Heating energy consumption of a passive house in a severe cold region based on human behavior

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ABSTRACT

Human behavior is one of the reasons for the discrepancy between the actual operational and designed energy consumption of a building. A passive ultra-low-energy residential building in Harbin was used as a case study to explore the relationship between indoor heating temperature settings, window-opening behavior of occupants, and building energy consumption. The field test results revealed that the indoor temperature of the passive house exceeded the upper limit of the winter comfortable indoor temperature range 78.7% of the time during the test period. Window-opening rates for winter are low but vary significantly with time, with the average value on weekends being 2.5 times higher than that on weekdays. The simulation results showed that the high heating temperature and window-opening behavior of occupants mainly contributed to the heating energy consumption exceeding the design standard in the actual operation of this passive house. For every 1 °C increase in indoor heating temperature, heating energy consumption increased by 5.2%. Heating energy consumption increased by 5.6% for every additional 5 min of window opening. The results highlight the influence of occupant adaptive behavior on building energy consumption, which could guide occupants to use energy reasonably.

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Introduction

The importance of studying human behavior in nearly zero energy buildings

The Global Status Report for Buildings and Construction states that energy use in buildings accounts for 34% of the total final energy consumption (United Nations Environment Programme 2022). Countries have been researching building energy-saving techniques to reduce energy usage in buildings, which has led to “net zero energy buildings” (Deng, Wang, and Dai 2014). Because it is difficult to achieve “net zero energy buildings,” European countries have proposed easy-to-implement “nearly zero energy buildings” (Kurnitski et al. 2011; BPIE 2015).

Although “nearly zero energy buildings” have been implemented in various countries, there is a significant difference between the actual and designed energy-saving effects (Wang et al. 2019). The heating energy consumption of a nearly zero energy building in Berlin was 2.7 times higher than the design condition, and the actual operational energy consumption of the building had a strong relationship with the energy-use habits of the occupants (Ascione et al. 2016). Different energy-use behaviors can lead to twice the difference in energy consumption (Sun and Hong 2017a).

The impact of occupant energy-use behaviors on the energy consumption of a building cannot be ignored (Liu et al. 2021; Guerra Santin 2012). Carpino et al. (2017) pointed out that occupant behaviors must be considered when evaluating the performance of “nearly zero energy buildings.”

Literature review

Yan et al. (2017) defined human behavior mainly as occupant presence, movement, and interaction with building energy devices and systems. According to Hong et al. (2017), occupant behavior affecting building energy consumption includes adaptive actions and nonadaptive actions.

Many scholars worldwide have studied human behavior and established corresponding energy consumption models using different statistical methods. Simultaneously, a simulation analysis of building energy consumption was conducted based on the established human behavior model; Table 1 summarizes such relevant studies in the past 10 years.

Most studies by Chinese scholars focused on hot summer and cold winter climate zones, while few considered severe cold climate zones. The standard (MOHURD 2019a) pointed out that in severe cold regions the average January temperature is lower than or equal to −10 °C, while in hot summer and cold winter regions it is 0–10 °C. There are differences in the performance of buildings under different climatic conditions (Ding et al. 2021; Schnieders, Feist, and Rongen 2015). Second, the current research is mainly based on ordinary buildings, and research on nearly zero energy buildings is scarce. There are also some differences in the personal energy use mentality for different types of buildings. Finally, only a few studies have considered the impact of human behavior on building heating energy consumption (Cui, Yan, and Chen 2017; Sun and Hong 2017b; Bian et al. 2023; Duan et al. 2023). Only Duan et al. (2023) studied severe cold climate zones, but they did not study nearly zero energy buildings and did not consider window-opening behavior.

Therefore, it is necessary to study human behavior in buildings with nearly zero energy consumption in severe cold regions and its impact on building heating energy consumption to guide people to use energy rationally.

Research content of this study

Occupants directly or indirectly influence building energy consumption by adopting different methods, such as using thermal comfort or opening windows (He, Hong, and Chou 2021; Moeller et al. 2020; Bae et al. 2023). This article focuses on human behavior that affected heating energy consumption. In this study, the behavioral patterns of occupants in nearly zero energy buildings were statistically analyzed over a large dataset, and typical schedules were obtained. In addition, a logistic regression-based probabilistic model for window opening was developed. Based on this, EnergyPlus (2019) software was used to simulate building energy consumption, analyze the influence of various personal behaviors on building heating energy consumption, guide people to use energy reasonably, and provide a theoretical basis for future energy-saving building designs and operations.

Methodology

Field test

Field tests consider three main aspects: monitoring and recording indoor and outdoor heat and humidity environment parameters, real-time monitoring of the occupancy by occupants, and real-time monitoring of the window-opening behavior of occupants.

The indoor thermal and humidity parameters were monitored using WSZYW-1 temperature and humidity self-recording loggers. According to the standard (ASHRAE 2020), temperature and humidity self-recording loggers were placed at heights of 0.1, 0.6, and 1.1 m in the center of the rooms and synchronized to record every 5 min. Continuous measurement of outdoor parameters was carried out by a temperature and humidity self-recording logger placed outdoors; the logger was placed in a box at heights of 0.1, 0.6, and 1.1 m from the ground near the testing object to continuously record outdoor air temperature and relative humidity (Wang, Ji, and Ren 2017; Wang et al. 2018b).

Occupancy data were collected using a passive infrared sensor (hereinafter PIR sensor). When a person passes through the monitoring range, one of the electrodes of the PIR sensor is blocked, resulting in a certain difference between the two electrodes, which releases a high voltage. When the person leaves the monitoring range, the two electrodes return to their normal state. The PIR sensor records a digital signal once per second; it records a high level of “1” when a person is within the monitoring range and a low level of “0” when no one passes by. The counting device can accumulate data every 5 s to get the number of times a high level is recorded.

An intelligent displacement recorder consisting of a magnet, a probe, and a storage body was used to test the state of the window. The magnet was attached to the moving end of the window, while the probe was attached to the fixed end. The state of the window was determined by judging whether the magnet and probe were separated or not. When the window is opened, the magnet and probe are separated, and the instrument records “1”; when the window is closed, the instrument records “0.” The instrument automatically records the opening and closing status of the window and stores the data.

In order to avoid the impact of instrument damage, power failure, and other conditions on the test, we would export the data on time and check the data. The test instruments are shown in Figure 1; their precision errors and other information are listed in Table 2.

(a) Temperature and humidity self-recording logger (b) PIR sensor (c) Intelligent displacement recorder

Fig. 1. Test instruments.

Table 2. Basic information of test instruments. (Table view)

Modeling of window-opening behavior

The window-opening problem is a dichotomous problem with only two cases: on (taking a value of 1) and off (taking a value of 0). Logistic regression analysis is applied to model the window-opening problem. This involves dividing the probability of the event occurring by the probability of the event not occurring and then taking the logarithm of the ratio. The relationship between the probability of window-opening and the impact parameters is shown in Equation 1 (Cornfield, Gordon, and Smith 1961):

$$\log it(p)= \ln (p1-p)=a1x1+a2x2+\cdots+anxn+b \tag{1}$$

From this, we obtain the following equation:

$$p= \exp (a1x1+a2x2+\cdots+anxn+b)1+ \exp (a1x1+a2x2+\cdots+anxn+b), \tag{2}$$

where p is the probability of an event occurring, x1,x2…, xn are factors affecting the occurrence of an event, a1,a2…,an are the regression coefficients of the model, which indicate how much a variable affects the probability of window opening, and b is a constant.

The paired sample t-test is an extension of the single overall t-test, as shown in Equation 3 (Fisher 1987). The difference between two paired samples is represented by d_i. The unknown overall mean μ_d, represented by the sample mean d¯ of the difference, is compared with the known overall mean μ_0 to determine whether the null hypothesis $\mu = \mu_0$ is true:

$$t=d¯-\mu0sd/n, \tag{3}$$

where d_i is the paired sample difference, d¯ is the mean of the paired sample differences, μ_0 is the known overall mean, s_d is the standard deviation of the paired samples, and n is the total number of paired samples.

The p value was obtained by querying the table of t-boundary values through the n and t values obtained from the calculation. The null hypothesis was accepted if the p value satisfied the significance requirement.

The model was validated using SPSS software to obtain a paired-sample test table. If $p < 0.05$, the null hypothesis is rejected, indicating a significant difference between the two paired samples; otherwise, the null hypothesis is accepted.

Energy consumption simulation

The authors chose EnergyPlus as the simulation engine for calculating building heating energy consumption. EnergyPlus is a simulation engine that allows users to design and output the required hourly energy consumption data according to the actual geographic location of the building, envelope, indoor heat disturbance, and HVAC system.

