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Analysis of the influence of the stay-at-home order on the electricity consumption in Chinese university dormitory buildings during the COVID-19 pandemic

Tingting Zhoua, Xi Luob, Xiaojun Liua, Guangchuan Liuc, Na Li, Yongkai Suna, Menglin Xinga, Jianghua Liua

a School of Management, X’ian University of Architecture and Technology, Xi’an 710055, China
b State Key Laboratory of Green Building in Western China, School of Building Services Science and Engineering, X’ian University of Architecture and Technology, Xi’an 710055, China
c School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China

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A B S T R A C T

During the COVID-19 pandemic, strict stay-at-home orders have been implemented in many Chinese universities in virus-hit regions. While changes in electricity consumption in the residential sector caused by COVID-19 have been thoroughly analysed, there is a lack of insight into the impact of the stay-at-home order on electricity consumption in university dormitory buildings. Based on questionnaire survey results, this study adopted the statistical Kaplan–Meier survival analysis to analyse the energy-use behaviours of university students in dormitories during the COVID-19 pandemic. The electricity load profiles of the dormitory buildings before and during the implementation of the stay-at-home order were generated and compared to quantitatively analyse the influence of COVID-19 pandemic on the energy-use behaviours of university students, and the proposed load forecasting method was validated by comparing the forecasting results with monitoring data on electricity consumption. The results showed that: 1) during the implementation of the stay-at-home order, electricity consumption in the university dormitory buildings increased by 41.05%; 2) due to the increased use of illuminating lamps, laptops, and public direct drinking machines, the daily electricity consumption increased most significantly from 13:00 to 18:00, with an increase rate of 97.15%; and 3) the morning peak shifted backward and the evening peak shifted forward, demonstrating the effect of implementing the stay-at-home order on reshaping load profiles.

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1. Introduction

During the COVID-19 pandemic, many governments worldwide have taken blockade control measures with varying intensities and durations to control the epidemic [1], such as travel restrictions, facility shutdowns, and social distancing [2]. In cases of increasingly severe epidemics, the Chinese government has adopted strict social distancing measures, i.e., the stay-at-home order [3], to stop the spread of the epidemic. Affected by the stay-at-home order, working and studying remotely from home has gradually changed the lifestyle of most people. Consequently, the electricity consumption patterns of people have also changed [4–5], which has significantly impacted the operation and dispatch of power systems [6–8]. Load forecasting is the foundation of stable operation of power systems [9–11]. Electricity loads are correlated with many factors, such as the temperature, time, and the living habits of people. All influencing factors were found to show remarkable periodic trend changes, and most of the trends are already well known [10]. Thus, the accuracy of the current electricity load forecasting method currently meets the requirement of power dispatch. However, during the COVID-19 pandemic, the implementation of the stay-at-home order significantly influenced the lifestyles and electricity consumption behaviours of most people, making electricity loads difficult to forecast [12]. Thus, an increasing number of researchers have conducted studies on the impact of COVID-19 on the energy consumption of residential buildings. For example, Kawka et al. [13] compared residential energy use before and during the COVID-19 pandemic based on energy using data from 225 residential buildings in the United States from 2018 to 2020. Krarti et al. [14] analysed the impact of stay-at-home living patterns on the energy consumption of res-
identical buildings before and after the COVID-19 lockdowns. In China, the per capita electricity consumption in universities is four times that in residential buildings. Being one of the main locations where students study and live, electricity consumption in university dormitory buildings account for 18 % of the electricity consumption in the entire campus [15]. Therefore, reducing the electricity consumption of university dormitory buildings is very important. Although there has been a large amount of research on energy conservation in university dormitory buildings [16–18], the impact of COVID-19 has seldom been considered. The electric equipment used in dormitories differ considerably from those used in residential buildings from the perspective of either equipment type or rated power. Moreover, unlike general residential buildings, students in dormitory buildings show almost identical electricity consumption patterns [19], particularly when they are required to stay in dormitories. Thus, significant differences in energy consumption exist between residential buildings and university dormitory buildings, making existing research results on the impact of COVID-19 on electricity consumption in residential building inapplicable to university dormitory buildings. Therefore, it is necessary to investigate how the implementation of the stay-at-home order influences the electricity-consumption behaviour of students and the electricity consumption in dormitory buildings.

