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Energy saving impact of occupancy-driven thermostat for residential buildings

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ABSTRACT

Heating, ventilation, and air conditioning (HVAC) systems account for more than half of the residential energy consumption in the United States. Since most people do not have the expertise to control the HVAC system efficiently, unnecessary energy consumption is often caused by wasteful behaviors (overheating/overcooling and operation without occupancy). New Internet of Things (IoT) products for a smart home have the potential for energy saving by reducing the unnecessary operation of the energy system in a residential house. However, many people still hesitate to adopt this product with uncertain economic benefit. This work explores a co-simulation platform to assess energy saving impact and economic benefits of occupancy driven thermostat in a residential house. An occupancy simulator was devised and utilized to consider the random nature of the occupancy in a typical single family residential house. Six HVAC system control strategies were explored based on three types of thermostats (always on; schedule based; and occupancy driven) as well as two setpoint control algorithms (fixed setpoint; and adaptive control). Energy-plus was integrated into the co-simulation platform, which evaluated energy consumption and indoor temperature of a residential house in five climate conditions. User's comfort level was evaluated using the adaptive model for the six different control strategies in each location. The result showed that the occupancy information-based control algorithm can save about between 11% and 34% of energy without significantly risking the occupant's comfort level. The work also suggests that the adaptive control model has a more tangible saving impact as IoT products can easily integrate outside temperature. Depending on the locations, adaptive control can save up to 54% of energy consumption, and the occupancy information can add additional energy saving impact by 20%. Payback period varies for different control strategies and depends on the rate of utility as well as the amount of energy saving. Compared with the most wasteful control strategy (fixed setpoint - always on), adding a thermostat with adaptive – occupancy driven control strategy can lead to less than one year of payback period regardless of location.

1. Introduction

In 2017, about 39% (or about 38 quadrillion BTU) of total US energy was consumed by the residential and commercial buildings [1]. The majority of this energy is used by the HVAC system to maintain thermal comfort for occupants. Without active control by users, the HVAC system keeps running in a building even when a building is not occupied. In the commercial sector, the Building Energy Management Systems (BEMS) have often been designed and employed to reduce unnecessary operation [2]. However, the use of such a system is not economically justified for residential buildings so that an impact at a large scale cannot be achieved.

The conventional programmable thermostat on the market requires users to input operation schedule. Although energy can be saved by turning off the HVAC system during the unoccupied period, such energy saving requires consistent occupancy pattern. Occupancy behavior depends on individual and shows too much irregularity to define a consistent pattern. A survey in 2008 [3] shows that more than 50% of the respondents do not have fixed schedules. Unless a user makes a frequent adjustment of the schedule per special occasions, such energy saving cannot be achieved. Meier et al. [4] reported that 90% of users rarely or never adjusted the thermostat to set a weekend or weekday program. As such, in 2009 the U.S. Environmental Protection Agency's (EPA) stated "EPA has been unable to confirm any improvements in terms of the savings delivered by programmable thermostats and has no credible basis for continuing to extend current Energy Star specification [5]." Furthermore, schedule based thermostats have

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the risk to put users in thermal discomfort if they are in the building when HVAC system is off.

In recent years, the advent of smart household appliances has drawn attention as they can engage more people into energy saving practices. Caicedo [6] and Peruffo [7] developed their own smart lighting control systems which use multiple motion and light sensors to measure the occupancy state and illuminance and adjust the local dimming levels for the lights to meet the luminosity requirement with minimum power consumption. Some studies proposed using energy loading management systems to schedule or curtail electric appliances' loads. Mohseni [8] utilized a day-ahead planning energy management framework to reduce the energy costs by about 17% and also cut the peak power by about 32%. Current smart thermostat products [9–11] have the potential for significant energy saving by reducing the unnecessary operation of the HVAC system in a residential house. Occupancy information is one of the most critical factors for HVAC system control [12]. Instead of inputting the user's occupancy information manually, a more advanced occupancy driven smart thermostat uses different sensors to detect and collect occupancy information. Multiple studies use passive infrared sensors (PIR) or switches to detect occupancy information [13–15]. Other methods include using light sensors [6,7], CO_2-based systems [16,17], camera-based systems [18], or sonar-based system [19] have also been examined. Previously, the present authors suggested an economic way of detecting occupancy information [20], by detecting temperature change in a door knob. Some smart thermostats even forecast the future occupancy information based on previously collected data and some other environmental factors and controls the HVAC system based on not only current occupancy information but also future occupied probability [21,22]. Shi [23] provided a real-time building occupancy prediction algorithm using the logistic regression model. The occupancy prediction is only based on the current time and occupancy state in the previous time step. And they only considered the weekday data in a residential house, which has a higher probability of following a fixed schedule. Besides environmental sensor data, Wang [24] also used Wi-Fi data with an artificial neural network model to predict building occupancy information. Abade [25] proposed a Logistic Regression Algorithm based occupancy detection system using sensors such as temperature, noise, CO_2, and light intensity. Candanedo [26] tested the accuracy of the occupancy prediction using data from light, temperature, humidity and CO_2 sensors with different statistical classification models. The result showed that a Linear Discriminant Analysis model has the best accuracies followed by Classification and Regression Trees and Random Forest models. Nesa [27] also proposed a Dempster-Shafer evidence theory based occupancy detection system with temperature, humidity, light, and CO_2 data in a room. Such sensor network-based systems are highly dependent on installation condition, and the energy-saving impact in an individual house may not be large enough to economically justify the adoption of such systems. The potential energy saving in an individual house must be readily available in order to engage as many users into energy saving practice as possible.

Most of the existing smart thermostats advertised that average energy saving is between 10% and 30% by comparing the energy usage of two groups of houses (installation group / a control group of non-participant homes) [28]. The thermostat savings in any given home can vary significantly from the average values, and the experimental validation takes a long time and resources. In this paper, we evaluate the energy saving impact of an occupancy driven thermostat in a residential building via simulation. Although existing building energy software [29], such as EnergyPlus, can estimate the energy load of a building model, it cannot readily consider a newly developed occupancy-based thermostat control algorithm or the random nature of occupancy. To overcome this limitation, we developed our occupancy simulator and HVAC controller. The occupancy simulator provides the occupancy information based on a stochastic model, which can show the variation of occupancy pattern. The HVAC controller changes the heating/cooling setpoint based on the occupancy information as well as the outdoor temperature. Since the interoperability of the building energy software is restricted, we used a co-simulation platform to integrate self-developed simulation entities with existing building energy software.

