Comparing economic benefits of HVAC control strategies in grid-interactive residential buildings

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ABSTRACT

Energy consumption in buildings continues to rise with increased deployment of energy-consuming equipment such as Heating, Ventilation, and Air Conditioning (HVAC) amid a growing world economy. Renewable energy is projected to comprise a majority of the future electricity supply, but the intermit-tent nature of renewables means that consumption must respond to dynamic supply for optimal utiliza-tion. This paper proposes a novel HVAC control strategy for residential buildings using the adaptive comfort model, considering occupancy through probability and real-time information, and optimizing the HVAC schedule to reduce cost, maintain thermal comfort, and respond to the dynamic availability of renewable energy while being generalizable to different situations. To validate this approach, the Universal CPS Environment for Federation (UCEF) co-simulation platform is used to connect advanced building controls with the building energy simulation software EnergyPlus. Simulations are performed for a residential building in Sacramento, CA during a typical summer week. Economic impacts, energy consumption, and thermal comfort are analyzed for traditional, adaptive, and occupancy-based control strategies under demand-based, tiered, and fixed electric tariff systems. Simulation results show that occupancy consideration, adaptive thermal comfort, and optimization can reduce cost by 50.1 %, electric-ity consumption by 52.9 %, and discomfort by 56.2 % compared to traditional fixed setpoints. The ability of the proposed HVAC control strategy to shift energy consumption away from peak times under a demand-based tariff system is qualitatively analyzed and findings suggest that maximum load-shifting on a grid-scale is attained using occupancy consideration with optimized control and demand-based pric-ing. For individual residential buildings, similar economic benefits can be gained using the less-complex adaptive HVAC control strategy with existing tiered or simple electric tariff systems.

1. Introduction

Global energy consumption is expected to increase by 1.3 % annually between 2020 and 2050, and electricity in particular is projected to grow even faster, at 1.8 % annually over the same period [1]. Buildings will be a major contributor, as their electricity usage is projected to increase by 70.1 % between 2020 and 2050 [1], and Heating, Ventilation and Air Conditioning (HVAC) makes up 49.4 % of the increase [2]. While many studies focus on industrial or commercial sector energy usage because each individual building has a larger economic impact, the residential building sector offers an equally large potential for energy saving and peak shaving. As of 2020, residential buildings in the United States consume 29.5 % of the total energy, and space heating and cooling consist of 39.4 % of the energy consumption in residential buildings [3]. While a single home has minimal effect on the overall grid, at scale the total energy consumption and balance of supply and demand can be positively impacted by more effective use of energy in residential buildings.

Along with growing consumption, the growth of factors including renewable energy sources (RESs), electric vehicles (EVs), and cooling demand will create new challenges for the management and stability of the electric grid. RESs generated 28 % of the total global electricity consumed in 2020, and are projected to supply 56 % of all electricity in 2050 [1]. Increased reliance on RESs requires improvements to managing supply and demand because the intermittent nature of some RESs limits the electricity supply at certain times. Along with RESs, the transition to sustainable transportation can create more variability in the grid. While electric vehicles currently make up less than 1 % of the global light-duty vehicle fleet, by 2050, electric vehicles are projected to comprise 31 % of all light-duty vehicles [1]. Since many EV charging stations are connected to the grid, increased penetration of EVs may significantly increase the peak demand if actions are not taken to shift EV charging times as well as operation of other equipment on the grid [4]. Another factor affecting electricity consumption is cooling demand, which is expected to increase by 182.1 % globally between 2020 and 2050 [2]. Demand for cooling is greatest in the late afternoon, when generation from some RESs, in particular solar, decreases.

As RESs are less able to adjust rapidly to demand, balancing the overall load on the grid will require flexible demand. Consumers, such as buildings, need to respond proactively to the dynamic supply of electricity to fully utilize the available energy when intermittent energy sources are producing effectively and reduce consumption when RESs are less plentiful [5]. One approach is to allow active buying and selling of energy among utility providers, prosumers – consumers with electricity generation capability such as rooftop solar – and regular consumers [6]. This multidirectional energy market concept is known as "transactive energy," which uses dynamic electric cost and associated controls to balance the supply and demand of electricity for the grid [6]. Each building becomes a participant in the market and needs an advanced control method with the flexibility to adapt to a varying energy supply to implement a transactive energy approach. Internet of Things technology will be used to coordinate and control appliances and electrical devices within each building [7]. Such control will actively and automatically interact with the transactive energy market, encouraging energy conscious behavior through financial incentives without negatively affecting thermal comfort or becoming burdensome to the user [7]. The Pacific Northwest Smart Grid Demonstration project evaluated the distribution system reliability, automation, and communication infrastructure for demand response and distributed generation and storage [8]. Other researchers explored efficiency in transactive energy systems via simulations [9,10]. A large scale network simulation model is used in Nguyen et al. to show how transactive control can help solve the problem of peak demand and to improve system efficiency and reliability [9]. The model showed that energy-conserving behavior in homes can save up to 65 % of energy compared to wasteful behavior [9]. Bejestani et al. [10] propose optimal allocation of resources with consideration of uncertainty in RES generation and load by implementing a hierarchical transactive control architecture that combines market transactions at the higher levels with inter-area and unit-level control at the lower levels. While numerous studies demonstrate the positive effects of transactive energy including peak shaving and optimal allocation of resources, the majority of individual consumers have little understanding of demand-based energy tariffs and few are able to adjust their consumption [11]. Thus, price signals need to be interpreted and handled automatically in order to have a large-scale effect [11].

One method for peak load shifting and cost saving in a dynamic energy market is pre-heating and pre-cooling a building before the peak demand and high cost period. One study uses a decentralized grey-box building model of a real office building to simulate pre-cooling energy saving potential with a tiered electricity tariff, and found that energy cost can be reduced by up to one third [12]. Simulations of pre-cooling a single-family residence using rule-based control and an optimized rule-based control were shown to reduce overheating during heat waves [13]. At a district-level with over 800 varying type residential buildings, pre-cooling controls increased thermal comfort by 60 % using the unmet degree hours metric, but increased costs as well under a time-of-use pricing system [13].

When adopting pre-heating, pre-cooling, and other setpoint changes, the thermal comfort of occupants must be considered. Predicted Mean Vote (PMV) is the most common method for determining thermal comfort in literature [14], as well as in standards in many regions, including ISO 7730:2005, ANSI/ASHRAE Standard 55–2020, and EN 16798–1:2019 [15–17]. PMV depends on metabolic rate, clothing, radiant temperature, air speed, air temperature, and humidity [16]. PMV is often used alongside Predicted Percentage of Dissatisfied (PPD) to predict what percentage of people are uncomfortable in a given condition [18]. Both PMV and PPD are based on studies of people wearing standard uniform clothing while sedentary in temperature controlled chambers [18]. Izhar et al. detected metabolic rate and clothing using smartphone applications, combining wireless sensors for air velocity, relative humidity, and air temperature to implement all PMV factors in determining HVAC controls [19]. Espejel-Blanco et al. implemented PMV to design HVAC control systems to respond to thermal comfort and yielded energy savings of 33 % to 44 %, assuming constant values for metabolic rate, air velocity, and clothing insulation [20]. Some criticisms of PMV include that it does not account for behavioral changes when people start to feel uncomfortable, or to acclimation to different climates [18,21]. Other variations of PMV have been developed; Li et al. found that the variables of climate and building type played a significant role in determining thermal sensation and developed an adapted PMV model to reduce this discrepancy [21].

According to the adaptive thermal comfort model, the range of comfortable indoor temperature is a linear function of mean effective outdoor temperature because the human body adapts to different climates and seasonal temperature shifts throughout the year, as well as thermal adaptation [22]. Thermal adaptation is a behavioral response to temperature changes, which can be personal, often by adding clothing; technological, such as opening windows or operating HVAC; and cultural changes in activity based on the weather [18]. The adaptive thermal comfort model was introduced by de Dear and Brager [22] based on approximately 21,000 observations from around 160 buildings. Adaptive thermal comfort has been adopted into ANSI/ASHRAE Standard 55–2020 [16]. The adaptive model was refined to specific region, climate, ventilation, and building type by Parkinson, de Dear, and Brager [23] and has been supported by field studies around the world [24–26]. Rijal, Humphreys, and Nicol demonstrated that comfort temperature was not significantly affected by relative humidity and that behavioral adaptations to increase air movement helped maintain thermal comfort in hot and humid environments using over 13,000 observations from residences in Japan [24]. A field study recording thermal sensation votes of 430 occupants in office buildings during the summer season showed a linear relation between outdoor temperature and preferred indoor temperature, and showed that more occupants were comfortable in temperature ranges prescribed by the adaptive thermal comfort model compared to PMV [25]. Additionally, the adaptive model was shown to be applicable in air conditioned buildings [25]. A field study of residential buildings in different climate zones in China found that the comfortable indoor temperature using a thermal sensation model was linear with outdoor temperature, and thermal adaptations increased in climates with the largest discrepancy between summer and winter temperature [26]. The relation between indoor and outdoor temperature is consistent with the PMV model, which shows an increased comfortable temperature as the outdoor temperature increases and vice versa if the other factors are held constant [16]. An adaptive-rational thermal comfort model was proposed by Zhang et al. to account for thermal adaptations by adding an adaptive thermal comfort coefficient to PMV [27].

