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Publication Date
2017-02-01

DOI
10.1016/j.enbuild.2016.12.010

Peer reviewed

A Simulation Approach to Estimate Energy Savings Potential of Occupant Behavior Measures

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Abstract

Occupant behavior in buildings is a leading factor influencing energy use in buildings. Low-cost behavioral solutions have demonstrated significant potential energy savings. Estimating the behavioral savings potential is important for a more effective design of behavior change interventions, which in turn will support more effective energy-efficiency policies. This study introduces a simulation approach to estimate the energy savings potential of occupant behavior measures. First it defines five typical occupant behavior measures in office buildings, then simulates and analyzes their individual and integrated impact on energy use in buildings. The energy performance of the five behavior measures was evaluated using EnergyPlus simulation for a real office building across four typical U.S. climates and two vintages. The Occupancy Simulator was used to simulate the occupant movement in each zone with inputs from the site survey of the case building. Based on the simulation results, the occupant behavior measures can achieve overall site energy savings as high as 22.9% for individual measures and up to 41.0% for integrated measures. Although energy savings of behavior measures would vary depending upon many factors, the presented simulation approach is robust and can be adopted for other studies aiming to quantify occupant behavior impact on building performance.

Keywords

Occupant behavior, behavior measure, building performance simulation, energy savings, behavior modeling, EnergyPlus

1. Introduction

Occupant behavior in buildings refers to occupants' comfort preference, presence and movement, and interactions with building systems that have an impact on building performance (thermal, visual, acoustic, and indoor air quality or IAQ). The interactions include adjusting thermostat settings, opening or closing windows, dimming or turning on/off lights, pulling up or down window blinds, switching on or off plug loads, and consuming domestic hot water [1]. People spend most of their time in buildings; energy-related occupant behavior in buildings is one of the six influencing factors of building performance [2][3], which include climate, building envelope, building equipment, operation and maintenance, occupant behavior, and indoor environment conditions. Daily interactions between building systems and occupants drive total energy use. Occupants' expectations of desired comfort and satisfaction within their indoor environment drive the occupant to perform various actions to satisfy their physical and non-physical needs. These actions not only affect the built environment (e.g., indoor temperature, humidity level, lighting, CO2, etc.) and the energy use [4][5], but also affect the energy-saving potentials of energy conservation measures (ECMs) [6]. Indirectly, this has economic, physiological, and psychological impacts on the occupant. Clearly understanding and accurately modeling occupant behavior in buildings is crucial to reducing the gap between design and actual building energy performance, especially for low-energy buildings relying more on passive design features, occupancy controlled technologies, and occupant engagement [7][8].

Developing and adopting new technologies can improve the energy efficiency of equipment in buildings. However, technologies alone do not necessarily guarantee low energy use in buildings because (1) the interaction between humans and new energy technologies makes their adoption challenging, (2) the rebound effect, where the increased efficiency of a technology results in its increased use and, thus, increased energy consumption reduces the savings attributable to energy-efficiency measures [9][10][11], (3) the energy savings will be largely reduced if technologies are not designed, implemented or maintained appropriately [12]. Meanwhile, technical measures are generally an expensive way to reduce energy consumption, which usually requires an initial investment [13]. In the future, the energy saving potentials from technology development will gradually encounter bottleneck due to theoretical energy efficiency limits [14]. Therefore, more options should be considered regarding energy conservation.

Low-cost behavioral solutions demonstrated significant potential energy savings in multiple industry areas such as buildings [15], transportation [9][16], and even food processing [17]. Energy savings in the building stocks are the main focus of this study. A recent study by McKinsey quantified the savings potential of behavioral interventions at 16%-20% for total U.S. residential energy use [18]. Meier, et al. [19] analyzed that reasonable changes in operators' behaviors can save 5%-30% of building energy consumption theoretically; these savings are not taken in many buildings. Davis [15] deployed a series of

experimental behavioral interventions in a wide variety of settings throughout America. For example, a household’s electricity usage is compared to that of its neighbors in the "Home Energy Reports." The results convincingly demonstrated that simple behavioral interventions are effective at reducing energy demand in residential buildings. Utilities and governments are playing an important role in deploying and promoting the behavioral energy saving programs [20][21][22], gradually turning from technical measures to behavioral programs to grow their energy efficiency portfolios. Utility behavioral energy efficiency programs not only have the potential to deliver massive energy savings, but also have been found to improve customer engagement and increase the effectiveness of other programs [23]. For example, the behavioral programs potentially could save up to 132 GWh per year in Colorado utility Xcel Energy’s service territory [24]; in New Jersey, EnerNOC found that behavioral program potential in the state could save up to 544 GWh of electricity and 25 million therms of natural gas over a three-year period [25]. However, there is still much room for improvement: results from 218 large-scale behavioral feedback programs conducted by Opower across more than 8 million households and 88 U.S. utilities showed that utilities and states are currently underinvesting in behavioral savings. Deployment of behavioral programs, at their full economic potential, could generate 19,000 GWh in annual electricity savings and $2.2 billion in end-consumer savings per year. This represents 1.6% of current residential use, and is enough energy to take the entire state of Arkansas off the grid [26]. It should be noted that the majority of the existing behavioral research and programs focus on residential buildings. More research is needed on the impact of behavioral measures on commercial buildings.

Estimating behavioral savings potential is important for a more effective design of behavior change interventions, which in turn will support more effective energy efficiency policies. A variety of methods have been used to evaluate the impact of behavioral (ECMs), such as the survey-based approach, the municipal behavior wedge (MBW) model, and building performance simulation (BPS) [27]. Poortinga, et al. [13] found that behavioral measures that can directly save energy are modestly acceptable, based on completed questionnaires from 455 households. Ouyang and Hokao [28] conducted a series of surveys on 124 households in three typical residential buildings in Hangzhou, China, and concluded that electricity use can be reduced by more than 10% with improved occupant behavior. Significant energy savings can be achieved using strategies to stimulate shifts in the choices and behaviors of residents at a municipal level. Ehrhardt-Martinez [29] developed a low-cost approach to determine the scale of city-specific savings opportunities based on household eligibility (technology saturation and existing use patterns), likely participation rates, and savings from a particular shift in behavior. She used the approach to estimate the savings opportunities associated with 32 different residential behaviors. Davis [15] performed a series of experimental behavioral interventions over 11 different utility service areas encompassing more than 750,000 households across the United States. The results convincingly

demonstrated that simple behavioral interventions, such as comparing electricity usage between neighborhoods, are effective at reducing energy demand in residential buildings. Kane and Srinivas [30] used publicly available datasets from the Energy Information Administration and monthly savings measurements from 218 behavioral feedback programs at 88 utilities to build a forecasting regression model for predicting energy savings of behavioral efficiency programs. Lopes, et al. [31] used EnergyPlus/DesignBuilder as a simulation tool to estimate the energy savings potential of behavioral conservation measures. The simulation results demonstrated a significant energy savings potential associated with both usage and investment energy behaviors. The survey-based approach can reflect the reality and obtain relatively more accurate energy savings, but can't be applied to estimate the energy savings of other un-surveyed behaviors or to predict savings for future or at a larger scale. The MBW model can estimate energy savings at a very large scale as well as predict future savings, but has lower accuracy. Building performance simulation is able to estimate the energy savings of behavioral measures at a very detailed and precisely controlled building level, but is relatively time consuming; many detailed inputs are required and validation is difficult to do. It is important to select the appropriate approach to perform the energy saving estimation according to actual needs, data availability, and experience.

BPS programs are widely applied to evaluate the performance of building energy systems and technologies. Currently, occupant behavior is represented in oversimplified and pre-defined static schedules or fixed settings and rules, which are input into current BPS programs resulting in deterministic and homogeneous results that ignore the stochastic nature, dynamics, and diversity of occupant behavior. For example, occupants can open windows due to various reasons: (1) feeling hot – thermal comfort driven, (2) feeling stuffy – IAQ driven, and (3) arriving in a space – event driven. Field-measured data and large-scale surveys confirmed that these window opening behaviors, which are represented as probabilistic models (logit or Weibull functions), have been adopted by several BPS programs to determine when occupants open windows [32][33]. Occupant behavior stochastic models are data driven and improve modeling assumptions of occupant activities in the BPS programs [34][35][36][37]. BPS is used to quantify the energy savings potentials of behavioral ECMs in this case study.

This study defines five typical occupant behavior measures in office buildings, then simulates and analyzes their individual and integrated impacts on energy use in buildings. Although actual energy savings of occupant behavior measures depend upon many factors, including building type, energy services systems (lighting, plug loads, HVAC), climate, and occupants in the buildings, the presented methodology is robust and can be adopted for other studies aiming to quantify occupant behavior impact on building performance.

2. Methodology

2.1 Overview

A methodology was established in this study to investigate the energy saving potential of occupant behavior measures, shown in Figure 1. A real office building was field investigated, including the geometry, zoning, occupancy schedule, lighting schedule, plug load power density, and schedule. This case study was based on the selected real building instead of the DOE prototype models [38] which simplify building zoning and occupant inputs. With realistic geometry, zoning, and schedules, the case study can better reflect the realistic occupant behaviors in buildings.

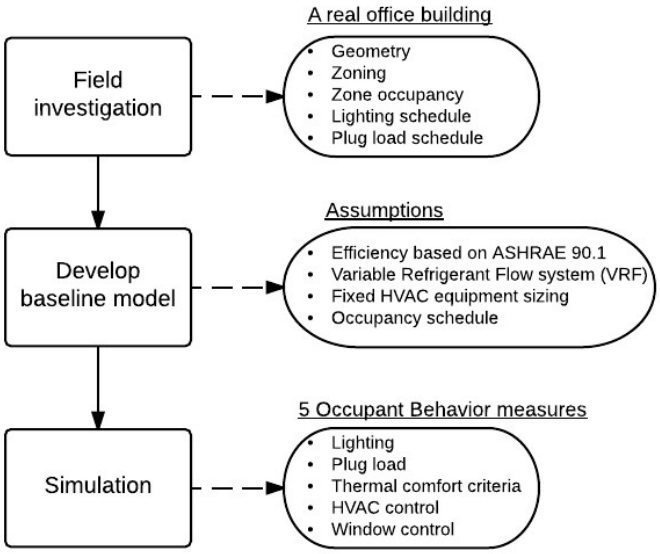


Figure 1 Overall methodology

Whole building simulation, using EnergyPlus, was used to evaluate the energy performance of the occupant behavior measures. EnergyPlus is an open source program that models heating, ventilation, cooling, lighting, water use, renewable energy generation, and other building energy flows [39] and is the flagship building simulation engine supported by the United States Department of Energy (DOE). It includes many innovative simulation capabilities including sub-hourly time-steps, natural ventilation, thermal comfort, co-simulation with external interfaces, renewable energy systems, and user customizable energy management systems (EMS). Some of the innovative capabilities such as natural ventilation, thermal comfort and EMS were used in this case study. Based on the investigated office building, a baseline model was developed in Energy V8.4. A few assumptions were made in the baseline model, which will be described in detail in Section 2.3.

There are many behavioral measures studied in previous research, however, mainly focusing on five categories: lighting, plug load, thermal comfort, HVAC and windows [40][1]. In our study, one occupant behavior measure was selected as the representative of each category to investigate their energy savings potential. Therefore, five occupant behavior measures were investigated in this study: lighting, plug load, comfort criteria, HVAC control, and window control. The energy performance of the five occupant behavior measures was evaluated in four climate types (Chicago, Fairbanks, Miami, and San Francisco) and two vintages (1989 and 2010). These selected cities represent the four typical climate types in the US: humid continental, subarctic, tropical (subtropical), and Mediterranean. The two vintages represent the characteristics of the existing buildings and new constructions. In this case, the influence of climates and vintages on the energy savings of occupant behavior measures can be evaluated. In this study, electricity consumption (site energy) per square meter is used as the energy metric to estimate energy savings as electricity is the only energy source of the case building.

2.2 Field investigation

To get a more realistic estimation of the potential energy savings of occupant behavior measures, a real office building was investigated and modeled in this case study. This building has two above-ground stories with a total conditioned floor area of 1,723 m^2. Main room functions include office, conference room, classroom, and lounge (corridor). Smaller corridors are merged into office zones for simplification. The perimeter zones have operable windows, which allow the occupants to open windows for cooling or ventilation. The total number of occupants in the case building is 63. Figure 2 and Figure 3 show first and second floor plans of the case building, including the room functions.

