serve as a guideline to estimate the building-level DR performance. Since DR programs are usually deployed during hot days, the performance of DR events on hot days (with the averaged outdoor temperature higher than 80°F between 12noon and 3PM) is of interest.

TABLE I.
SUMMARY OF OBSERVATION

	HVAC set point adjustment during the DR period				
	+1°F	+2°F	+3°F	+4°F	+5°F
Ave kWh savings (T>80°F)	0.3%	0.6%	0.9%	1.2%	1.6%
Ave kW savings, (T>80°F) during DR period	1.2%	2.3%	3.3%	4.3%	5.2%
Ave kW savings (T>80°F), 24-hour	0%	-0.1%	-0.1%	-0.1%	-0.1%
Number of days (T>80°F) with DR restrike	11	11	11	13	13
Max kWh savings	14.5%	14.5%	16.5%	16.5%	16.5%
Max kW savings, DR window	61.5%	61.5%	61.5%	61.5%	61.5%
Max kW savings, 24hrs	49.5%	49.5%	49.5%	49.5%	49.5%
Max restrike	-1.5%	-2.7%	-3.9%	-5.1%	-6.3%
Ave restrike	-1.2%	-2.3%	-3.4%	-3.8%	-4.8%

Based on Table I, the following additional observations can be made:

- The average daily energy savings (%) during the DR period appears to linearly increase with the increase in HVAC set point. An average of 1.6% daily energy savings can be achieved with 5°F increase in set point.
- While the peak demand reductions can be achieved during the DR window (5.2% average peak reductions with +5°F set point adjustment), raising the HVAC set point will result in higher daily building peak demand due to load compensation, which is known as demand restrike. For this building, the average demand restrike at 5°F increase in set point is -4.8%.
- It is observed that there are around 11 days in a year that DR restrike happens. The largest demand restrike is found at 6.3% increase for the +5°F adjustment.
- The highest energy saving (about 16.5%) and highest peak load reductions (about 61.5%) are observed on both mild weather days.

IV. Conclusion

In this study, results of an eQUEST model for quantifying energy savings/peak demand reduction potentials of commercial buildings are presented. A three-story 17,340 square foot building was selected as the test-case of the study. The building model was developed using eQUEST and validated against hourly electricity consumption data from a smart meter. The validated model is then used for analyzing energy savings and peak demand reduction potentials.

It is observed that the average outdoor temperature during the DR period impacts the energy savings/peak demand reduction potentials of a building in three different patterns. For days with low outdoor temperatures (lower than the base-case set point), no DR benefit through thermostat control was achieved. For days with high outdoor temperatures (much higher than the base-case set point), a relatively constant and predictable percentage of daily energy savings were experienced. For days with moderate outdoor temperatures, benefits from thermostat control are not intuitive to predict, and depend highly on building load shape and outdoor temperature profiles outside the DR period. Demand restrike is found to be common with higher set point adjustments.

The methodology presented in this paper can help estimate DR potentials of commercial buildings. It can also help guide building owners to adjust HVAC set points wisely to achieve energy savings/peak demand reduction targets. For future work, the same methodology can be applied to other buildings for predicting their DR performance, and analyzing how different building types, load distributions, HVAC capacities and other factors can influence the results.

Acknowledgment

The work presented in this paper was supported by the project "Assessment of Economic/Transactive Opportunities for Building Energy Management Systems in Distribution System Operator Environment" and sponsored by the Commonwealth Edison Company, Chicago.

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