This paper is not the first attempt to use co-simulation to overcome the limitation of the single building energy software. Hensen [30] coupled a general-purpose building simulation package with a CFD approach to depict the heat and air flow in buildings. Zhai and Chen [31] developed their integrated building design tool, E + MIT_CFD, which incorporated a CFD program (MIT-CFD) into EnergyPlus. Trcka [32] integrated a building model in EnergyPlus and an air system model in TRNSYS through both loose coupling strategy and strong coupling strategy. Co-simulation with more than two simulation entities is not well explored to be readily used by others. Few works [33–35] exploited Building Controls Virtual Test Bed (BCTVB) as a middleware to couple more than two simulation entities. However, BCTVB can only work with limited types of simulation tools and is not compatible with other languages such as Java or Python, which are often used in recent research works or products. Hence, the prior works are not readily scalable and cannot consider the random nature of occupancy information as well as new thermostat models. In order to address the aforementioned issues, researches always prefer to use the simulation entities that are best suited to model various aspect of control systems. This work exploits an open source co-simulation platform that utilizes the IEEE standard (High Level Architecture (HLA)) to integrate multiple heterogeneous simulation entities.

Users' comfort level should not be sacrificed for the sake of energy saving, which will affect occupants' health [36]. Tanabe [37] observed a near-infrared spectroscopy based brain imaging, and he found a reduction in productivity as comfort level decrease. Seppanen [38] developed a quantitative relationship between work performance and the cost of HVAC electricity. The ratio of productivity gains to energy used by HVAC varied from 32 to 120. The human comfort level is not only based on the indoor temperature, it is also highly influenced by many other factors, including but not limited to humidity, cloth level, metabolism, and outdoor temperature. Thermal comfort standards have significant impacts on the energy consumption of HVAC systems by affecting the cooling and heating setpoints. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55 introduced two thermal comfort criteria: (1) predicted mean vote (PMV) comfort zone limits [39,40]; (2) adaptive comfort [39,41]. The PMV comfort zone model is the most often used model in the last 20 years, which is based on human body energy balance and an empirical fit to thermal sensation. Recently, many researchers [42–44] conducted multiple surveys and questioned the applicability of the PMV to general public. Howell [42] showed that numeric scale of thermal sensation for PMV model was not entirely valid, so the prediction is warmer than how users feel. Croome et al. [43] stated that the steady-state assumption in the PMV model made the predicted conditions less comfortable. Humphreys [44] analyzed the original database used to derive PMV model, and found that the PMV model is only reliable near the comfort condition. The error was getting more significant when the thermal condition moved further from the neutral. Since the PMV model is based on the thermal sensation of college-aged students in air-conditioned buildings in moderate climate zone, it cannot accurately evaluate human thermal comfort level in any other kind of building in different climate zones. As a result, a field study [45] showed that the energy consumption of PMV

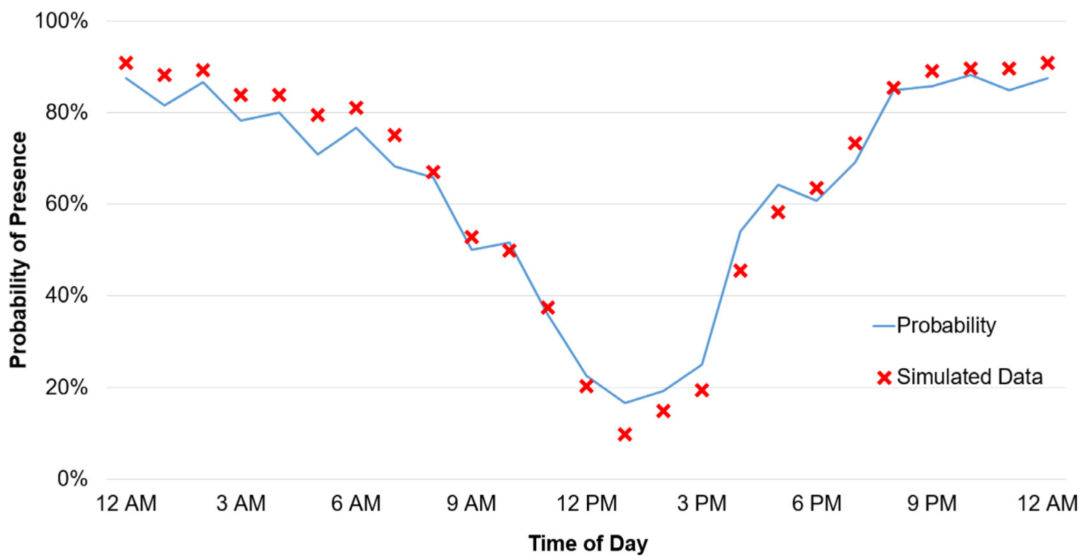

Fig. 1. Demonstration of the probability of occupancy in a typical US residential house at different times of day.

model is unnecessarily high without providing a better comfort level.

In contrast, the adaptive comfort model defines the indoor human comfort level in residential house based on mean outdoor temperature, and therefore the issues associated with the PMV model can be avoided. For example, a room temperature of 20 °C makes people feel chilly in the summer but warm in the winter. Based on the adaptive comfort model, thermal comfort in a building can sometimes be achieved only with natural ventilation during warm season, accompanied by significant energy saving. Although adaptive comfort was originally designed for naturally ventilated buildings, it is also recommended for use with buildings that have HVAC systems [39,41]. Parkinson [46] also validates the ASHRAE 55 adaptive comfort standard with a larger and more representative dataset (over 100,000 thermal comfort field data from all around the world). The results showed that adaptive comfort processes are relevant to the occupants of all buildings, both air conditioned and naturally ventilated.

Multiple studies suggest using an adaptive or predictive HVAC control system, which is summarized in a review paper by Song et al. [47]. Among those, Lute and Paassen [48] identified the adaptive fuzzy controllers as one of the most capable models for buildings. The fuzzy control does not require the exact information of building system, however some system parameters such as fuzzification, inference, and defuzzification, need to be tuned. Nesler [49] suggested a parameter estimation method based on Recursive Least-Squares estimation (RLS). Tigrek [50] introduced a model using gradient descent for the estimation of the parameters. By utilizing the estimation methods with HVAC control system, the model can calculate the system parameters automatically. Such methods require a data collection period and the long run time of the system. These previous works target commercial buildings in which the controllability of the HVAC is far more complicated than residential building. ASHRAE Standard 62.2 is the only recorded document we found which considers adaptive HVAC control system in a residential house [51]. The standard focuses on the ventilation system to provide acceptable indoor air quality in residential buildings. To the best of our knowledge, there is no documented study providing the energy-saving impact of an adaptive HVAC control system in residential buildings.

This paper presents simulation results on the energy consumption and comfort level with respect to different thermostat algorithm benefited by occupancy simulator and thermal comfort model. Three different thermostat control schematics have been simulated: (1) always-on, (2) schedule based, and (3) occupancy driven. Occupants' comfort level is determined by ASHRAE Standard 55 on adaptive comfort model [39]. The energy saving impact of the adaptive setpoint control is evaluated. The whole simulation has been repeated in five US cities with distinctive climate zones. The key contributions of our work are: (A) utilization of a co-simulation tool to analyze energy saving impact with occupancy-driven HVAC control algorithms, (B) consideration of random nature of occupancy information in a residential house, and (C) formulation of an adaptive control approach to further save energy in a residential house. To the best of our knowledge, there is no prior work on the co-simulation tool that integrates all of these simulation entities, and our work can assist other researchers with development of control algorithms or occupancy simulators.

