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A Framework for Quantifying the Impact of Occupant Behavior on Energy Savings of Energy Conservation Measures

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Abstract

To improve energy efficiency—during new buildings design or during a building retrofit—evaluating the energy savings potential of energy conservation measures (ECMs) is a critical task. In building retrofits, occupant behavior significantly impacts building energy use and is a leading factor in uncertainty when determining the effectiveness of retrofit ECMs. Current simulation-based assessment methods simplify the representation of occupant behavior by using a standard or representative set of static and homogeneous assumptions ignoring the dynamics, stochastics, and diversity of occupant's energy-related behavior in buildings. The simplification contributes to significant gaps between the simulated and measured actual energy performance of buildings.

This study presents a framework for quantifying the impact of occupant behaviors on ECM energy savings using building performance simulation. During the first step of the study, three occupant behavior styles (austerity, normal, and wasteful) were defined to represent different levels of energy consciousness of occupants regarding their interactions with building energy systems (HVAC, windows, lights and plug-in equipment). Next, a simulation workflow was introduced to determine a range of the ECM energy savings. Then, guidance was provided to interpret the range of ECM savings to support ECM decision making. Finally, a pilot study was performed in a real building to demonstrate the application of the framework. Simulation results show that the impact of occupant behaviors on ECM savings vary with the type of ECM. Occupant behavior minimally affects energy savings for ECMs that are technology-driven (the relative savings differ by less than 2%) and have little interaction with the occupants; for ECMs with strong occupant interaction, such as the use of zonal control variable refrigerant flow system and natural ventilation, energy savings are significantly affected by occupant behavior (the relative savings differ by up to 20%). The study framework provides a novel, holistic approach to assessing the uncertainty of ECM

energy savings related to occupant behavior, enabling stakeholders to understand and assess the risk of adopting energy efficiency technologies for new and existing buildings.

Keywords: Occupant behavior; energy conservation measures; building performance simulation; energy use; building retrofit; uncertainty assessment

1. Introduction

Buildings consume more than one-third of the world's total primary energy [1]. Building energy demand was the principal cause of the 58% growth in net electricity generation in the United States from 1985 to 2006 [2]. The building industry faces the critical challenge of aggressively reducing energy use. Energy retrofits to implement energy conservation measures (ECMs) are an effective means of reducing energy consumption in buildings. According to the *Advanced Energy Retrofit Guide* by the Pacific Northwest National Laboratory, building energy use can be reduced by up to 15%–25% by implementing no- and low-cost measures, and over 45% with extensive retrofits using ECMs [3][4]. Currently, high-efficiency equipment is being developed and applied to retrofit buildings to improve performance and reduce energy use. However, the energy savings and economic effectiveness of building energy retrofits are subject to uncertainties, such as weather variations [5][6], building operations [7][8], human behavior changes [9–11], and government policy changes [12][13]. All of these factors directly affect the effective selection of building technologies and, hence, the success of a retrofit project. Working with these uncertainties is a considerable technical challenge in any sustainable building retrofit project [14].

Occupant behavior has a significant impact on building energy use [15] and represents one of the most significant uncertainties affecting the effectiveness of building retrofits. Owens and Wilhite [10] concluded from their survey that about 10%–20% of domestic energy use in the Nordic counties can be saved by changing occupant behavior alone. According to an investigation of householders' energy behavior by Yohanis [9], significant energy savings can be achieved by improving occupant energy awareness. Santin, et al. [11] studied the importance of householder characteristics and occupant behavior on energy use for space and water heating in the Netherlands, concluding that occupant characteristics and behavior significantly affect building energy use. Virote and Neves-Silva found that the expected return of energy-efficient technologies could be weakened by occupant behavior within the building. To better predict the energy savings, they implemented occupant behavior models in a building performance simulation model based on the stochastic Markov chains [16]. Li examined the impact of actual building occupancy on the assessment of ECMs and observed big differences in energy savings [17]. Marshall, et al. [18] investigated the effectiveness of ECMs on different occupancy patterns in the residential buildings in the United Kingdom; he found that savings vary depending on the occupancy pattern of the household. These studies all showed that occupant behavior can significantly affect energy use in buildings as well as the saving potentials of building retrofits. However, most studies have used survey results to obtain findings. Few studies have quantified occupant behavior effects on the energy savings of ECMs.

Occupant behavior in buildings has been widely acknowledged as a major factor contributing to gaps between measured and simulated energy consumption in buildings [19–21][22]. Building performance simulation (BPS) programs are commonly applied to evaluate the performance of building energy systems and technologies. However, in current practices, simulation users choose one of the default standard or representative settings for occupants that are defined according to building use type, in a simplified and homogeneous way, using the temporal schedules and static assumptions. Such simplified inputs result in poor representation of actual dynamic, stochastic, and diverse occupant behavior in buildings—with consequently poor energy use prediction. Previous studies [23][24] pointed out that simulation results frequently vary widely from actual energy use of buildings. Eguaras-Martinez, et al. [25] proved that the inclusion or exclusion of occupant behaviors in building simulation resulted in up to 30% of the differences in energy use predictions. Furthermore, Hoes, et al. [21] used BPS to quantify the impact of occupant behavior on ECMs savings with results showing that the influence of the uncertainty of occupant behavior becomes even larger in buildings with passive design such as heavy thermal mass and low window-to-wall ratio. The International Energy Agency Energy in Buildings and Communities' *Annex 53: Total Energy Use in Buildings* [1] recognized the impact of occupant behavior as one of the six driving factors of energy use in buildings along with climate, building envelope, building energy and services systems, indoor design criteria, and building operation and maintenance.

Three approaches are primarily used for occupancy modeling: the stochastic approach, the agent-based approach, and the random-walk approach [26]. 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 [27][28][29]. 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 [30][31][32][33]. It should be noted that the stochastic approach and the agent-based approach are not mutually exclusive. The agent-based approach can use stochastic models or deterministic models, e.g. the agent movement can be simulated using Markov Chain models. The random-walk approach presents a new concept, which views occupancy pattern as unpredictable in certain cases. It was obtained from occupancy experiments in 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 [26].

To represent more realistic occupant behaviors in building performance simulation, researches have focused on probabilistic model development using monitored, sensor, and/or surveyed data from observational studies that demonstrate the relationships between the indoor and outdoor environmental factors and occupant behaviors under consideration [19]. Hong, et al. [34,35] reviewed published simulation models and identified major types of occupant behavior in buildings including occupant presence and movement as well as occupant actions on windows, shades (blinds), lighting, thermostat, HVAC, and plug-in equipment. Several stochastic models were developed for these occupant behavior types and data were collected in various locations and types of buildings around the world [36–44]. 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 or close windows [45][46]. However, the use of these occupant behavior data are usually limited to observed building types, locations, climates, and cultural and social contexts—inevitably the corresponding models have the same limitations unless the models are validated using separate and independent measurement data from the model development [19][47]. Therefore, the challenges remain for building energy modelers to adopt proper occupant behavior models for their use unless they have full access to occupant data on their targeted buildings. Occupant behavior stochastic models are data driven and improve modeling assumptions of occupant activities in the BPS programs [27,28,48]. Furthermore, as denoted in recent studies, stochastic models do not necessarily produce better results than other simpler and/or non-probabilistic models of occupancy [47] (for instance, when it comes to annual building energy consumption) [49]. In other words, the applicability of occupant behavior models could vary according to the purpose of building simulation as well as the data availability to modelers. In this regard, Yan, et al. [19] argued that simple occupancy-related models, such as code-based or descriptive representation of occupant behavior, could be adopted in determining the likely performance of design options in the design development phase using aggregated indicators such as annual heating and cooling loads. Otherwise, more detailed occupant behavior scenarios and modeling methods need to be considered.

This study proposes a framework to quantify the impact of occupant behavior on energy savings of ECMs using BPS. The framework provides a novel holistic approach to assessing the uncertainty of ECM energy savings related to occupant behavior, which directly supports risk assessment during decision making regarding energy technology investment for new and existing buildings. The framework is introduced in Section 2. A pilot study, which applies the framework to analyze a retrofit of a real building, is presented in Section 3. The discussion section addresses some important considerations for applying the proposed simulation framework.

The proposed framework aims to provide guidance to help decision makers evaluate benefit of ECMs rigorously with quantitative investment risk, especially considering the uncertainties brought by the occupant behaviors on energy savings of ECMs. It would help to largely reduce the risks of energy retrofit associated with the occupants, which is one of the largest uncertain factors in the building industry.

2. Methodology

2.1. Overview of the Framework

As illustrated in Figure 1, the traditional method to evaluate energy savings of an ECM consists of four steps: (1) developing a baseline model where user inputs weather data, internal heat gains, configuration, operation, and efficiency of energy systems (HVAC, lighting, plug loads) as well as a static set of assumptions on occupant behavior; (2) performing a simulation of the baseline model to calculate its energy use; (3) applying the ECM to the baseline model to create a new alternate model and running a simulation on the new model to calculate its energy use; and (4) calculating energy savings (can be other metrics, e.g., energy cost savings and peak demand reduction) of the ECM by comparing simulated results between the alternate model and the baseline model. The calculated energy savings of the ECM using the traditional method are static or deterministic values.

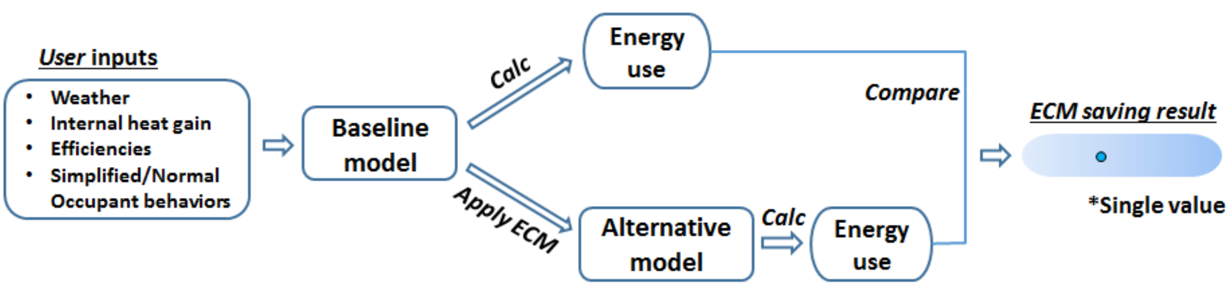

Figure 1 The traditional method to calculate energy savings of an ECM

However, the ECM energy savings are influenced by many factors such as the building type, weather data, building operation, and occupant behavior. For example, a high-efficiency chiller can save very limited energy in cold climates due to minimal cooling load, and a well-designed natural ventilation building wouldn't work if the occupants don't open the windows when outdoor air favors cooling. Estimating the uncertainties of the ECM energy savings is critical, especially during risk analysis and decision making for ECM investment [50]. Decision makers should be aware of the potential risks of implementing different ECMs before selecting the most appropriate ECMs for a specific building. However, traditional ECM evaluation methods adopt deterministic inputs and calculate a static single result of energy savings, which cannot reflect the uncertainty of the ECM energy savings.

Even though the same model inputs of weather data and occupant behavior are used in both the baseline model and the alternate model implementing the ECM, the energy savings of the ECM (determined by comparing the energy uses of the baseline model and the alternate model) would depend upon different packages of model inputs. Hong, et al. [5] show that the use of different weather files changes the energy savings of ECMs. A similar situation may apply to the assumptions of occupant behavior in energy models. However, no studies have yet looked at how occupant behavior assumptions influence the energy savings of ECMs.

