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An occupancy-based model for building electricity consumption prediction: A case study of three campus buildings in Tianjin

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ABSTRACT

The accurate prediction of a building's electricity consumption can provide baselines for energy management and indicate the building's energy-saving potential. However, electricity utilization indicators based on the building area are no longer applicable because of the overall increase in the building area per person and occupant energy demand of buildings.

To tackle this challenge, the building electricity consumption was split into 'basic' and 'variable' forms in this study and a two-part building electricity consumption prediction model based on human behavior was established. The basic electricity consumption is related to the building area, while the variable electricity consumption is related to the building occupancy. The probability function and Markov model were used to describe the electricity consumption caused by the randomness of occupancy in buildings. The model was validated using three campus buildings. Based on the comparison of the actual electricity bills of the campus buildings with the model prediction results, the model accuracy error is less than 5%.

The results show that the building electricity consumption of a building has a growth limit when multiple people share a room, which is related to a person's initiative or ability to control the electricity use.

Introduction

Buildings consume more than one-third of the world's primary energy [1]. It is important to improve the building energy efficiency. Because occupants and building interaction consume approximately 27% to 43% of the total commercial building energy, the occupant behavior has a large impact on the building energy consumption [2,3]. Mastering the behavior of occupants can provide an important basis for building operation management [4,5]. Modeling the occupant behaviours could help to improve the building simulation accuracy and to understand the building design–operation performance gap [6]. When establishing an occupant behavior model, the error in the energy consumption prediction is often caused by the simple model. On one hand, information about occupants must be considered in the building energy simulation. On the other hand, a too detailed investigation will cause a privacy problem [7]. Therefore, it is necessary to establish an accurate and realistic energy consumption prediction model using short-term research.

The current researches of the relationship between the occupant behavior and building energy consumption is mainly based on three approaches: static schedule, stochastic occupancy model, and data mining method [8]. Many existing simulation programs consider the impact of occupant behavior on the building electricity consumption in the simulation. It is a common practice to treat occupant behaviours as static, deterministic schedules or settings in building performance simulations [9]. Cho et al. carried out a real-time dynamic simulation of the building energy consumption. Based on the results for varying operating parameters, such as personnel's work schedules and person density, they concluded that human behavior has an impact on the building energy consumption [10]. Shabunko et al. [11] calculated the energy consumption of 400 residential buildings by applying the EnergyPlus simulation tool. The main difference between the post-occupied and occupied stages is the energy consumption based on the occupant behavior in the buildings. Hong standardized occupants and their behavior and used the results to improve the occupant behavior module in the DeST work [12]. Duarte mentioned that standardized occupancy diversity factors are provided as reference for modelers in ASHRAE 90.1 2004. According to the simulation software, as the number of occupants increases, the building energy consumption increases [13]. However, the electricity consumption and building area do not have a simple linear relationship. Representative

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settings for occupants use temporal schedules in a simplified and homogeneous way, which leads to discrepancies between simulated and measured data [14]. The randomness of the occupant behavior is the main reason for the difference between predictions of simulation software and the actual situation [15]. Randomness of occupancy has a statistically significant influence on the building's energy performance [16].

The stochastic model considers the occupancy as randomly changing and predicts the location of an occupant at the next point in time by analysing the appearance of the occupant at a previous point in time. The Markov model is the most widely used model and has been successfully applied for predictions of the number of occupants in a room [17]. Dong and Lam [18] used a semi-Markov model coupled with the data flow of a multi-sensor system to predict the occupancy rate. Sun et al. [19] also used a stochastic model. Their results showed that the number of people in a room presents a quadratic distribution and the arrival and departure time of occupants are exponentially distributed for a certain time period. Wang et al. [20] used a first-order homogeneous Markov model to simulate the movement of a person relative to a building and obtained a quantitative relationship between the occupancy rate and amount of time people moved in and out of a building. Stoppel and Leite [21] used a probabilistic occupancy model to simulate the annual occupancy rate of a building and utilized the building users' movement frequency, occupancy, and seasonal long-term vacation as input parameters. Yang and Becerik-Gerber [22] combined a stochastic model with regression, time series, and pattern recognition models to simulate expected presences for each point in time and compared them with actual data. Virote and Neves-Silva analysed the use of luminaires, established a stochastic model of the space occupancy of building occupants and their actions, and evaluated the applicability of the model by calculating the residuals [23].

In addition to the stochastic model, some researches also applied data mining methods. Mahdavi and Tahmasebi [24] designed a non-random model called non-probabilistic model. Based on five years of data, an empirical model of the occupancy rate was generated. It was demonstrated that the occupancy rate can be expressed with a quadratic polynomial with a prediction accuracy of more than 80%. Virote and Neves-Silva [23] proposed a building energy consumption model. Making use of luminaires, a stochastic model of the space occupancy and user actions was established. The applicability of the model was determined by calculating the residuals of the simulation results and measured data. Similarly, research on the behavioural patterns of shading models and their impact on the lighting energy consumption has also been conducted [25]. James A. Davis III analysed the occupancy rate of university campuses using a large amount of test data [26]. Masoso and Grobler [27] measured the electricity consumption of six buildings and classified them by the type of electrical equipment and running time (working and non-working hours) and concluded that the building EUI (energy consumption intensity) is higher during working hours. This indicates that changes in the behavioural patterns of building occupants can lead to a reduction in the building energy consumption. However, such a study requires an excessive amount of data while compromises may create models specifically for small areas or a certain research problem [28].

The above-mentioned studies provide alternative approaches for the analysis of occupant behavior. However, most research only qualitatively determined the effect of activities on the electricity consumption, which is insufficient to provide a basis for the establishment of building energy-consumption quotas and commissioning strategies for building energy systems. Although previous studies showed that a close relationship exists between occupants and the building energy consumption, it is difficult to obtain precise activities of occupants in the building over the long term. Therefore, the building manager must use the data that were obtained within the limited test time combined with the energy platform to acquire more accurate energy predictions. Thus, it is difficult to identify the intrinsic link between the occupancy and energy consumption through simple regression. A model used to express the logical relationship between the occupancy and building energy consumption is needed. To fill this gap and resolve the above-mentioned issues, a building electricity consumption prediction model, which considers the occupant behavior, is proposed in this study. The occupancy and electricity consumption are divided into basic and variable parts for the analysis. In this study, an occupancy-based model for the prediction of the building electricity consumption was established. Three university buildings, that is, a dormitory, teaching building, and office building, were selected as the research objects. The association of variable building electricity consumption with occupants can be used as guidance for the energy use behavior.

2. Methodology

2.1. Framework of the electricity consumption model

The model structure is shown in Fig. 1. In practice, the electricity consumption, which is indirectly related to the occupant behavior, can be calculated with an area index method, while the remainder of the electricity consumption can be calculated based on direct connections between the real-time occupancy and hourly power rate of equipment in buildings.

As shown in Fig. 1, a two-part building electricity consumption model based on occupant behavior was established by splitting the building electricity consumption into 'basic' and 'variable' parts. The basic electricity consumption of a building includes the emergency lighting, service, and safety electricity consumption, which are basically constant throughout the day. The variable electricity consumption mainly refers to the socket, indoor lighting, and air conditioning, which change depending on the needs of the occupants. The socket energy consumption is entirely based on the occupant demand. The indoor lighting and air conditioning electricity consumptions depend on the control modes used in the building.

2.2. Occupancy rates in buildings

The occupancy distribution in a building has two important long-term properties. The first is definitive; long-term statistics show that the number of people in a building has a certain regularity with time. The second is randomness; the occupancy at a specific moment randomly changes. In this study, an occupancy submodel was established using two approaches: 1) binomial fitting of the numerical certainty, and 2) stochastic Markov chain for a building. The Monte–Carlo method was used to generate the fluctuating number of occupants of the initial state for calculation. The first-order homogeneous Markov process was then used to establish a submodel of the fluctuating number of occupants in a room.

