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A Novel Stochastic modeling method to simulate cooling loads in residential districts

Jingjing An[1], Da Yan[1], Tianzhen Hong[2], Kaiyu Sun[2]

[1]School of Architecture, Tsinghua University, Beijing, China

[2]Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, USA

Abstract

District cooling systems are widely used in urban residential communities in China. Most district cooling systems are oversized; this leads to wasted investment and low operational efficiency and thus energy wastage. The accurate prediction of district cooling loads that supports rightsizing cooling plant equipment remains a challenge. This study developed a new stochastic modeling method that includes (1) six prototype house models representing a majority of apartments in the district, (2) occupant behavior models in residential buildings reflecting the temporal and spatial diversity and complexity based on a large-scale residential survey in China, and (3) a stochastic sampling process to represent all apartments and occupants in the district. The stochastic method was employed in a case study using the DeST simulation engine to simulate the cooling loads of a real residential district in Wuhan, China. The simulation results agree well with the actual measurement data based on five performance metrics representing the aggregated cooling loads, the peak cooling loads as well as the spatial load distribution, and the load profiles. Two currently used simulation methods were also employed to simulate the district cooling loads. The simulation results showed that oversimplified occupant behavior assumptions lead to significant overestimations of the peak cooling load and total district cooling loads. Future work will aim to simplify the workflow and data requirements of the stochastic method to enable its practical application as well as explore its application in predicting district heating loads and in commercial or mixed-use districts.

Keywords: stochastic modeling, occupant behavior, residential district, DeST, cooling load, building performance simulation

1. Introduction

Energy consumption in residential buildings accounts for a large proportion of the total energy consumption around the world. In 2006, the U.S. residential sector accounted for more than 20% of the total U.S. primary energy consumption [1]. In the northern part of the European Union, residential buildings account for 30% of the total final energy consumption [2]. In China, it is estimated that the existing building stocks will account for about 35% of the total energy consumption in 2020, with heating, ventilation, and air-conditioning (HVAC) systems accounting for 65% of the residential energy consumption [3]. Therefore, energy consumption reduction in residential buildings has been attracting increasing attention and new technologies have been developed and implemented.

District heating and cooling (DHC) systems have become increasingly popular in recent years in China and other countries [4–6]. A DHC system can simultaneously provide heating and/or cooling to many buildings usually in a campus or urban district. Therefore, it must use larger capacity equipment with higher efficiency than decentralized smaller capacity equipment (e.g., split-type air-conditioners) as well as community-scale renewable energy sources (e.g., underground water) [6,7]. To exploit DHC systems, high efficiency and low energy consumption must be accomplished. To this end, the thermal load demand of building users in a district must be accurately understood.

Two conventional methods are used to estimate the building thermal loads in a district. The first one is the so-called full-time full-space (FTFS) method, which considers climate conditions as the most important factor influencing the loads and gives lesser importance to internal heat gains in buildings. In the simulation of thermal loads, the FTFS method assumes that the internal heat gains remain constant and do not change with time or space and the air-conditioning is always on in every room in every building. The FTFS method is still used in the present design standard of China and is widely used in the HVAC system design [8]. With the development of dynamic simulation tools for energy consumption in residential building and the awareness of occupant behaviors in buildings, more and more researchers have realized that the inputs of occupant behaviors significantly influence building performance and more realistic inputs of occupant-related schedules (i.e., occupancy schedules and appliance use schedules) should be used to simulate building thermal loads; otherwise, the predicted results could significantly deviate from the actual measurement [9]. The second conventional method is the Fixed Schedules method, which uses predefined time schedules for occupancy and appliances based on the building type and climate zones that are derived from investigations of real buildings. Several researchers have performed investigations to determine input schedules for simulating building energy. Based on a questionnaire survey, Zhang [10] summarized a group of fixed schedules for occupancy, lighting, and equipment among other factors for office buildings and applied these schedules to determine the building energy consumption indicators for China's standard for energy consumption in non-residential buildings. Jian [11] and Xia [12] performed measurements in residential buildings and presented typical household schedules for estimating the thermal performance of residential buildings. They recommended that typical uniform schedules should be simple and limited to one or a few sets of schedules for practical engineering purposes. In addition, Chow[13] and Gang[14] considered different schedules of serveral building types (e.g., office, school, hotel) for cooling load prediction in their studies, and analyzed the system performance based on predicted loads.

In contrast to a single house or residential building, a district has tens or hundreds of households with varying thermal demands. Thus, their load profiles present significant spatial and temporal diversity.

Weissmann et al. [5] used load profiles of two buildings to show the load diversity and its impact on the central supply peak load. Fonseca and Schlueter [15] emphasized the importance of understanding the characteristics of spatial and temporal load diversity of district systems for equipment sizing and control strategy application. Moreover, Brounen et al. [16] investigated 305,001 dwellings in 2008–2009 and found a wide variation in household consumption. Therefore, a method is needed to represent the load diversity in districts.

Previous studies have analyzed load diversity mainly based on the building type, orientation, and envelope performance [5,15,17]. However, occupant behavior could be another key influencing factor in the load diversity among buildings. Gilani et al. [18] and Hoes et al. [19] examined the importance of occupant behavior models in simulation-aided design and code compliance in Canada and the Netherlands. Sun et al. [20] concluded that energy-saving occupant behaviors could achieve overall energy savings as high as 22.9% for individual behaviors and up to 41.0% for integrated behaviors. Ruan et al. [21] pointed out that the age of occupants should be considered in residential community planning as the age of occupants may significantly affect the dwelling time and use of air conditioners. They [21] also performed simulations for Qingdao city with uniform correction coefficients for various household types to determine optimal residential community planning. Zhou et al. [22] demonstrated that the stochastic feature of air-conditioning use modes was the main factor contributing to the difference between the design and actual building performance. However, Zhou et al. [22] only considered one type of occupant behavior (i.e., air-conditioning use) and assumed that air-conditioning control was only influenced by the occupant's thermal comfort.

In the simulation of building performance, previous research has described realistic occupant behaviors using probabilistic model development based on monitoring, sensor, and/or survey data. These observational studies demonstrated the relationships between the indoor and outdoor environmental factors and the occupant behaviors under consideration [23]. Hong et al. [24] identified the major types of occupant behaviors in buildings, including occupant presence and movement as well as occupant actions on windows, shades (blinds), lighting, thermostat, HVAC, and plug-in equipment. Data were collected from various locations and types of buildings around the world to construct a library of stochastic models for these occupant behaviors [25–33]. For example, window-opening behaviors were described by probabilistic models (logit or Weibull functions) based on field-measured data and large-scale surveys; these models have been adopted by several building performance simulation (BPS) programs to determine when occupants open or close windows [34,35]. Note that stochastic models do not necessarily produce better results than other simpler and/or non-probabilistic models of occupancy, especially in terms of annual building energy consumption [36]. Yan et al. [23] concluded that simple occupancy-related models, such as code-based models or descriptive representations of occupant behaviors, could be adopted to determine aggregated indicators such as annual heating and cooling consumptions. However, in other situations, more detailed occupant behavior models must be considered.

BPS programs are commonly employed to evaluate the performance of building energy systems and technologies. Occupant behaviors in buildings have been widely acknowledged as a major factor contributing to the gaps between measured and simulated energy consumption in buildings [19,23,37,38]. Eguaras-Martinez et al. [39] demonstrated that the inclusion or exclusion of occupant behaviors in building simulations resulted in up to a 30% difference in energy use predictions. The International Energy Agency Energy in Buildings and Communities' Annex 53: Total Energy Use in

Buildings [40] recognized the impact of occupant behaviors as one of the six driving factors of energy use in buildings along with climate, building envelope, building energy and services systems, indoor design criteria, and building operation and maintenance. However, in current practices, simulation users tend to apply default standards or representative settings for occupants in a simplified and homogeneous way using temporal schedules and static assumptions. This might result in significant discrepancies between simulation and measurement data.

In conclusion, these studies either only applied occupant behavior models to a single house or used simplified methods to represent the occupant behavior diversity in a district. Few studies have applied detailed occupant behavior models at the district level, and the influence of realistic occupant behaviors on district load prediction is an unknown problem. The present study aims to tackle this important topic and provide insights into the following questions:

(1) How must occupant behaviors be considered in district load prediction?

(2) What are the actual occupant behaviors in residential districts?

(3) What are the pros and cons of using the stochastic occupant behavior models in district load prediction compared with the conventional simplified methods?

(4) What are the potential applications of stochastic occupant behavior models in residential districts?

This study proposes a novel stochastic occupant behavior method (the SOB method) to consider multiple occupant behaviors in district load prediction, and based on questionnaire surveys, presents typical occupant behavior patterns, models, and their distributions in the hot summer cold winter (HSCW) climate zone in China. A case study in Wuhan, China, is performed to demonstrate the workflow of this new method and to evaluate the performance of three methods (i.e., the SOB method, the FTFS method, and the Fixed Schedules method) in district load prediction based on a comparison of the simulation and measurement results. Finally, the influence of simulation repetitions using this method and one application of this method in cooling equipment sizing at the district scale are discussed.

The remaining of sections of this article are organized as follows: Section 2 introduces the basic approach of SOB method, as well as the models and tools to realize the SOB modeling method. Section 3 elaborates the questionnaire survey conducted to determine the inputs of occupancy schedules and occupant behavior modes for each occupant behavior type. In addition, a case study was performed for a real residential district in China to demonstrate the application and workflow of the proposed SOB method in Section 4. Section 5 carries out some discussions from the perspective of performing simulation, application and limitation of the new proposed SOB method. Section 6 draws conclusion of the study.

2. Methodology

2.1. Overview

The bottom-up approach illustrated in Figure 1 was developed to simulate the building thermal loads in

residential districts. Instead of making a simplified assumption that all apartments in the same district have uniform/homogeneous occupant behaviors and load characteristics, this study proposed a SOB method to generate the occupancy schedule and occupant behavior for each apartment. Then, Simulations of the dynamic thermal load of each apartment were performed based on detailed occupant behavior models and finally added them up to obtain the aggregated building thermal loads of the residential district.

