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RESEARCH ARTICLE

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Investigation on typical occupant behavior in air-conditioned office buildings for South China's Pearl River Delta

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Abstract

The excessive simplification of occupant behavior is considered as the most important factor that affects the uncertainty of building performance simulation, thus affects the reliability and generalizability of simulation-based design and forecast. In this paper, occupant behavior in air-conditioned office buildings of the Pearl River Delta (PRD) region was investigated and defined. Copies of 873 questionnaires about the occupant behavior in air-conditioned office buildings in the PRD region were collected to study the relationship between indoor environment quality and adaptive behaviors. Eight typical office occupant schedules were defined via K-means clustering method. A probability prediction model of cooling temperature set-point was established by using the Ordinal Logistic Regression method. According to the different control modes of air conditioning, window, blind and lighting equipment, four types of typical behavior patterns were proposed using the K-prototype clustering method, which could be developed into 20 typical occupant behavior styles of office buildings in the PRD region.

Keywords: Building performance simulation, Occupant behavior model, Office building, Pearl River Delta, Indoor environment quality

1 Introduction

Due to the increasing demand for indoor environment and energy consumption, research related to building energy is considered a hot topic around the world. With the rapid development of computer science, building performance simulation is becoming a widely accepted method for building energy-related studies. However, there often exists a significant gap between the simulated and the actual energy consumption.

A report of International Energy Agency, Energy in the Buildings and Communities Program (IEA-EBC) Annex 53 stated that building energy consumption is influenced by mainly six parameters, namely meteorological parameters, building envelope, system equipment, indoor design criteria, system operation management and occupant behavior (Yoshino et al., 2017). Among them, occupant behavior in buildings has been widely recognized as a major factor contributing to the gaps between measured and simulated energy consumption in buildings (Chen et al., 2017; Sun et al., 2014; Sun et al., 2016; Yan et al., 2015). Zhou et al. (2016) showed that the stochastic characteristics of air conditioning use patterns were the main factor for the difference in energy consumption between the predicted and the actual performance. However, only one type of user behavior (air conditioning) was considered in some study, regardless of other office equipment (lighting, window, and blind). Sun & Hong, 2017 simulated and analyzed five typical occupant behavior, which concluded that individual occupant behavior could cause a difference of up to 22.9% of energy consumption, with respect to integrated behavior, the difference could be 41%. Eguaras-Martínez et al. (2014) showed that the difference between predicted energy

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consumption inclusion and exclusion of occupant behavior in building simulations could be up to 30%. The randomness of occupant behavior was often oversimplified or neglected, by using full-time full-space static assumptions or applying default settings according to building types and climate zones. From a simulation perspective, occupant behavior is a vital input part of the simulation process, it is essential to conduct an in-depth study on occupant behavior, achieving accurate occupant behavior module input value.

Scholars conducted various studies, indicating that the reason why occupant can affect building energy consumption was that occupant will perform a series of adaptive behaviors to achieve a new comfortable environment status (Yamaguchi et al., 2013; Yan et al., 2017). Therefore, information about the comfort desires of the occupant could be collected to improve the management of building energy consumption without sacrificing users' comfort or productivity (Pérez-Lombard et al., 2011; Chung, 2011). Besides, it was also crucial for simulation of occupant behavior to study the motivation of occupant interaction with the building environment (Yan et al., 2017).

Yan & Hong, 2018 focused on the definition or simulation of occupant behavior in buildings and attempted to conduct a comprehensive description of the random occupant behavior. Data from various locations and types of buildings worldwide were collected by scholars to build a library of stochastic occupant behavior models. A newly developed algorithm (the Yun algorithm) has been described to simulate the occupant behavior of window-control in dynamic building simulation software (Yun et al., 2009). The research discovered the relationship between occupant behavior and environmental parameters (Mahdavi et al., 2008). A probabilistic model to simulate and predict occupancy in a single-person office was proposed by examining the statistical properties of occupancy (Wang et al., 2005). Taking the university office with irregular occupancy as a case study, a static and dynamic model of the individual occupant and occupant behavior in an office environment in relation to building control systems were validated (Zimmermann, 2007). A new, open-source modeling tool was set for stochastic simulation to predict occupant services demand in buildings (Rysanek & Choudhary, 2015). Coupling of dynamic building simulation with stochastic modeling of occupant behavior in offices was introduced that can be used in energy uncertainty analysis. (Parys et al., 2011). A stochastic model of occupant behavior regarding ventilation is proposed to study time-series of window angle (Fritsch, 1990). The statistical occupancy time-series data at a ten-minute resolution was generated to describe realistic occupancy in UK households, that presented to provide a stochastic simulation of active occupancy patterns (Richardson et al., 2008). A stochastic bottom-up model based on data that occupancy patterns and daylight availability observed in measured lighting demand in detached houses has been presented and validated (Widén et al., 2009).

Presence models and action models were both included in the model base, the presence models (often referred as the occupancy schedule) describes the presence, absence and movement of occupants in space. The action model describes various types of adaptive and non-adaptive behavior, such as switching on/off air conditioning equipment, lighting, window and blind. Typical cooling load curves were used by Chow et al. (2004) and Gang et al. (2015) to simulate the different schedules of several building types (such as offices, residential buildings, and hotels), the performance of the system was analyzed according to the predicted load. The occupancy schedule was established by mining the energy consumption data of office building equipment, comparing with the occupancy schedule of medium-sized office building proposed by the DOE prototype, the results showed that there was a 36.67–50.53% difference between the "prototype" and the actual specific office (Zhao et al., 2014).

Pearl River Delta is an alluvial plain located in the subtropical climate zone of southern Guangdong, China, which covers an area of around 55,000 km^2, and a population of about 57 million. Considered as one of the most prosperous bay areas in the world, Pearl River Delta contains a huge scale of developed urban agglomeration, which emphasizes the importance of urban energy design and management. Occupant behavior, which is considered as the most important factor that affects the energy performance of buildings, has been the research focus of scholars.

At present, there is no first-hand data for occupant behaviors within buildings in this area in the ASHRAE database (ASHRAE, 2013). In this study, a questionnaire was proposed from the literature review, which contains questions on thermal comfort, occupant behavior and sharing authority within air-conditioned office buildings. From the analysis of the survey results, the preference of occupant adaptive behavior in air-conditioned indoor environment was investigated. A prediction model of cooling temperature set points were obtained. A series of occupant behavior styles for air-conditioned office buildings in the PRD region were summarized.

2 Methodology

2.1 Basic information of questionnaire

The occupant behavior within the building is affected by various "driving forces", both internal (such as lifestyle, age, gender, attitude, preference, etc.) and external (such as temperature, humidity, wind speed, building property etc.) (Sun & Hong, 2017). In order to investigate the intention behind the behavior as well as the interaction between thermal comfort and occupant behavior in the office, a questionnaire survey was conducted in the PRD region from March to April 2019. The questions could be divided into thermal comfort, equipment control preference, office type as well as the personal basic information, as shown in Table 1. Yan et al. (2015) pointed out that the occupant behavior mainly includes the operation of air conditioning, lighting, window, blind and plug-in appliances. Based on the large-scale questionnaire survey, the typical pattern of various kinds of occupant behaviors was mined by the clustering method and then combined to form the occupant behavior style model. In this study, the occupant behavior on plug-in electric appliances was not considered, because in the office building, high power plug-in electric life appliances such as TV sets, refrigerators or washing machines were quite rare.

The questionnaires were distributed both online and on-site. The e-questionnaire was released on March 11, 2019, and recalled on April 30, 2019. During the survey period, though not every day, the air temperature often exceeds 30 °C. In the downtown area the peak temperature was even as high as 32 °C. Due to the high relative humidity, natural ventilation is not applicable especially in offices with multiple occupants. In this case, it is believed that the questionnaire result could reflect the occupants' behavior toward air-conditioned indoor environment. While a submission was made, the location, as well as the time of the submission, could be identified. Only those submissions with all the questions answered, located within the 9 main cities of the PRD and submitted during office hours were considered valid. Questionnaires with contradictory or casually random answers were also excluded. The number of interviews of online survey reached 4571, within which 667 valid questionnaires were collected. For the filed survey, a total of 206 valid questionnaire were collected till May 15, 2019.

2.2 Occupancy schedule analysis

Occupancy schedule is a major issue in occupant behavior model for occupants would make adjustment according to comfort or behavior habits only when they are presented in the building (Sun et al., 2014; Wang et al., 2011). Currently, the static occupancy schedule is widely applied for building performance simulation. Many relevant government institutions and academic organizations provide occupancy for different building types in local design or evaluation standards. However, the movement and spatial change of users within one building could not be fully reflected by one single static schedule (Sun & Hong, 2017). In this study, occupancy schedules for different office scenes were defined by 3D scatter diagram method and the K-mean clustering analysis method. The random motion of occupants was simulated by the Markov chain method proposed by Wang et al. (2011), which indicates that the random movement probability of the person is related to time, and the future state depends on the current state. The random user motion was simulated with the application of the DeST software using the Markov chain model, and the results were stored in the SQLite database. This method can reflect the changes of the user's presence and movement indoor, which can reflect the user's diversity and random features.

2.3 Cooling temperature set point prediction

The indoor cooling temperature set point is the most critical and direct factor affecting cooling load, which reflects occupant thermal comfort requirements. In this study, the influencing factors of the cooling temperature set point were analyzed by the IBM SPSS Statistics 23 Ordinal Logistic Regression method to establish the prediction model, which can predict the cooling temperature set-point probability based on the office case information. Ordinal logistic regression model fitting information test is based on the original hypothesis that all constant coefficients of the independent variable are 0. When P (Sig.) < 0.05, it means 95% probability believes that the original hypothesis is not valid, which indicates that the prediction model has statistical significance.