The current validation of energy consumption simulations is mainly based on two metrics given in ASHRAE Guideline 14 (ASHRAE 2014): the mean bias error (MBE) and the coefficient of variation of the root-mean-square error (CV(RMSE)) as given in Equations 4 and 5, respectively. MBE indicates the overall bias in a regression model. CV(RMSE) indicates how much variation or randomness exists between the data and model:

$$MBE=\sum i=1Ni(Mi-Si)\sum i=1NIMi, \qquad (4)$$

$$CV(RMSE)=\sum i=1Ni[[(Mi-Si)]2Ni]1Ni\sum i=1NiMi, \qquad (5)$$

where M_i and S_i are the tested and simulated energy data, respectively, and N_i is the number of data items used for validation.

ASHRAE Guideline 14 states that model validation is reliable if MBE is within ±10% and CV (RMSE) is less than 30%.

Case study

The overall methodology links field test, modeling human behavior, and energy consumption simulation as shown in Figure 2. A case example was selected in a severe cold region for study.

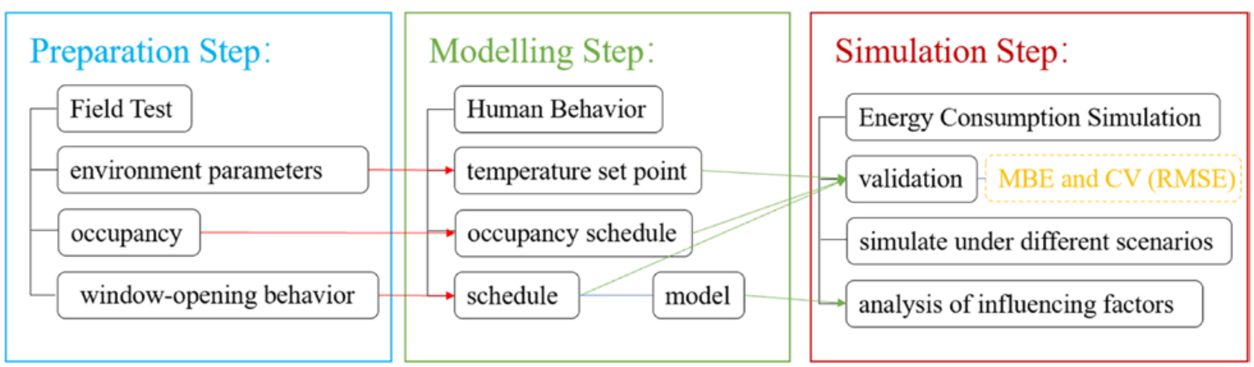


Fig. 2. Flowchart methodology.

Typical building and sample selection

Harbin is located in Heilongjiang Province, China, where the temperature in winter is extremely low and the heating season is long. Continuous heating was applied yearly from October 20 until April 20 of the following year. We consider a passive ultra-low-energy residential building (hereinafter referred to as a passive house) in Harbin, which is the first Chinese–German nearly zero energy consumption building demonstration project.

The building has 11 floors and a size factor of 0.25; the floor plan and energy system represent severely cold regions. Figure 3 shows the exterior of a passive house and a typical floor plan.

(a) Building appearance (b) Typical household plan

Fig. 3. Building appearance and typical household plan.

The building contains 11 floors above ground and an underground garage with a total floor area of 9153.34 m^2. The house consists of three units with 66 households, each with an area of approximately 80–90 m^2. Each home contains a living room, two or three bedrooms, a kitchen, and a bathroom, and is used by approximately two to four people.

From November 25, 2017, to April 20, 2018, the research group continuously monitored the indoor and outdoor environmental parameters, occupancy, and window-opening behavior of four households in the passive house. Table 3 presents basic information on the test households. The instrument arrangements of measurement points are shown in Figure 4a. Liu et al. (2022) pointed out that family structure is one of the most significant factors affecting energy consumption behavior. Due to the limited number of test instruments, we only selected four typical households as test objects, whose family structure can represent all the construction type of the passive house.

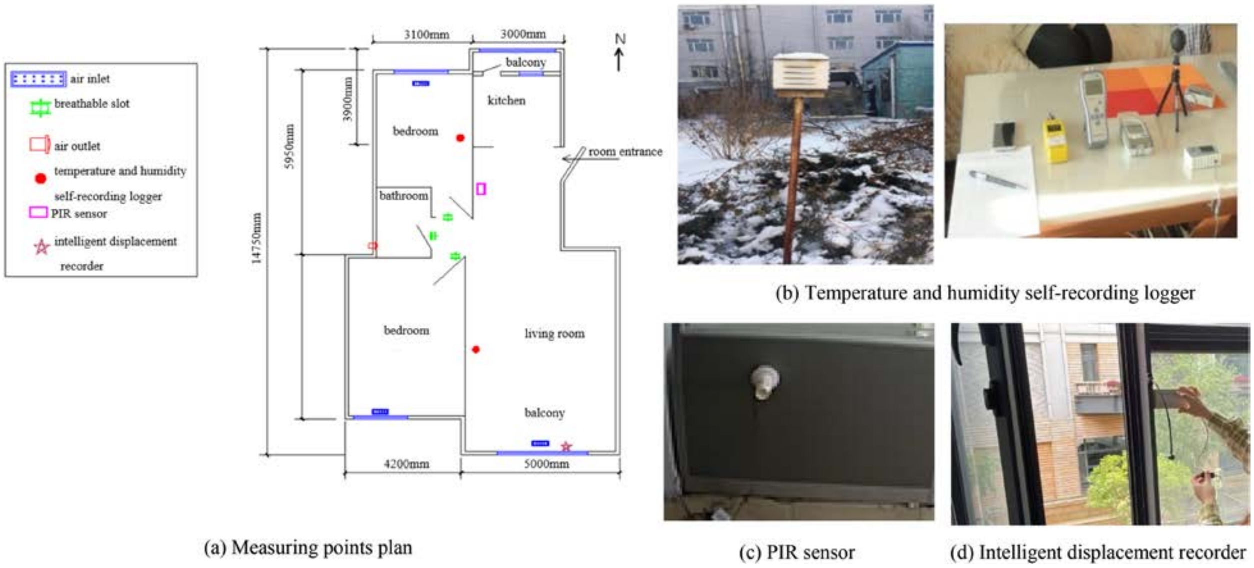


Fig. 4. Measuring points map of instruments.

Table 3. Basic information of test households. (Table view)

Physical building construction

Based on the field test building, a physical model was established using SketchUp software, as shown in Figure 5. The building size, envelope structure, and HVAC systems were built according to the real conditions of the field test building.