Six key influencing factors are considered in this approach, including apartment type, occupancy schedule, indoor cooling temperature set point, lighting control, window operation, and HVAC control. The occupancy schedule is influenced by the number of occupants and their movement styles, which can be simulated by events and the Markov chain model [41]. Four types of occupant behaviors—cooling temperature set point, lighting control, HVAC control, and window operation—are considered in this study. The SOB method defined several typical modes for each occupant behavior by using different probability models [23,42]. Using the stochastic sampling method based on the distribution of each factor, this method assigned specific occupancy schedules and occupant behaviors for each apartment in the district. With the probability models, this method can estimate the occupancy and behaviors at every moment as well as the thermal load of each apartment. Therefore, the proposed method can represent the occupant diversity in space and time, which is the main difference from the currently used conventional methods.
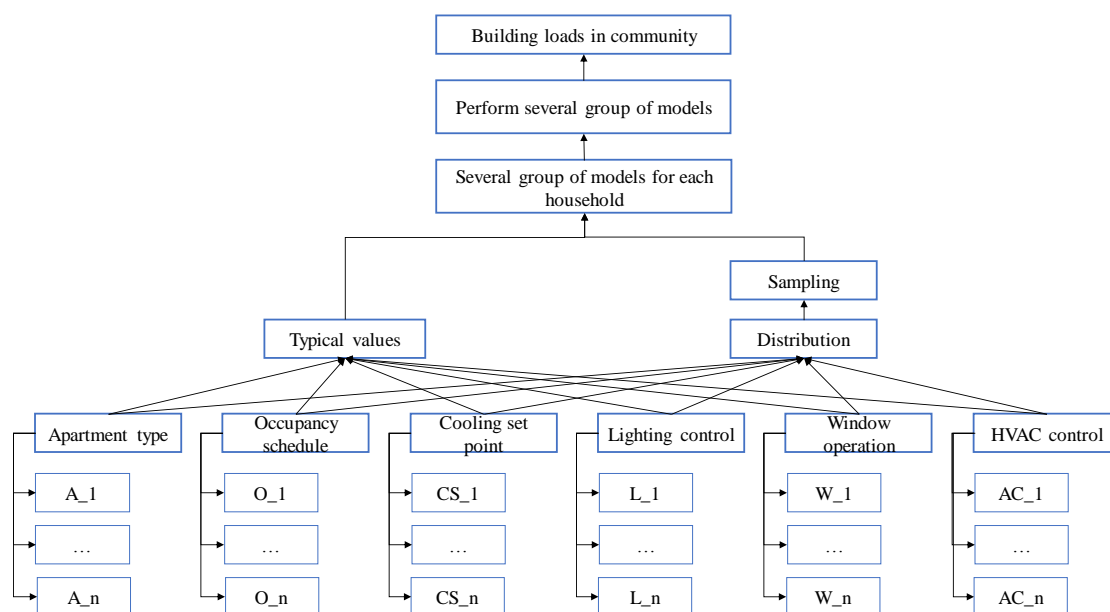

Figure 1 Bottom-up approach for simulating building thermal loads of a residential district

Figure 2 illustrates the key differences between the proposed SOB method and the two conventional methods. Considering the occupancy and air-conditioning control as an example, the FTFS method assumes that all apartments are always occupied and air-conditioning is always on. The Fixed Schedules method assumes that all occupants in all apartments have the same schedules, e.g., occupants go to work during the daytime and come home at night on workdays. They turn on air-conditioning when the room is occupied. In other words, this method partly reflects the occupant diversity in time, as rooms are not conditioned during unoccupied periods. In contrast, the SOB method can represent the temporal and spatial diversity of occupancy and occupant behavior. For example, some apartments are occupied all the time (retirees stay at home during daytime), while some apartments (working families with parents go to work during the day and kid(s) go to school) are only

occupied at night. Air-conditioning control also varies with apartments and time. Some people always turn on air-conditioning when they are at home, while others only need cooling when they feel hot (determined by a probability model). It should be noted that Figure 2 is only used to demonstrate the characteristics and differences among three simulation methods, and the variations among four periods within a day, including morning, afternoon, night before sleeping and bedtime. It does not necessarily reflect the real situation of specific households. In this figure, 8:00 – 12:00 is morning, 12:00 – 18:00 is the afternoon, 18:00 – 23:00 is the night before sleeping, and 23:00– 8:00 is the bedtime.
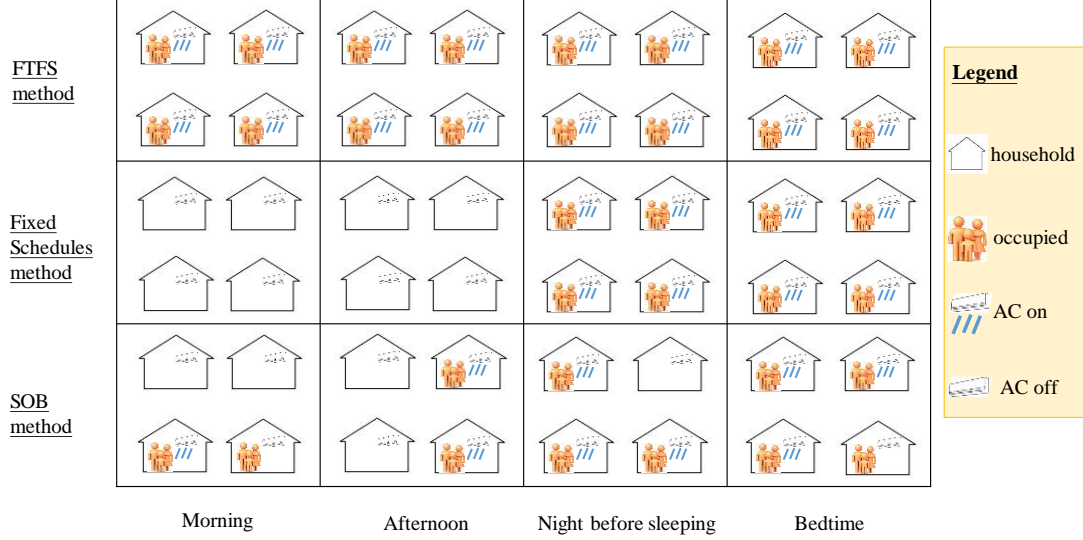

Figure 2 Comparison of three simulation methods for building cooling loads of a residential district

The remainder of Section 2 describes the models and tools to realize the SOB modeling method.

2.2. Occupancy schedules

Occupancy schedules are the basis for performing building energy simulations. They influence not only the internal heat gains from humans but also the operational status of building equipment or personal devices because occupants can adjust and control them (e.g., air-conditioning, lighting, windows) when they are in the building [37,43]. A non-realistic input of occupancy can significantly affect the energy consumption simulation, especially for a community with hundreds of households. Static occupancy schedules, such as the average results for all occupancy schedules or fixed schedules from design standards, are widely used in building performance simulations. However, static schedules could not reflect the realistic occupant movement and the variations between spaces within the buildings owing to their temporally and spatially stochastic nature [20].

This study adopted the approach for building occupancy simulation proposed by Wang et al. [41]. Events (e.g., reaching home) represent the time-related movement, while Markov chain is used to simulate the occupant stochastic movement process. Markov chain is a relatively more accurate and mature method in occupancy prediction[44]. The future state relies on the present state and the probability of the state change, which is represented by the transition probability matrix, is time independent as shown in Equation (1).

$$p\{X_{k+1} = j | X_k = i\} = p_{i,j} \tag{1}$$

Here, k and k+1 indicate the present and next time step; i, j represent two states; p is the transition

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probability; and $p_{i,j}$ is an element of the transition probability matrix.

Finally, the location of each occupant and the occupancy of each zone in a house or building can be generated. The occupancy schedules generated by this method can reflect the variation, diversity, and stochastic characteristics of realistic occupant presence and movement. These generated schedules are more reasonable than the simplified static occupancy schedules.

2.3. Occupant behavior types

Yan et al. [23] pointed out that occupant behaviors mainly include interactions with operable windows, lighting, blinds, thermostats, and plug-in appliances. This study considers all behaviors, i.e., indoor temperature set point, lighting control, control of plug-in appliances, HVAC control, and window operation, excluding the control of blinds owing to its infrequency in residential buildings. The actions of occupants vary. Numerous studies have proposed several typical users. One way is to define some typical users according to their energy consumption attitudes, which is a combination of multiple occupant behavior types. Hong [45] described three behavior styles for office workers based on their workstyles: austerity, normal, and wasteful. Each occupant behavior style includes a corresponding energy consumption performance, such as temperature set points and HVAC control. Similar to Hong's study, Santin [46] defined five behavior styles: spenders, affluent-cool, conscious-warm, comfort, and convenience-cool. On the other hand, other researchers separately considered the typical modes of each behavior type (e.g., HVAC control and window operation) according to their research object instead of defining the user styles. Feng et al. [47] derived five typical air-conditioning control modes from a large-scale questionnaire survey on HVAC control. D'Oca et al. [48] combined user profiles for window opening and thermostat set point adjustment into one building energy model and analyzed their influence on household energy consumption. This study adopted the second approach to separately define the typical modes of each occupant behavior based on a large-scale questionnaire survey and combined them to compose the behaviors for each apartment.

2.3.1. Cooling temperature set point

The indoor cooling temperature set point influences the air-conditioning load. The cooling temperature set point reflects people's thermal comfort requirement level. Some people like a lower cooling set point, such as 20°C, while most Chinese prefer a relatively high cooling set point, such as 26°C, which is also the suggested default cooling set point in the design standard of China [8]. Several typical cooling set points and their distributions that are close to the realistic distributions in the examined community were defined. In the case study, we classified some typical cooling set points and derived their distributions based on the large-scale questionnaire survey conducted in the same climate zone for a similar residential community.