2. Literature review

2.1. Impact of the COVID-19 pandemic on energy consumption

Since the start of COVID-19, numerous studies have explored the impacts of COVID-19 on national energy consumption in countries such as Canada [20], Spain [21], the United States [22], India [23], China [24], and others [25–26]. All the results showed that the COVID-19 pandemic led to reduction in national energy consumption, with reduction rates ranging from 10 to 20 %. Bahmanyar et al. [25] found that the reduction in national energy consumption was highly affected by the intensity of local restrictions. For countries with severe restrictions, power consumption was considerably reduced. However, for countries with fewer restrictive measures, power consumption decreased to a lower degree.

In addition to analysing how COVID-19 impacts energy consumption at the national scale, many studies have focused on its impacts on different energy-consuming sectors. For example, Farrow [27] found that the lockdown measures in Australia led to significant changes in energy consumption, with commercial, industrial, and residential electricity consumption decreasing by 7 %, 1 %, and 14 %, respectively. However, Elavarasan et al. [23] found a sharp decrease in industrial and commercial electricity consumption in India, whereas electricity consumption in households and hospitals/emergency services increased significantly. To investigate changes in the energy-consumption behaviours of residents in detail, scholars have gradually shifted their attention from a macro perspective to a micro perspective. Existing studies have found that, during the COVID-19 period, the energy peak shifted and the load shape changed significantly [28–29]. For example, Chinthavali et al. [28] found that the stay-at-home measures implemented during the COVID-19 pandemic led to an overall higher energy consumption in residential buildings, and most of the increased energy consumption occurred before the evening peak. Fan et al. [29] found a decrease in energy consumption during conventional peak hours and an increase in energy consumption during potential new peak hours after the COVID-19 outbreak. However, existing research on the residential sector has mainly focused on general residential buildings, with little focus on university dormitories [30]. The functions of university dormitories are different from those of residential buildings. When faced with a COVID-19-related stay-at-home order, responses in the energy-consumption behaviours of residents are totally different, resulting in remarkably different changes in electricity demand [31].

Data acquisition is necessary for conducting studies on energy-consumption behaviour, and the methods used to collect energy-use behaviour data are either monitoring or questionnaires. Among these, the energy consumption monitoring method is the most widely used [7,32–33]. For example, Sánchez-López et al. [33] used data obtained from smart meters to study the impact of COVID-19 on the electricity consumption of residential buildings in various communities in Chile. By monitoring the real electricity consumption data of kindergartens, schools, apartments, and townhouse buildings in Norway, Ding et al. [7] found that demand variation existed only in residential buildings. However, because of the difficulty of obtaining sub-metering data, the above studies focused more on the total energy consumption of buildings, while the separate energy consumption of different equipment, for example, HVAC and lighting, were not analysed in detail. In most Chinese university dormitories, sub-metering is not available because of its relatively high cost, thereby posing difficulties in studying the energy-use behaviour of students. To overcome this problem, studies have used questionnaires to obtain information on energy consumption. For example, Zanocco et al. [34] used an online survey in California’s shelter-in-place order to determine variations in household energy activity in terms of the use of electronics. Mustapa et al. [35] investigated the consumption patterns of household appliances across Malaysia before, during, and after the movement-control order (MCO) and found a significant increase in electricity consumption during the MCO period. All the above reference demonstrated that questionnaire surveys are effective for obtaining detailed information on energy-consumption behaviour, especially when data monitoring is unavailable [36].

2.2. Building energy simulation based on resident behaviour modelling

Building energy simulation is essential for calculating building energy consumption [37–38], while the calculation accuracy is subject to multiple factors [39–41]. Depending on how the data are collected, building energy simulation methods can be divided into top-down and bottom-up methods [42–43]. The top-down method identifies the correlation between energy consumption and external objective factors by analysing the monitored information, whereas the energy-use behaviour of residents are seldom considered [44]. However, existing research has suggested that the systematic interaction between residents and buildings causes great uncertainty in predicting residential energy demand, and the energy consumption of a residential building is heavily dependent on the behaviour of the residents [45–48]. Thus, the forecasting accuracy of the top-down method is usually unsatisfactory and cannot explain load fluctuations under certain circumstances. However, the bottom-up method determines the contribution of residents to a building’s energy consumption by analysing the residents’ energy-consumption behaviour [49–50]. Unlike the top-down method, the bottom-up method does not rely on historical energy consumption data; thus, the simulation results are more accurate in exceptional cases [51–52]. An increasing number of scholars have modelled the energy-consumption behaviour of residents, linking the energy-consumption behaviour of occupants to energy consumption, thereby calculating building energy consumption [53–56].