Home Energy Management Systems (HEMS) have been developed to assist users in more efficiently managing their home equipment including HVAC, lighting, and appliances. Many HEMS implement simple rule-based controls [28], while others use information from the electrical grid to optimize energy consumption in the home [29]. Researchers from NREL created Foresee, [30] an algorithm for generating and solving a multiobjective convex optimization problem that considers user-preferences to determine how to control the home equipment. Chen et al. used Model Predictive Control (MPC) to determine the optimal schedules of flexible thermal and non-thermal appliances using energy price information from the grid [29].

HEMS require extensive configuration to accommodate each building's unique thermal capacitance, HVAC configuration, local climate, and occupancy patterns. To avoid losing performance if users do not properly configure the HEMS, this work takes a more generalistic strategy that considers occupancy and thermal comfort inherently and operates using automatic input data without requiring user interaction. While previous studies optimize the home equipment based on information from the electrical grid and maintain an acceptable thermal comfort level, most use PMV for thermal comfort and require user inputs or rely on assumptions about metabolic rate and clothing. Many studies assume occupancy follows a predictable schedule. In contrast, the strategy proposed here addresses the random nature of occupancy in residential buildings by using probability to limit the discomfort caused by the setback. Aggregate historical occupancy data and current occupancy status are used directly in setpoint calculation, a method that is transferable to different types of buildings and occupants where occupancy data is available.

The present work extends from several prior works by the research team of the presenting authors. Singer et al. [31] developed a co-simulation environment using UCEF, Transmission Control Protocol/Internet Protocol, and Functional Mock-up Interface, that allowed for setpoints from an external controller to be used in an EnergyPlus simulation. An economically viable method for detecting and processing human presence in real-time using non-invasive sensors was presented by Wang et al., but no associated control method was implemented [32]. Wang, Pattawi, and Lee [33] demonstrated that using the current occupancy information, HVAC energy consumption can be reduced while still maintaining a high level of thermal comfort in comparison to traditional setpoint controllers. An occupancy-driven thermostat that switched between adaptive setpoints when occupied and an expanded range between 12 °C and 32 °C when unoccupied was used to show the impact of occupancy detection alone on energy savings in residential buildings [33]. One challenge of using occupancy detection without probability is that when occupants return, the HVAC system may require time to return to a comfortable temperature, during which the occupant may experience thermal discomfort. HVAC efficiency may decrease if occupancy changes at a high frequency, requiring frequent cycles of setting back and returning to a comfortable temperature. This work attempts to solve this dilemma by incorporating occupancy prediction using historical occupancy data, and adjusting the temperature constraints based on the probability of occupancy at that time. In McCurdy et al. [34], optimization with adaptive and fixed comfort zone models and wholesale-based pricing was simulated for several one-week periods to demonstrate the cost saving potential for heating a residential building. The optimization was validated using co-simulation, demonstrating load shifting to times of lower price, with the majority of benefits during extreme weather [34]. While previous works demonstrate energy-saving HVAC control strategies and simulation capabilities, the present research adds the ability to account for the random nature of occupancy using probability, expands optimized control to consider separate direct and diffuse solar radiation components in addition to indoor temperature and outdoor temperature, and analyzes economic savings for the end user and load-shifting benefits at utility scale.

The contribution of this work is presenting and validating a demand-based electric tariff and novel HVAC control strategy to increase efficiency and cost savings for grid-interactive residential buildings. Thermal comfort is considered requiring only current weather data. Adaptive thermal comfort is adjusted to use current conditions rather than a recent average temperature to improve efficiency in climates with a larger temperature variation within a 24-hour period. The random nature of occupancy is considered using an occupancy generator to enable testing of real-time occupancy information and the historical probability of occupancy for that time of day to determine the temperature constraints while reducing equipment cycling and discomfort when occupants return unexpectedly. An optimization strategy to schedule HVAC operation attempts to reduce the electricity cost to the consumer under tariff systems in which the price of electricity changes throughout the day in response to supply and demand. Potential benefits to utility operators in terms of load shifting to low demand times are analyzed. A total of five HVAC control strategies are modeled: fixed setpoint, adaptive, adaptive with optimization, occupancy-based, and occupancy-based with optimization. Economic effects of conventional electric tariff systems and a demand-based pricing system where electricity cost is proportional to wholesale energy prices are compared by simulating four pricing models: demand-based, simple (fixed-rate), tiered (time of use), and extreme tiered tariffs. A co-simulation framework for simulating residential buildings with advanced controls is utilized to compare the economic benefits, energy consumption patterns, and thermal comfort under each scenario.

2. Methods

This work demonstrates a strategy for optimizing HVAC control to decrease cost and increase occupant's thermal comfort based on electricity rate pricing, occupancy probability, and real-time occupancy information. To test the efficacy of this new HVAC control strategy against existing conventional control algorithms, this work utilizes a framework for simulating buildings with complicated controls using co-simulation to integrate each of the simulation entities.

2.1. Co-simulation platform

EnergyPlus, a building energy simulation program developed by the United States Department of Energy, is used to model a single-family house [35]. While EnergyPlus has settings for scheduling lighting, home appliances, and HVAC operation, it can only follow pre-defined schedules. The present work uses the external computing platform powered by Universal Cyber-Physical System Environment for Federation (UCEF) developed in Singer et al. [31] to compute and transmit variables that change during the simulation such as real-time occupancy, weather conditions, and optimization between the different simulation components. This configuration allows a single EnergyPlus house model to simulate advanced control strategies calculated in Java and Python. The series of communication between EnergyPlus and the simulation entities is summarized in Fig. 1.

The external computing platform also enables realistic HVAC equipment operation cycle time controls, instead of the default EnergyPlus model, which assumes equipment can be run continuously at lower power settings. Equipment operation cycles are simulated by keeping the air conditioning active until it has cooled

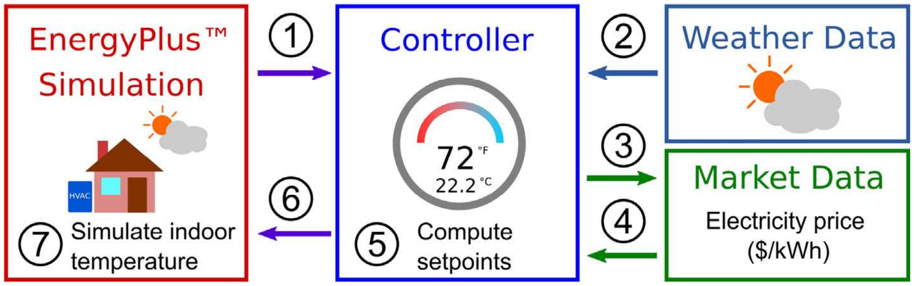

Fig. 1. The transfer of information through the simulation for each timestep. (1) EnergyPlus transmits the current building energy and environment information to the Controller. (2) The Controller queries stored weather, occupancy, and building constants. (3) The Controller sends the building energy consumption information to the Market. (4) The Market sends electricity price to the Controller. In future works, the Market will adjust or recompute the electricity price based on the energy consumption it receives. (5) The Controller computes the HVAC indoor air temperature setpoints using weather, occupancy, electricity price, and building parameters (6) The controller sends the setpoints to EnergyPlus. (7) EnergyPlus uses the setpoints to simulate the indoor temperature for the new timestep.

1 °C below the setpoint, then shutting the cooling off until the temperature rises within 0.1 °C of the setpoint.