2. Methodology

2.1. Occupancy simulator

The American Time Use Survey (ATUS) [52] provides detailed 24-hour diaries estimates of how, where, and with whom Americans spend their time. It completed at ten-minute resolution by over 190,000 interviews conducted from 2003 to 2017. At each 10-minute period within a day, the data includes the activity and location of the interviews so it can be used to recognize the occupancy information of a house. Fig. 1 shows the probability of occupancy in a house.

Since variation of occupancy pattern exists, a simple stochastic model based on the probability density function is used to model the random nature of the occupancy. The probability of occupancy in Fig. 1 is compared with a random number generated during the simulation. If the random number is smaller than the occupancy probability, the resident is in the house. Otherwise, no one is in the house during the time step. The flowchart of the occupancy simulator is illustrated in Fig. 2. After a one-year simulation period, the average occupancy follows the distribution as shown in Fig. 1.

2.2. Building energy simulation tool

EnergyPlus [29], a widely adopted open source building simulation tool, can effectively model building energy consumption at each time step. The energy consumption incorporates the physical

Table 1
Summary of the detailed weather features of the chosen cities from five different climate zones.

Location	Climate zone by RECS	Note	HVAC size [k Btu/h*]	
			Heating	Cooling
Fairbanks	Subarctic	Outdoor temperature in winter can be lower than −30°C	42	18
New York City	Cold	Outdoor temperature in winter is around −10°C	18	14
San Francisco	Marine	Environment temperature change is significant during the year	5	8
Miami	Hot-Humid	Relative humidity is high need extra energy to handle it.	5	18
Phoenix	Hot-Dry	Hottest outdoor temperature can be 50°C in summer.	8	27

* 1000 Btu/h = 293 W.

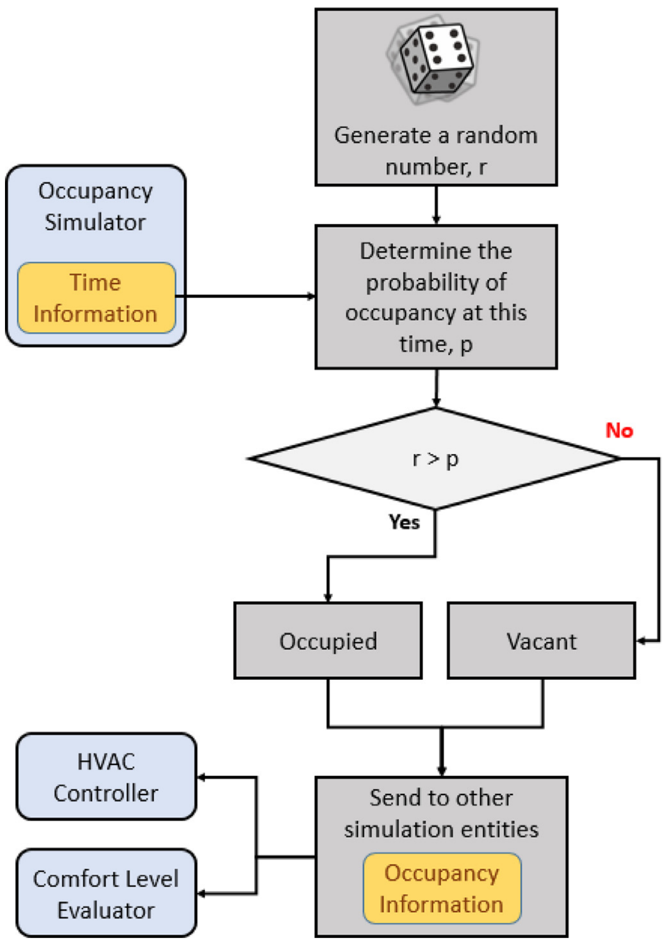

Fig. 2. Illustration of the flowchart of the occupancy simulator.

building parameters and environment condition such as floorplan, material, HVAC system setup, and building location. The U.S. Department of Energy (DOE) provides residential prototype buildings models with different heating system type and foundation type [53]. We chose the 2400 ft^2 two-story single house models for the 2012 edition of the International Energy Conservation Code with gas furnace heating system and crawlspace foundation type. A direct expansion cooling coil and condensing unit is used for cooling, and a natural gas furnace is utilized for heating. The footprint of the model does not change depending on location, but the materials and wall structures of the house are varied to take care of local climate conditions in the models. Five different cities (Fairbanks, New York City, San Francisco, Miami, and Phoenix) have been chosen to cover the diverse climate zones defined by RECS 2009 [54] in the USA. To handle the different weather conditions and provide an indoor comfort environment to the occupants, the size of the HVAC system vary in different cities. The auto-size function in Energy Plus tends to oversize the HVAC system, which may not be practical due to high capital cost. To determine the HVAC sizing at each location, first we determined a size that could maintain the setpoints at least 99% of the time. Then we checked that on extreme days the duty cycle of HVAC system is less than four times per hour. After that the sizing was rounded to the nearest commercially available size. After that, we also checked the indoor air quality (relative humidity and CO_2 concentration) to make sure the flow rate of the HVAC system is able to keep the air quality healthy and comfortable, which requires relative humidity between 25% to 70% and CO_2 concentration lower than 1000 ppm. The detailed weather features and corresponding HVAC size in these climate zones are listed in Table 1.

2.3. Thermostat control

Three different control algorithms are simulated in this paper. First is the most basic thermostat, which continuously operates to accommodate room temperature at a fixed setpoint based on a conventional comfort zone (the heating set point at 21°C and cooling set point at 23°C) [39]. This type of the thermostat cannot change operation schedule unless setpoint is manually changed. The second type is a schedule-based thermostat algorithm, which switches the HVAC on and off with a pre-defined schedule. We define the daily operation schedule based on the probability of occupancy (Fig. 1): The HVAC system operates for the time period with the probability greater than 0.6 (between 5 PM to 9 AM on the next day). This schedule is not optimized for a specific house or region, and the actual energy saving and user comfort can change with different schedules. The third one is the occupancy-driven algorithm, which operates the HVAC system based on the current occupancy information. It turns on the HVAC system when the house is occupied and turns it off right after the occupant leaves. Although the current available thermostats may not have accurate occupancy information, we assume that such information can be gathered in the future with the advent of many Internet of Things products. All of the control algorithms have heating and cooling set points at 21°C and 23°C, respectively. Since some thermostats do not allow turning off, we set the setback temperature at its lowest and highest setpoints, 55°F (12 °C) and 90°F (32 °C). The detailed HVAC control algorithms are listed in Table 2 and Fig. 3. To avoid turning the HVAC system on and off too frequently, the actual HVAC setting inputted into EnergyPlus are +/- 0.5°C from the heating/cooling setpoint determined by the algorithm. As a result, the room temperature fluctuated around the setpoint in the range of 1°C.