Table 1 Questionnaire structure and content in this study

Structure	The questionnaire content
Thermal comfort	Thermal sensation vote (TSV), wet sensation vote (WSV), indoor environment quality (IEQ), adaptive behavior
Equipment control pattern	Seasonal demand for air conditioning, adjustment pattern, equipment status, behavior preference, whether to use heating equipment, energy-saving consciousness
Share permission	Control authority, deliberative frequency, collective interaction
Office information	Commuting schedule, office size
Personal information	Gender, age, work city, profession, office activity, the relative position of office

When the goodness of fit test (χ^2) of the model is $P > 0.05$, which shows that the goodness of fit of the model is better. The parallel line test is one of the most essential characteristics of the logistic regression model with ordered multi-classification. The original hypothesis of the parallel test is that the coefficients of independent variables of multiple binary logistic regression are equal, and when the value of P (Sig.) is >0.05, the original hypothesis can be considered valid.

$$Y = \log it(p_j) = \ln\left(\frac{p_j}{1-p_j}\right) = A_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

Where, $P_j = P(y \le j|x)$, represents the cumulative probability of y taking the first j values.

Cumulative dependent variable probability follows a formula (2).

$$P_j = p(Y \le j|x) = \left\{ \begin{array}{c} \frac{\exp(\alpha_j+\beta_n x_n)}{1+\exp(\alpha_j+\beta_n x_n)}, when\ 1 \le j \le k-1 \\ 1 \quad , \quad when\ j = k \end{array} \right\} \tag{2}$$

j is a dependent variable partition point, α_j is the constant term corresponding to the x cooling temperature, x_n is the n influencing factor, β_n is the regression coefficient of the n influencing factor.

Probability prediction formula of the single dependent variable (3).

$$p(Y = j|) = P_j - P_{j-1}, \quad j = 1, \cdots, k \tag{3}$$

j is a dependent variable partition point, k is the k cooling temperature.

In this study, the influencing factor of the cooling temperature set point is defined as IDV (X_1, X_2, ... X_k): X_1-age, X_2-the effect of IAQ on work efficiency, X_3-the effect of temperature on work efficiency, X_4-control authority, X_5-activity intensity, X_6-thermal sensation voting (TSV), X_7-whether the air conditioning run all the time in summer, X_8-air velocity range, X_9-status of window when the air conditioning on, X_{10}-office nature, X_{11}-office scale, X_{12}-the effect of humidity on work efficiency, X_{13}-air condition demand, X_{14}-distance from air outlet.

2.4 Equipment control models

It is a random event that whether someone in the office control equipment at a specific time or not. The occupant may take different behaviors facing the same environment or event that related to the indoor environment, daily events (commuting, leaving temporarily) and person. The clustering method is conducted by this study to classify occupants, and the probability of occupant behavior that corresponds to different types of users is further counted (Silva et al., 2009).

The factors affecting equipment control are divided into environmental triggers and event triggers. The mode of "open when feeling hot" (related to indoor temperature) or "open when feeling stuffy" (related to indoor humidity) is considered as an environmental trigger, which is described as (4).

$$P_{\text{on}} = \begin{cases} 1 - e^{-\left(\frac{t-u}{l}\right)^k \nabla\tau} t \le u, \\ 0 \quad t < u \end{cases} \tag{4}$$

Where P_{on} is the probability that the user will control the equipment; t is the indoor temperature (°C), u is threshold temperature (°C), l is the scale parameter, which is dimensionless to the temperature, k is the shape parameter, which indicates the sensitivity to the environment, $\nabla\tau$ is the time step in measurement and simulation, which is typically set at 10 minutes.

The mode of "turn on when at work", "closed when leaving temporarily" and "closed at work" are considered as event triggers, and the probability of which is described as (5).

$$P_{\text{on}} = \begin{cases} P & \tau = \tau_0 \\ 0 & \tau \ne \tau_0 \end{cases} \tag{5}$$

Where P_{on} is the probability that the user will control the equipment, τ is the current time spot in the simulation, τ_0 is the time spot when the relevant event occurs.

3 Result and discussion

3.1 Impact of IEQ factors on occupant behavior

The impact factors of IEQ that affect productivity was studied in this study. According to the survey result, a seven-latitude radar chart was applied here as in Fig. 1. It is clear that humidity has a relatively low impact on work efficiency. 634 out of the 873 subjects, accounting for 72.3%, believe that temperature had a more considerable influence than humidity, which was also the difference of the main adaptation behavior between temperature and humidity discomfort. 5.5% of subjects did not take any adaptive actions to improve the thermal comfort status even under cold conditions, while a proportion of 15.2% subjects did not take any actions in the case of highly humid environment.

The evaluation of the satisfaction level of indoor environment quality is shown in Fig. 2. It can be concluded that the subjects generally believed that indoor temperature and indoor air quality have an influence on their working efficiency, but the corresponding satisfaction degree is not so high. Subjects thought that the humidity environment only has an average impact on work efficiency.

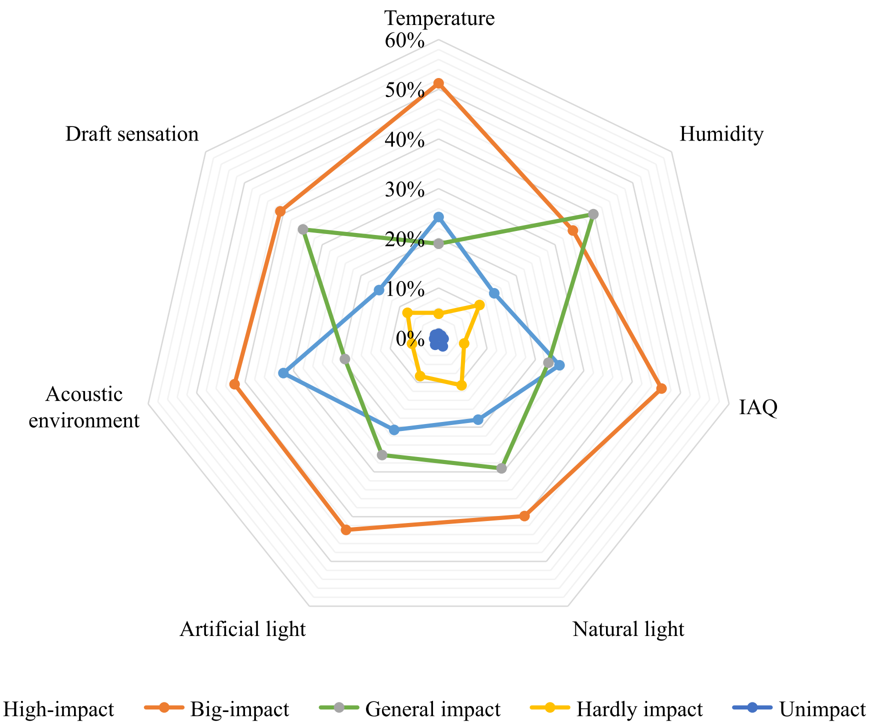

Fig. 1 The evaluation of the influence of indoor environment quality on work efficiency

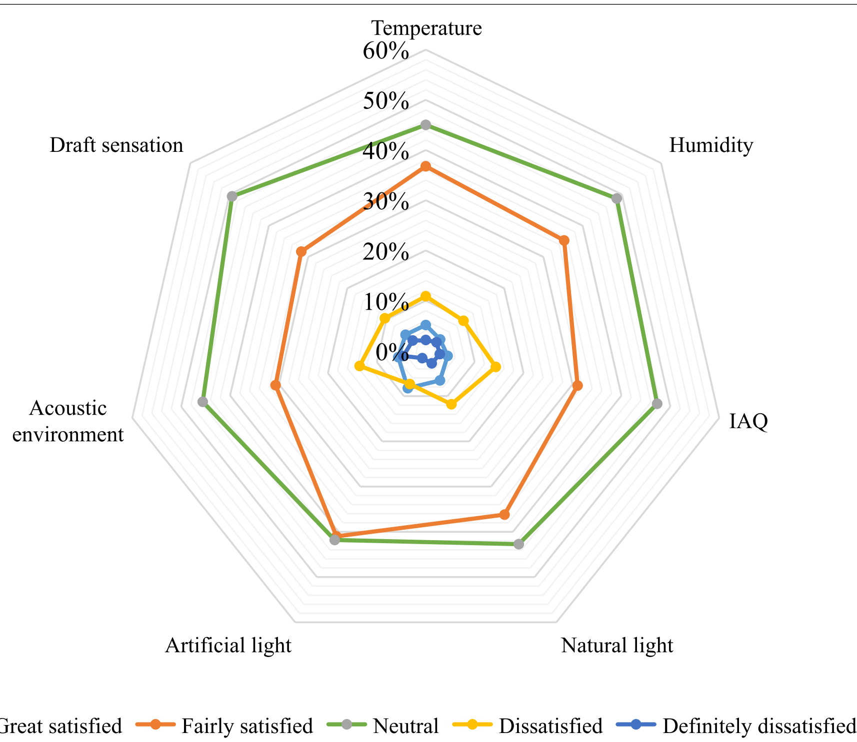

Fig. 2 The evaluation of the satisfaction level of indoor environment quality

Indoor thermal comfort within office buildings is an essential factor affecting health, work efficiency, and energy consumption. In this study, while analyzing subjects' vote on indoor temperature and humidity, it was found that 18.9% of subjects thought that the indoor temperature of the office is slightly too low in summer. In order to study the influence of office staff's temperature and humidity perception, a 3-D cross-analysis was conducted to analysis temperature and humidity perception voting, as shown in Fig. 3. When the thermal environment is relatively satisfactory, most of the humidity complaint were in a neutral state. In general, when occupants feel hot in summer and cold in winter (discomfort conditions), humidity perception voting is hugely diversified. The result showed that in the PRD region, the temperature has a positive impact on