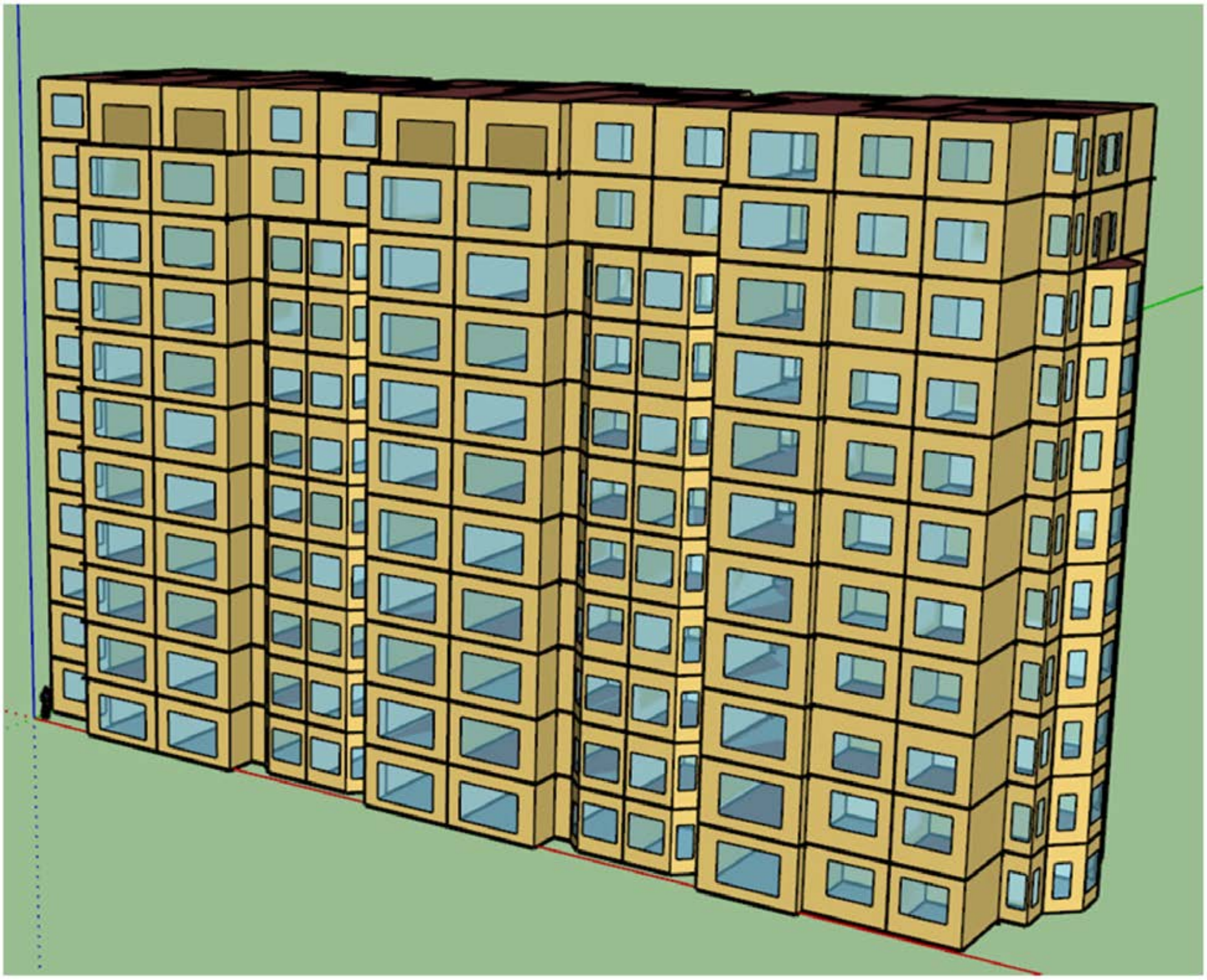


Fig. 5. Schematic of the physical model.

Passive house HVAC systems use composite ceiling radiation systems and displacement ventilation. The water medium was sent to the pipes embedded in the ceilings of the rooms through the machine room, and the radiation heat exchange of the ceiling regulates the indoor air temperature.

Owing to the high airtightness of the envelope of this passive house, a centralized fresh-air unit was set up to meet the physiological and hygienic needs of the occupants for fresh air, as shown in Figure 6.

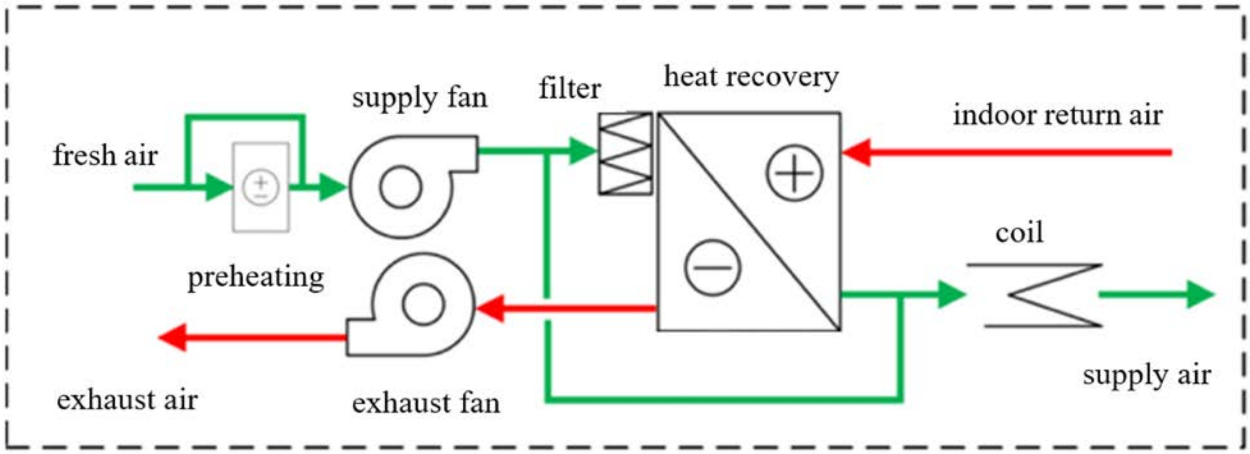


Fig. 6. Schematic of fresh air unit.

To reduce heat conduction loss, the enclosure structure of the passive house has good airtightness and high thermal insulation performance; the thermal performance parameters of the enclosure structure are shown in Table 4. The thermal parameters of the external windows are the heat transfer coefficient (U value) and the solar heat gain coefficient, set to 0.8 W/(m·°C) and 0.6, respectively.

Table 4. Thermal performance parameters of the enclosure structure. (Table view)

The indoor heat gain mainly consists of lighting, equipment, and people. The most common equipment in residential buildings is refrigerators and televisions. The heat gains and schedules obtained in this study are listed in Table 5.

Table 5. Indoor heat. (Table view)

Results and discussion

Testing results

Indoor thermal and humidity environments

The indoor thermal and humidity environments of the four households were monitored continuously during the heating period. The values are listed in Table 6.Table 6. Indoor thermal and humidity environment parameters statistics table. (Table view)

Wang, Ji, and Ren (2017) noted that the thermal comfort standards (ASHRAE 2020; EN 15251 2007) provide a comfortable indoor temperature range of 20–24 °C in winter. As shown in Figure 7, compiling the results of the hourly monitoring of indoor air temperatures for the four households indicates that the indoor air temperatures in each household exceed 24 °C most of the time.

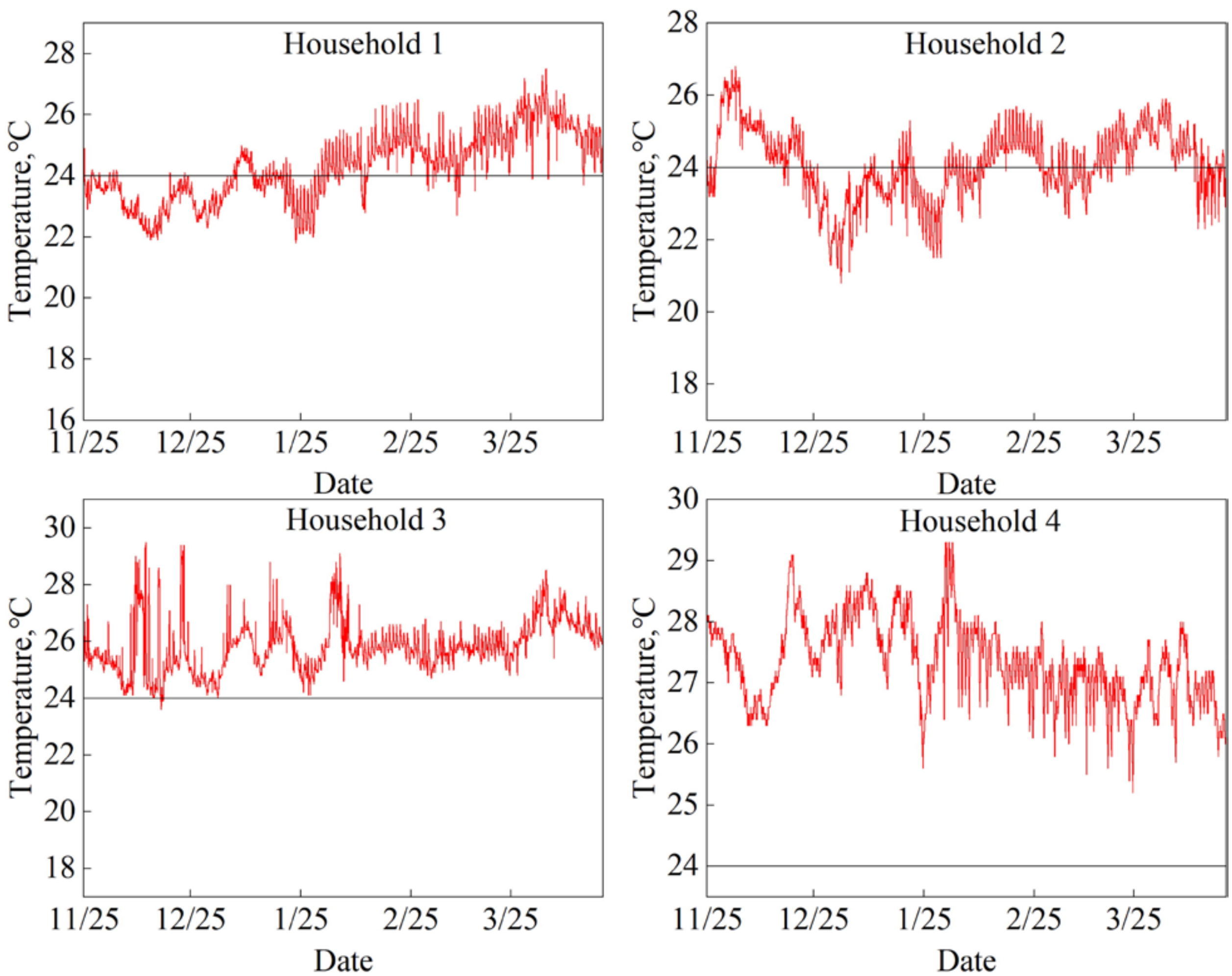


Fig. 7. Indoor air temperature monitoring results.