2.2. House model

All simulations use a residential building model obtained from the U.S. Department of Energy and based on the 2018 International Energy Conservation Code, consisting of a single-family detached home with a heat pump for electric heating and cooling and a crawlspace foundation type in the Northern California region [36]. The house is approximately 110 m^2, is located in the suburbs, has a single floor, single cooling zone, and uses appliance and lighting schedules from the IECC model [36]. Weather and pricing data from a representative summer week of August 1–7, 2020 are used to simulate recent conditions and prices. Weather information is from MesoWest, a historical weather database by the University of Utah and the weather station located at the Sacramento International Airport [37].

2.3. Electric rate models

Utility companies throughout the United States have implemented electricity rate programs where customers pay a function of the wholesale price [38–40]. Customers are expected to plan

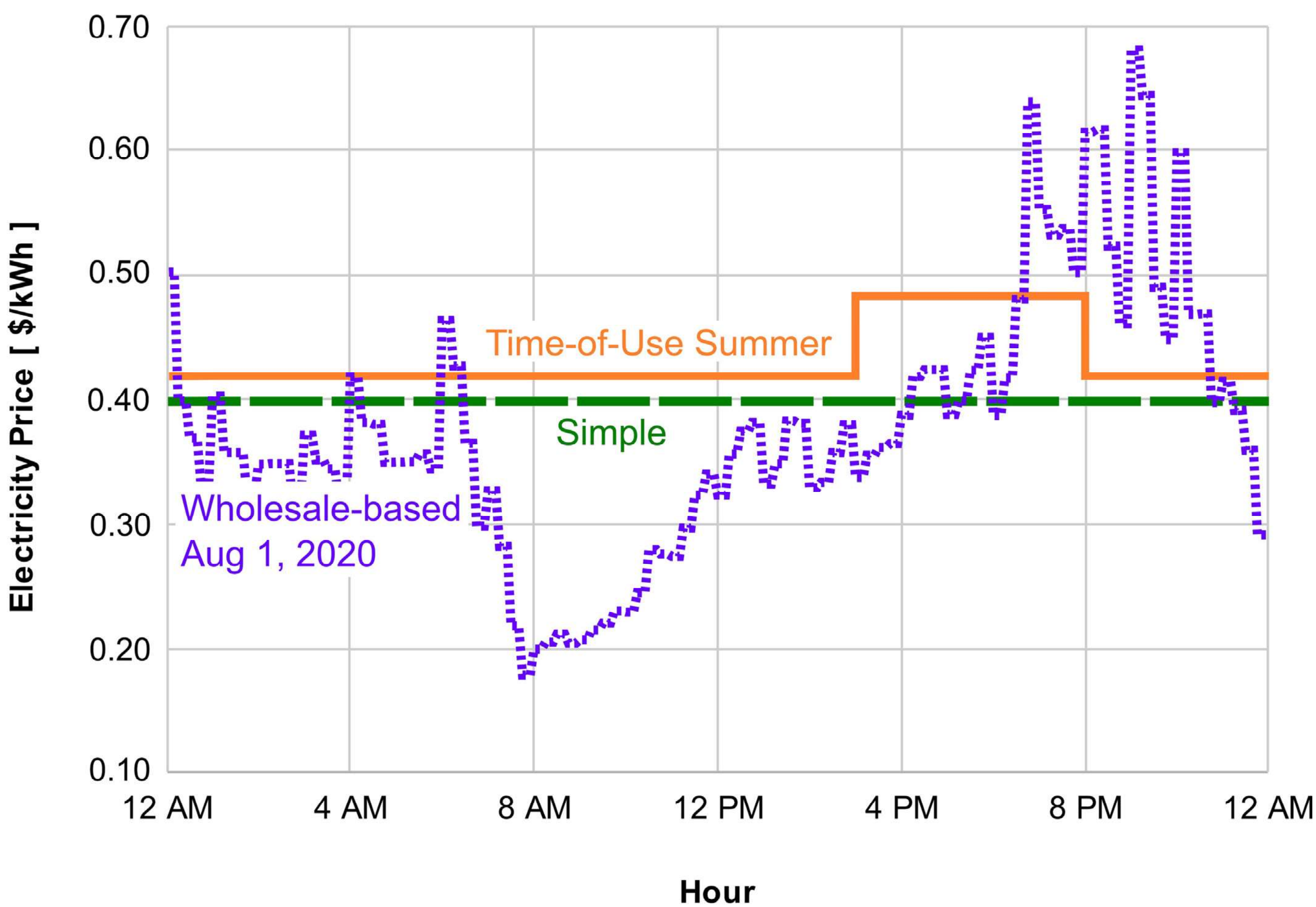

Fig. 2a. Comparison of the simple, seasonal time-of-use, and one example day of the wholesale-based electricity pricing schemes used to demonstrate occupancy and optimization. Note that the wholesale-based price varies by day.

ahead and manually adjust their energy consumption so day-ahead hourly forecasts are used [40]. This work uses real-time wholesale pricing in 15 min intervals because grid-interactive buildings can respond with less planning and it provides a more accurate view of the current supply and demand. Prices are from Pacific Gas and Electric Company (PG&E), the utility company for the simulated region [41]. Similar to the tariff systems used in Ref. [38–40], a realistic demand-based electricity retail price is calculated using the linear relation in Eq. (1).

$$RetailPriceofElectricity = \alpha \times WholesalePriceofElectricity + \beta \qquad (1)$$

Values of α and β are computed such that the time average demand-based price matches the average retail price charged by PG&E during the duration of the simulation. In this work, a period between August 1, 2020 and August 7, 2020 was simulated with $\alpha = 17.1 \times 10^{-3}$ and $\beta = 0.0094$ USD/kWh to match the average time-of-use summer price of 0.438 USD/kWh [42]. To compare the impact of the demand-based pricing scheme, comparison simulations are run using the time-of-use summer and simple rate plans offered by PG&E. A hypothetical schedule with extreme price jumps between 0.01 USD/kWh and 10.00 USD/kWh is also simulated to model wholesale pricing trends during extreme weather events, in which the peak price may be greater than ten times the price on a median or typical day. This is a time-of-use schedule inspired by a series of days such as August 13, 2020 to August 20, 2020 in which wholesale energy prices increase by at least 10 times the average price and sometimes more than 70 times the average for one or more time periods [43]. These rate plans along with demand-based pricing for typical and extreme event days are compared in Figs. 2a & 2b.

2.4. Thermal comfort model

The PMV thermal comfort model may be more challenging to implement using current technology because it can be difficult to obtain clothing type, metabolic rate, and radiant temperature [16]. Barriers to implementation include detection, which would require advanced vision sensors or continuous self-reporting by the occupants, and that multiple occupants may have a different comfort level if they partake in different activities or wear different levels of clothing. The adaptive thermal comfort model, as described in Section 1, is defined using a function of outdoor air temperature only [16]. This simplification provides a thermal comfort range while eliminating the challenge of obtaining the parameters needed for PMV thermal comfort. Instead of a historical mean daily temperature, this work follows prior works in using an instantaneous adaptive setpoint based on current outdoor temperature, which may provide greater energy savings particularly in climates where there is a large difference between daily high and low temperatures [33,34]. The mean comfortable temperature at any time is computed as a function of the current outdoor temperature as shown in Eq. (2).