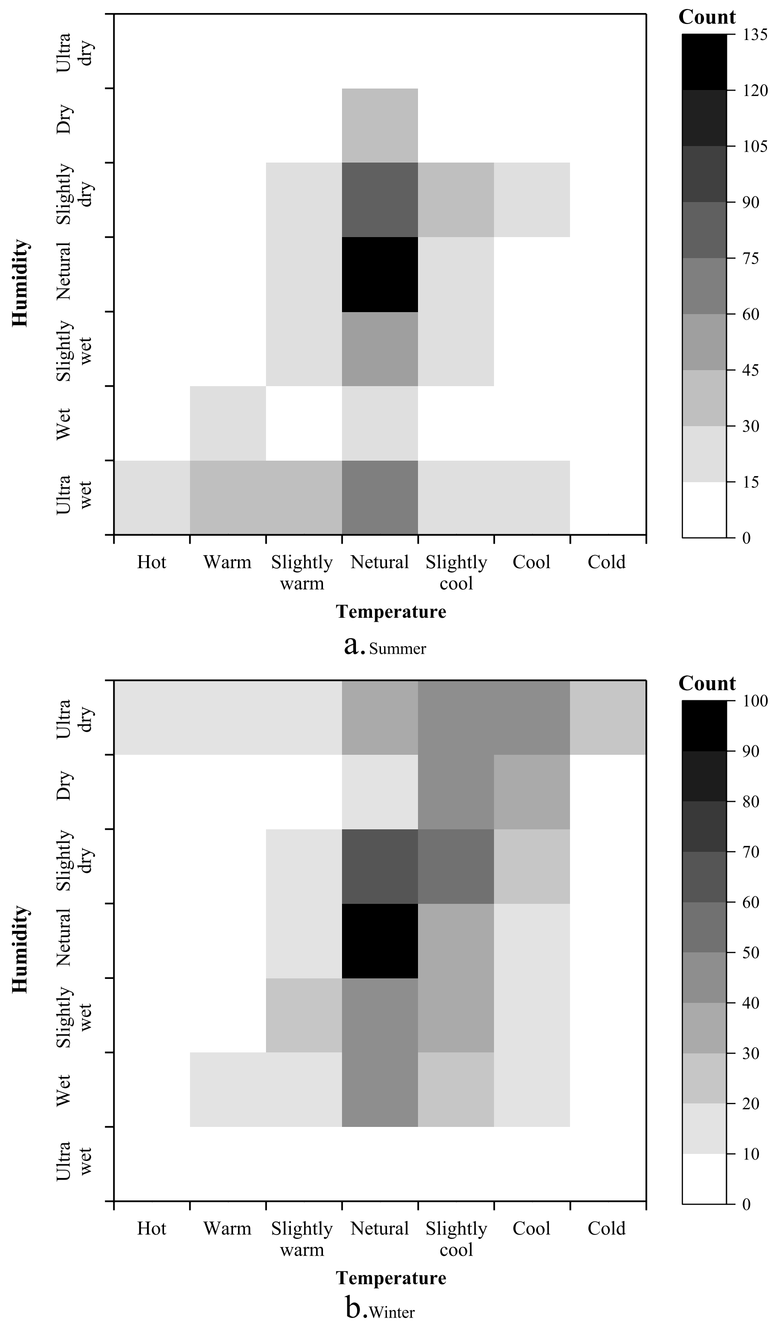

Fig. 3 Distribution of indoor temperature and humidity

wet feeling. When subjects are in a comfortable thermal environment, the acceptance rate of humidity will increase. The temperature and humidity of the indoor thermal environment are mutually coupled, and the influence of one factor on occupant comfort can be compensated by the corresponding change of the other factor.

Occupant behavior of office building is diversified while facing the same thermal discomfort, which can be interpreted as individual adaptive preference. During the interview about temperature-related adaptive behavior, subjects were asked about their preference for behavior during a temperature-related uncomfortable period. The result is shown in Fig. 4. In a hot and humid area such as PRD, the air conditioning is the first choice by 71.0% of subjects while they feel hot. On the contrary, in the case of a cold situation, clothes are chosen by 50.0% - 59.0%, and closing the doors and windows is chosen by 41.0%. The probability of switching on air-conditioning behavior decreases dramatically to under 20.0%, which is consistent with the trend that only 19.5% of subjects in the PRD region have heating systems.

Occupant behavior under humidity related discomfort situation is shown in Fig. 5. The probability of air conditioning switching is 32.0%. While 27.2% of subjects choose to close doors or windows, 20.0% choose to open fans. In dry cases, the probability of taking non-actions have been increased to 21.0%.

So far, most studies on occupant behavior only focus on one specific behavior, while in practice, multiple behaviors may be taken by occupants to adjust the indoor environment in many cases (e.g., opening office doors and windows to provide cross ventilation). The applicability of these multi-behavior models was not clear (Yan et al., 2015). In this study, relevant data were collected to study the probability of multiple actions triggered and how to restrict or negotiate each action under uncomfortable conditions.

In order to study the probability between behaviors triggered by thermal discomfort, Fig. 6 was obtained after data analysis and statistics. As shown in the figure, the probability of single behavior is relatively small under extreme thermal discomfort. Under opening air conditioning behavior, a combination of turning on air conditioning and reducing clothing is 11.7%, While the combination of turning on air conditioning and opening fans is 5.16%. It indicates that while facing extreme thermal discomfort, multiple behaviors would be triggered in most cases.

In order to further study the balance among different occupant adaptive behaviors under the thermal discomfort status, the correlation among the possible adjust behaviors of the four devices was analyzed, and the P/Sig. value and the correlation coefficient (Phi) were obtained, as shown in Table 2.

The results show that air conditioning behavior has a significant effect on the adjustment actions of clothing, fan, door, and window during the hot period. When the air conditioning switching behavior occurs, the probability of reducing clothing increase, while the probability of opening fans and windows decrease. However, for any thermal discomfort situation, the action towards air

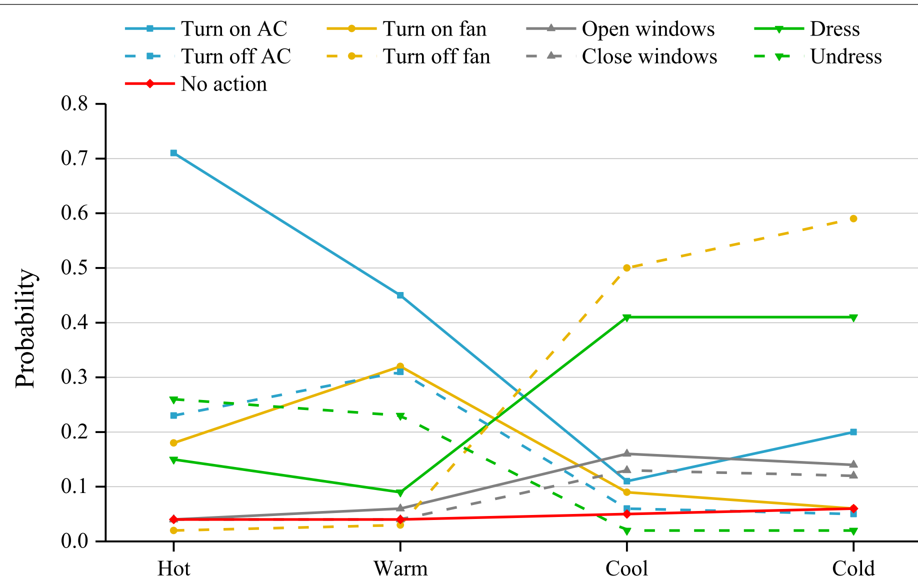

Fig. 4 The tendency of temperature-related occupant behaviors to restore thermal comfort

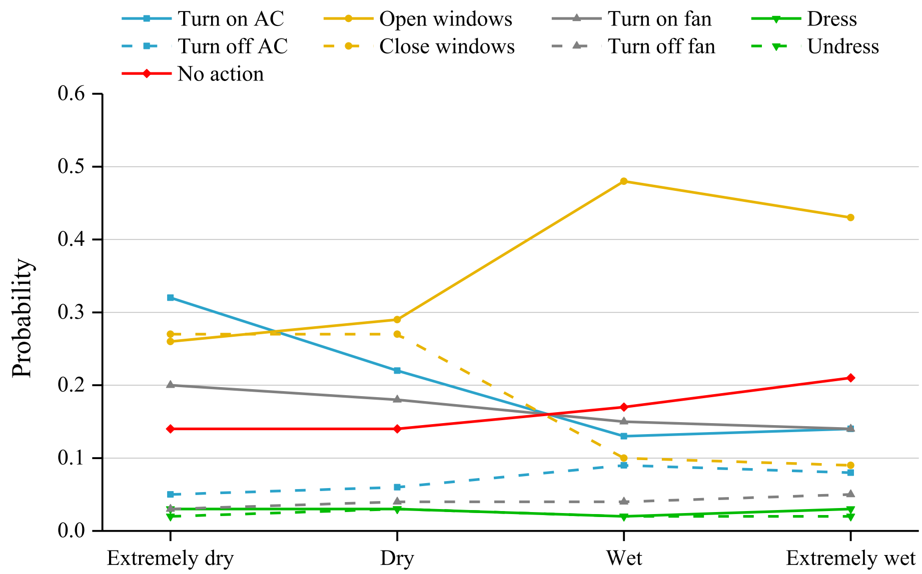

Fig. 5 The tendency of humidity-related occupant behaviors to restore thermal comfort