2.3.2. HVAC control

HVAC is the most important and direct influencing factor in cooling loads. HVAC control varies with users. However, the air-conditioning usage schedule has been generally defined with few variations among the residents in typical HVAC system design. For a community with hundreds of households, a quantitative random usage model must be adopted to describe the diverse HVAC control modes in

residential buildings.

This study adopted the method proposed by Wang et al. [49] to simulate the state of air-conditioning for each apartment. The control actions are grouped into environment- and event-triggered based on factors influencing the occupants switching on/off air-conditioning. For example, occupants switch air-conditioning on when they feel hot and switch it off when it is sufficiently cool; this is referred to as the environment-triggered mode. On the other hand, some occupants turn on air-conditioning as soon as they reach home; this is a case of an event-triggered mode. The control of air-conditioning is presented as a probability function correlated with the indoor environment (e.g., temperature) or a daily event (e.g., reaching home) and varies among modes.

The environment-triggered mode, such as "switch on when feeling hot," follows the three-dimensional Weibull distribution as follows.

$$P_{on} = \begin{cases} 1 - e^{-(\frac{t-u}{l})^k \Delta \tau} & t \geq u, \text{when occupied} \\ 0 & t < u \end{cases} \tag{2}$$

Here, P_{on} is the probability that occupants will turn on the air-conditioning; t is the indoor temperature (°C); u is the threshold temperature (°C) representing the lowest temperature for switching on the air-conditioning; l is the scale parameter (°C) to non-dimensionalize (t-u); k is the slope parameter showing sensitivity to temperature; and $\Delta \tau$ is the time step used in the simulation, typically 5 or 10 min.

The probability of the event-triggered mode is one constant value when the event occurs and equals 0 in other conditions. For instance, "switch on after reaching home" can be described by the following function.

$$P_{on} = \begin{cases} p & \tau = \tau_0 \\ 0 & \tau \neq \tau_0 \end{cases} \tag{3}$$

Here, P_{on} is the probability that the occupants will turn on the air-conditioning; τ is the current time in the simulation; and τ_0 is the moment when the event occurs.

The parameters of the probability functions for each occupant behavior mode are usually determined based on field investigations or some other criteria. For example, Ren et al. [42] conducted a long-term survey on air-conditioning use, indoor temperature and humidity, and CO_2 concentration in three families and developed an air-conditioning probability model for each family. This case study adopted probability models from reference studies. For some occupant behavior modes unavailable in previous studies, different approaches were used to determine the parameter values.

2.3.3. Lighting control

Lights are the main appliance in residential buildings. The average energy consumed by appliances and lighting is 12% of the total energy consumption and 60% of the total electricity consumption in European households [50]. In China, lighting consumes 5.8% of the total energy consumption in the residential sector [51]. The control of lights affects the building thermal loads through changes in the internal heat gains from lights, which can be influenced by indoor environmental parameters (e.g., illuminance) and events; thus, this study used the same probability function structure as the HVAC control.

2.3.4. Window operation

Natural ventilation, i.e., letting fresh air in and out through windows, is the main ventilation method in Chinese residential buildings. The habit of operating windows varies greatly. Some people tend to keep windows open on all days, even when it is cold outside, while others prefer to open windows only when the weather is comfortable and clear. Tthe occupant behavior model structure introduced in Section 2.3.3 was adopted.

2.3.5. Control of plug-in appliances

Plug-in appliances include domestic appliances such as TV, laptops, and refrigerators. Yamaguchi et al. [52] performed measurements in numerous households in Japan and proposed event-triggered models for the control of plug-loads. They concluded that the appliances have a strong relationship with events. For example, inhabitants use electric water heater when they take a shower. As the related measurement data is limited, this study adopted a simpler method to assign a fixed schedule for each household. Mahdavi et al. [53] indicated that there exists a relationship between inhabitants' presence, their respective installed equipment power, and the resulting electrical energy consumption. Therefore, the corresponding plug-load schedules of every room were designed for each combination of occupancy schedule and apartment type, and the schedules of plug-loads were determined based on practical investigations [11,12]. For example, the results of a field survey conducted in China illustrated that the main appliance in a living room is TV with a power of around 100 W; therefore, the plug-load schedule in the living room is the schedule of TV usage when inhabitants are in the living room The control of plug-loads is not an independent variable as it is determined by occupancy schedule and apartment type. Therefore, it has not been shown in Figure 1.

2.4. Stochastic sampling

This study assigned the occupancy schedule and occupant behavior for each apartment by using the stochastic sampling method. There are two main steps in establishing the inputs for every apartment: (1) determining the apartment types and their numbers for a residential district according to actual building design; (2) randomly selecting the occupancy schedule and four types of occupant behaviors for every apartment one by one based on their distributions. Note that these five parameters are independent; therefore, the order of selection does not matter.

2.5. Building simulation engine

The case study used Designer's Simulation Toolkit (DeST)—a whole-building energy modeling program developed by Tsinghua University, China, [54] based on a state-space multi-zone heat balance calculation method [55,56]. The occupant movement and behavior models, including lighting control, HVAC control, and window operation, have been implemented in DeST [57]. The building energy models are built in the DeST environment, and the information of occupants' presence and behaviors is stored in an extra file in a SQLite database. The occupant behaviors in BPS are considered by the following three steps: (1) the occupancy is calculated using the Markov chain model and the results are stored in the SQLite database; (2) the lighting is calculated based on occupants' presence and indoor

illuminance level, and the results are also stored in the SQLite database; and (3) as the HVAC control and window operation are strongly coupled with the indoor thermal condition, the simulation module should be discretized into time steps of 5 or 10 min. In each time step, this method first determines the state of HVAC and windows and then simulates the indoor air temperature, humidity, and cooling/heating energy consumption. Finally, the state schedules of the appliances, indoor environment, and energy consumption are saved in the output file.

This study used time steps of 10 min for a compromise between accuracy and computation time [58].

The stochastic sampling is performed in MATLAB (matrix laboratory), which is a multi-paradigm numerical computation environment, and a fourth-generation programming language developed by MathWorks.

2.6. Comparison method

To validate the proposed method, five metrics are proposed as shown in Table 1.

Table 1 Metrics used to evaluate the simulation methods for district cooling loads

Number	Metrics	Applications
1	Total cooling consumption	Total building cooling consumption prediction
2	Peak cooling load	Chiller sizing
3	Load distribution	Chiller sizing and energy conservation measures (ECMs) evaluation
4	Load profile	Evaluation of control strategy of DHC plants and pumps
5	Household cooling consumption distribution	Representing the demand difference of each household, evaluating various policy and techniques

The total cooling consumption and the peak load are the two most popular and common metrics for evaluating the performance of a thermal load simulation method [59], and they are very useful and significant in real projects and research. Therefore, this study chose these two metrics in our comparison analysis.

This study also considered the load distribution as it influences the selection of multiple chillers with different capacities to maximize the operation efficiency under various load conditions [60]. The two-sample Kolmogorov-Smirnov test (K-S test) was used to calibrate the load distribution of the simulation results in this study [61]. The K-S test is a non-parametric test for the equality of continuous one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample K-S test) or to compare two samples (two-sample K-S test). This study used the K-S test to quantify the discrepancy between the statistical distributions of the simulation results and the measurement results. The null distribution of this statistic test was calculated under the null hypothesis that the samples are drawn from the same distribution. If the hypothesis test result H is 0, the hypothesis is accepted at the 5% significance level. On the other hand, the hypothesis

is rejected if H is 1. The decision to reject the null hypothesis occurs when the significance level equals or exceeds the P-value.

In addition, hourly loads are required to perform the analysis of the equipment control strategy; thus, this study adopted the load profile of the entire district as the metric. This study used the coefficient of variation of the root mean square (CVRMSE) and the normalized mean bias error (NMBE) to quantify the differences among multiple simulations. The CVRSE and NMBE were determined by comparing the measurement results (y_i) with the predicted results of simulation ($\hat{y}_i$) using the following formulas.

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n \times \bar{y}} \times 100 \tag{4}$$

$$CVRMSE = \frac{\left[\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{n}\right]^{1/2}}{\bar{y}} \times 100 \tag{5}$$

Here, n is the number of data points used in the calibration, and $\bar{y}$ is the average value of y_i.

The ASHRAE Guideline 14 [62] is a useful guide for calibrating energy models, and the calibration criteria can be applied to two time scales: monthly and hourly. The NMBE and CVRMSE should be less than 10% and 30%, respectively, if the hourly calibration data is used.

As there is increasing concern regarding the diversity of thermal demand from different households and its impact on policy and technology deployment [63,64], the household cooling consumption distribution should also be considered as one metric. This study also applied K-S tests to analyze the household cooling consumption distribution calculated by the three different methods.

3. Questionnaire survey

Tsinghua University conducted a household questionnaire survey to investigate occupant behavior in residential buildings in the summer of 2013 in Chengdu, China. The questionnaire survey was distributed to 287 districts by the local survey team. The surveyed districts were randomly chosen to cover the urban area of Chengdu. A total of 1426 valid responses to the questionnaire survey were received, among which 431 respondents answered questions on the AC on/off control. Multiple choices were allowed in the survey, for example, respondents could choose both "AC turned on when feeling hot" and "AC turned on after reaching home."

The questionnaire included the following:

(1) Basic information regarding family members, house characteristics, HVAC system equipment, and the hot water system.

(2) Household energy consumption including monthly usage of electricity, gas, coal, and water.

(3) Lifestyle including the occupancy schedules of each room and the occupant behavior in terms of cooling temperature set point, AC control, lighting control, and window operation.

(4) Evaluation and expectation of the indoor environment.

The questionnaire results were analyzed as follows.