The exceedance rate is the rate at which the indoor air temperature exceeds 24 °C during the test period.An Exceedance rates of 59.0%, 56.1%, 99.7%, and 100% were obtained for households 1, 2, 3, and 4, respectively. This passive house had excessive indoor air temperatures during the test period, exceeding the upper limit of the winter comfort indoor air temperature range by 78.7%.

Wang, Ji, and Ren (2017) mentioned that the occupants adopt window-opening and other adaptive behaviors when the indoor air temperature is too high, and the indoor air temperature in winter in a severe cold region should be controlled at the lower limit of the comfort range. The test results found that the indoor air temperature was too high and the occupants felt overheated.

Occupancy

Ding et al. (2021) summarized the methods for describing occupancy in building simulations and identified three main approaches for modeling occupancy: deterministic, stochastic, and machine learning. This study adopts a deterministic schedule to characterize the occupants' indoor situations. The modeling method is simple and does not require a large dataset.

Referring to the method by Chang and Hong (2013), the hourly occupancy rate was used to characterize the indoor situation of the occupants. Hourly occupancy rate is the proportion of time spent in the room per hour. However, owing to the limitation of the number of instruments and testing capacity, field tests cannot be conducted on all the occupants of this passive house. Therefore, we used the concept of "typical occupants" (Yan et al. 2015) for data analysis, calculated the hourly occupancy rate of each household in the passive house, and took the average to obtain the overall schedule of the occupants.

Based on the occupational attributes of the occupants, which were categorized into two time periods, weekdays and weekends, the hourly occupancy rate of occupants in winter was derived, as shown in Figure 8, with 6 representing the period [6:00,7:00).

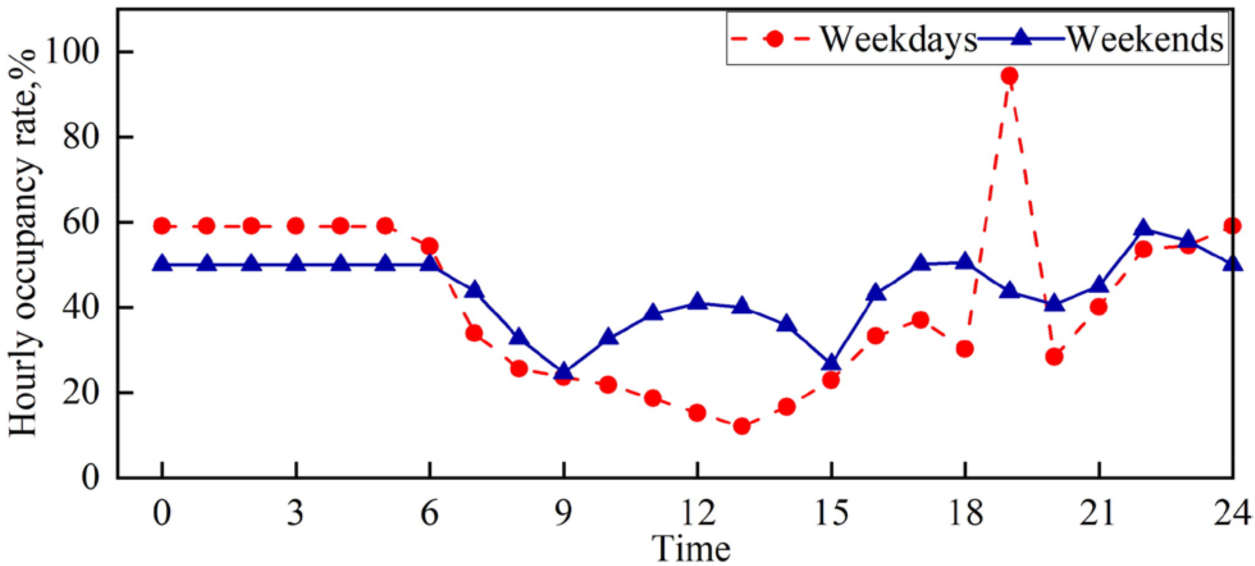


Fig. 8. Hourly occupancy rate of occupants.

The average occupancy rate for winter was 41.2% on weekdays and 44.1% on weekends, with more time spent in the rooms on weekends. The lowest room occupancy rate occurs when people go to work. A small peak is reached between 19:00 and 20:00 when most occupants eat at home. During the winter testing period, some occupants traveled outside, resulting in an occupancy rate of less than 100% during sleeping hours.

Window-opening behavior

Hong, Langevin, and Sun (2018b) mentioned that modeling the human–building interactions is a significant challenge. Direct input or control (Hong et al. 2018a), where users can directly input temporal schedules into the energy consumption simulation software, is most commonly used by simulators.

Field tests revealed that occupants also opened windows for ventilation; however, in winter, the time and number of window openings were reduced throughout the heating period. The test data for household 4 were abnormal and were excluded from the analysis. Considering the occupational differences among the occupants, the statistical results were analyzed for two time periods: weekdays and weekends.

As shown in Figure 9, the number of times the window-opening action occurred was counted, and its frequency in each period was calculated. The window-opening behavior of passive house occupants has a certain time pattern and is mainly concentrated at 9:00–11:00 and 15:00–16:00. Occupants have the habit of waking up and returning home from work to open windows for ventilation.

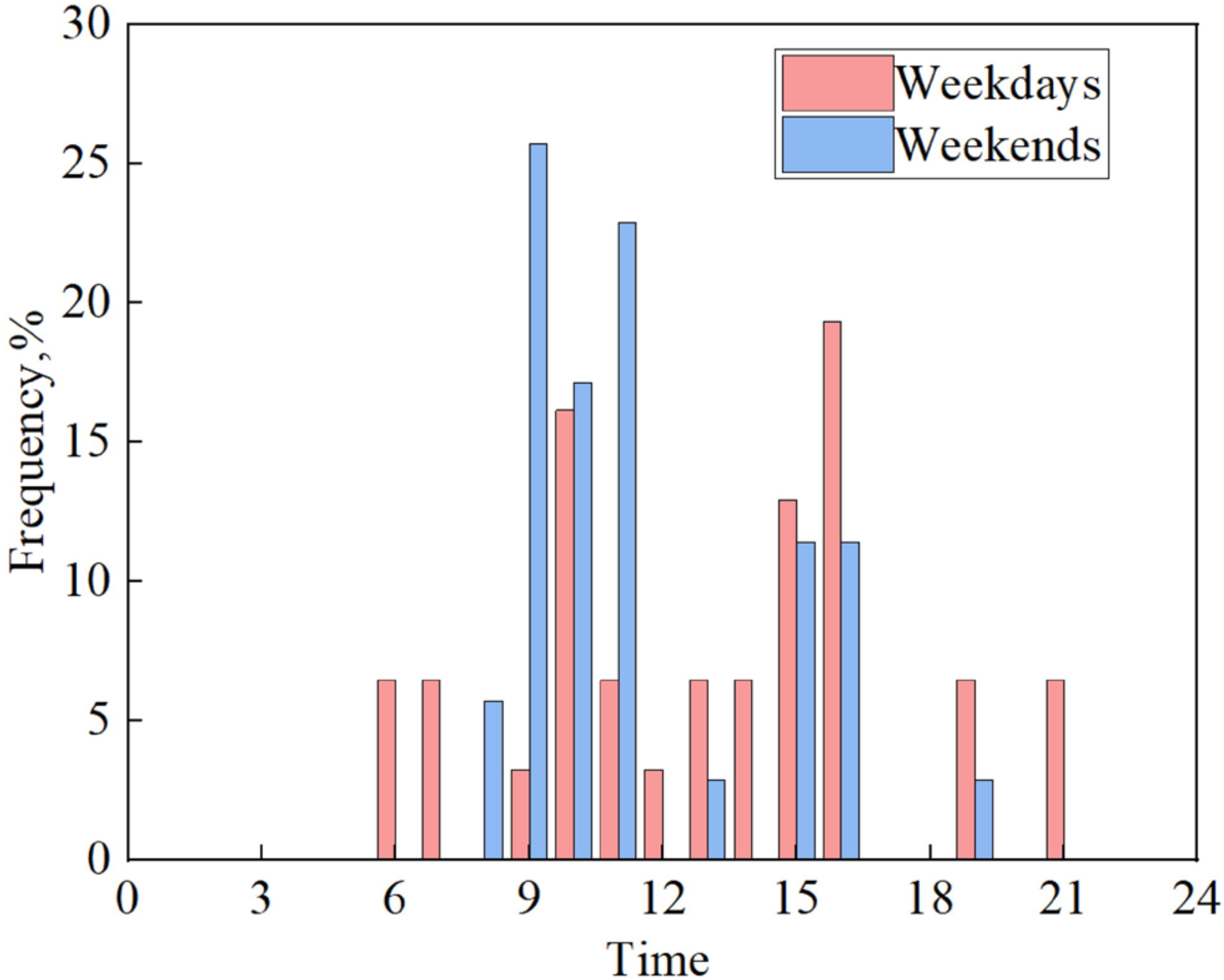


Fig. 9. Frequency of window opening at different times during the heating period.

