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VALIDATION APPROACH FOR ENERGY OPTIMIZATION MODELS OF GRID-INTERACTIVE BUILDINGS USING CO-SIMULATION

Patrick J. McCurdy[1], Kaleb Pattawi[1], Chenli Wang[2], Thomas Roth[2], Cuong Nguyen[2], Yuhong Liu[3], and Hohyun Lee[1]

[1]Mechanical Engineering Department, Santa Clara University, Santa Clara, CA
[2]National Institute of Standards and Technology, Gaithersburg, MD
[3]Computer Science Engineering Department, Santa Clara University, Santa Clara, CA

ABSTRACT

The consumption and production of energy are more dynamic as distributed energy resources (DERs) such as solar photovoltaics (PV) are deployed within the electric distribution system. The existing techniques for bulk generation do not take full advantage of DERs and can lead to wasted energy and higher costs for both utility companies and consumers. Commercial and residential building energy management systems are usually on a fixed schedule and are not able to respond to changes in energy price instantaneously. There is a need for a real-time pricing structure that can accommodate the fluctuating cost of energy based on supply and demand, and for an energy management system that is able to respond to the dynamic utility rate. As such, there is a need for a robust energy management control strategy and methodology to validate new approaches.

To address this gap, a strategy to control heating, ventilation, and air conditioning (HVAC) systems in a residential house was developed along with a validation methodology. A model of predictive control was implemented to optimize the thermostat setpoints and minimize energy cost for an individual residential house while maintaining thermal comfort of residents. This model was integrated with EnergyPlus simulation via an open source co-simulation platform previously developed at the National Institute of Standards and Technology (NIST). Total energy consumption and cost for consumers were compared between a case with the proposed model and a baseline case that used fixed-temperature setpoint control. The simple dynamic pricing model used in simulations was proportional to the demand of energy at that time of day. This work will contribute to the development of dynamic utility pricing models and residential control strategies for grid-interactive buildings and homes. The outcome of this research can be expanded to different building models or locations in future work.

Keywords: optimization; transactive energy; residential buildings; cost savings; co-simulation

NOMENCLATURE

α	Proportional constant of utility rate
β	Delivery charge per kWh [$/kWh]
T_{indoor}	Indoor temperature [°C]
$T_{outdoor}$	Outdoor temperature [°C]
Q_{solar}	Solar radiation [W/m^2]
U	Overall heat transfer coefficient [W/m^{2}K]
A	Surface area of the building envelope [m^2]
m	Mass of the building materials [kg]
c	Specific heat of the building materials [J/kgK]
Q	Energy [J]
C_i	Constants for energy prediction model
E_{used}	Energy consumption [kWh]
CF	Cost function
P	Price of energy [$/kWh]
$T_{comfort,lower}$	Lower bound of temp. comfort zone [°C]
$T_{comfort,higher}$	Upper bound of temp. comfort zone [°C]

1. INTRODUCTION

The use of transactive energy concepts has the potential for a significant amount of energy savings. Transactive energy is a broad term that covers economic and control techniques used to manage the flow or exchange of energy within an existing power system [1]. Realizing the potential energy savings of transactive energy requires increased communication between the wholesale market and consumers. This increased communication is coming naturally as distributed energy resources (DERs) such as solar photovoltaics (PV) are deployed within the electric distribution system, leading to more dynamic consumption and production of energy. The wholesale market must react to real-time demand and price fluctuations, whereas traditionally residential consumers purchase energy at a predetermined rate. Predetermined rates cannot accommodate these dynamics and may lead to wasted energy and higher costs for both utility companies and consumers. Shifting the energy load from high-demand period to high-supply period can alleviate the wasted energy and unnecessary costs.