3.1. Typical occupancy schedules

This study derived six typical occupancy schedules based on the number and type of occupants (i.e., office workers, students, and retirees) residing in the same apartment. The occupancy schedules of office workers, retirees, and students were summarized from the questionnaire survey: office workers go to work from 7:00 to 18:00 on weekdays and do not work on weekends; retirees go to bed early and wake up early and often stay home except for going out for shopping at 9:30–10:30 and 15:30–16:30; students spend more time at home during summer school holidays and they wake up late in the morning and go out at 10:30–11:30 and 16:00–17:30. The occurrence time of an event is within a range rather than at a fixed time. The occupants' positions (room/space granularity) at home were determined by the Markov chain model. Overall, the occupants prefer to stay in living rooms when they are at home, with some probabilities of staying in their own bedroom, dining room, among other areas.

Table 2 Typical occupancy schedules

Modes	Maximum occupancy	Resident composition
O_1	1	One office worker
O_2	2	Two office workers
O_3	2	Two retirees
O_4	3	Two office workers and one student
O_5	4	Two office workers, one student, and one retiree
O_6	5	Two office workers, one student, and two retirees

Figure 3 shows the investigated average occupancy schedule and the simulated occupancy schedule in the bedroom on one day for mode O_1. The stochastic occupancy schedules represent the diversity of occupancy among different apartments.
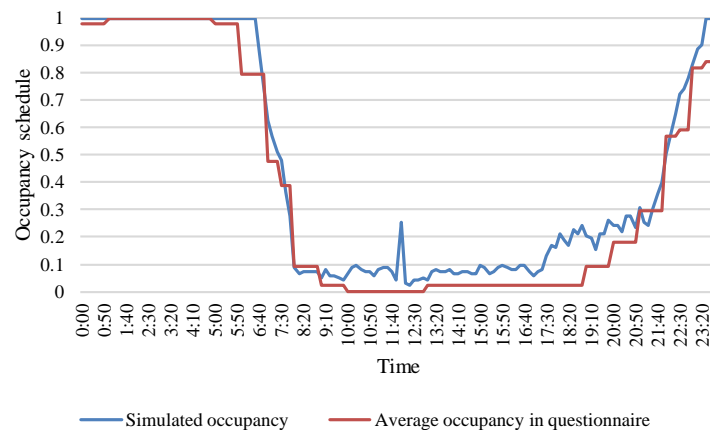

Figure 3 Comparison of occupancy schedules from the simulation and survey for Mode O_1

In addition, this study analyzed the distribution of the occupancy schedules and concluded that the distribution is influenced by the apartment size (floor area). The more people there are in the same apartment, the larger the apartment is, when the floor area is less than 100 m^2, However, if the floor area is greater than 100 m^2, it no longer influences the number of occupants of an apartment. Therefore,

this study separately calculated the proportions of each occupancy schedule based on apartment size to establish the distribution matrix.

## 3.2. Typical modes of occupant behavior types

Based on the questionnaire results, the typical modes of each occupant behavior type can be derived according to the corresponding number of votes for each occupant behavior mode. The typical cooling temperature set points and their corresponding proportion are listed in Table 3.

Table 3 Typical cooling temperature set points

Modes	Cooling temperature set point (°C)	Proportion
C_1	24	13%
C_2	25	31%
C_3	26	38%
C_4	27	8%

The approach to determine the typical models for the other three occupant behavior types is described using AC control as an example.

As the survey respondents could choose multiple behavior modes in each question, numerous responses were obtained for each occupant behavior type. To simplify the answers, this study first individually summarized the typical AC on/off modes (Figure 4). Note that because the respondents could choose multiple modes, the total number of on/off modes can be greater than the number of respondents. Figure 4 shows that the behavior mode "on when feeling hot" was the most common and received 298 votes. Moreover, the top four AC off modes were "off when leaving living room," "off when leaving home," "off when sleeping," and "off when feeling cold." Therefore, this study selected one AC on mode and four AC off modes to further analyze their combinations.
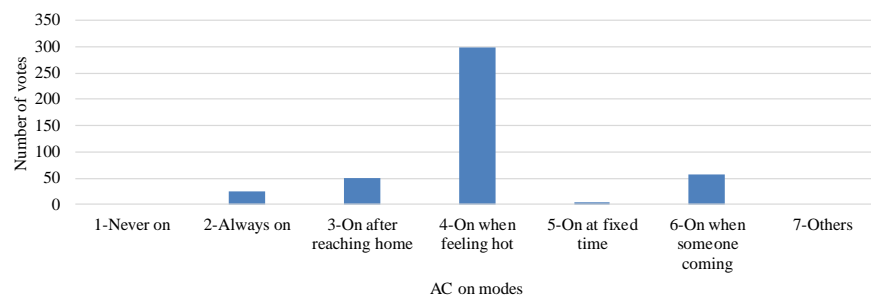
(a) AC on mode profiles
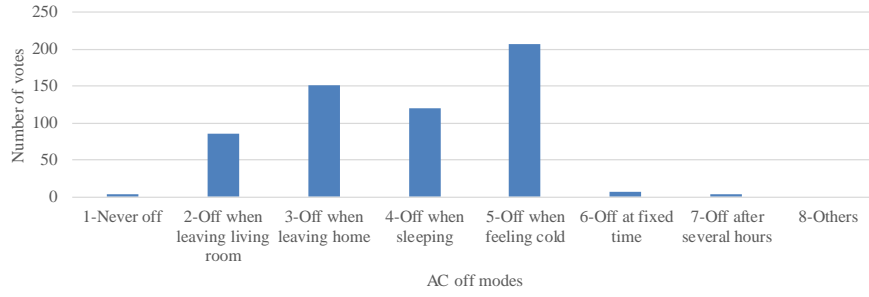
(b) AC off mode profiles

Figure 4 Survey results for behavior modes of air-conditioning use

Then, this study summarized the proportions of the combinations of the selected AC on and off modes and ranked them from the highest to the lowest as shown in Figure 5. The top five AC control modes were choosen as the typical modes in Table 4.
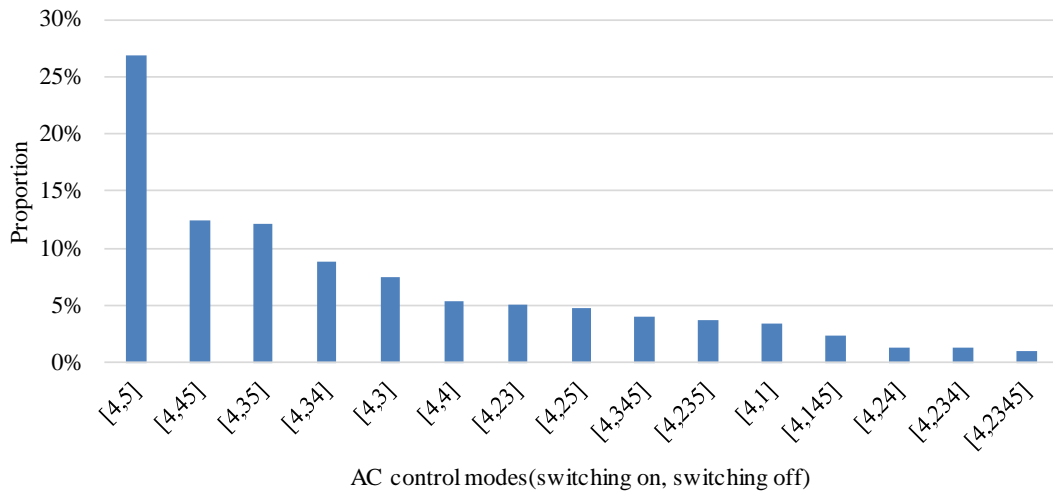

Figure 5 Survey results for the combined air-conditioning use behavior (the control modes are the same as those in Figure 4)

Table 4 Typical AC control modes

Modes	AC on and off control	Proportion
AC_1	On when feeling hot, off when feeling cold	42.2%
AC_2	On when feeling hot, off when feeling cold or when sleeping	18.2%
AC_3	On when feeling hot, off when feeling cold or leaving home	18.2%
AC_4	On when feeling hot, off when leaving home or when sleeping	11.2%
AC_5	On when feeling hot, off when leaving home	10.2%

This study also analyzed other occupant behavior types by the same approach; the results are shown in Tables 5 and 6.

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Table 5 Typical lighting control modes

Modes	Light on and off control	Proportion
L_1	On when its dark, off when falling asleep	37%
L_2	On when its dark, off when falling asleep or the room has sufficient brightness	24%
L_3	On when its dark, off when there is sufficient brightness	14%
L_4	On when its dark, off when leaving home	14%
L_5	On when its dark, off when leaving home, falling asleep, or when there is sufficient brightness	11%

Table 6 Typical window operation modes

Modes	Window operation	Proportion
W_1	Always open	65%
W_2	Open after reaching home, close before leaving home	14%
W_3	Open when the room is hot or smelly, close when feeling cold or sleeping	13%
W_4	Open after waking up, close before falling asleep	8%

Then, this study translated these qualitative descriptions of air-conditioning control, lighting control, and window operation to the quantitative occupant behavior models introduced in Section 2.3. The parameters (i.e., u, k, l, and p) in the corresponding models were determined by three methods:

(1) This study directly used the parameters and probability functions from the literature.