The duration of each window-opening action by the occupants was recorded, as shown in Figure 10. The longest window-open duration throughout the heating period was 64 min, the average window-open duration on weekdays was 8 min, and that on weekends was 23 min. On weekends, the occupants were at home for a longer period and had their windows open for a longer period.

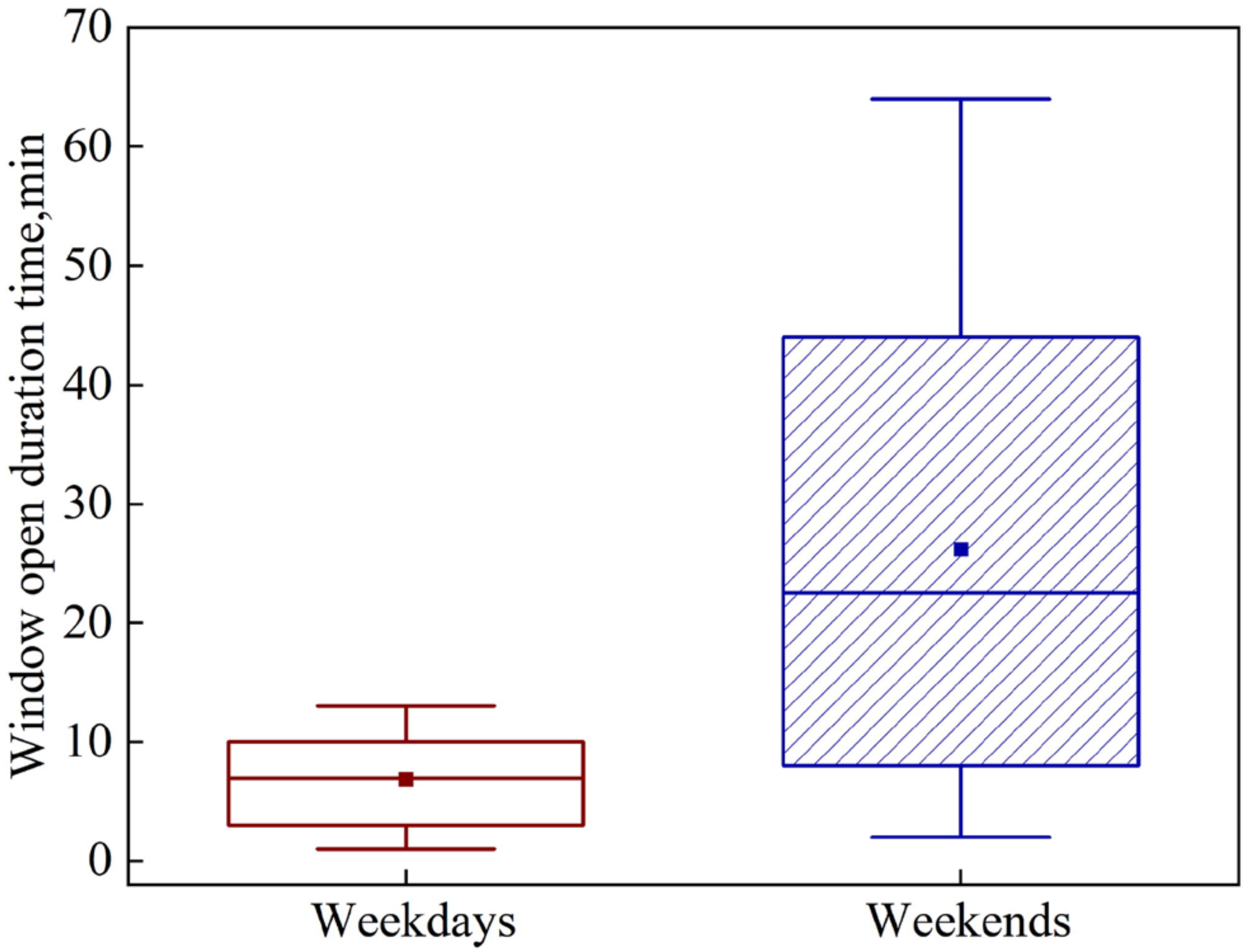


Fig. 10. Duration of window opening.

Lai et al. (2018a) argued that the schedule of window-opening can be determined by the "open time" (the time at which the window is opened) and the "open duration" (the length of time for which a window is open). D'Oca and Hong (2014) identified time as one of the main reasons that occupants opened windows. Therefore, this study used time as a predictor variable to analyze the test data, using statistical methods to determine the relationship between window-opening behavior and time. The hourly window-opening rate, which is the proportion of the window-opening time per hour, is used to characterize the window-opening pattern of the occupants to obtain a definite schedule of window-opening.

As the window-opening pattern varied among different households, the window-opening rate of each household in this passive house was calculated and averaged to obtain the overall window-opening pattern of the occupants. The window-opening rates for this passive house at different times during the winter are shown in Figure 11.

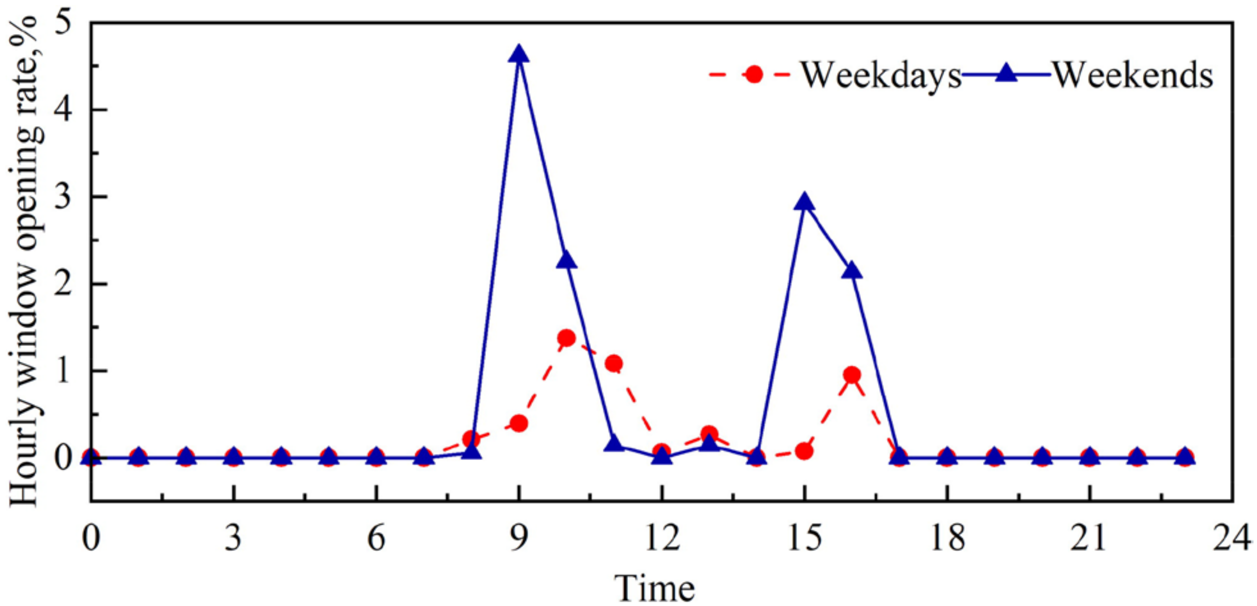


Fig. 11. Hourly window-opening rate for occupants.

The highest window-opening rate on weekdays was between 10:00 and 11:00, reaching 1.4% with an average of 0.2%. The highest window-opening rate on weekends was between 9:00 and 10:00, amounting to 4.6%, with an average of 0.5%. Window-opening rates for winter are low but vary significantly with time, with the average value on weekends being 2.5 times higher than that on weekdays.