A definitive occupancy in a building can be obtained with the classic multiple regression model as follows [29]:

$$y = c_0 + (c_1x_1)^{p_1} + (c_2x_2)^{p_2} + \cdots + (c_kx_k)^{p_k} + \varepsilon = c_0 + \sum_{i=1}^{k} (c_ix_i)^{p_i} + \varepsilon \quad (1)$$

where c_0 is a constant term; k is the number of independent variables; c_i ($i = 1, 2, \ldots, k$) is the coefficient of the independent variable; x_i is the independent variable; p_i is the regression function series for the respective variables; and ε is the random error, which can be ignored when the accuracy reaches an acceptable level (usually 85%) [30].

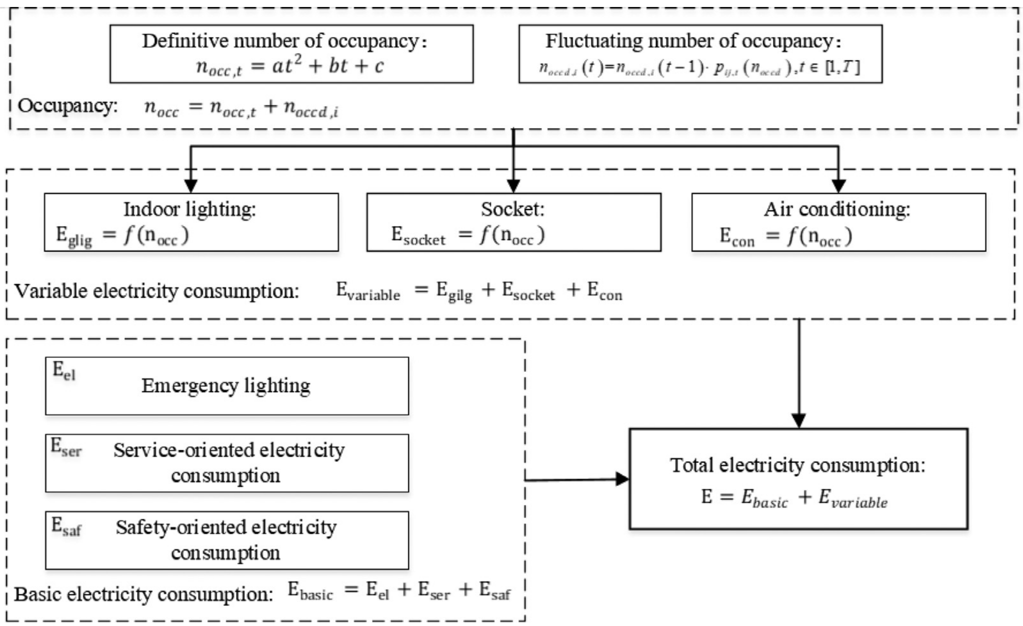


Fig. 1. Model of the building electricity consumption.

To describe the randomness of the number of occupants in a room, a combined model, including the Markov chain and Monte–Carlo method, was applied in this study to improve the accuracy of the prediction results and retain the time consecutiveness of the presumed state. The procedures of the Markov chain–Monte–Carlo method for the prediction of the number of occupants [31] are as follows.

The Markov chain for the fluctuation of the number of occupants at time t is:

$$n_{occd,i}(t) = n_{occd,i}(t-1) \cdot p_{ij,t}(n_{occd}), t \in [1, T] \tag{2}$$

where T is the total number of hours a building is functional and n is the number of occupants. The model transition matrix $P_{ij,t}(n_{occd})$ is a constant time-invariant matrix, which is independent of the step number n_{occd}:

$$p_{ij,t}(n_{occd}) = A^{(n)}$$

$$A^{(n)} = \begin{bmatrix} a_{11}^{(n)} & a_{12}^{(n)} & \dots & a_{1N}^{(n)} \\ a_{21}^{(n)} & a_{22}^{(n)} & \dots & a_{2N}^{(n)} \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ a_{N1}^{(n)} & a_{N2}^{(n)} & \dots & a_{NN}^{(n)} \end{bmatrix} \tag{3}$$

where $a_{ij}(n)$ is the probability of a particle moving to state j at time t in state i.

To obtain the statistical laws related to the number of occupants and the probability density distribution of the actual number of people, groups of simulation calculations were performed based on the field monitoring data. The Monte–Carlo method was applied to generate the n_{occd} value used for the iteration.

2.3. Growth limit of the building electricity consumption

However, although the equipment utilization is closely related to occupant activities, the electricity consumption of buildings does not necessarily increase with increasing number of occupants. In a multi-occupant room, the electricity consumption changes after the first person enters the room until the time the room is occupied; it is different when the last person enters the room. For example, if the lighting and air conditioning systems are fully operational, a person coming into a room does not likely affect the electricity consumption of the public appliances but only that of personal appliances. Therefore, the electricity consumption of the entire room slightly changes. With respect to the entire building, the growth of the electricity consumption gradually slowed down when the occupancy increase. Until the occupant number reaches a certain stage, electricity consumption of the building will not continue to grow.

Therefore, it is assumed that the building electricity consumption has a growth limit. The key point in describing the electricity consumption of a building with occupant behavior models is to determine the limit point. The limit of electricity consumption based on an increase in the number of occupants can be obtained using cluster analysis. Cluster analysis is suitable for the analysis of data with certain central distribution characteristics. It divides objects into a series of groups that is unknown before clustering. The K-modes clustering [32], an extension of k-means clustering, is a clustering method, which is based on the distance function and is expressed as follows [33]:

$$D(X, C) = \sum_{1}^{k} \sum_{x_i \in c_k} d(x_i, c_k) \tag{4}$$

where $D(X, C)$ is the sum of the within-cluster distance; $X = \{x_1, x_2, \cdots x_n\}$ is the dataset with n objects, where each object can be described as a vector of $\{A_1, A_2, \cdots, A_m\}$ containing m elements; x_i denotes the i th object of X; $C = \{c_1, c_2, \cdots c_k\}$ is the center of K different clusters; c_k is the center of the k-th cluster; and $d(x, c)$ is the distance between two clustered vectors.

After the electricity consumption is classified according to the number of occupants, the mathematical description of the electricity consumption using the number of occupants and duration of each category can be obtained through regression analysis. For building electricity consumption with a 'growth limit' with respect to occupant behavior, the regression function is a piecewise

Table 1
Basic building information.

Building type	Building area	Number of floors	Story height	Orientation	Operation duration	Usage rate
Dormitory building	3400 m^2	5	2.8 m	south	entire day	Bedrooms occupy 80% of the building area; other rooms are washrooms, machine rooms, and corridors.
Teaching building	6340 m^2	4	4.5 m	south	6:30–22:30	Classrooms occupy 80% of the building area; others are corridors.
Office building	3690 m^2	3	3.0 m	south	6:30–22:30	Offices occupy 60% of the building area; others are corridors.
Exterior view	 Dormitory building		 Teaching building		 Office building	

function with time and number as independent variables:

$$E_h = \begin{cases} f_1(n_{occ}) & [t_{md}, t_{mw}] \le t < [t_d, t_{nd}], 0 \le n_{occ} \le n_{\lim.} \\ f_2(n_{occ}) & [t_d, t_{nd}] \le t \le t_s, 0 \le n_{occ} \le n_{\lim.} \\ f_3(n_{occ}) & n_{\lim.} \le n_{occ} \le n_t \end{cases} \tag{5}$$

where f_1, f_2, and f_3 are the functions of the first, second, and third categories of power varying with the number of occupants, respectively; $n_{\lim.}$ is the minimum value for the third category, which represents the limit point for the number of occupants;n_t is the maximum value for the third category, which represents the total number of occupants in a building; and t_{md}, t_{mv}, t_d, t_{nd}, and t_s are the times to go to work or start work in the morning, duration of working time, dinner time, time to leave a room at night, and time to go to sleep, respectively.

The above-mentioned electricity load prediction method is based on the occupant energy demand. After predicting the number of occupants in a building, the electricity consumption can be estimated. This method is more suitable for a fixed number of occupants, where everyone has control access to the electrical appliances in a room or building. There is a gathering effect when people come together and electrical appliances will not be operated according to the wishes of a single person or a small group of people. Based on the deterministic description of a building electricity load, the fluctuations of the electricity consumption due to the occupant behavior are considered in this study and the electricity load at the building level is obtained.