In this study, a framework was proposed to evaluate ECM savings considering the variations of occupant-related inputs and their influence on the ECM energy savings (Figure 2). This proposed framework includes several steps: (1) defining the three occupant behavior styles using quantitate occupant behavior models (definition is illustrated in 2.2 in detail); (2) developing three baseline models using each of the three occupant behavior styles and other similar model inputs; (3) calculating the energy uses of the three baseline models; (4) applying the ECMs to each baseline model to create the alternate models for each ECM, and (5) simulating the ECM energy models to calculate their energy use. The simulated ECM saving results, gathered using the proposed framework, are a range of values instead of a single fixed value, which reflects the possible variations of the ECM savings due to different occupant behaviors in the building. Therefore, the framework can be adopted to evaluate ECM energy savings in a more comprehensive and robust way, giving decision makers information they need to recognize and assess the potential risks of investing in ECMs in buildings with different occupant behaviors. ECMs with consistent large energy savings can be prioritized for investment compared to those ECMs with savings that are sensitive to occupant behavior style.

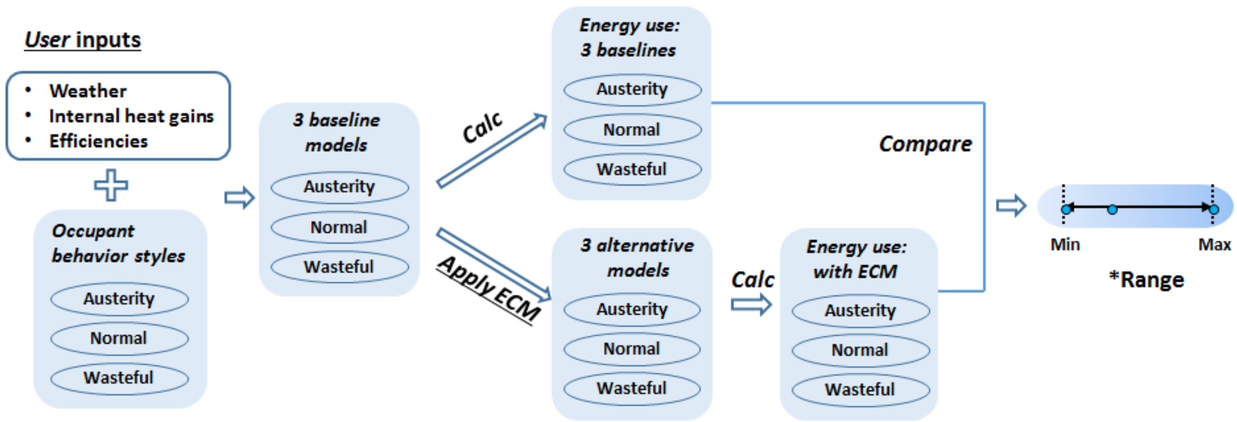

Figure 2 A framework to quantify the impact of occupant behavior on performance of ECMs

There are four approaches that are used to simulate occupant behaviors in BPS programs [49]. (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 occupant behavior models: an advanced occupant 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., energy management system, or EMS, in EnergyPlus [51]) to implement new or overwrite existing or default building operation and supervisory controls. (4) Co-Simulation: a simulation methodology allows individual components to be simulated by different simulation tools running simultaneously and exchanging information in a collaborative manner [19]. In this study, the first and third approaches were used to simulate different occupant behavior styles.

2.2. Definition of occupant behavior styles

In previous studies, occupant behaviors were distinguished based on the user types. Parys, et al. [52] and Reinhart [53] used four user types in terms of their active and passive attitudes on lighting and blind controls. Santin [54] defined behavioral patterns as spenders, affluent-cool, conscious-warm, comfort, and convenience-cool based on behavior factors such as the use of appliances, energy-intensive, and ventilation in housing. In this study, three occupant behavior styles are defined based on the three office workstyles previously proposed by Hong, et al. [55]. To represent the diversity of occupants and their behaviors in building performance simulation, occupant energy-use styles are first categorized into three distinguished attitudes in regard to their energy consciousness during interactions with building energy systems including HVAC, windows, lights, and plug-in equipment: austerity, normal, and wasteful. The normal behavior represents the typical design assumptions of occupant behavior in a building, the austerity behavior represents the boundary conditions of energy savers, while the wasteful behavior represents the boundary conditions of energy spenders. This is a simplified representation of the complexity and diversity of occupant energy-related behaviors in buildings. This method does not necessarily represent the actual realistic occupant behavior in buildings; rather, it represents the boundary conditions of two behavioral extremes of the energy savers and the energy spenders. It helps to quantitatively evaluate the possible occupant-related risks on energy savings potential of ECMs in retrofit analysis by integrating occupant behavior models with building performance simulation. As described in Table 1, the occupant behaviors considered in this study include comfort temperature setpoints for heating and cooling, lighting control, plug-load control, HVAC control, and window operation. For each occupant behavior, three behavior styles are defined representing the proactive energy savers, average (norm) occupants, and the energy spenders. The chosen occupant behaviors and their related performance of the three occupant behavior styles are an example for the purpose of describing the framework. They could vary for different cases under different circumstances. Future research, such as the large-scale international survey of occupant behavior conducted by the IEA EBC Annex 66 [56], will help provide more realistic data on occupant behaviors as inputs.

Table 1 Three occupant behavior styles

Occupant Behavior	**Austerity**	**Normal**	**Wasteful**
Cooling Setpoint (°C)	26	24	22
Heating Setpoint (°C)	18	21	22
Control of lights	Dim lights if unoccupied	Follow standard schedule	Always on during working hours
Control of plug-loads	turn 30% off if unoccupied	Follow standard schedule	Always on during working hours
HVAC occupancy control (For VRF ECM only)	Off if unoccupied	Off if unoccupied	Always on
HVAC startup control (For VRF ECM only)	Turn on HVAC only when occupants feel hot, based on a probabilistic model of HVAC operation	None	None

Window operation (For natural ventilation ECM only)	Concurrent HVAC and natural ventilation	Either HVAC or natural ventilation	HVAC and natural ventilation both on all the time

2.2.1. Cooling and heating temperature setpoints

The setpoints of the normal behavior style are either the design setpoints or consistent with the actual setpoints of a building, such as the case building described later in Section 3. The setpoints of the austerity behavior have a wider range (a higher cooling setpoint and a lower heating setpoint) but they are both within the temperature range of the comfort zone in ASHRAE Standard 55-2010 [57]. The setpoints of the wasteful behavior have an extreme narrow range (same cooling and heating setpoints).

2.2.2. Control of lights and plug loads

The occupants have the option to control their personal plug-in 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 the total plug loads, based on previous research on occupant-based control of plug loads showing 5%–32% of the electricity savings [58–62].

The control logic of lights and plug loads are similar. The designed standard lighting and plug-load schedules, or the average schedules of a real building, were used as the normal behavior. For the wasteful behavior, both lights and plug loads were always on during working hours of the building. For the austerity behavior, the lights will be dimmed manually based on available daylight, and the plug loads will be reduced by 30% when the zone is unoccupied.

2.2.3. HVAC control

For HVAC systems that have zonal control, occupants can turn on or off the HVAC in their zone without affecting other zones; for centralized controlled HVAC systems serving multiple zones, occupants are not able to control their HVAC operation individually. For the baseline models, the HVAC system is a packaged variable air volume (PVAV) system, which doesn't have zonal control, so the PVAV system is centralized controlled with a fixed schedule throughout the working hours. Therefore, the occupant-based control of HVAC is not applicable for the baseline models. For the ECMs that are using the variable refrigerant flow (VRF) system, which allows zonal control, the occupant-based control of HVAC is applied with the following logic: (1) for the austerity and normal occupant behaviors, the HVAC will be turned off when the occupants leave the room (occupant-based HVAC control) and (2) the austerity occupants would not turn on the HVAC unless they feel hot/cold (HVAC startup control).

The probability of turning on the HVAC system relates to the current conditioning mode (cooling or heating) and the indoor air temperature. Ren [63] 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. Because residents have independent control of their HVAC systems, a fact that applies to the condition of our study, Ren's model was adopted to estimate the time-step HVAC control status in our models. The function used to calculate the probability of turning on the HVAC system is shown as follows:

$$P = \begin{cases} 1 - e^{-(\frac{T-u}{L})^{k}\Delta\tau}, \ T \geq u, when\ occupied \\ 0, \ T < u \end{cases} \tag{1}$$

Where,

P : Probability of turning on the HVAC system.

T : Indoor air temperature, the independent variable.

u : Threshold of independent variable T, beyond which the probability of an occupant taking action becomes 0.

L : The scale of the function, which is used for non-dimensionalization (T-u).

k : 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 of 18°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 of 26°C (cooling setpoint satisfies thermal comfort for 80% of the population) and about 50% at the upper limit of ASHRAE comfort zone 28.3°C.

For this study, the assumption is made that when the indoor air temperature T falls within the comfort zone between the cooling and heating setpoints, occupants will not turn on the HVAC. The indoor temperature T will be used to calculate the probability of turning on the HVAC only when: (1) the HVAC status of last time step is off, (2) the zone is occupied, and (3) the indoor temperature T is higher than the cooling setpoint or lower than the heating setpoint. 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. HVAC will be turned on as long as one of the present occupants needs it. On the other hand, the occupants will turn off the HVAC on two conditions: (1) the zone is unoccupied, or (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 EnergyPlus models, the simulated indoor air temperature per time step is the input for determining the action of the next time step. To model this HVAC control strategy, the EMS function of EnergyPlus was employed to interpret the conditional logics, generate random numbers, and manipulate the HVAC schedules per time step.

There are potential limitations on purely occupant-based HVAC control in colder climates: if the occupants leave the room for a short period of time, the room temperature will not drop much due to heat transfer and airflow from adjacent rooms; however, if the occupants leave the room for long period of time (e.g., at night), heating up the room may take a while, which might cause potential occupant discomfort. This could be mitigated by thermostat setback control. For example, if the room temperature drops below a certain temperature say 10°C, the HVAC system will be automatically turned back on. This can be incorporated in future studies.

2.2.4. Window operation

In the baseline model, the window operation is not applicable as the PVAV system is centrally controlled with a fixed schedule throughout the working hours. The window operation is only applicable for the ECMs that employ a VRF system with zonal control. In this study, three ventilation modes discussed in Wang's research [64] were adopted for the three occupant behavior styles: (1) concurrent mix-mode ventilation for the austerity behavior, (2) change-over mix-mode ventilation for the normal behavior, and (3) HVAC and windows both on all the time for the wasteful behavior.

Concurrent mix-mode ventilation is an optimized window operation strategy: 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 turned off; otherwise, conditioned air from the VRF indoor unit is available to provide supplementary cooling in order to meet thermal comfort. Both natural ventilation and HVAC are only available when the room is occupied. Adaptive comfort criteria with 80% acceptability limits, developed by the Center for the Built Environment in UC Berkeley [57,65], were adopted to calculate a dynamic comfort range based on ambient temperature. This range was then used for the dynamic cooling setpoints for naturally ventilated perimeter zones, while the interior zones use the same cooling setpoints as the baseline model. The windows in perimeter zones are favorable to be open when all the following conditions are satisfied: (1) the outdoor air temperature is lower than the zone air temperature, (2) the zone air temperature is greater than the heating setpoint, and (3) the outdoor air temperature is greater than the temperature that is 3°C lower than the heating setpoint, to avoid overcooling thermal zones when outdoor air temperature is too low [65]. When windows in perimeter zones are favorable to be open, the fractions of window opening are modulated based on a linear relationship with indoor-outdoor temperature difference, illustrated in Figure 3 [65]. 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.