A method to encourage load shifting is to implement dynamic pricing. As energy infrastructure has evolved, utility companies have been able to change their pricing structure to motivate customers to alter their energy usage. Specifically, some utility companies have implemented Time-of-Use (TOU) pricing methods so the energy cost to the consumer will reflect the actual cost of energy at that time of day. If residential customers can change their energy consumption in response to changes in price, TOU pricing will result in a shift in energy consumption.

A real-time pricing structure could accommodate the fluctuating cost of energy based on supply and demand. For now, TOU pricing is a step closer to representing the actual cost of energy than flat-rate pricing, but is still an estimate of the appropriate price for that time period. As home energy management systems (HEMS) become more complex with the ability to respond to the varying price of energy, the utility company can continue to alter its pricing strategy to better reflect the true cost of energy. Eventually, this could significantly reduce peak demand and wasted energy. However, TOU pricing alone is often not enough motivation for a customer to effectively alter their energy usage, and a recent study [2] shows that there is no evidence that TOU pricing can contribute to peak load shaving or reduced energy consumption.

There is a need for an energy management system that is able to respond to a dynamic utility rate. While commercial buildings benefit from a building management system, residential energy system control strategies have not received significant attention due to the low economic viability to individual end users, in spite of their large impact at scale. In 2019, residential and commercial building energy usage accounted for 39 % of energy consumption in the United States [3]. Heating, ventilation, and air conditioning (HVAC) accounts for over 50 % of that use [4]. One method to control residential energy usage is model predictive control (MPC). MPC is a control strategy that uses a model to predict the future of a complex system and alters its control accordingly. Often, a cost function is used with MPC to optimize the control under a set of constraints. It has been used to minimize energy usage, cost, and peak electricity demand [5]. MPC has been used with standard HEMS. A few studies have tried to integrate demand costs into MPC [6, 7]. TOU pricing has been used with MPC [8 - 10]. Further work can be done to create a cohesive model integrating various points of interest. Specifically, ensuring thermal comfort is critical to creating a control method that occupants will use. Occupancy sensing to save energy usage while maintaining thermal comfort has been previously investigated by the team. Adaptive control can save up to 54 % of energy consumption, and the occupancy information can increase the energy saving impact by 20 % [11].

A validation tool is needed to evaluate the effectiveness of energy management techniques and dynamic pricing strategies. The validation tool should be able to assess the different factors taken into account within the MPC. This paper proposes a validation tool based on EnergyPlus, the most widely adopted building simulator, and an open-source co-simulation platform called the Universal Cyber-Physical Systems Environment for Federation (UCEF) [12, 13]. MPC can be used to optimize the thermostat setpoints and minimize energy cost for an individual residential house while maintaining the thermal comfort of users. Minimizing cost rather than energy consumption takes into consideration the surplus of energy during off-peak hours and the increased cost of energy during times of high demand. As the utility company's pricing method better correlates to the actual cost of energy, minimizing residential energy costs will in turn minimize overall energy consumption.

This simulation strategy is adaptable to incorporate additional considerations and will contribute to the development of dynamic utility pricing models and residential control strategies for grid-interactive buildings and homes. Utility pricing models and control strategies can be tested independently so that a wide range of options can be considered. The outcome of this research can be expanded to different building models or locations in future work.

2. MATERIALS AND METHODS

The simulation was composed of EnergyPlus and UCEF. The input to EnergyPlus was a building model and weather file obtained from the U.S. Department of Energy [14]. The residential prototype building model was for an approximately 2400 square foot single-family home in San Francisco with a heat pump and a crawlspace foundation type. The typical meteorological year (TMY3) weather file for Climate Zone 3C, where San Francisco is located, was used [15]. The residential building model was modified to send and receive information with a Functional Mockup Unit (FMU) external interface [16].