3. Case study

The case study buildings were built in 2015, opened in 2016, and entered normal use in the end of 2016. The basic information about the buildings is provided in Table 1.

An eight-month field test, monitoring, and investigation of the buildings was conducted from June 2017 to January 2018. The air conditioning and heating were tested from June 20 to August 31, 2017, and from November 15, 2017, to January 20, 2018, respectively. Because the synchronised electricity consumption and cooling and heating demand are required for the model, the cooling and heating capacity and human activities were simultaneously measured within a certain time period. The total cooling and heating supply capacities of the case study buildings were tested in the energy plant. The building electricity consumptions in spring and autumn were obtained by subtracting the average air conditioning and heating electricity consumptions in summer and winter, respectively, because the air conditioning and heating equipment were not used in spring and autumn.

The case study buildings were uniformly supplied with electricity by an energy plant. The indoor and outdoor air temperature and humidity were measured by data loggers (HOBO MX1101, with an accuracy of ±0.2 °C). The flow rate of the cooling/heating supply was measured with ultrasonic flowmeters (TDS-100P, with an instrument display value accuracy of ±1%) and the water temperature was measured by data loggers (HOBO ZW001, with an accuracy of ±0.2 °C) installed on water pipes. The data log interval was 10 min and the model prediction step was 30 min. Infrared sensors were used to detect the number of people entering and leaving a building. The number and type of electrical appliances used, mainly lighting, computers, and other electrical appliances, were recorded by testers. Out of respect for personal privacy, the utilization of electrical appliances in dormitory buildings was not monitored. Instead, an energy monitoring platform was used to monitor the electricity consumption of each dormitory room. Other buildings required on-site meter readings to record the hourly electricity consumption in the low-voltage power distribution room. The general layout of the distribution box in the power distribution room is shown in Fig. 2.

Buildings are powered by low-voltage electricity after the electricity is distributed by high-voltage power sources. Generally, subentry power meters are used for buildings in power distribution plants. The subentry power meters measure the electricity consumption of different functional demands of buildings. Fig. 2 shows the general layout of the distribution box in the power distribution room. In each electricity consumption subitem, the incoming lines of the socket, indoor lighting, and air-conditioning are directly related to the occupant behavior, while other lighting and the safety and service can be calculated using the area index method. The variations in the basic electricity consumption and the variable electricity consumption of the building can be obtained by monitoring the distribution box. Different buildings have different equipment types and power metering systems. Parts of the electricity consumption are always directly related to the activities of the people in the building. Therefore, this prediction method is applicable to buildings with different functions or in different regions.

Table 2
Definitive number of occupants in the dormitory building.

Season	Mathematical description
Summer	$n_{occ,dor,t} = \begin{cases} 313 & t \in 1:00-6:00 & \\ 14.669t^2 - 134.91t + 418.47 & t \in 7:00-13:00 & (R^2 = 0.9615) \\ 4.83t^2 - 48.486t + 215.47 & t \in 14:00-0:00+d & (R^2 = 0.9619) \end{cases}$
Winter	$n_{occ,dor,t} = \begin{cases} 300 & t \in 0:00-6:00 & \\ 19.654t^2 - 163.48t + 422.41 & t \in 7:00-12:00 & (R^2 = 0.9883) \\ 4.34t^2 - 37.056t + 152.52 & t \in 13:00-23:00 & (R^2 = 0.9532) \end{cases}$

4. Analysis and validation of the results

4.1. Occupancy analysis

The definitive number of people can be fitted in each peak segment with a parabola [31]. Demarcation points generally occur during the lunch break and after work. The fitting accuracy was measured using R^2; $R^2 \geq 0.9$ represents an accurate fit. The data acquisition and analysis were performed in 1 h time steps.

In Tables 2–4, $n_{occ,dor,t}$ is the number of occupants in the dormitory building; $n_{occ,off,t}$ is the number of occupants in the office building; $n_{occ,cls,t}$ is the number of occupants in the teaching building; n_{cls} is the number of classrooms in use; and t denotes the time in numeric form, where the function of time can be stored as decimal within [0, 1], for example, 12:00 can be converted to 0.50, and 15:00 can be converted to 0.625.

Students on campus have different living habits in summer and winter; some of them go to lunch earlier in the summer than in winter. Therefore, the demarcation points of the two parabolas slightly differ (summer: 13:00, winter: 12:00). The demarcation points of the teaching and office buildings also show a difference in the definitive description, which is due to the student schedule arrangement. The calculations for the teaching building show that the accuracy of the deterministic numbers is very high (both above 0.95), that is, the average number of people corresponding to each time is small. The definitive number of occupants is obtained by binomial fitting. Actually the occupancy at the same time may be various in different days. The teaching building was taken as an example to calculate the floating part of the occupant number. Fig. 3 illustrates the fluctuating of the number of occupants at different time.

Fig. 3 shows that the variation range of the occupant number is different in different time period. The actual occupant number varies between the maximum and minimum values of box plot. To obtain the regularity of the variation range, the fluctuation of the occupant number was discretized. And the probability of variation range was shown in Fig. 4.

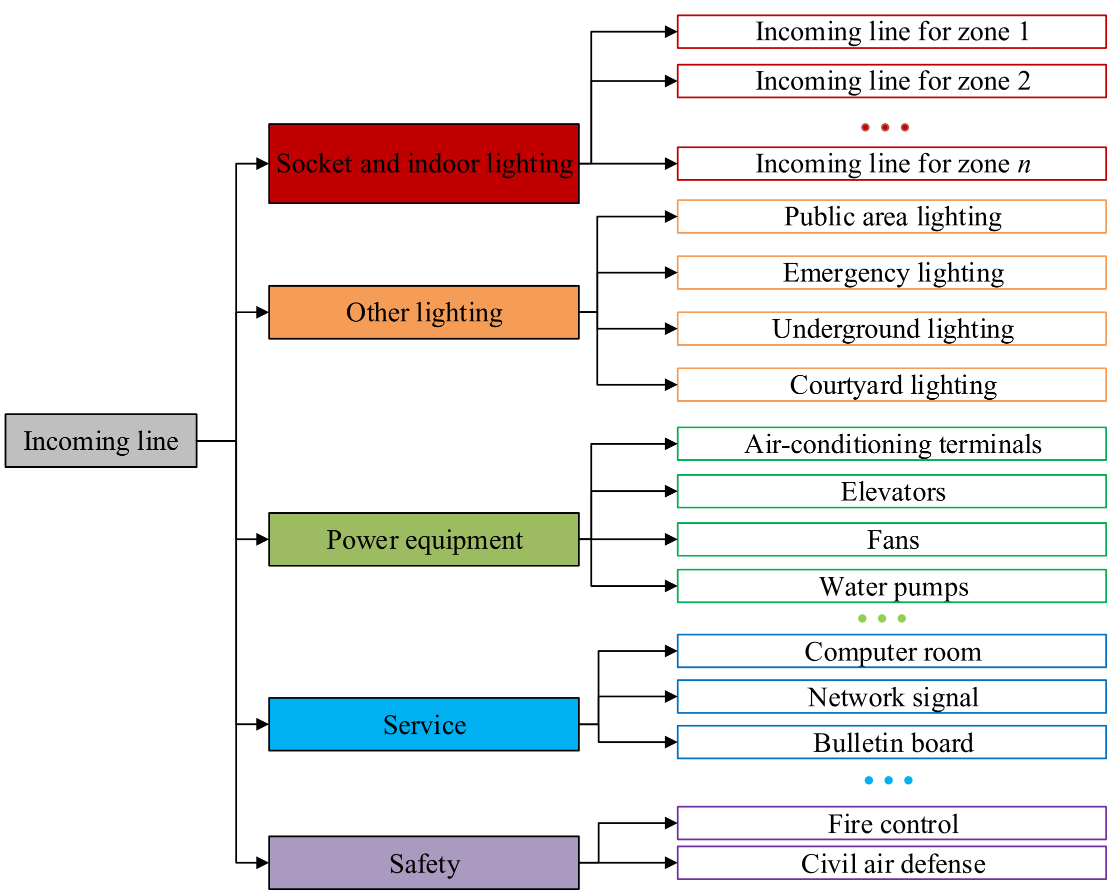


Fig. 2. Schematic diagram of building subentry electricity.

