Energy-consumption simulation of a distributed air-conditioning system integrated with occupant behavior

Jiantong Xie[a], Yiqun Pan[a,*], Wenqi Jia[a], Lei Xu[b], Zhizhong Huang[c]

[a] Department of Mechanical and Energy Engineering, Tongji University, Shanghai 201804, China
[b] Department of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA
[c] Sino-German College of Applied Sciences, Tongji University, Shanghai 201804, China

HIGHLIGHTS

- The occupancy schedule and set-point distribution of a hotel building are obtained.
- The Markov Chain method is applied to simulate the occupancy.
- The Monte-Carlo model is proposed to simulate the set-point adjustment.
- The split-type air conditioner model in EnergyPlus is modified.
- Models can reflect the features of occupant behavior and split-type air conditioners.

ARTICLE INFO

ABSTRACT

Occupant behavior (OB) has been recognized as a significant factor that influences the energy consumed by the occupants of a building. For buildings equipped with distributed air-conditioning systems, the stochastic influences of occupants are particularly salient. This paper presents a method for simulating the occupancy and air-conditioning usage; it integrates the OB model with a modified distributed air-conditioning system in EnergyPlus (E+). First, we develop a monitoring system that uses motion sensors and thermostats to measure the occupancy and air-conditioning usage in a hotel building. Then, we use the Markov Chain method and a Monte-Carlo stochastic model to simulate the occupancy and set-point adjustment, respectively. We modify the distributed air-conditioning system in E+ to reflect the intermittent operation and temperature fluctuation characteristics of split-type air conditioners (ACs). Finally, to demonstrate the applicability of the proposed method, we conduct a simulation of a hotel building that integrates the OB model with the modified distributed air-conditioning system. The results show that the method can incorporate the features of both the OB and the split-type ACs. Significant differences (7.86%) can be observed in the energy consumption results between the original and modified models. The modified E+ model can be used to perform a more accurate simulation for split-type ACs with a shorter time step, integrating OB at the scale of an entire building.

1. Introduction

Buildings account for approximately 30% of global energy use [1]. Therefore, there is an urgent need for energy saving in buildings. With the development of computer technology, building-energy simulation has become a widely recognized method for evaluating the energy-saving potential of various building-energy efficiency technologies and for improving the energy consumption in building-energy systems.

A distributed air-conditioning system is widely used in various types of buildings such as residences, offices, and hotels, owing to its flexibility. It offers advantages that include easy adjustment, good partial load performance, easy installation, and convenient energy consumption measurement. It mainly uses direct-expansion (DX) coils and has no intermediate heat exchange system, thereby providing a shorter response time and less energy loss. Distributed air-conditioning systems are usually divided into two types: constant-speed and variable-speed. This study mainly focuses on a constant-speed distributed system wherein the compressor switches between the on and off states so as to cause small temperature fluctuations around the temperature set-point.

A certain number of studies based on distributed air-conditioning

---

Nomenclature

Abbreviations

OB	occupant behavior
AC	air conditioner
DX	direct expansion
COP	coefficient of performance
CFD	computational fluid dynamics
PID	proportional integral derivative
VCASHP	variable capacity air source heat pump
E+	EnergyPlus
VRF	variable refrigerant flow
TUS	time-use survey
EIR	energy input ratio
PLR	part load ratio
PLF	part load fraction
RTF	running time factor
FDD	fault detection and diagnosis

Symbols

N	number of observed values
q	number of estimate parameters
P_n	transition matrix at time n
$p_{ij}(t)$	probability of transition from state i to state j at time step t
U	random number
$n_{ij}(t)$	number of transitions from occupancy state i to state j
$n_i(t)$	number of rooms at occupancy state i at time t
X	sample value
$\dot{Q}_{total}$	corrected capacity calculated according to the correction curves, W
$Power$	energy consumption per time step, W
$\rho_{X,Y}$	Pearson correlation coefficient
$cov(X, Y)$	covariance between the two variables
σ	standard deviation of the variable
$E(X)$	expectation of the variable

---

systems have explored the improvement of the coefficient of performance (COP) and alternative refrigerants through experiments and simulations. Joudi and Al-Amir [2] studied the steady-state-operation characteristics of four refrigerants in a split-type AC system in a high-temperature environment through experiments and simulation. Elgendy [3] investigated the performance characteristics of split air conditioners (ACs) using R-417A fluid (as compared with R-22) under different indoor and outdoor conditions. Martínez et al. [4] coupled a condensing coil with an evaporative cooling plate to improve the energy efficiency of a system by reducing the outdoor unit inlet air temperature during summers. Nada and Said [5] adopted a computational fluid dynamics (CFD) simulation to study the layout of an optimal outdoor unit to avoid problems involving the high temperature of the condensing coil and to improve system performance. Mohammed et al. [6] designed a hybrid proportional-integral derivative (PID) controller to control the fan speed and water mist flow rate for improving the performance of a split air-conditioning system.

Some researchers have developed the static and dynamic simulation models of a whole AC unit or each component of a split-type AC. Chen et al. [7] established a dynamic simulation model for a household compression refrigeration air-conditioning system considering the heat and mass exchange between each component and the surrounding environment. St-Onge [8] performed laboratory tests for mini-split variable capacity air source heat pump (VCASHP) performance and created a VCASHP model in "TRNSYS". Although the static and dynamic models in various simulation platforms can basically reflect the operation of a system, there are limitations in building-energy consumption simulations that often require collaborative simulation with energy simulation software. Therefore, there is a need for a simulation model for engineers to better understand the operation behavior of split-type ACs and to better estimate their energy consumption.

It is faster and more convenient to directly add or modify a corresponding device model in existing building-energy simulation software such as EnergyPlus (E+). The open source and modular features of E+ facilitate the addition of new simulation modules for developers. Some researchers have developed or modified distributed air-conditioning system models in E+ for specific purposes. A. Gomes et al. [9] established a physical model for constant-speed ACs that can simulate loads and the actual operation of ACs at a multi-room scale while considering the on-off operation states and fluctuations in indoor temperature. Nevertheless, the calculation of the building load is too simplistic, and the operating characteristics of the constant-speed ACs are not considered comprehensively enough. Hong et al. [10] developed a new variable refrigerant flow system (VRF) model in E+ and used measured

data to verify the model. Zhou et al. [11] developed a system module for improving a single DX coil model in E+ and applied the module to a typical commercial building model in China. However, the current version of E+ has some blemishes in its distributed air-conditioning model; it cannot present the intermittent operation and temperature fluctuation characteristics of a split-type AC. This study analyzes the calling logic of the E+ program and the calculation process of the split-type AC model in E+. Then, the E+ software source code is modified to reflect the operating characteristics of the split-type AC and the fluctuations in room temperature.

For buildings equipped with flexible and controllable distributed air-conditioning systems, occupant behavior (OB) significantly affects building-energy consumption and is a leading source of uncertainty in the prediction of building-energy usage [12]. Significant differences have been observed in building-energy predictions based on energy simulation results using different OB models. In other words, the performance gap is mainly affected by the OB characteristics [13]. Wang [14] investigated office buildings in Beijing with different air-conditioning systems and found that the indoor temperature set-point and the AC starting time were highly depended on the OB patterns. Gaetani et al. [15] proved the influence of OB including occupant presence, light use, equipment use, blind use, and temperature setpoint on heating and cooling energy demands by evaluating newly-developed impact indices based on simulation results. Ouyang and Hokao [16] compared the electricity consumption of energy-conservation-trained and untrained households and found that the average energy-saving potential for energy-aware OB can reach 14.8%. Credible outcomes from integrating interdisciplinary approaches to the study of OB indicate that the potential behavioral energy savings range from 5 to 20% [17]. Therefore, the impact of OB cannot be ignored in the study of energy consumption in buildings.

The complexity of research based on OB arises from the uncertainty of OB, the existence of multiple influencing factors, and limited amount of measured data [18]. The way in which OB can be accurately and effectively described remains worthy of in-depth study and exploration. With the wide application of simulation software in recent years, increasing attention has been paid to OB simulation. OB simulation mainly includes four aspects [19]: (1) occupant monitoring and data collection; (2) model development; (3) model evaluation; and (4) integration of OB models in building-energy modeling programs. A traditional energy simulation uses fixed profiles to describe occupancy, lighting, equipment usage rate, and the temperature set-point of the air-conditioning system in the building. However, unlike other deterministic input parameters, OB tends to be random [20,21]. OB is related to

factors such as the environmental state and event at that time. More-over, differences in perception and response to the environment also lead to different behaviors [22,23]. Li et al. [24] conducted a survey based on air-conditioning energy consumption in five residential buildings in Beijing in summer and found that the consumption varies considerably among households. They also revealed that the impact of the indoor temperature set-point on air-conditioning energy consumption is significant. If the indoor temperature set-point is increased from 25 °C to 26 °C, the air-conditioning energy consumption can be reduced by approximately 23%.

With the progress of monitoring technology and data analysis methods, researchers have proposed several methods for modeling OB, occupancy information in particular. Ryu and Moon [25] developed an occupancy prediction model based on the measured indoor environmental data and occupancy history data using a hidden Markov model. Yang and Becerik-Gerber [26] proposed a framework for simulating occupancy based on indoor monitoring data (light, sound, motion, carbon dioxide concentration, temperature, door magnet, etc.). The accuracies of several modeling methods (regression, time series, pattern recognition, stochastic process) were tested. These models were used in an occupancy simulation of one or several rooms but were not verified on a whole-building scale simulation.

Typical behavior pattern study is a common method in OB research. To extract typical behavior patterns from diverse OBs, Yu et al. [27] classified the influence of OB on energy consumption using cluster analysis based on monitored energy consumption data. Abreu et al. [28] adopted cluster analysis to obtain three types of energy usage characteristics from the data obtained from a network survey and constructed hourly schedules of energy use under three types. Ren [29] used cluster analysis and a decision tree to classify heating usage behavior patterns into five types based on an indoor temperature curve. However, this data mining method of extracting typical behavior patterns is limited by the number of measured cases, and there is a lack of description of the OB itself.