The behaviour of occupants can be modelled using either deterministic or probabilistic methods [57]. Deterministic models mainly adopt statistical analysis methods to quantitatively present the behavioural patterns of residents and simulate resident beha-
behaviour based on predefined fixed schedules or rules. In general, deterministic models are either rule- or fixed-schedule-based. Rule-based deterministic models assume a direct and fixed causal link between one or more drivers and an action [58]. For example, in a previous study [59], it was assumed that the residents opened windows only when the indoor temperature threshold was exceeded. In contrast to rule-based models, fixed schedule-based models describe the behaviour of residents using a fixed schedule; therefore, the energy consumption of residents during each time period can be determined in advance. The schedules are usually obtained by statistically analysing the monitoring results [60]. For example, in [61–62], the fixed schedules of resident energy-consumption behaviour were identified using cluster analysis. Although they are easy to use, deterministic models ignore the stochastic and flexible nature of residents’ energy-consumption behaviours, leading to unavoidable calculation error [63].

Owing to the accuracy problem of deterministic methods, probabilistic models have received increasing attention in recent years [64–65]. Probabilistic models typically use statistical data to predict the probability of a certain action [58]. Probabilistic models can better capture the stochastic characteristics of resident behaviour and provide probability distributions based on performance metrics to represent more diverse resident behaviour, thereby significantly improving the accuracy of energy simulation results [66–69]. The most frequently used analysis methods for constructing probabilistic models are logistic regression and Markov chains [41]. The modelling method based on logistic regression uses the multivariate logistic regression of the interaction between selected variables to infer the probability of a given resident behaviour occurring, which not only simulates the behaviour of residents in real buildings but also reveals the role of potential drivers in influencing the occurrence of a given behaviour. For example, Andersen et al. [70] constructed a window-opening and window-closing model using multiple logistic regression based on observations from 15 residential buildings in Denmark. Jones et al. [38] verified the correctness and validity of the logistic regression method used by Andersen et al. [70] based on data collected in the UK. Naspi et al. [71] analysed the influence of environmental and non-environmental factors on the window opening/closing behaviours of residents and used logistic regression to propose a behavioural model for predicting the state of windows and lights.

Although widely used, a limitation associated with using the logistic regression method to infer the probability of resident behaviour is the difficulty in predicting the transfer probabilities of different energy consumption activities [70,72]. To overcome this problem, Fritsch et al. [73] first attempted to mathematically model window open states based on a probability model using a Markov chain and then validated the scientific validity of the proposed model. Subsequently, Rouleau et al. [68] used the first-order Markov chain method to calculate the transfer probability of various family activities and introduced a proportion factor to construct Canada’s electricity consumption model. Widén et al. [49] used nonhomogeneous Markov chains to create resident activity distributions over time and generated the activity sequence of each family member to calculate the probability distribution of electricity demand. However, the main problem of the Markov chain is the fixed time step. A fixed time step must be chosen first to construct a model of resident behaviour, which limits the application of the method to an extent [74–75].

In the field of medicine, survival analyses, most commonly Kaplan–Meier (KM) curves, are frequently used to measure the fraction of subjects living for a certain amount of time [76]. In general, the KM method is used to estimate the probability of the duration until an event occurs [77]. Existing research has shown that the KM method can better characterise the duration probability of a study subject at any given time step when simulating resident behavior [56]. This method considers event duration by using flexible time steps to more realistically simulate the uncertainty characteristics of the occurrence and duration of resident behaviour [78–79]. This study adopted the statistical concept of KM used in medicine to construct a stochastic behaviour model for students in university dormitories based on questionnaire results. The electricity load profiles of the dormitory buildings before and during the implementation of the stay-at-home order were generated and analysed, and the forecasted results were compared with monitoring data to demonstrate the validity of the proposed method. Compared to existing studies, the main contributions of this study are as follows:

- A method was developed to calculate the probability of single energy-use behaviour of students in dormitory buildings using a KM survival analysis.
- The impacts of the stay-at-home order on the energy-use behaviours of students in dormitory buildings were investigated.
- The load profiles before and during the implementation of the stay-at-home order were generated to provide a reference for power system dispatching during the COVID-19 pandemic.