Due to the limitation of testing instruments, indoor and outdoor air quality were not considered in this study. Using indoor and outdoor temperatures as the independent variables, models of occupant window-opening probability were obtained. The *p* values from the window-opening models are 0.014 and 0.439, respectively. The indoor air temperature significantly affects the probability of window opening, while the outdoor air temperature does not. The logistic regression model obtained is shown in Equation 6:

$$\log it(p)=0.51Ti-12.832 \tag{6}$$

As shown in Figure 12, the window-opening probability of passive house occupants shows a positive correlation with the indoor air temperature; the probability of occupants opening windows increases with increasing indoor air temperature.

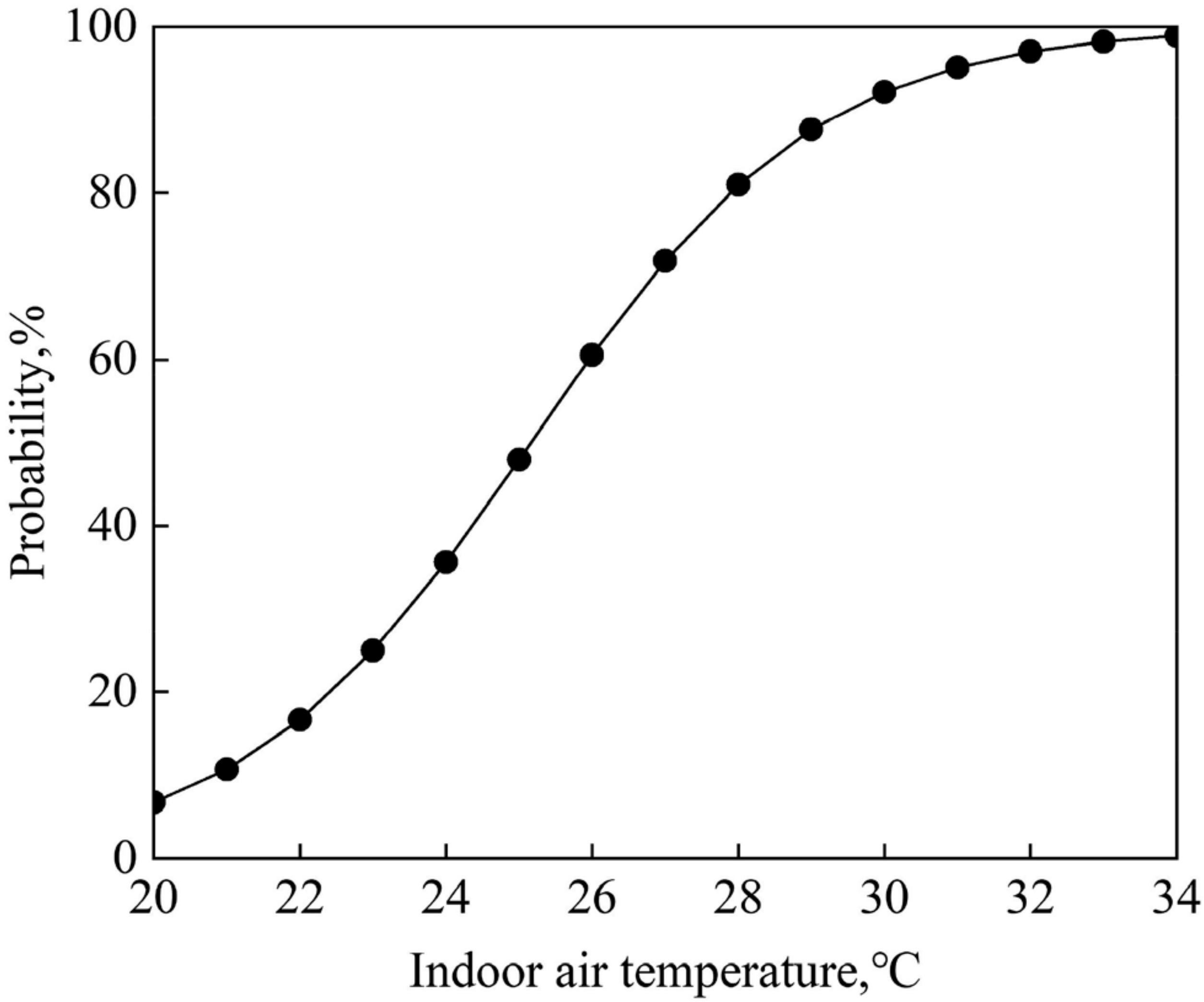


Fig. 12. Probabilistic model of window opening.

When the indoor air temperature is above 25.2 °C, the window-opening probability is greater than 50%. We obtained p = 0.475 from the paired-sample t-test, indicating that the model can better explain the winter window-opening behavior of occupants in severe cold regions.

Energy consumption simulation

Simulation validation

The building energy standards of European countries give a minimum ventilation rate of 0.5 h^{-1} (Dimitroulopoulou 2012), and the ventilation rate reduction can significantly reduce the building heating energy consumption (Chen et al. 2012). According to the requirements of the regulations of indoor environmental parameters of buildings in the Chinese standard (MOHURD 2019b), the indoor air temperature in winter should be ≥20 °C, while the indoor fresh air volume per person of residential buildings should not be less than 30 m^3/h. This fresh air volume complies with the standard (SAMR 2022) and meets human physiological and hygienic requirements.

Therefore, this study used a fresh air volume per person of 30 m^3/h for analysis. The area of each household in this passive house is approximately 80–90 m^2 and the floor height is 3.1 m. Each household has two to three people, and the range of the required ventilation rates is calculated to be 0.22–0.36 h^{-1}.

Based on the field test results, the actual heating temperatures were adjusted, and the determined schedules of the occupants' indoor situations and window-opening behavior were entered. The ventilation rate was taken as 0.36 h^{-1}, and the heating energy consumption was obtained from the simulation. The actual heating energy consumption of this passive house was 46.22 kWh/(m^2·a) (Xue 2021), while the simulation yields a heating energy consumption of 45.43 kWh/(m^2·a) with a relative error of 1.7%.

The model was validated for energy consumption based on two metrics given in ASHRAE Guideline 14 (ASHRAE 2014): MBE and CV(RMSE). The simulated and actual monthly heating energy consumptions are compared, and the results are shown in Figure 13. MBE and CV(RMSE) are calculated to be 1.70% and 20.43%, respectively. The simulation results satisfy the regulations of MBE being within ±10% and CV(RMSE) of less than 30%, which can be regarded as reliable for simulating the energy consumption of the model.