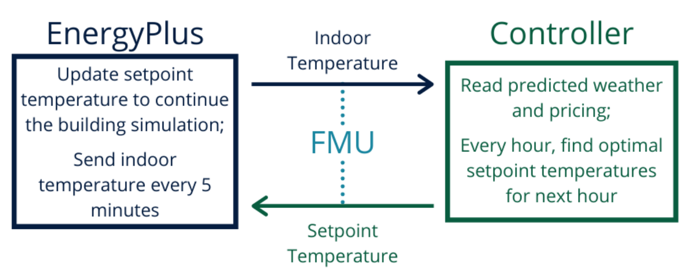

FIGURE 1: THE EXCHANGE OF INFORMATION BETWEEN ENERGYPLUS AND THE CO-SIMULATION PLATFORM TO FIND THE OPTIMAL SETPOINT TEMPERATURE

The transfer of information is shown in Figure 1. Both EnergyPlus and the Controller were implemented in UCEF to facilitate the exchange of information between the two agents. Each timestep, EnergyPlus sends the current indoor temperature to the controller. The controller is where the EnergyPlus simulation is paused, so that it can process current simulation data and return commands for continuing the simulation, specifically the future indoor setpoint temperature. The controller uses the indoor temperature and the weather information, i.e., the outdoor temperature and solar radiation it reads from a weather file, to perform optimization and set the setpoint temperatures for the next hour at five-minute timesteps. The setpoint information is sent back to EnergyPlus.

2.1 Pricing Models

To create a pricing model based on the real-time demand of the market, the day-ahead market price of energy for Pacific Gas and Electric Company (PG&E), California's biggest utility company, was obtained from California Independent System Operator (CAISO), which oversees the operation of California's bulk electric power system, transmission lines, and electricity market generated and transmitted by its member utilities [17]. The day-ahead market price is recorded hourly by CAISO.

The day-ahead hourly market price was recorded for two seven day periods: January 1 - 7, 2021 and February 12 - 18, 2021 as shown in Figure 2. As seen in the figure, the wholesale price during the week in January acted periodically with a range of $50/MWh between its peak and trough. However, the wholesale price for the week in February grew dramatically to a peak of $953/MWh. The week in January may represent an average week whereas the week in February represents a period of significant demand changes, causing the wholesale price to rise.

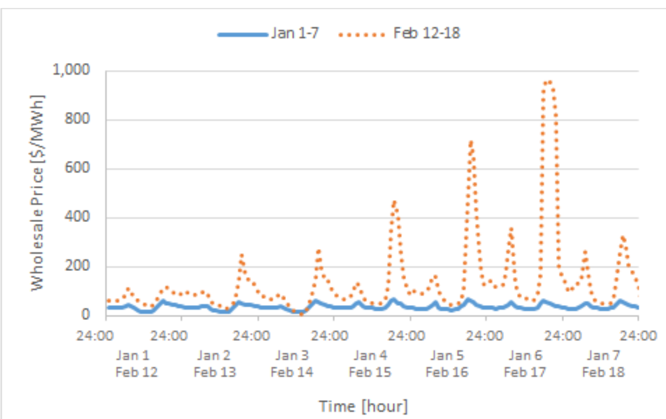

FIGURE 2: WHOLESALE MARKET PRICE OF ENERGY ACCORDING TO CAISO FOR JANUARY 1 TO 7, 2021 AND FEBRUARY 12 TO 18, 2021

A linear relationship between the market price and retail price of energy was created by comparing PG&E's range of electricity cost with the range of market price [18]. For dynamic pricing, the difference in pricing based on demand should be significant enough to motivate changes in user behavior during high demand so that the energy management system shifts usage appropriately. The linear relationship follows the equation:

$$Retail\ Price = \alpha \times Wholesale\ Price + \beta \quad (1)$$

where α is the proportional constant of utility rate and β represents a delivery charge per kWh. For these simulations, the constants $\alpha = 4$ and $\beta = \$0.10$ were used, which results in a retail price range of $0.15 to $0.38 for the one week period in January and a range of $0.11 to $3.94 for the one week period in February. The pricing structure can be changed and tested in the future.