The remainder of this paper is organised as follows: Section 3 presents the research methods, Section 4 presents the survey and analysis results, and Section 5 summarises the findings and insights of this study.

3. Methodology

3.1. Research framework

At the end of December 2021, an epidemic occurred in Xi’an, China. A stay-at-home order was implemented from 25 December 2021 to 24 January 2022, which is the coldest period in Xi’an. The strict lockdown implemented in university dormitories prevented students from entering or leaving the dormitories to slow the spread of the coronavirus. To understand changes in the energy consumption in school dormitories before and during the implementation of the stay-at-home order, this study conducted the following research, with the research framework shown in Fig. 1.

1. Questionnaire survey and data analysis. Data on the energy-use behaviour of students in dormitories were obtained using a questionnaire survey conducted at a university in Xi’an. The collected information included the use time, use frequency, and rated power of the electrical equipment in the dormitory buildings. After the data were collected and analysed, the energy-use behaviours of students before and during the implementation of the stay-at-home order were obtained and compared.
2. Investigation on energy consumption patterns. The probability distributions of the starting time and duration of students’ electricity consumption behaviour were calculated based on the questionnaire survey results, and then the data were aggregated to investigate the energy consumption patterns of the students in the entire dormitory building before and during the implementation of the stay-at-home order.
3. Generation of electricity load profiles. The hourly electricity consumption was calculated to generate the electricity load profiles of the whole dormitory building, and changes before and during the implementation of the stay-at-home order were analysed.

3.2. Questionnaire survey and data analysis

To fully investigate the electricity-consumption patterns of students, a 28-floor dormitory building with students of mixed genders, grades, and majors was surveyed. The dormitory building
has 20 rooms on the first floor and 28 rooms on each of the remaining floors.

Because the local government prohibited face-to-face survey activities, the questionnaire was conducted online. This study adopted a random sampling design. The survey lasted for one week, from 21 January 2022 to 28 January 2022. A total of 200 replies were received, and 150 valid questionnaires were used after excluding invalid ones.

In the dormitory buildings investigated, each floor is equipped with a direct public drinking machine and two hair dryers. The entire building has 17 washing machines and two water boilers. Air conditioning was not considered in this study, because coal-powered central heating was widely utilised for space heating in the surveyed university in winter. Only natural ventilation was used in the dormitory buildings, so the energy consumption of ventilation system was not considered either. The lighting load in dormitory bathrooms and balconies has a minor contribution to the overall building electricity load; therefore, they were also not considered. In summary, the eight types of electrical equipment considered in this study were divided into two categories according to whether or not the students pay for the electricity cost: pay-to-use equipment (illuminating lamps, desk lamps, laptops, and indoor water dispensers) and free-to-use equipment (washing machines, hair dryers, public direct drinking machines, and water boilers). A questionnaire survey was conducted based on the use patterns of the above equipment before and during the implementation of the stay-at-home order. The survey contents included information on equipment use in the dormitory (usage time, usage frequency, and rated power). The survey contents are shown in Fig. 2.

### 3.3. Investigation on energy consumption patterns

The energy-consumption behaviour of students in dormitories are highly variable and random. In this study, $S_{it}$ represents the probability of students starting to use electrical equipment $i$ at time $t$, calculated using Eq. (1).

$$S_{it} = \frac{N_{it}}{N}$$  \hspace{1cm} (1)

where $N_{it}$ is the number of respondents who started using electrical equipment $i$ at time $t$ in the questionnaire survey and $N$ is the total number of respondents in the questionnaire survey.

To obtain the survival function of each electricity consumption activity based on the questionnaire data, $\hat{S}_{it}$ was used to estimate the probability that the activity using electrical equipment $i$ continued after time $t$. For any type of electrical equipment $i$, $\hat{S}_{it}$ was calculated using Eq. (2).

$$\hat{S}_{it} = \prod_{j=1}^{t} \left(1 - \frac{d_{ij}}{n_{ij}}\right)$$ \hspace{1cm} (2)

where $d_{ij}$ is the number of activities ceased at time $t_j$ and $n_{ij}$ is the number of activities that continue up to time $t_j$ (not including $t_j$).