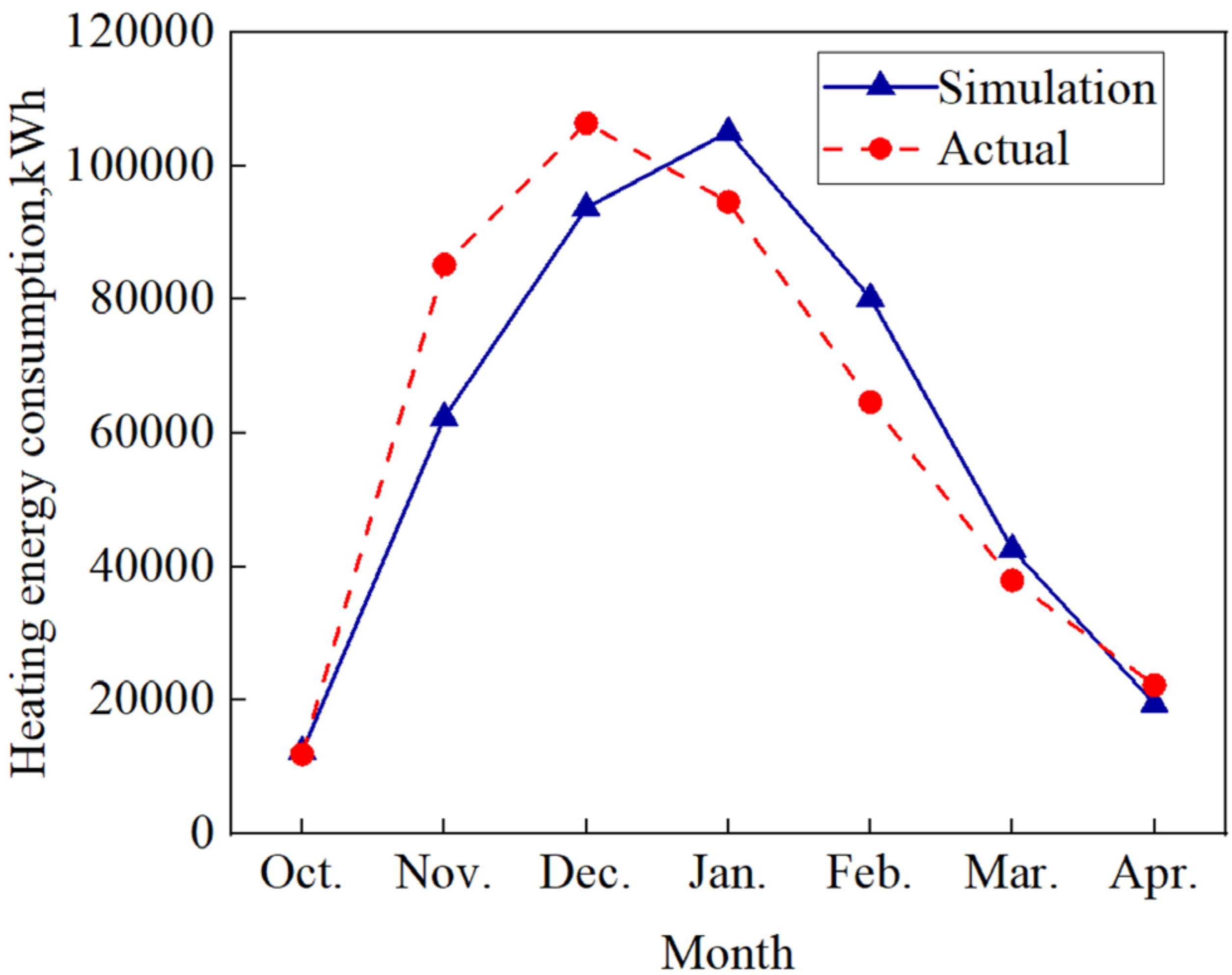


Fig. 13. Simulation verification results.

The heating energy consumption was tested from November 25, 2017, to April 20, 2018, but the simulation was based on outdoor meteorological parameters for a typical year. As shown in Figure 14, the difference between the simulated and actual daily outdoor temperatures is significant. During the actual test period, the temperature plummeted in December, which led to a sudden increase in heating energy consumption. As shown in Figure 14, the actual heating energy consumption does not change completely with the change of outdoor temperature, so the peak months are different. The relative error in heating energy consumption is only 1.7%, so the effect of outdoor temperature differences is ignored in this article.

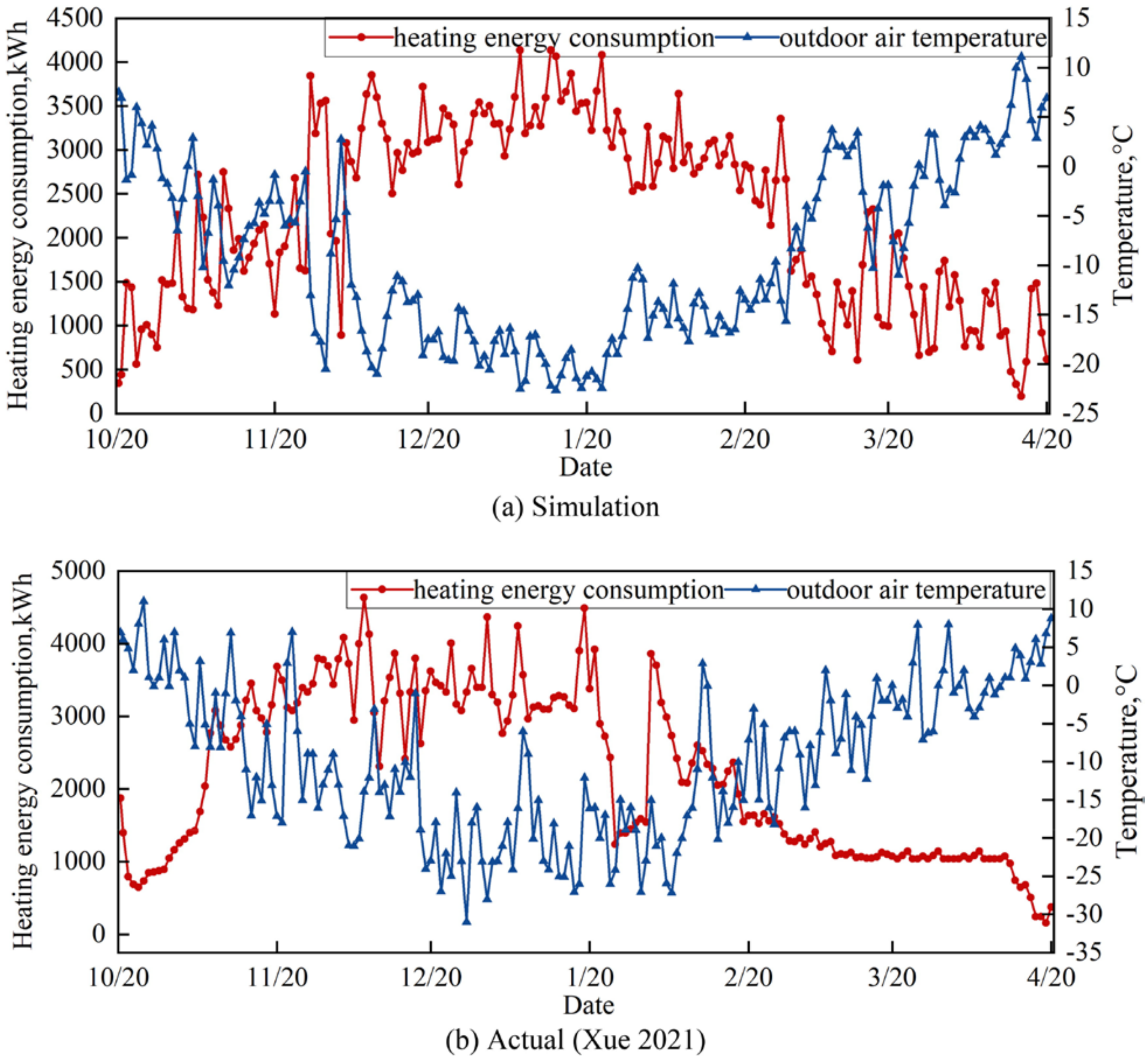


Fig. 14. Daily heating energy consumption.

Energy consumption results under design condition

The German standard specifies that the annual heating demand of passive house buildings should be <15 kWh/(m^2·a) (Passive House Institute 2023). However, owing to differences in climatic conditions, the Chinese standard (MOHURD 2019b) specifies a different energy efficiency index for ultra-low-energy residential buildings, stating that the annual heating demand in severe cold regions should be ≤30 kWh/(m^2·a).

The measured and simulated results show that the heating energy consumption of the passive house exceeds the standards. To verify whether the energy consumption of the passive house under the design conditions meets the energy-saving requirements, we set the indoor temperature to 20 °C and the ventilation rate to 0.36 h^{-1}, and closed the windows during the heating period. The monthly heating energy consumption in a typical year is shown in Figure 15. The heating energy consumption of the passive house building under design conditions is 27.6 kWh/(m^2·a), which meets the relevant regulations.