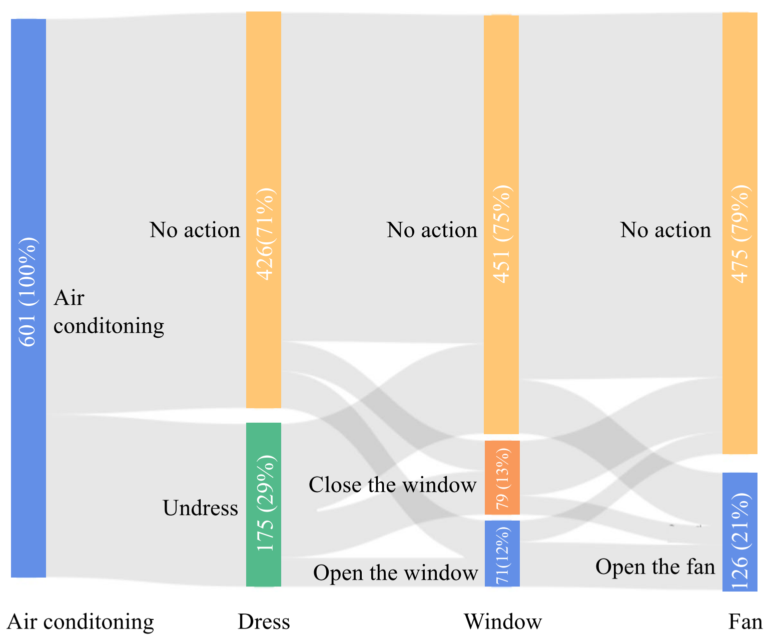

Fig. 6 Adaptive behaviors under opening air conditioning to restore extreme heat discomfort

conditioning has no significant effect on window related behavior. It is also found that the probability of air conditioning switching behavior is reduced when the fan switching behavior occurs. In extreme discomfort conditions, occupants would choose the air conditioning rather than the fan.

In order to further study the occupant adaptive behavior under humidity related discomfort, the correlation among the behaviors toward the four devices was analyzed. The P/Sig. value and the correlation coefficient (Phi) were obtained, as shown in Table 3.

Table 2 The correlation between interaction behaviors to restore thermal discomfort

Discomfort	Main behavior	Other behavior	P/ Sig.	Significance	Phi	Relevance
Hot	Turn on air conditioning	Turn off window	0.000	***	−0.270	–
		Undress	0.001	**	0.110	+
		Turn on fan	0.002	**	−0.102	–
	Turn on fan	Turn off window	0.090	–	−0.049	0
		Turn off air conditioning	0.020	*	−0.270	–
Warm	Turn on air conditioning	Turn off window	0.000	***	−0.359	–
		Turn on fan	0.000	***	−0.257	–
		Undress	0.078	–	−0.055	0
	Turn on window	Turn off window	0.295	–	−0.021	0
		Turn on fan	0.000	***	0.130	+
		Undress	0.000	***	0.169	+
Cool	Dress	Turn off window	0.172	–	−0.034	0
Cold	Dress	Turn off window	0.000	***	0.252	+
		Turn on air conditioning	0.000	***	−0.165	–
		Turn off fan	0.000	***	0.106	+

$P < 0.05$ means that independent variables have a statistically significant influence on dependent variables. The correlation coefficient (Phi) represents the degree to which the independent variable affects the dependent variable. Significance code: "***" if P-Value < 0.001, "**" if 0.001 ≤ P-Value < 0.01, "*" if 0.01 ≤ P-Value < 0.05, "-" if P-Value ≥0.05. Relevance code: "+" if positive correlation, "0" if uncorrelated, "-" if negative correlation

Table 3 The correlation between interaction behaviors to restore discomfort of humidity

Discomfort	Main behavior	Other behavior	P/ Sig.	Significance	Phi	Relevance
Ultra wet	Turn on air conditioning	Turn off window	0.103	–	0.046	0
		Turn on window	0.000	**	−0.305	–
		Turn on fan	0.004	**	−0.091	0
	Turn off window	Turn on window	0.000	*	−0.315	–
		Turn on fan	0.227	–	−0.029	0
		Turn off air conditioning	0.000	***	−0.260	–
Wet	Turn on window	Turn off window	0.000	***	−0.352	–
		Turn on fan	0.417	–	−0.011	0
	Turn off window	Turn off air conditioning	0.372	–	−0.014	0
		Turn on fan	0.033	*	−0.065	0
Dry	Turn off window	Turn on fan	0.012	*	−0.080	0
		Turn on air conditioner	0.000	***	−0.210	–
Ultra dry	Turn off window	Turn off fan	0.430	–	−0.009	0
		Turn on air conditioning	0.000	***	−0.183	–

The results show that air conditioning switching behavior has a significant effect on the behavior of opening windows under the extremely humid situation. When the air conditioning switching behavior occurs, the probability of opening the window is reduced. The air conditioning has no significant effect on the behavior of closing window action. It can reflect that the subjects prefer to pursue a higher indoor air quality, but have weak awareness of window behavior impacting on air-conditioning energy consumption.

3.2 Occupancy schedule

It was found that the commuting time is affected by the size and nature of the office, which would, in turn, affects the occupancy schedule of office buildings. Based on survey data, it was observed that the difference between the large office occupancy schedule and the open office occupancy schedule is not significant. Therefore, in this study, multi-person office and open-plan office are collectively referred to as large office. The size range of small office and large office were set at $50m^2$ (Lv et al., 2019). The weekly working time data were classified into 3D scatter plots, as shown in Fig. 7.

K-mean clustering method was used to cluster the occupancy schedule of the office with different sizes and functions, and finally, eight typical office timetables were achieved, as shown in Table 4.

3.3 Cooling temperature set point

The cooling temperature set point data was shown in Fig. 9. A Q-Q graph is used to verify the normal distribution of the cooling temperature set point, as shown in Fig. 10. Each point is approximately distributed near the standard line, which indicates that the cooling temperature set point could be considered to follow a normal distribution. It can be concluded that the most common set points was 26 °C in the office building of the PRD.

Multivariate ordinal logistic regression in IBM SPSS Statistics 23 was applied to analysis the cooling temperature set point prediction model of the air-conditioning system. The test results are as follows: Model Fitting Information Test P (Sig.) $=0.000<0.001$, Goodness of fit test $P=1>0.05$, Test of Parallel Lines Test P (Sig.) $=0.87>0.05$, which indicates that the prediction model of cooling temperature setting in this study is valid.

The research results show that the office occupation nature, office size, air conditioning demand and the influence of humidity on office work efficiency have no significant influence on the cooling temperature set point. The probability of high cooling temperature set point increases by 1.27 times when occupant's age increase. Indoor temperature and air quality have a significant influence on the cooling temperature set point. The probability of a low cooling temperature set point increases when people realize that temperature/air quality has a greater impact on work efficiency. Meanwhile, the larger the control permissions, the more diverse and the lower and more diverse the temperature setpoints; The frequency of occupant activities increase the probability of low temperature set point by 64.0%, compared with those who rarely move. Leaving the other variables unchanged, increasing the thermal sensation voting (from -3 to 3) leads to an increase of a low temperature set point by 5 times. The probability of a low temperature set point can also be reduced by 68.0% when air conditioning can be functioned all day round in summer. Compared with that in the somatosensory temperature system, the low temperature set point probability of under high air velocity situation is reduced by 52.0%, while the low air velocity situation the probability by 2.23 times. While the AC system is on, the opening window will increase the probability of a low temperature set point by 1.42 times. Logical regression coefficients P values, significance levels and OR standardized estimations of cooling temperature setting are reported in Table 5.

The logistic regression function formula (2) can be expressed as Formula (6), as the prediction model of the cooling temperature of office buildings in the PRD region.

$$Log(p_i) = A_i + \sum_{j=1,\eta=1,P=1}^{j=9,\eta=6,p=30} \beta_j X_j(\eta, P) \tag{6}$$

$A_i$is the constant corresponding to the i cooling temperature set point; B_j stands for the regression coefficient of the ***j*** influence factor; ***X_j (η,p)-j*** is the influencing factor, ***η*** is the option of the ***j*** influencing factor, and ***P*** is the number of an occupant who selects ***η***.

The office case information was substituted into the 12 model prediction equations obtained by function (6), and then the cumulative probability value was obtained by substituting the model prediction formula into the inverse function formula (2) above. The cumulative probability value was substituted into a function (3) above to calculate the prediction probability of a single dependent variable. The category with the highest forecast probability can be considered as the category of the case.

Taking a small office (1 person) as an example, the probability distribution of the cooling temperature set point is predicted as shown in Table 6.

An example of the cooling temperature prediction for a large office (10 persons) is also given below. Influencing factors information and the probability distribution of predicting cooling temperature setpoints are shown in Table 7.

