Performance Assessment of HVAC Control Strategies with Application to DR

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ABSTRACT

Demand response (DR) programs have been growing in number and magnitude in the past decade to reduce load during the peak hours. Despite efforts to automate DR, we lack methods and tools to support facility/building managers with '*how to respond*' decisions at building-scale. This is because there are multiple control strategies available at commercial buildings as response to a DR signal and quantifying the trade-off of these mechanisms for power management has remained a challenge. Hence, it is important to rigorously evaluate power performance of different heating, ventilating, and air conditioning (HVAC) control strategies under different scenarios. This cannot be achieved without quantifying performance. The authors have developed a set of quantifiable performance indicators (PIs) in their previous work by applying an engineering perspective on performance-based building design and operation. These PIs include the ratio of maximum to average power consumption, deviation of demand from nominal power use, energy consumption, and two measures of thermal comfort. This paper examines these PIs by systematically quantifying them under different scenarios of use to show how they can be used for power and energy assessment and management with application to DR. Scenarios defined were modeled and simulated in a controlled environment as a set of experiments. The platform used to model and simulate these experiments is EnergyPlus. Each PI was calculated in the post-processing stage to assess and compare performance of different control strategies. Quantification and assessment of power performance of HVAC control strategies enable development of decision support tools to facilitate building managers' decisions in the context of DR.

Introduction

Historically, the goal of the electric power grid has been to balance the supply and demand and deliver electricity to consumers in a cost-effective and reliable way. The energy crisis of the 1970's raised the need for energy efficiency; hence, sustainability became a new objective for the electricity system. Today, the increasing diversity and variability of loads and the growing penetration of intermittent renewable generation sources have introduced more volatility to the power system requiring new components and methods to sustain its stability and reliability. This includes deployment of new mechanisms and techniques at building level commonly known as ancillary services and demand side management (DSM) techniques. DSM techniques include energy efficiency and conservation, peak load management, and DR.

Furthermore, "while energy efficiency measures have been widely understood by many audiences including facility managers, building owners, utility program managers, auditors, and policy makers, there are not many documents introducing frameworks or guidelines for measures and strategies to participate in demand response programs. Commercial buildings have been only minor participants in demand response programs" (Motegi et al. 2007). This statement is still valid today despite all efforts and work done in the areas of DSM and building integration in the power system since 2007.

This paper aims to address this issue by quantifying a set of measurable performance indicators (PIs) previously defined to evaluate power performance of buildings and their control strategies in the power system. This is an essential part of understanding, assessing, and comparing systems, mechanisms, and strategies systematically and effectively. These measureable PIs are necessary to develop methods, frameworks and decision support tools that can be used to enhance integration of buildings in the power system. Quantifying performance using measurable PIs enable development of a multi-scale decision making framework to calculate the trade-off between different choices in presence of multiple objectives. In the case of building-grid interactions, these objectives are maximizing service provided to the grid (e.g., reducing peak) and minimizing energy consumption of buildings while considering thermal comfort of occupants.

Background

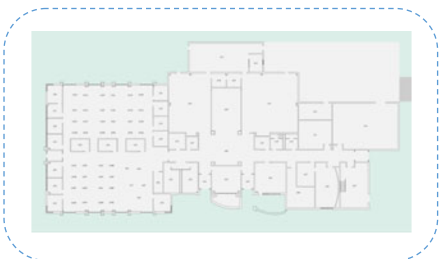
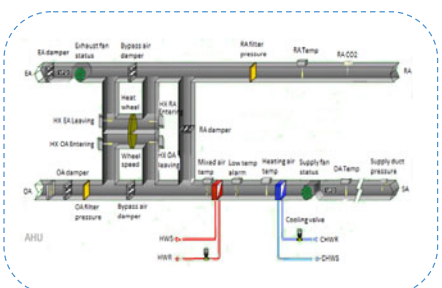
DR is defined as intentional modifications in electricity usage of end-use customers from their normal consumption patterns (in terms of both timing and magnitude) in response to "changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" (DOE, 2006). DR has been considered as a promising technique. This is because there are about 5.6 million commercial buildings in the U.S., comprising 87.4 billion square feet of floor space, consuming 36 % of electricity generated, and contributing to 1/3 of peak demand (DOE 2006; EERE 2011; EIA 2012). The large amount of power consumed by buildings, variations in consumption and load type, and enormous thermal storage capability of commercial buildings make them a great resource for DR (Oldewurtel et al. 2011; Hughes et al. 2015; and Wang et al. 2014).