Table 3
Definitive number of occupants in the office building.

Season	Mathematical description
Summer	$n_{occ,off,t} = \begin{cases} 0 & t \in 0:00-6:00 \\ -3.75t^2+20t+8.75 & t \in 7:00-11:00 \\ -4t^2+26t-10 & t \in 12:00-17:00 \\ -3.5689t^2+17.83t+22.057 & t \in 18:00-23:00 \quad (R^2=0.9276) \end{cases}$
Winter	$n_{occ,off,t} = \begin{cases} 0 & t \in 0:00-6:00 \\ -3.75t^2+20t+8.75 & t \in 7:00-11:00 \\ -4t^2+26t-10 & t \in 12:00-17:00 \\ -6.9413t^2+41.93t-0.7286 & t \in 18:00-23:00 \quad (R^2=0.9552) \end{cases}$

Table 4
Definitive number of occupants in the teaching building.

Season	Mathematical description
Summer	$\mathrm{n}_{occ,cls,t} \begin{cases} 0 & t \in 0:00-6:00 \\ (-0.77t^2+7.2\mathrm{t}-5.47)\times(30-n_{cls}) & t \in 7:00-12:00 \quad (R^2=0.9847) \\ (-0.73t^2+6.2t+4.03)\times(30-n_{cls}) & t \in 13:00-18:00 \quad (R^2=0.9115) \\ (-1.22t^2+7.94t+6)\times(30-n_{cls}) & t \in 19:00-23:00 \quad (R^2=0.9358) \end{cases}$
Winter	$\mathrm{n}_{occ,cls,t} \begin{cases} 0 & t \in 0:00-6:00 \\ (-2.17t^2+15.91\mathrm{t}-13.37)\times(30-n_{cls}) & t \in 7:00-12:30 \quad (R^2=0.9847) \\ (-0.54t^2+4.31t+0.52)\times(30-n_{cls}) & t \in 12:30-18:30 \quad (R^2=0.9115) \\ (-2.57t^2+14.68t+8.61)\times(30-n_{cls}) & t \in 18:30-23:00 \quad (R^2=0.9358) \end{cases}$

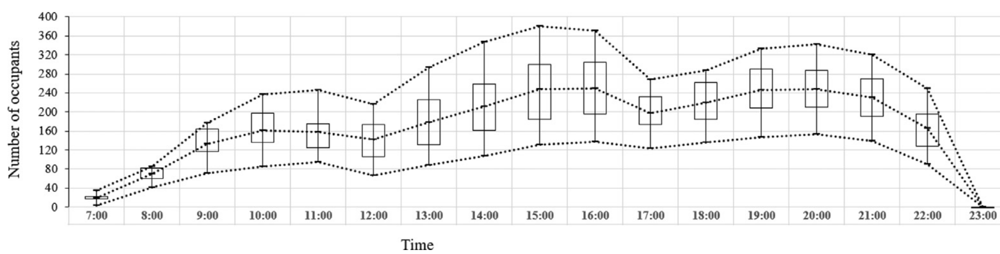


Fig. 3. The variation range of the number of occupants (summer -teaching building).

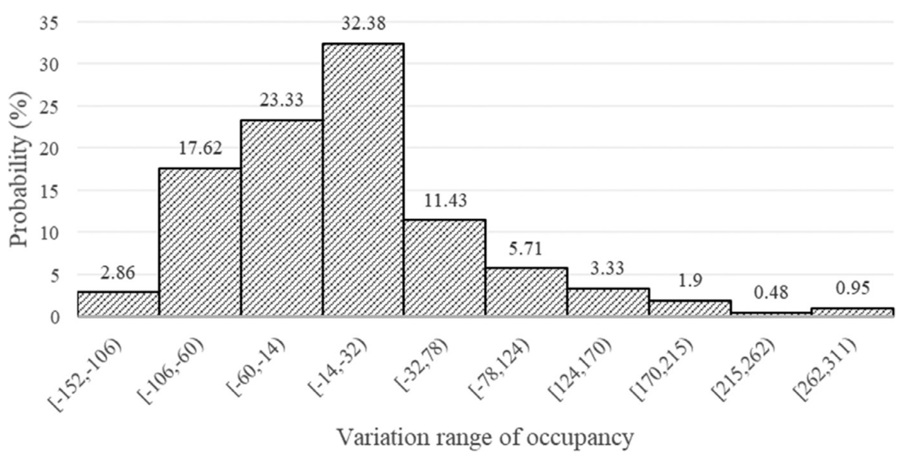
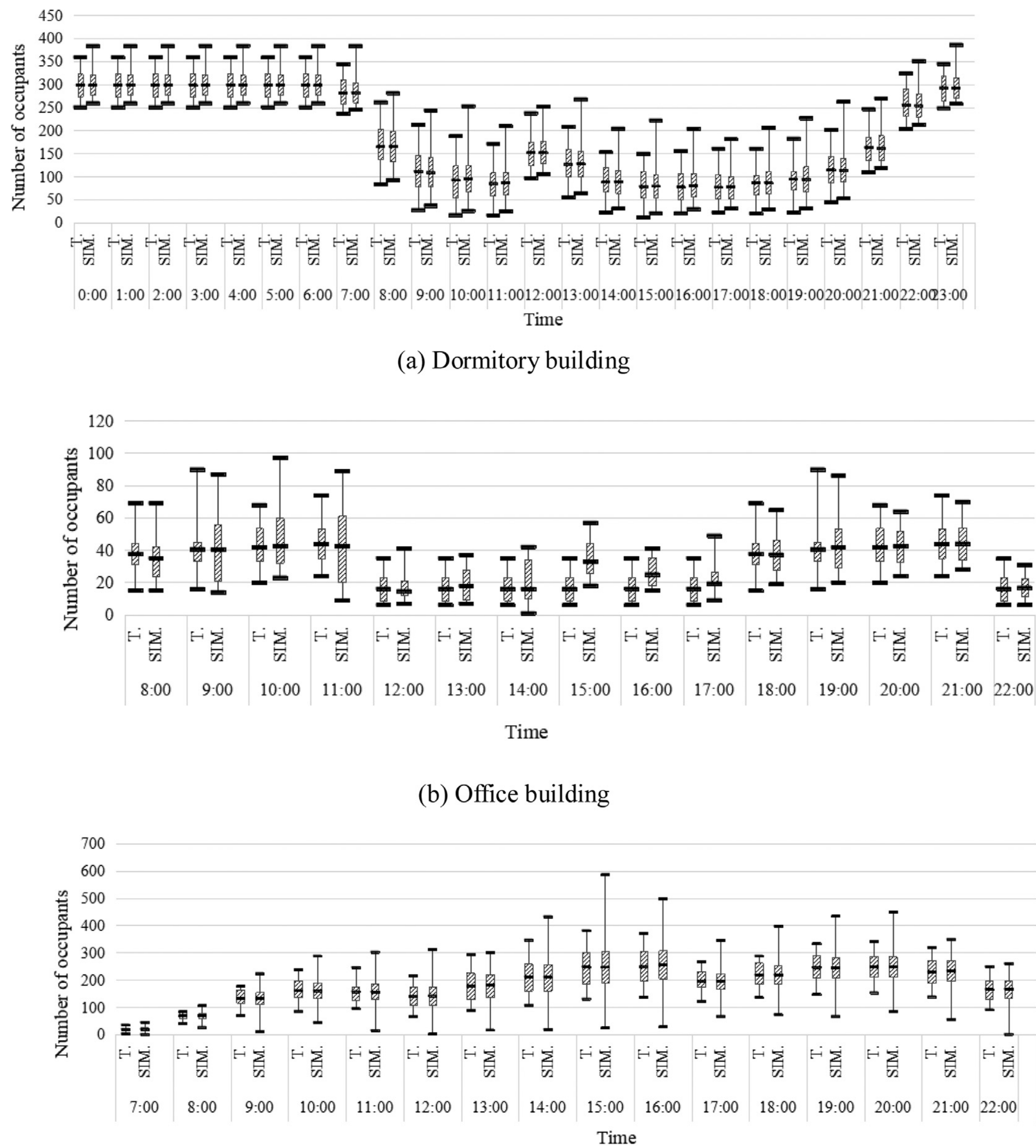


Fig. 4. Probability distribution of fluctuation values (summer -teaching building).