2.2 Optimization

In order to optimize future energy consumption, there was a need to predict the relationship between indoor temperature and energy consumption.

The indoor temperature is a function of energy used, outdoor temperature, solar radiation, and building materials. An approximate representation of the change in indoor temperature is given by:

$$\frac{dT_{indoor}}{dt} = \frac{UA}{mc}(T_{outdoor} - T_{indoor}) + \frac{1}{mc}Q + C_3 Q_{solar} \quad (2)$$

where T_{indoor} is the indoor temperature, U is the overall heat transfer coefficient, A is the surface area of the building envelope, m is the mass of the building materials, c is the specific heat of the building materials, Q is the amount of energy added to the space, $T_{outdoor}$ is the outdoor temperature, Q_{solar} is the solar radiation, and C_3 is a constant which defines a relationship between solar radiation and the energy gain in a house.

Equation 2 can be rewritten to solve for the indoor temperature at the next timestep as:

$$T^n_{indoor} = dt \times (C_1\,(T^n_{outdoor} - T^{n-1}_{indoor}) + C_2\,E^n_{used} + C_3\,Q^n_{solar}) + T^{n-1}_{indoor} \quad (3)$$

where superscript n represents the timestep number, dt is the number of seconds in a timestep, and C_1, C_2, and C_3 are unknown constants.

The constants cannot be precisely found theoretically due to the intricacies of a building thermal model, inaccuracies between design and build, and inconsistencies in factors such as insulation. Rather, the constants can be determined by analyzing data from the building model. In order to estimate the constants, an annual EnergyPlus simulation was run with the identical building model. The energy used, indoor temperature, outdoor temperature, and solar radiation were recorded. Linear regression was performed with the dataset to solve for the constants: $C_1 = 1.72\text{e-}05$, $C_2 = 3.10\text{e-}03$, and $C_3 = 3.58\text{e-}07$ [19].

With a relationship between energy consumption and indoor temperature found, optimization could be done. For optimization, an open source software package for convex optimization based on the Python programming language, CVXOPT, was used [20]. In this case, the goal was to find the values of energy usage that would minimize the following cost function, CF:

$$CF = \sum_{n=1}^{N} P^n \times E^n_{used} \quad (4)$$

where P^n is the cost of electricity at each timestep and E^n_{used} is the energy used at each timestep.

A set of constraints were used with the objective equation to limit the energy consumption to be positive or negative for heating and cooling, respectively, and for the indoor temperature at each timestep to be within the comfort zone as shown in:

$$E^n_{used} \geq 0 \quad \text{(when heating)} \tag{5a}$$
$$E^n_{used} \leq 0 \quad \text{(when cooling)} \tag{5b}$$
$$T^n_{indoor} \geq T^n_{comfort,lower} \tag{5c}$$
$$T^n_{indoor} \leq T^n_{comfort,higher} \tag{5d}$$

where $T^n_{comfort,lower}$ and $T^n_{comfort,higher}$ are the lower and upper bound of the indoor temperature comfort zone at each timestep. With the inputs of the current indoor temperature, the future outdoor temperature and solar radiation, and the price of energy, the energy consumption can be optimized to minimize the total cost of energy while keeping the indoor temperature within the comfort zone.

3. RESULTS AND DISCUSSION

Three sets of simulations were run for one week periods: January 1 - 7, February 12 - 18, and September 27 - October 3. The week in January was chosen to represent a random week in winter months. The week in February tests optimization when there is a significant change in cost throughout the day. The week in September was chosen to test the optimization in summer months. September 27 - October 3 required the highest amount of cooling energy out of any week in summer months with the building model. Since wholesale pricing data for September 27 - October 3, 2021 is unavailable, the data from February 12 - 18 was used. The following four energy control strategies were implemented for each time period:

1. Baseline: Fixed Heating Setpoint Without Optimization
2. Optimization with a Fixed Comfort Zone
3. Adaptive Control without Optimization
4. Adaptive Control with Optimization

The baseline control strategy represents the most common user behavior of setting a fixed setpoint. Optimization with a fixed comfort zone represents a fixed setpoint with preheating or precooling. Adaptive control has been shown to provide significant energy savings while maintaining thermal comfort. The adaptive control without optimization strategy sets the setpoint temperature as the lower bound of the adaptive comfort model for heating and the upper bound of the adaptive comfort model for cooling, given by ASHRAE Standard 55 [21]. The last control strategy examines the effects of adding optimization to adaptive control.