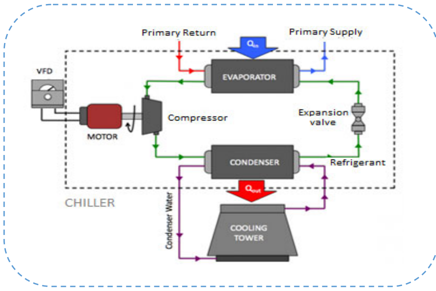
Despite this potential, commercial buildings do not participate in DR programs or do not respond even if they receive DR signals from their utility. This is because of the complexity of systems and their control in commercial buildings and lack of DR automation at building level. Even in AutoDR, we lack methods and measures that support implementation of advanced control strategies in building automation systems unless the facility manager is knowledgeable and willing to define different control mechanisms to respond to DR (OpenADR, 2015; DRRC, 2015; Koch & Piette, 2009). Even in this case, the facility manager does not have a systematic framework to quantify and assess power performance of buildings under different control strategies to select the optimum strategy in terms of energy, power, and comfort. As the old management adage says: "you can't manage what you can't measure," measurement methods illustrate relationships between parameters and interaction among systems. Effective energy and power management relies on measuring performance using quantifiable PIs.

Makhmalbaf (2016) defined a set of quantifiable PIs using an engineering perspective on performance based building design and operation. This approach is based on a top-down functional decomposition and bottom-up technical system aggregation approach to capture quantifiable PIs. This step-by-step method helps to define an application or case specific performance tree for categorization of functionality and their mapping into sets of performance criteria. Through structuring this performance framework and identifying certain "power" performance criteria e.g., power resiliency, it is possible to systematically formulate measures (i.e., PIs). Each PI can robustly measure how well a system fulfills building function while satisfying performance criteria identified. These PIs include: maximum to average power ration (MAPR), load disparity, energy use intensity per day, and the degree and magnitude of indoor air temperature deviating from thermostat setpoint. These PIs will be explained and quantified in the next section.

There are different controllable loads in commercial buildings that can be used in DR, such as HVAC system, lighting, and plug loads. HVAC system is identified as a flexible load for DR (Motegi et al., 2007; Wang et al., 2014; and Watson et al., 2006). The focus of this study is also on HVAC control strategies and its performance as a result of a DR event. In this section, a broader number of control strategies applicable at different system and components levels are discussed. However, in the following sections, certain control strategies are selected for further evaluation and discussion. There are different controllable inputs (i.e., parameters) in an HVAC system and a number of control points with sensors to collect and report data and status. The common control inputs are: temperature, pressure, humidity, air flow, and CO_2. Voltage and current may also be monitored at certain locations. Sensors used to collect time series data including status of these inputs are installed at certain control points or embedded inside each component. There are common HVAC control algorithms used for normal operation of the system and there are a number of them that are specifically deployed in commercial building HVAC systems for DSM/DR to reduce or shift load. These can be summarized as: global temperature setpoint adjustment, supply air temperature increase, supply fan speed reduction, duct static pressure reduction, rooftop unit shutdown, chilled water temperature increase, chiller demand reduction, boiler lockout, pre-cooling of building thermal mass, and light dimming (Motegi, et al., 2007 and Kim et al., 2013). These control strategies are classified and listed in Table 1.

Table 1 Summary of Control Strategies Used in DR. Classified by Location of Control Point.

Control Space	Control Point	Control Strategy
Thermal zone (Demand)		Setpoint adjustment Pre-cooling
Air Handling Unit (AHU) (Distribution)		Reducing duct static pressure Limiting fan Variable Frequency Drive (VFD) (change speed or flow rate) Demand control ventilation (DCV) Increasing supply air temperature Reducing fan quantity Limiting cooling valve

Plant (Supply)		Increasing chilled water temperature Limiting chiller demand Reducing chiller quantity (staging)

Approach

To assess power performance of building energy systems in presence of DR, a set of experiments are defined. Experiments are populated by implementing different control strategies in a small office building during different DR scenarios. Hence, each experiment has a control strategy, a state of variation, time of DR, and duration of DR. The advantage of modeling these experiments is that we can study, assess, and compare performance of systems under controlled conditions. Therefore, the building, system type, and weather conditions remain constant in this study (i.e., one building type, one system type, and one day) in order to evaluate performance of different control strategies under different scenarios but in a controlled environment. By keeping the building, system, and weather conditions the same, we can ensure consistent and robust performance assessment. This shall yield to identification and selection of the most effective mechanism for a given scenario. Furthermore, comparison of different control strategies for the same building under different scenarios indicate applicability and potential use of PIs selected in automated building energy management systems.