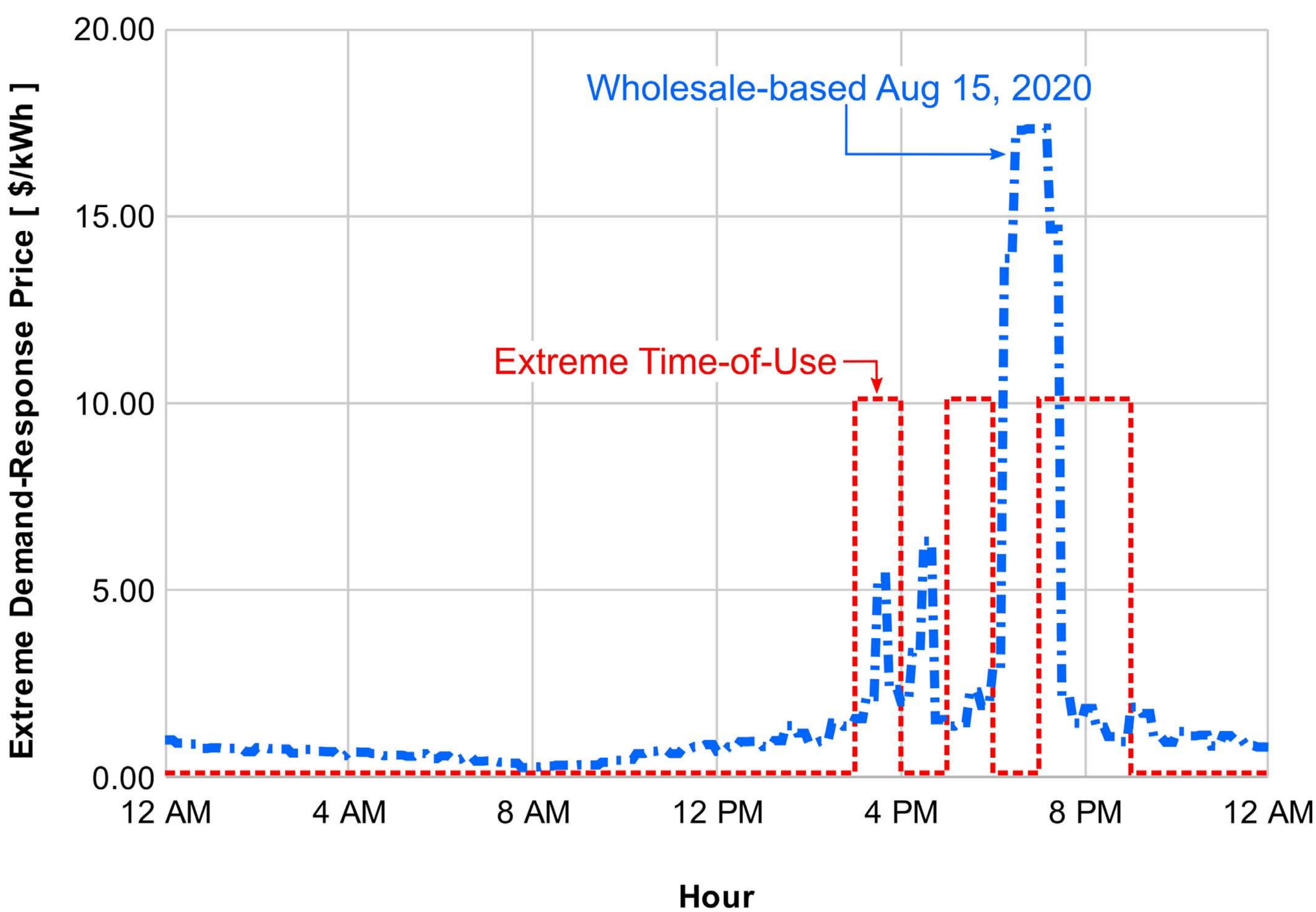

Fig. 2b. Extreme time-of-use has three periods in which the electricity price jumps from $0.01 to $10.00. Wholesale-based prices for August 15, 2020, when prices spiked for about two hours because of power shortages and a heat wave, are shown as an example of a real life extreme event although this day is not part of the simulation [43].

$$\text{Mean Comfortable Temperature} = \begin{cases} 20.9 & T_{outdoor} < 10 \\ 17.8 + 0.31 * T_{outdoor} & 10 \leqslant T_{outdoor} \leqslant 33.5 \\ 28.185 & T_{outdoor} > 33.5 \end{cases} \quad (2)$$

The temperatures in Equation 2 are in degrees Celsius. The equation has bounds at 20.9 °C and 28.185 °C to account for extreme outdoor temperatures. Data from the study shows that 90 % of occupants would be comfortable within ±2.45 ℃, creating a "comfortable zone" and 80 % would be comfortable within ±3.50 ℃ such that this region is considered an "acceptable zone" [22,16]. These comfort ranges are shown in Fig. 3 alongside a conventional "always on" thermostat setpoint with a constant temperature range regardless of outdoor temperature.

Using the adaptive comfort model can help reduce HVAC operation because the comfortable temperature is proportional to the outdoor temperature such that the temperature difference between indoor and outdoor is reduced.

2.5. Occupancy simulator

To consider occupancy information, an occupancy simulator determines when the building is vacant or occupied. This work uses the probability that a residential building will be occupied during a given hour aggregated from the American Time of Use (ATUS) study [44]. First, a random number generator is used to generate a uniformly distributed random value between 0 and 1. If that number is less than the occupancy probability for that hour, the building is considered occupied. If the random number is greater than the probability of occupancy, the building is vacant. The building may occasionally be unoccupied during times of high probability of occupancy and vice versa due to the random nature of occupancy, but an average of many days will match the expected probability for each time. Using this strategy, 11 trials of duration 1 year (365 days) of simulated occupancy data matched the occupancy probability data with an average mean squared error of 4.58×10^{-4}. Aggregated occupancy averages for the median case are shown in Fig. 4.

2.6. Considering occupancy probability & current status

The probability and real-time based occupancy consideration allows the proposed HVAC control strategies to be transferable to different buildings and different occupants, provided occupancy data is available. The occupancy-based HVAC controls consider both the simulated occupancy state from Section 2.5 and the per-

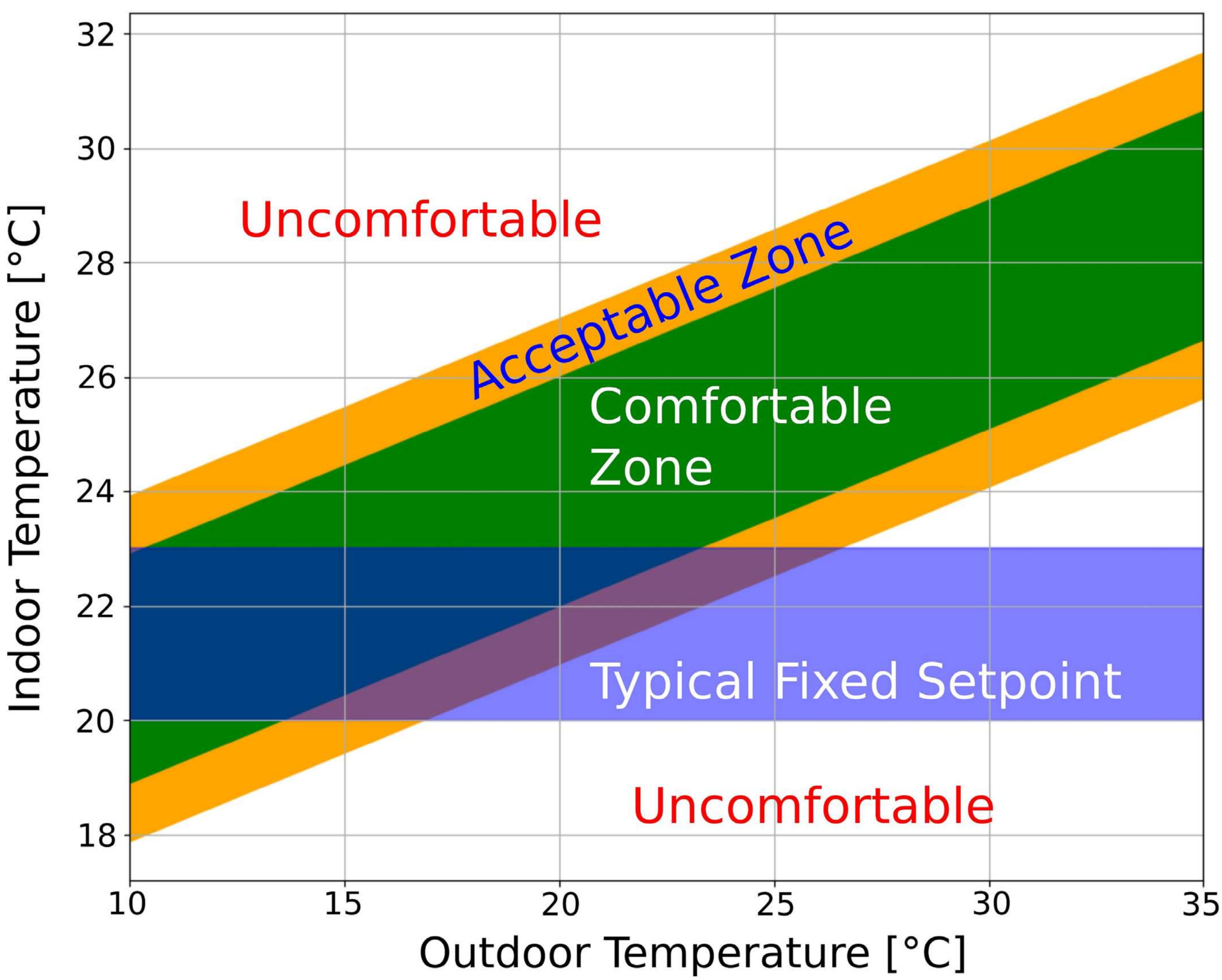

Fig. 3. Instantaneous adaptive comfort zones compared to fixed setpoints.