(2) For the environment/temperature triggered behavior modes, i.e., switch on air-conditioning when feeling hot, switch off air-conditioning when feeling cold, open window when feeling hot, and close window when feeling cold, this study adopted the method in Sun et al. [20] to determine the parameters. This study assumed that the probability of turning on air-conditioning is about 20% at the suggested cooling temperature set point in the Chinese design standard (i.e., 26°C) [8] and about 50% at the upper limit of the Chinese comfort zone in HSCW (i.e., 29.8°C) [65]. Therefore, the parameters for the occupant behavior model of the AC on mode [a] were u = 20, l = 33, and k = 2.22 with a cooling temperature set point of 26°C. This study assumed that only parameter u changes with the cooling temperature set point. The parameters were u = 18, l = 33, and k = 2.22 with the cooling temperature set point of 24°C; u = 19, l = 33, and k = 2.22 with the cooling temperature set point of 25°C; and u = 21, l = 33, and k = 2.22 with the cooling temperature set point of 27°C. It was assumed that there is a 20% probability of turning off air-conditioning when the indoor temperature decreases to the suggested cooling temperature set point of 26°C and about 50% probability at the lower limit of the Chinese comfort zone in HSCW (i.e., 24.2°C) [65]. Therefore, the parameters for the occupant behavior model of the AC off mode [a] were u = 28.3, l = 16, and k = 1.95 with the cooling temperature set point of 26°C. This study also assumed that only the parameter u changes with the cooling temperature set point. The parameters were u = 26.3, l = 16, k = 1.95 with the cooling temperature set point of 24°C; u = 27.3, l = 16, and k = 1.95 with the cooling temperature set point of 25°C; and u = 29.3, l = 16, and k = 1.95

with the cooling temperature set point of 27°C. In addition, both turning on air-conditioning or opening window when feeling hot in the summer are possible ways for occupants to decrease the indoor temperature, but because opening windows does not consume energy, this study assumed occupants will open windows first when feeling hot and then turn on air-conditioning if they still feel hot. Note that the windows stay closed when the air-conditioning is on. The parameters of the window-open models for mode [d] are the same as those of the AC on models. Occupants may still keep windows open at a lower temperature compared with the AC on mode. Thus, this study assumed the probability of turning off air-conditioning was about 20% at 24.2°C and about 50% at the suggested heating temperature set point in the design standards (i.e., 18°C) with the parameters u = 32, l = 53, and k = 2.

(3) For the window operation triggered by events and indoor CO_2, this study adopted the suggested models using the simulation tool DeST.

Table 7 Models and parameters for the AC on mode

AC on modes	Probability function
[a] On when feeling hot	$P_{on} = \begin{cases} 1 - e^{-(\frac{t-\mu}{l})^k \times 10} & t \geq \mu, when\ occupied \\ 0 & t < \mu \end{cases}$

Table 8 Models and parameters for AC off modes

AC off modes	Probability function
[a] Off when feeling cold	$P_{off} = \begin{cases} 1 - e^{-(\frac{\mu-t}{l})^k \times 10} & t \leq \mu, when\ occupied \\ 0 & t > \mu \end{cases}$
[b] Off before sleeping	$P_{off} = 0.8, when\ going\ to\ sleep$ [47]
[c] Off when leaving home	$P_{off} = 1 - e^{-(\frac{t_{leave}}{l2.79})^{21.91} \times 10}, when\ leaving\ home$ [47]

Table 9 Models and parameters for switching on lights

Light on modes	Probability function
[a] On when its dark	$P_{on} = \begin{cases} 1 - e^{-(\frac{325-E}{427.32})^{9.15} \times 10} & E \leq 325, when\ occupied \\ 0 & E > 325 \end{cases}$ [49]

Table 10 Models and parameters for switching off lights

Lights off modes	Probability function
[a] Off before sleeping	$P_{off} = 0.8, when\ going\ to\ sleep$ [49]
[b] Off when brightness is sufficient	$P_{off} = \begin{cases} 1 - e^{-(\frac{E-175}{2300.53})^{1.3} \times 10} & E \geq 175, when\ occupied \\ 0 & E < 175 \end{cases}$ [49]
[c] Off when leaving home	$P_{off} = 1 - e^{-(\frac{t_{leave}}{l2.79})^{21.91} \times 10}, when\ leaving\ home$ [49]

Table 11 Models and parameters for opening windows

Window open modes	Probability function
[a] Always open	$P_{on} = 1$
[b] Open when arriving home	$P_{on} = 0.8, when\ arriving\ home$
[c] Open when room is smelly	$P_{on} = \begin{cases} 1 - e^{-(\frac{C-1300}{100})^3} \times 10 & C \geq 1300, when\ occupied \\ 0 & E < 1300 \end{cases}$
[d] Open when feeling hot	$P_{on} = \begin{cases} 1 - e^{-(\frac{t-\mu}{l})^k \times 10} & t \geq \mu, when\ occupied \\ 0 & t < \mu \end{cases}$
[e] Open after waking up	$P_{on} = 0.8, when\ waking\ up$

Table 12 Models and parameters for closing windows

Window closed modes	Probability function
[a] Never closed	$P_{off} = 0$
[b] Closed before leaving home	$P_{off} = 1 - e^{-\left(\frac{t_{leave}}{120}\right)^2 \times 10}, when\ leaving\ home$
[c] Closed when feeling cold	$P_{off} = \begin{cases} 1 - e^{-(\frac{25-t}{26.5})^2 \times 10} & t \leq 25, when\ occupied \\ 0 & t > 25 \end{cases}$
[d] Closed before sleeping	$P_{off} = 0.8, when\ going\ to\ sleep$

When multiple options were chosen in the proposed typical occupant behavior modes—such as AC off mode in AC_2: off when feeling cold or sleeping—the total probability of the occupants to operate air-conditioning, windows, and lighting, which meant at least one event in these options would occur, should be calculated in terms of the stochastic processes defined as follows [47].

$$p\left(\bigcup_{i=1}^{n} A_i\right) = \sum_{i=1}^{n} P(A_i) - \sum_{i<j}\sum P(A_i)P(A_j) + \sum_{i<j<k}\sum\sum P(A_i)P(A_j)P(A_k) - \cdots \qquad (6)$$
$$+ (-1)^{n+1} P(A_1)P(A_2) \dots P(A_n)$$

Here, A_1, A_2, ..., A_n are treated as independent events.

4. Case study

4.1. Workflow of the case study

A case study was performed in a real community located in Wuhan, China, to demonstrate and evaluate the proposed SOB method, which can reflect the occupant diversity in space and time. Figure 6 shows the overall workflow of the case study.

First, a field investigation of the real community was performed to determine the building geometry, number of apartments, apartment types, climate data, and actual vacancies, which can be used to

establish the prototype household energy models. In addition, the inlet and outlet temperature and flow rate of the chilled water in the cooling station were measured. Thus, the supplied cooling load of the centralized plant system can be calculated and used as the ground truth to evaluate the results of various simulation methods. The monthly household cooling cooling consumptions were recorded by the building operator.

Second, seven prototype household energy models were chosen according to various apartment types. As this community was built in 2009, the envelope performance follows the 2001 edition of the Design Standard for Energy Efficiency of Residential Buildings in the Hot-Summer and Cold-Winter Zone [8] (the next version of the standard was released in 2010).

Third, a questionnaire survey was used to acquire the inputs of occupancy schedules and occupant behaviors (i.e., cooling temperature set point, lighting control, window operation, and HVAC control). As described in Section 3, six occupant schedules and four or five typical modes were derived for each occupant behavior type, whose values and distributions were then used to generate occupant behavior models for every apartment in the district.

Then, this study performed stochastic sampling to assign the occupancy schedules and occupant behaviors for each apartment based on the investigated distribution of each variable. For each sampling, this study generated one group of energy models using the prototype models and inputs of occupant behaviors and ran these household energy models to simulate the household cooling loads, which were further aggregated to derive the district cooling load.

Finally, this study verified the performance of the proposed SOB method by comparing its results with the measurement results as well as the results of the other two conventional simulation methods, i.e., the FTFS method and the Fixed Schedule method.
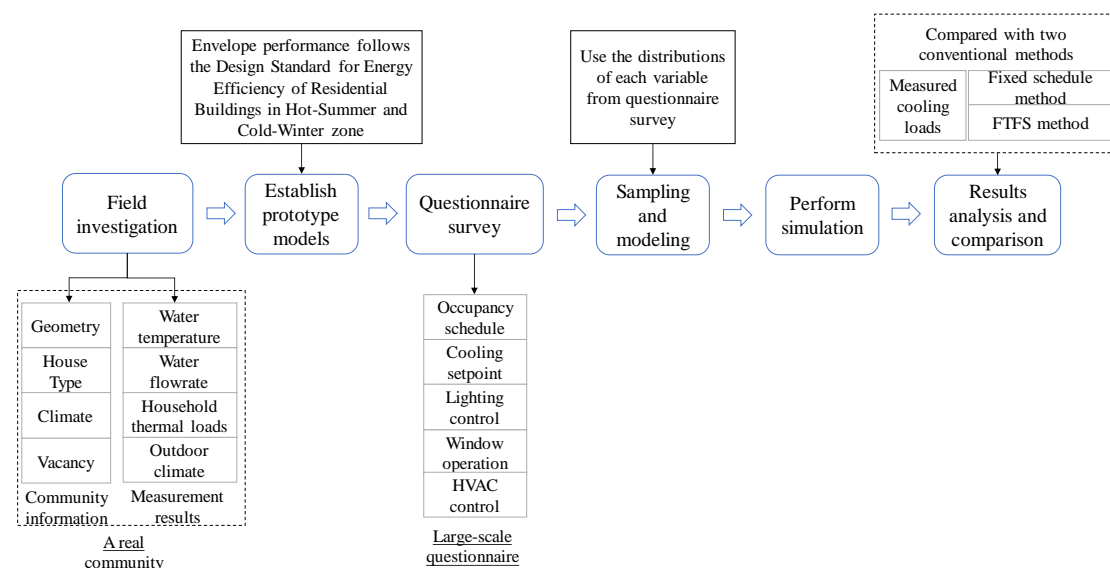
Figure 6 Workflow of the case study

4.2. Case building models

The field investigated residential district, located in Wuhan City, Hubei Province, China, has five