The controller optimized the setpoint temperature schedule for the next two hours to ensure a thorough prediction, and the setpoint schedule for the next hour was sent back to be implemented in EnergyPlus.

Based on constraints used in optimization, the indoor air temperature is always within the comfort region. A cost function for thermal comfort could be determined in the future and added to the optimization process.

The total cost for the consumer was compared between the four simulations for the three time periods as shown in Table 1. January 1 - 7 resulted in the most savings between simulations with and without optimization whereas September 27 - October 3 resulted in the least savings. All three time periods found savings of over \$2 when comparing optimization with an adaptive comfort zone to a fixed setpoint.

TABLE 1: SUMMARY OF COST SAVINGS BETWEEN SIMULATIONS WITH OPTIMIZATION AND THE CORRESPONDING SIMULATIONS WITHOUT OPTIMIZATION

Simulation Period	Savings from Optimization with Comfort Zone Compared to a Fixed Setpoint	Savings from Optimization with Adaptive Comfort Zone Compared to Adaptive Comfort Alone	Savings from Optimization with Adaptive Comfort Zone Compared to a Fixed Setpoint
January 1 - 7	\$5.65	\$3.89	\$7.16
February 12 - 18	\$0.92	\$0.05	\$2.87
September 27 - October 3	\$0.03	\$0.19	\$5.20

The total cost and energy usage between the four simulations are shown in Figure 3 for January 1 - 7. Adding optimization resulted in less energy consumption and less cost for both sets of simulations.

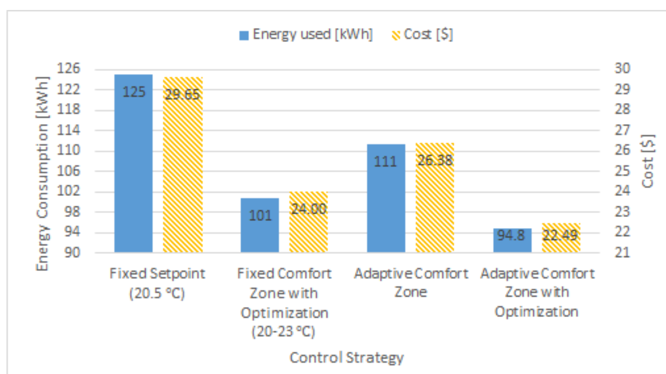

FIGURE 3: ENERGY CONSUMPTION AND COST FOR EACH HVAC CONTROL STRATEGY FOR JANUARY 1-7

The total cost and energy usage between the four simulations are shown in Figure 4 for February 12 - 18. When compared to a fixed setpoint temperature, optimization provided a reduction in both cost and energy consumption. However, when compared to an adaptive comfort zone, optimization reduced the cost by \$0.05. The week in January saw more significant savings than the week in February since the weather was colder, resulting in 3 to 4 times higher energy consumption.

Adaptive control with optimization saved around $3 compared to the fixed setpoint behavior.