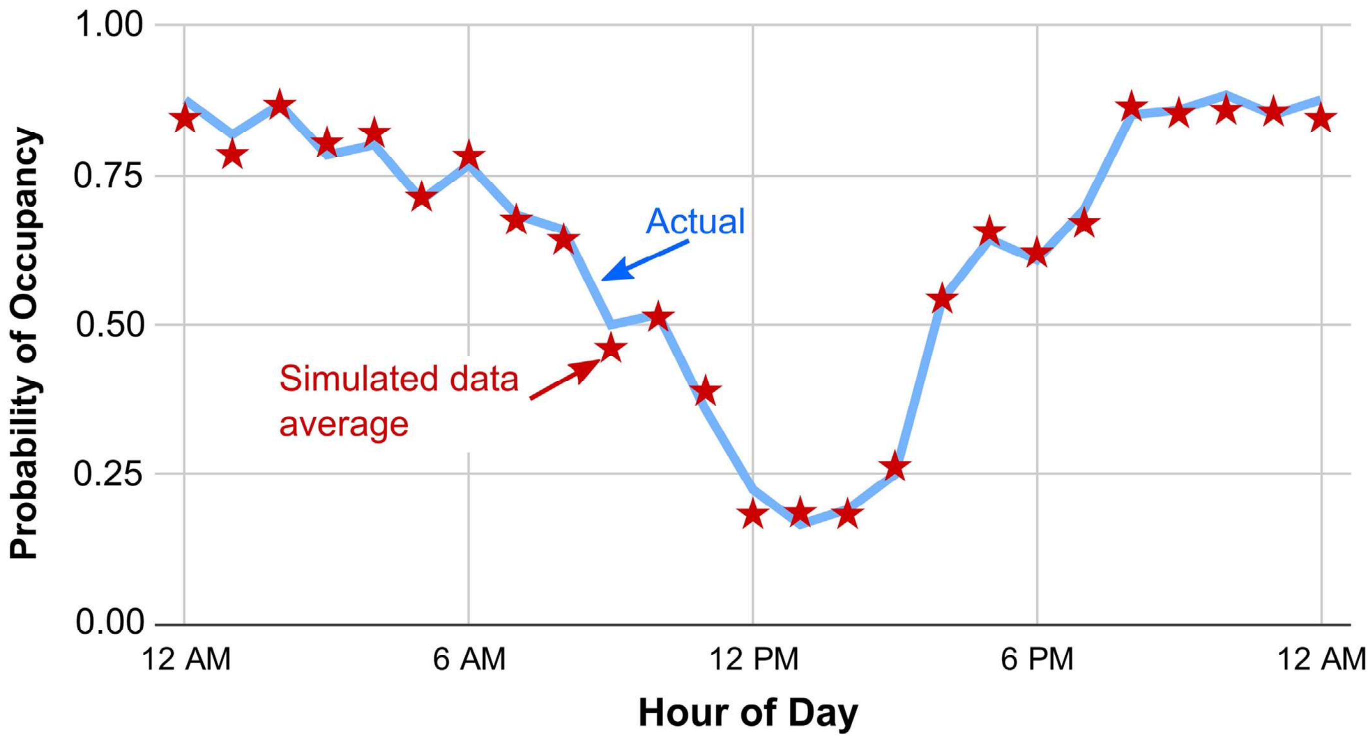

Fig. 4. Comparison of occupancy probability data from ATUS [44] and a 365-day average of the generated occupancy data.

cent probability of occupancy. The simulated current occupancy is used to determine if the temperature constraints can be relaxed, allowing the system to adjust so that an occupant who appears at an unexpected time is not left thermally uncomfortable. The HVAC controller calculates two types of setpoints: expanded setpoints based on occupancy probability to reduce space heating or cooling, and adaptive setpoints where 90 % of occupants are comfortable. If the house is occupied, the adaptive setpoints are used.

When the building is vacant, adaptive thermal comfort values from de Dear and Brager [22] and the occupancy probability values from the ATUS [44] are combined to determine occupancy probability-based adjustments to the temperature constraints. The central limit theorem is applied to the thresholds described in Section 2.4 where 80 % and 90 % of occupants are comfortable to create a normal distribution for the percentage of occupants who are comfortable at a given temperature difference from the ideal comfortable temperature in Equation 2. The comfort range expansion in degrees Celsius is computed using the probability of occupancy and a normal distribution with a standard deviation of 3.937. During timesteps in which the building is unoccupied, the temperature constraints are the ideal comfortable temperature in Equation 2 plus and minus the comfort range expansion. Incorporating occupancy probability helps reduce the frequency and severity of uncomfortable temperatures when occupants return by making more gradual adjustments to the temperature constraints when a return is more likely. The combined occupancy responsive HVAC control strategy for one day is illustrated in Fig. 5.

2.7. Optimization of HVAC schedule

The adaptive and occupancy-based HVAC control strategies may be further improved using optimization to consider future weather conditions and electricity prices when deciding when and how much to operate the HVAC system. The solver from CVXOPT, a Python-based convex optimization software library [45], is implemented to predict the optimal HVAC schedule. Using the electricity prices and the relationship between indoor temperature, energy consumption, and environmental factors, CVXOPT solves for the next two hours of indoor temperature values that result in the minimum electricity cost while remaining within the comfortable indoor temperature constraints provided. Because CVXOPT is forecasting future indoor temperature with varying HVAC operation, a method for predicting the indoor temperature for a series of timesteps into the future is used.

The relationship to predict indoor temperature was derived in a previous work by the presenting authors [34], using the energy consumption by the HVAC system, outdoor temperature, direct solar radiation, and building material information. Using historical HVAC energy consumption during the initial regression allows the model to inherently account for factors affecting HVAC efficiency such as equipment type and coefficient of performance. Since indoor temperature is affected by all heat gains, other heat gains are addressed in the regression as well. In this work, diffuse solar radiation is added as a factor to improve prediction accuracy when clouds, smoke, or other obstructions reduce the direct solar radiation. Eq. (3) computes the predicted indoor temperature for the next timestep.

$$T^{n}_{indoor} - T^{n-1}_{indoor} = dt \times [C_1\left(T^{n}_{outdoor} - T^{n-1}_{indoor}\right) + C_2\dot{E}^{n}_{HVAC} + C_3 Q^{n''}_{direct\ solar} + C_4 Q^{n''}_{diffuse\ solar} \tag{3}$$

Removed:

In Eq. (3), the next timestep is designated by the superscript n, and the previous timestep is n-1. T^{n}_{indoor} is the indoor temperature at the nth timestep, dt is the duration of one timestep, $T^{n}_{outdoor}$ is the outdoor temperature at the nth timestep, T^{n-1}_{indoor} is the indoor temperature in Kelvin at the previous timestep. $\dot{E}^{n}_{HVAC}$ is the amount of thermal energy in watts added to or removed from the building by the HVAC during the nth timestep. $Q''^{n}_{directsolar}$ and $Q''^{n}_{diffusesolar}$ are the amount of direct and diffuse solar radiation respectively in watts per square meter during the nth timestep. The coefficients