Building Description

The building used in this case study is a 2,120 square meter single story building constructed in 2015 providing both office and laboratory spaces. This building is located at the north end of Pacific Northwest National Laboratory's campus in Richland, WA. In addition to office spaces, there are three control rooms (including the campus control center), laboratories focused on power electronics and interoperability, outdoor testing pads, EV charging stations, data storage and computing capability. The center used to monitor energy use and system performance of buildings across campus is also located in this building. This building was modeled in EnergyPlus using design, construction, and material specifications of the building extracted from architectural and mechanical drawings. The lighting intensity in the building was modeled to be 3.28 W/m^2, the number of people (m^2/person) varies between 4.6 to 18.5 m^2/person from zone to zone with an average of 14.8 m^2/person. Plug and process loads have a minimum of 1 W/m^2 and maximum of 53 W/m^2 with an average of 13.6 W/m^2.

Thermal zoning

Five air handling units (AHUs) using district steam for heating and cold water for cooling serve this LEED Gold-certified facility. EnergyPlus is the modeling and simulation engine used in this study. The layout of the building, thermal zones, and building model in EnergyPlus are shown in Figure 1. This study focuses on AHU1 for the purpose of analysis and discussion included. AHU1 serves the largest thermal zone in this building. The typical meteorological year (TMY3) data set is used to simulate the buildings.

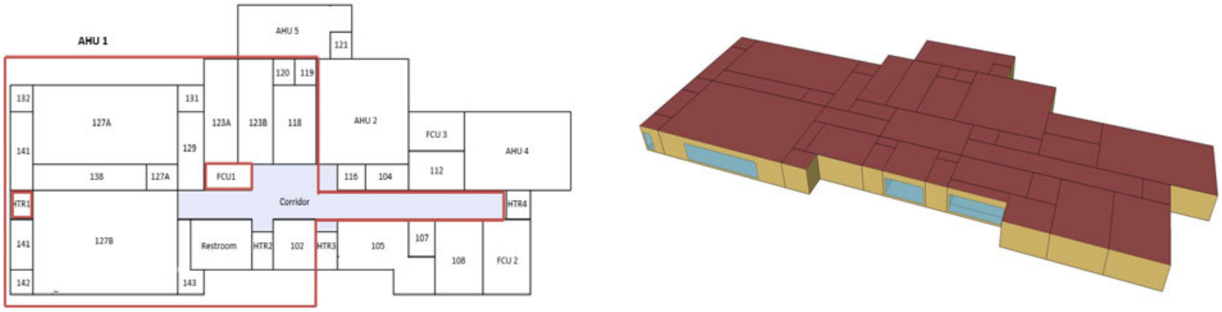


Figure 1. Thermal Zones (left) and Building as Modeled in EnergyPlus™ (right).

HVAC

The AHU utilizes the campus central chiller to provide the chilled water needed for cooling within the building. The VAV air flow set point is reset to maintain the zone temperature at set point. The zone temperature setpoint is within 23 °C ± 1 °C range during occupied hours and 18°C to 27 °C during unoccupied hours. When zones are not occupied, the zone temperature setpoint is 23 °C ± 3°C as the standby mode. The terminal box collects all the occupancy information from each zone to adjust the system operating specifications. The air flow has minimum and maximum setpoints. The minimum airflow setpoints are determined by the ASHRAE standard 62.1 for ventilation requirements based on occupancy. The zone damper is modulated to maintain the measured airflow at the set point. The controllable points are minimum airflow setpoint, maximum airflow setpoint, zone temperature setpoint, heating offset, cooling offset, standby offset, un-occupied heating setpoint, unoccupied cooling setpoint, heating valve output, and damper output.

Schedules in the base models are determined mostly based on regular office building schedules as specified in DOE prototype commercial buildings for fan, occupancy, lighting, plug load, and temperature setpoints during weekdays and weekends.