Fig. 4 demonstrates heating setpoint data of the occupancy-driven control algorithm on a winter day. From the plot, the heating setpoint changes based on the occupancy information and indoor room temperature fluctuates within 0.5 °C from the setpoint (21 °C). At 14:00, due to the cold weather, the HVAC system takes up to an hour to increase the room temperature from 12 °C to 21 °C, occupant feels comfort after 14:15 (room temperature greater than 18.5 °C). Because the HVAC system is turned off

Table 2
Summary of the HVAC system setpoint based on three different control algorithm and operation conditions. P is the probability of occupancy.

Operation condition	Heating set point [°C]	Cooling set point [°C]
A. Always on		
Always	21	23
B. Schedule based		
9AM- 5PM (OFF) $P < 0.6$	12	32
5PM-9AM (ON) $P > 0.6$	21	23
C. Occupancy driven		
Current with occupant (ON)	21	23
Current without occupant (OFF)	12	32

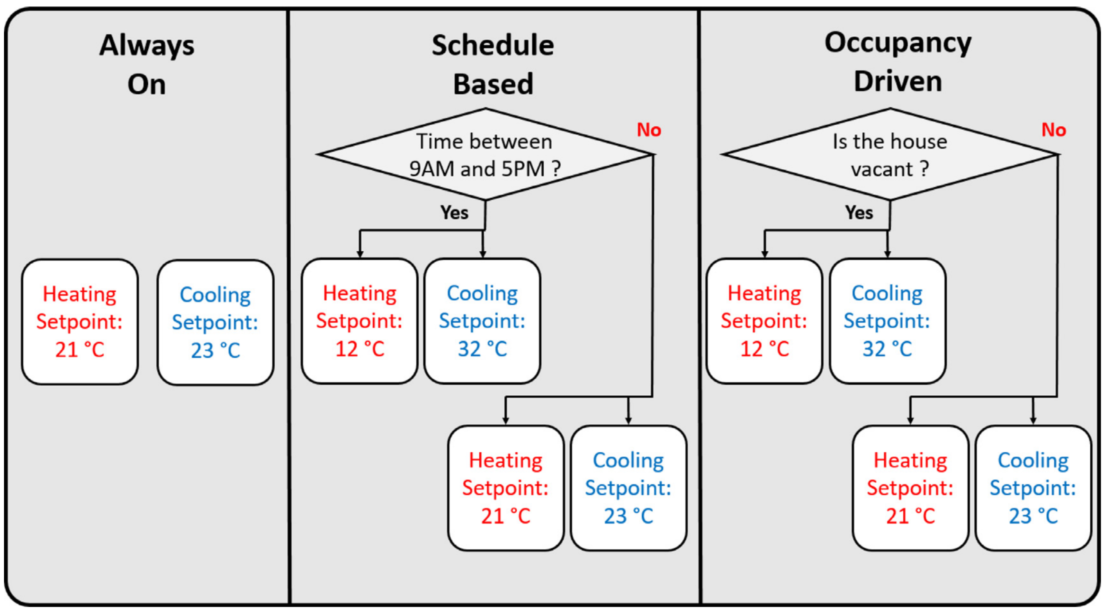

Fig. 3. Demonstrate the flowchart of the HVAC system controller based on three different control algorithm and operation conditions.

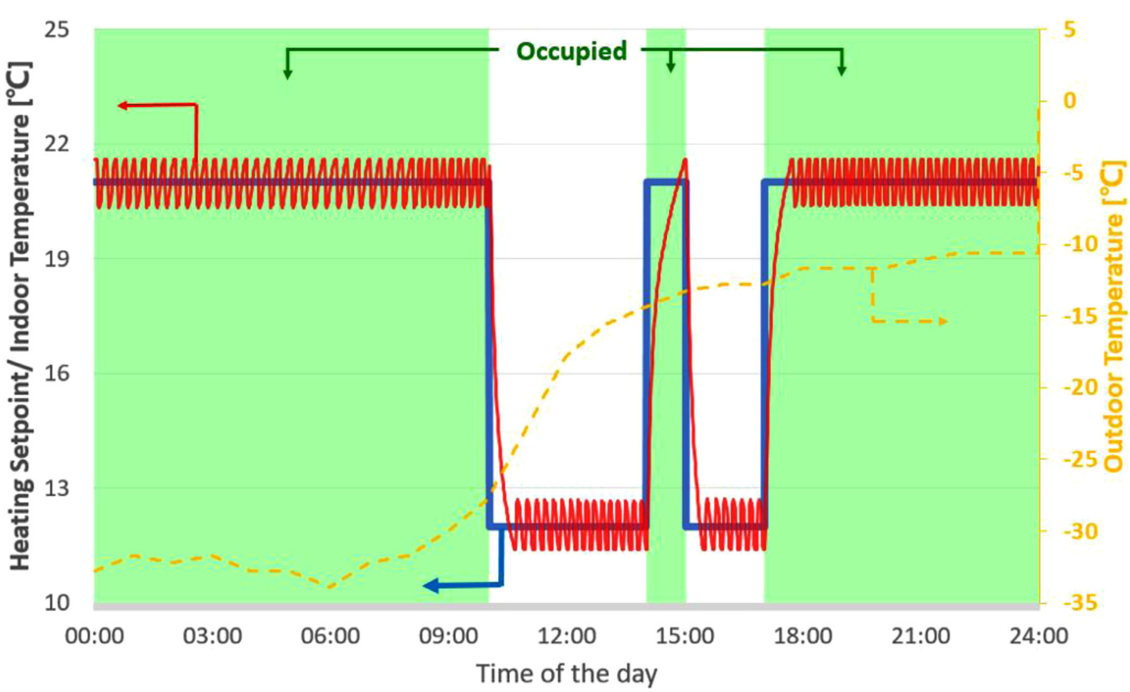

Fig. 4. Illustration of the occupancy-driven control algorithm on a cold day in Fairbanks, AK. The outdoor temperature is represented by the yellow dashed line. The HVAC system turns on and off based on the occupancy information (shaded area), and the room temperature (red thin solid line) fluctuates around the setpoint (blue thick solid line) when the room is occupied. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