Various models of air-conditioning usage behavior have been established in the existing research, including statistical models, data mining models, and stochastic models. Yasue et al. [30] collected AC usage data in residential buildings and used a sigmoid function to describe the relationship between indoor temperature and AC switching probability. Schweiker et al. [31] measured the AC usage of 320 single rooms in Japan and used logistic regression to establish a statistical correlation between the switch-on probability of ACs and the average outdoor temperature. Carmo [32] measured the heating energy consumption in 139 houses and used clustering and regression analysis methods to obtain three heating usage modes: high, medium, and low demands. Tanimoto et al. [33] established a stochastic model based on a two-state Markov Chain to predict the transition probability of an AC state from on to off or from off to on through indoor and outdoor temperatures. Wang [14] proposed a research framework and quantitative description method. He considered OB as actions that change the state of objects and introduced behavioral pattern and characteristic parameters to simplify and quantify the description of all actions. For a mathematical description of OB, he established an OB model based on a conditional probability function. Haldi and Robinson [34] used goodness-of-fit as an indicator to select various influencing factors of OB and established a regression model that was optimized by the Markov Chain and survival analysis.

The existing research pays more attention to AC-switching behaviors, and there are fewer studies based on AC-adjusting behaviors. In a study of the interactions of occupants with a thermostat, Moon et al. [35] described the effect of adjusting the temperature set-point on air-conditioning energy consumption in different climate zones using different schedules. Urban et al. [36] studied the effect of the temperature set-point on energy consumption by randomly generating sample schedules from measured data sets. Jian et al. [37] established a threshold-based model, assuming that actions occur when

environmental factors are above or below a certain threshold. Through the actual measurement and investigation of air-conditioning usage of 42 residential houses in Beijing, it was found that the room temperature at the switch-on moment is generally 29 °C and that the temperature set-point is usually 26 °C. However, there is a lack of OB simulation models available for temperature set-point prediction on a whole-building scale for a more accurate simulation of building-energy consumption.

This study focuses on two aspects of OB: the occupancy and the interactions of occupants with the thermostat. We establish a stochastic model to simulate these two parts and incorporate them into a modified distributed air-conditioning system module in E+. First, the scope of the research based on OB in this study is defined (Section 2.1.1). Then, we introduce a monitoring system to measure OB on a whole-building scale (Section 2.1.2). Next, the Markov Chain method and Monte-Carlo stochastic model are proposed to simulate the occupancy and set-point adjusting behavior (Section 2.1.3 & Section 2.1.4). We then modify the split-type AC model in E+ to reflect the operating characteristics of the split-type AC (Section 2.2). The monitoring results of OB and simulation results before and after the split-type AC model improvement are analyzed (Section 3.1 & Section 3.2). In addition, a case in Shanghai is presented to verify the validity of the modified split-type AC model integrated with OB (Section 3.3). Finally, we discuss and explore the advantages and limitations of this model (Section 4).

2. Methodology

2.1. Occupant behavior (OB)

2.1.1. Definition of research scope

In recent studies based on energy simulation, researchers have concentrated on the impact of occupancy and OB on building-energy consumption. The study of occupancy can be divided into four levels [38]: (1) the number of occupants in a building; (2) occupancy (whether a space is occupied or not); (3) the number of occupants in a space; (4) the space in which an occupant is located. Major OBs of interest include light-switching, blind-adjusting, window-opening, and thermostat-adjusting. This study concentrates on whether a space is occupied or not and the adjustment behavior of an air-conditioning thermostat.

In terms of spatial dimensions, the research based on OB in this study mainly focuses on a simulation on a whole-building scale instead of the behavior of a single individual or the change of a single room. Therefore, in the simulation of OB, we do not consider the driving factors of individual behavior; we only consider the distribution and characteristics of the occupancy rate and the temperature set-point on a whole-building scale.

2.1.2. OB monitoring
2.1.2.1. Occupancy rate. Adaptive OB monitoring is one of the most common and well-developed methods for collecting OB data. The monitoring methods for occupancy mainly include motion detection, carbon dioxide concentration monitoring, camera monitoring, wearable sensors, and smartphone location (with Wi-Fi connectivity). Motion detectors are the most widely used sensors for detecting the occupancy of a room [39], but motion sensors face difficulty in identifying occupants who are sitting or standing still. To improve the accuracy of detection, motion monitoring can be combined with carbon dioxide concentration monitoring, seat pressure sensing, and other monitoring methods.

In this study, we use motion sensors together with a hotel guest room control system to detect the occupancy in a hotel building. Because guests often forget to pull out the power card before leaving, determining the occupancy of a room just by checking the power on-off condition is not a reliable method. Therefore, it is necessary to detect the occupancy of a room using a different method. Considering the

privacy concerns in hotels, a non-intrusive monitoring method using motion sensors is adopted. Each room has an ultrasonic motion detector on the ceiling. When the ultrasonic motion detector is working, it emits and receives ultrasonic waves. Similar to the Doppler effect, motion is detected through deviations produced by acoustic emission and reception. Additionally, magnetic detectors are installed on the doors to detect the opening and closing of the doors. When a door movement is detected, the sound wave motion detector in the room is activated and it monitors the movement of the occupant in the room. If any detector in the room detects an action, the room is considered occupied. Then, the occupancy data is recorded in the database software "MySQL" for subsequent processing.

2.1.2.2. Occupant's interactions with thermostat. The most common method for collecting thermostat usage data is using a questionnaire survey, but it is difficult to establish a detailed statistical model based on a survey. Advanced thermostats already enable the recording, storage, and transfer of data, thereby making it possible to record thermostat adjustment behavior. In this study, we measure the thermostat-adjusting behaviors of the occupants using thermostat recording.

We can assume that each guest room has different guests every day, so the daily data of each guest room can be regarded as a random sample. For the probability distribution of the temperature set-point, the number of parameters is 15, because the adjustable range of the thermostat is 16–30 °C. To obtain statistically significant data, a minimum sample size of 150 is required (N:q = 10:1) [40].

2.1.3. Simulation method of the occupancy rate

Owing to the randomness of OBs, the stochastic model can be used to describe and simulate OBs. We choose a Markov Chain stochastic method because it can not only reflect the randomness of the movement of an occupant, but it can also comply with the overall trend of occupancy. The Markov Chain can predict the next moment through the current state and a transition matrix composed of transition probabilities. For a Markov Chain with m states, the transition matrix at time n is usually in the following form:

$$P_n = (p_{ij})_{m \times m} = \begin{vmatrix} p_{11} & p_{12} \cdots p_{1(m-1)} \\ p_{21} & p_{22} \cdots p_{2(m-1)} \\ \cdots\cdots\cdots \\ p_{(m-1)1}p_{(m-1)2}\cdots p_{(m-1)(m-1)} \end{vmatrix}$$

(1)

A Markov Chain Monte-Carlo method has been recognized for simulating occupancy. Richardson et al. [41] used this method to simulate occupancy in a residential building based on a large amount of survey data from a time-use survey (TUS). Widen and Wackelgard [42] also adopted the Markov Chain method to randomly simulate the state of occupancy. Unlike Richardson who used the number of occupants as the state parameter, they used the ongoing activities of the occupants including leaving, sleeping, and cooking, as the state parameters. The data is also derived from the time schedule survey of the occupants. The acquisition of the transfer matrix is the focus of this approach. In both the studies mentioned earlier, the transfer matrix of the occupancy is obtained by statistical data regression. In this study, considering each room as a simulation object and the occupancy of a room as the state parameter, we calculate an hourly transition matrix according to field measurement so as to generate an hourly occupancy rate schedule. The schematic for generating the occupancy rate is shown in Fig. 1.

The specific methods are as follows. First, to generate a Markov Chain, we set the initial state. Supposing that we know the hourly occupancy rate of the entire building from field measurements, the initial state of each room can be determined by the Monte Carlo method. For example, a random number U (0,1) is generated for each room. If we assume that the occupancy rate at 0:00 is 0.75, meaning 75 out of 100 rooms are occupied, the initial state of the room is considered occupied

if U is less than 0.75,; otherwise, the initial state is considered vacant.

To generate the hourly occupancy schedule, we need to calculate 24 transfer matrices for 24 h a day, each of which has a size of 2 × 2. An example of transfer matrices is shown in Table 1. For a room, there are 2 possible states (occupied or vacant). From time step t to time step $t + 1$, the number of transitions from occupancy state i to state j is $n_{ij}(t)$, and the number of rooms at occupancy state i at time t is $n_i(t)$, where

$$n_i(t) = \sum_{j=1}^{2} n_{ij}(t)$$

(2)

Then, the probability of transition from state i to state j at time step t is as shown in Eq. (3).

$$p_{ij}(t) = \frac{n_{ij}(t)}{n_i(t)}$$

(3)

From the occupancy state at time t and the transition matrix from time t to time $t + 1$, we can determine the state at time step $t + 1$. We generate a random number U (0,1) by the Monte-Carlo method and compare U with the transition probability to determine the occupancy state at time step $t + 1$. This process is repeated until an hourly occupancy schedule is generated for each room. In addition, according to the occupancy schedule and the recommended hourly lighting and equipment utilization rate schedule (from design standards for energy efficiency in public buildings) [43], we can obtain the hourly lighting and equipment utilization rate schedule for each room. When a room is occupied, the usage rates of lighting and equipment follow the recommended value; otherwise, the usage rates are 0.

2.1.4. Simulation method of occupant's interactions with thermostat

This study focuses on the simulation of the interactions of the occupants with the thermostat on a whole-building scale. Because we can obtain the indoor temperature probability distribution on the whole-building scale from the field measurement, the Monte-Carlo method is
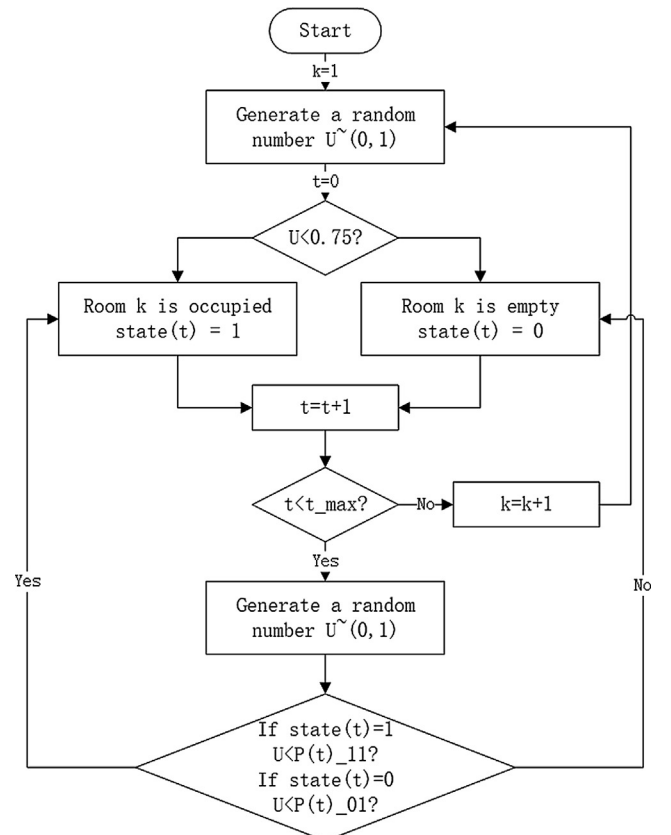

Fig. 1. Schematic for generating occupancy rate.