Control Strategies and Scenarios Implemented

As was mentioned earlier, each experiment includes a HVAC control strategy and a DR specification (time and duration). The building used in this study utilizes district heating and cooling; therefore, there is no control option that can be specified at building or plant level. Control strategies described and implemented in this building are either specified at zone level (e.g., increasing or decreasing the zone temperature) or at AHU level (e.g., air flow setpoint change). The control strategies considered and implemented in this case study are: 1) setpoint increase, 2) setpoint reduction, i.e., pre-cooling, 3) fan shut-down, 4) reducing fan flow rate, 5) demand control ventilation (DCV), and 6) combined strategy.

Each control strategy has a definition (e.g., changing setpoint) and a degree of variation (e.g., -4°C to +4°C). These control specifications combined with DR specifications (hour and duration) result in a scenario. More than 100 scenarios were defined and most of them were modeled in EnergyPlus. However, a subset of these scenarios was selected for the purpose of performance assessment study included here to better present the results. It is possible to model DR specifications in EnergyPlus by modifying the schedules for each scenario defined. Scenarios implemented were simulated at 5-minute time intervals for a few days in July. July was chosen because of the higher electric cooling load and annual peak usually observed in this month. Results were extracted from EnergyPlus™ output files for one day (July 6th) for post processing to analyze data using performance metrics that will be discussed in the next section.

Assessment of DR Control Strategies

PIs selected include: maximum to average power ratio (MAPR), load disparity, power performance coefficient (PPC), energy use intensity per day, and two measures of thermal comfort. Each of these is explained, quantified and discussed in this section.

Max-to-average power ratio (MAPR)

Max-to-average power ratio (MAPR) is the ratio of maximum power demand to the average demand as shown in Equation 1. This PI measures load performance in terms of power 'peak' and/or 'rebound[1].' MAPR indicates: 1) peak and hence flexibility for load reduction if assessing load profile (the higher the MAPR, the more flexible the load is for DR) and 2) rebound if assessing performance of control strategies (the higher the MAPR, the higher the rebound). Although MAPR can be used to assess the extent (i.e., height) of peak or rebound, it is not a good indicator for the duration of peak.

$$MAPR = \frac{Max(P_i)}{\frac{1}{n}\sum_{i=1}^{n} P_i} \qquad 1$$

This PI is calculated for each experiment. For instance, Figure 2 presents calculation of MAPR for one variation of one control strategy, which is increasing setpoint by 3°C for different durations of DR (10, 30, 60, 90, and 120 minutes) in the morning and in the afternoon. Similarly the PI is quantified for all other experiments, e.g., increasing setpoint by 2 and 4°C, precooling, reducing air flow, powering off the fan, and DCV. Only a sample of detailed calculations are shown in this section. Results are then summarized and included the Results section.

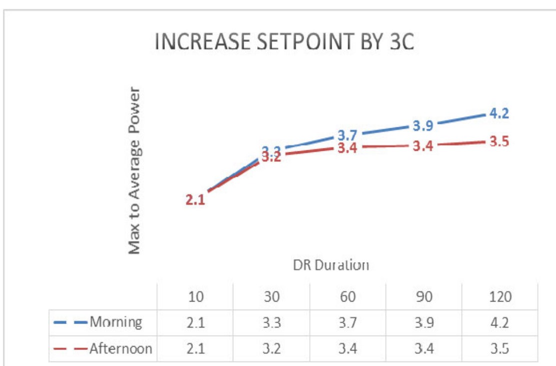


Figure 2 Performance of the system in terms of MAPR for different durations [minutes] of DR when increasing setpoint by 3°C.

Load Disparity Coefficient

Demand disparity is a coefficient of variation for a period of time e.g., daily, monthly, or annually as shown in Equation 2. The higher the demand disparity, the more power demand is

[1] A power rebound is an unwanted increase in demand immediately following any energy efficiency intervention or load reduction mechanism.

deviating from the average power consumption in a given time period. The closer it is to zero, the less disperse load is from average load in a given time (a day in this case). Demand disparity also indicates the length of a peak or rebound. Flexibility of load in terms of both demand reduction and excess absorption can also be realized from demand disparity. To minimize the length of rebound, demand disparity should be lower than 0.5 after a DR event i.e., after applying any HVAC control strategy intervention to minimize load. The lower the demand disparity (between 0 to 0.2), the closer it is to average power use and hence not flexible.

$$\text{Demand disparity} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(P_i - \bar{P})^2}{n-1}}}{\frac{1}{n}\sum_{i=1}^{n} P_i} \qquad (2)$$

Figure 3 presents calculation of demand disparity coefficient for one variation of one control strategy, which is increasing setpoint by 3°C for different durations of DR (10, 30, 60, 90, and 120 minutes) in the morning and in the afternoon. Similarly the PI is quantified for all other experiments, e.g., increasing setpoint by 2 and 4°C, precooling, reducing air flow, powering off the fan, and DCV.