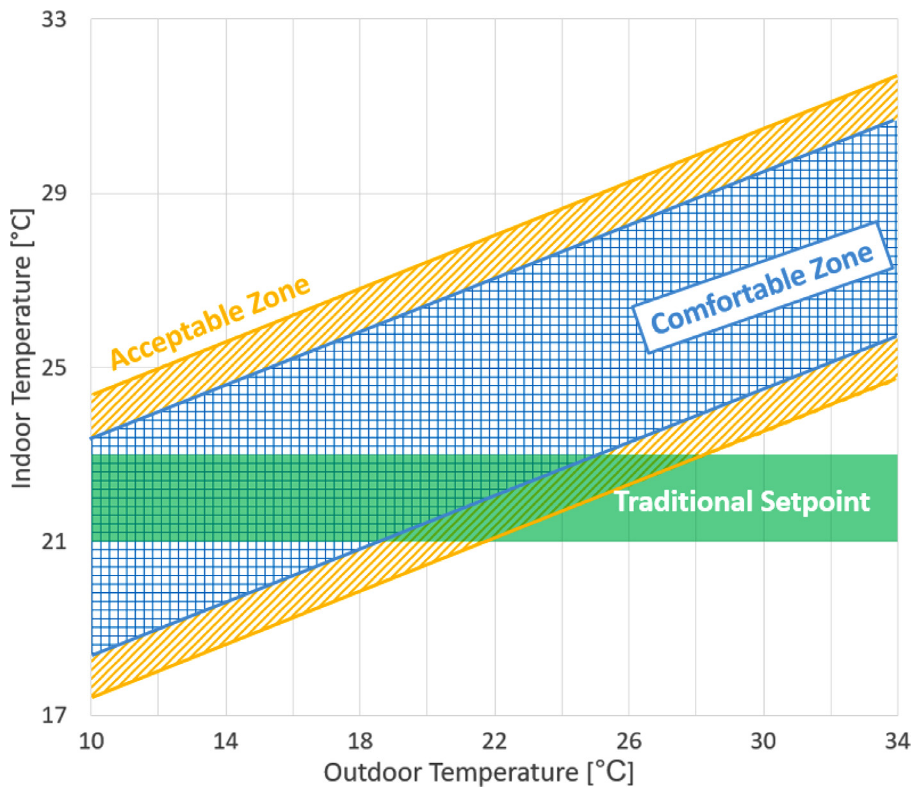

Fig. 5. Acceptable operative temperature ranges based on mean outdoor temperature defined by the adaptive model. The comfortable zone (blue grid area) and acceptable zone (yellow lined area) depict the temperature ranges accepted by 90% and 80% of people accordingly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

during non-occupied period, as shown by natural cooling of the house until the setback point (12 °C), unnecessary energy usage can be saved.

2.4. Thermal comfort evaluator

ASHRAE 55 [39] introduced the adaptive comfort model to estimate the occupant's comfort level. The adaptive model is based on the idea that outdoor climate influences indoor comfort because humans can adapt their clothing level to indoor and/or outdoor thermal conditions during different times of the year. Researchers survey building occupants about their thermal comfort while taking simultaneous environmental measurements. Analyzing a global database of 21,000 measurements showed that occupants' accepted or preferred temperature range depends on outdoor conditions. These results were incorporated in the ASHRAE 55–2004 standard as the adaptive comfort model.

Fig. 5 presents the detailed indoor HVAC operative temperature range based on the mean outdoor air temperature. The comfortable zone (blue grid area) is the temperature range which satisfies 90% of the people, the acceptable zone (wider yellow dashed area) is the temperature band where 80% of the people feel comfortable. We treat out of the acceptable zone as the uncomfortable zone. The green solid area indicates the ideal room temperature range with the traditional setpoint, fixed between 21 °C and 23 °C.

Fig. 6 shows the flowchart for the comfort level evaluator. After receiving the occupancy information from occupancy simulator and outdoor temperature from building simulator, the comfort level evaluator will determine the temperature range of the comfortable/ acceptable/ uncomfortable zone based on Fig. 5. By comparing the indoor temperature with the three different zones, the occupancy evaluator will record the current comfort level information in the database.

In our initial simulation, the comfort level was determined based on this model, although the temperature setpoint was fixed between 21 °C and 23 °C. The traditional setpoint is unable to provide a comfort environment (too cold) to the occupants with additional energy consumption when the outdoor temperature is high. In order to provide a more comfortable environment for the users without unnecessary energy consumption, we explored an adaptive thermostat control algorithm, which changes the setpoint based on the outdoor temperature. We chose the heating and cooling setpoint 0.6 °C higher and lower than the border between the comfort zone and acceptable zone, and the fluctuation of the indoor temperature was limited to 0.5 °C. As a result, the room temperature will remain inside of the comfort zone. The flowchart of the HVAC controller with adaptive setpoints is displayed in Fig. 7. The saving impact and comfort level of this adaptive thermostat is also simulated and shown in the result section.

2.5. Co-simulation platform

The National Institute of Standards and Technology (NIST) developed an open-source Cyber-Physical System (CPS) experiment and testing environment called Universal CPS Environment for Federation (UCEF). Our precious work [55] introduced how UCEF integrates multiple different simulation software, federates, coded in different operating system and development environments, which makes co-simulation with different software doable and straightforward. UCEF accomplish timing synchronization and data transfer among a group of federates by utilizing the IEEE's High Level Architecture (HLA) standard [56].

EnergyPlus has a preset co-simulation interface through the Functional Mock-up Interface (FMI) standard created by Modelisar [57]. The standard connects EnergyPlus simulation platforms to an external model by using a Functional Mock-up Unit (FMU). In our

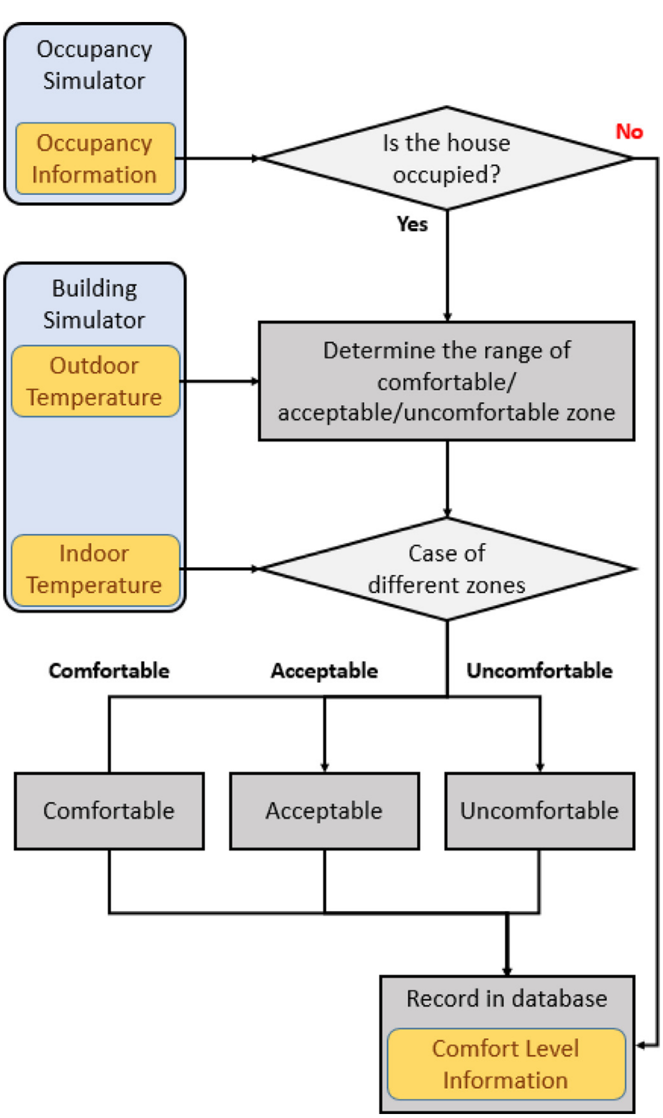

Fig. 6. Display the flowchart of the comfort level evaluator.