Table 1
An example of occupancy rate transfer matrices.

Time	State at time t	State at time $t + 1$	
		Vacant	Occupied
0:00–1:00	Vacant	0.8360	0.1640
	Occupied	0.0052	0.9948
1:00–2:00	Vacant	0.8151	0.1849
	Occupied	0.0010	0.9990
2:00–3:00	Vacant	0.8986	0.1014
	Occupied	0.0019	0.9981

applicable. The Monte-Carlo method mainly consists of two parts: random sampling and random number generation.

In this study, the inverse transform algorithm of the direct sampling method is chosen as the sampling algorithm. The principle of the inverse transform algorithm is as follows. If the probability distribution function of a random variable X is $f(x)$, and the cumulative distribution function $F(x)$ is a non-decreasing function, then the inverse function is defined as

$$F^{-1}(y) = \inf\{x \in [a, b]: F(x) \geq y, \quad 0 \leq y \leq 1\} \tag{4}$$

First, the inverse transform algorithm generates the random number U; then, the sample value is the inverse of the cumulative distribution function.

$$X = F^{-1}(U) \tag{5}$$

In terms of random number generation, true random numbers are generated by means of physical methods and require considerably high hardware costs and expenses. Therefore, we mathematically construct a pseudo-random number that is as close as possible to the characteristics of the true random number.

We can know the probability distribution of the temperature set-point from measurement. For simplicity, we set the range of temperature set-point as $(\mu - 2\sigma, \mu + 2\sigma)$, that is, 23–27 °C. The probability of each temperature set-point is as shown in Eq. (6):

$$f(x) = \begin{cases} 0.11, & x = 23 \\ 0.21, & x = 24 \\ 0.35, & x = 25 \\ 0.22, & x = 26 \\ 0.11, & x = 27 \end{cases} \tag{6}$$

We generate a random number U (0,1) through the Monte Carlo method to select the minimum sample value X that satisfies Eq. (7). For example, if the randomly generated U value does not exceed $\sum_{k=1}^{k} f(x_k)$, the sample value is the value of the minimum variable satisfying this condition.

$$X = F^{-1}(U) = \begin{cases} 23, & 0 < U \leq f(23) = 0.11 \\ 24, & 0.11 < U \leq f(23) + f(24) = 0.32 \\ 25, & 0.32 < U \leq \sum_{k=23}^{25} f(x_k) = 0.67 \\ 26, & 0.67 < U \leq \sum_{k=23}^{26} f(x_k) = 0.89 \\ 27, & 0.67 < U < 1 \end{cases} \tag{7}$$

According to the above method, the simulation process for the set-point is shown in Fig. 2. First, we read the occupancy status of each room at the current time one-by-one. If the room is vacant, the set-point at this hour is set to 40 °C, meaning that the AC is turned off. If the room is occupied, we use Monte-Carlo method to generate two random numbers to obtain two sample values by the method mentioned above and set the two values as temperature set-points for each half hour.

2.2. Modification of split-type air conditioner (AC) model

A constant-speed split-type AC is intermittently operated. For example, when the room temperature is higher than the temperature set-point in a cooling condition, the AC keeps running until the room
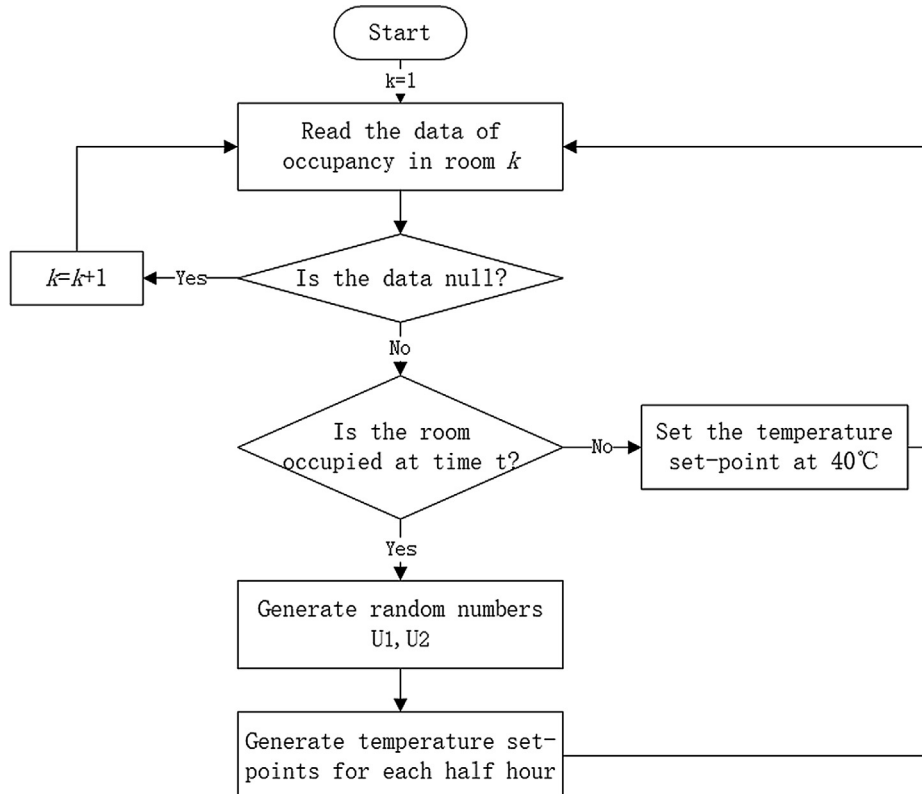

Fig. 2. Schematic of temperature set-point simulation.

temperature drops to a certain temperature (typically 0.5 °C or 1 °C) below the set-point. The AC restarts when the room temperature rises above an upper limit temperature (typically 0.5 °C or 1 °C above the set-point), and the compressor returns to equilibrium pressure. The intermittent operation causes the indoor temperature to fluctuate around the temperature set-point. A constant-speed split-type AC runs at full load during operation and cannot adjust the unit output. However, the above-mentioned operation characteristics are not reflected in the split-type AC model in E+. In fact, there is no separate split-type AC module in E+ [44]. Therefore, we simulate a split-type AC model by setting the corresponding heating and cooling DX coil in a unitary system. For a constant-speed split-type AC, we choose a single-speed DX coil (Coil: cooling, DX: single speed and Coil: heating, DX: Single Speed), and set the outdoor fresh air volume to 0. A user must set the coil capacity, sensible heat ratio, COP, and air flow ratio for the cooling DX coils. In addition, the user must set five correction curves describing the capacity and efficiency at partial load including temperature versus capacity correction, air flow ratio versus capacity correction, temperature versus energy input ratio (EIR) correction, air flow ratio versus EIR correction, and part load fraction (PLF) versus part load ratio (PLR). The energy consumption per time step is calculated as follows:

$$\text{Power} = (\dot{Q}_{total})(\text{EIR})(\text{RTF}) \tag{8}$$

Here, $\dot{Q}_{total}$ is the corrected capacity as calculated according to the correction curves, and EIR is the corrected EIR according to the correction curves. A running time factor (RTF), which differs from the general power calculation formula, is introduced here, and it is calculated as

$$\text{RTF} = \frac{PLR}{RLF}$$

$$\text{RLF} = a + b(\text{PLR}) + c(\text{PLR})^2 \ or \ \text{RLF}$$
$$= a + b(\text{PLR}) + c(\text{PLR})^2 + d(\text{PLR})^3 \tag{9}$$

$$\text{RLR} = \frac{sensible \ cooling \ load}{steadystate \ cooling \ capacity}$$

The RTF reflects the characteristics of the intermittent operation of the constant-speed split-type AC to a certain extent, but the calculated energy consumption and room temperature changes are different from the actual results.

To modify the split-type AC model, we need to know the call logic of E+. In E+, the split-type AC is a part of a zone equipment module. Therefore, a heating, ventilation, and air conditioning (HVAC) module will call the zone equipment module at each time step so as to call the unitary system module including the split-type AC. Fig. 3 shows that the unitary system contains multiple calling functions including GetUnitarySystemInput, InitUnitarySystem, UpdateUnitarySystem, and, most importantly, ControlCoolingSystemtoSP, which calculates the PLR of the system at the current time step and passes this value to the following calculation function.

In this study, we modify the RTF calculation to reflect the intermittent operation of the split-type AC model. The following four points need to be noted and modified:

(1) The RTF is determined by the PLR; thus, we modify the PLR instead. If the PLR is greater than a certain threshold, we set the current PLR to 1, meaning that the AC operates at full load. When the PLR is less than the threshold, we set the PLR to 0, meaning that the AC is off.
(2) In a warm-up stage, the judgment procedure is not employed in order to avoid a situation wherein the parameters at the same moment in adjacent days converge slowly because of the on-off operation of the AC.
(3) For a split-type AC, it takes approximately 3 min for the pressure to return to equilibrium before restarting. Therefore, the time step is set to 3 min in the simulation so as to ensure that when the split-

type AC is off, it needs at least 3 min to restart.
(4) There is a statement in the E+ program for judging the difference of zone temperatures between two adjacent time steps. If the temperature difference exceeds 0.3 °C, the simulation step of the latter time step is halved. This is repeated until the temperature difference of the adjacent time step does not exceed 0.3 °C. Because of the intermittent operation of the split-type AC, the indoor temperature fluctuates around the temperature set-point, and the temperature change between the two adjacent time steps is likely to be greater than 0.3 °C. Therefore, for the simulation of the split-type AC model, the temperature difference between the two time steps is not judged.