In Fig. 4, taking the teaching building as an example, probability distribution of occupancy fluctuation is exhibited. In the same way, the probability distribution of occupancy fluctuation in the dormitory and office building can be obtained. In general, the occupancy fluctuation is random. So a statistical method was applied to the occupancy calculation model. The Monte–Carlo method was used to get the random number of the initial state. Markov transfer matrix can be established based on the probability distributions in Fig. 4 with the time step of 1 h. The occupancy in time $t+1$ can be predicted based on the occupancy at time t. Then the description of occupancy randomness was established.

To verify the accuracy of the occupancy predicted model, 1000 groups of fluctuated occupant number were calculated and added to the deterministic occupancy description to be the time series of the number of occupants in each building. These iterative calculations rely on the implementation of the Visual Basic for Application programming language in Microsoft Office Excel 2013. The results of the 1000 calculations were analysed and the ranges of the number of occupants in the buildings at various times were obtained using simulations and compared with the measured number of occupants. The results are shown in Figs. 5 and 6.

In Figs. 5 and 6, the x-axis represents the time of day. The parameter T. in the graphs indicates the measured value and SIM. represents the simulated value. Based on Figs. 3 and 4, the variation trend in the number of occupants in the simulation is the same as that of the measured trend; however, the simulation value



(a) Dormitory building

(b) Office building

(c) Teaching building

Fig. 5. Actual and simulated numbers of occupants in each building (summer).

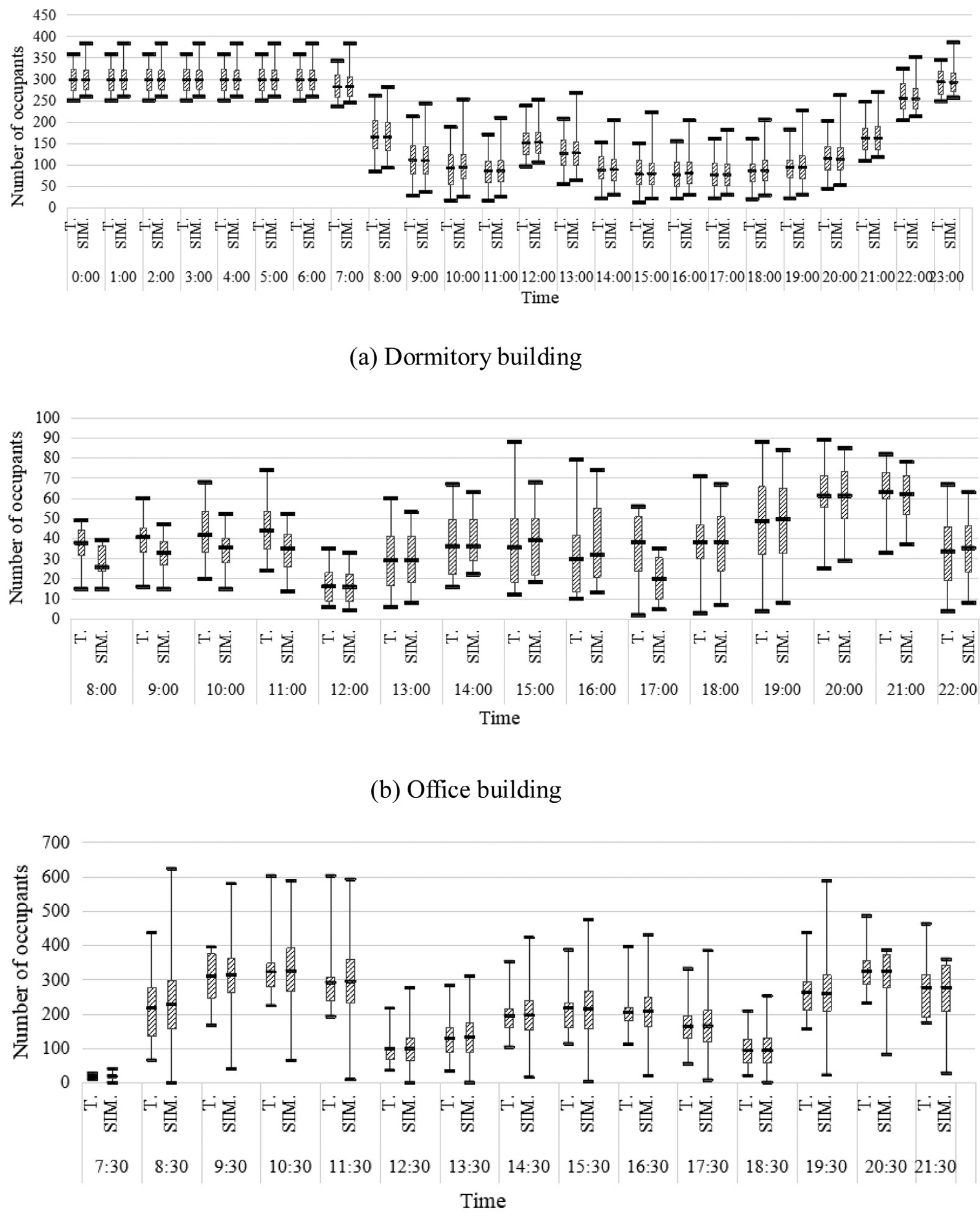
is mostly greater than that the measured value. Therefore, when the data were used for a certain probability distribution law, all possible values could be reproduced using the simulation and potential values had to be larger than the range of the measured data. However, the simulated maxima were sometimes much larger than the measured maxima. In normal applications, data that perform at a low probability are abandoned. Some of the simulated data values were smaller than the measured data, such as the data simulated for the office building at night, because the measured data were concentrated. After several simulations, the data tend to be much more concentrated.

To quantitatively compare the degree of closeness of the two sets of random data, the relative entropy Kullback–Leibler divergence (KLD) and coefficient of variation of the root-mean-square error (CVRMSE) were used in this study. If the distributions of these two sets are the same, KLD = 0. The lower the KLD value is, the closer are the distributions of these two sets of random data. The smaller the CVRMSE is, the closer are the two sets of random data. Generally, a CVRMSE below 30% [34] is considered to meet the requirements for the prediction accuracy and verifies the efficiency of a model.

Table 5
Statistical comparison between the numbers of occupants based on simulated and measured data.

Building type	KLD		CVRMSE (%)	
	Summer	Winter	Summer	Winter
Dormitory	0.09	0.08	8.83	4.69
Office	0.18	0.13	14.85	14.56
Teaching	0.06	0.17	2.64	7.35

Table 5 shows the comparison of the predictions for the number of occupants between the simulated and measured data. From a numerical point of view, an accuracy of the predictions for the dormitory and teaching buildings surpassing 90% and prediction accuracies for the office building above 85% were obtained through



(a) Dormitory building

(b) Office building

(c) Teaching building

Fig. 6. Actual and simulated numbers of occupants in each building (winter).

the above-mentioned method because of the overdistribution of the original data.

The model was based on the measured number of occupants in a building. According to the random nature of the number of occupants in a building, a combination of definitive and random descriptions was used to establish the time distribution of the number of occupants in each building. The two-step calculation improves the accuracy of the occupant submodel.

4.2. Mathematical description of the electricity consumption

4.2.1. Basic electricity consumption

The basic electricity consumption of the three buildings was fitted based on the building area and the mathematical description is:

$$E_{bas.} = 1.2894 \cdot A\left(R^2 = 0.91\right) \quad (6)$$

where E_{bas} represents the basic average electricity consumption of the three buildings (W) and A is the building area (m^2).