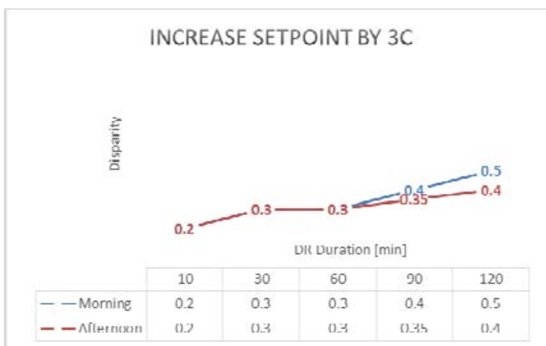


Figure 3 Performance of the system in terms of demand disparity for different durations [minutes] of DR when increasing the setpoint by 3°C.

Power Performance Coefficient (PPC)

PPC is the ratio of average power in a given time period (one day in this case study) to power consumption at the current timestep (or any instance of time the performance is being assessed). Therefore, this is a time series calculation that should be carried out at every time interval to make informed decision about HVAC operation at that time. For instance, in this case study, PPC is calculated every five minutes. If analyzing a load profile, having PPC below one means load is peaking and hence flexible to participate in DR, peak management, or load reduction to conserve energy. If analyzing power performance of a system and the control strategies applied to select the most applicable control mechanism, having a PPC equal or close to one means the strategy is ideal but as it gets closer to zero (PPC<1), it means current power consumption is getting larger than average, which indicates rebound shaping. As PPC gets larger and larger (PPC>1), it means current power use is smaller than average consumption. This is not a concern if the goal is to conserve energy, however, any deviation from average power consumption means stress to the power system.

Figure 4 presents calculation of PPC for one variation of one control strategy, which is increasing setpoint by 3°C for different durations of DR (10, 30, 60, 90, and 120 minutes) in the morning and in the afternoon. Similarly the PI is quantified for all other experiments, e.g., increasing setpoint by 2 and 4°C, precooling, reducing air flow, powering off the fan, and DCV.

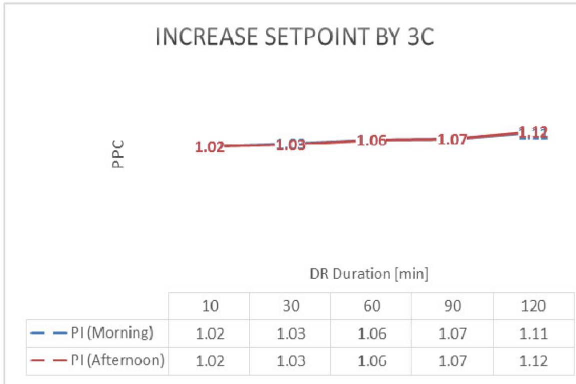


Figure 4 Performance of the system in terms of PPC for different durations [minutes] of DR when increasing the setpoint by 3°C.

Energy Use Intensity

One of the most emphasized concerns about DR at building scale is the trade-off between peak reduction and energy efficiency. Hence, it is important to take into account the energy use intensity of systems when different control strategies interventions are applied as a response to a DR signal. The energy consumption of the base case (without any control strategy applied during DR) is about 16 kWh/day. Results indicate that the AHU consumes about (very close to) the same amount of energy in most scenarios implemented except for pre-cooling strategies, which consume more energy especially if implemented for more than 10-30 minutes in the morning. Increasing the thermostat setpoint by 2°C for 120 minutes results in the lowest energy consumption. Figure 5 presents calculation of energy use intensity for one variation of one control strategy, which is increasing setpoint by 3°C for different durations of DR (10, 30, 60, 90, and 120 minutes) in the morning and in the afternoon. Similarly this PI is quantified for all other experiments, e.g., increasing setpoint by 2 and 4°C, precooling, reducing air flow, powering off the fan, and DCV.