3. Results and discussion

3.1. OB monitoring

3.1.1. Occupancy monitoring

Occupancy data was obtained from the monitoring system of the four-star hotel located in downtown Shanghai, and 315 single rooms were equipped with the monitoring system. Data recorded by the monitoring system from May 20 to September 30, 2017, was selected for analysis. We exported the occupancy data from the MySQL database and processed it. Each room was marked "1" if occupied, and "0" if vacant. The average hourly occupancy rate of all rooms was considered the hourly occupancy rate at the whole-building scale as shown in Fig. 4.

Fig. 4 shows that the occupancy rate basically reaches a plateau at night. From 7 am to 10 am, which is the time when a large number of guests check out, the rate drops significantly. From 10:00 am to 11:00 am, as some new guests check in and some guests return to their rooms, the occupancy rate increases. From 12 am to 1 pm, owing to the large number of check-outs by hotel guests, the occupancy rate drops significantly. From 2 pm to 6 pm, because guests gradually leave the room, the rate drops gradually. From 7 pm, the rate increases significantly, indicating that the guests return to the hotel after a day of travel. This curve is consistent with our general understanding, which shows that the data from the hotel is representative.

3.1.2. Occupant interaction monitoring using thermostat

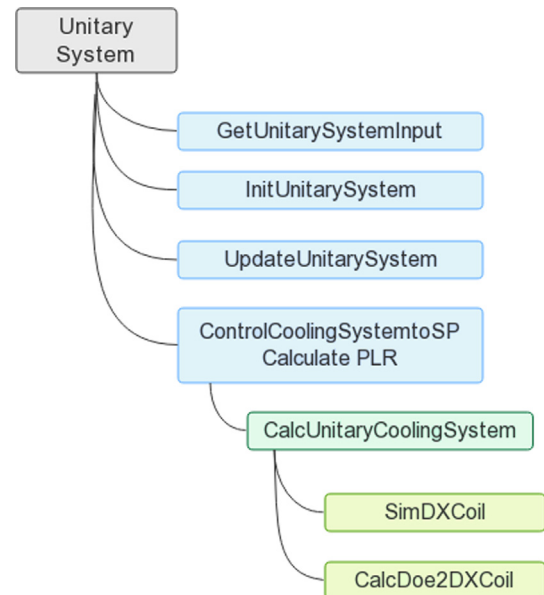Occupant interactions can be directly monitored using a thermostat

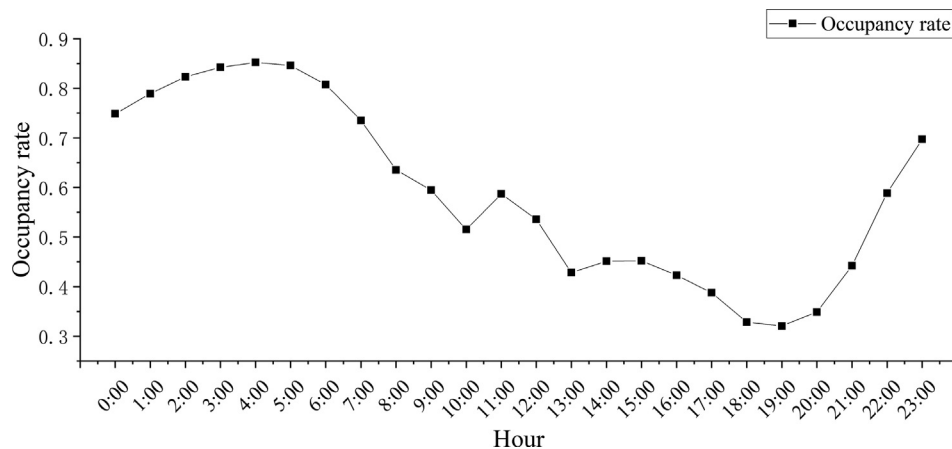**Fig. 3.** Call order of unitary system in EnergyPlus.

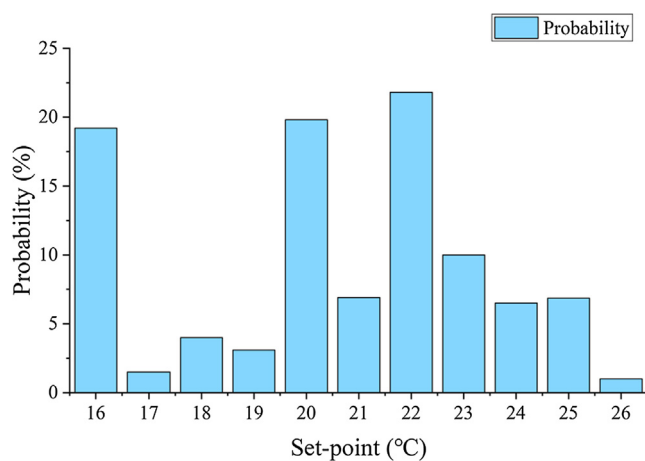Fig. 4. Monitoring results of hourly occupancy rate of the hotel.

Fig. 5. Monitoring results of temperature set-point distribution.
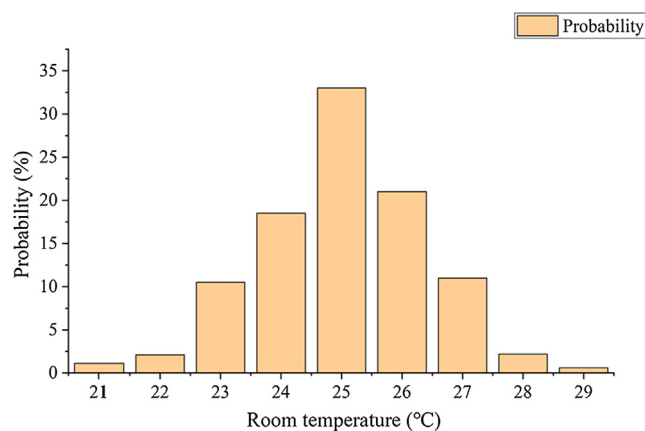

Fig. 6. Monitoring results of room temperature probability distribution.

sensor. Because this study focuses on the behavior during the cooling season, data from June 1 to September 30, 2017, were selected for analysis. To avoid the impact of multiple people in a single room and ensure the independence of events, only the data of single rooms in the hotel (a total of 315 rooms) were selected for analysis. The sample size of the hotel is far beyond the minimum requirement, so the results can be considered credible.

The distribution of the temperature set-point of the thermostat for all the rooms of the hotel in cooling conditions is shown in Fig. 5. Fig. 5 shows that there is no evident distribution of the temperature set-point.

In cooling conditions, guests tend to set the temperature to a lower value such as 16, 20, or 22 °C. Because 22 °C is the default set-point value on the thermostat panel, many guests tend to maintain it. At the same time, certain guests raise the temperature set-point. The change of the temperature set-point affects the indoor temperature, so we pay attention to the corresponding indoor temperature distribution when the thermostat is adjusted; this is shown in Fig. 6. A comparison of Figs. 5 and 6 reveals that although people tend to adjust the set-point to a lower temperature, they prefer an indoor temperature above the set-point. We infer that the thermostat adjustment behavior reflects a lack of understanding of the actual operation of the air-conditioning system. People tend to think that the lower the set-point is, the faster the room temperature drops, which is also proposed by Kempton [45]. In addition, the difference between the two distributions may also be caused by the deviation of the occupants' perception of temperature from the actual room temperature.

Fig. 6 shows that the selection of the room temperature has a probability distribution that approximates the normal distribution whose average is 24.95 °C and standard deviation is 1.36 °C. More than 94% of the occupants prefer the indoor temperature to be in the range of 23–27° C, which is consistent with our general understanding.

3.2. Simulation of the modified split-type AC model

We monitored the temperature and AC power changes on the days when the AC was turned on using a smart socket and a temperature recorder in a room equipped with the split-type AC. Fig. 7 shows that the room temperature drops rapidly after the AC is turned on, and the AC continuously operates for a prolonged period until the room temperature drops below the set-point. Thereafter, the AC intermittently operates to maintain the room temperature by fluctuating around the set-point. The measured results confirm the characteristics of the operating characteristics of the split-type AC and the room temperature fluctuations described above.

We compare the simulation results of the split-type AC model before and after the modification to verify whether it can effectively reflect the characteristics of a split-type AC. The simulation model we built in DesignBuilder is an office building model as shown in Fig. 8. We focus on four rooms with different orientations (marked with an asterisk). All rooms have the same temperature set-point, so the inner wall can be regarded as adiabatic. Each room has a unitary system mainly composed of a single-speed heating and cooling DX coil and a fan. The input parameters comply with the "Design Standard for Energy Efficiency of Public Buildings of China" as shown in Table 2. The indoor occupancy, lighting, and equipment schedules are shown in Fig. 9. The simulation period is from June 1 to Sept 31, 2017.

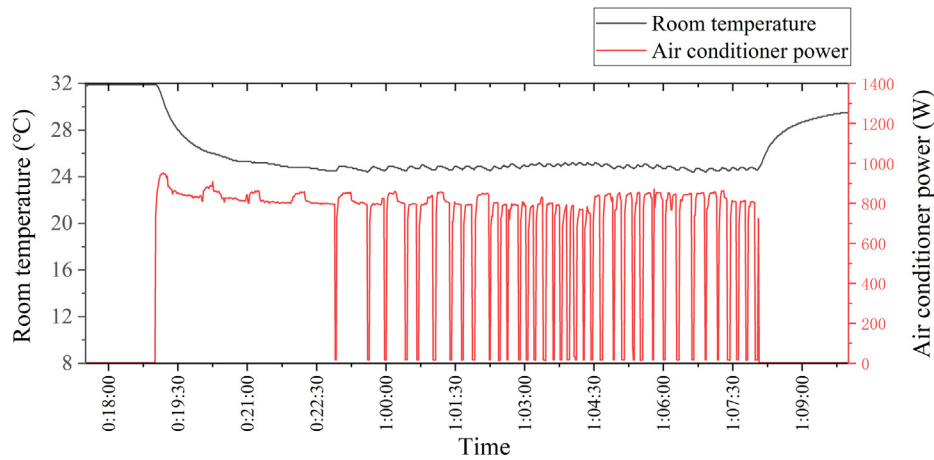The simulation results of the original model and the modified model

Fig. 7. Monitoring results of room temperature and air conditioning power changes from 19:00 July 23rd to 8:00 July 24th.
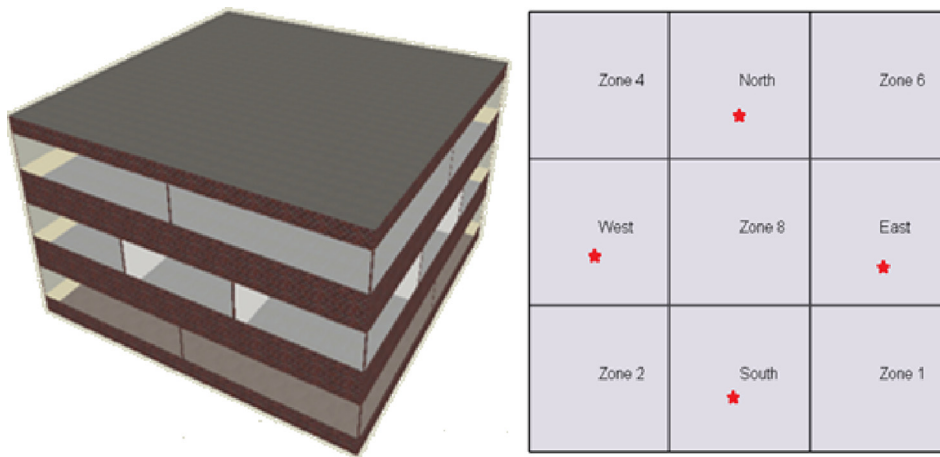

Fig. 8. Geometry rendering and plan of the EnergyPlus Model.