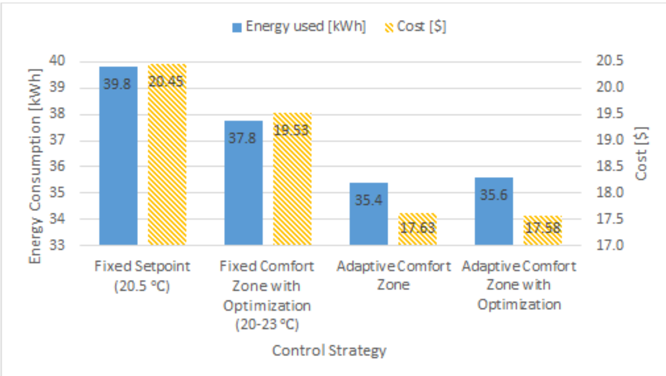

FIGURE 4: ENERGY CONSUMPTION AND COST FOR EACH HVAC CONTROL STRATEGY FOR FEBRUARY 12-18

The total cost and energy usage between the four simulations are shown in Figure 5 for September 27 - October 3. This simulation resulted in the least amount of cost reduction. This time period was chosen to test optimization during summer months with cooling energy. Although this week was chosen since it resulted in the highest consumption of cooling energy during a simulation with a fixed setpoint, the building model does not consume enough energy for the optimization to make an impact comparable to that in January or February. The location chosen for simulations, San Francisco, does not experience long-term high temperatures and does not require high amounts of air conditioning in the summer. The simulations still resulted in a decrease in cost of $0.03 to $0.19 and a decrease in energy consumption of 0.13 kWh to 0.18 kWh. Optimization with an adaptive comfort zone resulted in $5.20 savings when compared to a fixed setpoint.

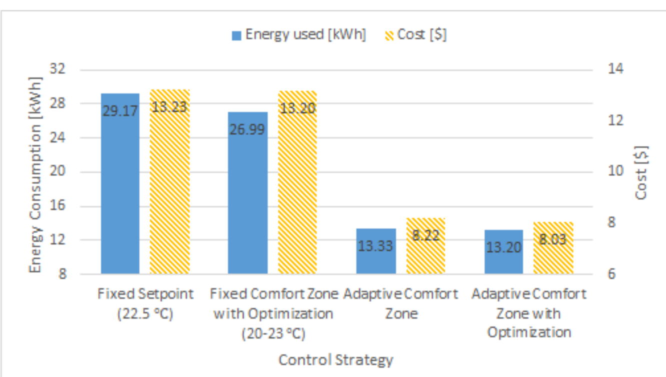

FIGURE 5: ENERGY CONSUMPTION AND COST FOR EACH HVAC CONTROL STRATEGY FOR SEPTEMBER 27 – OCTOBER 3

There are several areas of interest within the results including preheating, deviation from the comfort zone, and possible limitations of cost savings. To take a closer look at how the optimization is affecting the HVAC system, the energy consumption of the simulation under a fixed setpoint and under optimization are plotted in Figure 6a together with the price of energy at each hour. The optimized energy consumption can be seen to increase in comparison to the fixed setpoint energy consumption directly before an increase in price. The increase in the optimized energy consumption represents the optimization of preheating the house to take advantage of the lower cost of energy. For a closer look, the results are shown for a shorter timeframe, January 2 12:00 - 24:00, in Figure 6b. The energy usage in the hours leading up to a higher price is significantly greater for the simulation with optimization than the one with a fixed setpoint. After the price increase, the simulation with optimization is able to continue to use less energy than the one with the fixed setpoint due to the effect of preheating.