3.4 Typical occupant behavior model

3.4.1 HVAC

K-prototype clustering analysis was conducted to analyze the factors affecting air conditioning behavior. According to the actual situation, the clustering categories were classified by the combination of opening and closing modes, as shown in Table 8.

In all models, air conditioning switching behavior is carried out if colleagues and supervisors propose, which highlights the collective interactivity in a large office. In this study, air conditioning behavior pattern is regarded as a combination of environmental and event drivers, which are independent of each other. For example, air conditioning behavior of the indoor temperature does not depend on the event when it is temporarily left. The probability of AC on/off is calculated using independent

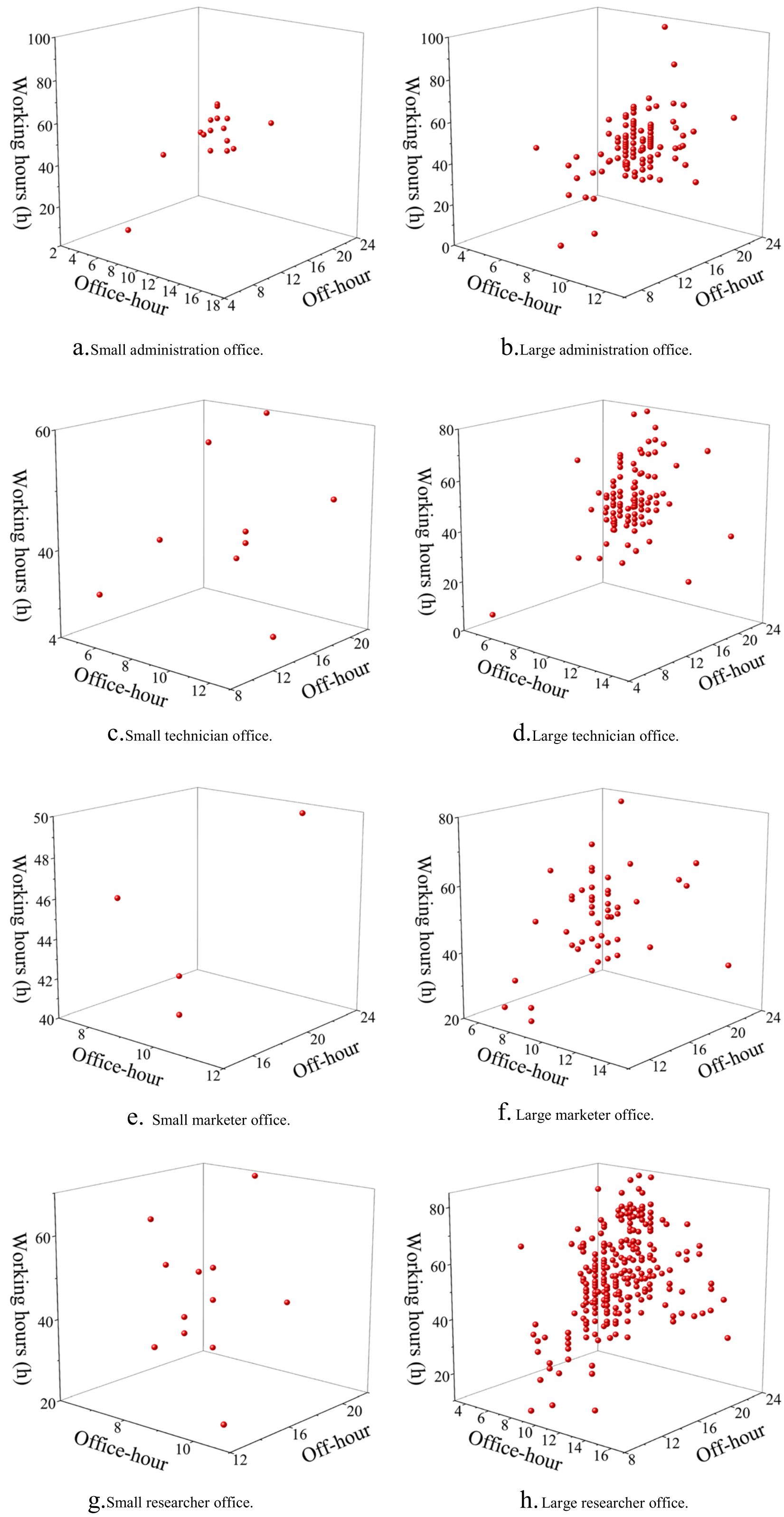

Fig. 7 3D scatter plot distribution of commuting time in this study

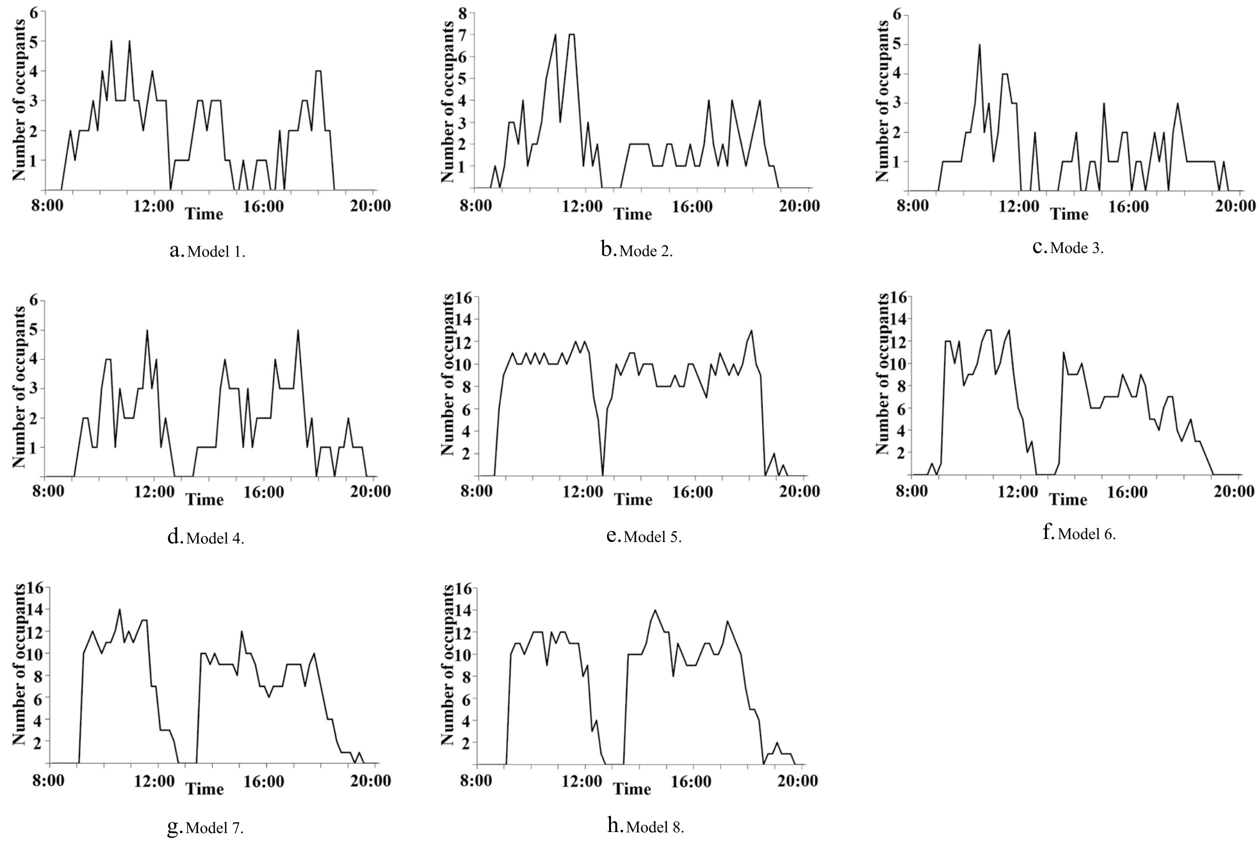

Fig. 8 Occupancy schedule on workday of all modes randomly simulated by DeST software

Table 4 The occupancy schedule of different types of movement models obtained by clustering

Mode	Office nature	Office size	Office hours	Off time	Work hours per week
Mode 1	Administration	Small Office	8:00	18:00	49
Mode 2	Technician	Small Office	8:00	17:30	42
Mode 3	Marketer	Small Office	8:30	17:30	42
Mode 4	Researcher	Small Office	8:00	18:20	56
Mode 5	Administration	Large office	8:40	17:35	44
Mode 6	Technician	Large office	9:10	19:00	59
Mode 7	Marketer	Large office	9:00	18:30	56
Mode 8	Researcher	Large office	8:50	20:00	61

Office nature: administration (office staff, accounting, etc.), technician (IT, finance, design etc.), marketer (sales, business, customer manager, etc.), researcher (teachers, professors, researchers, etc.). After clustering analysis, the real-time occupant presence status obtained from questionnaires were input into the DeST software to simulate the random occupancy schedule of the office building by using the Markov chain model, as showed in Fig. 8. The small office size is set as 28m^2, and the large office size is set as 76m^2 in the DeST software.