Fig. 3 outlines the process of generating the daily activity profiles of $N$ students using the stochastic behaviour model. It is assumed that only 8 typical electrical equipment are considered in this model, and the energy use behaviors of students are independent with each other. The model starts to run when time equals 01:00 and $k$ equals 1, and terminates when $t + \Delta t$ equals 24 and $k$ equals $N$ ($N$ is the total number of students living in the dormitory building). The specific model runs as follows:

At time $t$, $S_{it}$ was compared with the randomly generated number $m$ ($0 < m \leq 1$). If $S_{it}$ was greater than $m$, electrical equipment $i$ was started from time $t$. The use duration of electrical equipment $i$ was determined by comparing $\hat{S}_{it}$ with the randomly generated number $n$ ($0 \leq n \leq 1$). If random number $n$ was smaller than $\hat{S}_{it}$ and larger than $\hat{S}_{it+1}$, the use duration of electrical equipment $i$ after time $t$ was recorded as $\Delta t$. The above process repeated until $t + \Delta t$ reached 24, then the activity profile of electrical equipment $i$ of each student on a typical day could be obtained. The activity profiles of all the students in the dormitory building were obtained by repeating the simulation process $N$ times.

The probability of using equipment $i$ at time $t$, which was represented by $R_{it}$ in this study, was calculated using Eq. (3).

$$R_{it} = \frac{N_{it}}{N}$$ \hspace{1cm} (3)

where $N_{it}$ is the number of students using electrical equipment $i$ at time $t$ and was obtained from the generated activity profiles.

### 3.4. Generation of electricity load profiles

In addition to the eight types of electrical equipment investigated, the electrical consumption of the public lights in the corridor were calculated to generate the load profile of the entire building. The hourly electricity consumption of each electrical equipment was used to estimate the probability that the activity using electrical equipment $i$ continued after time $t$. For any type of electrical equipment $i$, $\hat{S}_{it}$ was calculated using Eq. (2).

$$\hat{S}_{it} = \prod_{j=1}^{t} \left(1 - \frac{d_{ij}}{n_{ij}}\right)$$ \hspace{1cm} (2)

where $d_{ij}$ is the number of activities ceased at time $t_j$ and $n_{ij}$ is the number of activities that continue up to time $t_j$ (not including $t_j$).

The probability of using electrical equipment $i$ at time $t$, which was represented by $R_{it}$ in this study, was calculated using Eq. (3).

$$R_{it} = \frac{N_{it}}{N}$$ \hspace{1cm} (3)

where $N_{it}$ is the number of students using electrical equipment $i$ at time $t$ and was obtained from the generated activity profiles.
building. According to the field survey, some of the public lighting (186 units, 25 W/20 W) were kept on for 24 h a day before and during the implementation of the stay-at-home order, while others (168 units, 25 W/20 W) were only kept on from 17:00 to 6:00 before the implementation of the stay-at-home order and turned off during the implementation of the stay-at-home order. These usage patterns were considered when calculating the electricity consumption of the entire dormitory building.
This study adopted the bottom-up method to generate the load profile of the entire building. The hourly electricity consumption of electrical equipment $i$ at time $t$ ($P_{it}$) was calculated using the use probability and rated power, as follows:

$$P_{it} = (P_{i\text{standby}} \cdot (1 - R_{it}) + P_{i\text{rated}} \cdot R_{it}) \cdot Q_i$$  \hspace{1cm} (4)

where $P_{i\text{rated}}$ is the rated power of electrical equipment $i$, $P_{i\text{standby}}$ is the standby power of electrical equipment $i$, and $Q_i$ is the number of electrical equipment $i$ in a dormitory building.

The hourly electricity consumption of the entire building was calculated using Eq. (5).

$$P_{h,t} = \sum_{i=1}^{n} P_{i,t}$$  \hspace{1cm} (5)

To verify the validity of the proposed model, the forecasted electricity consumption of the dormitory building was compared to the monitored electricity consumption of the surveyed dormitory building. The monitored electricity consumption data of the dormitory building was collected from the school energy monitoring platform. The hourly monitoring data series from 25 December 2021 to 24 January 2022, which was the entire implementation period of the stay-at-home order, was used. The hourly monitoring data series for the implementation period of the stay-at-home order was used to calculate the average daily hourly electricity consumption curves for comparison.