Based on Eq. (6), the basic average electricity consumption of the building area is 1.29 W/m^2. Therefore, the basic electricity consumption of a building can be estimated if the building area is known.

4.2.2. Variable electricity consumption

The growth limit theory consists of the limit of the number of occupants and the limit of electricity consumption. Based on the clustering analysis, the upper limit of occupancy and the limit of

Table 6
Clustering results for the electricity consumption and number of occupants in the dormitory.

CLdor	Statistical Parameter	Average	Maximum	Minimum	Upper Quartile	Median	Lower Quartile
Summer							
	Power (kW)	1.80	5.28	0.10	2.60	1.35	0.85
$CL_{dor}1$	Number of occupants	317	346	275	330	322	306
	Power (kW)	2.82	6.65	0.50	3.38	2.45	1.65
$CL_{dor}2$	Number of occupants	121	233	25	157	112	91
	Power (kW)	9.72	26.81	5.40	10.11	8.55	7.15
$CL_{dor}3$	Number of occupants	224	338	38	304	220	148
Winter							
$CL_{dor}1$	Power (kW)	1.20	4.78	0.20	1.59	0.86	0.50
	Number of occupants	304	363	237	331	301	277
$CL_{dor}2$	Power (kW)	2.79	6.08	1.35	3.11	2.60	2.22
	Number of occupants	118	241	16	185	118	82
$CL_{dor}3$	Power (kW)	8.81	13.88	3.80	1.19	8.60	6.81
	Number of occupants	97	290	12	220	84	56

Table 7
Clustering results for the lighting electricity consumption and number of occupants in teaching rooms.

Category	1		2		3	
	Electricity consumption (kW)	Number of occupants	Electricity consumption(kW)	Number of occupants	Electricity consumption(kW)	Number of occupants
Average	18.50	128	20.84	232	18.82	298
Lower Quartile	18.15	98	20.03	204	18.43	259
Maximum	20.09	178	22.89	300	20.43	381
Minimum	15.87	62	19.42	131	18.12	196
Upper Quartile	19.42	149	21.56	265	19.04	342

electricity consumption are reached if the electricity consumption no longer significantly increases with increasing number of occupants. By taking the upper limit as the boundary, the building electricity consumption can be described with the piecewise function, which represents the variable description of the building electricity consumption.

The total electricity consumption of the dormitory consists of the energy consumption of the sockets, lighting, and air conditioning. In winter, the dormitory building was equipped with an underfloor heating system and air conditioning was not used. In summer, approximately 98 split-system air conditioners were working during the test period. Due to the difference in the use of air conditioners, the dormitory electricity consumption in the winter and summer seasons were considered separately.

Table 6 shows the clustering results for the dormitory building.

In Table 6, the number of occupants in the first category is basically the same, and the electricity consumption varies slightly. By analysing the time in the first category, the electricity consumption of the first category reflects the situation of occupants sleeping at night. The electricity consumption of the second and third categories varies greatly with the fluctuation of the occupant number. With further analysis of the second and third categories, the per capita electricity consumption of the third category is larger than that of the second category. By comparing the occurring time of occupancy and electricity consumption, the second category represent the time period from the start of work in the morning to the dinner time, and the third category represent the time period from the dinner time to the time before sleeping.

Actually, the schedule of the occupant is not strictly segmented, so each category has a partial overlap at the boundary. Based on the schedule, the median value of the number of coincident segments was set as the demarcation point. There were overlaps between the third and the first categories, so the occupant number at the demarcation point represents the upper limit of the occupant number in the dormitories. Under this classification, the upper limits of the occupant are 321 in summer and 290 in winter respectively.

In contrast to the dormitory building, the utilization modes in the office and teaching buildings were quite different. The teaching building is unique in that the occupants have unequal control rights over the use of electrical appliances. There are more active people than passive people. Teaching rooms are typical multi-people rooms. During lectures, only half of the lamps are on because of the use of PowerPoint displays, but lamps are freely used during self-study time. The clustering results of the electricity consumption and number of lamps used are given in Table 7 and Fig. 7 respectively.

Fig. 7 shows that the lighting electricity consumption increases with the number of occupants in the morning. At noon, it does not decrease because the number of occupants decreases, but it further increases in the afternoon because the number of occupants increases. These results show that some people took the initiative to turn lights on but did not turn them off. Based on the combination of the data in Table 3 and Fig. 3, the maximum number of occupants in the afternoon used as the limit for the teaching building is 265.

Subsequently, the lighting electricity consumption of office buildings was analysed. Based on clustering the lighting electricity consumption of the office building, the total was divided into three categories and the results are shown in Table 8.

The number of occupants and electricity consumption of the first category are both low, indicating that this is the time when a person had just arrived or left a room. In terms of time, the first category is distributed between 8:00–12:00 and 21:00–22:00. The occupancy and electricity consumptions of the second category are both larger than those in the first category and most of the time periods are working hours and night time. The time period of the third category represents the working hours. Based on the above-mentioned values and time distributions, the lighting power of the office building first increases and then decreases with time, which is a result of the change in the number of occupants. When the occupancy gradually increases to a certain value, the lighting electricity consumption no longer increases. Similarly, when the number of occupants decreases to a certain value, the lighting electric-

Table 8
Description of the lighting electricity consumption in the office building.

Category	1		2		3	
	Electricity consumption(kW)	Number of occupants	Electricity consumption(kW)	Number of occupants	Electricity consumption(kW)	Number of occupants
Average	3.35	20	7.52	38	7.38	83
Lower Quartile	1.54	10	5.79	29	5.92	70
Maximum	6.71	42	14.67	74	15.15	132
Minimum	0.90	2	2.84	3	3.26	59
Upper Quartile	5.68	32	8.60	49	8.71	90

Table 9
Description of the electricity consumption of the dormitory building.

Season	Mathematical description
Summer	$E_{h,dor.acw} = \begin{cases} 570.66e^{0.0122 n_{occ.dor.}} & 8:00 \le t < 18:00 & (R^2 = 0.94) \\ 4403.4e^{0.0027 n_{occ.dor.}} & 19:00 \le t \le 2:00 + day & (R^2 = 0.94) \\ 171.41 n_{occ,dor.} - 54716 & 321 \le n_{occ,dor.} \le 345 & (R^2 = 0.91) \end{cases}$
Winter	$E_{h,dor.hw} = \begin{cases} 1454.2e^{0.005 n_{occ.dor.}} & 8:00 \le t < 17:00 & (R^2 = 0.99) \\ 4873.4e^{0.0058 n_{occ.dor.}} & 18:00 \le t \le 1:00 + day & (R^2 = 0.90) \\ 23.98 n_{occ,dor.} - 6244.4 & 290 \le n_{occ,dor.} \le 345 & (R^2 = 0.91) \end{cases}$

Table 10
Description of the electricity consumption of the teaching building.

Power (kW)	Mathematical description
Equipment	$E_{h,equ.,cls.} = \begin{cases} 0.1 \times e_{lap.,cls.} \cdot n_{occ,cls.} \cdot (n_{cr} - n_{cls}) + n_{cls} \cdot e_{com.,cls.} & 0 \le n_{occ,cls.} < 8 \\ 8e_{lap.,cls.} \cdot (n_{cr} - n_{cls}) + n_{cls} \cdot e_{com.,cls.} & n_{occ,cls.} \ge 8 \end{cases}$ $= \begin{cases} 1.799 n_{occ,cls.} \cdot (n_{cr} - n_{cls})/1000 + 96.13 n_{cls}/1000 & 0 \le n_{occ,cls.} < 8 \\ 143.92(n_{cr} - n_{cls})/1000 + 96.13 n_{cls}/1000 & n_{occ,cls.} \ge 8 \end{cases}$
Lighting	$E_{h,lig.,cls.} = \begin{cases} 6.9242 n_{occ,cls.}{}^{0.2062} & 0 \le n_{occ,cls.} < 265, R^2 = 0.96 \\ 18.8 \times (1 \pm 10\%) & n_{occ,cls.} \ge 265 \end{cases}$
Air conditioning	$E_{h,fc.,cls.} = \begin{cases} 4.1239 \ln(n_{occ,cls.}) & 0 \le n_{occ,cls.} < 317, R^2 = 0.93 \\ 31.26 \times (1 \pm 10\%) & n_{occ,cls.} \ge 317 \end{cases}$

ity consumption decreases. As shown in Table 4, the limit point is within the range of 59–74. Therefore, the limit number is regarded as 70 or 50% of the maximum. Because the maximum number of visitors in an office building is approximately four times the number of employees, the lighting electricity consumption reaches the limit and no longer increases with increasing number of occupants when the number of staff corresponding to this limit is 12.5%.