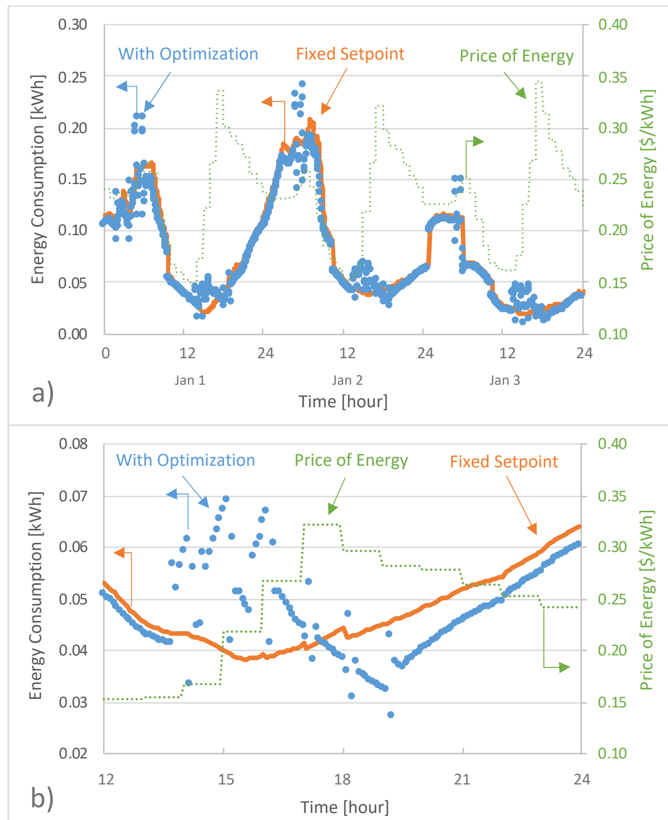

FIGURE 6a: ENERGY CONSUMPTION FOR THE TWO CASES OVER THE THREE-DAY TIME PERIOD WITH THE PRICE OF ENERGY AT EACH TIMESTEP
6b: ENERGY CONSUMPTION FOR THE TWO CASES OVER A 12-HOUR PERIOD (JANUARY 2, 12:00-24:00) WITH THE PRICE OF ENERGY AT EACH TIMESTEP

The indoor temperature of the simulations with a fixed setpoint and with optimization with a fixed comfort zone are shown in Figure 7. The indoor temperature for the fixed setpoint temperature case oscillates within 1 °C of the setpoint temperature as expected whereas the indoor temperature for the optimization case increases before the price of energy increases to take advantage of lower costs. The indoor temperature remains within the set comfort zone of 20 °C to 23 °C. Preheating is only effective for a limited period until the indoor temperature decreases to the lower bound of the comfort zone. This limitation hinders the ability to shift the load more than approximately an hour.

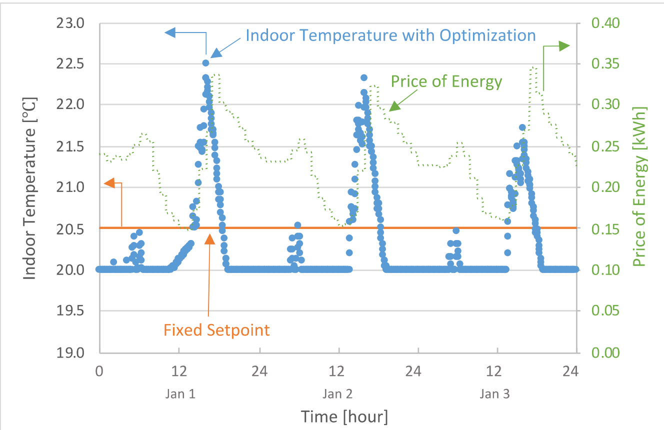

FIGURE 7: INDOOR TEMPERATURE FOR THE TWO CASES OVER THE THREE-DAY TIME PERIOD WITH THE PRICE OF ENERGY AT EACH TIMESTEP

Another area of interest is the cause of the week in February savings to be less than those of the week in January. One contributing factor is that there was no energy usage during the times of extreme high prices. The indoor temperature and energy consumption during one of the times of extreme price increase is shown in Figure 8 and Figure 9 respectively. As shown in the figures, no energy is consumed with or without optimization during the time of extremely high price. The indoor temperature naturally remains within the adaptive comfort zone during that time. Therefore, any potential savings from optimization are not brought to fruition.