21-story high-rise residential buildings: Building 112#, Building 113#, Building 116#, Building 117# and Building 118#, with a total floor area of around 50,000 m^2. Each building has a different geography, floor area, and number of households. A central cooling station is used to supply cooling for the entire district. The layout of this district is shown in Figure 7. As this community represents a typical and normal residential district in southern China, this study chose it as the case district in this study. The thermal properties of the envelope are shown in Table 13.
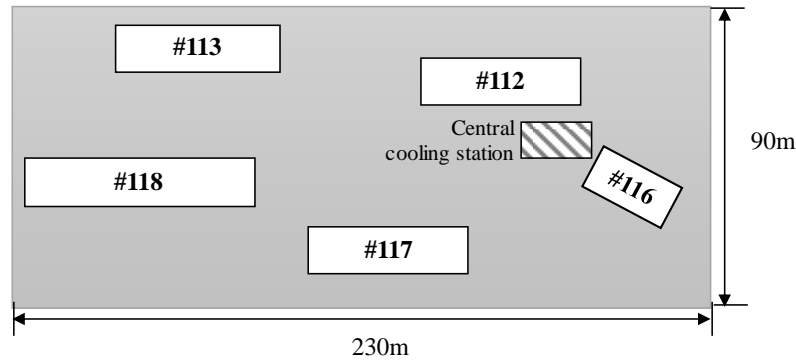
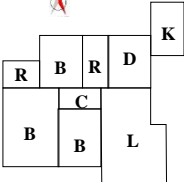Figure 7 Layout of the case district (five buildings and a central cooling plant)
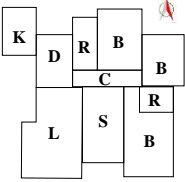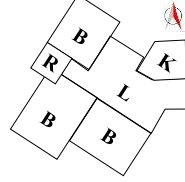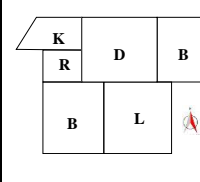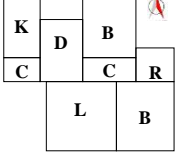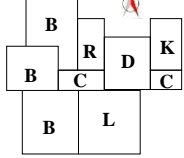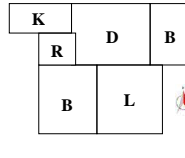
Table 13 Envelope thermal properties based on Chinese design standard [8]

Wall U-factor W/(m^2·K)	Roof U-factor W/(m^2·K)	Window U-factor W/(m^2·K)	Window SC
1.5	1.0	3.2	0.83

This residential district has a total of 414 apartments, which can be grouped into seven typical apartment types based on their geography, zoning, floor area, and orientation. The details of each apartment type are presented in Table 14. This study built seven prototype apartment energy models. The actual vacancy rate is around 11%, which translates into 45 unoccupied apartments out of the total 414 apartments.

Table 14 Details of the seven apartment types

Apartment type	A_1	A_2	A_3	A_4
Floor area (m^2)	116	103	69	68
Rooms	3 bedrooms 1 study room 1 living room 1 dining room 1 kitchen 2 restrooms	3 bedrooms 1 living room 1 dining room 1 kitchen 2 restrooms	2 bedrooms 1 living room 1 dining room 1 kitchen 1 restroom	2 bedrooms 1 living room 1 dining room 1 kitchen 1 restroom

Floor plan				
Apartment type	A_5	A_6	A_7	
Floor area (m²)	68	88	71	
Rooms	2 bedrooms 1 living room 1 dining room 1 kitchen 1 restroom	3 bedrooms 1 living room 1 dining room 1 kitchen 1 restroom	2 bedrooms 1 living room 1 dining room 1 kitchen 1 restroom	
Floor plan				

Notes: In the floor plans, K represents Kitchen, D represents Dining room, R represents Restroom, B represents Bedroom, L represents Living room, S represents Study room, and C represents Corridor.

The central plant system is responsible for 24 h cooling/heating in the cooling/heating season and comprises three water-source heat pumps: two with a rated cooling capacity of 633 kW and an input power 112 kW and one with a rated cooling capacity of 928 kW and an input power 156 kW. The operators control the number of chillers being operated to adjust the supply cooling loads. There are four identical constant-speed chilled water pumps. Therefore, the chilled water flow rate is controlled by changing the number of chilled water pumps being operated and the on/off state of the bypass valve. The air handling equipment in the households is a fan coil unit (FCU) that can be switched on or off by the occupants. Each main room in an apartment (i.e., bedrooms, living room, dining room, and study room) has an FCU. As the HVAC expenses of each household depend on its cooling/heating energy consumption, this study can assume that the supply energy should be approximately equal to the demand, which this study intends to estimate.

4.3. This study performed a field investigation in the summer of 2013. This measurement phase lasted around two months. This study recorded the water temperature every 5 min with thermometers from 9:00 h, July 5, to 24:00 h, August 31, 2013. As the water flow rate is only influenced by the number of operating pumps and the on/off state of the bypass valve, this study only measured the flow rate of the chilled water in certain scenarios (e.g., one pump with the bypass valve off, one pump with the bypass valve on) several times and monitored the state of chilled water pumps and the bypass valves by measuring the water temperature every 5 min. In this manner, this study calculated the supplied cooling of this central cooling station. In addition, this study obtained each apartment's cooling consumptions from the building operators, who recorded the cooling consumption of each apartment every month to bill the HVAC energy expenses. This study also recorded the outdoor air temperature and humidity every 5 min with a hygrothermograph from 0:00 h, July 7, to 10:00 h, August 26, 2013. **Input data collection**

To evaluate and verify the performance of the SOB method through a comparison with the measurement results, this study applied the SOB method as well as the two conventional methods to simulate the district cooling loads of the same community. The SOB method is based on the stochastic occupancy movement and occupant behavior models. The FTFS method assumes all apartments are

occupied all the time, have constant internal heat gains, have a constant ventilation rate of 1 ACH, and AC is always on [8,66]. The Fixed Schedules method considers the temporal diversity in internal heat gains, ventilation, and air-conditioning control [66] and uses the inputs schedules of occupancy, lighting, appliances, windows, and air-conditioning from references [11,12]. Table 15 summarizes the energy model inputs in the three simulation methods.

Table 15 Energy model inputs in three simulation methods

Inputs	SOB method	FTFS method	Fixed Schedule method
Geography	Real community	Real community	Real community
Vacancy rate	11%	11%	11%
Envelope performance	Follows the 2001 design standard	Follows the 2001 design standard	Follows the 2001 design standard
Weather data	2013 weather data	2013 weather data	2013 weather data
Occupancy schedules	Simulated by occupancy movement models	The internal heat gains stay constant in space and time with a lighting density of 0.0141 kWh/m^2, and heat gains from occupants and appliances of 4.3 W/m^2	Maximum density of occupants, lights and appliances, and fixed schedules for occupancy, lighting, and appliance in different rooms
Control of lights	Simulated by light on/off control models		
Control of appliances	Fixed schedules for each occupancy schedule		
Cooling temperature set point	26°C	26°C	26°C
AC control	Simulated by AC on/off control models	Always on	Fixed schedules in each room with a trigger temperature of 29°C
Window operation	Simulated by window on/off control models	Always open with a ventilation rate of 1 ACH	Variable ventilation rate from 0.5 to 1 ACH
Air-conditioned rooms	Main rooms except kitchen, restrooms, and corridors	Main rooms except kitchen, restrooms, and corridors	Main rooms except kitchen, restrooms, and corridors

4.4. Results analysis

DeST was used to simulate the district cooling loads using energy models for each apartment based on

the three methods. This study compared the simulation results of the three methods with the measured supply cooling loads in the real case community by using the method described in Section 2.6. This study compared the simulation results with the measurement results with the same time interval (i.e., 5 min) during the same measurement period (i.e., 9:00 h, July 5 to 24:00 h, August 31, 2013). This study compared the measured data and simulation results for the total cooling consumption of each apartment in July and August 2013. Five performance metrics, representing the aggregated district cooling consumptions, peak district cooling loads, district cooling load distributions and profiles, and the spatial (apartment level) distribution of the district cooling consumptions, were used to compare and evaluate the results of the three simulation methods while using the actual measured district cooling loads as the ground truth results.

(1) Metric 1: Total cooling consumption of the district

This study calculated the total cooling consumption of the district from 9:00 h July 5 to 24:00 h August 31, 2013 using the measured data and the simulated loads from the three methods and then compared the total cooling consumption results as shown in Figure 8. The simulation results of the SOB method and the Fixed Schedules method are close to the measurement results within −7% and 4%, respectively. This indicated that these two methods could be used to predict the total cooling consumption at the district level. However, the FTFS method overestimated the total district cooling consumption by 81%.
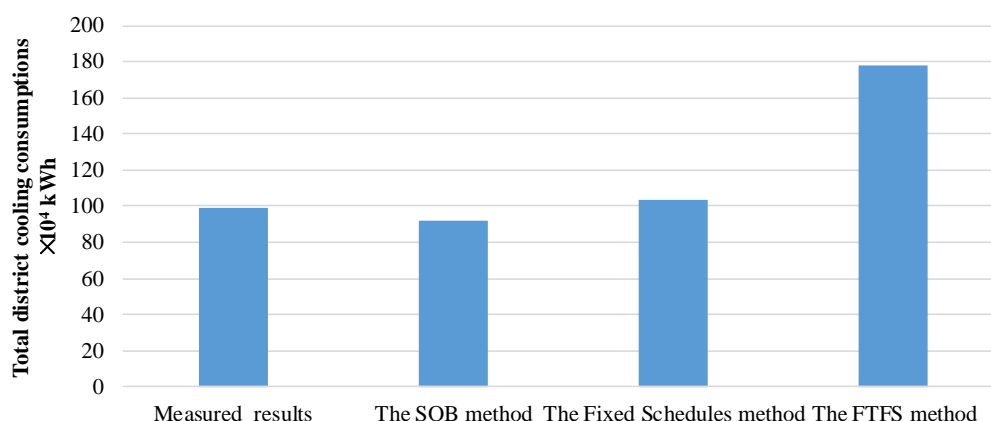