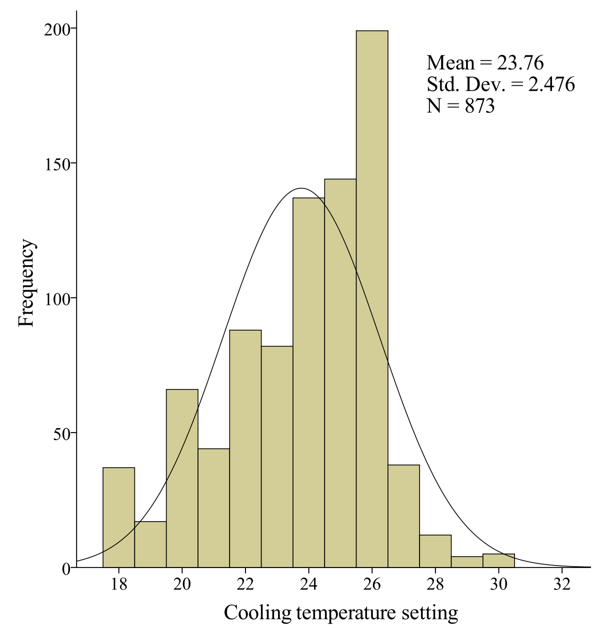

Fig. 9 Survey result of the cooling temperature setting

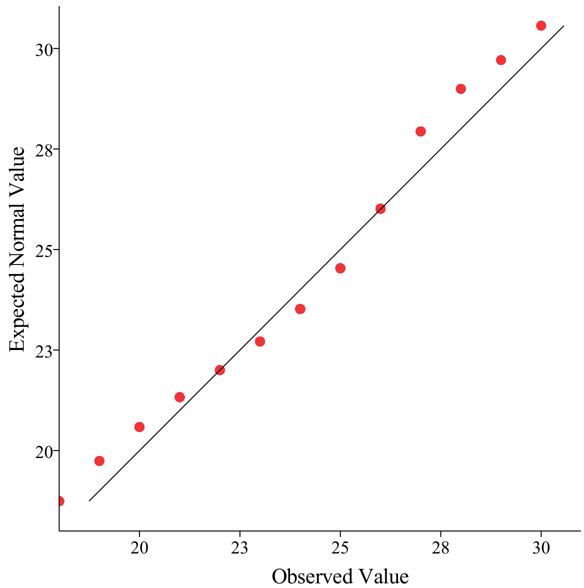

Fig. 10 Cooling temperature set point standard Q-Q chart

events, as presented in formula (7). ***P(ζ)*** is the probability of opening air conditioning in driving event ***ζ***, ***P(η)*** is the probability of opening air conditioning in driving event ***η***, the probability of office buildings to turn on air conditioning can be calculated by independent events (Feng et al., 2016).

$$P(\zeta \cup \eta \cup \lambda) = P(\zeta)+P(\eta)+P(\lambda)-P(\zeta).P(\eta)-P(\zeta).P(\lambda)-P(\eta).P(\lambda)+P(\zeta).P(\eta).P(\lambda) \tag{7}$$

The model obtained by clustering was statistically classified with questionnaire data, and the behavior mode probability driven by various factors in the model was obtained. The total probability was obtained up by the independent events in the questionnaire that affect various mode behaviors, as shown in Table 9.

In the questionnaire, only the probability of occupant behavior driven by the even can be calculated. As the specific parameters driven by the environmental need to be measured later, the probability of occupant behavior driven by the environment has been converted into the probability calculation of event-driven factors.

3.4.2 Lighting

It is found that 24.7% of the subjects have no energy-saving awareness, which leads to lighting (all or part of) being turned on beyond working hours. 6.9% of the subject do not care about the on/off status of the lighting system, while 68.3% of the energy-saving users would turn it off. 36.8% of the subjects with better energy-saving consciousness will partially reduce or completely close the number of lighting fixtures when the daylight is sufficient. Therefore, the K-prototype clustering analysis method was used to distinguish groups in lighting behavior models, as shown in Table 10.

The lighting model obtained by clustering is statistically classified with questionnaire data to obtain the probability of control mode driven by various factors in this mode, as shown in Table 11.

3.4.3 Window

For window related behavior, it is found that the window of the office in the PRD region is in a state of constant closed with a probability of 26.69%. The reason is that in order to prevent objects from dropping, opening a window requires permission from supervisors if the office is in high-rise buildings, which greatly reduces the probability of window-related behavior. According to the adaptive behavior of thermal discomfort, it can be concluded that air conditioning systems and windows have a coupling effect on indoor environmental thermal comfort or energy use, which means that window-related behaviors may be affected by different air conditioning modes. Therefore, window behavior was considered under different air conditioning models, and the cluster categories were achieved, as shown in Table 12.

3.4.4 Blind

Although blinds behavior has not been added to the DeST occupant behavior module, the purpose of this study is to comprehensively define the user behavior style of office buildings in the PRD region. Therefore, the classification of blind's behavior is still defined, as shown in Table 14.

3.4.5 Typical occupant behavior model

This section comprehensively defines the behavior of office buildings to adapt to the uncomfortable environment of various user styles. According to the combination of typical human behaviors of each cluster, 20 typical office user behavior styles are obtained. It can comprehensively define the behavior styles of users' various kinds of equipment in office buildings in the PRD region, as shown in Table 16.

4 Conclusions and future work

A questionnaire survey investigating occupant behavior patterns in air-conditioned office buildings in the PRD region has been conducted in 2019. Based on the

Table 5 Cooling temperature set point prediction model related factors

Influence factor	Option	Regression coefficient	*P*	Significant level	OR estimated value	OR 95%CI
Thresholds	T = 18 °C	−4.83	0.000	***	–	–
	T = 19 °C	−4.42	0.000	***	–	–
	T = 20 °C	−3.51	0.001	***	–	–
	T = 21 °C	−3.15	0.002	***	–	–
	T = 22 °C	−2.55	0.011	***	–	–
	T = 23 °C	−2.11	0.036	***	–	–
	T = 24 °C	−1.45	0.015	**	–	–
	T = 25 °C	− 0.69	0.049	**	–	–
	T = 26 °C	1.15	0.255	–	–	–
	T = 27 °C	2.17	0.033	**	–	–
	T = 28 °C	3.06	0.001	***	–	–
	T = 29 °C	3.58	0.000	***	–	–
	T = 30 °C	0^a	–	–	–	–
X_1	–	−0.24	0.013	*	1.27	0.21–1.74
X_2	High-impact	2.22	0.025	*	0.11	0.02–0.76
	Big-impact	2.15	0.027	*	0.12	0.02–0.78
	General impact	2.06	0.034	*	0.13	0.02–0.86
	Hardly impact	1.91	0.054		0.15	0.02–1.03
	Unaffected	0^a	–	–	1.00	–
X_3	High-impact	2.07	0.030	*	0.13	0.02–0.82
	Big-impact	2.02	0.031	*	0.13	0.02–0.83
	General impact	1.91	0.042	*	0.15	0.02–0.94
	Hardly impact	1.83	0.057	–	0.16	0.025–1.06
	Unaffected	0^a	–	–	1.00	–
X_4	1 person	−0.21	0.743		1.11	0.61–2.02
	2 to 4 persons	0.39	0.047	*	0.68	0.46–0.99
	5 to 8 persons	0.40	0.049	*	0.67	0.45–0.99
	9 to 15 persons	0.53	0.015	*	0.59	0.38–0.90
X_5	Frequent	0.41	0.027	*	0.64	0.43–0.95
	Occasional	−0.16	0.035	*	0.84	0.59–1.19
	Motionless	0^a	–	–	1.00	–
X_6	3	−1.24	0.000	***	4.07	2.05–8.11
	2	−1.47	0.003	**	3.15	1.46–6.80
	1	−1.70	0.003	**	3.04	1.47–6.26
	0	−1.53	0.000	***	3.39	1.72–6.71
	−1	− 1.80	0.000	***	3.97	1.98–7.98
	−2	−1.83	0.001	**	3.40	1.60–7.20
	−3	0a	–	–	1.00	–
X_7	Yes	−0.47	0.001	**	0.68	0.53–0.87
	No	0^a	–	–	1.00	–
X_8	High	−0.65	0.019	*	0.52	0.30–0.90
	Medium	−0.22	0.284		0.80	0.54–1.20
	Low	0.80	0.000	***	2.23	1.43–3.48
	Automatic	0.12	0.552		1.13	0.75–1.70
	Sense set	0^a	–	–	1.00	–
X_9	Off	−0.35	0.027		1.42	1.04–1.94
	On	0^a	–	–	1.00	–
X_{10}	–	–	0.102	–	–	–
X_{11}	–	–	0.736	–	–	–

Table 5 (continued)

Influence factor	Option	Regression coefficient	*P*	Significant level	OR estimated value	OR 95%CI
X_{12}	–	–	0.275	–	–	–
X_{13}	–	–	0.328		–	–
X_{14}	Close	0.13	0.058		1.06	0.59–1.88
	Medium	0.07	0.071		1.05	0.78–1.41
	Distant	0^a	–	–	1.00	–

0^a is the reference value; the logical regression coefficient OR indicates that each time the independent variable changes by one unit, the dependent variable increases the odds ratio of one level. Significant level code: "* * *" if< *P*-values < 0.001; "* *" if 0.001 < *P*-values < 0.01; "*" if 0.01 < *P*-values < 0.05; "-" if 0.05 < *P*-values. The symbol of regression coefficient indicates the case of low level and high level, "+ "if positive correlation, "- "if negative correlation

Table 6 Validation example of cooling temperature prediction model of small office