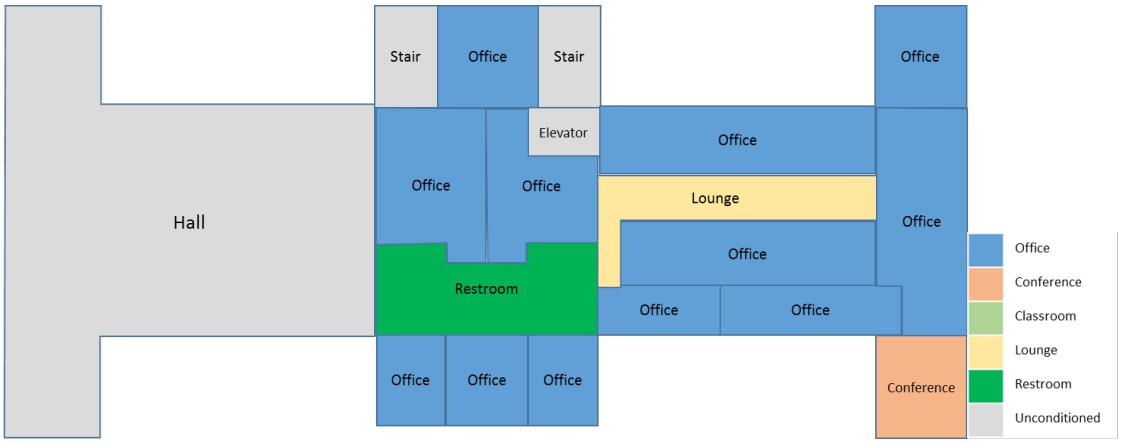


Figure 2 The 1st floor plan

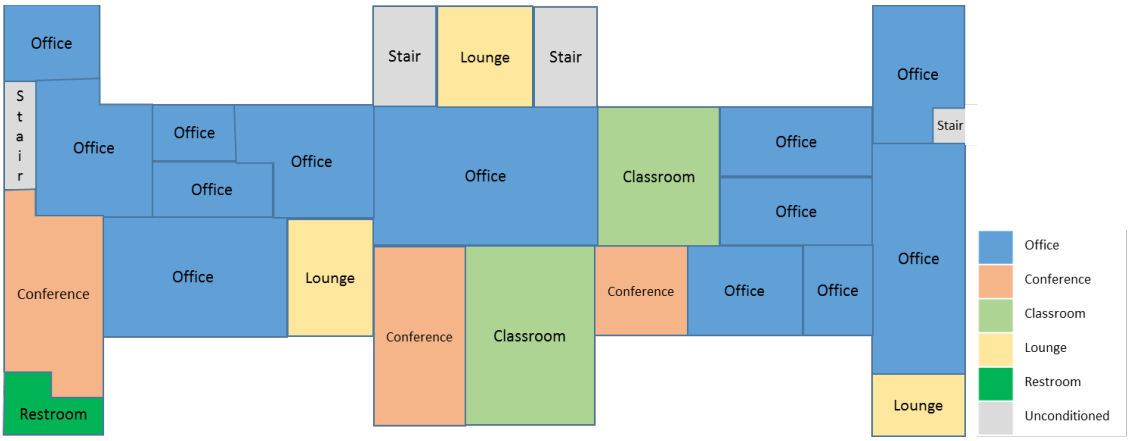


Figure 3 The 2nd floor plan

Detailed information on the case building, including zone occupancy, lighting schedule, plug load power density, and schedule, was also obtained via the field investigation. The zone functions and their maximum number of people are summarized in Table 1.

Table 1 Zone function and occupancy

Zone Function	Maximum Number of People	Number of zones
Office	0	1
	1	12
	2	10
	3	5
	4	4
Classroom	3	1
	5	1
Meeting Room	4	2
	13	1

2.3 The baseline model

A baseline model was developed using EnergyPlus Version 8.4 (Figure 4), based on the realistic geometry and zoning of the case building. The main assumptions of the baseline model are described as follows.

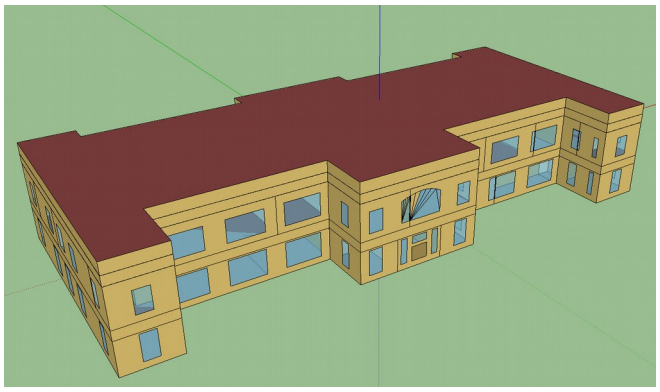


Figure 4 The 3D view of the baseline model

2.3.1 Generation of stochastic occupancy schedule

Occupancy plays a critical role in the energy performance of occupant behavior measures. However, an average whole building occupancy schedule is normalized and not able to reflect the realistic occupant movement and the variations between different zones within the buildings. For example, when the average occupancy schedule of offices is 0.1 at 7am, it is impossible for a single private office to have 0.1 persons. The reality could be that only 1 out of 10 private single offices is occupied at this time. It may not be a problem to estimate the total internal load of the building with a normalized occupancy schedule. However, for occupant-based controls, normalized occupancy schedule is not able to reflect the realistic occupancy, which is critical input for estimating energy performance of occupant-based controls. Implementing realistic occupancy schedules is crucial to accurately estimate the energy savings of occupant behavior measures.

Three approaches are primarily used for occupant modeling: stochastic approach, agent-based approach, and random walk approach [41]. The stochastic approach considers the occupant movement as probabilistic. Markov Chains' transition probabilities were generally utilized to generate a stochastic model for the occupant presence [34][35][42]. The agent-based approach aims to describe the interactions between occupants based on their perception, desire, and intention—focusing on what an occupant perceives and does in a certain situation. Agent-based models were developed to simulate autonomous occupants in previous research [7][36][43][44]. The random walk approach presents a new concept, which views occupancy pattern as unpredictable in certain cases. It was obtained from occupancy experiments in the university laboratories, which are quite different from process-driven buildings such as residential buildings and schools. Though its application might be limited to certain building types, it provides another method to predict occupant presence [41].

The authors used the Occupancy Simulator to simulate the realistic occupant movement in each zone, with inputs from the site survey of the case building. The Occupancy Simulator, developed by Lawrence

Berkeley National Laboratory (LBNL), is a user-friendly app that uses Markov chain modeling to simulate occupancy in buildings [45]. The app takes high-level inputs of occupants, spaces, and events to simulate the stochastic occupant presence and movement in buildings, capturing the spatial and temporal occupancy diversity [34][35]. Each occupant and each space in the building are explicitly simulated as an agent with their profiles of stochastic behaviors. The occupancy behaviors were represented with three types of events, including: (1) the status transition events (e.g., first arrival in office) simulated with Reinhart's LIGHTSWITCH-2002 model [46], (2) the random moving events (e.g., from one office to another) simulated with Wang's homogeneous Markov chain model [35], and (3) the meeting events simulated with a new stochastic model. The Occupancy Simulator is a web application with cloud computing. It reduces the amount of data inputs by allowing users to group occupants with similar behaviors as an occupant type and spaces with similar function as a space type. The theoretical mathematical distribution of the occupancy pattern properties have been verified using collected occupancy data in real buildings [47]. The generated schedules capture the diversity and stochastic nature of occupant activities. These schedules can be downloaded and used for building simulations.

The maximum occupancy and space types from Table 1 are inputs of the simulator. For the offices, three prevailing types of work schedules on weekdays were summarized based on the survey: 8am – 5pm (70%), 7am – 6pm (20%), and 6am – 11pm (10%). The occupants don't work on weekends. The classrooms and meeting rooms only hold events during several fixed time slots on weekdays with certain possibilities. With the above inputs, the occupancy schedules for each space were generated by the Occupancy Simulator.

Figure 5 shows the hourly variation and profile of total occupancy schedule in all the offices throughout the weekdays of a whole year. Likewise, Figure 6 and Figure 7 show the occupancy schedules on weekdays in all the classrooms and meeting rooms, respectively. Figure 8 shows the occupancy schedule of a four-person office on the second floor during a weekday with the time step of 15 minutes. According to the normalized occupancy schedule in the DOE office building prototype models [38], the unoccupied hours during weekdays are 1,564, while the average unoccupied hours of all the offices during weekdays are 3,800 based on the generated stochastic occupancy schedule. This was calculated by averaging the total unoccupied hours during weekdays of each office. With the stochastic occupancy schedule, the spaces are unoccupied for more than twice the time of the normalized occupancy schedule, which leads to a significant difference in the energy performance of occupant-based ECMs.

The generated schedules can reflect the variation, diversity, and stochastic characteristic of the realistic occupant movements. Compared with the normalized identical occupancy schedule in all spaces, these generated schedules are more reasonable and can help improve the simulation accuracy. To make it

consistent for all the studied measures, the same set of generated schedules is applied to both the baseline model and the five occupant measures.

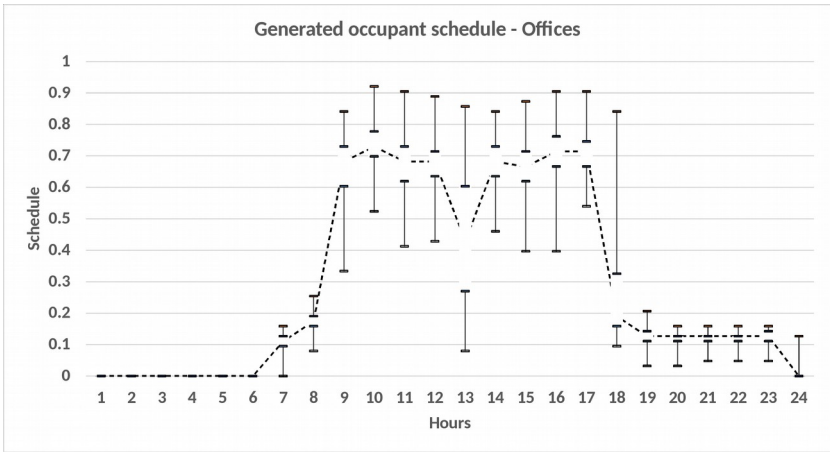


Figure 5 Box-Whisker plot of the hourly schedule of total occupancy in all offices on weekdays. The four marks on each time scale stand for (from top to bottom): maximum, upper quartile, lower quartile, and minimum. The dotted line connects the median value of all.

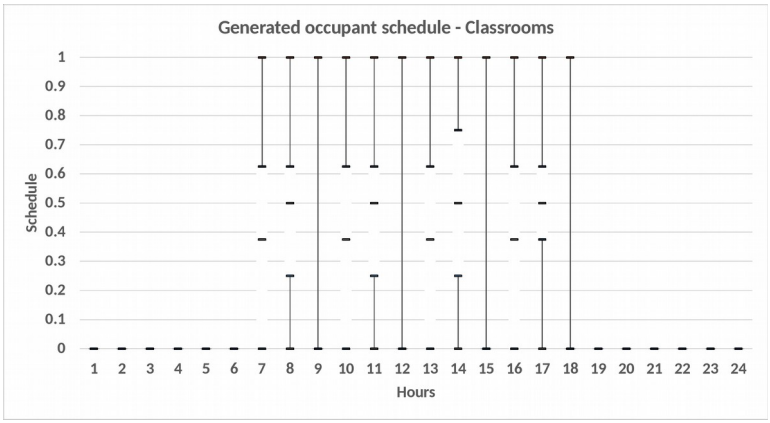


Figure 6 Box-Whisker plot of the hourly schedule of total occupancy in all the classrooms on weekdays. The five marks on each time scale stand for (from top to bottom): maximum, upper quartile, median, lower quartile, and minimum.