To compare differences between the forecasted data series and the monitoring data series, the coefficient of determination ($R^2$) was used to estimate the extent to which the model reflects the monitored electricity consumption data [80–81]. $R^2$ was calculated using Eq. (6):

$$R^2 = 1 - \frac{\sum_{t=1}^{n} [P_{\text{fore}}(t) - P_{\text{mon}}(t)]^2}{\sum_{t=1}^{n} [P_{\text{mon}}(t) - \bar{P}_{\text{mon}}(t)]^2}$$  \hspace{1cm} (6)

where $P_{\text{fore}}(t)$ and $P_{\text{mon}}(t)$ denote the model output electricity consumption at time $t$ and monitored daily electricity consumption at time $t$, respectively. $\bar{P}_{\text{mon}}(t)$ is the mean of $P_{\text{mon}}(t)$.

4. Results and analysis

4.1. Analysis of energy consumption patterns before and during the implementation of the stay-at-home order

The rated power, standby power, and number of electrical equipment in the dormitory building investigated in this study are presented in Tables 1 and 2.

4.1.1. Differences in electrical equipment usage

Differences in the duration and frequency of use of the eight types of electrical equipment were analysed using the $t$-test. Fig. 4 shows the differences in the duration of use of these electrical devices. There were significant differences in the duration of use of the eight electrical equipment, except for the hair dryers.

### Table 1

| Pay-to-use equipment      | Rated power | Stand-by power | Number of equipment (before and during the implementation of the stay-at-home order) |
|---------------------------|-------------|----------------|----------------------------------------------------------------------------------|
| Illuminating lamp         | 0.02 kW     | /              | 1552                                                                              |
| Desk lamp                 | 0.01 kW     | /              | 2739                                                                              |
| Indoor water dispenser    | 0.25 kW     | 0.65 W         | 388                                                                               |
| Laptop                    | 0.06 kW     | 5.00 W         | 1553                                                                              |

The largest difference was found in the duration of laptop use, followed by illuminating lamps, desk lamps, and public direct drinking machines. The smallest difference was found in the duration of washing machine use. Generally, the use duration of the electrical equipment increased during the implementation of the stay-at-home order, especially those of the pay-to-use equipment. When students spent more time in the dormitory, their use of lighting equipment and laptops increased significantly.

### Table 2

| Rated power, stand-by power, and number of free-to-use equipment in the surveyed university dormitory building. |
|--------------------------------------------------|--|--|--|
| Number of equipment (before and during the implementation of stay-at-home order) |
| Hair dryer                                      | 1.20 kW | 1.15 W | 56 |
| Washing machine                                 | 0.74 kW | 0.69 W | 17 |
| Public direct drinking machine                  | 6.00 kW | 5.00 W | 28 |
| Water boiler                                    | 3.00 kW | 42.50 W | 2 |

The demand for drinking water and laptop use has also increased because of the long-term stay of students in the dormitory.

4.1.2. Probability distributions of electrical equipment usage

Fig. 6 shows a comparison of the probability of starting to use an electrical equipment at a particular time ($S_{it}$) before and during the implementation of the stay-at-home order. In terms of time at which equipment-use started, the dormitory illuminating lamp and desk lamp had similar probability distribution function shapes before and during the implementation of the stay-at-home order. During the implementation of the stay-at-home order, the morning peak for starting using illuminating lamp and desk lamp was delayed by approximately 2 h, and the peak initially occurring at noon became nonsignificant. Before the implementation of the stay-at-home order, the peak for starting to use laptops generally occurred at 22:00. During the implementation of the stay-at-home order, the laptop-use starting time reached the highest probability at 11:00 and 16:00. The distribution function of the probability to start using indoor water dispenser was fairly constant with low values before and during the implementation of the stay-at-home order, which may be attributed to the long duration of use for indoor water dispensers. There were minor differences in the probability distributions of the free-to-use equipment before
and during the implementation of the stay-at-home order, suggesting that the stay-at-home order did not significantly affect students’ equipment-use habits for these appliances. However, the peak time for starting to use free-to-use equipment during the implementation of the stay-at-home order occurred slightly later in the morning. One possible explanation is that the students’ bathing time was delayed because of their less tight schedules.

Fig. 7 shows a comparison of the probability distributions for the use durations for the eight kinds of electrical equipment before and during the implementation of the stay-at-home order. The use duration probability distributions of the hair dryers, washing machines, and water boilers before and during the implementation of the stay-at-home order largely coincided. This may be attributed to the relatively short and fixed running times of the equipment. During the implementation of the stay-at-home order, the use-duration probability distributions curves of the lighting equipment, laptops, indoor water dispensers, and public direct drinking machines were significantly right-shifted, indicating that the use duration of these equipment increased to different extents during the implementation of the stay-at-home order.