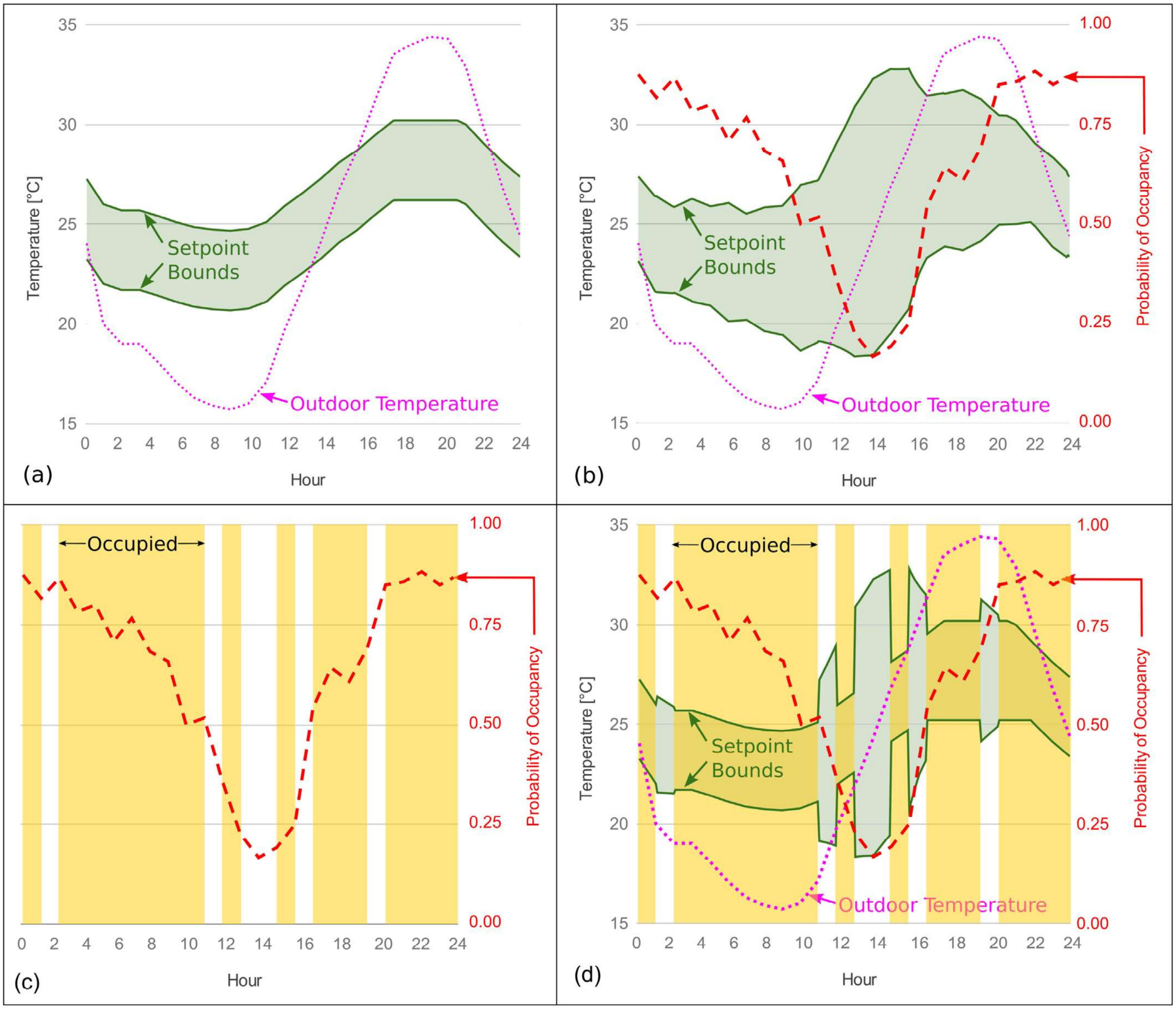

Fig. 5. Illustration of setpoint generation method with August 1, 2020 data. (a) Adaptive setpoint bounds based on outdoor temperature only. (b) Setpoints based on the probability of occupancy and outdoor temperature at a given time. (c) The randomly generated occupancy status, indicated by shaded regions, alongside the probability of occupancy at that time, using the method described in Section 2.5. (d) Setpoints that use the adaptive bounds when occupied, and occupancy probability when unoccupied.

Table 1
Thermal model & indoor temperature prediction constants from the linear regression.

Constant	Value
C_1 [1/s]	5.31×10^{-05}
C_2 [K/(kWh*s)]	0.0108
C_3 [(K*m^2)/(kWh*s)]	5.27×10^{-07}
C_4 [(K*m^2)/(kWh*s)]	9.58×10^{-07}

C_1, C_2, C_3, & C_4 are constants shown in Table 1, which are determined using a linear regression of historical indoor temperature, HVAC energy, and weather data generated in EnergyPlus for the specific building model.

For the training dataset, the model overall RMS error was 8.62×10^{-4} K per 5 min timestep. Thus, these constants are able to produce a sufficiently accurate prediction of indoor temperature for the next timestep.

Table 2
Simulation results for a typical summer week using the demand-based pricing strategy.

Pre-cooling optimization	Temperature setpoint method	Cost [$]	Electricity [kWh]	Fraction of occupied time within 90 % comfort zone [%]
No	Fixed (baseline)	27.89	61.19	42.29
Yes	Occupancy	13.91	28.85	98.44
No	Occupancy	13.92	28.86	98.44
Yes	Adaptive	14.25	30.18	99.93
No	Adaptive	14.38	30.34	99.93

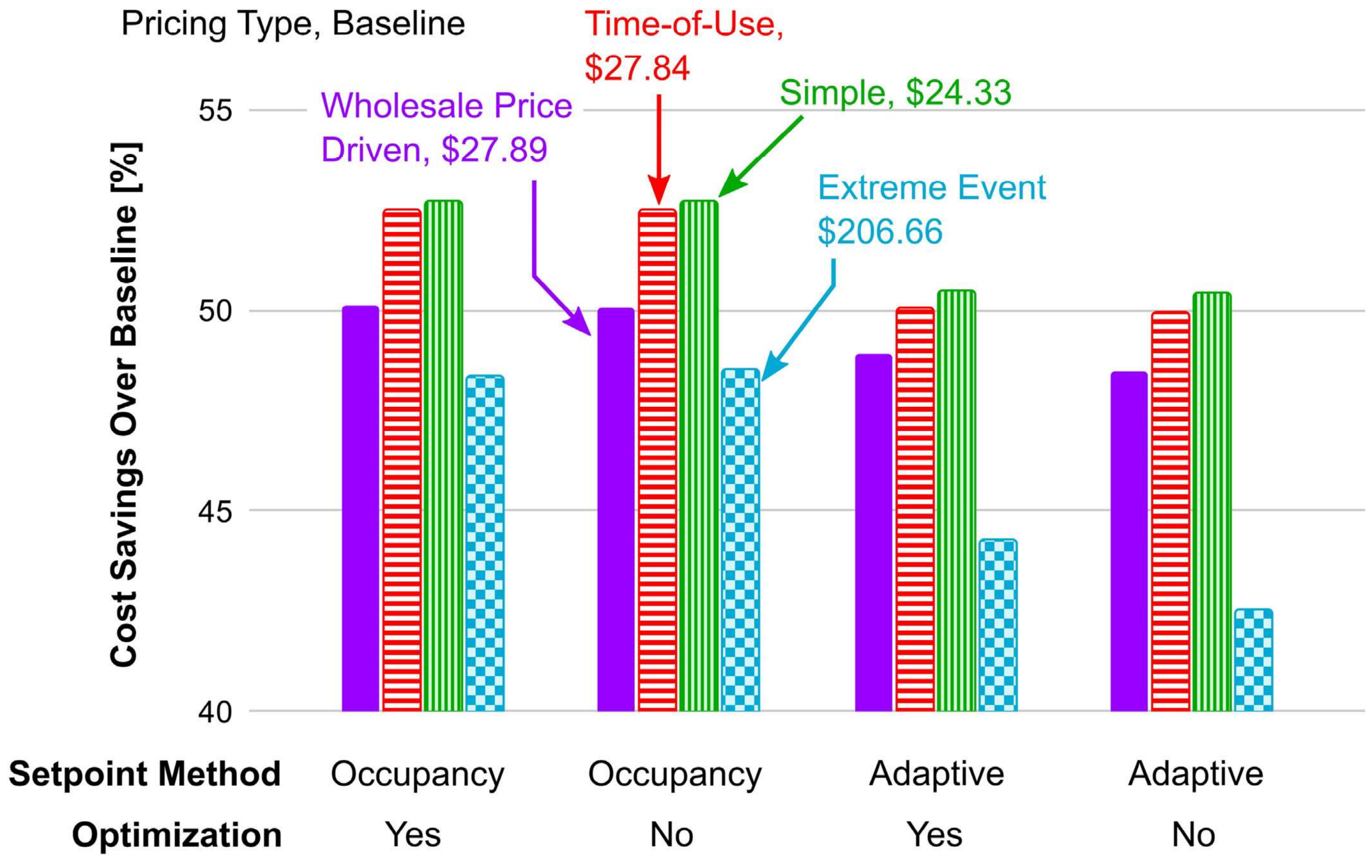

Fig. 6. Percentage of energy cost savings for the consumer comparing the baseline fixed, non-optimized controller to alternative controller strategies under different pricing schemes.