Figure 8 Total district cooling consumptions from the actual measurement and the three simulation methods from July 5 to August 31, 2013

(2) Metric 2: Peak cooling load of the district

The peak district cooling loads are summarized in Figure 9. The SOB method has significant advantages in estimating the peak cooling load within 9% from the actual measurement results. The performance of the two conventional methods is not satisfactory owing to their much larger errors, 151% and 55%, respectively. The peak cooling load estimated by the Fixed Schedules is even worse than that estimated by the FTFS method. In the Fixed Schedules method, the occupants were assumed to always have the same schedules instead of constantly operating air-conditioning (i.e., 24 h on both weekdays and weekends). A large coincident peak occurs when the occupants start to run the air-conditioning at the same time. In contrast, the FTFS method assumes that the occupants always run air-conditioning. The estimated cooling loads of the FTFS method are often greater than the measured cooling load, but

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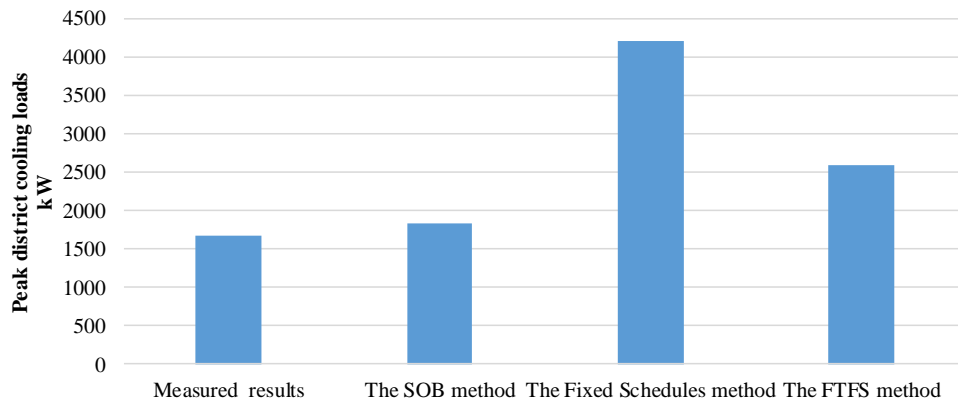its peak cooling load is not as large as that estimated using the Fixed Schedules method.

Figure 9 Peak district cooling loads from the actual measurement and the three simulation methods from July 5 to August 31, 2013

(3) Metric 3: District cooling load distribution

As aforementioned, the measured cooling loads were recorded every 5 min. However, the simulations were performed with a 10 min time interval. To compare the cooling load distributions of the measured and simulation results (Figure 10), this study generated new simulation results of the three presented methods with a 5 min interval by using the finite difference method.
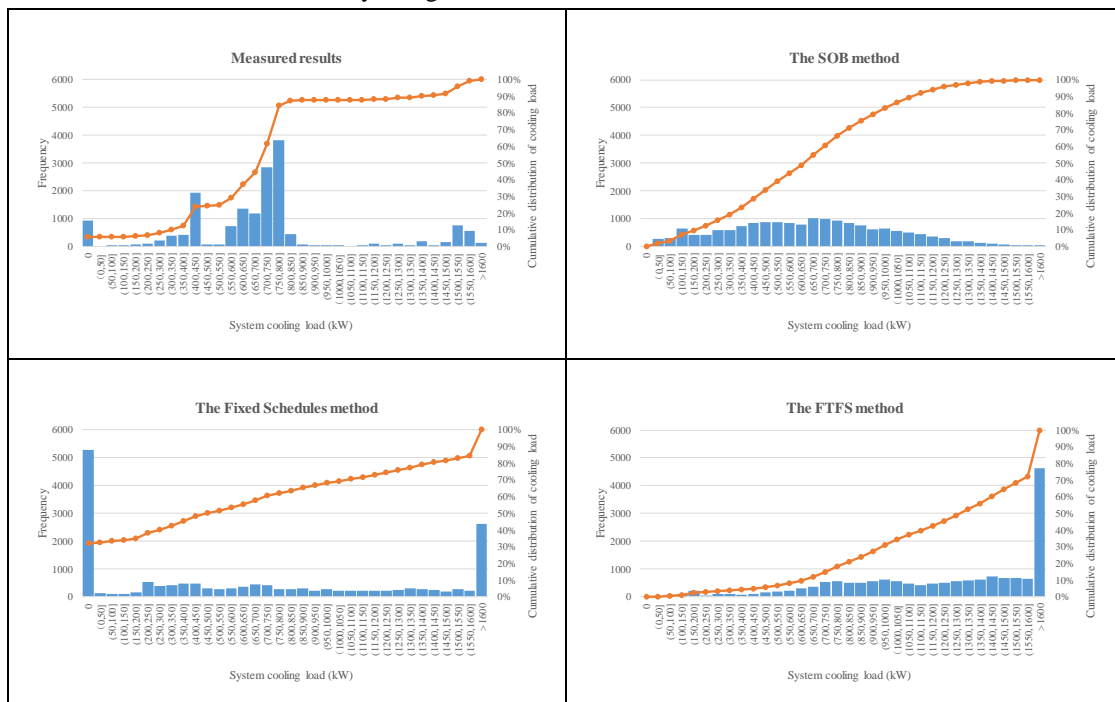

Figure 10 District cooling load distributions of the measured and simulated results

As can be observed from the figure, all simulated cooling load distributions are obviously different from the measured cooling load distribution and none of them passes the K-S test. The main reason could be that the measured cooling load is the cooling supplied by the chillers, which were manually controlled by the substation cooling plant operator. The multiple chillers and associated chilled water pumps were sequentially switched on to meet the cooling load. Therefore, the flow rate of the chilled

water and supplied cooling load did not vary continuously, leading to over- or undersupply of cooling to households in the district. In other words, the supply cooling loads are always at certain values, such as 400 kW, 800 kW, and 1600 kW. On the other hand, the simulated district cooling load is the aggregated cooling demand of each apartment of the district, which varied continuously. Although the cooling load distributions from the measurement and simulation results using the SOB method significantly differ, they did show some similarities. Most cooling loads fall between 700 and 800 kW and only around 20% of the cooling loads are greater than 1000 kW. In the Fixed Schedules method, the cooling loads were either too small (equal to 0 kW) or too large (greater than 1600 kW), which is completely different from the measurement. In the FTFS method, the cooling loads were always relatively large values and around 30% of the cooling loads were greater than 1600 kW.

(4) Metric 4: District cooling load profile

This study compiled one-week cooling load profiles from the measurement and three simulation methods, as shown in Figure 11. It can be observed that the actual cooling loads were relatively low in the morning and increased at night before the bedtime of the occupants. Thus, it can be inferred that most occupants went out to work in the morning and some of them returned home for lunch at noon, while majority stayed at home at night. The proposed SOB method can reflect the occupant diversity quite well. As can be seen from Figure 11, the simulated cooling loads match the actual loads. The Fixed Schedules method assumes all occupants are out during daytime; thus, there is no cooling load during daytime. Furthermore, occupants will return home at the same time and turn on air-conditioning once they arrive home. At that time, the air-conditioning has to handle the heat stored in the indoor air and building structure (envelopes, interior partitions, and furniture), leading to a large coincident peak of the cooling load. From the peak, the cooling load started to decrease until occupants went to sleep in bedrooms and turned on the air-conditioning in bedrooms, which created another peak cooling load before bedtime. Hence, although the cooling load estimated by the Fixed Schedules has a very large peak, the total aggregated cooling consumption is close to the measurement because the air-conditioning does not work in the daytime. In the FTFS method, the cooling loads are always at a high level and vary with outdoor weather.
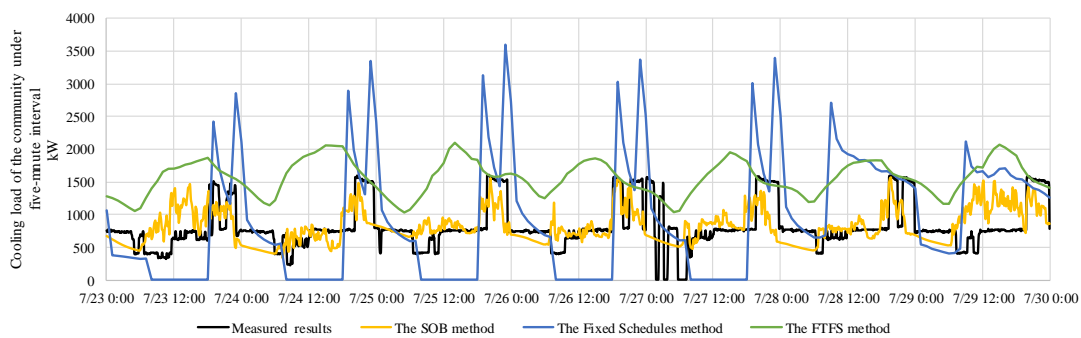

Figure 11 District cooling load profiles in one typical week based on the measurement and three simulation methods

This study generated hourly cooling load data and calculated the NMBE and CVRMSE for the cooling load results of the three simulation methods, as shown in Table 16. It can be seen that all CVRMSEs are greater than 30%, which exceeds the upper limit defined in ASHRAE Guidance 14. As mentioned before, the simulation results are the cooling demand/loads of households while the measured data are

the supply cooling energy/loads of the chillers in the substation cooling plant. Therefore, the supply cooling loads have multiple certain values. In reality, the supply-cooling load at a certain time is the cooling demand of households at different times owing to the time lag between the measurement and simulation cooling loads. These could be the main factors contributing to the large errors. However, compared with the two conventional simulation methods, the SOB method performed remarkably well.