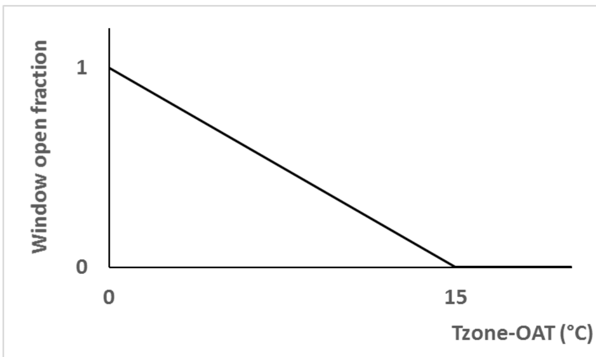

Figure 3 Modulation of window opening according to indoor and outdoor temperature difference

In change-over mix-mode, whenever a window in a perimeter zone is open, the VRF indoor unit of that zone will be turned off. During natural ventilation hours, the adaptive comfort criteria were adopted as the cooling setpoints; during HVAC hours, the cooling setpoints were set the same as the baseline model. For the wasteful behavior, both the HVAC are always on and the windows open during working hours. This study assumes that the natural ventilation rate through the windows is five air changes per hour.

For all three ventilation modes, natural ventilation only applies to the perimeter zones while mechanical systems serve cooling and heating for core zones. The heating setpoints remain the same as the baseline model. The EMS function of EnergyPlus was used to interpret the conditional logics and manipulate the natural ventilation schedules per time step for the concurrent mix-mode and change-over mix-mode ventilations.

2.3. Occupant schedules

Occupancy has a significant impact on the energy-saving potentials of ECMs [16]. The occupant schedules adopted in the simulation are supposed to reflect the realistic occupant movement in the buildings. An average whole-building occupant schedule is normalized and not able to reflect the realistic occupant movement and the variations between different zones within the buildings. Especially for occupant-based control, occupant schedules are critical input for accurately estimating the energy performance, as elaborated in Sun's study [66].

The method used in this study to generate realistic occupant schedules is similar to the method used in previous Lawrence Berkeley National Laboratory (LBNL) research on estimating the energy saving potentials of occupant behavior measures [66]. The Occupancy Simulator was used to simulate the realistic occupant presence and movement in each zone, with inputs from the site survey of real buildings. The Occupancy Simulator, developed by LBNL, is a user-friendly web-based application that uses the stochastic Markov chain modeling to simulate occupancy in buildings [67]. The app takes high-level inputs of occupants, spaces, and events to simulate the occupant presence and movement in buildings, capturing the spatial and temporal occupant diversity [27][28]. Each occupant and each space in the building are explicitly simulated as an agent with their profiles of stochastic behaviors. 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 occupant pattern properties have been verified using collected occupant data in real buildings [68].

The generated schedules can reflect the variation, diversity, and stochastic characteristics of the realistic occupant movement. These generated schedules are more reasonable than the normalized occupant schedule and can help improve the simulation accuracy. To make it consistent for all the studied ECMs, the same set of generated schedules is applied to both the baseline model and the ECM models.

3. Pilot Study

A pilot study was performed in a real office building, using the proposed framework, to quantify the influence of occupant behavior on ECM energy savings. Figure 4 shows the overall workflow of the pilot study. Field investigation was conducted in the building to gather information for creating the baseline energy model, including the geometry, zoning, number of occupants in each zone, and occupant schedules. It can better reflect the realistic occupant behaviors in buildings with realistic geometry, zoning, and schedules than the United States Department of Energy (DOE) prototype models [69], which simplify building zoning and occupant inputs. The impact of occupant behavior on ECM energy savings was evaluated in four different climates—Chicago, Fairbanks, Miami, and San Francisco—so that the potential sensitivity to climate could be studied as another dimension. The selected cities represent the four typical climate types in the United States: humid continental, subarctic, tropical (subtropical), and Mediterranean, respectively.

The three occupant behavior styles defined in Section 2 were adopted to represent different levels of energy consciousness and the boundaries of either extreme (as in energy savers and spenders). The occupant behavior style was assumed to be consistent before and after the ECMs were implemented; the three occupant behavior styles were applied to generate three baseline models for the ECM evaluation in each climate type. Also, occupant schedules, generated by the Occupancy Simulator with inputs from the site survey of the case building, were used in the energy models.

An effective useful life of building equipment varies from 5 to 25 years [70][3]. The case building is about 15 years old; the efficiencies of the baseline models are compliant with ASHRAE Standard 90.1-2001. The more recent ASHRAE Standard 90.1-2013 was used as a representative energy efficiency level for the new building technologies, which was adopted as the source of the efficiencies of the ECMs in the pilot study.

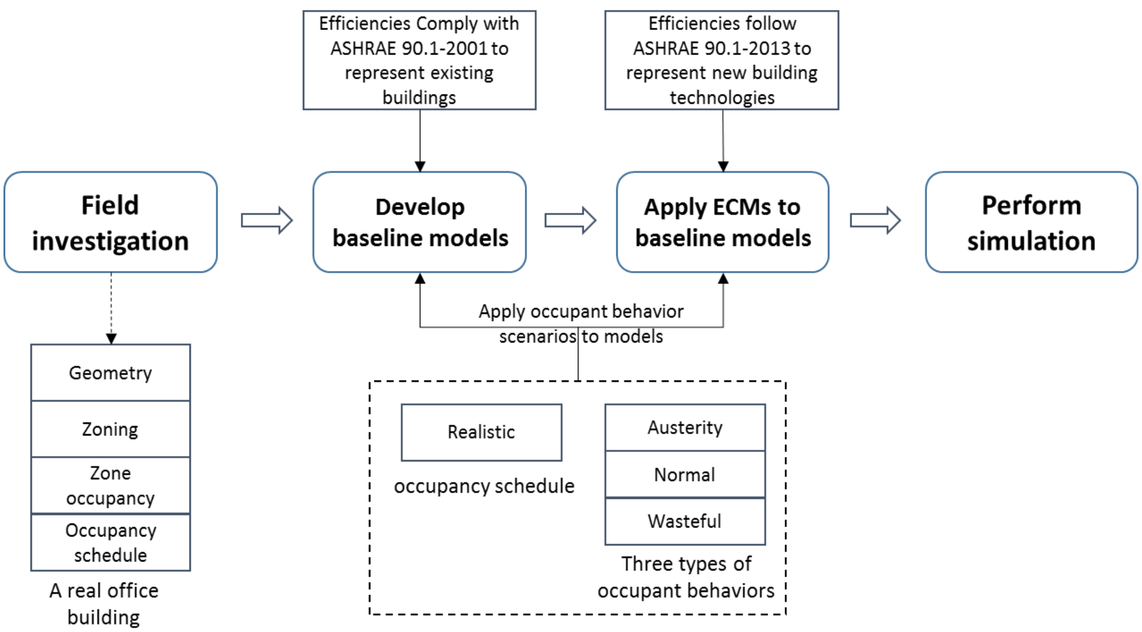

Figure 4 The workflow of the pilot study

Whole-building simulation using EnergyPlus was used to evaluate the impact of occupant behavior on the energy savings of ECMs. Based on the investigated office building, baseline models were developed in EnergyPlus version 8.5. EnergyPlus is an open-source program that models heating, ventilation, cooling, lighting, water use, renewable energy generation, and other building energy flows [71] and is the flagship building simulation engine supported by DOE. It includes innovative simulation capabilities (e.g., sub-hourly time-steps, natural ventilation, thermal comfort, co-simulation with external interfaces, renewable energy systems, and user customizable EMS). Some of the innovative capabilities, such as natural ventilation, daylighting, external schedules, and EMS, were used in this pilot study.

3.1. The case building energy model

The field-investigated office building has two above-ground stories with a total conditioned floor area of 1,723 m2. Main room functions include office, conference room, classroom, and lounge. 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 5 and Figure 6 show first- and second-floor plans of the case building, including the room functions. Detailed information on the case building, including number of occupants in each zone, lighting schedule, plug-load power density, and plug-load schedule, was also obtained via the field investigation. The zone functions and their maximum number of people are summarized in Table 2.

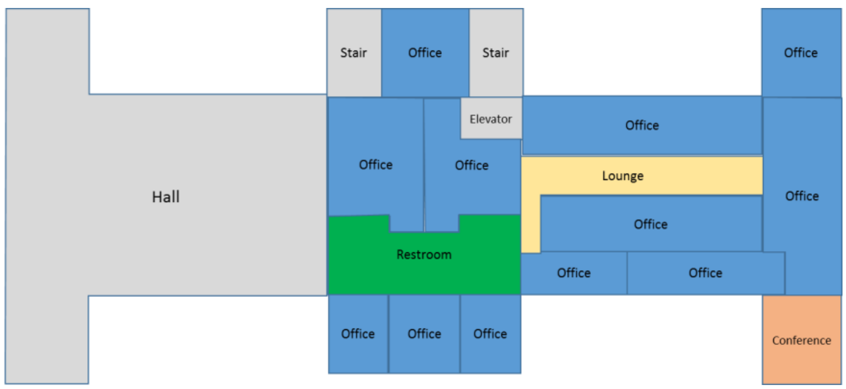

Figure 5 The 1st floor plan

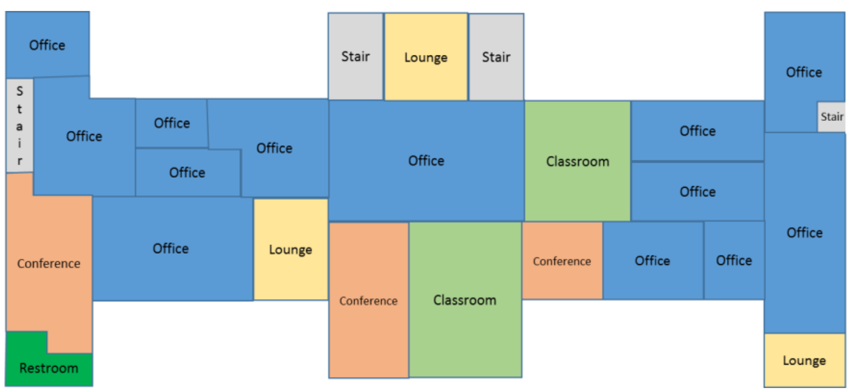

Figure 6 The 2nd floor plan

Table 2 Zone function and number of occupants

Zone Function	Maximum Number of Occupants	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

Based on realistic geometry and zoning of the case building, the three defined occupant behavior styles, and the generated realistic occupant schedules (details in Section 3.2), the three baseline models were developed in EnergyPlus Version 8.5 for each climate type, as Figure 7 shows. The efficiency inputs of the baseline models are based on ASHRAE 90.1-2001. The lighting power density is 14 W/m^2. The thermal properties of the building envelope are shown in Table 3.