In the optimization, the amount of energy transfer must remain within the capabilities of the HVAC system. The energy transfer is negative when cooling to represent thermal energy removal, and positive when heating such that thermal energy is added. Eq. (4) ensures that no heating occurs when in cooling mode and vice versa.

$$0 \leqslant |\dot{E}^n_{HVAC}| \leqslant |\dot{E}_{HVAC,Max}| \tag{4}$$

The indoor temperature setpoint associated with the optimal energy consumption is computed using Eq. (3) by manipulating $\dot{E}^n_{HVAC}$ E^n_{HVAC} to minimize the cost function in Eq. (5).

$$\text{Cost Function} = \Sigma\,(\,\text{Electricity Price} \times E^n_{HVAC} \tag{5}$$

The predicted optimal indoor temperature, T^n_{indoor}, is constrained using Eq. (6) to stay within the setpoint bounds computed using the adaptive thermal comfort or the occupancy-based methods, limiting the amount of variation of $\dot{E}^n_{HVAC}$in Eq. (5).

$$T^n_{comfort,lower} \leq T^n_{indoor} \leq T^n_{comfort,upper} \tag{6}$$

2.8. Cases simulated

Three methods are used to determine the allowable temperature constraints. “Occupancy” uses the current occupancy and historic probability described in Section 2.6 along with the adaptive thermal comfort model to determine HVAC setpoints. To benchmark the HVAC control strategy proposed in this work, existing HVAC control strategies are simulated for comparison. “Adaptive” refers to the strategy discussed in Section 2.4 based on the adaptive thermal comfort model for the 90% comfort zone without occupancy information. “Fixed” uses constant setpoints between 20 °C and 23 °C. “Optimization” refers to the method described in Section 2.7. When simulating without the optimizer, the temperature constraints are the setpoints, such that energy and cost savings can be gained from more effective thermal comfort management but no precooling or load shifting can occur.

Each of the setpoint generation methods is simulated for the building model in Section 2.2 with each of the electricity tariff systems in Section 2.3 for a total of 20 simulations.

Thermostat setpoint methods.

1. Baseline: Fixed, no optimization.
2. Occupancy, with optimization.
3. Occupancy, no optimization.
4. Adaptive, with optimization.
5. Adaptive, no optimization.

Electricity tariff systems.

1. Simple.
2. Time-of-use.
3. Wholesale-based.
4. Extreme event time-of-use.

3. Results and discussion

The simulations are shown in Table 2 and are categorized by whether or not the optimizer is used to precool the space and the type of temperature constraint/setpoint.

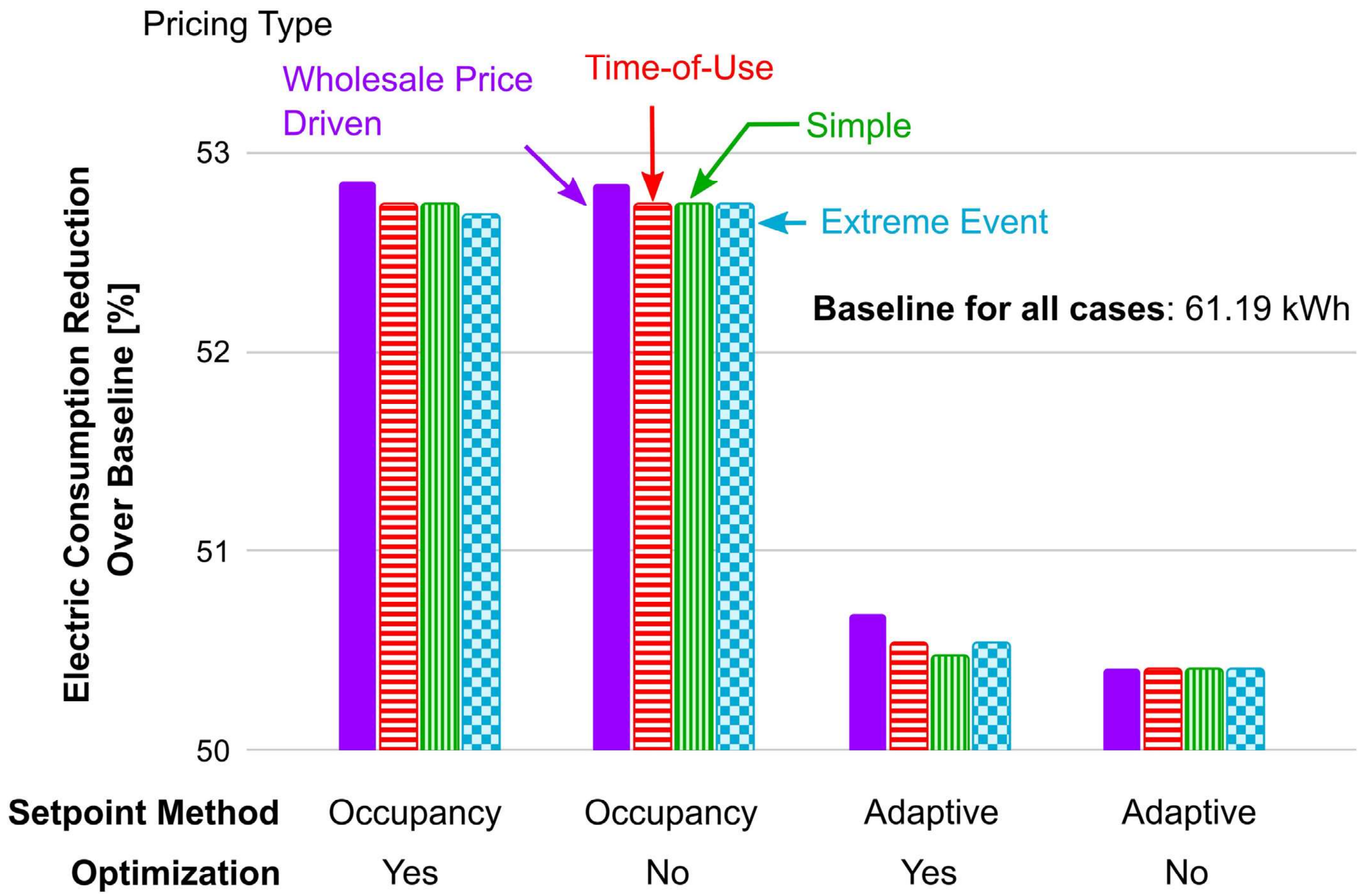

Fig. 7. Amount of electricity saved compared to the baseline fixed, non-optimized controller using alternative controller strategies and different pricing schemes.

The ‘‘occupancy" and ‘‘adaptive" simulations produce relatively similar results with demand-based pricing. The weekly cost ranges from $13.91 to $14.38, the electricity consumption ranges from 30.34 kWh to 28.85 kWh, and the adaptive comfort condition is met for above 98% of the occupied time. All of the proposed improved HVAC control strategies reduced cost, electricity consumption, and discomfort compared to the ‘‘fixed" simulations. The fixed setpoint causes thermal discomfort by over-cooling when the outdoor temperature is high, which can be seen in the behavior of the thermal comfort model compared to the fixed setpoints in Fig. 3.

These findings suggest that using occupancy data with an optimizer over a two hour horizon reduces the electricity cost and consumption compared to an adaptive control strategy without optimization and occupancy consideration. The effect of pre-cooling is relatively small because under typical conditions the optimizer predicts that pre-cooling by amounts less than 0.5 °C is most efficient. However, small fluctuations are not reflected in the actual indoor temperature because of HVAC equipment operation cycle time controls which operate on 0.9 °C cycles. Given the thermal mass of the building, pre-cooling to the coldest allowable temperature is often less efficient than simply keeping the building close to the maximum allowable temperature because the additional HVAC operation and temperature difference is not justified. The average price change with wholesale-based pricing between any two timesteps is 3.86 %, but the price can vary between $0.01 and $1.15 over one day. The two-hour optimization horizon is not long enough to consider price fluctuations over a longer period, such as pre-cooling during the morning then allowing the house to gradually warm up during the afternoon.

These general patterns occur for all of the different pricing models. The economic and energy-saving impact for the simulated week of the four different pricing schemes with each thermostat model are compared in Figs. 6 and 7, respectively.