Table 16 NMBE and CVRMSE of the cooling load results of the three simulation methods

Simulations	The SOB method	The Fixed Schedule method	The FTFS method
NMBE (%)	7.2	−4.4	−80.7
CVRMSE (%)	47.7	106	103

(5) Metric 5: Household cooling consumption distribution

This study summarized the cooling consumption of each household in July and August and arranged them from small to large as shown in Figure 12. The x-axis represents different households and the y-axis represents the sum of the cooling loads of the corresponding households in July and August. It can be seen that the SOB method predicts similar household cooling consumption distributions as the measurement data. However, the maximum value of the measured cooling consumptions is around 8000 kWh during July and August, which is greater than the simulation results of the SOB method. In the SOB method, each sampling could lead to different results. Therefore, ideally, an average of multiple sampling results should be used for a better comparison with the measurement results. Furthermore, this study only considered the occupant behaviors of the majority of the population in the district; the behavior of occupants who consumed the most cooling (tend to be a minority of the population) was not considered in our case study. The Fixed Schedule method assumes that all occupants behave uniformly and cooling is supplied for the living room and the occupied bedrooms, which leads to small differences in the cooling consumptions of different apartments. On the other hand, the FTFS method assumes that all apartments have constant internal heat gains and air-conditioning operates all the time in every room of the house except the kitchen, restrooms, and corridor. Thus, the household cooling consumptions only vary with the size (total floor area) of the house.
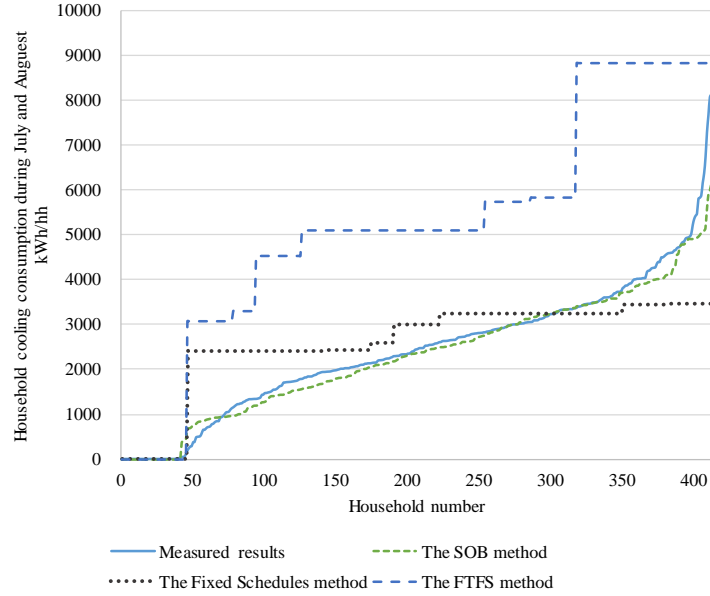
Figure 12 Household cooling distribution according to measurement and simulation results

The K-S test was performed for the three simulation methods, as shown in Table 17. Only the SOB method passed the test, which confirms the conclusion drawn from Figure 12.

Table 17 K-S test results of household consumption distribution from the three simulation methods

Simulations	The SOB method	The Fixed Schedules method	The FTFS method
H	0	1	1
P	0.2630	1.4853e-27	3.2249e-88

In summary, the SOB method is superior in terms of all five performance metrics considered in this case study, namely, the total district cooling consumption, the peak district cooling load, the district cooling load distribution, the district cooling load profile, and the household cooling consumption distribution. Regarding the measurement data, i.e., the supply cooling load data, the simulation results of the SOB method could not match the measurement in terms of the district cooling load distribution and the district cooling load profile but it still performs better than the other two conventional methods.

5. Discussion

5.1. Influence of stochastic sampling

The proposed method adopts stochastic sampling to assign the occupancy schedules and occupant behaviors for each apartment in the district. Thus, different samplings, by running the SOB method multiple times, will produce different simulation results for the district cooling loads. Ten repetitions were recommended by Feng et al. [58] to estimate the average or aggregated results of stochastic occupant behavior modeling.

To quantify and evaluate variations in the results of the SOB method, this study conducted ten simulations. The differences in the five performance metrics among the ten runs were found to be insignificant. Therefore, multiple simulation runs are not necessary to predict the district cooling loads by the SOB method.

5.2. Applications of the SOB method

The proposed SOB method can be applied to building and district cooling plant design, especially to determine the peak cooling loads and thus the maximum capacity of the HVAC system and to determine the load profiles for the optimal selection (sizes) of multiple HVAC equipment. Occupant behavior is usually simplified as deterministic and homogeneous across all buildings in a district, for example, in the case of the FTFS method and the Fixed Schedules method, which are the two conventional methods used for load calculation in China and most other countries. The FTFS method could result in a significant overestimation of the peak cooling load, leading to a significantly oversized district cooling system that would require much more capital investment to build the cooling plant as well as low operational efficiency owing to the low-load operating conditions of the cooling plant. For example, in our case study, the total chiller capacity (2194 kW) was oversized by about 30% compared with the measured peak cooling load (1678 kW) in Figure 13.

Figure 13 also shows the calculated peak cooling load of the case district using the FTFS method and the proposed SOB method for design purposes. Since information such as vacancy and actual weather data would not be available at the design stage, the vacancy was set to 0 (assuming all apartments are occupied) and the typical meteorological year (TMY) was adopted for this calculation. TMY data, which comprises weather data from a combination of 12 calendar months usually selected from 30 historical years, are often used for building design. In addition, a coincidence factor of 0.85 for the district cooling and heating was adopted in the FTFS method based on interviews with a number of experienced mechanical engineers. The peak cooling load calculated by the FTFS method (2113 kW) is very close to the installed chiller capacity (2194 kW), which validates the adoption of the FTFS method in the design process. On the other hand, the peak cooling load calculated by the SOB method (1835 kW) is much less than the installed chiller capacity (2194 kW) but close to the actual measured peak cooling load (1678 kW), which indicates that the SOB method can represent the realistic load diversity within a district. Therefore, the proposed SOB method could be employed in the building design process to provide a more accurate estimation of the peak cooling load of the district, which will effectively avoid oversizing of the equipment (chillers, cooling towers, and pumps) in the substation cooling plant.

However, note that the application of the new SOB method requires the use of typical occupant behavior modes extracted from large-scale questionnaire surveys. As the occupant behavior modes vary significantly with culture and climate zones, a nation-wide questionnaire survey should be conducted before actually implementing the new SOB method in the design standard.
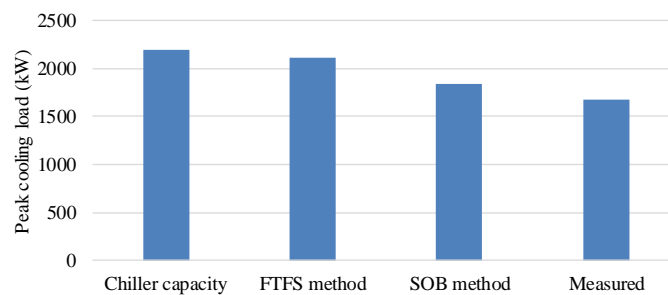

Figure 13 Comparison of the installed chiller capacity, the calculated cooling capacities, and the actual

measured peak cooling load

5.3. Limitations

This study has several limitations. First, this study assumed that the typical occupant behaviors in the residential questionnaire investigation in Chengdu, China, could represent the typical occupant behaviors in the hot summer and cold winter climate zone of China. This study used them as the inputs of simulations to estimate the district cooling load in Wuhan, China. Chengdu and Wuhan are both located in the hot summer and cold winter climate zone of China. However, it is better to conduct broader surveys in more cities in the same climate zone to have a better understanding of typical occupant behaviors in residential buildings.

Second, although the inputs of the Fixed Schedules method are from different data sources than our questionnaire survey, there are no significant differences between occupant behaviors in these surveys. Because both surveys were conducted in the same hot summer and cold winter climate zone with a large number of respondents rather than in the exact same district as the case study, this study can assume both surveys effectively represent the typical occupant behaviors in Chinese residential buildings. In the future, it is recommended to obtain more measurement results to determine consistent inputs for the SOB method and the Fixed Schedules method.

Third, this study used defaults for some occupant behavior modes owing to the lack of measurement data to determine the probability functions. More household measurements of occupant behaviors and corresponding influencing factors can benefit the accuracy of occupant behavior models.

Fourth, the proposed SOB method is slightly complicated for implementation by regular users. It should be simplified by creating a database of occupant behavior models and distributions of typical occupant behaviors in various cities based on measurements and surveys and develop a user-friendly graphical user interface to select the input values, enabling the adoption of the method by a broader audience. This will improve HVAC equipment sizing and lead to more efficient operation and lower energy use in real district energy projects.

Lastly, this study consider less about the uncertainty of building envelope performance. Although there are definitely differences on building envelope performance between design and reality, leading to disparate building loads, the gap would not be so big as the final construction was checked and accepted by professional institute according to Chinese standard. This uncertainty should be considered in future researches.

6. Conclusions

Occupant behavior assumptions significantly influence the calculation of district cooling loads. The proposed SOB method represents the detailed occupant behaviors and the spatial diversity of apartments in a residential district by using stochastic occupant behavior models. The district cooling loads simulated using the SOB method agree with the actual measurement data for the five performance metrics, which proves the applicability of the SOB method. This is the first application and evaluation of detailed occupant behavior models for district load prediction, which is of great importance in application of detailed occupant behavior models for thermal loads prediction in districts. The two currently used conventional simulation methods (the FTFS method and the Fixed Schedules method) oversimplify the complexity and diversity of occupant behaviors, leading to

well-overestimated annual energy use and peak cooling loads.

Although the proposed SOB method significantly improves the district cooling load prediction, it requires much more detailed inputs of the occupant behavior models; it can be challenging for most users to obtain such data. Therefore, future work will investigate the simplification of the proposed SOB method for practical use. Future work will also extend the proposed SOB method to commercial districts or mixed-use districts with both residential and commercial buildings. The proposed SOB method can also be examined for simulating district heating loads.

Acknowledgments

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