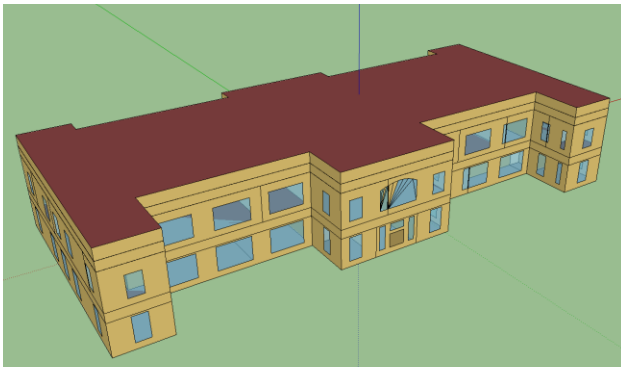

Figure 7 The 3D view of the baseline models

Table 3 Envelope thermal properties based on ASHRAE 90.1-2001

	Chicago	San Francisco	Miami	Fairbanks
Wall U-factor W/(m^2.K)	0.701	0.857	3.293	0.453
Roof U-factor W/(m^2.K)	0.36	0.527	0.36	0.273
Window U-factor W/(m^2.K)	3.24	6.93	6.93	2.61
Window SHGC	0.39	0.61	0.25	0.45

The baseline models are equipped with PVAV systems, which use direct expansion (DX) cooling coil to supply cooling and gas heating coil for reheat. As the baseline models are based on ASHRAE 90.1-2001, economizers are not required for PVAV systems. Minimum requirement of outdoor air is assumed to meet ventilation requirement. The sizing of the HVAC equipment for each baseline model standardized through all the ECM 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.

3.2. Occupant schedules

The maximum number of occupants and space types, listed in Table 2, are inputs to the Occupancy 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 occupant schedules for each space were generated by the Occupancy Simulator. Figure 8 shows the hourly variation and profile of total occupant schedule in all the offices throughout the weekdays of a whole year. Likewise, Figure 9 shows the occupant schedules on weekdays in all the meeting rooms, respectively. Figure 10 shows the occupant schedule of a four-person office on the second floor during a weekday with the time step of 15 minutes. According to the normalized occupant schedule in the DOE office building prototype models [69], 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 occupant schedule. This was calculated by averaging the total unoccupied hours during weekdays of each office. With the stochastic occupant schedule, the spaces are unoccupied for more than twice the time of the normalized occupant schedule, which leads to a significant difference in the energy performance of occupant-based ECMs.

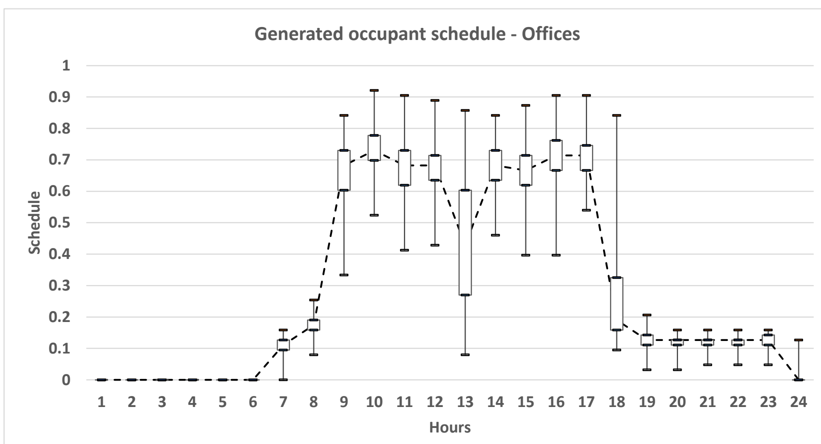

Figure 8 Box-Whisker plot of the hourly schedule of total occupants in all offices on weekdays. The four marks on each time scale stand for (from top to bottom): maximum, upper quartile, lower quartile, and minimum. The dotted line connects the median value of all.

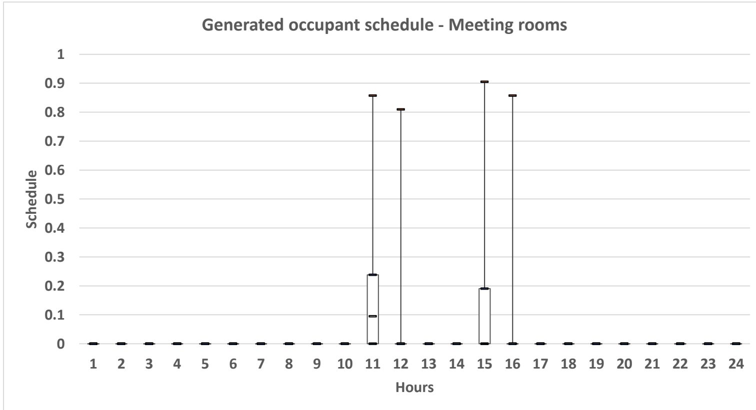

Figure 9 Box-Whisker plot of the hourly schedule of total occupants in all the meeting rooms on weekdays. The five marks on each time scale stand for (from top to bottom): maximum, upper quartile, median, lower quartile, and minimum.

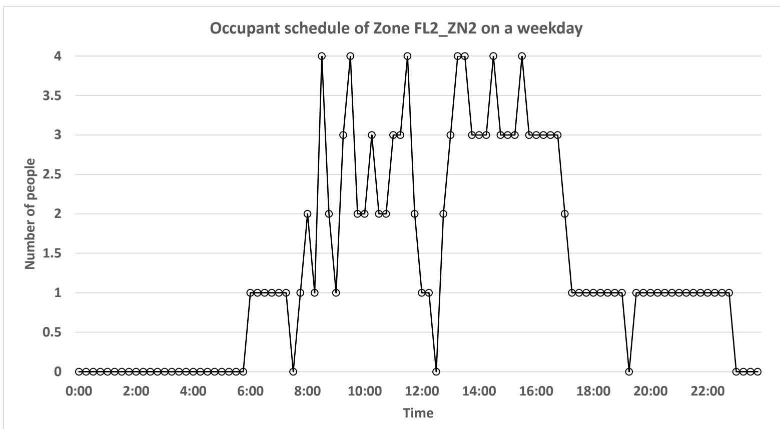

Figure 10 The occupant schedule of an office room on the 2nd floor on a typical weekday (Time interval: 15 min).

3.3. Energy conservation measures

To investigate the impact of occupant behavior on performance of ECMs, seven individual ECMs and one packaged ECM (integrating several individual ECMs) were evaluated in this study. These ECMs were chosen considering their application to a 15-year-old building designed to comply with ASHRAE Standard 90.1-2001 standards [72], which were adopted in the baseline models to represent existing buildings. The efficiencies of the ECMs in this study were obtained from the more recent ASHRAE 90.1-2013 [73] standards. The details of the ECMs are described as follows.

3.3.1. Reducing lighting power density (LPD)

For this ECM, the lighting system is upgraded with more efficient light bulbs and the lighting power density is reduced from 14 to 8.83 W/m^2.

3.3.2. Reducing plug-in electric equipment power density (EPD)

There are no requirements on the efficiencies of plug-in electric equipment in the standard. Therefore, the new upgraded electric equipment is assumed to be 25% more efficient than the old equipment, considering the adoption of efficient plug-in technologies. Thus, the average electric equipment power density is reduced from 14 to 10.5 W/m^2.

3.3.3. Improving envelope performance

This ECM improves the thermal properties of the building envelope from those defined in ASHRAE 90.1-2001 (Table 3) to ASHRAE 90.1-2013 (Table 4).

Table 4 Envelope thermal properties based on ASHRAE 90.1-2013

	Chicago	San Francisco	Miami	Fairbanks
Wall U-factor W/(m^2.K)	0.513	0.701	3.293	0.273
Roof U-factor W/(m^2.K)	0.184	0.220	0.273	0.158
Window U-factor W/(m^2.K)	2.38	2.84	3.24	2.16
Window SHGC	0.4	0.25	0.25	0.45

3.3.4. Improving HVAC system efficiency

This ECM improves the cooling system efficiencies (DX cooling coil for PVAV is categorized as air-cooled unitary air conditioner) from the 2001 ASHRAE 90.1 to 2013, as shown in Table 5. The gas burner efficiency remains the same.

Table 5 Improvement of the HVAC system efficiencies

Capacity (kW)	ASHRAE 90.1-2001	ASHRAE 90.1-2013
<19	9.7 SEER(1)	14 SEER
19-40	10.1 EER(2)	12.7 IEER(3)
40-70	9.5 EER	12.2 IEER
70-223	9.3 EER	11.4 IEER
≥223	9.0 EER	11.0 IEER

Notes:

(1) SEER, Seasonal Energy Efficiency Ratio, is the cooling output (in British thermal units [Btu] per hour) during a typical cooling season divided by the total electric energy input (in Watts) during the same period.

(2) EER, Energy Efficiency Ratio, is the ratio of the cooling capacity (in British thermal units [Btu] per hour) to the power input (in Watts).

(3) IEER, Integrated Energy Efficiency Ratio, is an integrated performance for commercial unitary air conditioning and heat pump equipment, expressing cooling part-load EER efficiency on the basis of weighted operation at various load capacities.

3.3.5. Daylighting control

In this ECM, daylight sensors are installed in perimeter zones to allow automatic daylighting control. The lights will automatically dim continuously from maximum to minimum electric power as the daylight illuminance increases. The lights stay on at the minimum point with further increase in the daylight illuminance.

3.3.6. Variable refrigerant flow system

VRF systems vary the refrigerant flow to meet the dynamic zone thermal loads. They can provide flexible controls and individual thermal comfort and consume less energy due to: (1) more efficient operation during part-load conditions with the help of variable speed compressor and fans; (2) minimal or no ductwork reducing air leakage and heat losses; and (3) smaller indoor unit fans consuming less energy while reducing indoor noise [74,75]. Furthermore, VRF heat recovery (VRF-HR) system can deliver simultaneous heating and cooling to different zones and transfer heat from the cooling zones to the heating zones.

This ECM replaces the original PVAV system with VRF system to enable flexible zonal control and more efficient operation. It should be noted that the VRF system generally does not have an airside economizer due to small air duct design to only provide the minimal amount of outdoor air directly to zones meeting the ventilation requirements. Therefore, the amount of supplied outdoor air is the same between the baseline PVAV system and the VRF system. The efficiency curves of the VRF systems were provided by VRF manufacturers.

3.3.7. Natural ventilation coupled with the VRF system

As mentioned above, occupant-based control of HVAC system and window operation are only applicable to the VRF system, which allows zonal control. In this case, the ECM of natural ventilation is implemented together with the VRF system ECM.

As discussed in Section 2.2.4, three ventilation modes were adopted for the three occupant behavior styles for this ECM: (1) concurrent mix-mode ventilation for the austerity behavior, (2) change-over mix-mode ventilation for the normal behavior, and (3) HVAC on and windows open all the time for the wasteful behavior.

3.3.8. The integrated ECM

All previous ECMs have been integrated as a new ECM, with the exception of the ECM of improving system efficiency, which is excluded because the HVAC system is changed to the VRF system with new efficiency curves and the improvement of cooling system efficiencies does not apply.

3.4. Simulation results

The energy performance of the baseline models and the models implemented with the ECMs was simulated using EnergyPlus Version 8.5. Site energy is used as the energy metric. The results are elaborated as follows.

3.4.1. Impact of occupant behavior styles on baseline energy use

Before evaluating the impact of occupant behavior styles on ECM savings, the impact of each behavior style on the energy consumption of the baseline models was analyzed. Figure 11 shows the total energy use intensity of the baseline models with the three occupant behavior styles in four climate types. Compared with the normal behavior style, the model with the austerity behavior style consumes 17.8%–32.1% less energy while the model with the wasteful behavior style consumes 27.8%–47.8% more energy. When comparing the wasteful behavior style with the austerity behavior style, the energy use differences can be 55.6% (Fairbanks) and even as high as 117.6% (San Francisco).