Key trends observed are consistent across all pricing cases. Over 40 % cost savings for the homeowner are attained using adaptive setpoints. Pre-cooling optimization has relatively small savings potential because the optimizer determined that pre-cooling more than 0.5 °C is less efficient than staying close to the adaptive or occupancy-based setpoint bounds.

Simulations using wholesale-based, time-of-use, simple, and extreme event pricing demonstrate the effect of the pricing scheme in incentivizing changes in energy consumption habits. With the simple and tiered rate pricing, there were similar reductions in price and electricity consumption between the different control strategies compared to the wholesale based price. Although the cost saving percentage was lower, the extreme event pricing showed a large total savings potential – reducing the cost from $206.66 with a fixed thermostat, to $118.77 with an adaptive thermostat and $106.40 using occupancy. The outdoor temperature is the highest between 3 PM and 10 PM, the price is highest between 4 and 5 PM, 5–6 PM, and 7–9 PM, and average probability of occupancy during the extreme-price hours is 61 %, which combines to limit the potential for energy saving using adaptive, occupancy, and optimization. Thermal comfort changes by less than 0.1 % across the different tariff systems.

The results comparing the pricing schemes may give the appearance that the demand-based or extreme-event pricing is not as economically rewarding for consumers. While demand-based pricing results in the greatest reduction in energy consump-

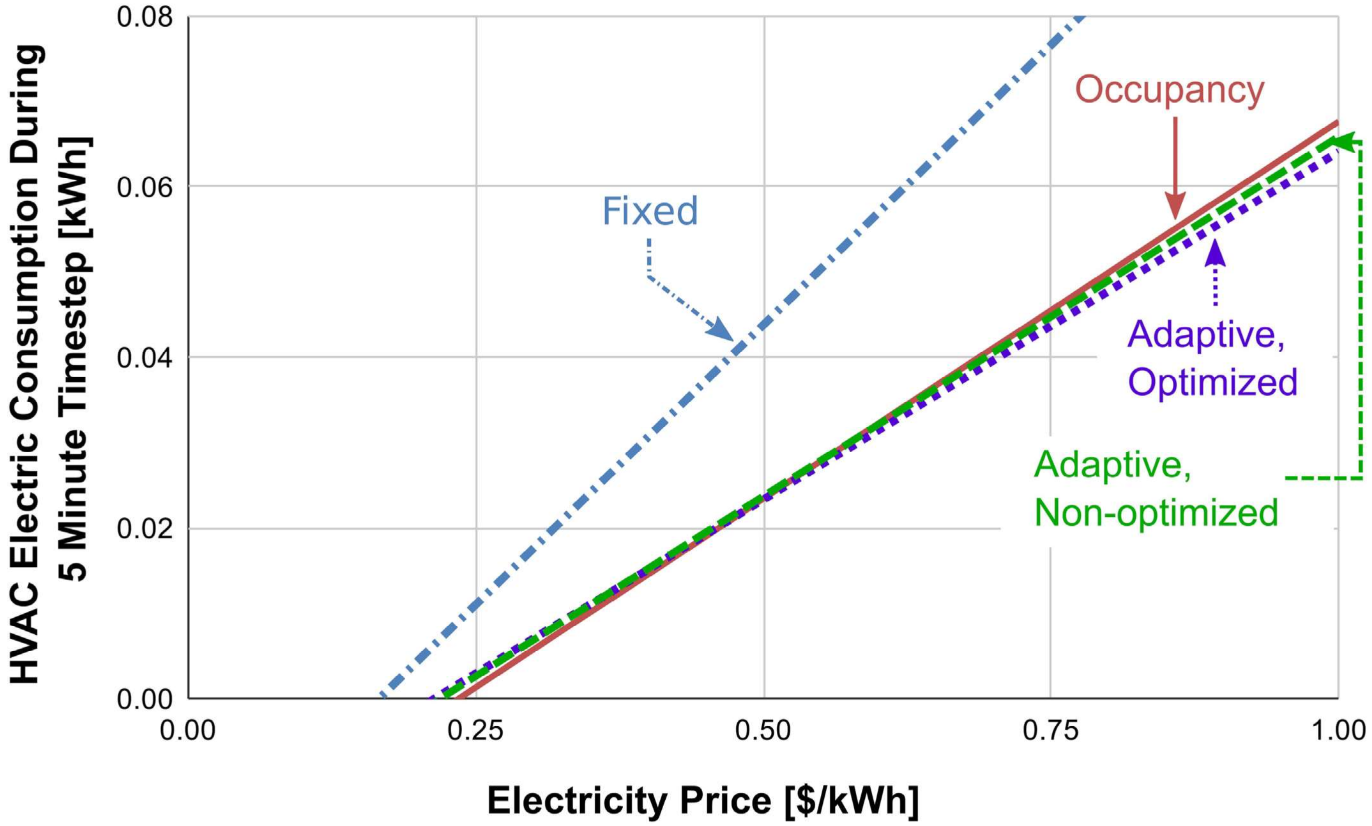

Fig. 8. Linear fit of electricity price to the amount of energy consumption at each timestep for the different control models with wholesale price driven electric rates. Note that the occupancy with and without optimization overlap so they were shown as a single line.

tion, it causes the customer to pay about two percentage points more over the time-of-use plan. The cost increase using wholesale-based pricing could be caused by the fact that when outdoor temperature is far from the comfort zone and probability of occupancy is high, demand tends to increase across the entire grid, driving up the wholesale price. During these times, pre-cooling is not sufficient and the HVAC in the model building is required to operate more frequently.

The benefit of optimization and occupancy-based control can be better appreciated at the utility scale. The best fit of electricity price and amount of consumption for all timesteps for the one-week simulation under each control strategy is plotted in Fig. 8.

Under a wholesale-based tariff system, lower electric consumption at higher electric price is shown with all of the adaptive and occupancy-based simulations. A smaller initial electricity price represents an offset due to times when energy usage is very small, indicating that timesteps where price was higher generally had little or no energy usage. In systems where price is proportional to the ratio of energy demand versus production capacity, adding optimization to an adaptive system improves load shifting from high demand to low demand times, which causes a decrease in slope, particularly for adaptive with optimization. Occupancy consideration decreases the total energy consumption by increasing the timesteps in which little to no energy is used, explained via the increased price axis intercept for all of the novel control strategies. The probability of a better correlation is below 0.2 %, indicating a highly significant result. If widely implemented, these features can decrease peak load across the grid, allowing for more efficient production and enhanced stability of the electric grid during extreme weather events.

4. Conclusion

This work develops a simulation framework to implement advanced controls in EnergyPlus for a single building model. The simulation results demonstrate that an adaptive and occupancy-based HVAC control strategy can reduce cost, electricity consumption, and discomfort for building occupants compared to a conventional always on thermostat. All of the novel control strategies reduce electricity costs by approximately half. Users can experience significant benefits with adaptive-based HVAC control alone, which may be easier to implement because it only requires adding the current outdoor temperature and a simple mathematical formula. In practice, outdoor temperature and solar radiation can be obtained by Internet-connected controllers from local weather forecasts. Depending on the cost of controllers using pre-cooling optimization and occupancy, these strategies may not yield significant economic incentives for the end user over basic adaptive control. Around 5 % of additional savings can be attained using optimization and occupancy consideration, the exact amount varying based on pricing rate schedule. At utility scale, optimization to reduce costs in a wholesale price based tariff system can shift energy consumption away from peak times, helping to reduce the burden on the electrical grid. This work can benefit research related to building energy management, HVAC control, smart grids, and transactive energy by providing routes to more efficient electricity consumption by combining wholesale-based prices, optimization, and thermal comfort considering occupancy.

This work simulated a single random occupancy case with an average occupancy rate of 63 %, so the setpoints can be relaxed only 37 % of the time. Under these conditions, occupancy consideration reduced energy consumption and cost by an additional 5 % over the adaptive-based strategy alone. Future studies could expand upon this scenario by demonstrating the effect of occupancy-based control on buildings with more consistent occupancy patterns or fewer occupied hours, situations where there is a larger potential for energy savings.

This work showed significant benefits to different HVAC control strategies for one middle-income single-family residence. In order to understand the applicability of these methods to communities, another direction for future work is developing more diverse building, appliance, and occupancy models. Expanding this simulation framework to synchronize multiple buildings can reveal the effect of different electricity tariffs and HVAC control on grid-scale demand trends and different demographics, especially low-income households for whom energy-saving controllers and other retrofits may not be affordable.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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