Table 2
Main input parameters of the model.

Area of each room	25 m²	
Window-wall ratio	0.5	
Story height	3.5 m	
Envelope	U-value (W/(m² K))	
Roof	0.5	
Exterior wall	0.8	
Exterior window	U-value (W/(m² K))	1.96
	Transmission coefficient of visible light (VT)	0.74
	Solar heat gain coefficient (SHGC)	0.69
Indoor load	Lighting (W/m²)	7
	Equipment (W/m²)	15
	Occupancy (person/room)	2
Design indoor temperature (°C)	25	
Design indoor relative humidity (%)	40–60	

are shown in Figs. 10 and 11, respectively. The figures show the PLR and indoor temperature of an occupied room facing the east on a day in winter (July 15). Although the results in Fig. 10 can reflect the overall operation of the AC and the change of PLR in one day, they cannot reflect the on-off characteristics. In Fig. 11 shows that the indoor temperature drops rapidly after the AC is turned on at 7:00; then, it fluctuates around the set-point. The PLR is 1 when the AC is turned on, and the PLR is 0 when the AC is turned off. By comparing the simulation results before and after the improvement, we observe that the improved model can better reflect the on-off characteristics of the split-type AC.

Table 3 demonstrates a comparison of the monthly energy consumption between the original model and the modified model. The difference between the simulation results of the original and modified models is 0.39%, which is significantly less than the simulation error limit of 5%. This indicates that the modified model can realize a more detailed simulation of the split-type AC on a smaller time scale than the original model without deviating from the calculated energy consumption results of the two models. Fig. 12 shows a comparison of the monthly energy consumption results for rooms with different orientations between the original model and the modified model. The energy consumptions of the orientations are different, and the energy consumption of rooms facing the east or west is higher than that of rooms facing the north or south in the cooling season; this is consistent with the results in [46].

3.3. Modified split-type AC model integrated with OB

3.3.1. Case study

A hotel building simulation is performed to verify the improvement of the modified split-type AC model due to the integrated OB model. We build a hotel model with DesignBuilder. The hotel has 7 floors wherein the 2nd to 6th floors have guest rooms. There are 100 guest rooms evenly distributed on 5 floors. The appearance of the model is shown in Fig. 13, and the plane schematic of a standard floor is shown in Fig. 14. The model is L-shaped with a 2-m-wide aisle and a uniform room size of 5 m × 5 m. All areas are air conditioned, and each guest room is equipped with a split-type AC system, whereas other areas use ideal load systems.
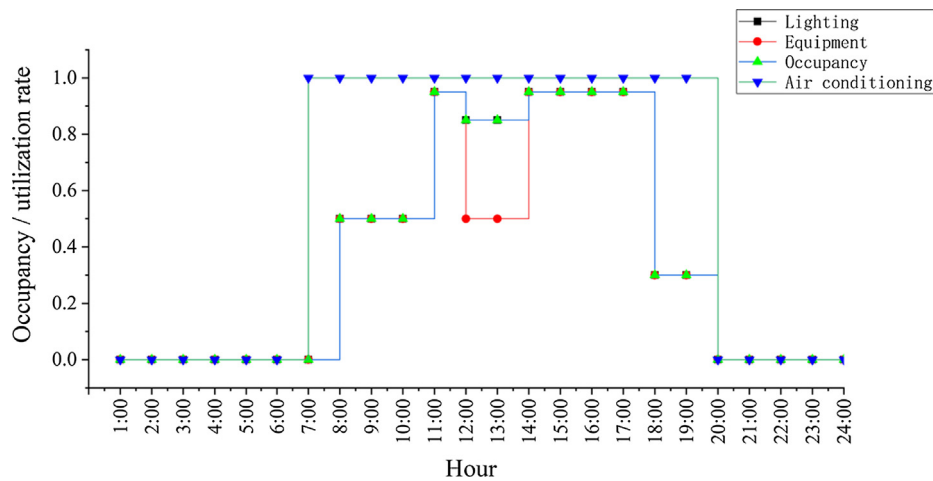
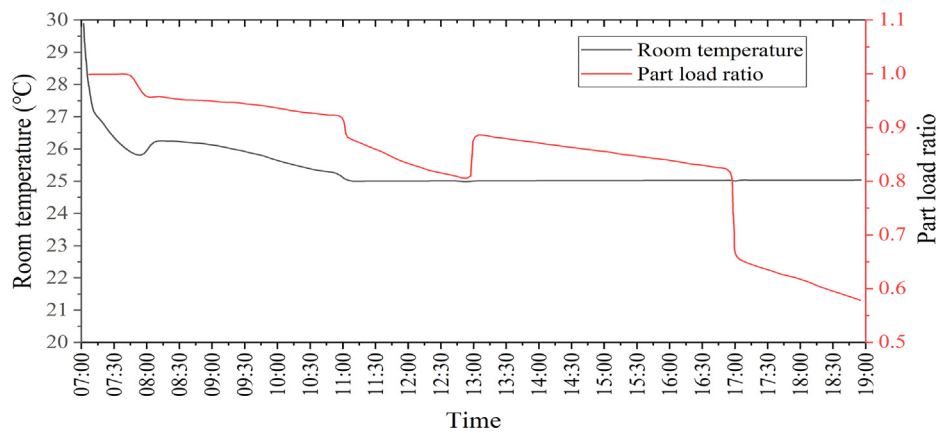**Fig. 9.** Simulation input of indoor occupancy, lighting, and equipment utilization rate schedule.

Fig. 10. Simulation results of an east-facing room on design day by original split-type AC model.
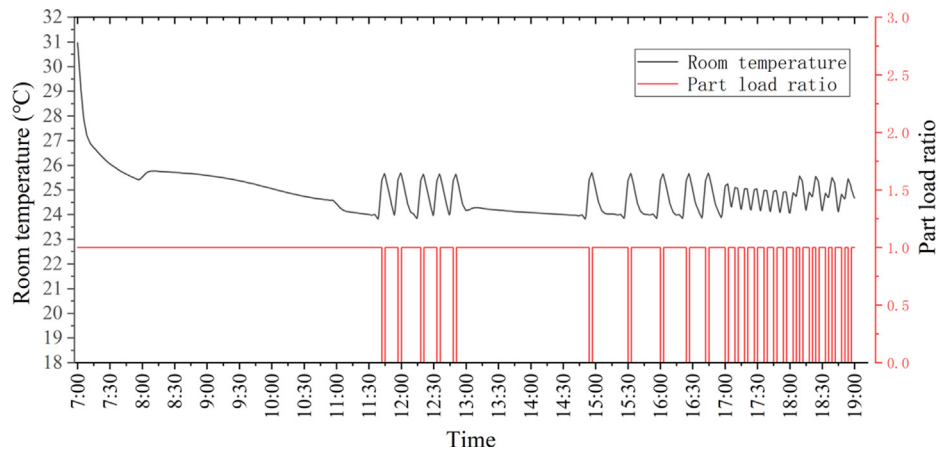

Fig. 11. Simulation results of east-facing room on design day by modified split-type AC model.

Table 3
Comparison of monthly energy consumption as calculated by the original model and the modified model.

Type	Air conditioning energy consumption (kWh)					Percentage of difference
	June	July	August	September	Total	
Modified	308.32	435.75	470.26	271.39	1485.72	0.39%
Original	310.28	430.20	471.77	267.63	1479.88	