The occupant behavior style has significant influence on building energy use. Even though the buildings are physically identical, they consume significantly different amounts of energy when occupied by different types of energy users. Some energy spenders consumed more than twice the energy of the energy savers.

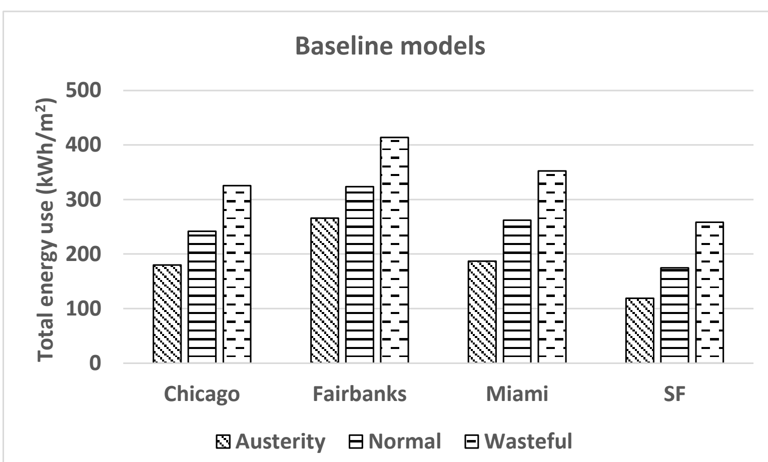

Figure 11 Total site energy use of the baseline models

3.4.2. Impact of occupant behavior styles on ECM energy savings

Each ECM was implemented in the three baseline models with different occupant behavior styles in each climate type. The energy performance of each ECM was then simulated and compared with the baseline models. Figure 12 to Figure 15 illustrate the ECM energy saving percentages compared to the baseline models under the three behavior styles in each climate type. The simulation results indicate that the ECM saving percentages of LPD, EPD, envelope, system efficiency, and daylighting control are minimally affected by occupant behavior styles. This is because they are all purely technology-driven ECMs, which don't rely on the interactions with the occupants to save energy. For example, the ECM of reducing lighting power density doesn't require any actions from the occupants, thus its saving percentage varies minimally with behavior styles.

On the other hand, the ECM saving percentages of the VRF system, natural ventilation, and integrated ECM are significantly affected by occupant behavior styles. Energy performance in these ECMs is closely related to how the occupants interact with the ECM. For example, once the VRF system is installed, which allows zonal control, the occupants have decisions to make on how to control their indoor units: the austerity occupants only turn on the indoor units when they feel hot, normal occupants turn on the indoor units as long as they are in the room, while the wasteful occupants keep the indoor units on during the entire working hours. Also, cooling and heating setpoints are different among the behavior styles. Therefore, the energy performance of each ECM heavily depends on how the occupants behave. Even though the same VRF system is installed, different amounts of energy are consumed with different occupant operation modes. Likewise, the saving potentials of natural ventilation also heavily depend on how the occupants control the windows and the HVAC system. The integrated ECM includes the VRF system and natural ventilation, so it is also largely affected by behavior styles.

In summary, for ECMs that are purely technology driven and have little interaction with the occupants—such as reducing LPD, reducing EPD, improving envelope properties, and improving system efficiency and daylighting control—energy saving percentages are minimally affected by occupant behavior styles. For ECMs that have strong interaction with the occupants, such as the VRF system and natural ventilation, energy saving percentages are significantly affected by occupant behavior styles.

For occupant-dependent ECMs, austerity and normal behavior styles tend to have larger saving percentages compared to the wasteful behavior style (one exception is that the VRF-HR system operated by wasteful behavior occupants has the highest saving percentage in San Francisco) (Figure 15). In mild climates like San Francisco, the close or even equal cooling and heating setpoints of the wasteful behavior style generate a significant simultaneous cooling and heating load. In the baseline model with PVAV systems, this can only be satisfied by cooling coupled with reheat. However, the VRF heat recovery system can easily handle a simultaneous cooling and heating load by recovering heat from cooling zones to heating zones—significantly improving system efficiency and reducing energy consumption. Therefore, VRF has the greatest saving potential for the wasteful behavior and the least saving potential for the austerity behavior in San Francisco. On the other hand, in climates with distinct cooling and heating seasons such as Chicago, Miami, and Fairbanks, a simultaneous cooling and heating load is much less frequent than that in mild climates, so the saving percentages for the wasteful behavior are less than those of the normal and austerity behaviors.

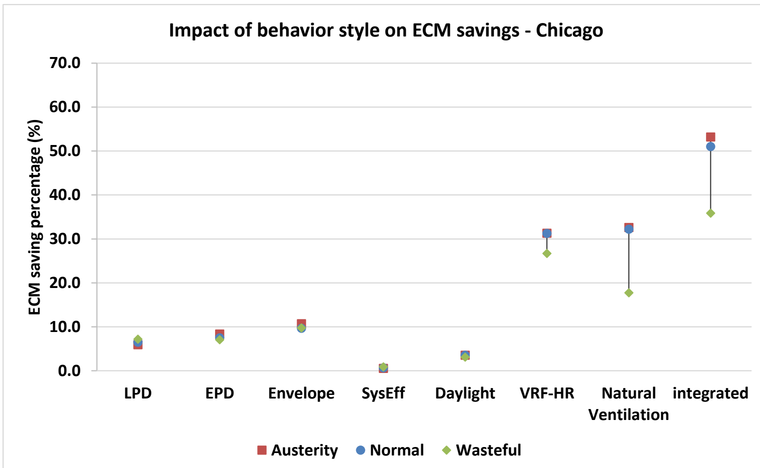

Figure 12 ECM saving percentages compared to the baseline models with different behavior styles in Chicago

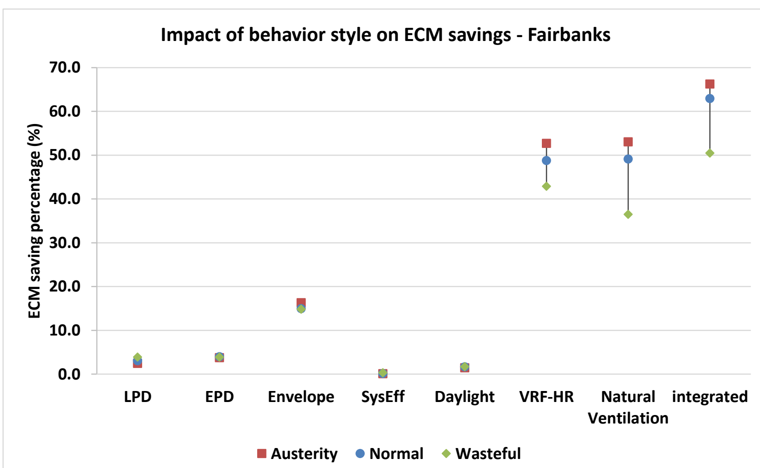

Figure 13 ECM saving percentages compared to the baseline models with different behavior styles in Fairbanks

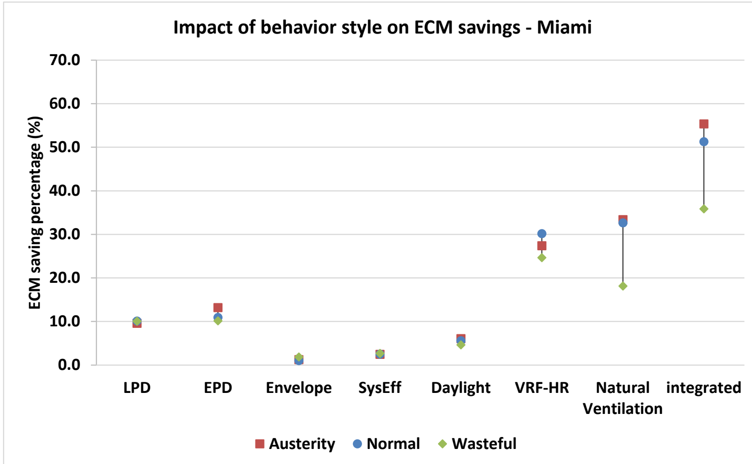

Figure 14 ECM saving percentages compared to the baseline models with different behavior styles in Miami

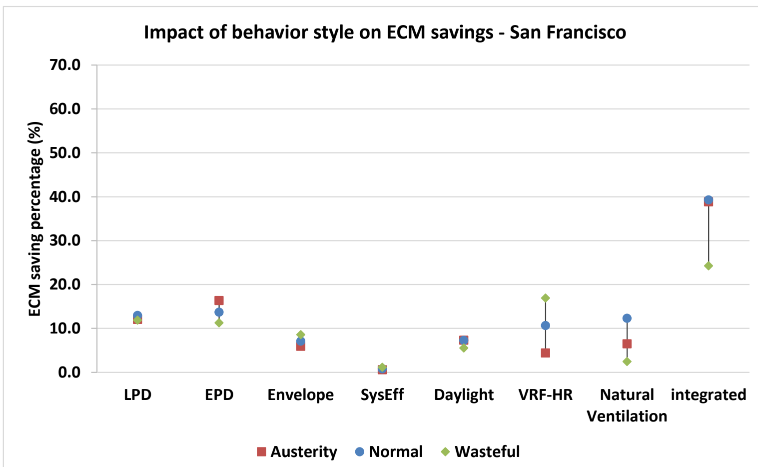

Figure 15 ECM saving percentages compared to the baseline models with different behavior styles in San Francisco

4. Discussion

4.1. Relative saving percentages vs. absolute savings

It should be noted that ECM energy saving percentages are not equivalent to their absolute energy savings. While the saving percentages are similar, the absolute savings could be different. Figure 16 through Figure 19 show the absolute energy savings of the ECMs under the three behavior styles in each climate. There are two main findings:

(1) the wasteful behavior style generally results in the greatest absolute energy savings while its saving percentages are mostly close to those of the austerity and normal behavior styles for occupant independent ECMs and even lower than those of the austerity and normal behavior styles for occupant dependent ECMs. This is mainly because the energy consumption of the

baseline model with the wasteful behavior style is much higher than that of the other two behavior styles, leading to huge saving potentials.

(2) The wasteful behavior style results in less absolute savings on the natural ventilation ECM. This is due to the fact that HVAC is on and windows are open all the time, increasing cooling/heating load significantly especially when outdoor environment is not beneficial to indoor thermal comfort.

Knowing absolute energy savings is very important to retrofit planning. Though buildings with the wasteful occupant behavior styles tend to achieve less saving percentages than other behavior styles, their absolute energy savings are generally higher. One finding of this study is that decision and policy makers would do well to target big consumers with wasteful behavior styles, which have more potential energy savings, especially for the promotion of technology-driven occupant-independent ECMs.