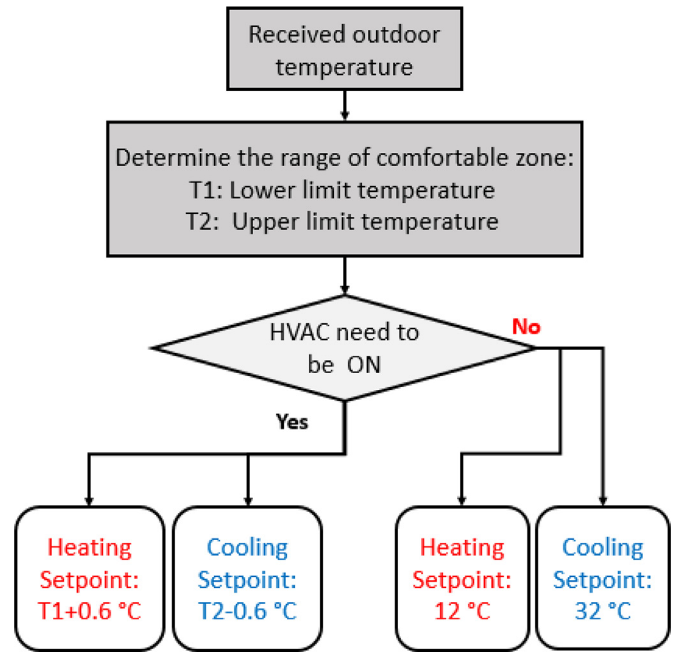

Fig. 7. The flowchart of the HVAC controller with adaptive setpoints based on different operation conditions.

previous work [58], we interfaced the FMU with UCEF via TCP/IP. For each time step, the Energyplus sends the time information to the occupancy simulator, which in turn provides simulated occupancy information to the HVAC controller. The HVAC controller determines the HVAC setpoint (cooling and heating) based on the occupancy information and outside temperature when adaptive controller is employed. EnergyPlus receives and updates the new setpoint via FMU and evaluates energy consumption until the next time step. At the same time, the comfort level evaluator checks and record the current comfort level based on the indoor and environment information from EnergyPlus and occupancy information from the occupancy simulator. The detailed schematic graph is shown below in Fig. 8.

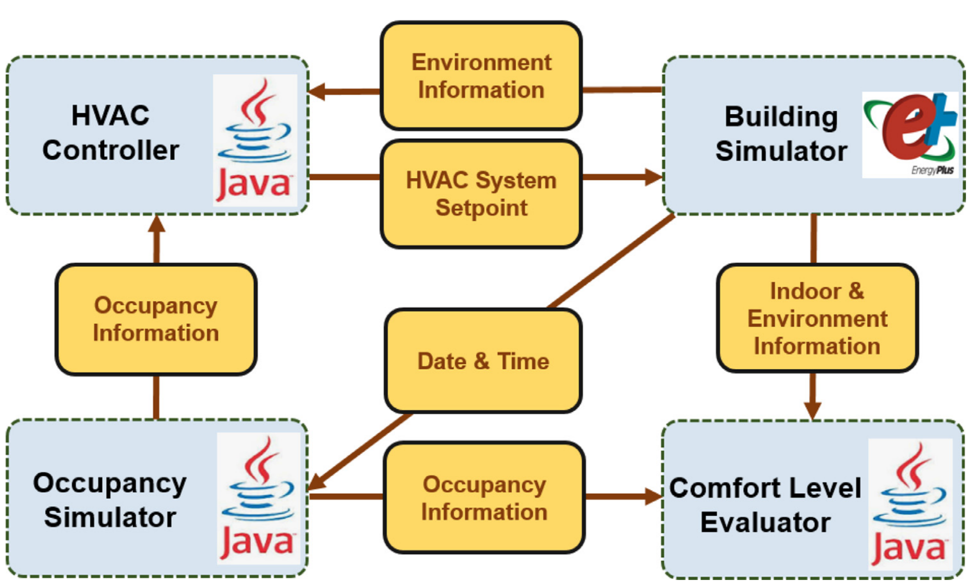

Fig. 8. Representation the schematic of data transfer between building simulator, occupant simulator and HVAC controller.

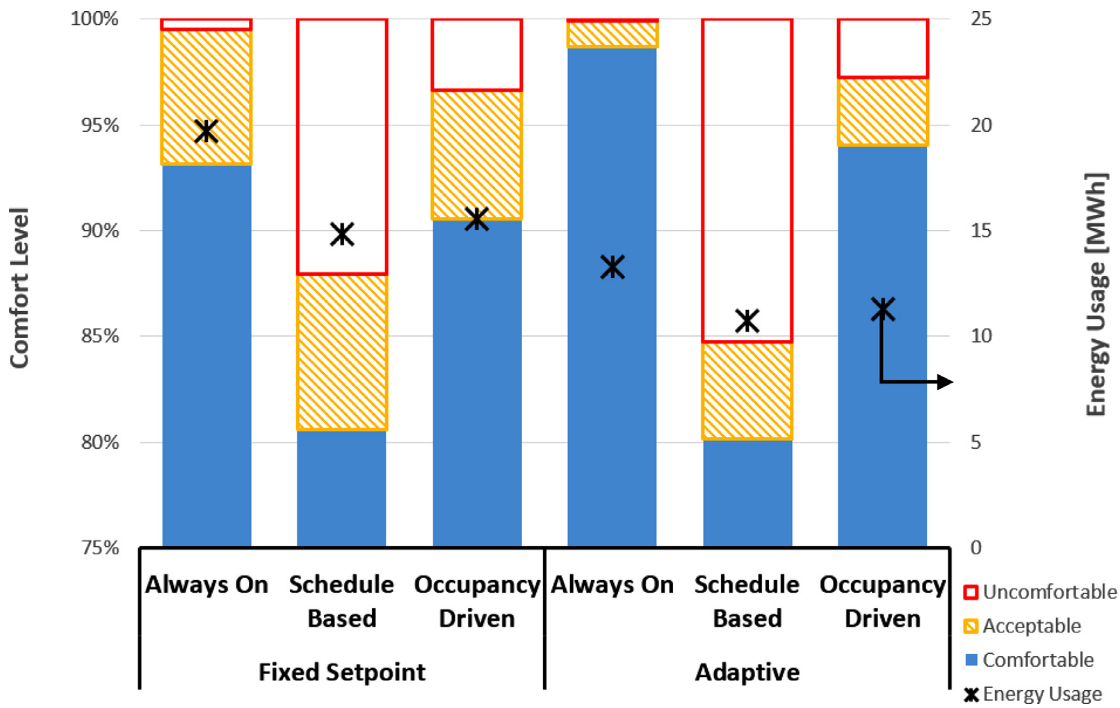

Fig. 9. Demonstration of the result of annual comfort result and energy consumption at New York City, NY. The stacked bar chart shows the ratio of comfort zone (blue shaded area), acceptable zone (yellow pattern area) and uncomfortable zone (red blank area). Annual energy usages are displayed with black star marks and *y*-axis on the right. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