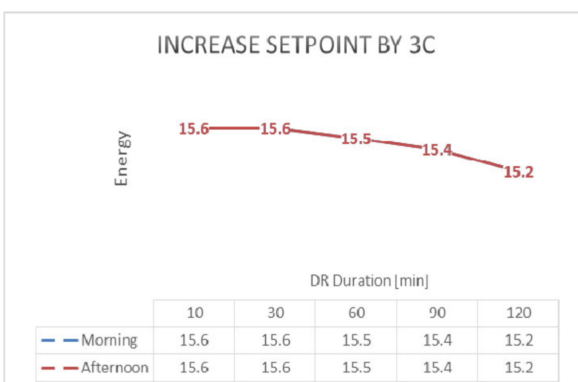


Figure 5 Performance of the system in terms of energy use intensity for different durations [minutes] of DR when increasing the setpoint by 3°C.

Thermal Comfort

Thermal comfort is assessed in terms of two indicators. One is the duration of zone temperature deviating from setpoint temperature and the second is the magnitude or intensity of space temperature varying from setpoint. Based on results obtained, shutting off AHU fan or applying DCV cause the maximum variation from setpoint temperature followed by reducing air flow and pre-cooling. Figure 6 presents calculation of duration of thermal discomfort (left) and its intensity (right) for one variation of one control strategy, which is increasing setpoint by 3°C for different durations of DR (10, 30, 60, 90, and 120 minutes) in the morning and in the afternoon. Similarly this PI is quantified for all other experiments, e.g., increasing setpoint by 2 and 4°C, precooling, reducing air flow, powering off the fan, and DCV.

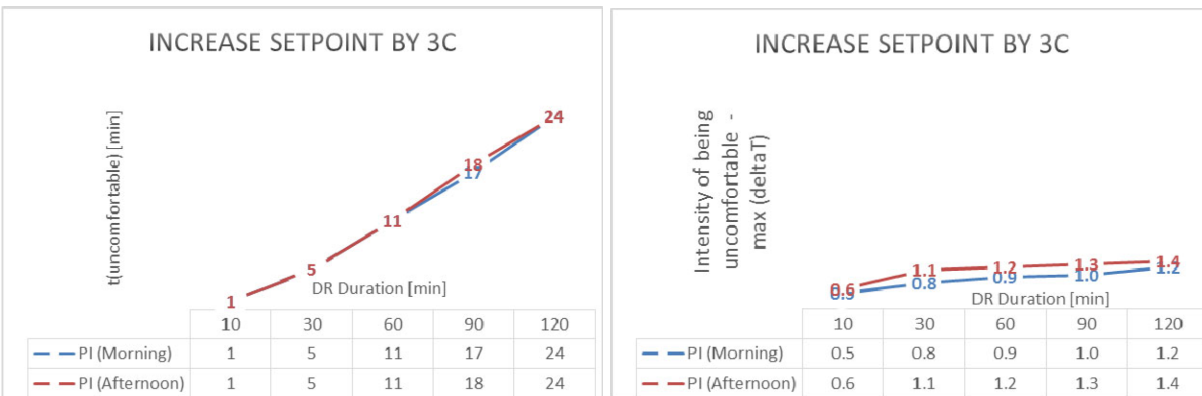


Figure 6 Performance of the system in terms of duration of thermal discomfort (left) and its intensity (right) for different durations [minutes] of DR when increasing the setpoint by 3°C.

Results

PIs quantified are compared and a summary of how they compare is illustrated in Figure 7. Each radar chart shows how PIs compare for each control strategy for different experiments. In these charts S1 to S6 represent control strategies one to six[2]. D1 to D5 represent different durations of DR (10, 20, 60, 90, and 120 minutes) and PIs one to six represent the six PIs used for performance quantification[3]. Based on this performance quantification, we can assess performance and strategies. This assessment indicates that: 1) pre-cooling in the morning hours results in a large peak in power consumption without noticeable energy and power reduction in the afternoon hours which are high electricity demand hours, 2) increasing setpoint by 2°C, 3°C, or 4°C have the same performance in terms of PIs selected, 3) reducing amount of outdoor air during afternoon hours results in a large rebound after DR period, and 4) increasing setpoint has better performance in terms of all PIs on average when compared to other strategies.