Temperature	Case information	Logical function	Cumulative probability	Prediction probability
18 °C	$X_1 = 20$	−5.923	0.27%	0.27%
19 °C	$X_2 = 2$	−5.511	0.40%	0.14%
20 °C	$X_3 = 2$	−4.603	0.99%	0.59%
21 °C	$X_4 = 2$	−4.239	1.42%	0.43%
22 °C	$X_5 = 1$	−3.642	2.55%	1.13%
23 °C	$X_6 = 1$	−3.201	3.91%	1.36%
24 °C	$X_7 = 1$	−2.538	7.32%	3.41%
25 °C	$X_8 = 3$	−1.783	14.39%	7.07%
26 °C	$X_9 = 1$	0.053	51.32%	36.93%
27 °C		1.073	74.52%	23.19%
28 °C		1.969	87.75%	13.23%
29 °C		2.486	92.32%	4.57%

Table 7 Validation example of the cooling temperature prediction model of the large office building

Temperature	Case information	Logical function	Cumulative probability	Prediction probability
18 °C	$X_1 = (20,1)$	−2.734	6.10%	6.10%
19 °C	$X_1 = (21,1)$	−2.322	8.93%	2.83%
20 °C	$X_1 = (23,1)$	− 1.414	19.56%	10.63%
21 °C	$X_1 = (24,1)$	−1.05	25.92%	6.36%
22 °C	$X_1 = (25,2)$	−0.453	38.86%	12.94%
23 °C	$X_1 = (27,1)$	−0.012	49.70%	10.84%
24 °C	$X_1 = (28,2)$	0.651	65.72%	16.02%
25 °C	$X_1 = (30,1)$	1.406	80.31%	14.59%
26 °C	$X_2 = (1,5)$,	3.242	96.24%	15.93%
27 °C	$X_2 = (2,5)$	4.262	98.61%	2.37%
28 °C	$X_3 = (1,5)$,	5.158	99.43%	0.82%
29 °C	$X_3 = (2,5)$	5.675	99.66%	0.23%
	$X_4, X_8 = 2$			
	$X_5, X_6, X_7, X_9 = 1$			

questionnaire survey and data analysis, the influencing factors of occupant behavior related to the office building was studied, a cooling temperature set point prediction model was quantified, a series of occupant behavior model for office buildings in PRD were defined. The results of the cooling temperature set point

Table 8 The types and proportions of the occupant in the air conditioning behavior model

Model	Control behavior	Proportion
AT-1	Stay when at-work, close when temporary depart, close when off-duty, open when stuffy, open when hot, close when cold, air-conditioning works all work time.	27.6%
AT-2	Open at-work, open when temporary depart, close when off-duty, open when stuffy, open when hot, close when cold, air-conditioning works all work time.	32.9%
AT-3	Open at-work, close when temporary depart, close when off-duty, open when stuffy, open when hot, close when cold, air-conditioning doesn't work all the time.	21.3%
AT-4	Open at-work, stay when temporary depart, close when off-duty, open when stuffy, open when hot, close when cold, air-conditioning works all work time.	18.2%

Table 9 The probability of occupant in the air conditioning behavior model (on/off)

Model		At work	Off duty	Temporary depart	Stuffy	Hot	Cold	Total probability
AM-1	Open Probability	31.5%	–	–	57.7%	71.0%	–	91.4%
	Close probability	–	65.2%	48.1%	–	–	38.4%	81.9%
AM-2	Open Probability	96.9%	–	100%	72.1%	91.7%	–	100%
	Close probability	–	76.0%	–	–	–	38.4%	96.4%
AM-3	Open Probability	88.7%	–	–	60.2%	90.3%	–	99.6%
	Close probability	–	91.9%	50.5%	–	–	38.4%	99.4%
AM-4	Open Probability	98.1%	–	–	66.7%	88.7%	–	99.9%
	Close probability	–	92.5%	19.7%	–	–	38.4%	93.6%

Table 10 The types and proportions of the occupant in the lighting behavior model

Model	Control behavior	Proportion
LT-1	Do not have the habit of adjusting lighting equipment	44.0%
LT-2	Partly open when at work, open the window, sufficient outdoor light, insufficient indoor light daytime, indoor glare caused by sunshine; close when off-duty.	14.8%
LT-3	All open when at work or insufficient indoor light daytime; partly open when opening the window; all close when off-duty, sufficient outdoor light or indoor glare caused by sunshine.	28.0%
LT-4	All open when insufficient indoor light daytime; stay when at work, open the window, sufficient outdoor light or indoor glare caused by sunshine; all close when off-duty.	13.2%

Table 11 The probability of occupant in lighting behavior model (on/off)

Model		At work	Off duty	Window	Light	Un-light	Glare	SP	TP
LM-1	All open	Do not have the habit of adjusting lighting equipment						44.0%	44.0%
LM-2	All open	–	–	–	–	–	–	0%	97.2%
	Part open	37.7%	–	58.2%	40.0%	39.8%	37.7%	97.2%	
	All close	–	68.1%	–	–	–	–	68.1%	68.1%
LM-3	All open	46.7%	–	–	–	50.7%	–	73.7%	89.0%
	Part open	–	–	58.2%	40.0%	–	–	58.2%	
	All close	–	68.1%	–	–	–	40.9%	88.1%	88.1%
LM-4	All open	4.5%	–	4.8%	3.7%	50.7%	3.4%	58.2%	64.6%
	Part open	4.5%	–	4.8%	3.7%	–	3.4%	15.3%	
	All close	4.5%	68.1%	4.8%	3.7%	–	3.4%	73.0%	73.0%

Abbreviations: *window* The window is opened, *light* Outdoor light is sufficient, *Un-light* Indoor light is insufficient at daytime, *glare* Indoor glare caused by the sun, *SP* Single probability, *TP* Total probability

Table 12 The types and proportions of the occupant in the window behavior model

Model	Control behavior	Proportion
WT-1	The window is closed	24.9%
WT-2	All open when feeling odour; partly open when at work, cold, air condition on or sufficient outdoor light; all close when off duty, all-weather reason, outdoor damp or noise.	29.7%
WT-3	All open when feeling odour, cold or sufficient outdoor light; partly open when air condition on; stay when at work, off duty, all-weather reason, outdoor damp or noise.	10.3%
WT-4	All open when at work or cold; partly open when off duty, feel odour, sufficient outdoor light or outdoor damp; all close when air condition on, all-weather reason or noise.	12.4%
WT-5	All open when feeling odour or sufficient outdoor light; partly open when at work; all close when off duty, cold, air condition on, all-weather reason, outdoor damp or noise.	22.7%

The window model obtained by clustering was statistically classified with questionnaire data to obtain the probability of control mode driven by various factors in this mode, as shown in Table 13

Table 13 The probability of occupant in the window behavior model (on/off)

Model		Work	Off	Odour	AC	Cold	Light	Damp	Noise	Weather	SP	TP
WM-1	All close	The window is closed									100%	100%
WM-2	All open	–	–	65.8%	–	–	–	–	–	–	65.8%	97.3%
	Part open	57.6%	–	–	27.4%	45.7%	52.3%	–	–	–	92.0%	
	All close	–	67.9%	–	–	–	–	32.6%	70.3%	69.6%	98.6%	98.6%
WM-3	All open	2.9%	2.7%	65.8%	–	5.7%	32.4%	–	–	–	78.2%	96.3%
	Part open	2.9%	2.7%	–	27.4%	–	–	–	–	–	82.9%	
	All close	2.9%	2.7%	–	–	–	–	51.1%	70.3%	69.6%	22.2%	22.2%
WM-4	All open	65.8%	–	–	–	5.7%	32.4%	–	–	–	40.2%	88.7%
	Part open	–	18.3%	27.7%	–	–	–	51.1%	–	–	81.0%	
	All close	–	–	–	27.4%	–	–	–	32.6%	69.6%	96.3%	96.3%
WM-5	All open	–	–	65.8%	–	–	32.4%	–	–	–	76.9%	90.2%
	Part open	57.6%	–	–	–	–	–	–	–	–	57.6%	
	All close	–	67.9%	58.5%	42.7%	–	–	51.1%	70.3%	69.6%	98.6%	98.6%

Abbreviations: *AC* Air condition is turned on, *damp* outdoor is damp, *noise* Outdoor is noisy

Table 14 The types and proportions of the occupant in the blind behavior model

Model	Control behavior	Proportion
BT-1	The blind is closed	28.5%
BT-2	All open when at work, off duty, open the window or insufficient indoor light daytime; part open when cold or indoor glare caused by sun; all close when indoor overheat caused by the sun.	14.3%
BT-3	All open when insufficient indoor light daytime; part open when at work or open the window; all close when off duty, cold, indoor glare or overheating caused by the sun.	18.8%
BT-4	Stay when at work, off duty, open the window, cold, insufficient indoor light daytime, indoor glare or overheating caused by the sun.	10.4%
BT-5	All open when insufficient indoor light daytime; part open when at work, off duty, open the window, cold, indoor glare or over-heat caused by the sun.	29.3%

The blind model obtained by clustering is statistically classified with questionnaire data to obtain the probability of control mode driven by various factors in this mode, as shown in Table 15

prediction model were analyzed, which shows that factors, such as age, activity intensity, and TSV, etc., have a significant influence on the cooling temperature set point. It also shows that the probability of a low cooling temperature set point in the large office is higher than that in the small office.