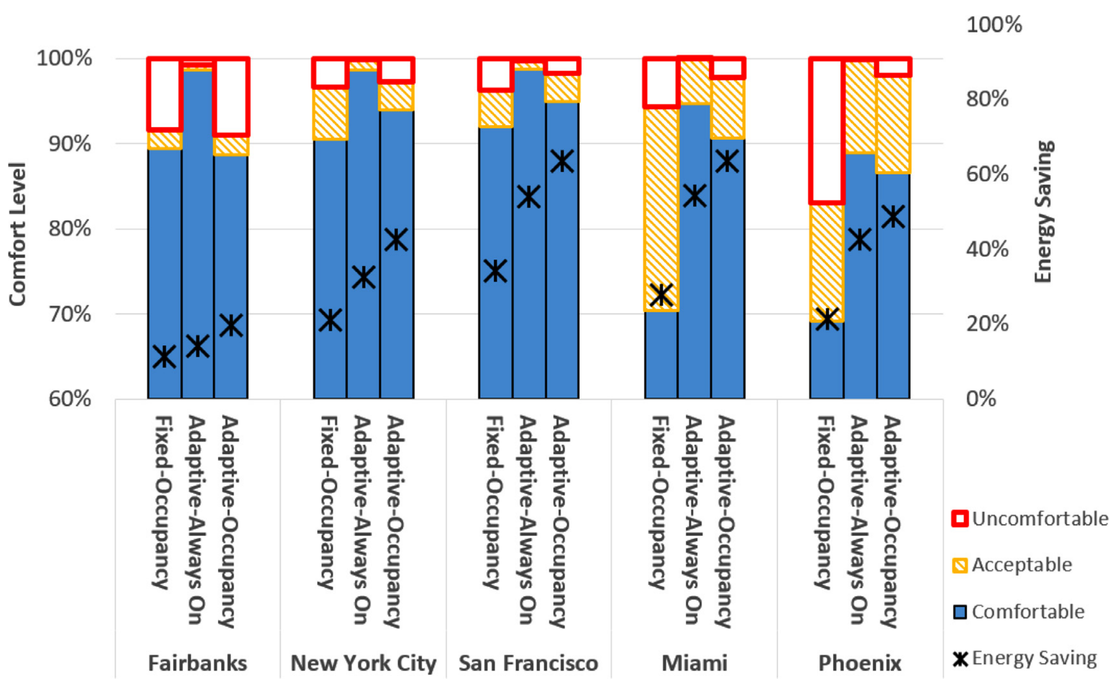

Fig. 10. Comparison of the annual comfortable ratio and saving impact of the Fixed setpoint - Occupancy, Adaptive - Always On, and Adaptive - Occupancy in five different locations.

3. Results & discussion

Fig. 9 illustrates annual simulation results of New York City for six different control strategies. The comfort level presents the ratio reflecting if the indoor temperature is comfortable, acceptable or uncomfortable when the building is occupied. With the fixed setpoint control, the always-on thermostat can only provide 93% comfort ratio, because 21 °C–23 °C is excluded from the comfort zone when the outdoor temperature is higher than 26 C (Fig. 3). The schedule based thermostat saved 5 MWh of energy but significantly increased the uncomfortable ratio by 12%. An occupant may feel uncomfortable when one does not come back as schedule. Schedule based thermostat may have larger energy saving potential but risk more discomfort. As we mentioned before, this schedule is just one setting and the energy saving and comfort level may vary with other schedules. By contrast, the occupancy-driven thermostat was able to improve this situation by turning on the system simultaneously when the occupant is back, raising the comfort ra-

Table 3
Comparison of the annually comfortable level, energy saving impact, and energy usage in Fairbanks, New York City, San Francisco, and Miami Phoenix.

			Comfortable Ratio [%]	Acceptable Ratio [%]	Uncomfortable Ratio [%]	Saving Impact	Energy Usage [MWh]
Fairbanks	Fixed Setpoint	Always On	95.5	1.7	2.8	0%	37.41
		Schedule Based	78.2	3.5	18.3	13%	32.65
		Occupancy Driven	89.5	2.2	8.4	11%	33.13
	Adaptive	Always On	98.6	0.6	0.8	14%	32.08
		Schedule Based	76.8	3.5	19.6	20%	29.90
		Occupancy Driven	88.7	2.3	9.0	20%	30.00
New York City	Fixed Setpoint	Always On	93.2	6.3	0.5	0%	19.70
		Schedule Based	80.6	7.3	12.1	25%	14.83
		Occupancy Driven	90.6	6.1	3.4	21%	15.53
	Adaptive	Always On	98.7	1.2	0.1	33%	13.29
		Schedule Based	80.2	4.6	15.2	45%	10.76
		Occupancy Driven	94.0	3.3	2.7	43%	11.31
San Francisco	Fixed Setpoint	Always On	99.6	0.3	0.1	0%	8.23
		Schedule Based	90.5	4.3	5.3	38%	5.08
		Occupancy Driven	92.0	4.2	3.7	34%	5.41
	Adaptive	Always On	98.7	1.0	0.3	54%	3.78
		Schedule Based	89.9	4.8	5.3	65%	2.90
		Occupancy Driven	94.9	3.3	1.8	64%	3.00
Miami	Fixed Setpoint	Always On	58.8	32.7	8.5	0%	29.48
		Schedule Based	61.5	21.8	16.7	35%	19.15
		Occupancy Driven	70.5	23.9	5.7	28%	21.28
	Adaptive	Always On	94.7	5.2	0.1	54%	13.51
		Schedule Based	77.3	5.9	16.8	67%	9.80
		Occupancy Driven	90.7	7.2	2.2	63%	10.78
Phoenix	Fixed Setpoint	Always On	65.6	14.9	19.5	0%	26.03
		Schedule Based	66.3	13.7	20.1	25%	19.47
		Occupancy Driven	69.2	13.9	17.0	21%	20.44
	Adaptive	Always On	89.9	10.9	0.2	43%	14.93
		Schedule Based	76.8	10.7	12.5	49%	13.26
		Occupancy Driven	86.5	11.4	2.1	49%	13.37

Table 4
List of monthly saving and payback period of three different control strategies (Fixed setpoint - Occupancy, Adaptive - Always On, and Adaptive – Occupancy), compared with the most wasteful control strategy (Fixed setpoint - Always On) and energy-conscious control strategy (Fixed setpoint – Schedule Based).