The input parameters are determined according to the "Design Standard for Energy Efficiency of Public Buildings of China". The simulation period is from June to September of the cooling season. Similarly, the temperature set-point of the auxiliary space is 25 °C, which is the average of the probability distribution of indoor temperatures in the hotel. The main input parameters of the model are the same as those in the former simulation as shown in Table 2. The AC system parameters are shown in Table 4.
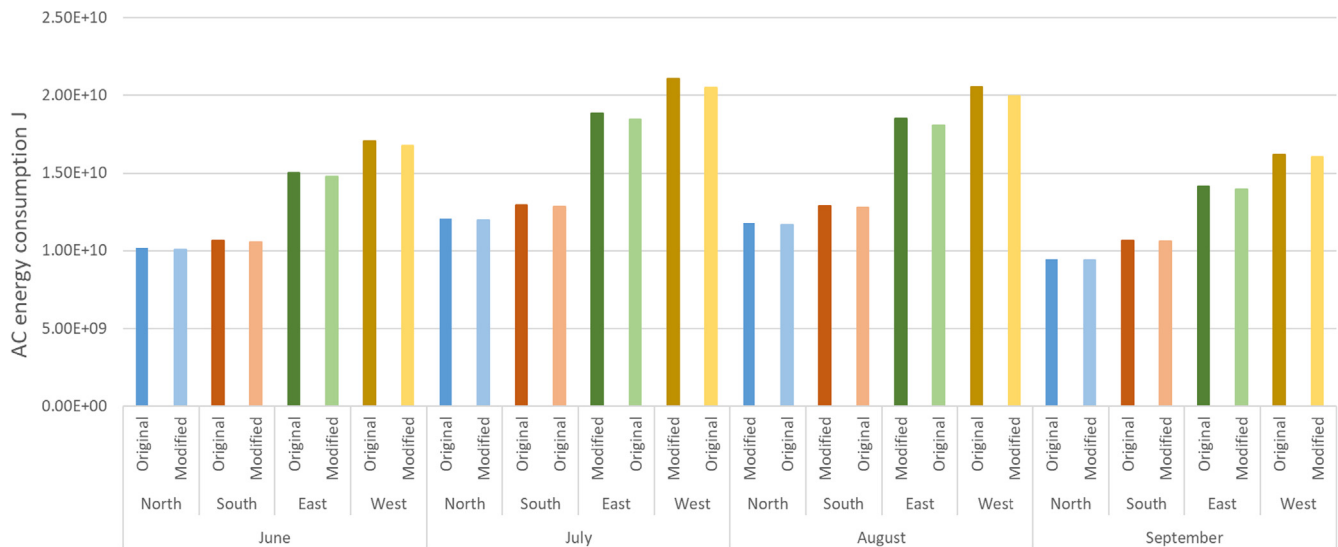
Fig. 12. Comparison of monthly energy consumption for rooms in different orientations as calculated by the original model and the modified model.
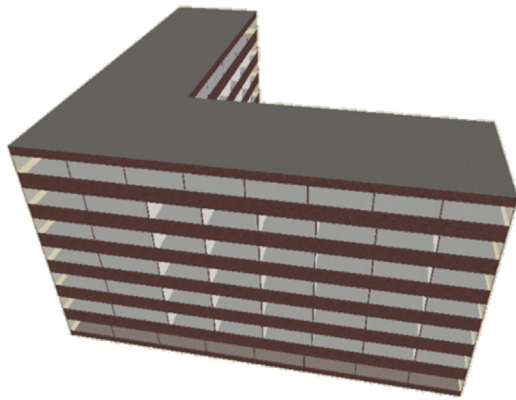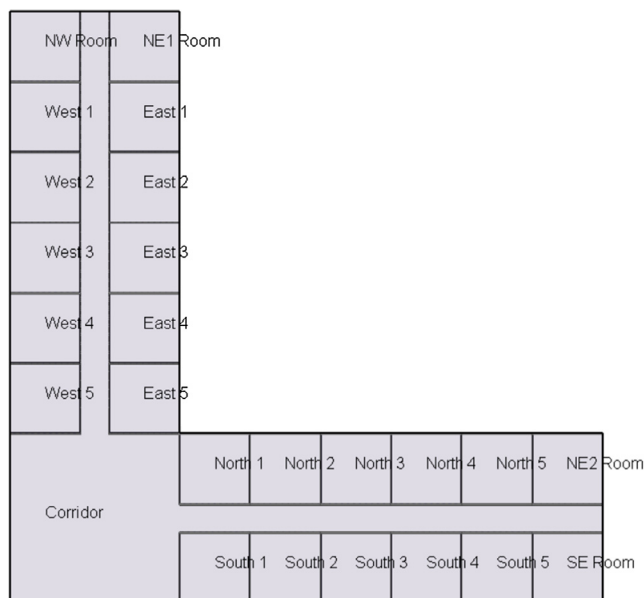

Fig. 13. 3D view of the hotel model.

Table 4
Main input parameters of the air conditioner (AC) system.

Parameters	Value
COP	3
Rated cooling capacity of coil	Autosize
Sensible heat ratio of coil	
Rated flow rate of coil	
Correction curves for coil capacity and EIR	Default
Outdoor fresh air volume	0
Fan type	Constant speed fan

3.3.2. Simulation of OB

In this section, we use the OB simulation method introduced in Section 2.1.3 and Section 2.1.4 to generate schedules for each room including the occupancy schedule, temperature set-point schedule, and lighting and equipment utilization rate schedule.

The occupancy rate schedule is obtained using the Markov Chain method. The lighting and equipment utilization rate schedule follows the recommended schedule according to the design standards for the energy efficiency of public buildings and the occupancy schedule. The air-conditioning set-point schedule is obtained using the Monte-Carlo method.

Fig. 15 shows the occupancy, lighting, and equipment utilization rate schedule for rooms with different orientations on July 1. The different occupancy, lighting, and equipment utilization rate schedules in different rooms reflect the randomness and diversity of OBs. A Markov Chain has "memory" that indicates that the state of occupancy of a room at any instance of time is related to the state of the previous instance. In addition, there is a transition matrix every hour, so that the change in occupancy status is time-related. The lighting and equipment utilization rates follow the occupancy change, which reflects their relationship.

Fig. 16 shows a comparison of the measured hourly average occupancy rate and the simulated hourly average occupancy rate of the 100 rooms. Both values and variation trends are almost the same, thereby indicating that the randomly-generated average occupancy rate at the whole-building scale can generally reflect the real occupancy rate.

To test whether the simulated occupancy rate curve and the real occupancy rate curve are statistically consistent, we adopt a Pearson correlation coefficient. The Pearson correlation coefficient between the two variables is calculated as follows:
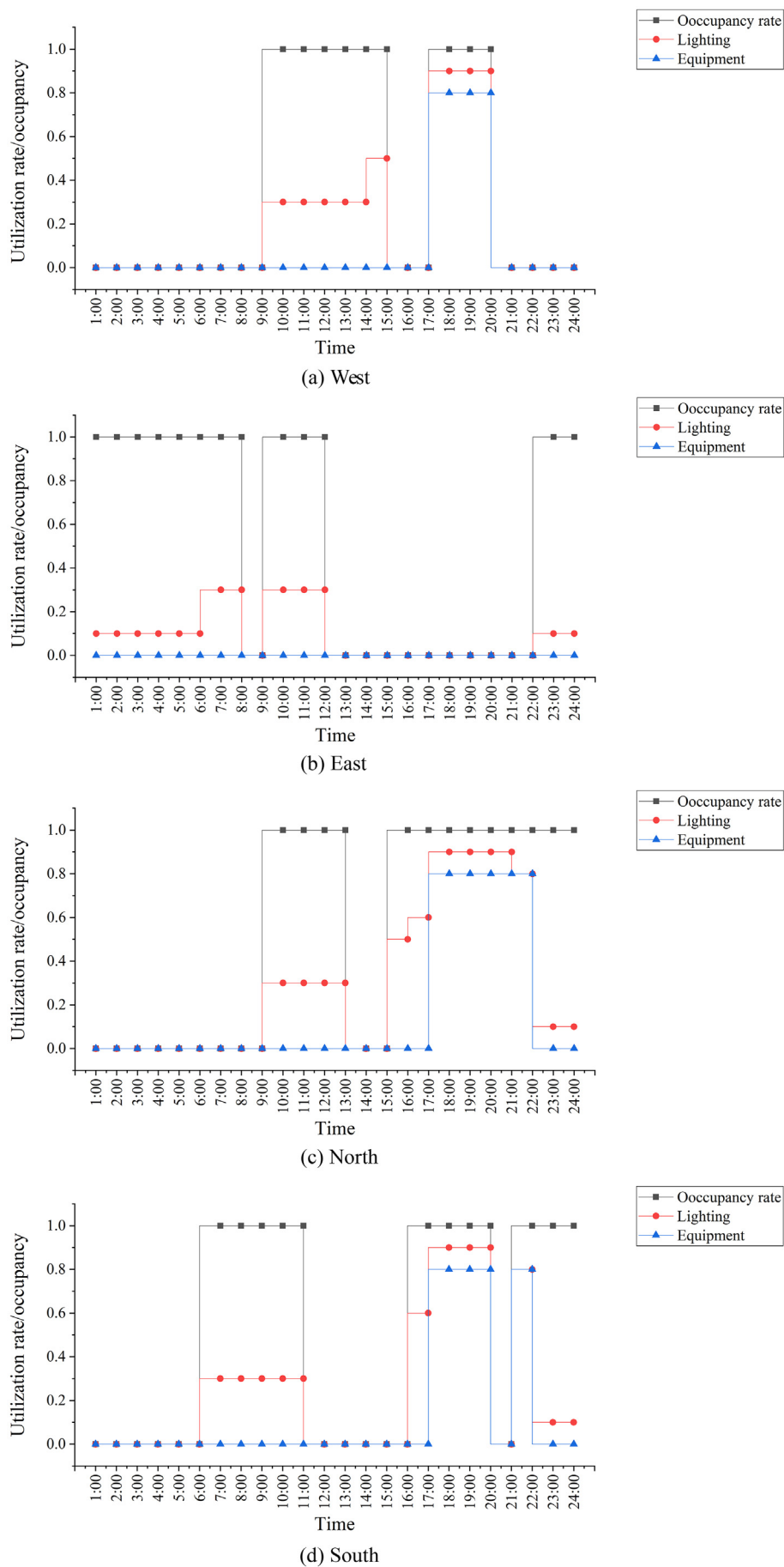

Fig. 14. Plane schematic of each floor.