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[2] S1: Increasing setpoint (results for increasing setpoint by 2, 3, or 4 ºC fall on top of each other)
S2: Decreasing setpoint or pre-cooling (results for decreasing setpoint by 2, 3, or 4 ºC fall on top of each other)
S3: Reducing air flow to 3 kg/s, S4: Reducing air flow to 1 kg/s, S5: Fan powered off, S6: DCV

[3] PI1: MAPR, PI2: Disparity, PI3: PPC, PI4: Energy use intensity, PI5: Thermal comfort (duration of uncomfortable minutes), PI6: Thermal comfort (intensity of uncomfortable temperature)

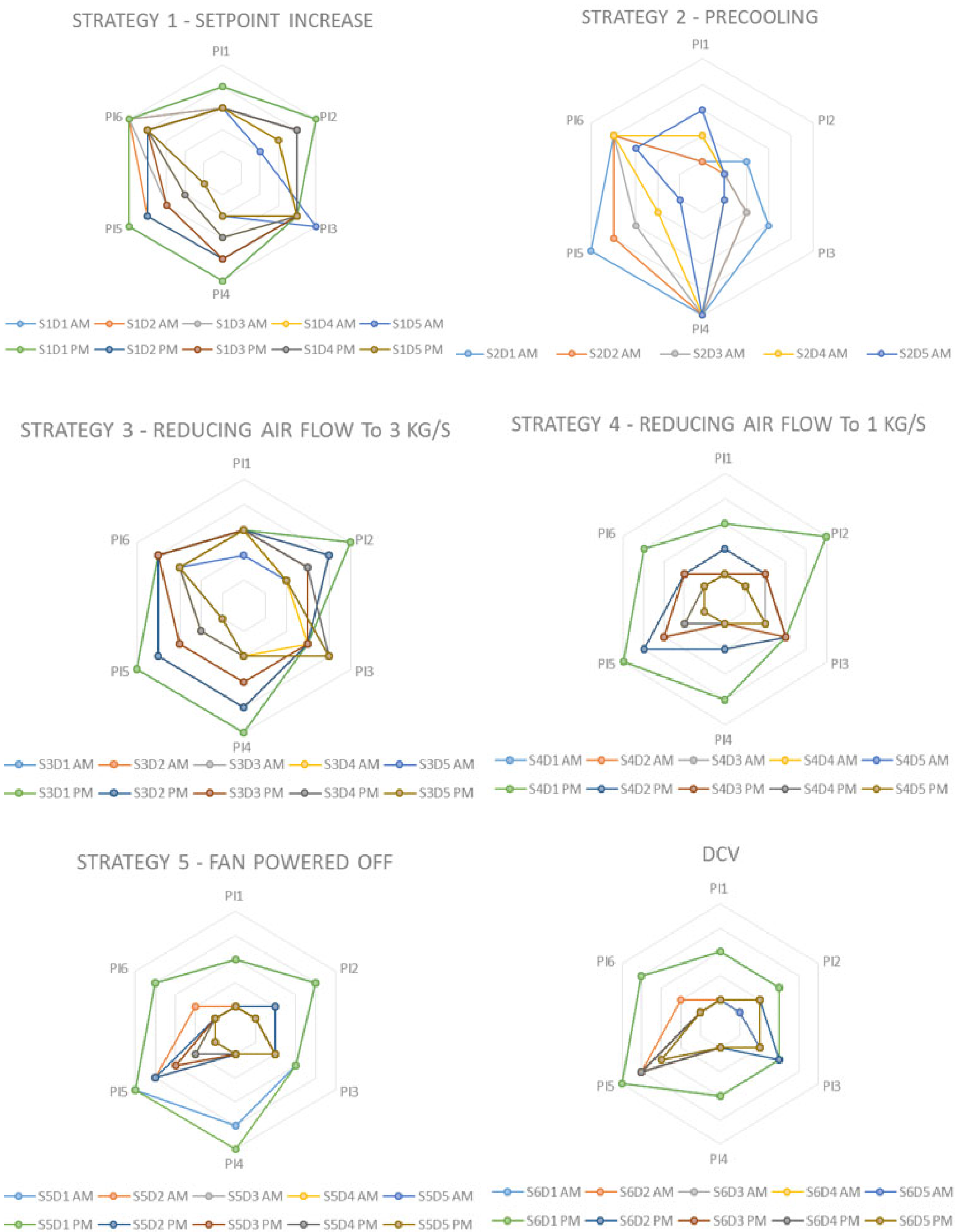

Figure 7 Comparing performance of different control strategies in terms of different PIs selected.

Conclusion

It is well realized that energy efficiency is only concerned with reducing consumption regardless of time of the day, excess generation caused by intermittent generators such as wind, and stability of the power system. While energy efficiency in buildings should not be compromised in order to provide service to the power grid, the large scale and global energy utilization should be taken into account in design and operation decisions of buildings. Today the importance of DSM and DR has increased to support operation of the power grid using buildings as a resource. Hence, it is important to better measure and understand energy and power performance of buildings in the modern power system. This is an essential part in understanding, assessing, and comparing systems, mechanisms, and strategies in a systematic and scientific way to support both building and power planning and management. Performance cannot be effectively evaluated without quantifying performance using measurable performance indicators (PIs).