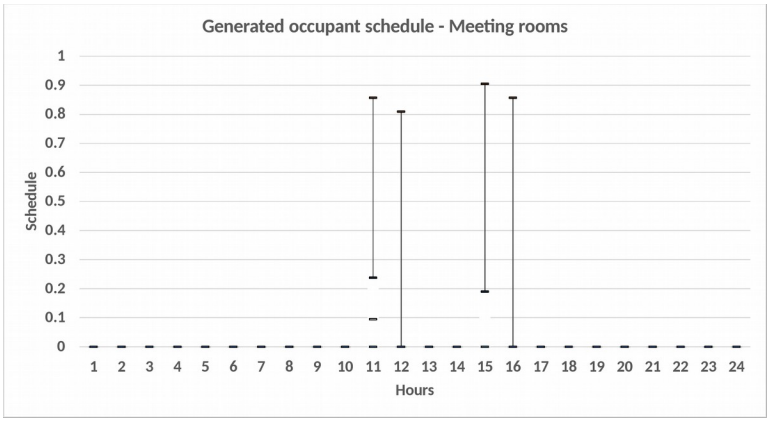


Figure 7 Box-Whisker plot of the hourly schedule of total occupancy in all the meeting rooms on weekdays. The five marks on each time scale stand for (from top to bottom): maximum, upper quartile, median, lower quartile, and minimum.

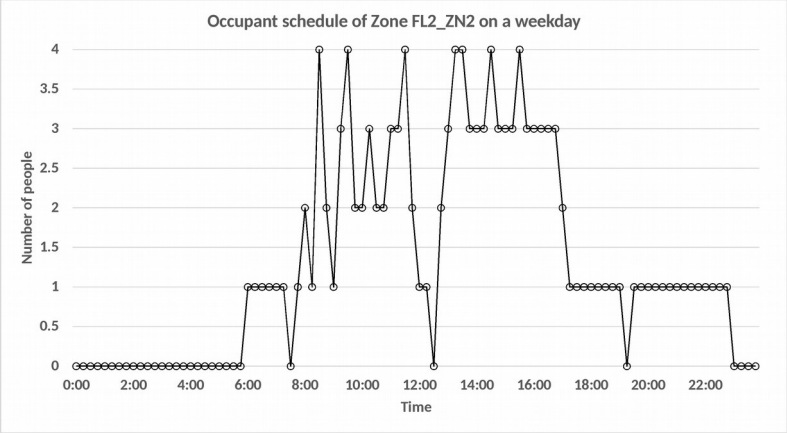


Figure 8 The occupancy schedule of an office room on the 2nd floor on a typical weekday (Time interval: 15 min).

2.3.2 Efficiency of the building based on ASHRAE standard 90.1

All the efficiency inputs, including lighting power density, envelope properties, and HVAC equipment efficiencies, are based on ASHRAE Standard 90.1. Two versions of ASHRAE 90.1 standards, 1989 [48] and 2010 [49], were used as the reference for efficiency inputs, as shown in Table 2 and Table 3. The 1989 scenario represents old buildings while the 2010 represents new buildings. The building envelope properties vary with climate types, while other customized inputs, such as schedules, plug load power density, etc., were kept the same as the original building. The visible transmittance (VT) is not regulated as are other thermal properties of the fenestration for each climate, so the study uses VT values from the DOE prototype models.

Table 2 Efficiency inputs of lighting power density and HVAC systems based on ASHRAE 90.1

	ASHRAE 90.1-1989	ASHRAE 90.1-2010
Lighting power density (W/m^2)	18.5	9.69
Water-cooled chiller COP	3.8	5.55
Gas boiler thermal efficiency (Et)	0.7	0.75

Table 3 Efficiency inputs of envelope properties based on ASHRAE 90.1

	Chicago		San Francisco		Miami		Fairbanks	
ASHRAE 90.1 version	1989	2010	1989	2010	1989	2010	1989	2010
Wall U-factor W/(m^2.K)	0.72	0.511	2.72	0.698	5.68	3.29	0.312	0.403
Roof U-factor W/(m^2.K)	0.3	0.27	0.514	0.27	0.43	0.358	0.176	0.273
Window U-factor W/(m^2.K)	3.35	3.12	4.09	3.69	6.98	6.81	2.95	2.56
Window SHGC	0.435	0.4	0.435	0.25	0.33	0.25	0.87	0.45

2.3.3 The variable refrigerant flow system

The case building uses variable refrigerant flow (VRF) systems. A VRF system varies the refrigerant flow rate using variable speed compressor(s) in the outdoor unit and the electronic expansion valves located in each indoor unit to meet the space cooling or heating loads while maintaining the zone air temperature at the comfort setpoint [50]. A VRF system's ability to control the refrigerant mass flow rate according to the cooling and/or heating load enables the use of as many as 60 indoor units with differing capacities in conjunction with one single outdoor unit. This unlocks the possibility of having individualized comfort control, simultaneous heating and cooling in different zones, and heat recovery from one zone to another [50][51][52]. The new VRF model in EnergyPlus V8.4 [53], developed by LBNL, was used for VRF system simulation in this study. The outdoor air volumes in each zone were kept at the same level as the original system.

2.3.4 Fixed HVAC equipment sizing

The sizing of the HVAC equipment was kept the same through all the calculations since HVAC equipment will stay the same unless replaced or removed during retrofits. The sizing information was first obtained by autosizing the equipment of the baseline model.

2.4 Simulation of the occupant behavior measures

There are four approaches that are used to simulate occupant behaviors in BPS programs [37]. (1) Direct input or control: occupant-related inputs are defined using the semantics of BPS programs, just as other

model inputs are defined (building geometry, constructions, internal heat gains, and HVAC systems). (2) Built-in occupancy behavior models: an advanced occupancy behavior control is implemented directly into the BPS program, usually in a dedicated software module. (3) User function or custom code: the user can write functions (e.g., user functions in DOE-2.1E) or custom code (e.g., EMS in EnergyPlus [54]) to implement new or overwrite existing or default building operation and supervisory controls. (4) Co-Simulation: a simulation methodology that allows individual components to be simulated by different simulation tools running simultaneously and exchanging information in a collaborative manner. In this study, the first and third approaches were used to simulate the five occupant behavior measures.

2.4.1 Measure 1: Lighting control

In the baseline model, the lighting schedule is static throughout the year, and the same in all the zones of the same room type. This occupant behavior measure evaluates the potential savings from occupant-based lighting control. Two scenarios of lighting control were considered: (1) occupants turn on lights when they enter the room and turn off lights when they leave the room; (2) occupants turn on lights when they are in the room and feel that it is dark; they turn off lights either when they leave the room or feel that the room is bright enough. According to previous studies [55][56] and the baseline schedule shown Figure 9, the emergency and security lights are always on, even during night time and weekends when the building is unoccupied. This part of lighting use is considered necessary, so the lighting schedule for this measure was set the same as the nighttime value of the baseline model during unoccupied hours.

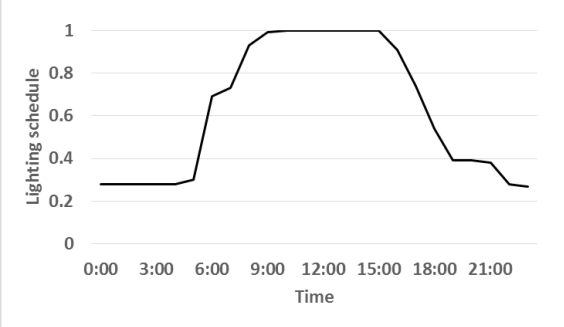


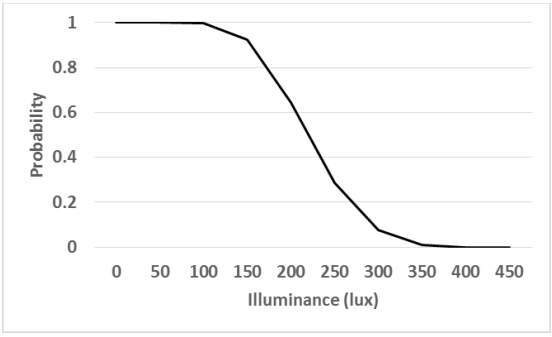
Figure 9 Office lighting schedule in the baseline model

The first scenario is directly associated with occupancy, which could be obtained according to occupancy schedule in each zone. The second scenario relates not only to the occupancy but also to the probability of turning on/off the lights at different daylighting levels. Wang, et al. [57] measured the occupant movement, daylight illuminance and lighting power in two private offices in an office building and found a relationship between daylight illuminance and occupant behavior of lighting control. They defined a three-parameter Weibull distribution function to describe the conditional probability of turning on/off the lights (Table 4), the independent variable x is the indoor illuminance level at a work-plane height:

Table 4 Three-parameter Weibull distribution describing the conditional probability of turning on/off the lights

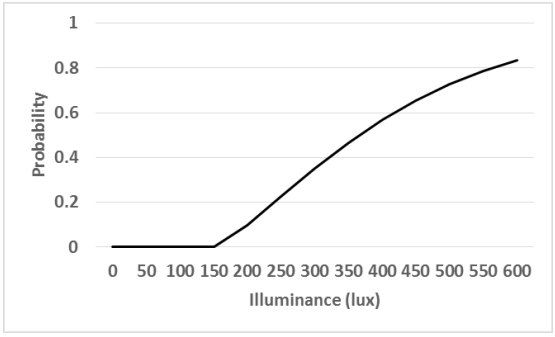
Turn on the light when feeling dark:	**Turn off the light when feeling bright enough:**
$P=\begin{cases}1-e^{-\left(\frac{u-x}{L}\right)^{k}\Delta\tau}, x\le u & ,when\ occupied\\ 0, x>u\end{cases}$	$P=\begin{cases}1-e^{-\left(\frac{x-u}{L}\right)^{k}\Delta\tau}, x\ge u & ,when\ occupied\\ 0, x<u\end{cases}$

Where parameter u stands for the threshold of independent variable x, beyond which the probability of occupant taking action would be 0. For example, when the indoor illuminance is greater than u, the probability of turning on the lights is 0. The parameter L describes the scale of the function, which is used to nondimensionalize (x-u). The parameter k represents the slope of the function. The greater k value is, the more sensitive the occupant is to the illuminance. In this study, we referred to the parameters' values in Wang's paper [57]. The profile of the probability of occupants turning on/off the lights is shown in Figure 10.



(a) Probability of turning on the lights

u = 450, L = 427.32, k = 5



(b) Probability of turning off the lights

u = 150, L = 2300, k = 1.3

Figure 10 Probability of occupants turning on/off the lights

Time-step daylight illuminance in each zone was simulated in EnergyPlus, which was used to calculate the time-step probability of turning on/off the lights according to the above probability function. If the zone is occupied, a random number between 0 and 1 will be generated for each occupant. This occupant will have the ability to take action (turn on/off the lights) if the random number is less than the relevant probability. When there is only one occupant, the status of the lights will be determined by this occupant. When the number of occupants is greater than 1, the lights will be turned on if one of the occupants has the desire to, and turned off only if all of the occupants agree to do so. The "direct input or control" approach was used to simulate the lighting control measure, where the generated lighting schedules will be imported into the EnergyPlus models to replace the original static lighting schedule.

2.4.2 Measure 2: Plug load control

In the baseline model, the plug load schedule is deterministic, and its control has nothing to do with the occupants. For this occupant behavior measure, the occupants have the option to control their personal electric equipment, such as laptops, desktop screens, chargers, and personal fans, based on their presence. This part of electric equipment is assumed to take up about 30% of total plug load. This is based on previous research on occupancy-based control of plug load, which shows that plug load controlled by the occupants can be reduced by up to 26% of the total electricity use during unoccupied hours [58–61]. In that case, the assumption of this measure is straightforward: when the zone is occupied, the electric equipment is 100% on; when the zone is unoccupied, the electric equipment will be reduced by 30%. In other words, the electric equipment schedule of each zone is directly associated with occupancy, which could be obtained according to occupancy schedule in each zone. The simulation method is the same as the lighting control measure.