(a) West

(b) East

(c) North

(d) South

Fig. 15. Simulation results of schedules for guest rooms in four orientations on July 1.
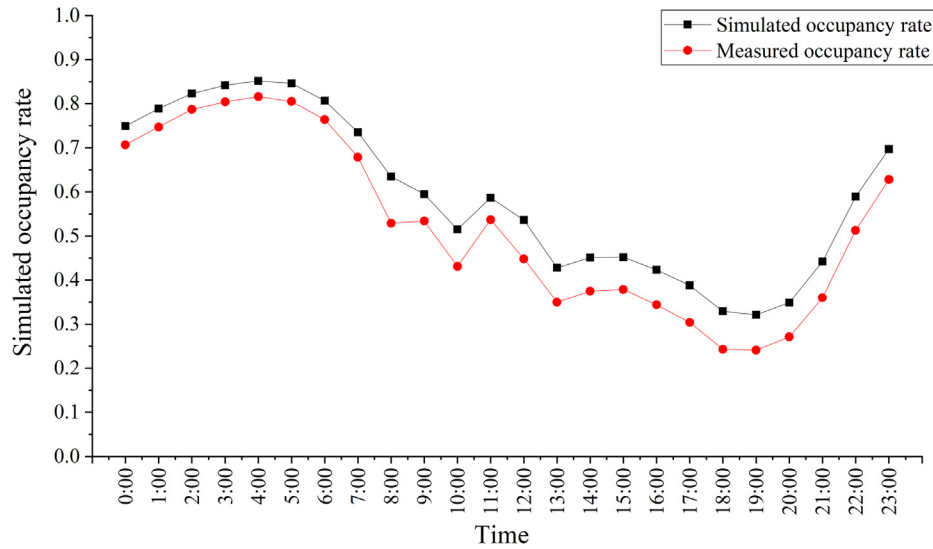
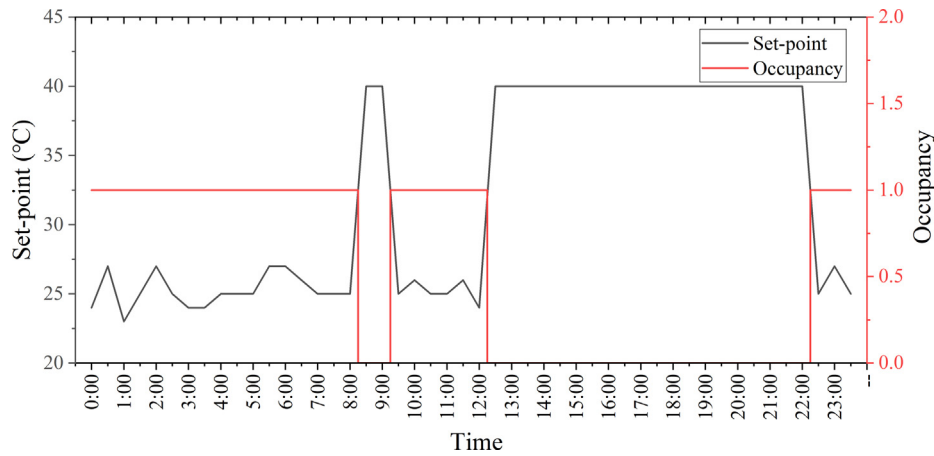**Fig. 16.** Comparison of occupancy rate between simulation and measurement.

Fig. 17. Simulated occupancy and set-point schedule of an eastern-facing guest room on July 1.

Table 5

Comparison of probability distributions from measurement and simulation.

Set-point (°C)	Probability distribution from measurement	Probability distribution from simulation
23	0.11	0.11
24	0.21	0.21
25	0.35	0.37
26	0.22	0.21
27	0.11	0.11

$$\rho_{X,Y} = corr(X, Y) = \frac{cov(X, Y)}{\sigma_X \sigma_Y} = \frac{E\left[(X - \mu_X)(Y - \mu_Y)\right]}{\sigma_X \sigma_Y} \qquad (10)$$

Here,

$cov(X, Y)$ represents the covariance between the two variables;
σ_X represents the standard deviation of the variable X;
σ_Y represents the standard deviation of the variable Y.

The Pearson correlation coefficient lies in the range $[-1, 1]$. The closer the value is to 0, the less is the correlation between the variables; the farther it is from 0, the higher is the correlation. The Pearson correlation coefficient between the two groups of occupancy rate data calculated by the above formula is 0.998; this indicates that the two groups are highly correlated.

Fig. 17 shows the air-conditioning set-point schedule and occupancy rate schedule for a room facing east on July 1. Similar to the lighting and equipment utilization rate schedule, the set-point schedule in each room also follows the occupancy schedule. It is evident that the AC is turned on only when the room is occupied. When the room is vacant, the set-point is 40 °C; when the room is occupied, the random generation of the set-point is carried out after every half hour to reflect the randomness of OBs.

We compare the set-point probability distribution obtained using the Monte-Carlo method with the measured probability distribution. Table 5 demonstrates that they are basically the same. Similarly, we use the Pearson correlation coefficient to test their correlation and the coefficient is 0.997, thereby indicating that the two groups of variables are highly correlated.

3.3.3. Simulation of modified split-type AC model integrated with OB

This section presents the simulation results of the modified split-type AC model integrated with the OB model. Fig. 16 shows a comparison of the indoor average temperature and temperature set-point in an east-facing room for a half-hour period on July 14 as simulated by the improved split-type AC model. The figure shows that when the AC is off (set-point at 40 °C), the room temperature gradually rises to a high temperature. When the AC is turned on, the indoor set-point is randomly generated after every half an hour. In Fig. 18, the set-point curve and the room temperature curve basically coincide, thereby indicating
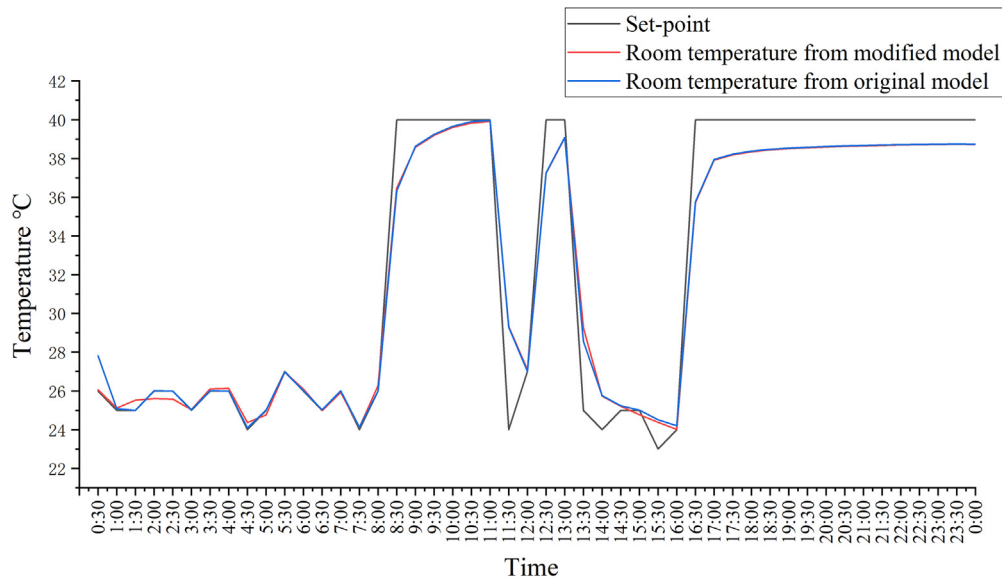
Fig. 18. Simulation results of temperature set-point and room average temperature of an eastern room calculated by the original and modified model on July 14th.
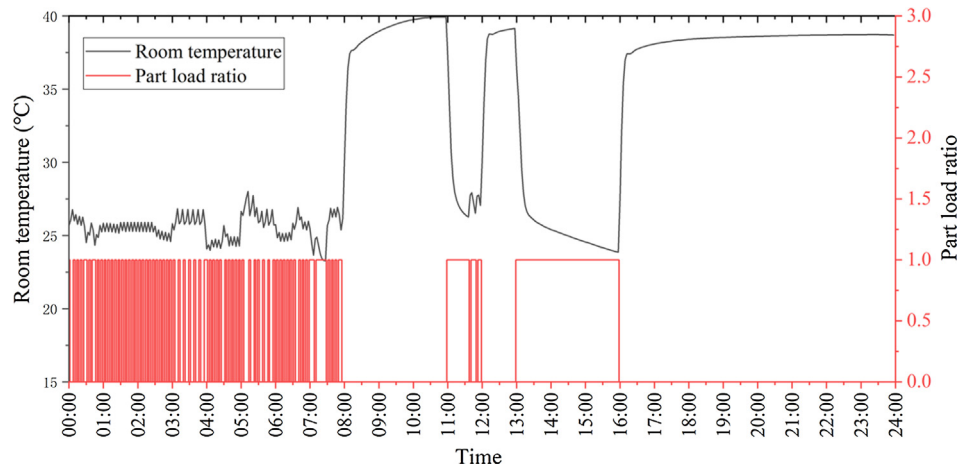

Fig. 19. Simulation results of the state of air conditioner (AC) and indoor temperature of an eastern room on July 14.

Table 6
Comparison of energy consumption from June to September in the two cases.

Energy consumption type	Modified (kWh)	Original (kWh)	Percentage of difference
Cooling	63,452	65,874	3.68%
Lighting	7935	9821	19.20%
Equipment	5258	9150	42.54%
Fan	31,762	32,807	3.19%
Total	108,407	117,652	7.86%

that the room temperature can change based on the set-point in most cases. In some cases, owing to the limited output of the AC, it is impossible to cool the indoor air to the set-point within a short duration of time, so that the indoor temperature curve and the set-point curve are separated. Overall, the improved model is able to simulate the random variation in room temperature following the set-point schedule.

Fig. 19 shows the operation of the split-type AC and the indoor temperature of an east-facing guest room on July 14. When the room is occupied, the indoor temperature fluctuates around the set-point. When the room is vacant, the PLR is 0 and the AC is switched off; thus, the room temperature rises rapidly. When the set-point is higher, the PLR curve appears to be "sparser", which is caused by the longer shutdown

and shorter start-up times of the AC. Similarly, when the set-point is lower, the PLR curve is "tighter", because the AC needs to turn on and off more frequently to maintain the indoor temperature around the set-point. The simulation results show that the combination of the modified split-type AC model and the OB model can not only reflect the randomness of the occupancy rate and thermostat-adjusting behavior but can also reflect the on-off characteristics of split-type AC and the resulting fluctuations in indoor temperature caused by them.

It is necessary to verify whether the simulation method combining the OB model and the modified AC model differs from the original simulation method. Therefore, we set a comparison case without stochastic modelling of OB wherein the occupancy and set-point schedules are determined according to the standard. Table 6 compares the energy consumption results calculated in the two cases; it demonstrates the impact of the integration of the OB model on the lighting and equipment energy consumption because this consumption depends on occupancy. The difference in energy consumption of AC is relatively small because it is affected by a variety of factors that include the temperature set-point, occupancy, and other indoor loads. The difference in total energy consumption results between the two cases is 7.86%, which exceeds the simulation acceptance error. Therefore, it is necessary to use the simulation method combining the modified split-air type AC model and OB model.