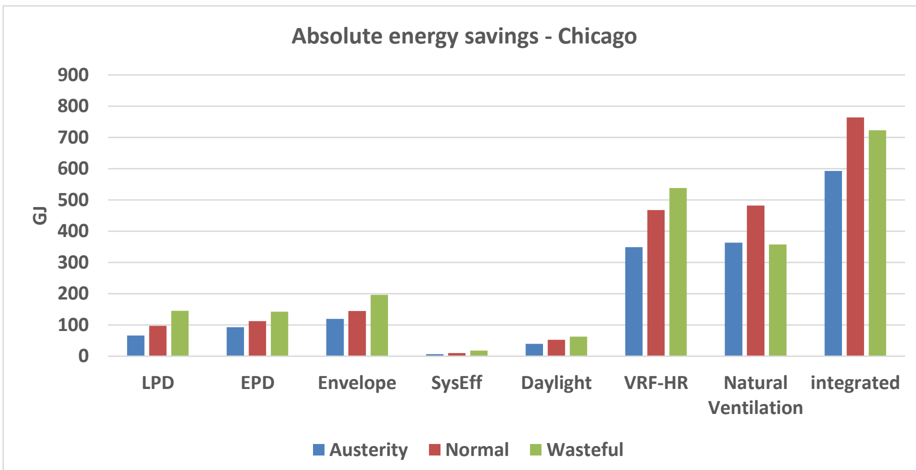

Figure 16 Absolute energy savings of the ECMs under three behavior styles in Chicago

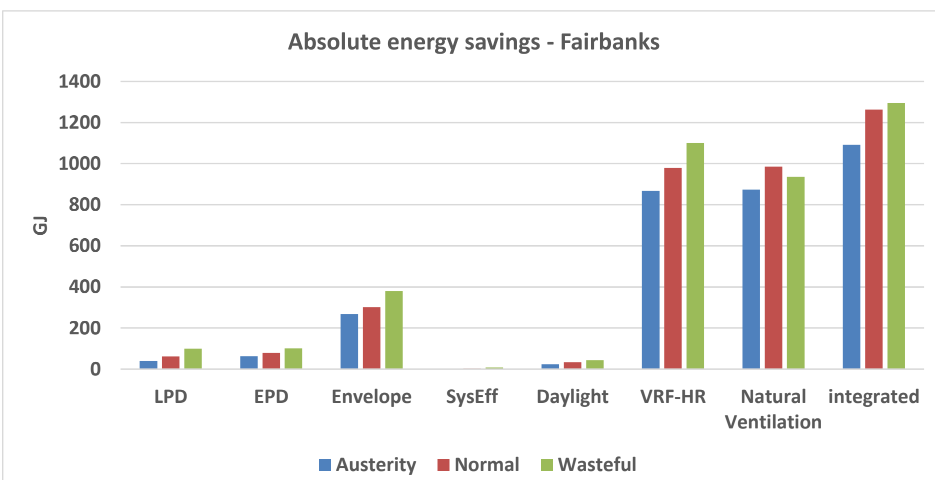

Figure 17 Absolute energy savings of the ECMs under three behavior styles in Fairbanks

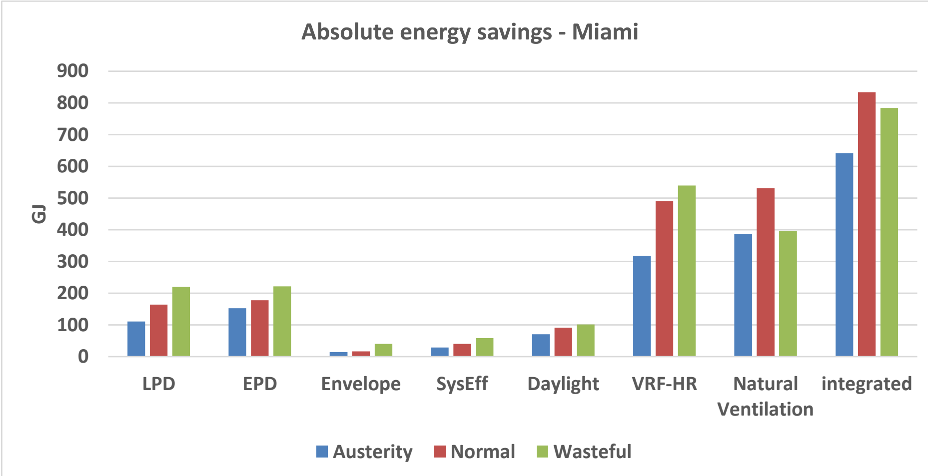

Figure 18 Absolute energy savings of the ECMs under three behavior styles in Miami

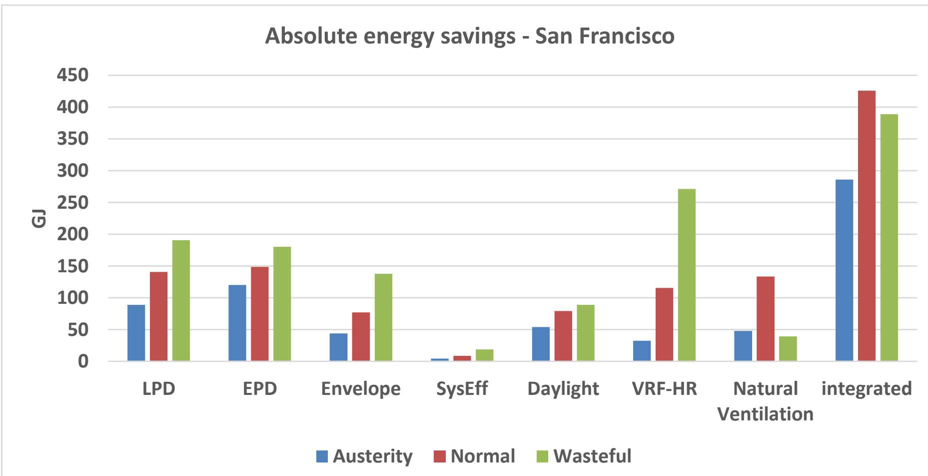

Figure 19 Absolute energy savings of the ECMs under three behavior styles in San Francisco

4.2. Impact of occupant schedules

The occupant schedules that are generally used in current energy models are static and normalized for the whole building, such as the office occupant schedule in the DOE prototype models for office buildings [69] (Figure 20). The normalized occupant 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 occupant schedules neither vary with the time (on a daily basis) nor vary with space. The normalized occupant schedule is not able to reflect the realistic occupant presence and movement and the variations between different zones within the buildings.

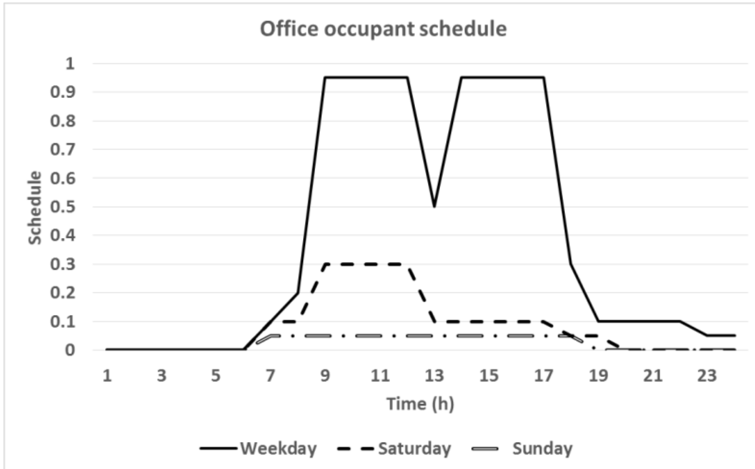

Figure 20 Office occupant schedule in the DOE reference model for office buildings

The author implemented the normalized occupant schedules in the DOE reference model for office buildings in both the baseline and ECM models and compared the simulation results with the realistic occupant schedule. Figure 21 through Figure 24 show the differences of energy saving percentages between the realistic and normalized occupant schedules in each climate type. The energy savings with the wasteful behavior style is not affected by occupant schedule regardless of ECM types, as its operation has nothing to do with occupants. For occupant-independent ECMs, only the energy savings with the austerity behavior style are slightly affected by the occupant schedule as only the austerity control of lights and plug load is partially related to the occupants. For occupant-dependent ECMs, the energy savings with both the austerity and normal behavior styles are significantly affected by the occupant schedule as their control of the VRF system and windows is closely tied to the occupants. From above, the occupant schedule does affect the simulated results of ECM savings, especially for the occupant-dependent ECMs coupled with the austerity behavior style. Adopting realistic occupant schedules rather than the normalized ones would help improve the accuracy of ECM saving evaluation.

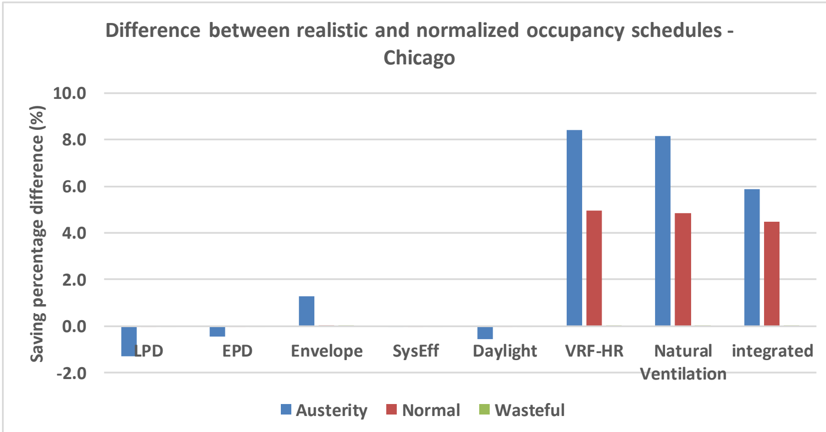

Figure 21 Difference of energy saving percentages between realistic and normalized occupant schedules in Chicago

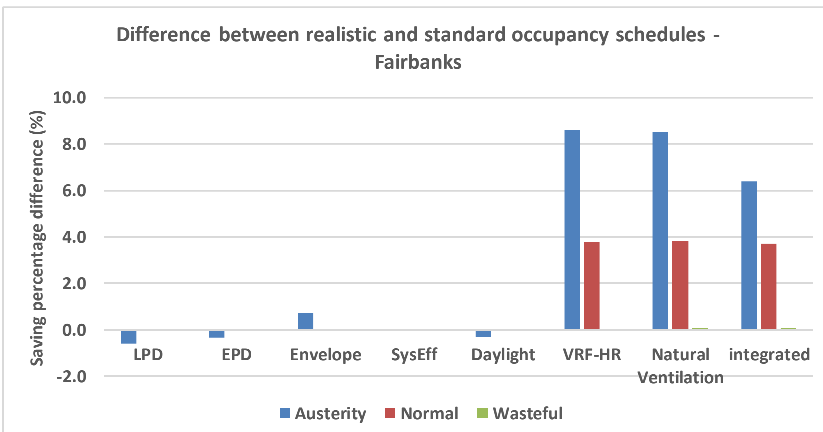

Figure 22 Difference of energy saving percentages between realistic and normalized occupant schedules in Fairbanks

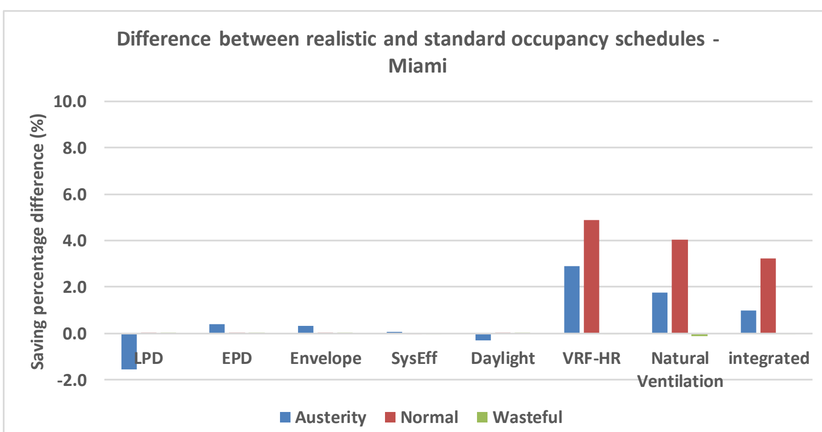

Figure 23 Difference of energy saving percentages between realistic and normalized occupant schedules in Miami