2.4.3 Measure 3: Thermal comfort criteria

Thermal comfort standards have significant impacts on the energy consumption of HVAC systems by affecting the cooling and heating setpoints. In buildings with centralized control, all the conditioned zones are set to the same cooling/heating setpoints. They usually form a narrow comfort zone to guarantee sufficient satisfaction. However, the way occupants experience thermal conditions varies considerably [57][62]. Outside the simulation, the operation strategy of setting a narrow comfort range can’t guarantee better comfort while consuming more energy. Just like the thermostat settings in the baseline model, which follows the original settings from the case building, which uses 24.4°C for cooling and 21.1°C for heating. Therefore, this measure considers an extreme situation where all the occupants have a broader thermal comfort acceptance range to explore the potential energy savings from changing thermal comfort criteria.

Two thermal comfort criteria were considered: (1) ASHRAE standard 55 comfort zone limits [63]; (2) adaptive comfort [63][64]. Adaptive comfort was proposed to complement the traditional Predicted Mean Vote (PMV)-based method in ASHRAE Standard 55. It allows warmer indoor temperatures for naturally ventilated buildings during warm seasons. Although adaptive comfort was originally developed for naturally ventilated buildings, it is also recommended for use with buildings that have mechanical cooling systems.

In the first scenario, the upper temperature limit of the ASHRAE 55 comfort zone was taken as the cooling setpoint in the simulation while the lower limit was taken as the heating setpoint. In the second scenario, the adaptive comfort model with 80% acceptability limits, developed by the Center for the Built Environment in UC Berkeley, was adopted to calculate a dynamic comfort range based on ambient

temperature, which was then used as dynamic cooling/heating setpoints in simulation (Figure 11). The "direct input or control" approach was used to simulate this measure, where the cooling setpoint schedule in the EnergyPlus models was adjusted according to different thermal comfort criteria.

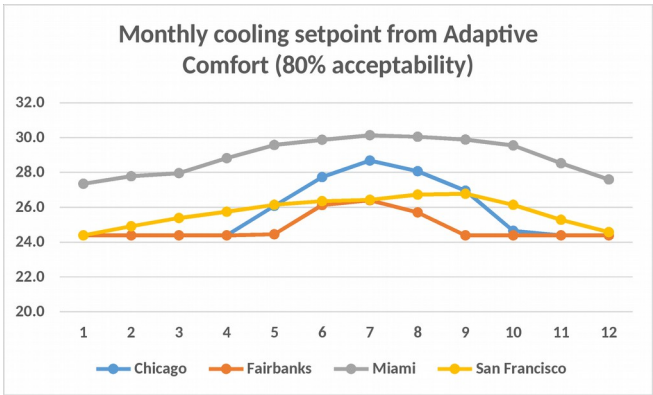


Figure 11 Monthly Cooling Setpoint from the Adaptive Comfort (80% acceptability) model

2.4.4 Measure 4: HVAC control

In the baseline model, the HVAC system is controlled by a fixed schedule (5:00-19:00 Mon-Sun). This occupant behavior measure aims to evaluate the potential energy savings of occupant-based HVAC control. The access to HVAC control for the occupants varies with HVAC system types. For HVAC systems that have zonal control, occupants are allowed to turn on/off the HVAC in their zone without affecting other zones; for centralized controlled HVAC systems, occupants are not able to control their HVAC operation individually. In the case building, VRF systems enable occupants to control their zone HVAC independently by turning on/off their indoor units without affecting others.

Similar to the lighting measure, two scenarios of HVAC control were considered: (1) occupants turn on HVAC when they are in the room and turn off HVAC when they leave the room; (2) occupants turn on HVAC when they are in the room and feel hot (in cooling mode) or cold (in heating mode), and turn off HVAC either when they leave the room or feel cold (in cooling mode) or hot (in heating mode).

For the first scenario, the HVAC schedule in each zone is directly generated according to its occupancy schedule. For the second scenario, the probability of turning on/off the HVAC system relates to the current conditioning mode (cooling or heating) and the indoor air temperature. Ren [65] investigated the indoor temperature and HVAC usage of 34 families in six Chinese cities and used a three-parameter Weibull distribution function to describe different air conditioning usage patterns. Since residential units have independent control of their HVAC system, which applies to the condition of our study, Ren's model was adopted to estimate the time-step HVAC control status in our models. The functions are shown in Table 5 (taking cooling mode as an example), with indoor air temperature T as the independent variable:

Table 5 The three-parameter Weibull distribution describing the conditional probability of turning on/off the HVAC system

Turn on AC when feeling hot:	**Turn off AC when feeling cold:**
$P=\begin{cases}1-e^{-\left(\frac{T-u}{L}\right)^{k}\Delta\tau}, T\geq u \\ 0, T<u\end{cases}$ *, when occupied*	$P=\begin{cases}1-e^{-\left(\frac{u-T}{L}\right)^{k}\Delta\tau}, T\leq u \\ 0, T>u\end{cases}$ *, when occupied*

The parameter u stands for the threshold of independent variable T, beyond which the probability of an occupant taking action would become 0. For air conditioning, when the indoor temperature T is lower than u, the probability of turning on the AC is 0. The parameter L describes the scale of the function, which is used to nondimensionalize (T-u). The parameter k represents the slope of the function. The greater k value is, the more sensitive the occupant is to indoor temperature. In each scenario, the three parameters are predetermined to meet certain criteria. For example, for the probability function of turning on HVAC when the occupants feel hot: (1) the heating setpoint 21.1°C was set as the u value. In other words, it is considered impossible for the occupants to turn on the HVAC because of feeling hot when the indoor temperature T is lower than the heating setpoint. (2) The L and k values were obtained assuming that the probability of turning on HVAC is about 20% at the cooling setpoint 24.4°C (cooling setpoint satisfies thermal comfort in 80% of the population) and about 50% at the upper limit of ASHRAE comfort zone 28.3°C.

For this study, the assumption is that when the indoor air temperature T locates in the comfort zone between the cooling and heating setpoints, the occupants will not turn on the HVAC. When the HVAC status of last time step is off, the zone is occupied, and the indoor temperature T is higher than the cooling setpoint or lower than the heating setpoint, the indoor temperature T will be used to calculate the probability of turning on the HVAC. A random number between 0 and 1 is generated for each occupant and compared with the above probability per time step to determine whether to turn on the HVAC. On the other hand, the occupants will turn off the HVAC on two conditions: (1) the zone is unoccupied, (2) the zone is occupied, the HVAC status of last time step is on, and the calculated probability of turning off the HVAC is greater than the generated random numbers of all present occupants. To implement the occupant-based HVAC control measure in the EnergyPlus models, the real-time simulated indoor temperature per time step is the input for determining the action of the next time step. In this case, the “user function or custom code” approach was used, where the EMS function of EnergyPlus was adopted to interpret the conditional logics, generate random numbers and manipulate the HVAC schedules per time step.

2.4.5 Measure 5: Window control

Natural ventilation can be effectively applied to utilize free cooling [66]. With operable windows, occupants are able to open and close windows on their demand. In the baseline model, however, there is no natural ventilation while the HVAC system is operating all the time. In this study, an optimized window control was considered, referring to the "concurrent mixed-mode ventilation" in Wang's research [67]: Natural ventilation is taken as the priority to provide cooling for perimeter zones, and mechanical systems provide supplementary cooling when natural ventilation alone is not enough to meet cooling setpoints. In other words, if natural ventilation can meet cooling loads for a thermal zone, its VRF indoor unit will be closed; otherwise, conditioned air from the VRF indoor unit is available to provide supplementary cooling in order to meet thermal comfort. Natural ventilation is only avaialble when the room is occupied. In case the impact of Measure 4 is interfused, the HVAC system is controlled by a fixed schedule, which is the same as the baseline model. Figure 12 shows the control logic. Adaptive comfort criteria were adopted as the cooling setpoints for naturally ventilated perimeter zones [64], and the interior zones use the same cooling setpoints as the baseline model. The heating setpoints remain the same as the baseline model.

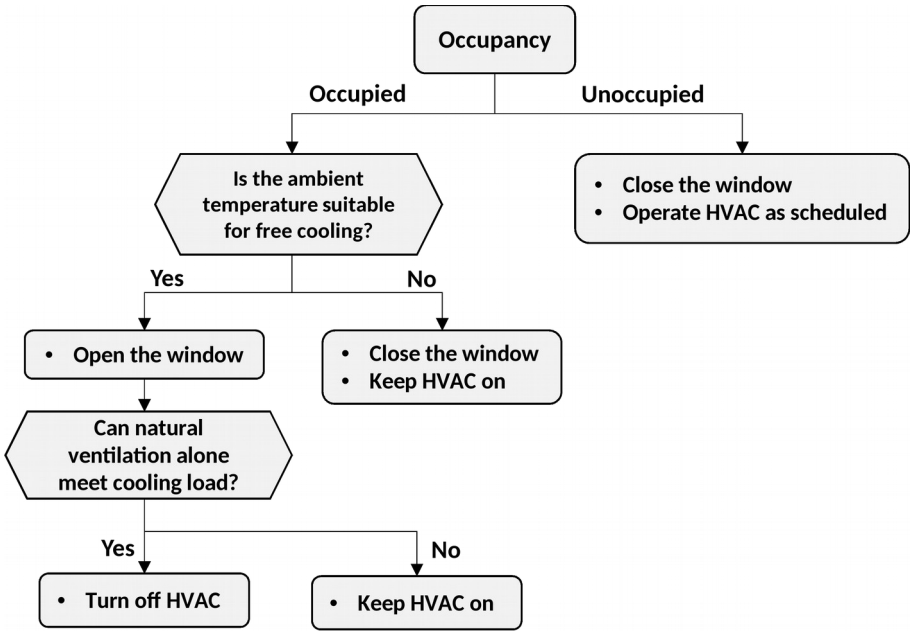


Figure 12 Control logic of Measure 5

When windows in perimeter zones are favorable to open, the fractions of window opening are modulated based on a linear relationship with indoor-outdoor temperature difference if zone air temperature is greater than outdoor air temperature and is also greater than the heating setpoint, illustrated in Figure 13 [67]. Windows will be fully closed when the indoor–outdoor temperature difference is greater than or

equal to 15°C and windows will be fully open for ventilation when the indoor and outdoor air temperatures are equal. The air change rate per hour with the windows fully open is assumed to be 10, which is comparable to mechanical ventilation systems. Windows in perimeter zones are favorable to open when outdoor air temperature is greater than the temperature which is 3°C below the heating setpoint in order to avoid overcooling thermal zones when outdoor air temperature is too low [67].

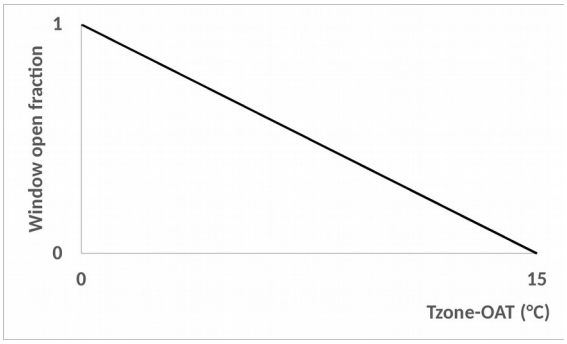


Figure 13 Modulation of window opening according to indoor and outdoor temperature difference (Tzone: zone air temperature; OAT: outdoor air temperature).

The “user function or custom code” approach was used, where the EMS function of EnergyPlus was used to interpret the conditional logics and manipulate the natural ventilation schedules per time step.

2.4.6 Integration of all five measures

After each occupant behavior measure was studied, the following question was asked: what energy savings would result from all five measures used together? To solve this problem, models with the integration of the five measures were developed, including: (1) lighting measure (scenario 2), (2) plug load measure, (3) thermal comfort criteria measure (adaptive comfort), (4) HVAC control measure (scenario 2), and (5) window control measure. Adaptive comfort criteria were adopted as the cooling setpoints for naturally ventilated perimeter zones, and the interior zones use the same cooling setpoints as the baseline model. The heating setpoints remained the same as the baseline model. The integration of (1), (2) and (3) is straightforward by replacing the corresponding schedules. For (4) and (5), the EMS codes will run first before each time step starts to determine the availability of the HVAC system and the availability of natural ventilation. If both are available, natural ventilation is taken as the priority to provide cooling for perimeter zones, and mechanical systems provide supplementary cooling when natural ventilation alone is not enough to meet cooling setpoints; otherwise, the HVAC system and natural ventilation will be operated based on their own availability.