4. Conclusion and future work

OB significantly influences the energy consumed by the occupants of a building. Field measurements in this study indicate that the influences of occupancy and OB on air conditioning are not deterministic but are stochastic with the changing schedule of occupancy, temperature set-point, etc. In this study, a stochastic model is proposed to simulate occupancy based on the Markov Chain method that can illustrate the randomness of occupancy. Using a Monte-Carlo stochastic method, thermostat-adjusting behaviors are simulated at the scale of an entire building, and a temperature set-point schedule is generated for each room. Furthermore, the split-type AC has characteristics of intermittent operation that are reflected by the fact that the measured room temperature repeatedly oscillates around the temperature set-point. To consider this characteristic in the simulation of the split-type AC, this study modifies its module in E+. The following are the main results:

(1) A monitoring system that combines motion sensors and a hotel guest room control system is developed to measure the occupancy of each guest room in the hotel building, and a general occupancy schedule of the building is obtained. The changes in the measured occupancy rate are consistent with our general understanding.

(2) The probability distribution of the AC temperature set-point and the indoor temperature of the hotel building during the cooling season is obtained using the data recorded by the thermostat. The choice of the temperature set-point does not have a significant distribution; however, the preference for room temperature has a distinctly normal distribution. Most customers tend to keep the room temperature between 23 and 27 °C.

(3) The proposed stochastic model based on the Markov Chain and Monte-Carlo methods is suitable for the simulation of occupancy and thermostat-adjusting behaviors. The model can demonstrate the randomness of OBs and reflect the actual OB.

(4) The split-type AC module in E+ is modified such that the simulation results reflect the on-off characteristics of the AC and indoor-temperature fluctuation in actual operation.

(5) A simulation of a hotel building that integrates the OB model with the modified split-type AC model is conducted to verify the improvement and applicability of the model. The results show that the model can reflect both the randomness of OBs and the room temperature fluctuations around the temperature set-point through the AC on-off control. The energy consumption results of the modified split-type AC model, together with the OB model, differ significantly from the original simulation methods by 7.86%, thereby indicating the necessity for the integration of the OB model.

The primary contribution of this study is the presentation of an integrated approach for estimating the occupancy and the influence of OBs on air conditioning at the scale of an entire building and accurately simulating the improved split-type AC in E+ with a shorter time step. Besides the direct application in the simulation of energy consumed by the occupants of a building, the developed model can be considered for a number of practical applications such as energy demand response and fault detection and diagnosis (FDD). When evaluating a demand response strategy, the energy consumption simulation software is required to reflect the change of the indoor temperature and the energy demand of the equipment at a short time step. Therefore, the improved module that is capable of reflecting the energy consumption behavior more accurately must have a higher application value for the demand response. In the field of FDD, a model that can reflect the actual operation of distributed ACs is appropriate for use as the algorithm of a model-based diagnostic method.

Certain unresolved issues and related extensions of the present study are worth exploring. The scope of OB research in this study is limited to the whole-building scale, and the simulation is conducted based on the statistical data of the building. Therefore, it is impossible to accurately depict and simulate individuals or individual rooms. To simulate individual behaviors, further monitoring is needed, and the driving factors of individual behavior must be considered. In addition, more accurate measured data are needed to verify the energy consumption simulation of the modified model in the future. Finally, the split-type AC compares the return air temperature with the temperature set-point to control the operation of the unit. Therefore, the on-off logic of the split-type AC model still needs to be improved for better accuracy.

Acknowledgements

References

[1] International Energy Agency IEA. World: Balances for 2012; 2017.

[2] Joudi KA, Al-Amir QR. Experimental assessment of residential split type air-conditioning systems using alternative refrigerants to R-22 at high ambient temperatures. Energy Convers Manage 2014;86:496–506.

[3] Elgendy E, Melike M, Fatouh M. Experimental assessment of a split air conditioner working with R-417A under different indoor and outdoor conditions. Int J Refrig 2018;85:268–81.

[4] Martínez P, Ruiz J, Cutillas CG, Martínez PJ, Kaiser AS, Lucas M. Experimental study on energy performance of a split air-conditioner by using variable thickness evaporative cooling pads coupled to the condenser. Appl Therm Eng 2016;105:1041–50.

[5] Nada SA, Said MA. Performance and energy consumptions of split type air conditioning units for different arrangements of outdoor units in confined building shafts. Appl Therm Eng 2017;123:874–90.

[6] Mohammed JAK, Mohammed FM, Jabbar MAS. Investigation of high performance split air conditioning system by using Hybrid PID controller. Appl Therm Eng 2018;129:1240–51.

[7] Chen ZS, Qi XG, Cheng WL. Dynamic simulation of compression refrigeration system. Cryogenics 2000;6:35–9.

[8] St-Onge G. Variable capacity mini-split air source heat pump model for TRNSYS. École Polytechnique de Montréal 2018.

[9] Gomes A, Antunes CH, Martinho J. A physically-based model for simulating inverter type air conditioners/heat pumps. Energy 2013;50:110–9.

[10] Hong T, Sun K, Zhang R, Hinokuma R, Kasahara S, Yura Y. Development and validation of a new variable refrigerant flow system model in EnergyPlus. Energy Build 2016;117:399–411.

[11] Zhou Y, Wu J, Wang R. Module development and energy consumption simulation analysis of multi-evaporator inverter air conditioner in EnergyPlus. J Syst Simul 2007;20:4808–11.

[12] Hong T, Taylor-Lange SC, D'Oca S, Yan D, Corgnati SP. Advances in research and applications of energy-related occupant behavior in buildings. Energy Build 2016;116:694–702.

[13] Ahn KU, Kim DW, Park CS, De Wilde P. Predictability of occupant presence and performance gap in building energy simulation. Appl Energy 2017;208:1639–52.

[14] Wang C. Simulation research on occupant energy-related behaviors in building. Tsinghua University; 2014.

[15] Gaetani I, Hoes PJ, Hensen JLM. Estimating the influence of occupant behavior on building heating and cooling energy in one simulation run. Appl Energy 2018;223:159–71.

[16] Ouyang J, Hokao K. Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China. Energy Build 2009;41(7):711–20.

[17] Hong T, Yan D, D'Oca S, Chen CF. Ten questions concerning occupant behavior in buildings: The big picture. Build Environ 2017;114:518–30.

[18] Azar E, Al Ansari H. Framework to investigate energy conservation motivation and actions of building occupants: The case of a green campus in Abu Dhabi, UAE. Appl Energy 2017;190:563–71.

[19] Yan D, O'Brien W, Hong T, Feng X, Gunay HB, Tahmasebi F, et al. Occupant behavior modeling for building performance simulation: Current state and future challenges. Energy Build 2015;107:264–78.

[20] Lee B, Trcka M, Hensen JLM. Building energy simulation and optimization: A case study of industrial halls with varying process loads and occupancy patterns. Build Simul 2014;7(3):229–36.

[21] Fabi V, Andersen RV, Corgnati SP, Olesen B. A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings. Build Simul 2013;6(4):415–27.

[22] Reinhart CF, Voss K. Monitoring manual control of electric lighting and blinds. Light Res Technol 2003;35(3):243–58.

[23] Al-Mumin A, Khattab O, Sridhar G. Occupants' behavior and activity patterns influencing the energy consumption in the Kuwaiti residences. Energy Build 2003;35(6):549–59.

[24] Li Z, Jiang Y, Wei QP. Survey on energy consumption of air conditioning in summer in a residential building in Beijing. J Heating Ventilation Air Conditioning 2007;37(4):46–51.

[25] Ryu SH, Moon HJ. Development of an occupancy prediction model using indoor environmental data based on machine learning techniques. Build Environ 2016;107:1–9.

[26] Yang Z, Becerik-Gerber B. Modeling personalized occupancy profiles for representing long term patterns by using ambient context. Build Environ 2014;78:23–35.

[27] Yu Z, Fung BCM, Haghighat F, Yoshino H, Morofsky E. A systematic procedure to study the influence of occupant behavior on building energy consumption. Energy Build 2011;43(6):1409–17.

[28] Abreu PH, Silva DC, Amaro H, Magalhães R. Identification of residential energy consumption behaviors. J Energy Eng 2016;142(4):4016005.

[29] Ren X, Yan D, Hong T. Data mining of space heating system performance in affordable housing. Build Environ 2015;89:1–13.

[30] Yasue R, Habara H, Nakamichi A, Shimoda Y. Modeling the occupant behavior relating to window and air conditioner operation based on survey results. In: Proceedings of the 13th Conference of International Building Performance Simulation Association, Cambery, France; 2013.

[31] Schweiker M, Shukuya M. Comparison of theoretical and statistical models of air-conditioning-unit usage behavior in a residential setting under Japanese climatic conditions. Build Environ 2009;44(10):2137–49.

[32] do Carmo CMR, Christensen TH. Cluster analysis of residential heat load profiles and the role of technical and household characteristics. Energy Build 2016;125:171–80.

[33] Tanimoto J, Hagishima A. State transition probability for the Markov Model dealing with on/off cooling schedule in dwellings. Energy Build 2005;37(3):181–7.

[34] Haldi F, Robinson D. Interactions with window openings by office occupants. Build Environ 2009;44(12):2378–95.

[35] Jin WM, Han SH. Thermostat strategies impact on energy consumption in residential buildings. Energy Build 2011;43(2–3):338–46.

[36] Urban B, Elliott D, Sachs O. Towards better modeling of residential thermostats. Simbuild 2012.

[37] Jian Y, Jiang Y. Investigation and analysis of the operation status of air conditioners in residential rooms. Heating Refrig 2005;6:66–8.

[38] Feng X, Yan D, Hong T. Simulation of occupancy in buildings. Energy Build 2015;87:348–59.

[39] Soltanaghaei E, Whitehouse K. Practical occupancy detection for programmable and smart thermostats. Appl Energy 2018;220:842–55.

[40] Jackson DL. Revisiting sample size and number of parameter estimates: Some support for the N: q hypothesis. Struct Equ Model 2003;10(1):128–41.

[41] Richardson I, Thomson M, Infield D, Clifford C. Domestic electricity use: A high-resolution energy demand model. Energy Build 2010;42(10):1878–87.

[42] Widén J, Wäckelgård E. A high-resolution stochastic model of domestic activity patterns and electricity demand. Appl Energy 2010;87(6):1880–92.

[43] China Architecture and Building Press. The People's Republic of China National Standard GB 50189-2015, Design Standard for Energy Efficiency of Public Buildings with Explanation, Beijing; 2015.

[44] USDOE, EnergyPlus, www.energyplus.gov.

[45] Kempton W. Two theories of home heat control. Cogn Sci 1986;10(1):75–90.

[46] Li M. Research and practice of residential energy-saving design in hot summer and cold winter zone. Wuhan University of Technology; 2009.