The prediction method for the electricity consumption of sockets and air conditioners in the office and teaching buildings is the same as that used for lighting. The specific expressions of the growth limits of each building are shown in Tables 9, 10 and 11, respectively.

In Tables 9–11, $E_{h,\ dor.}$ is the hourly electricity consumption (kW); $n_{occ,\ dor.}$ indicates the number of occupants in the dormitory building; t is the moment; subscripts acw and hw indicate summer and winter, respectively; a and b are the undetermined coefficients of the linear expression; nocc is the number of occupants; and e is the per capita electricity consumption (W); *lig.* Denotes the illumination; *lap.* denotes the laptop; *com.* denotes the desktop; *ac* denotes the air conditioner; *fc* denotes the fan coil; *cls.* denotes the teaching building; *off.* denotes the office building; and *occ* denotes the occupants.

The number of people after the classification agrees with that based on the electricity data; therefore, the description can be can

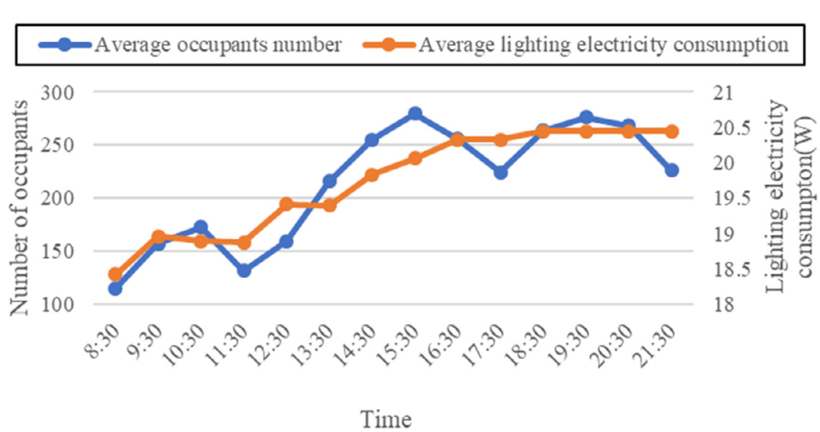


Fig. 7. Comparison of the lighting electricity consumption and number of occupants in the teaching building.

Table 11
Description of the electricity consumption of the office building.

Power (kW)	Mathematical description
Equipment	$E_{h,equ.,off.} = 1.1n_{occ,off.} \cdot e_{com.,off.} = 1.1 \times 89.88n_{com.,off.} = 98.87n_{com.,off.} \quad n_{com.,off.} \le 35$
Lighting	$E_{h,lig.,off.} = \begin{cases} a_{lig.,off.}n_{occ,off.} + b_{lig.,off.} & 0 \le n_{occ,off.} < 70 \\ 15 \times (1 \pm 10\%) & n_{occ,off.} \ge 70 \end{cases} = \begin{cases} 0.1757n_{occ,off.} + 0.4982 & 0 \le n_{occ,off.} < 70, R^2 = 0.95 \\ 15 \times (1 \pm 10\%) & n_{occ,off.} \ge 70 \end{cases}$
Air-conditioners	$E_{h,lig.,off.} = \begin{cases} 1.5623e^{n_{occ,off.}} & 0 \le n_{occ,off.} < 54, R^2 = 0.94 \\ 3.80 \times (1 \pm 30\%) & n_{occ,off.} \ge 54 \end{cases}$

Table 12
Daily variable electricity consumption of the buildings.

Daily variable electricity consumption (kWh/d)	Summer	Winter	Spring/Autumn
Dormitory building	205.99	141.54	141.54
Teaching building	440.70	436.90	243.23
Office building	320.75	320.34	295.41

Table 13
Campus building electricity bills during the test period in 2017 (RMB).

Building Type	Summer	Winter	Spring/Autumn
Teaching	25,092.27	34,063.71	32,078.94
Dormitory	15,529.97	15,620.89	15,767.62
Office	12,277.12	16,257.38	18,719.17

be obtained with the classic multiple regression model. The rated power of each device was obtained from the actual investigation.

4.3. Results of the electricity consumption calculations

Based on the model, the time series electricity consumption of each building consists of the variable and basic parts shown in Fig 8. The variable daily electricity consumption is listed in Table 12.

The dormitory building was not closed during the summer vacation but was closed for approximately 15 days during winter vacation. With respect to the teaching building, only half of the rooms were available during vacations. The office building was used approximately three days per week during the winter and summer vacations. Therefore, the teaching, dormitory, and office buildings were used for 310, 300, and 220 days, respectively. The annual variable electricity consumption of each building was obtained considering the hourly occupancy. Combined with the basic building electricity consumption, the annual variable electricity consumption in the dormitory, teaching, and office buildings is 0.74, 1.93, and 2.95 kWh/(person · d), respectively.

The electrical load demand at the occupant level was compared between buildings. Problems were detected with respect to the operating management of different buildings on the public power grid. For example, for each occupant, the average peak electricity load is 200 W in the teaching building, 300 W in the office building, and only 50 W in the dormitory building. This is caused by the computer type and control mode used for lighting and air conditioning. The data show that the more flexible the control mode is, the more energy is saved. Therefore, in a large area shared by many people, such as a multi-person office or classroom, distributing lighting switches to avoid turning on all lights with a single switch is an effective means to reduce the building electricity consumption.