2.5 The occupant behavior model of turning on/off the lights and HVAC

The Weibull distribution functions describing the conditional probability of turning on/off the lights and HVAC, which were defined by Wang [57] and Ren [65], were adopted in this study. There are three

parameters in the Weibull distribution functions: u, L, and k. Different sets of parameters represent different behavior patterns. Parameter u is the threshold for the uncomfortable domain that controls when the action will begin, L describes the range for the functional variable, and k describes the shape. In Ren and Wang's studies, field tests were performed to identify the lighting and HVAC usage patterns, based on which a set of parameters u, L, and k were generated to fit the measured data [65][57].

This case study referred to the parameter's values in Wang's paper for the lighting measure [57] and predetermined the parameters to meet certain assumptions for the HVAC measure scenario 2. These sets of parameters were considered consistent for all the occupants in the case building. This assumption is made based on the study's goal of estimating the theoretical energy saving potential of occupants, although not all occupants behave in the same patterns. In the future, more detailed field tests and surveys are recommended to develop a library of typical occupant behavior models that can be used in BPS.

2.6 The lighting usage in multi-occupant offices

In our study, we made assumptions on the lighting usage characteristics in multi-occupant offices: (1) Every occupant in an open-plan office has the same lighting use behavior pattern; (2) when there are other people in the office, the turning-off light action won't happen, while the turning-on light action is not influenced by others; (3) the lighting system is controlled by every occupant in the office with equal right. The simulation was performed based on these assumptions.

There are existing studies on the lighting usage in offices with multiple occupants. Hunt [68] and Yun [69] [70] both have observed the lighting usage in multi-person offices and found that lighting is usually turned on from the beginning until the end of the day. Wang, et al. [57] concluded that the more occupants in an office, the less volatile its lighting status is. In future work, more field investigation is recommended to collect more data to discover the behaviors of multiple occupants.

3. Results

Based on the assumptions made in Section 2, the energy performance of the five occupant behavior measures was simulated using EnergyPlus V8.4. Site energy is used as the energy metric. Since a VRF system is used for all the measures, electricity will be the only source of energy consumption. The results are shown as follows.

3.1 Measure 1: Lighting control

As mentioned in Section 2.4.1, two scenarios of occupant-based lighting control were considered: one is related with the occupancy only, the other is a combined decision based on occupancy and daylighting. Figure 14 shows the lighting electricity use reduction of these two scenarios in the four climates on the

90.1-1989 standard basis. Likewise, Figure 15 shows the results on the 90.1-2010 standard basis. For the first scenario, the lighting electricity consumption savings are the same across different climates of the same vintage; and the percentage of lighting electricity consumption savings for the two vintages are both 14%. For the second scenario that combines occupancy and daylighting, the lighting electricity savings, which vary among climates, are about 4%-11% more than the occupancy-only scenario. It is notable that the Miami case saves the least for both vintages. This is because the VT of the windows is very low in Miami, leading to insufficient daylight illuminance, which reduces the probability of turning off the lights.

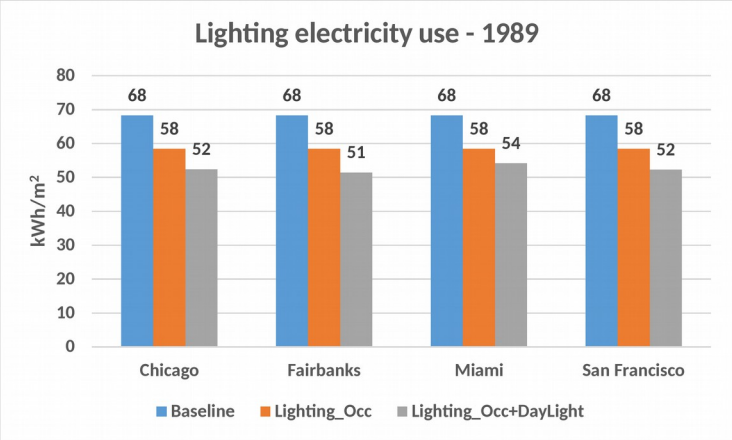


Figure 14 Lighting electricity savings of Measure 1, in four climates, 90.1-1989 scenario

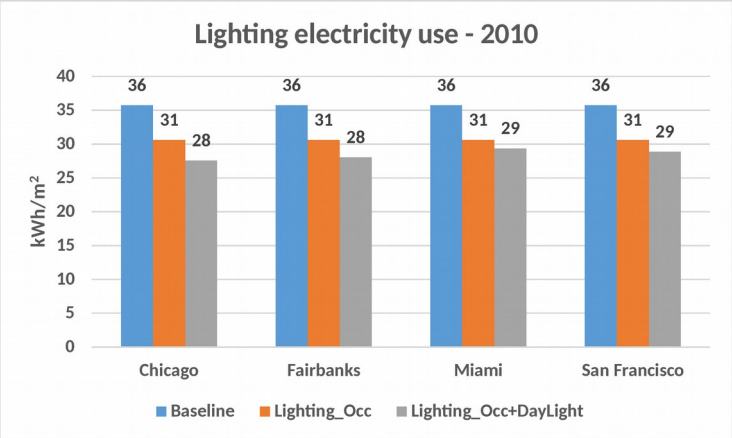
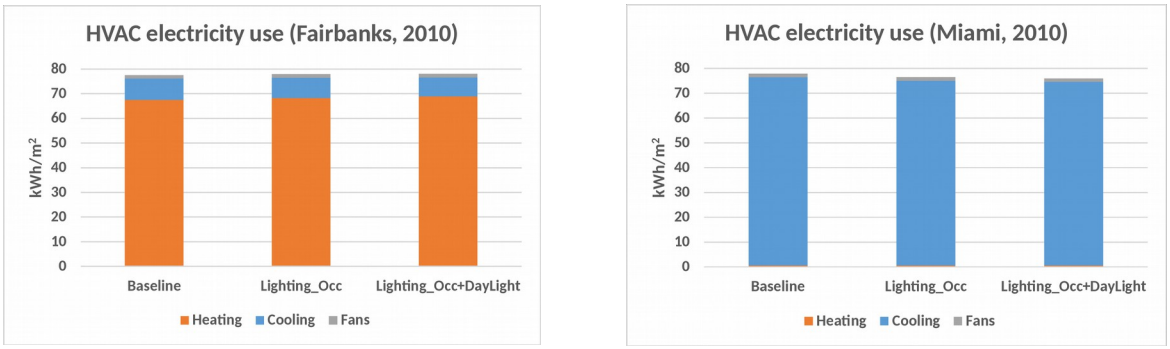


Figure 15 Lighting electricity savings of Measure 1, in four climates, 90.1-2010 scenario

The occupant-based lighting control measure also has a double impact on the energy consumption of the HVAC system: more use of daylight reduces internal heat gains from electrical lighting, which increases the heating consumption and decreases the cooling consumption. For a cold climate like Fairbanks (Figure 16 (a)), there is more heating demand than cooling demand, so lower internal heat gains tend to

have more influence on heating consumption. In this case, the total HVAC electricity consumption will slightly increase. On the contrary, the total HVAC electricity consumption will decrease in a hot climate like Miami (Figure 16 (b)). However, the indirect impact on HVAC system energy use is less than 20% of the lighting energy savings, which will not change the total effect of the measure.



(a) (b)

Figure 16 HVAC electricity changes of Measure 1

3.2 Measure 2: Plug load control

The measure of occupancy-based plug load control is theoretically the same as the first scenario of the lighting measure. The electric equipment is controlled based on occupancy. If the zone is occupied, the electric equipment will be 100% on. Otherwise, the electric equipment will be reduced by 30%.

The electric equipment density is consistent in all climates and vintages, making the percentage of plug-load electricity savings consistent at 21.2%. Meanwhile, as with lighting, the plug load measure also affects the HVAC system by reducing the internal heat gains, and the impact varies due to different climate types. The energy saving results are similar to those of the lighting measure, which will not be repeated here.

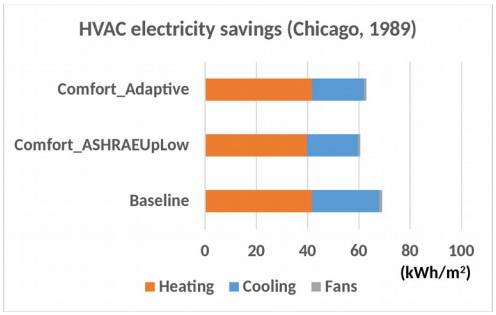
3.3 Measure 3: Thermal comfort criteria

As mentioned in Section 2.4.3, two thermal comfort criteria were simulated: (1) ASHRAE Standard 55 comfort zone—taking the upper limit as the cooling setpoint and the lower limit as the heating setpoint; (2) Adaptive comfort as the cooling setpoint. The thermal comfort criteria only impacts the energy consumption of the HVAC system, whose electricity savings are shown in Figure 17.

The first scenario reduces energy use for both heating and cooling while the second scenario only reduces cooling energy use. Therefore, the energy savings in climates that have significant winter seasons, such as Chicago, Fairbanks, and San Francisco, tend to be greater in the first scenario, especially when the adaptive comfort temperature is not as high as the upper limit of ASHRAE 55 comfort zone. On the contrary, there is no winter season in Miami, and most of the monthly adaptive comfort temperatures are

higher than the upper limit of the ASHRAE 55 comfort zone, so the energy savings are greater in the second scenario.

The building has better performance glazing (lower SHGC - Solar Heat Gain Coefficient) and lower lighting density (more efficient lighting) in the 90.1-2010 scenario, leading to higher heating load and lower cooling load than the 90.1-1989 scenario. The saving results are slightly different. However, the basic trends are the same in vintages 1989 and 2010.



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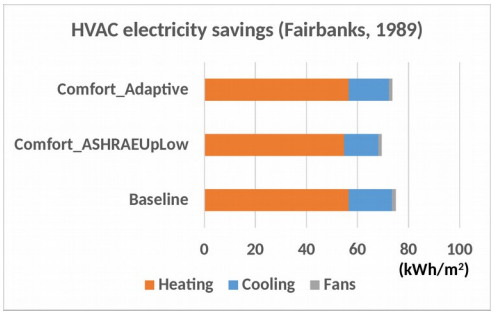

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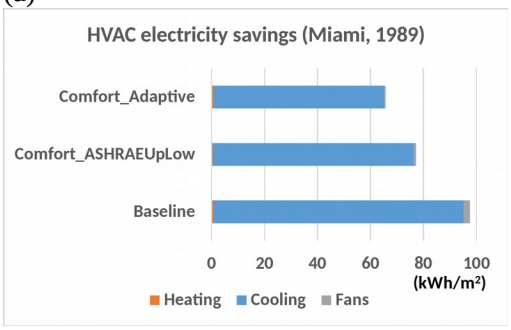

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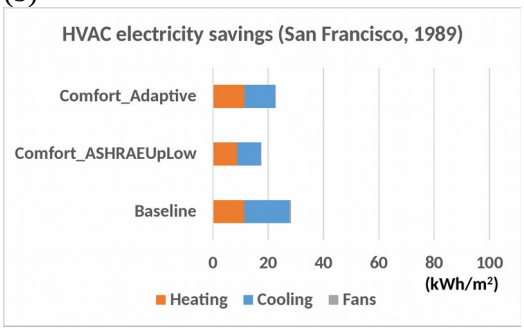

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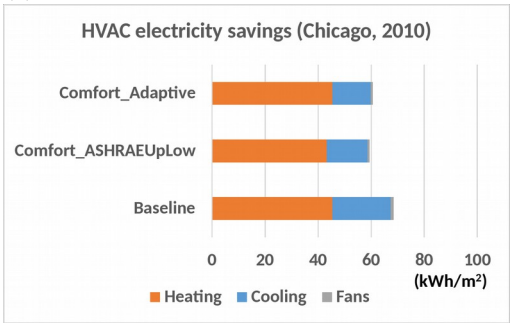