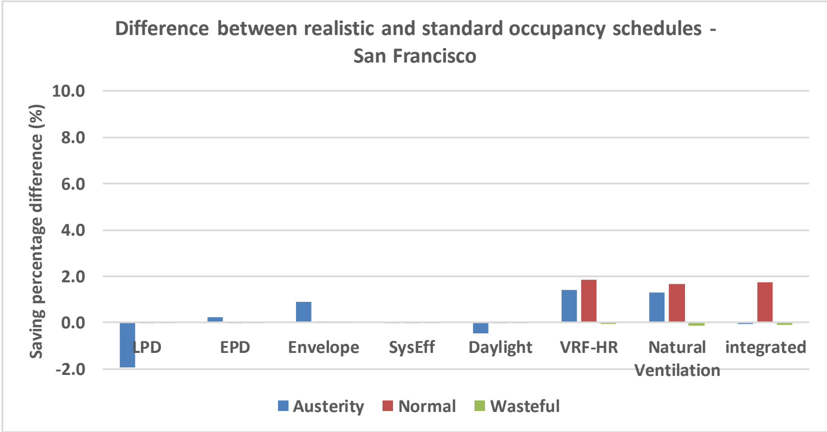

Figure 24 Difference of energy saving percentages between realistic and normalized occupant schedules in San Francisco

4.3. Occupant behavior styles

The defined three occupant behavior styles serve to illustrate the framing and application of the proposed framework, but they do not intend to represent actual occupant behavior in buildings. For users' specific buildings or applications, different occupant behaviors can be included. Future studies will use more realistic data of occupant behaviors, including different occupant behavior styles and their weighting factors, from research such as the large-scale international survey of occupant behavior in buildings under the IEA EBC Annex 66.

4.4. Interpretation of the simulation results

The simulated results using the proposed framework indicate a range of ECM savings with different occupant behaviors in buildings. The ways that the results are interpreted and adopted would vary by application purpose.

When the framework is applied to the retrofit analysis of existing buildings, the ECM saving range can be significantly reduced as the buildings are occupied and the types of occupant behaviors are recognized. In this case, the decision makers can minimize the investment risks by selecting the ECMs that benefit the most from the current occupant behavior style. On the other hand, when the framework is applied to the design of new buildings, the simulated range of ECM savings informs decision makers of the potential risk of technology choices due to variation and uncertainty of occupant behaviors. As the tenants are usually uncertain at the design stage, it is less risky to choose occupant-independent ECMs, such as reducing lighting power density, improving envelope properties, and improving HVAC system efficiencies. If occupant-dependent ECMs are considered as well, it would help to largely reduce the risk by educating and training occupants to understand the design intent of the building systems or by implementing automatic/intelligent control functions, such as automatic shading, lighting, and HVAC controls coupled with occupancy sensors.

4.5. Repetition of simulation runs

As some of the studied occupant behavior models are stochastic, the calculated ECM energy savings may vary if the annual performance simulations are repeated multiple times. Feng, et al. [76] recommended that a repetition of ten times is adequate for determining the mean results. D'Oca investigated the variation among simulation results due to stochastic models of window opening and heating setpoints within residential buildings by running each model more than 10 times. She concluded that the variation is very small (10%–12%). Commercial buildings, the focus of this study, have a much greater number of zones and occupants than residential buildings, leading to even smaller variations brought by stochastic models since the aggregated effect of diversities among multiple zones and occupants significantly reduce the overall variations [77].

This study explored the variation of ECM savings using the VRF ECM as an example. Per Section 2.2.3, the probability of turning on the HVAC system is calculated based on a three-parameter Weibull distribution function, and then compared with generated random numbers to determine whether occupants turn on the HVAC system, which is a stochastic result. Simulations of the VRF ECM in the four cities were repeated ten times each; Table 6 shows the results. As the variations of the annual HVAC site energy are less than 1% (even smaller if total site energy is compared), the repetition of annual simulation is not needed for this study. However, if metrics other than annual energy—for example, peak demand or hourly energy—are concerned, repetition may be needed.

Table 6 Simulated HVAC site energy of the VRF ECM under ten times repetition (Unit: GJ)

	Chicago	SF	Miami	Fairbanks
Min	144.8	82.98	221.38	159.75
Max	145.0	83.13	221.67	159.88
100(max/min - 1)%	0.14%	0.18%	0.13%	0.08%

5. Conclusions

This study introduced a simulation framework to quantify the impact of occupant behaviors on ECM energy savings. Three occupant behavior styles—austerity, normal and wasteful—were defined to represent different levels of energy consciousness in terms of the control of HVAC, window, lights, and plug-in equipment. These behavior styles don't necessarily represent realistic occupant behavior in buildings, but rather represent the boundary of either extreme, such as energy savers and spenders. The framework was then applied to a pilot study to evaluate the ECM energy saving discrepancies among different behavior styles. The main findings from this study are:

(1) The occupant behavior style has significant influence on building energy use. Buildings occupied by energy spenders could consume more than twice the energy of the energy savers.

(2) For occupant-independent ECMs, which are purely technology-driven and have little interaction with the occupants, such as reducing LPD, reducing EPD, improving envelope properties, and improving HVAC system efficiency and daylighting control, energy saving percentages are minimally affected by occupant behavior styles. For occupant-dependent ECMs, which have strong interaction with the occupants, such as the VRF system and natural ventilation, energy saving percentages are significantly affected by occupant behavior styles.

(3) The wasteful behavior style generally achieves the greatest absolute energy savings while its saving percentages are close to or even lower than those of the austerity and normal behavior. This is important information for decision makers in retrofit planning.

(4) The occupant schedule has certain impacts on the simulated results of ECM savings, especially for the occupant-dependent ECMs coupled with the austerity behavior style. Adopting realistic occupant schedules rather than normalized ones would help improve the accuracy of ECM saving evaluation.

The zero-net energy (ZNE) technologies are successful and growing today as energy performance requirements are becoming more and more stringent. ZNE technologies, such as natural ventilation, HVAC control, and demand response, tend to need more interaction with occupants. They are more sensitive to occupant behaviors and reactions to stimulations, which makes occupant behavior a significant uncertainty factor for the technology’s performance. In other words, occupant behavior may significantly change the way technologies are designed and expected to perform. The proposed framework provides a novel simulation approach enabling energy modelers to calculate the ECM savings as a range rather than a single fixed value considering the variations of occupant behaviors in buildings, which provides a critical input to the risk analysis of ECM investments.

Recommended future work include: (1) developing more realistic occupant behavior styles based on large scale survey of occupants in various climates, (2) pilot testing the methodology in a real design or retrofitting project, and (3) extending the study for other building types and building technologies.

Acknowledgments

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References

[1] International Energy Agency, Total energy use in buildings: Analysis and evaluation methods, 2013. http://www.iea-ebc.org/fileadmin/user_upload/images/Pictures/EBC_Annex_53_Main_Report.pdf.

[2] U.S. Department of Energy, Energy Efficiency Trends in Residential and Commercial Buildings, 2008.

[3] Pacific Northwest National Laboratory, Advanced Energy Retrofit Guides - Office Buildings, 2011. http://www.pnnl.gov/main/publications/external/technical_reports/PNNL-20761.pdf.

[4] Pacific Northwest National Laboratory, Advanced Energy Retrofit Guides - Retail Buildings, 2011. http://www.pnnl.gov/main/publications/external/technical_reports/PNNL-20814.pdf.

[5] T. Hong, W.K. Chang, H.W. Lin, A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data, Appl. Energy. 111 (2013) 333–350. doi:10.1016/j.apenergy.2013.05.019.

[6] W. Blyth, R. Bradley, D. Bunn, C. Clarke, T. Wilson, M. Yang, Investment risks under uncertain climate change policy, Energy Policy. 35 (2007) 5766–5773. doi:10.1016/j.enpol.2007.05.030.

[7] L. Wang, P. Mathew, X. Pang, Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building, Energy Build. 53 (2012) 152–158. doi:10.1016/j.enbuild.2012.06.017.

[8] C.C. Menassa, Evaluating sustainable retrofits in existing buildings under uncertainty, Energy Build. 43 (2011) 3576–3583. doi:10.1016/j.enbuild.2011.09.030.

[9] Y.G. Yohanis, Domestic energy use and householders' energy behaviour, Energy Policy. 41 (2012) 654–665. doi:10.1016/j.enpol.2011.11.028.

[10] J. Owens, H. Wilhite, Household energy behavior in Nordic countries-an unrealized energy saving potential, Energy. 13 (1988) 853–859. doi:10.1016/0360-5442(88)90050-3.

[11] O. Guerra Santin, L. Itard, H. Visscher, The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock, Energy Build. 41 (2009) 1223–1232. doi:10.1016/j.enbuild.2009.07.002.

[12] C.H. Baek, S.H. Park, Changes in renovation policies in the era of sustainability, Energy Build. 47 (2012) 485–496. doi:10.1016/j.enbuild.2011.12.028.

[13] L. Tobias, Retrofitting Office Buildings to Be Green and Energy-Efficient: Optimizing Building Performance, Tenant Satisfaction, and Financial Return, Washington D.C., 2009.

[14] Z. Ma, P. Cooper, D. Daly, L. Ledo, Existing building retrofits: Methodology and state-of-the-art,

Energy Build. 55 (2012) 889–902. doi:10.1016/j.enbuild.2012.08.018.

[15] T. Hong, D. Yan, S. D'Oca, C. Chen, Ten questions concerning occupant behavior in buildings: The big picture, Build. Environ. (2016) 1–13. doi:10.1016/j.buildenv.2016.12.006.

[16] J. Virote, R. Neves-Silva, Modelling the Occupant Behaviour Impact on Buildings Energy Prediction, in: Nearly Zero Energy Build. Refurb. A Multidiscip. Approach, 2014: pp. 119–141. doi:10.1007/978-1-4471-5523-2.

[17] N. Li, Z. Yang, C. Tang, N. Chen, B. Becerik-Gerber, Impact of Building Occupancy on Assessing the Effectiveness of Energy Conservation Measures, in: ISARC. Proc. Int. Symp. Autom. Robot. Constr., 2015: p. 1.

[18] E. Marshall, J.K. Steinberger, V. Dupont, T.J. Foxon, Combining energy efficiency measure approaches and occupancy patterns in building modelling in the UK residential context, Energy Build. 111 (2016) 98–108. doi:10.1016/j.enbuild.2015.11.039.

[19] D. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and future challenges, Energy Build. 107 (2015) 264–278. doi:10.1016/j.enbuild.2015.08.032.

[20] K. Sun, D. Yan, T. Hong, S. Guo, Stochastic modeling of overtime occupancy and its application in building energy simulation and calibration, Build. Environ. 79 (2014) 1–12. doi:10.1016/j.buildenv.2014.04.030.

[21] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy Build. 41 (2009) 295–302. doi:10.1016/j.enbuild.2008.09.008.

[22] K. Sun, T. Hong, S.C. Taylor-Lange, M.A. Piette, A pattern-based automated approach to building energy model calibration, Appl. Energy. 165 (2016) 214–224. doi:10.1016/j.apenergy.2015.12.026.

[23] K. Schakib-Ekbatan, F.Z. Çakici, M. Schweiker, A. Wagner, Does the occupant behavior match the energy concept of the building? - Analysis of a German naturally ventilated office building, Build. Environ. 84 (2015) 142–150. doi:10.1016/j.buildenv.2014.10.018.