Discount Rate:		6%/year		Capital Cost:		$300
Compare with Traditional Always On						
Location	Traditional Occupancy Driven		Adaptive Always On		Adaptive Occupancy Driven	
	Monthly Savings[$]	Payback Period [Month]	Monthly Savings[$]	Payback Period [Month]	Monthly Savings[$]	Payback Period [Month]
San Francisco	34.32	9.0	48.98	6.2	58.67	5.2
New York City	50.77	6.0	79.43	3.8	99.66	3.0
Phoenix	57.42	5.3	106.37	2.8	119.31	2.5
Miami	82.10	3.7	159.55	1.9	186.92	1.6
Fairbanks	15.37	20.6	22.52	13.8	32.65	9.4
Compare with Traditional Schedule Based						
Location	Traditional Occupancy Driven		Adaptive Always On		Adaptive Occupancy Driven	
	Monthly Savings[$]	Payback Period [Month]	Monthly Savings[$]	Payback Period [Month]	Monthly Savings[$]	Payback Period [Month]
San Francisco	-9.10	Never	5.55	54.0	15.24	19.7
New York City	-11.23	Never	17.43	17.2	37.67	8.0
Phoenix	-10.58	Never	38.37	7.8	51.31	5.8
Miami	-21.65	Never	55.80	5.4	83.17	3.6
Fairbanks	-7.31	Never	-0.16	Never	9.97	30.1

tio to 90%. Due to thermal mass of the house, an occupant may feel uncomfortable in the beginning of occupant period, which corresponds to the 3% uncomfortable ratio. In general, the occupancy-driven thermostat can save about 25% of the energy consumed by the always-on thermostat without increasing user's uncomfortable level.

With the adaptive control, the comfort ratio of the always-on thermostat is increased to 99%. The 1% acceptable ratio is attributed to the way we chose the size of HVAC system, which is undersized for few days with extreme weather condition. The total uncomfortable ratio has been reduced to almost 0 since the adaptive control algorithm sets the setpoint inside of the comfortable zone. Energy saving impact by adaptive control is larger than having an occupancy information alone. Uncomfortable ratio is decreased, and the reduction in energy consumption is quite significant. The always-on thermostat with adaptive control can save about 30% of the energy used by the always-on thermostat with fixed setpoint in New York City as shown in Fig. 9. Occupancy information additionally provides energy saving of 15%.

The detailed simulation results of all five cities are tabulated in Table 3. The energy consumption of the always-on thermostat with the fixed setpoint control was used as the baseline to evaluate the energy saving impact of the control strategies. Similar trend has been observed in different locations that with the adaptive control – always on thermostat saves more energy (between 14% and 54%) than occupancy driven thermostat with fixed setpoint, while it achieves similar or better thermal comfort level. The occupancy-driven adaptive thermostat save 8% more. Since 21 °C–23 °C is uncomfortable when the outdoor temperature is high, the adaptive control could dramatically increase the comfort level in the hot climate areas (Miami and Phoenix).

Since the energy saving and comfort level is not guaranteed with the schedule based thermostats (highly dependent on how the user set his schedule), we examine energy saving impacts (Fig. 10) and economic benefits (Table 4) of three control strategies; fixed setpoint control with occupancy driven thermostat, adaptive control with always on thermostat, and adaptive control with occupancy-driven thermostat. Occupancy information can save between 11% and 34%, while adaptive control alone can save between 14% and 54%. Hence, adaptive control is a more effective way of saving energy regardless of climate zones. Such saving impact is more apparent in a warmer climate, as there is more saving potential in cooling with adaptive control (Fig. 5). However, occupancy information can save additionally with adaptive control, and is more effective in colder climate. In Fairbanks, occupancy information contributes 28% to the total saving impact of adaptive control with occupancy-driven thermostat. This ratio decreases to only 12% in Phoenix. Although energy saving ratio in cold climate zones seems to be low, actual amount of energy saving can be larger. However, such saving does not directly correspond to economic benefits due to different utility rates or tariff.

Transforming an existing house into a smart home requires considerable investment. Michael [59] evaluates the payback analysis of each smart home components, including photovoltaic panels, wind turbines combined heating and power, energy storage systems, water heaters, electric vehicles, HVAC, and solar collectors. The result showed that the payback periods of most of the smart home components are higher than ten years. Since some smart home components have life-spans less than ten years, it is hard to convince customers adopting the smart home system with current products on the market.

Table 4 shows the monthly saving and payback period with respect to two energy usage behaviors: (1) most wasteful behavior (fixed setpoint – always on); and (2) energy conscious behavior without a smart thermostat (fixed setpoint – schedule based). Monthly saving was evaluated using an average electricity rate/tariff for cooling load and gas rate/tariff for heating load in each city [60–64]. Payback period was evaluated based on the capital cost of $300, the average retail price on the market for a smart thermostat, and the discount rate of 6% using Eq. (1)

$$P = \frac{\ln\left(\frac{M}{(M-Cr)}\right)}{\ln(1+r)} \tag{1}$$

Where P is the payback period, C is the capital cost ($300), M is the monthly saving and r is the monthly discount rate (0.5%/month). Compared to energy consumption with always on – fixed setpoint thermostat, the payback periods of three different control strategies are within a year in all locations but Fairbanks, due to low natural gas rate ($0.1427/therm). Compared to energy consumption with schedule based - fixed setpoint thermostat, occupancy information alone does not result in economic benefit but more comfortable ratio. Only with adaptive control, users with energy conscious behavior can get financial benefit in the most cities except Fairbanks. The payback period in San Francisco is almost four and half years, due to lower amount of energy consumption than other zones. More economical solution or incorporation of occupancy information will be necessary for shorter payback periods in San Francisco or Fairbanks. The payback period by the adaptive control is generally shorter in warmer climate than in colder climate zones due to more saving ratio. As outdoor temperature is easier to be integrated into a smart thermostat than an accurate occupancy information, adaptive control can lead to more tangible energy saving impact in an economically viable package.

4. Conclusions and future work

This work utilizes a co-simulation tool to demonstrate energy savings and economic benefits of occupancy-driven control strategies for residential buildings. In order to consider the random nature of the occupancy, an occupancy simulator was developed and integrated with building energy software, self-coded HVAC controller, and comfort level evaluator via an open source co-simulation platform. The results show that the occupancy driven thermostat leads to similar level of the energy saving with improved comfort ratio as the schedule based thermostat regardless of five distinct climate zones. Moreover, an adaptive thermal comfort model was implemented for the HVAC system control strategy to further save energy in a residential house. The energy saving impact of the adaptive control is more effective than the occupancy information alone. The economic analyses indicate that the payback period for an adaptive control can be less than 14 months for the capital cost of $300. As adaptive control is much easier to implement with more energy saving and shorter payback period, the direction of smart thermostats should focus more on adaptive control than occupancy-driven control. Once more reliable occupancy information is available, they lead to average of 20% additional saving on the top of the adaptive control. This work can benefit research in enhancing comfort ratio via demand response or predictive control. Another direction for the future work is to consider variable tariffs for further economic optimization.

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.

CRediT authorship contribution statement

Chenli Wang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Kaleb Pattawi:** Formal analysis, Validation, Investigation, Writing - review & editing. **Hohyun Lee:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.enbuild.2020.109791.

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