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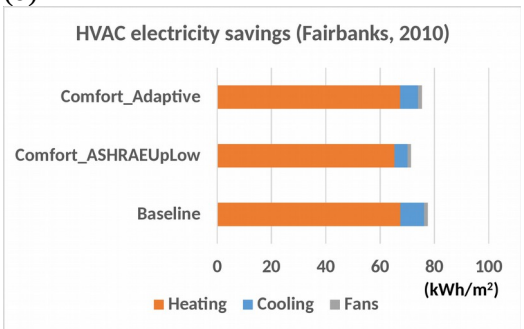

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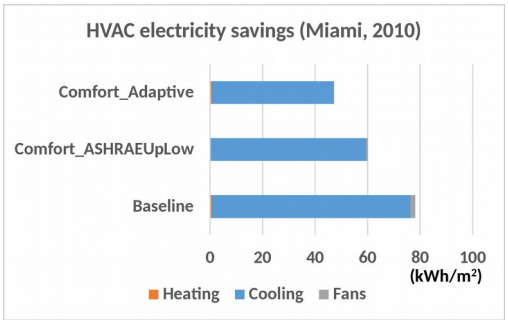

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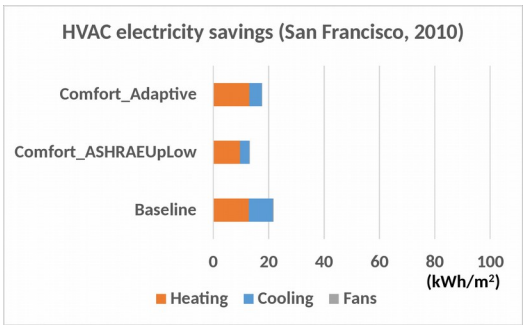

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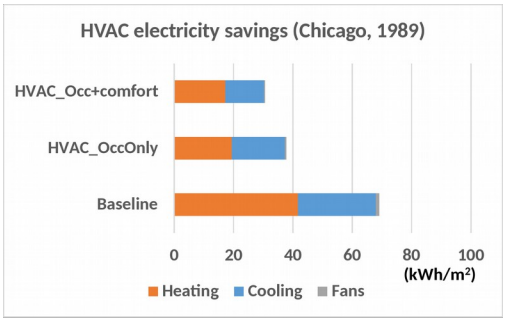
Figure 17 HVAC electricity savings of Measure 3

3.4 Measure 4: HVAC control

As mentioned in Section 2.4.4, two scenarios of HVAC control were considered: one is related to occupancy only; the other is a combined decision based on occupancy and thermal comfort. Only the energy use of the HVAC system is influenced by the HVAC control measure. Its electricity savings are shown in Figure 18.

In the baseline models, the HVAC system is always available to operate to meet temperature setpoint which observes setback during night time and weekends. As shown in Section 2.2, all of the offices are unoccupied an average of 3,800 hours during weekdays, and the occupants don't work on weekends. In this case, the HVAC systems will be off for at least half of the time for both scenarios. Furthermore, for the second scenario, the occupants only turn on the HVAC when they feel hot/cold and will turn off the HVAC when they feel overcooled/overheated. This further reduces the HVAC operation hours and cuts HVAC energy use (see Figure 18). For the studied four climates and two vintages, the first scenario reduces HVAC electricity use by 30.2%-52.0% and reduces whole building energy use by 4.9%-21.3%; the second scenario saves HVAC electricity use by 51.8%-56.4% and saves whole building energy use by 8.6%-22.9%.



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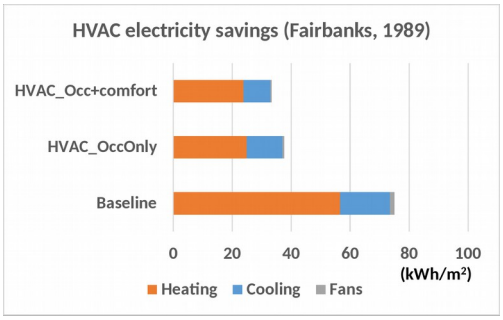

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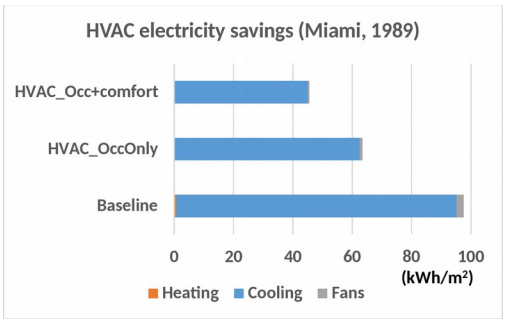

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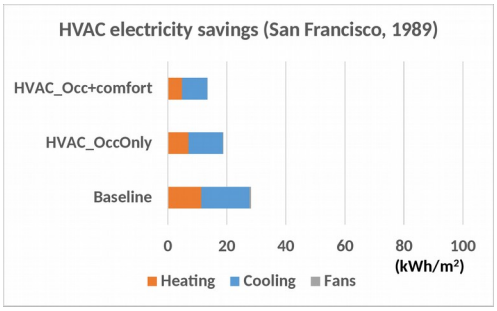

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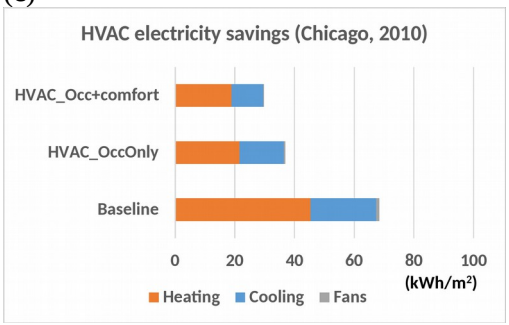

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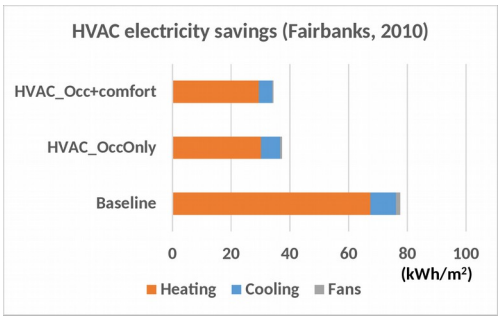

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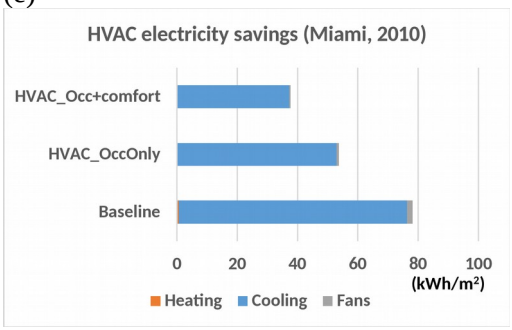

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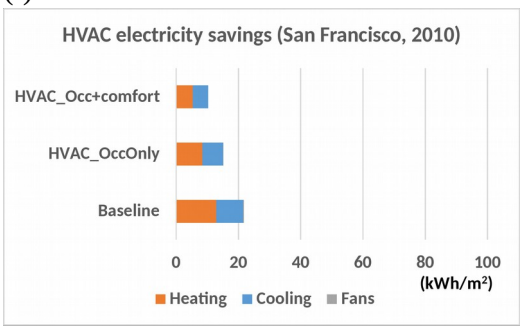


(h)

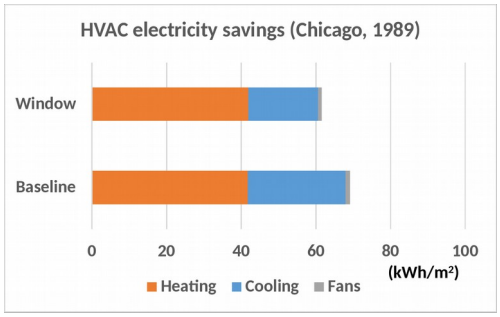
Figure 18 HVAC electricity savings of Measure 4

3.5 Measure 5: Window control

As discussed in Section 2.4.5, an optimized window control was considered: the natural ventilation and mechanical system serve the perimeter zones concurrently, and natural ventilation is taken as the priority to provide cooling for perimeter zones, while mechanical systems provide supplementary cooling when natural ventilation alone is not enough to meet cooling setpoints. The effect of the integration of natural ventilation and the mechanical system is similar to the effect of the air economizers, which makes full use of the cool outdoor air and maintains good thermal comfort. In this case, the cooling load is significantly reduced. Moreover, the adaptive comfort criteria for natural ventilation (mixed-mode in this study), which is more flexible than the tranditional comfort criteria for mechanical systems, helps further cut the cooling load.

For cold climates such as Fairbanks, the low-temperature outdoor air during cold winter and transition seasons is not allowed for natural ventilation as they may cause overcooling. Therefore, the available

hours of natural ventilation are minor, leading to little HVAC energy savings—about 3.5%-4% (Figure 19 (b), (f)). Similarly, the HVAC energy savings from natural ventilation are also limited in hot summer and cold winter climates such as Chicago, about 10.9%-12.0% (Figure 19 (a), (e)). On the contrary, it is warm in Miami all year round, leading to a higher adaptive comfort temperature, which takes credit for reducing the cooling load significantly. For mild climate such as San Francisco, the outdoor air is below 25°C almost all the time, which is suitable for free cooling, except the hours that might cause overcooling when the air is too cold for natural ventilation. According to Figure 19 (c), (d), (g) and (h), the HVAC energy savings for Miami and San Francisco are about 30.1%-34.1% and 14.0%-21.2%, respectively. Table 6 shows the total hours of natural ventilation as well as the percentage of total occupied hours.



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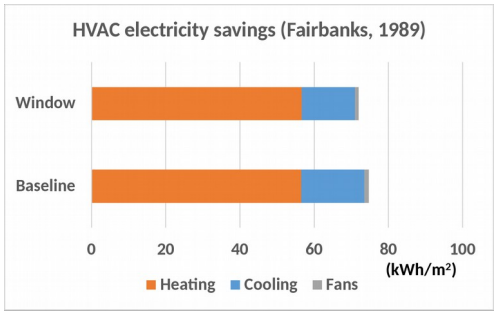

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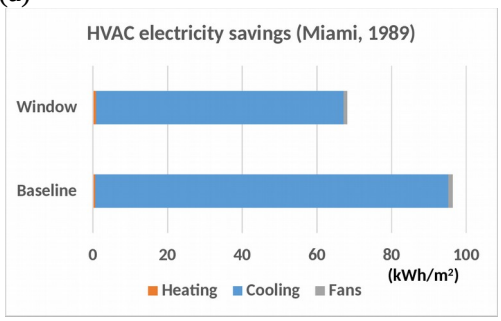

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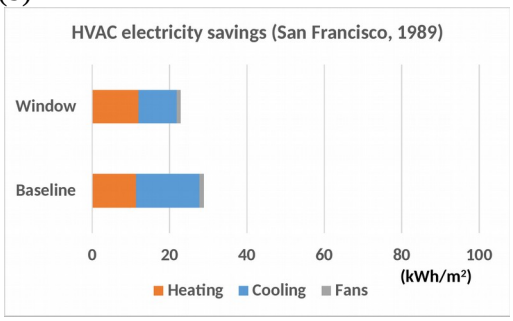

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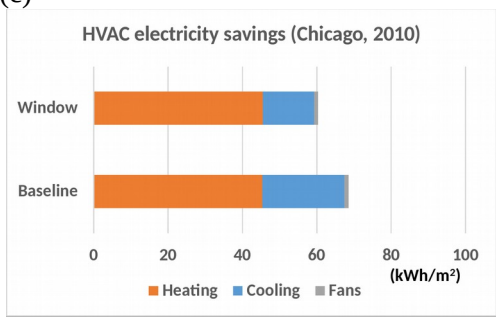

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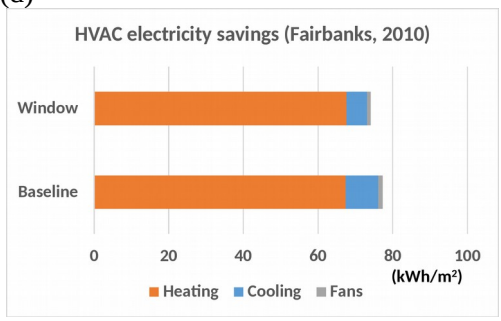