[24] C. Turner, M. Frankel, Energy Performance of LEED ® for New Construction Buildings, New Build. Inst. (2008) 1–46.

[25] M. Eguaras-Martínez, M. Vidaurre-Arbizu, C. Martín-Gómez, Simulation and evaluation of building information modeling in a real pilot site, Appl. Energy. 114 (2014) 475–484. doi:10.1016/j.apenergy.2013.09.047.

[26] K.-U. Ahn, C.S. Park, Different Occupant Modeling Approaches for Building Energy Prediction, Energy Procedia. 88 (2016) 721–724. doi:10.1016/j.egypro.2016.06.050.

[27] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings, Energy Build. 87 (2015) 348–359. doi:10.1016/j.enbuild.2014.11.067.

[28] C. Wang, D. Yan, Y. Jiang, A novel approach for building occupancy simulation, Build. Simul. 4 (2011) 149–167. doi:10.1007/s12273-011-0044-5.

[29] J. Page, D. Robinson, N. Morel, J.L. Scartezzini, A generalised stochastic model for the simulation of occupant presence, Energy Build. 40 (2008) 83–98. doi:10.1016/j.enbuild.2007.01.018.

[30] C.J. Andrews, D. Yi, U. Krogmann, J.A. Senick, R.E. Wener, Designing buildings for real occupants: An agent-based approach, IEEE Trans. Syst. Man, Cybern. Part ASystems Humans. 41 (2011) 1077–1091. doi:10.1109/TSMCA.2011.2116116.

[31] Y.S. Lee, A.M. Malkawi, Simulating multiple occupant behaviors in buildings: An agent-based modeling approach, Energy Build. 69 (2014) 407–416. doi:10.1016/j.enbuild.2013.11.020.

[32] D. Robinson, U. Wilke, F. Haldi, Multi Agent Simulation of Occupants'Presence and Behaviour, Proc. Build. Simul. (2011) 14–16. http://www.ibpsa.org/proceedings/BS2011/P_1671.pdf.

[33] J. Langevin, J. Wen, P.L. Gurian, Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors, Build. Environ. 88 (2014) 27–45. doi:10.1016/j.buildenv.2014.11.037.

[34] T. Hong, S. D'Oca, S.C. Taylor-Lange, W.J.N. Turner, Y. Chen, S.P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema, Build. Environ. 94 (2015) 196–205. doi:10.1016/j.buildenv.2015.08.006.

[35] T. Hong, S. D'Oca, S.C. Taylor-Lange, W.J.N. Turner, Y. Chen, S.P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema, Build. Environ. 94 (2015) 196–205. doi:10.1016/j.buildenv.2015.08.006.

[36] G.Y. Yun, P. Tuohy, K. Steemers, Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models, Energy Build. 41 (2009) 489–499. doi:10.1016/j.enbuild.2008.11.013.

[37] A. Mahdavi, A. Mohammadi, E. Kabir, L. Lambeva, Occupants' operation of lighting and shading systems in office buildings, J. Build. Perform. Simul. 1 (2008) 57–65. doi:10.1080/19401490801906502.

[38] D. Wang, C.C. Federspiel, F. Rubinstein, Modeling occupancy in single person offices, Energy Build. 37 (2005) 121–126. doi:10.1016/j.enbuild.2004.06.015.

[39] G. Zimmermann, Modeling and Simulation of Individual User Behavior for Building Performance Predictions, Summer Comput. Simul. Conf. (2007) 913–920. doi:10.1145/1357910.1358052.

[40] A.M. Rysanek, R. Choudhary, DELORES – an open-source tool for stochastic prediction of occupant services demand, J. Build. Perform. Simul. 8 (2015) 97–118. doi:10.1080/19401493.2014.888595.

[41] W. Parys, D. Saelens, H. Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices – a review-based integrated methodology, J. Build. Perform. Simul. 4 (2011) 339–358. doi:10.1080/19401493.2010.524711.

[42] R. Fritsch, A. Kohler, M. Nyg, / ~rd-Ferguson, J.-L. Scartezzini, A Stochastic Model of User Regarding Ventilation Behaviour, Build. Environ. 25 (1990) 173–181. doi:10.1016/0360-1323(90)90030-U.

[43] I. Richardson, M. Thomson, D. Infield, A high-resolution domestic building occupancy model for energy demand simulations, Energy Build. 40 (2008) 1560–1566. doi:10.1016/j.enbuild.2008.02.006.

[44] J. Widén, A.M. Nilsson, E. Wäckelgård, A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand, Energy Build. 41 (2009) 1001–1012. doi:10.1016/j.enbuild.2009.05.002.

[45] V. Fabi, R.V. Andersen, S. Corgnati, B.W. Olesen, Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models, Build. Environ. 58 (2012)

188–198. doi:10.1016/j.buildenv.2012.07.009.

[46] S. D'Oca, T. Hong, A data-mining approach to discover patterns of window opening and closing behavior in offices, Build. Environ. 82 (2014) 726–739. doi:10.1016/j.buildenv.2014.10.021.

[47] A. Mahdavi, F. Tahmasebi, Predicting people's presence in buildings: An empirically based model performance analysis, Energy Build. 86 (2015) 349–355. doi:10.1016/j.enbuild.2014.10.027.

[48] Y.S. Lee, A.M. Malkawi, Simulating multiple occupant behaviors in buildings: An agent-based modeling approach, Energy Build. 69 (2014) 407–416. doi:10.1016/j.enbuild.2013.11.020.

[49] Q. Wang, G. Augenbroe, J.H. Kim, A framework for meta- Analysis of the role of occupancy variables in the energy use of commercial buildings, 14th Int. Conf. IBPSA - Build. Simul. 2015, BS 2015, Conf. Proc. (2015) 2278–2285. http://www.scopus.com/inward/record.url?eid=2-s2.0-84976447996&partnerID=tZOtx3y1.

[50] Y. Heo, G. Augenbroe, R. Choudhary, Risk analysis of energy-efficiency projects based on Bayesian calibration of building energy models, Proc. Build. Simul. 2011 12th Conf. Int. Build. Perform. Simul. Assoc. 2002 (2011) 2579–2586. http://ibpsa.org/proceedings/BS2011/P_1799.pdf.

[51] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, Implementation and comparison of existing occupant behaviour models in EnergyPlus, J. Build. Perform. Simul. 1493 (2015) 1–46. doi:10.1080/19401493.2015.1102969.

[52] W. Parys, D. Saelens, H. Hens, Impact of Occupant Behaviour on Lighting Energy Use, Build. Simul. (2009) 1143–1150.

[53] F.C. Reinhart, Tutorial on the Use of Daysim Simulations for Sustainable Design, Harvard Des. Sch. (2010) 1–114.

[54] O.G. Santin, Behavioural patterns and user profiles related to energy consumption for heating, Energy Build. 43 (2011) 2662–2672. doi:10.1016/j.enbuild.2011.06.024.

[55] T. Hong, H.-W. Lin, Occupant Behavior: Impact on Energy Use of Private Offices, ASim 2012 - 1st Asia Conf. Int. Build. Perform. Simul. Assoc. (2013) 12.

[56] D. Yan, T. Hong, IEA EBC Annex 66 : Definition and Simulation of Occupant Behavior in Buildings, 2014.

[57] ASHRAE, ASHRAE STANDARD 55-2010: Thermal Environmental Conditions for Human Occupancy, 2010.

[58] GSA Public Building Service, Plug load control, 2012. http://www.gsa.gov/graphics/pbs/PlugLoadControl_508c.pdf.

[59] Leviton, Plug Load Control Solutions, 2014. http://www.leviton.com/OA_HTML/LevitonSearchResults.jsp?kw=Plug+Load+Control+Solutions&tbon=&minisite=10251.

[60] A. Mahdavi, F. Tahmasebi, M. Kayalar, Prediction of plug loads in office buildings: Simplified and probabilistic methods, Energy Build. 129 (2016) 322–329. doi:10.1016/j.enbuild.2016.08.022.

[61] I. Metzger, M. Sheppy, D. Cutler, Reducing Office Plug Loads through Simple and Inexpensive Advanced Power Strips, (2013). http://www.nrel.gov/docs/fy13osti/57730.pdf.

[62] S. Hackel, Advancing the Last Frontier – Reduction of Commercial Plug Loads, (2016) 1–12.

[63] X. Ren, D. Yan, C. Wang, Air-conditioning usage conditional probability model for residential buildings, Build. Environ. 81 (2014) 172–182. doi:10.1016/j.buildenv.2014.06.022.

[64] L. Wang, S. Greenberg, Window operation and impacts on building energy consumption, Energy Build. 92 (2015) 313–321. doi:10.1016/j.enbuild.2015.01.060.

[65] G.S. Brager, R. De Dear, Climate , Comfort & Natural Ventilation : A new adaptive comfort standard for ASHRAE Standard 55, Cent. Built Environmen. (2001) 19. doi:10.1016/S0378-7788(02)00005-1.

[66] K. Sun, T. Hong, A Simulation Approach to Estimate Energy Savings Potential of Occupant Behavior Measures, Energy Build. (2016) (Article in press). doi:10.1016/j.enbuild.2016.12.010.

[67] Y. Chen, X. Luo, T. Hong, An Agent-Based Occupancy Simulator for Building Performance Simulation, ASHRAE Annu. Conf. (2016).

[68] X. Luo, Performance Evaluation and Enhancement of a Probabilistic Occupancy Simulation Model, Master Thesis, Carnegie Mellon University, 2016.

[69] U.S. Department of Energy, Commercial Prototype Building Models, (2013). https://www.energycodes.gov/development/commercial/prototype_models.

[70] L.A. Skumatz, S. Economic, C. Hickman, Effective ECM and Equipment Lifetimes in Commercial Buildings : Calculation and Analysis, in: ACEEE Summer Study Energy Effic. Build., 1994.

[71] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W.F. Buhl, Y.J. Huang, C.O. Pedersen, R.K. Strand, R.J. Liesen, D.E. Fisher, M.J. Witte, J. Glazer, EnergyPlus: Creating a new-generation building energy simulation program, Energy Build. 33 (2001) 319–331. doi:10.1016/S0378-7788(00)00114-6.

[72] ASHRAE, ANSI/ASHRAE/IES Standard 90.1-2001: Energy Standard for Buildings Except Low-Rise Residential Buildings, 2001.

[73] ASHRAE, ANSI/ASHRAE/IES Standard 90.1-2013: Energy Standard for Buildings Except Low-Rise Residential Buildings, 2013.

[74] T. Hong, K. Sun, R. Zhang, R. Hinokuma, S. Kasahara, Y. Yura, Development and validation of a new variable refrigerant flow system model in EnergyPlus, Energy Build. 117 (2016) 399–411. doi:10.1016/j.enbuild.2015.09.023.

[75] X. Yu, D. Yan, K. Sun, T. Hong, D. Zhu, Comparative study of the cooling energy performance of variable refrigerant flow systems and variable air volume systems in office buildings, Appl. Energy. 183 (2016) 725–736. doi:10.1016/j.apenergy.2016.09.033.

[76] X. Feng, D. Yan, C. Wang, On the simulation repetition and temporal discretization of stochastic occupant behaviour models in building performance simulation, J. Build. Perform. Simul. 0 (2016) 1–13. doi:10.1080/19401493.2016.1236838.

[77] S. D'Oca, V. Fabi, S.P. Corgnati, R.K. Andersen, Effect of thermostat and window opening occupant behavior models on energy use in homes, Build. Simul. 7 (2014) 683–694. doi:10.1007/s12273-014-0191-6.