The electricity consumption patterns of all students in the dormitory throughout the day were obtained by running the stochastic behaviour model. The equipment-use probability distributions of the eight electrical equipment in the dormitory building before and during the implementation of the stay-at-home order are shown in Fig. 8.

It can be seen from Fig. 8 that, before and during the implementation of the stay-at-home order, the use probability distributions of the illuminating lamp was similar to that of desk lamp. The stay-at-home order caused a shift of the morning using peaks of both the illuminating lamp and desk lamp from 09:00 to 11:00 and a shift of their evening using peaks from 23:00 to 20:00. Before the implementation of the stay-at-home order, the use of laptops was mainly concentrated at 22:00–24:00, with a daily average using probability of 10.21 %. As the stay-at-home order significantly increased the using probability of laptop, the average using probability of laptop was 30.33 % during the implementation of the stay-at-home order.

Compared to the free-to-use equipment, the indoor water dispenser always had a higher use probability, regardless of whether the stay-at-home order was implemented. However, when the stay-at-home order was implemented, the peak times during which the indoor water dispenser was used was postponed from 10:00 to 15:00. The stay-at-home order significantly impacted the probability using of hair dryers. The average probability of using the hair dryers decreased from 6.26 % to 3.75 %. This was mainly reflected by the decrease in the use of hair dryers in the evening. For the washing machine, the using probability distribution changed slightly, with the average usage probability increasing by only 4.53 %. During the implementation of the stay-at-home order, the probability distribution curve of the public direct drinking machines exhibited more fluctuations and more peaks. The average probability of using public direct drinking machines increased from 5.43 % to 8.64 %. The stay-at-home order caused a shift in the morning use-probability peak of the water boilers from 08:00 to 09:00 and a shift of evening use-probability peak from
23:00 to 22:00. The average increase rate of use for the water boilers was slightly higher than that of washing machine and increased by only 9.21 %.

4.2. Calculation and validation of electrical consumption in the dormitory buildings

4.2.1. Calculation of electrical consumption in dormitory buildings

Before and during the implementation of the stay-at-home order, the electricity load consumption of the dormitory building obtained using the proposed method are shown in Fig. 9. According to the results, the entire dormitory building consumed a total of 2450.28 kWh per day during the implementation of the stay-at-home order, an increase rate of 41.05 % compared with that of before the implementation of the stay-at-home order. The daily electricity consumption data during the implementation of the stay-at-home order decreased between 00:00 and 08:00, followed by an increased between 09:00 and 23:00.

During the implementation of the stay-at-home order, the electricity consumption from 0:00 to 8:00 was 12.09 % less than that of before the implementation of the stay-at-home order. This was mainly due to a reduction in the use of indoor water dispensers, illuminating lamps, and desk lamps. As most students started to sleep early and wake up late during the implementation of the stay-at-home order, the hourly electricity consumption of lighting equipment decreased between 00:00 and 08:00. The demand for drinking water by students also decreased during this period, thereby reducing the electricity consumption of the indoor water dispenser. The stay-at-home order increased the electricity consumption, especially during the daytime. Increases in daily electricity consumption were most significant between 13:00 and 18:00, during which the rate of increase was 97.15 %. This period coincided with the typical working hours of many students, that
is, when they are generally out of their dormitories. During this period, the increase in electricity consumption was mainly attributed to the increase in the use of laptops, indoor water dispensers, lighting equipment, hair dryers, and public direct drinking machines.

The electricity consumption in the university dormitory showed significant backward shifts in the morning peaks and significant forward shifts in the evening peaks during the implementation of the stay-at-home order. It can be seen that the morning peak time was postponed from 8:00–9:00 to 10:00–12:00, and the electricity consumption from 9:00 to 12:00 increased by 31.43 %. It is worth noting that the evening electricity consumption peak was 1 h earlier than that of before the implementation of the stay-at-home order; specifically, it shifted from 22:00 to 21:00.