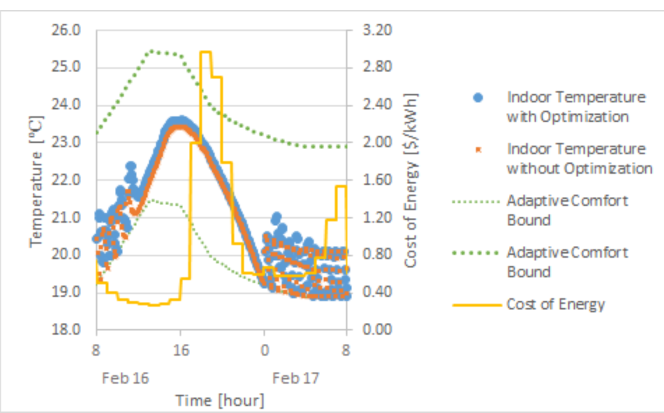

FIGURE 8: INDOOR TEMPERATURE IN FEBRUARY DURING A TIME OF HIGH PRICE INCREASE

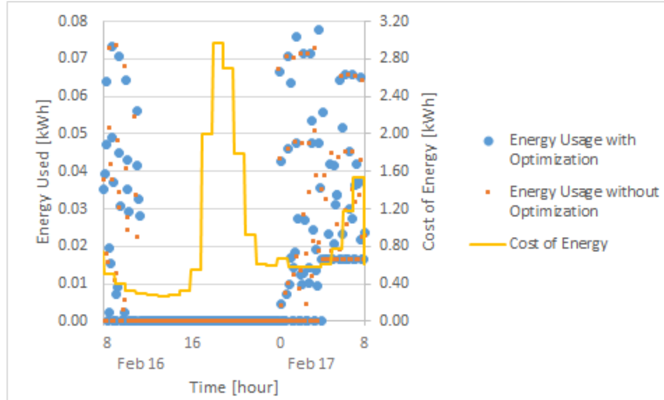

FIGURE 9: ENERGY CONSUMPTION IN FEBRUARY DURING A TIME OF HIGH PRICE INCREASE

A potential cause of this discrepancy is that the weather file and wholesale cost data are from two different years. Therefore, the wholesale price may not correspond to times of high energy consumption in this set of simulations.

Overall, the results of the study show the optimization working to preheat the house before a price increase. The greater the proportional constant, α, from Equation 1, between retail and wholesale price, the greater impact preheating will have on cost savings. This work calls for future work to determine the most effective pricing models for load shifting and decreasing overall costs. The simulation strategy can be expanded to include different building models, locations, timeframes, and setpoint control strategies, including occupancy sensing.

4. CONCLUSION

This work provides a validation approach for energy optimization models of grid-interactive buildings. Using co-simulation, the energy usage of a building can be optimized by taking into account the future pricing of energy. The optimization control strategy resulted in significant savings in the January, February, and September weeks compared to the fixed setpoint temperature schedule. The month of September resulted in the least cost savings since little cooling energy was used regardless of optimization due to the temperate climate of San Francisco. The optimization control strategy with a fixed comfort zone resulted in less savings compared to the adaptive setpoint temperature strategy. The adaptive setpoint control strategy already provides significant savings compared to a fixed setpoint temperature schedule, so that optimization can only provide a slight improvement.

The validation method of using UCEF and EnergyPlus allowed for testing the energy control strategy with the building simulator and is highly adaptable for different control strategies, pricing models, locations, and building models. The validation method is scalable to include multiple building models with different characteristics in the same simulation.

Further research can build on the developed simulation strategy of this work. Other building models and locations can be used in future work to expand the breadth of this work. Occupancy-driven setpoint control can be added. A cost function for deviation from the comfort zone can be determined and added to the objective function of the optimizer to allow the indoor temperature to leave the comfort zone in pursuit of increased savings. The simulation strategy can be utilized to develop a pricing model under transactive energy. With more wholesale pricing information, an annual simulation can be run for further analysis.

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