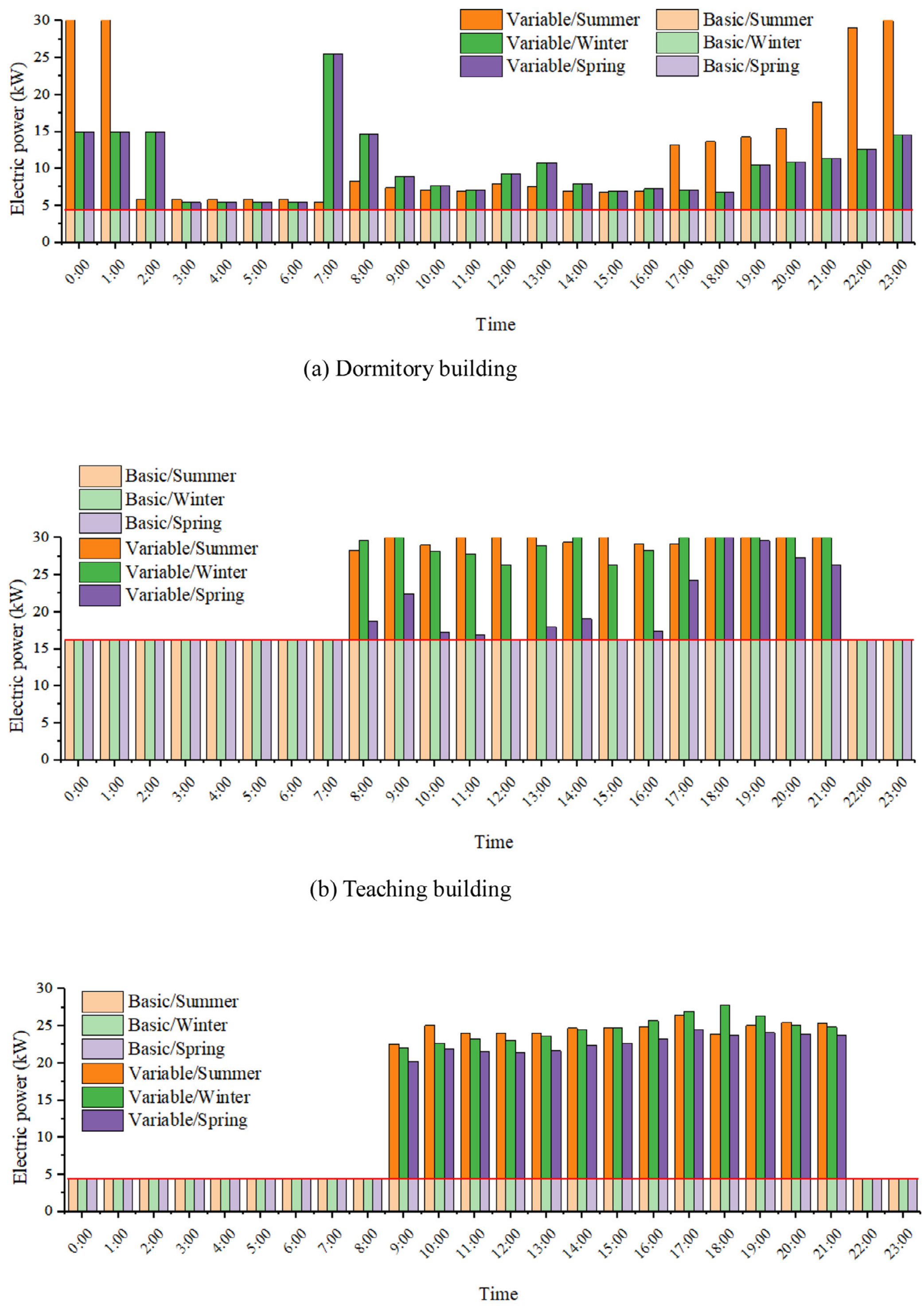
4.4. Annual electricity bill

The accuracy of the prediction method of the building electricity consumption based on the occupant behavior proposed in this study can be verified by comparisons with electricity bills generated during the actual operation. The 2017 electricity bills are provided in Table 13. The electricity price on campus was 0.515 RMB/kWh.

The actual electricity consumptions of the buildings during the test period are listed in Table 13 and the results of the comparison are shown in Table 14. The annual cooling and heating seasons are June 1 to September 15 and November 1 to March 15, respectively. The electricity consumption of air conditioners is based on these two periods. As shown in Table 14, the error between the calculated result and actual electricity consumption does not exceed 5%. Therefore, the model of the building electricity consumption can

Table 14
Comparisons of the predictions with the actual electricity consumptions.

Building Type			ElectricityConsumption (kWh/d)Summer	Winter	Spring/Autumn
Teaching Building	Prediction	Basic	196.20	196.20	196.20
	results	Variable	440.7	436.9	243.23
	Actual		649.63	664.75	441.62
Error	%		2.0	5.0	0.5
Dormitory Building	Prediction	Basic	105.21	105.21	105.21
	results	Variable	205.99	141.54	141.54
	Actual		301.55	256.99	250.94
Error	%		3.1	3.4	1.7
Office Building	Prediction	Basic	114.19	114.19	114.19
	results	Variable	320.75	320.34	295.41
	Actual		441.46	440.61	405.91
Error	%		1.5	1.4	0.9



(a) Dormitory building

(b) Teaching building

(c) Office building

Fig. 8. Total electricity consumption of the dormitory, office, and teaching buildings.

be used as a reference for building electricity consumption estimations.

5. Discussion

The association of the variable building electricity consumption with occupants can be used as guidance for the energy use behavior. If the electricity consumption per unit building area is used as an index, the annual electricity consumption of the dormitory, teaching, and office buildings is 26.57, 27.38, and 24.83 kWh/(m^2·a), respectively. The total area of the test buildings with 500 active occupants is 13,430 m^2, the annual electricity consumption is approximately 24.22 kWh/(m^2·a), and the per capita electricity consumption is 461.24 kWh/(person·a). The calculations based on the area index method do not show daily electricity consumption fluctuations. However, even if the buildings have identical functions, differences in the occupant behavior and number of occupants will cause variations in the building electricity consumption.

The occupant energy demand is based on the person's energy needs. It is easier to acquire and amend the occupant energy demand based on the energy prediction method. Usually the energy consumption quota of the area index is based on a large statistical dataset. The energy consumption quota based on occupant behavior can be obtained by categorizing the existing data by occupant or by surveys and tests of the building use. Even if a building is used for a short time and a small amount of energy consumption data are collected, the occupant energy consumption can be obtained and further standardised using the data for a longer time.

On the other hand, this prediction method can yield an ultra-short-term energy quota. In the hourly cycle, if the area or per capita indexes are used, it is difficult to predict the energy consumption. However, the electricity consumption per hour can be calculated based on the number of occupants in a building. Therefore, adopting the method of building energy quotas based on human behavior refines the management process and manages the energy consumption according to the building functioning time.

The electricity consumption prediction model proposed in this study is suitable for commercial buildings, but it might not be applicable in residential buildings. On the one hand, the occupant behavior in the residential buildings is difficult to be monitored because of privacy reasons. On the other hand, the electricity consumption in residential buildings is directly related to occupants' activities, and the basic part of electricity consumption will be very small or almost non-existent.

6. Conclusions

This study provides initial evidence about the extent to which the campus building electricity consumption is related to its occupants and can be benchmarked separately for the building area and number of occupants. A building electricity consumption prediction method is proposed in this study. The prediction method is based on the establishment of a mathematical model of the building electricity consumption in combination with basic and variable influencing factors. The basic electricity consumption is related to the building area, while the variable electricity consumption is related to the building occupancy. By establishing the occupancy-based model, the electricity consumption could be quantified at both the occupant and building levels in this study. The following conclusions can be drawn.

(1) The growth limit theory can be demonstrated by clustering analysis of the building electricity consumption and number of occupants in buildings. The upper limit of the occupancy and the limit of electricity consumption are reached if the electricity consumption no longer significantly increases with increasing number of occupants. When the occupancy gradually increases to a certain value, the lighting electricity consumption no longer increases. The upper limit of the total electricity consumption of the case dormitory building in this study is 321 people in summer and 290 people in winter. With respect to the electricity consumption of the lighting system, 70 is the upper limit of occupants in the office building, while 265 is the upper limit of occupants in the teaching building.

(2) Based on the occupancy-based model, the time series electricity consumption of each building consists of variable and basic parts. A piecewise function of the building electricity consumption submodel was established and the variable electricity consumption of three buildings was obtained. The basic electricity consumption of the three buildings was fitted based on the building area of all three buildings, which is $1.29\,W/m^2$. The error between the calculated result of the occupancy-based model and actual electricity consumption does not exceed 5%, which was verified with the annual electricity bill. The validation shows that the prediction accuracy of the energy consumption can be improved by dividing the building energy consumption based on two aspects, which is, directly and indirectly related to the occupant behavior.

(3) With respect to the variable electricity consumption, the average electricity consumption of a single occupant varies depending on the building function and control mode of electrical equipment. The more flexible the control mode in a campus building is, the more energy can be saved. The electricity load demands of occupants in dormitory, teaching, and office buildings were quantified. If occupants stay in the dormitory building for the entire day, the average variable electricity consumption is 0.74 kWh/(person·d) and includes the use of computers, lighting, and air conditioning. The average electricity consumption in the office and teaching buildings is 2.95 and 1.93 kWh/(person·d), respectively, and includes the total electricity consumption for computers, lighting, and fan coils.

(4) The impact of occupant actions on the building electricity consumption is not a simple superposition of the electricity consumption of a single person. For a building in which multiple people sharing a room, the impact of the occupant action on the building electricity consumption is a piecewise function because the building electricity consumption has a growth limit, which is related to a person's initiative or ability to control the electricity use.

From the perspective of human demands, the occupant-based electricity consumption prediction method proposed in this study has a larger energy-saving potential. The combination of the schedules of occupants can provide a basis for effective energy management in buildings. Future research is needed to explore the methodology using a larger dataset and to compare the energy-saving effects based on the management of different types of buildings.

Declaration of Competing Interest

On behalf of, and having obtained permission from all the authors, I declare that: All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication. I testify to the accuracy of the above on behalf of all the authors.

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