This paper uses a set of quantifiable PIs to assess power and energy performance of buildings and their control strategies in the power system. To achieve this, more than 100 experiments were defined and modeled in EnergyPlus using a small office building located in Richland, WA. Each experiment includes a simple or advanced HVAC control strategy, different variations (e.g., increasing setpoint by 2, 3, or 4°C), and a DR specification (time and duration). Simulated results were analyzed to quantify performance using a set of PIs. PIs selected include: maximum to average power ratio (MAPR), load disparity, power performance coefficient (PPC), energy use intensity per day, and two measures of thermal comfort. Each PI was quantified and performance of different strategies was compared using these PIs. The results presented show that increasing setpoint has better performance in terms of most PIs when compared with other strategies (in this case). However, this study did not consider the weight of PIs, which is an important factor in real life decisions. This will be addressed in our future work.

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References

Bliek, F., Van den Noort, A., Roossien, B., Kamphuis, R., De Wit, J., Van der Velde, J., & Eijgelaar, M. (2010). PowerMatching City, a living lab smart grid demonstration. Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES (pp.1-8).

DOE (2006). United States Department of Energy, Benefits of demand response in electricity markets and recommendations for achieving them, February 2006.

EERE (2011). Buildings energy data book. [Online]. Available: http://buildingsdatabook.eren.doe.gov/default.aspx

EIA (2012). Energy Information Administration, United States Department of Energy, Commercial Buildings Energy Consumption Survey (CBECS).

EIA (2014). Peak-to-average electricity demand ratio rising in New England and many other U.S. regions. Available at https://www.eia.gov/todayinenergy/detail.cfm?id=15051.

GridWise Architecture Council (2015) GridWise Transactive Energy http://www.gridwiseac.org/pdfs/te_framework_report_pnnl-22946.pdf

Hammerstrom, D. J., Ambrosio, R., Brous, J., Carlon, T. A., Chassin, D. P., DeSteese, J. G., ... & Katipamula, S. (2007). Pacific Northwest GridWise Testbed Demonstration Projects. Part I. Olympic Peninsula Project.

Hughes, J. T., Domínguez-García, A. D., & Poolla, K. (2015). Virtual battery models for load flexibility from commercial buildings. In 2015 48th Hawaii International Conference on System Sciences (HICSS), 2627-2635.

Heussen, K., You, S., Biegel, B., Hansen, L. H., & Andersen, K. B. (2012). Indirect control for demand side management-A conceptual introduction. In Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE International Conference and Exhibition on PES (pp. 1-8).

Koch, E., & Piette, M. A. (2009). Direct versus facility centric load control for automated demand response. Grid Interop. Technical report, Ernest Orlando Lawrence Berkeley National Laboratory, 2009.

Kosek, A. M., Costanzo, G. T., Bindner, H. W., & Gehrke, O. (2013). An overview of demand side management control schemes for buildings in smart grids. In IEEE International Conference on Smart Energy Grid Engineering (SEGE), August 2013. 1-9.

Li, D., Jayaweera, S. K., Lavrova, O., & Jordan, R. (2011, April). Load management for price-based demand response scheduling-a block scheduling model. In International Conference on Renewable Energies and Power Quality (ICREPQ'11), Las Palmas de Gran Canaria, Spain.

Motegi, N., Piette, M. A., Watson, D. S., Kiliccote, S., & Xu, P. (2007). Introduction to commercial building control strategies and techniques for demand response. *Lawrence Berkeley National Laboratory* LBNL-59975.

NERC (2007). North American Electric Reliability Corporation, Data collection for demand-side management for quantifying its influence on reliability results and recommendations, December 2007.

Oldewurtel, F., Ulbig, A., Morari, M., & Andersson, G. O. (2011, December). Building control and storage management with dynamic tariffs for shaping demand response. In Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition (pp. 1-8). IEEE.

Wang, S., Xue, X., & Yan, C. (2014). Building power demand response methods toward smart grid. HVAC&R Research, 20(6), 665-687.

Yin, R., Xu, P., Piette, M. A., & Kiliccote, S. (2010). Study on Auto-DR and pre-cooling of commercial buildings with thermal mass in California. Energy and Buildings, 42(7), 967-975.