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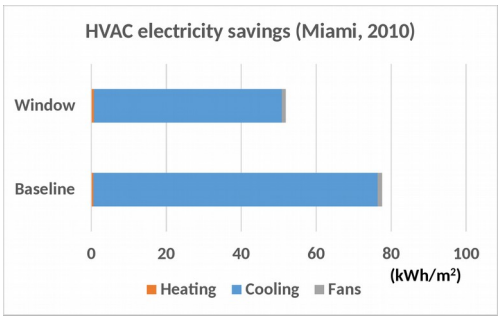

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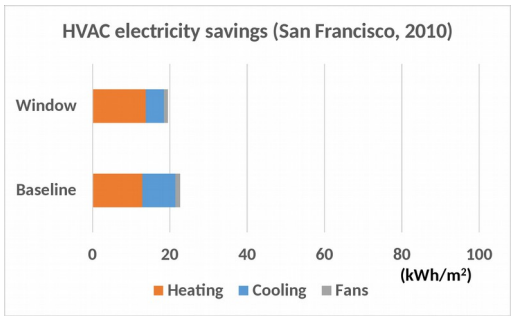


(h)

Figure 19 HVAC electricity savings of Measure 5

Table 6 The available natural ventilation hours

Vintage	Climate	Naturally ventilated time (hours)	Percentage of total occupied hours (%)
1989	Chicago	694	28.2
	Fairbanks	646	26.2
	Miami	1550	62.9
	San Francisco	871	35.4
2010	Chicago	680	27.6
	Fairbanks	595	24.1
	Miami	1522	61.8
	San Francisco	852	34.6

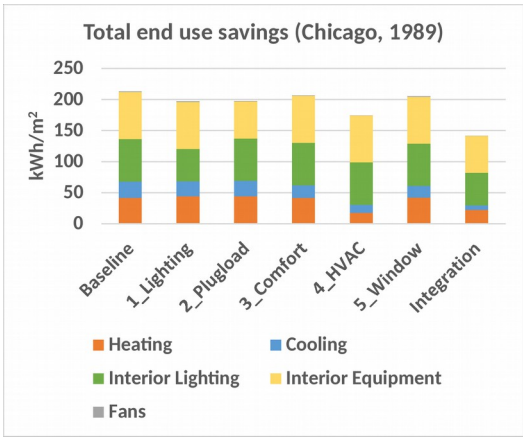
3.6 Integration of all five measures

All the five occupant behavior measures were integrated in Section 2.4.6, and their integral energy savings were simulated. Figure 20 shows the breakdown end uses of the baseline model, the five individual measures (see 2.4.6), and the integrated measure.

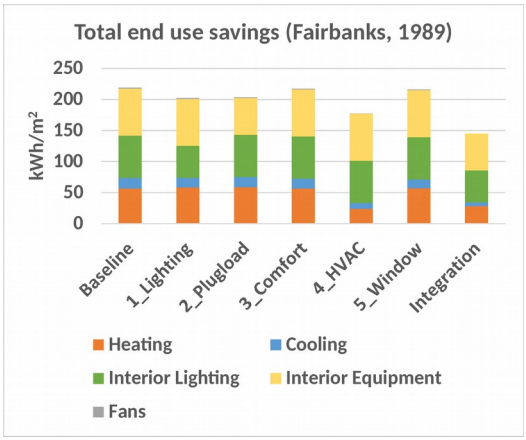
Each measure has its different impact on energy consumption: (1) the lighting measure and the plug load measure reduce the internal heat gains, which cut the cooling load but raise the heating load; (2) the comfort criteria measure reduces the heating/cooling load by enlarging the comfort boundary; (3) the HVAC measure and the window measure reduce the energy consumption by decreasing the HVAC operation time. When they are integrated, the effect of (3) is relatively weakened due to a lower cooling load level resulting from (1) and (2), and due to the higher heating load resulting from (1).

The integration of the five measures saves the whole building energy use by 27.9%-40.5% in the four climates of vintage 1989, and 24.7%-41.0% in the vintage 2010. According to the simulation results, the

occupant behavior measures can potentially cut the total energy consumption by at least a quarter, and as much as 41.0%.



(a)



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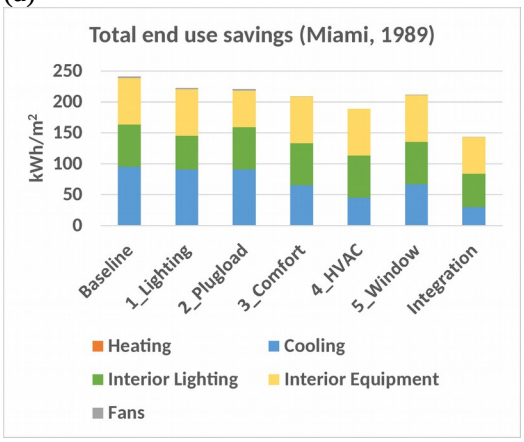

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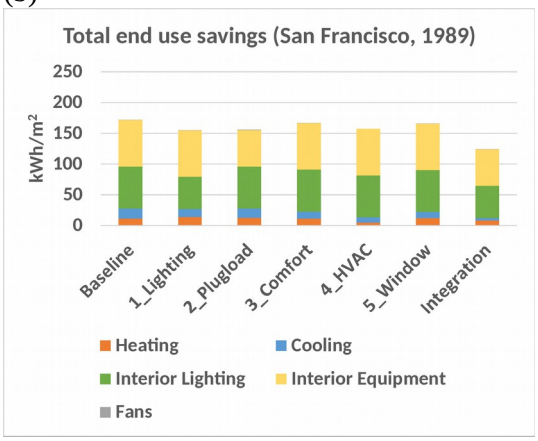

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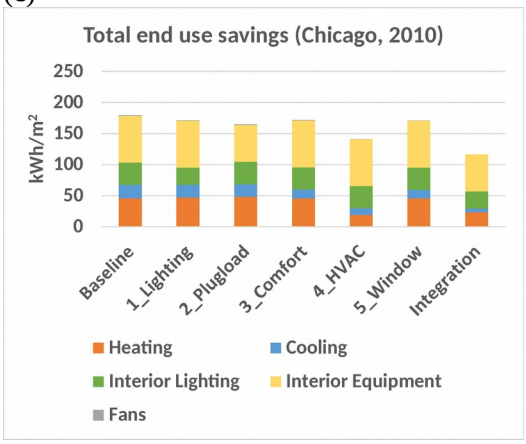

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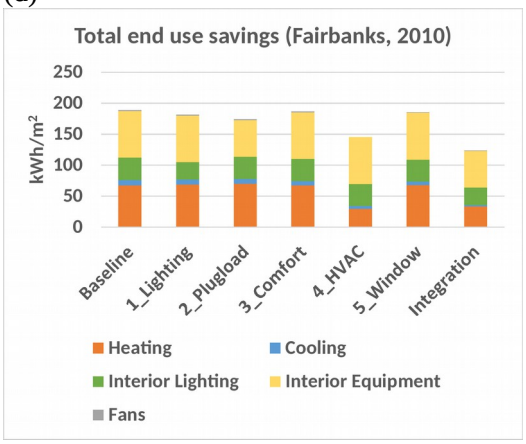

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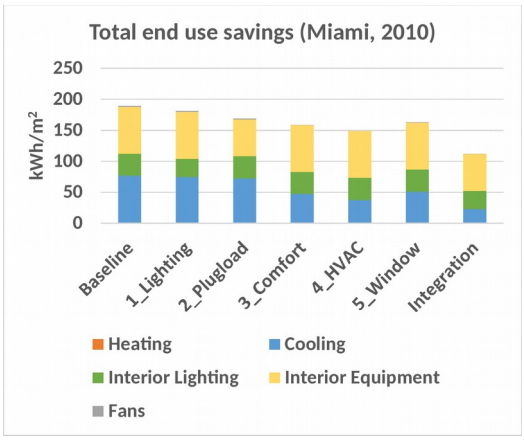

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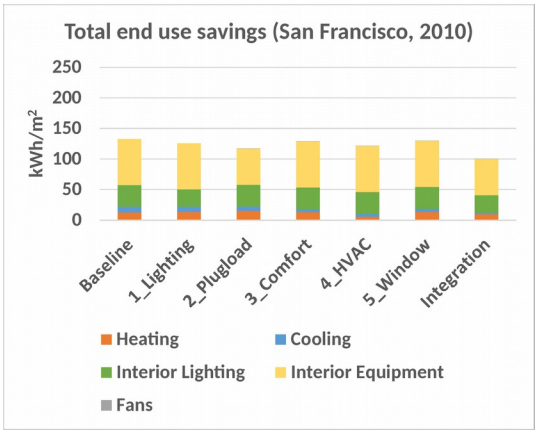


(h)

Figure 20 Total end-use savings of integration of all five measures

4. Discussion

4.1 Influence of occupancy schedule on occupant-based measures

Previous studies show that a significant proportion of wasted energy in buildings comes from unnecessary energy use in the unoccupied rooms [71][8]. The occupant-based measures studied in this paper are designed to eliminate this wasted energy. However, the occupancy schedules that are generally used in current energy models are static and normalized throughout the whole building, such as the office occupancy schedule in the DOE prototype models for office buildings [38] (shown in Figure 21). The normalized occupancy schedule only represents the average occupancy level for the whole building and stays the same on every weekday, every weekend and in each room, which means that the occupancy schedules neither vary with the time (on a daily basis) nor vary with space. Taking the DOE reference model as an example, all the zones will be considered occupied between 7am and midnight per Figure 21, which only allows the shaving of unnecessary energy consumption during the unoccupied period from midnight to 6am. In reality, the occupancy varies with time and space, each zone will be unoccupied for certain hours of the day. Duarte, et al. collected the actual occupancy sensor data from a real commercial office building in the U.S. [72]. Based on their observation, the measured private office diversity factors, which are defined as hourly fractions for a 24-hour day, namely the value in the occupancy schedule, do not come close to the 95% occupancy level as used in ASHRAE 90.1-2010 or the DOE reference model for office buildings. They peak at 50%; the open office data also do not reach beyond a 0.8 peak [72]. On the other hand, the average peak of the generated stochastic occupancy schedules of all the offices in the case building is 0.73, which better fits the measured occupancy data in Duarte's research. Therefore, when estimating the potential energy savings of occupant-related measures, it is crucial to apply the occupancy schedules, which can reflect the realistic characteristics of the occupancy variations in each

zone. Tools such as the Occupancy Simulator developed by LBNL can be used to generate the stochastic occupancy schedules for each zone that reflect the diversity and fluctuation characteristics of occupant activities.