Among the typical electrical equipment, laptops are a large contributor to total electricity consumption. The electricity consumption of laptops increased the most during the implementation of the stay-at-home order, with an increase rate of 159.87 %. This change was reflected in the increased electricity consumption of laptops throughout the day, as the dormitory has become the only place where laptops could be used during the implementation of the stay-at-home order. This was closely followed by public direct drinking machines and illuminating lamps, for which the electricity consumption increased by 66.11 % and 20.25 %, respectively. The electricity consumption of the indoor water dispensers and washing machines increased the least, during the implementation of the stay-at-home order, with increase rates of 4.30 % and 4.43 %, respectively. However, the peak demands of the indoor water dispensers and washing machines observed during the implementation of the stay-at-home order were higher than those of before the implementation of the stay-at-home order. It is worth noting that the electricity consumption of hair dryers had a decrease rate of 39.55 %. This was due to the restricted conditions in the dormi-
Fig. 8. Use probability distributions of electrical equipment.

Fig. 9. Comparison of electricity consumption in dormitory building before and during the implementation of the stay-at-home order.
4.2.2. Model validation

The proposed model was validated by monitoring electricity consumption in the same dormitory building where the questionnaire data were collected. Fig. 10 shows the comparison of the simulated and average monitored daily electricity consumption curves for the university dormitory building during the implementation of the stay-at-home order. The $R^2$, which was 0.93 in this study, indicating that 93% of the monitored daily electricity consumption data could be explained by the simulated data. However, the model overestimated the late afternoon peaks and underestimated electricity consumption at night. This may be due to recall and self-reported biases that arise from obtaining data through questionnaires, where respondents are unable to report activities exactly as they were performed. As a result, there were some differences between the modelled and monitored curves at night and in the late afternoon.

5. Conclusion

Based on a questionnaire survey of the energy-consumption behaviour of students in a university building, this study constructed a stochastic behaviour model to calculate the electricity consumption in the building and analysed the impact of the stay-at-home order implemented in response to COVID-19 on dormitory students’ energy-consumption behaviour and electricity consumption in a university in China. The main findings are summarised as follows.

1. The impact of the stay-at-home order on the electricity consumption in university dormitories was significant. The electricity consumption during the period of the stay-at-home order was significantly higher than that before the period of the stay-at-home order, with an increased electricity consumption of 41.05%. The daily electricity consumption data during the implementation of the stay-at-home order decreased during the period from 00:00 to 08:00, followed by an increase during the period from 09:00 to 23:00. The increase in daily electricity consumption was most significant between 13:00 and 18:00, with an increase rate of 97.15%.

2. The electricity consumption in the university dormitory showed significant backward shifts of the morning peaks and significant forward shifts of the evening peaks during the implementation of the stay-at-home order. The morning peak time was postponed from 8:00–9:00 to 10:00–12:00, and the evening peak time shifted from 22:00 to 21:00. Meanwhile, there was a high similarity between the energy consumption pattern curves and the of the hourly electricity consumption of each electrical equipment, indicating potential synchronisation of the electricity consumption in the dormitories and the energy-consumption behaviour of students.

3. The stay-at-home order significantly changed the energy consumption patterns of students in the university dormitories. The behavioural pattern of laptop use changed most significantly before and during the implementation of the stay-at-home order. The electricity consumption of laptops increased most, with an increase rate of 159.87% during the implementation of the stay-at-home order, while the use probability distribution of the washing machines changed the least.

The COVID-19-related stay-at-home order had a significant impact on the energy consumption patterns and electricity consumption of students in the university dormitory building. This study calculated and compared the electricity consumption in dormitories before and during the implementation of the stay-at-home order, to provide reference for power system dispatching during the COVID-19 pandemic. According to the conclusions obtained in this study, the impact of COVID-19 lockdown measures on electricity consumption of university dormitory buildings is generally consistent with that of general residential buildings, with the increase in electricity consumption ranging from 17% to 49% [14,82–85]. However, the electricity consumption of residential buildings increased significantly at the “middle of the day” (9:00–17:00) [4,86], while the electricity consumption of dormitory buildings increased most in the afternoon (13:00–18:00). In this study, only one university dormitory building was investigated. In future studies, the sample size would be increased, and higher temporal resolution would be considered.

Due to the implementation of the stay-at-home order, the electrical consumption of university dormitory buildings has increased significantly. From the results of this study, the increase in electricity consumption mainly comes from the use of laptops, illuminat-
ing lamps, and desk lamps. Therefore, the specific measures to reduce energy consumption in dormitory buildings during COVID-19 include reduce standby power consumption of the laptops, and reduce the use of lighting equipment during the daytime.

**Data availability**

Data will be made available on request.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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