However, this study has two limitations. First, the influencing factors of occupant's behavior of various electrical appliances (such as air conditioning, lighting, window, etc.) is studied by questionnaire, the event-driven behavior probability can only be established initially. The environmental driving factors lack the support of measured data, the

Table 15 The probability of occupant in the blind behavior model (on/off)

Model		Work	Off	Window	Un-light	Cold	Glare	Overheat	SP	TP
BM-1	All close	The blind is closed							100%	100%
BM-2	All open	36.8%	–	36.1%	62.5%	–	–	–	86.6%	96.1%
	Part open	–	–	–	–	36.6%	53.7%	–	70.6%	
	All close	–	50.1%	–	–	–	–	43.4%	43.4%	43.4%
BM-3	All open	–	–	–	62.5%	–	–	–	62.5%	90.5%
	Part open	49.8%	50.1%	49.6%	–	37.9%	–	–	74.7%	
	All close	–	–	–	–	–	33.8%	43.4%	88.4%	88.4%
BM-4	All open	3.4%	6.0%	2.9%	2.1%	4.5%	1.8%	1.9%	15.6%	28.7%
	Part open								15.6%	
	All close								15.6%	15.6%
BM-5	All open	–	–	–	62.5%	–	–	–	62.5%	90.2%
	Part open	49.8%	20.5%	49.6%	–	36.6%	53.7%	34.3%	80.3%	

Table 16 User style defined by the behavior model of office builders in Pearl river delta

Model	WT-1	WT-2	WT-3	WT-4	WT-5	Model
AT-1	AT-1\WT-1\ BT-1\LT-1	AT-1\WT-2\ BT-2\LT-1	AT-1\WT-3\ BT-3\LT-1	AT-1\WT-4\ BT-4\LT-1	AT-1\WT-5\ BT-5\LT-1	LT-1
AT-2	AT-2\WT-1\ BT-1\LT-2	AT-2\WT-2\ BT-2\LT-2	AT-2\WT-3\ BT-3\LT-2	AT-2\WT-4\ BT-4\LT-2	AT-2\WT-5\ BT-5\LT-2	LT-2
AT-3	AT-3\WT-1\ BT-1\LT-3	AT-3\WT-2\ BT-2\LT-3	AT-3\WT-3\ BT-3\LT-3	AT-3\WT-4\ BT-4\LT-3	AT-3\WT-5\ BT-5\LT-3	LT-3
AT-4	AT-4\WT-1\ BT-1\LT-4	AT-4\WT-2\ BT-2\LT-4	AT-4\WT-3\ BT-3\LT-4	AT-4\WT-4\ BT-4\LT-4	AT-4\WT-5\ BT-5\LT-4	LT-4
Model	BT-1	BT-2	BT-3	BT-4	BT-5	Model

quantitative relationship between environmental factors and behavior cannot be captured. Second, the samples of this study were mainly young people less than 35 years old, which may lead to a large deviation in the cooling temperature set point prediction model. It is suggested that samples over 35 years old should also be considered in the future.

It should also be noted that, as previously mentioned, the occupants' behavior can be affected by various "driving forces", their behaviors cannot be the same in different climate regions. However, the research method described in this paper contains no climate sensitive factors, and can be applied to similar studies in other regions.

In the future, the effort will be spent on investigation of the verification and improvement of the proposed occupant behavior model for practical use. A laboratory has been built for the on-site measurement of occupant behavior in the office building of the PRD. Over 20 occupants' daily behavior (including the adjustment of the air-conditioning system, lighting system, shading system and office equipment), as well as the indoor environment status (including temperature, RH, black globe temperature and air velocity), are measured and recorded. Besides the verification through laboratory tests, both survey and measurement studies are planned on occupant behaviors in the hotel, shopping centers, transport station and finally, residential buildings.

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Authors' contributions
Manning He: original draft preparation, data investigation and visualization. Huiwang Peng: data collection and validation. Meixiang Li: data collection and validation. Yu Huang: Supervision. project administration and funding acquisition, draft review. Da Yan: Methodology. Siwei Lou: software and draft review. Liwei Wen: data validation. The author(s) read and approved the final manuscript.

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Availability of data and materials
The raw data generated from the survey during the current study are not openly available due to protection of subjects' personal information as well as their privacy. The raw data are available from the corresponding author upon reasonable request, via a Material Transfer Agreement.

Declarations

Competing interests
The authors have no competing interests to declare that are relevant to the content of this article.

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References
ASHRAE. (2013). *ANSI/ASHRAE standard 62.1-2013: Ventilation for acceptable indoor air quality*. American Society of Heating, Refrigerating and air-Conditioning Engineers.
Chen, Y., Liang, X., Hong, T., & Luo, X. (2017). Simulation and visualization of energy-related occupant behavior in office buildings. *Building Simulation, 10*, 785–798.
Chow, T. T., Chan, A. L. S., & Song, C. L. (2004). Building-mix optimization in district cooling system implementation. *Applied Energy, 77*(1), 1–13.
Chung, W. (2011). Review of building energy-use performance benchmarking methodologies. *Applied Energy, 88*(5), 1470–1479.
Eguaras-Martínez, M., Vidaurre-Arbizu, M., & Martín-Gómez, C. (2014). Simulation and evaluation of building information modeling in a real pilot site. *Applied Energy, 114*, 475–484.
Feng, X., Yan, D., Wang, C., & Sun, H. (2016). A preliminary research on the derivation of typical occupant behavior based on large-scale questionnaire surveys. *Energy and Buildings, 117*, 332–340.
Fritsch, R. (1990). A stochastic model of user behaviour regarding ventilation. *Building and Environment, 25*(2), 173–181.
Gang, W., Wang, S., Gao, D., & Xiao, F. (2015). Performance assessment of district cooling systems for a new development district at planning stage. *Applied Energy, 140*, 33–43.
Lv, Y. J., Peng, H. W., He, M. N., Huang, Y., & Wang, J. W. (2019). Definition of typical commercial building for South China's Pearl River Delta: Local data statistics and model development. *Energy and Buildings, 190*, 119–131.
Mahdavi, A., Mohammadi, A., Kabir, E., & Lambeva, L. (2008). Occupants' operation of lighting and shading systems in office buildings. *Journal of Building Performance Simulation, 1*(1), 57–65.
Parys, W., Saelens, D., & Hens, H. (2011). Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices– A review-based integrated methodology. *Journal of Building Performance Simulation, 4*(4), 339–358.
Pérez-Lombard, L., Ortiz, J., Coronel, J. F., & Maestre, I. R. (2011). A review of hvac systems requirements in building energy regulations. *Energy and Buildings, 43*(2–3), 255–268.
Richardson, I., Thomson, M., & Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings, 40*(8), 1560–1566.
Rysanek, A. M., & Choudhary, R. (2015). Delores – An open-source tool for stochastic prediction of occupant services demand. *Journal of Building Performance Simulation, 8*(2), 97–118.
Silva, K. P., Carvalho, F., & Csernel, M. (2009). Clustering of symbolic data using the assignment-prototype algorithm. International Joint Conference on Neural Networks. IEEE Press.
Sun, K., & Hong, T. (2017). A simulation approach to estimate energy savings potential of occupant behavior measures. *Energy and Buildings, 136*, 43–62.
Sun, K., Hong, T. Z., Taylor-Lange, S. C., & Piette, M. A. (2016). A pattern-based automated approach to building energy model calibration. *Applied Energy, 2016*(165), 214–224.
Sun, K., Yan, D., Hong, T., & Guo, S. (2014). Stochastic modeling of overtime occupancy and its application in building energy simulation and calibration. *Building and Environment, 79*, 1–12.
Wang, C., Yan, D., & Jiang, Y. (2011). A novel approach for building occupancy simulation. *Building Simulation, 4*(2), 149–167.
Wang, D., Federspiel, C. C., & Rubinstein, F. (2005). Modeling occupancy in single person offices. *Energy and Buildings, 37*(2), 121–126.
Widén, J., Nilsson, A. M., & Wäckelgård, E. (2009). A combined markov-chain and bottom-up approach to modelling of domestic lighting demand. *Energy and Buildings, 41*(10), 1001–1012.
Yamaguchi, Y., Shimoda, Y., & Kitano, T. (2013). Reduction potential of operational carbon dioxide emission of nakanoshima business/cultural area as a model for low-carbon districts in warm climates. *Building and Environment, 59*, 187–202.
Yan, D., Hong, T. (2018). EBC annex 66 final report - definition and simulation of occupant behavior in buildings. IEA.
Yan, D., Hong, T. Z., Dong, B., Mahdavi, A., D'Oca, S., Gaetani, L., & Feng, X. H. (2017). IEA EBC annex 66: Definition and simulation of occupant behavior in buildings. *Energy and Buildings, 156*, 258–270.
Yan, D., O'Brien, W., Hong, T. Z., Feng, X. H., Gunay, H. B., Tahmasebi, F., & Mahdavi, A. (2015). Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy and Buildings, 107*, 264–278.
Yoshino, H., Hong, T., & Nord, N. (2017). IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods. *Energy and Buildings, 152*, 124–136.
Yun, G. Y., Tuohy, P., & Steemers, K. (2009). Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models. *Energy and Buildings, 41*(5), 489–499.
Zhao, J., Lasternas, B., Lam, K. P., Yun, R., & Loftness, V. (2014). Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining. *Energy and Buildings, 82*, 341–355.
Zhou, X., Yan, D., Feng, X., Deng, G., Jian, Y., & Jiang, Y. (2016). Influence of household air-conditioning use modes on the energy performance of residential district cooling systems. *Building Simulation, 9*(4), 429–441.
Zimmermann, G. (2007). *Modeling and simulation of individual user behavior for building performance predictions*. Society for Computer Simulation International.

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