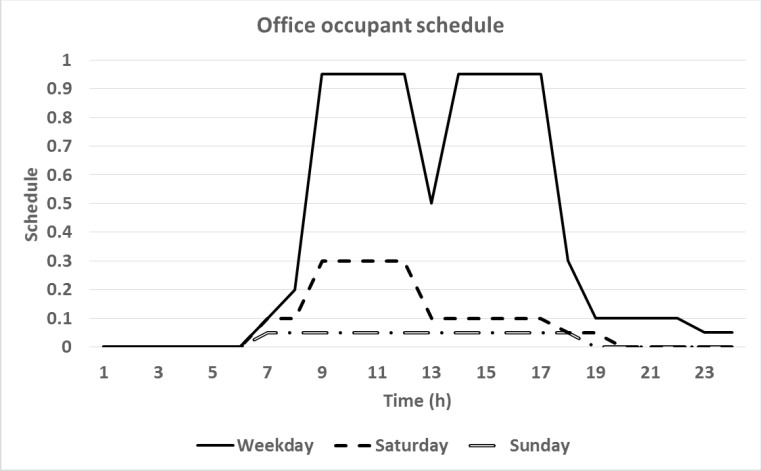
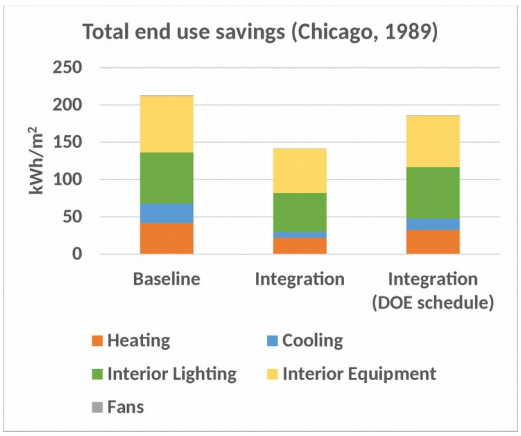


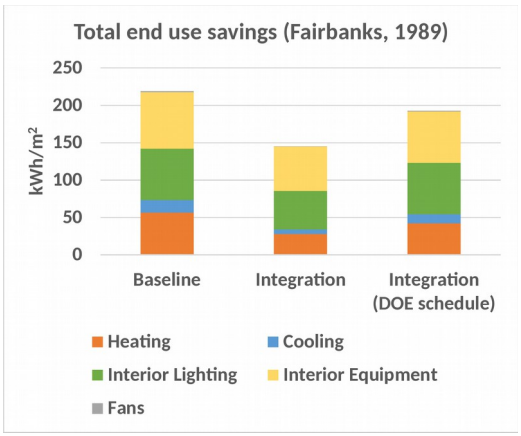
Figure 21 Office occupancy schedule in the DOE reference model for office buildings

If the DOE reference occupancy schedule is used in the models, the application of some occupant behavior measures would be different: (1) Lighting—during the daytime, the rooms are always "occupied," even with 0.1 persons. As the numbers of the occupants are not an integer, it makes no sense to calculate the probability of turning on/off the lights at different daylighting levels from the perspective of each occupant. During night time and weekends, the building is unoccupied, and the emergency and security lights are on. Therefore, the lighting schedule is basically the same as the baseline model. (2) Plug load—similar to the lighting measure, there are no savings on the plug load during daytime as the rooms are always "occupied." During night time and weekends, the 30% reduction was applicable. (3) HVAC—similar to the plug load measure, it only applied to the night time and weekends.

Using such static occupancy schedule, the total energy savings of the integrated five measures would be 8.8%-20.0% in the four climates for vintage 1989, and 8.6%-22.5% for vintage 2010, which are basically less than half of the energy savings simulated using the stochastic occupancy schedule (Figure 22). Therefore, the occupancy schedule makes a significant difference on the energy savings of occupant-based measures.


Total end use savings (Chicago, 1989)
kWh/m²
250
200
150
100
50
0
Baseline
Integration
Integration (DOE schedule)
Heating
Cooling
Interior Lighting
Interior Equipment
Fans

(a)


Total end use savings (Fairbanks, 1989)
kWh/m²
250
200
150
100
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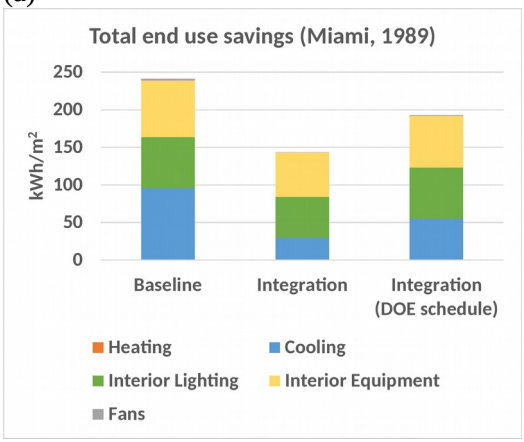
Baseline
Integration
Integration (DOE schedule)
Heating
Cooling
Interior Lighting
Interior Equipment
Fans

(b)


Total end use savings (Miami, 1989)
kWh/m²
250
200
150
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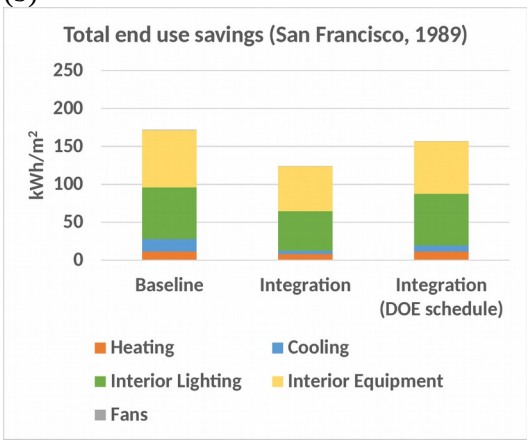
50
0
Baseline
Integration
Integration (DOE schedule)
Heating
Cooling
Interior Lighting
Interior Equipment
Fans

(c)


Total end use savings (San Francisco, 1989)
kWh/m²
250
200
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Baseline
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Integration (DOE schedule)
Heating
Cooling
Interior Lighting
Interior Equipment
Fans

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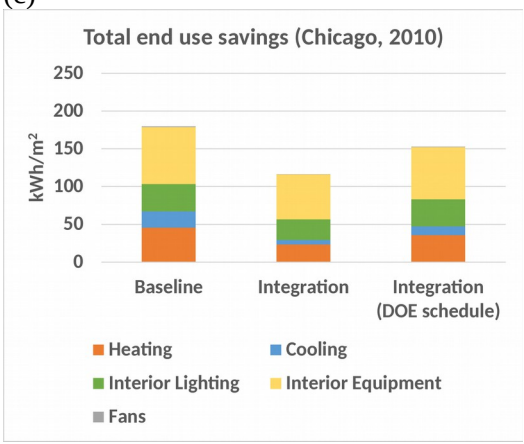
Total end use savings (Chicago, 2010)
kWh/m²
250
200
150
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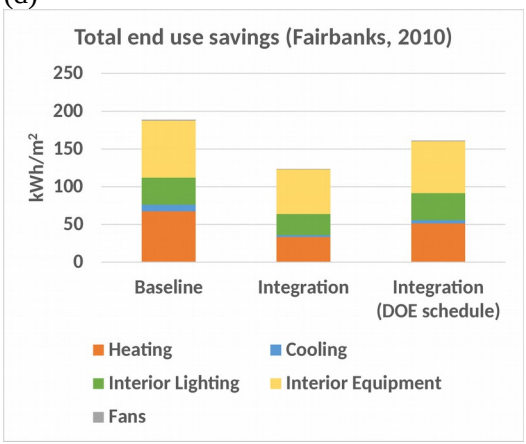
0
Baseline
Integration
Integration (DOE schedule)
Heating
Cooling
Interior Lighting
Interior Equipment
Fans

(e)


Total end use savings (Fairbanks, 2010)
kWh/m²
250
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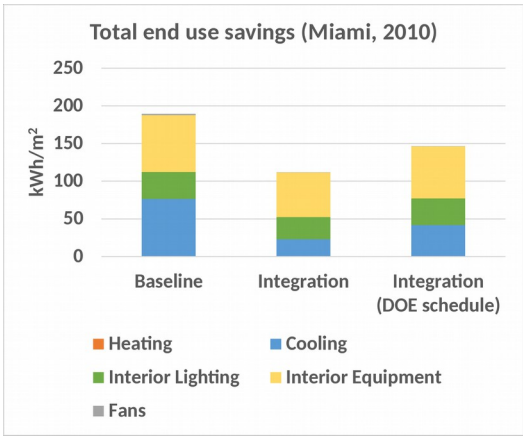

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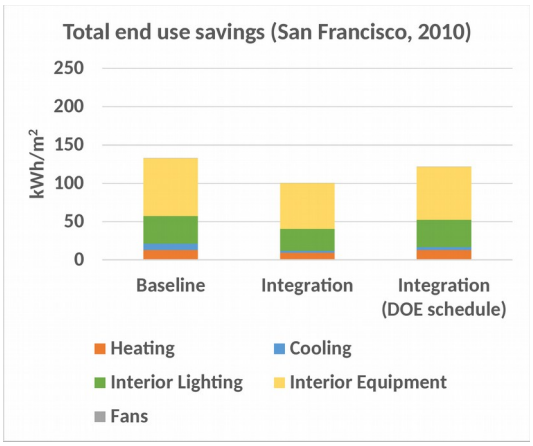

(h)

Figure 22 Comparison of the energy savings that are simulated using the stochastic occupancy schedule and the deterministic occupancy schedule from DOE reference models

4.2 Actual vs. simulated potential energy savings

Many factors determine energy savings from the use of energy efficiency technologies. Behavior measures are the same. Key influencing factors are the capability of individual controls of the building systems, the occupants' knowledge of energy conservation, and the occupants' adoption rate of energy savings behaviors in buildings. This study quantified the theoretical saving potential of typical behavior measures in office buildings with assumptions that: (1) the building systems, including HVAC, lighting, plug load, and windows, enable individual zonal controls by occupants; (2) the occupants are very well educated regarding energy conservation and can effectively operate the building systems in correspondance to their presence and the surroundings to save energy; (3) the electric equipment controlled by the occupants is assumed to be reduced by 30% when the zone is unoccupied; (4) the simulation of window control didn't use detailed airflow calculations which would need details of windows configurations. Instead, we adopted a maximum air change rate of 10, which is comparable with mechanical ventilation systems, and modulated the air change rate according to a linear relationship with indoor-outdoor temperature difference when windows in perimeter zones are favorable to open (zone air temperature is greater than outdoor air temperature and is also greater than the heating setpoint).

4.3 Correlation between passive design and behavioral measures

The saving potentials of behavioral measures are also affected by building designs, especially passive designs. Passive design strategies, such as daylighting or natural ventilation, are intentionally designed to decrease or eliminate the need for energy. In that case, the integration of appropriate behavioral measures and passive building designs will achieve maximum saving potentials. However, the benefit of passive design may be largely discounted if the occupants don't behave as they are expected to [73]. Furthermore,

there may be adverse impacts on the overall building energy use if occupants do not understand how to operate building systems effectively [74]. For example, window blinds allow the occupants access to natural daylight as well as to block glare and heat if necessary. However, a window blind left open on the south side during a hot summer day over the weekend may contribute to excess heat gains, requiring additional mechanical cooling on the next workday. Alternatively, if an operable window is left open overnight during the cold winter months, it would lead to unnecessary heating. In either scenario, the occupant behaviors have significant impact on the energy performance of passive designs, which might lead to discrepancies between the estimated and actual measured energy savings of passive designs [73–75]. Future work can include investigating and quantifying the correlation between passive design and behavioral measures.

5. Conclusions

This study introduced a simulation approach to estimate the potential energy savings of occupant behavior measures. The approach was applied to a case study to calculate and analyze the individual and integrated impacts of five typical occupant behavior measures on energy use in a real office building. The five behavior measures include lighting, plug load, comfort criteria, HVAC control, and window control. The main findings from this study include the following. (1) Based on the simulation results, the occupant behavior measures can achieve considerable energy savings as high as 22.9% for individual measures and up to 41.0% for the integrated measures. (2) The main energy savings captured by the occupant behavior measures come from the avoidance of energy waste in unoccupied rooms especially for their lighting, plug load, and HVAC systems. (3) The occupancy schedule makes a significant difference on the energy savings of occupant-based measures. When estimating the potential energy savings of occupant-related measures, it is crucial to apply the occupancy schedules, which can reflect the realistic characteristics of the occupancy variations in each room.

Although the current study covers five typical occupant-behavior measures, four U.S. climates, and two building energy efficiency levels, it is a case study with limited scope and not designed to estimate the energy savings potential at larger scales. Future studies can expand to cover: (1) a larger scale with more population, such as the city, state, and country scales; (2) other occupant behaviors such as operation of window shades; (3) other building types, such as residential and retail. Future work can also look for opportunities to implement the occupant-behavior measures in real buildings. If the actual energy savings by occupant-behavior measures are available, the method of quantifying the energy savings potential can be verified, and necessary enhancements to the method can be implemented to improve its accuracy.

Acknowledgments

This study is supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the U.S. DOE under Contract No. DE-AC02-05CH11231 through the U.S.-China joint program of Clean Energy Research Center on Building Energy Efficiency. Authors appreciated Zheng O'Neill of the University of Alabama for providing the energy model of the actual office building. This work is also part of the research activities of IEA EBC Annex 66, definition and simulation of occupant behavior in buildings. Authors thank Yixing Chen and Xuan Luo for assistance on the use of the Occupancy Simulator.

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