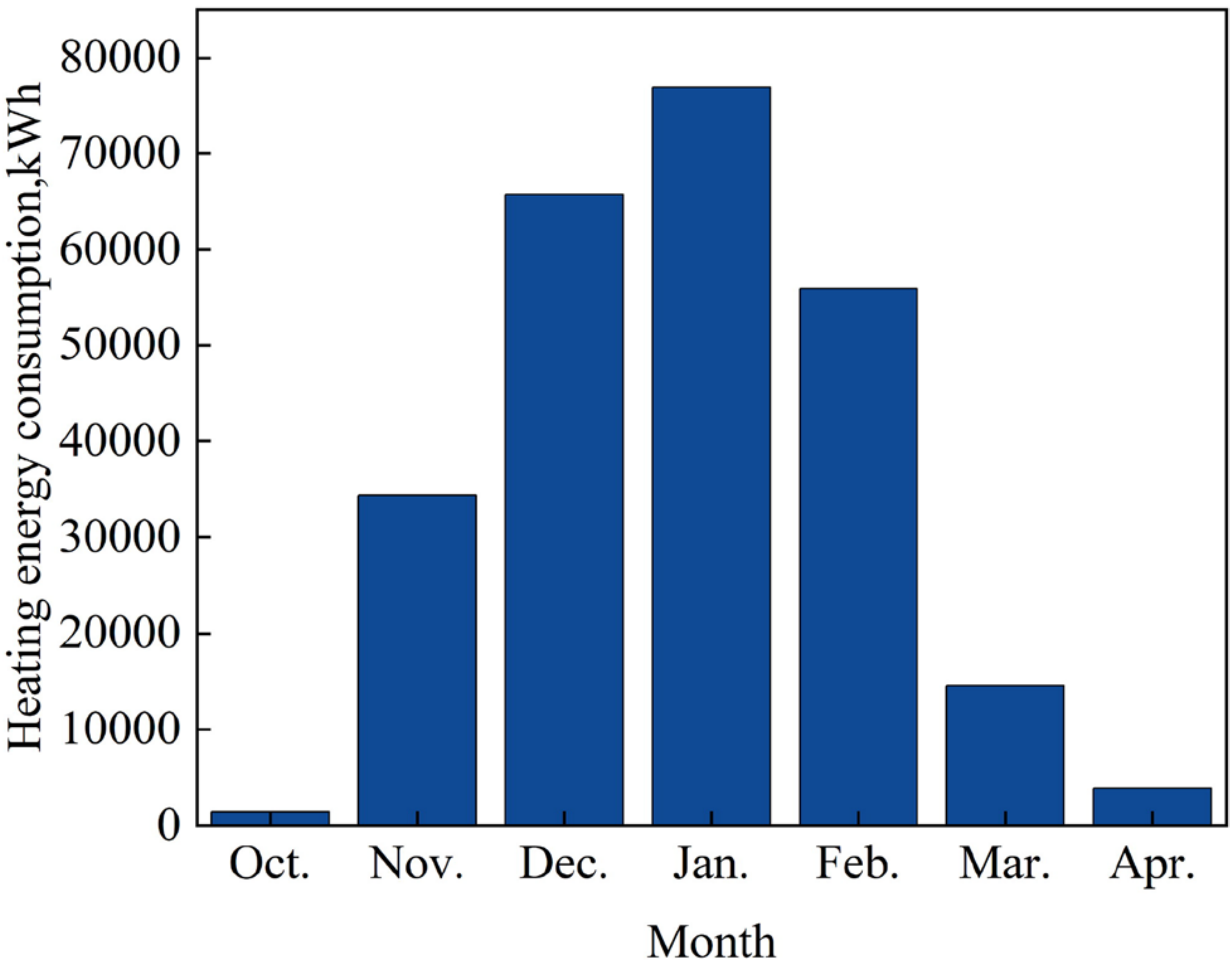


Fig. 15. Monthly calculation results of typical annual heating energy consumption.

Based on the preceding results, we conclude that the high heating temperature and occupants' window-opening behavior were the main reasons for exceeding the standard heating energy consumption of this passive house. The irrational energy use by occupants resulted in a 64.6% increase in building heating energy consumption.

Analysis of influencing factors

JEPlus (2012) was used to simulate scenarios with different indoor temperatures and window openings to study the influence of indoor temperature settings and window-opening behavior on heating energy consumption. JEPlus is a parametric simulation tool based on EnergyPlus that allows users to define the discrete values of the parameters that need to be changed and then commands EnergyPlus to perform the simulation automatically, saving time by manually changing the parameters individually.

Indoor heating temperature setting

Only the set of indoor heating temperatures is changed to study the effect of indoor heating temperature on heating energy consumption. The energy consumption results from 16 to 26 °C are simulated and counted, as shown in Table 7.Table 7. Calculation results of heating energy consumption at different indoor heating temperatures. (Table view)

The difference in heating energy consumption is not obvious when the indoor heating temperature is lower than 20 °C due to the high outdoor temperatures in October and April. However, the results for other months and indoor heating temperatures show that the heating energy consumption increases with increasing indoor and decreasing outdoor temperatures.

As shown in Figure 16, the linear fitting of the heating energy consumption per unit area at each temperature yielded an R^2 value of 0.993, indicating an improved linear growth trend in the heating energy consumption with increasing indoor heating temperature.

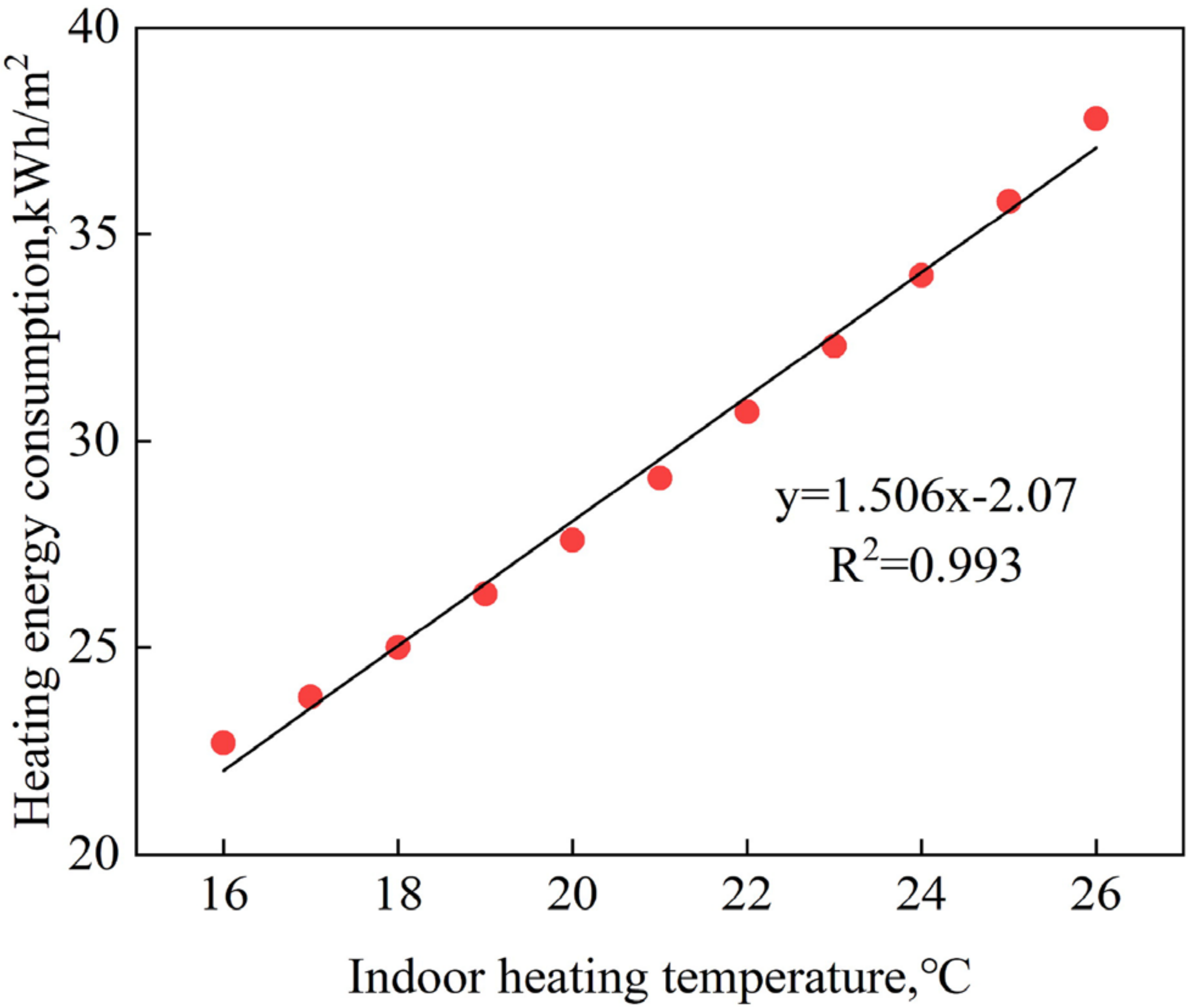


Fig. 16. Results of linear fitting of heating energy consumption to indoor heating temperature.

For every 1 °C increase in indoor heating temperature, heating energy consumption increases by 5.2%. According to the field test data, the average indoor temperature of the passive house is 25.5 °C (Wang et al. 2018b), which exceeds the standard indoor heating temperature of 20 °C. As estimated from the fitting results, the deviation in the indoor air temperature increases the heating energy consumption in this passive house by 28.6%. The difference in the indoor air temperature between different floors is evident, and it is recommended that the heating temperature be reasonably controlled to reduce heating energy consumption and reduce the occupants' tendency to open windows for ventilation.

Window opening

According to the results of the field tests, the occupants' window-opening actions occurred from 6:00 to 21:00; the average duration of each window opening on weekdays and weekends was 8 and 23 min, respectively. The heating energy consumption was simulated for different window-opening scenarios to investigate the effects of window-opening time and duration. The heating temperature is set to 20 °C, and the window-opening action is from 6:00 to 21:00. According to the different window-open times, 16 scenarios were simulated, and the duration time of each window opening was 5 min. Based on the different window-open duration times, the energy consumption at 9:00, when the window was continuously opened for 5–60 min, was simulated, with 12 scenarios in 5 min steps.

As shown in Figure 17, different window-opening times influence heating energy consumption, but the difference is insignificant. The maximum and minimum heating energy consumption are 35.9 and 34.0 kWh/(m^2·a), respectively, with a difference of 5.3%. The temperature difference between indoors and outdoors is relatively small at noon, so the heating energy consumption is the lowest when the windows are open. At other times when the windows are open, the heating energy consumption fluctuates slightly with changing outdoor temperatures.

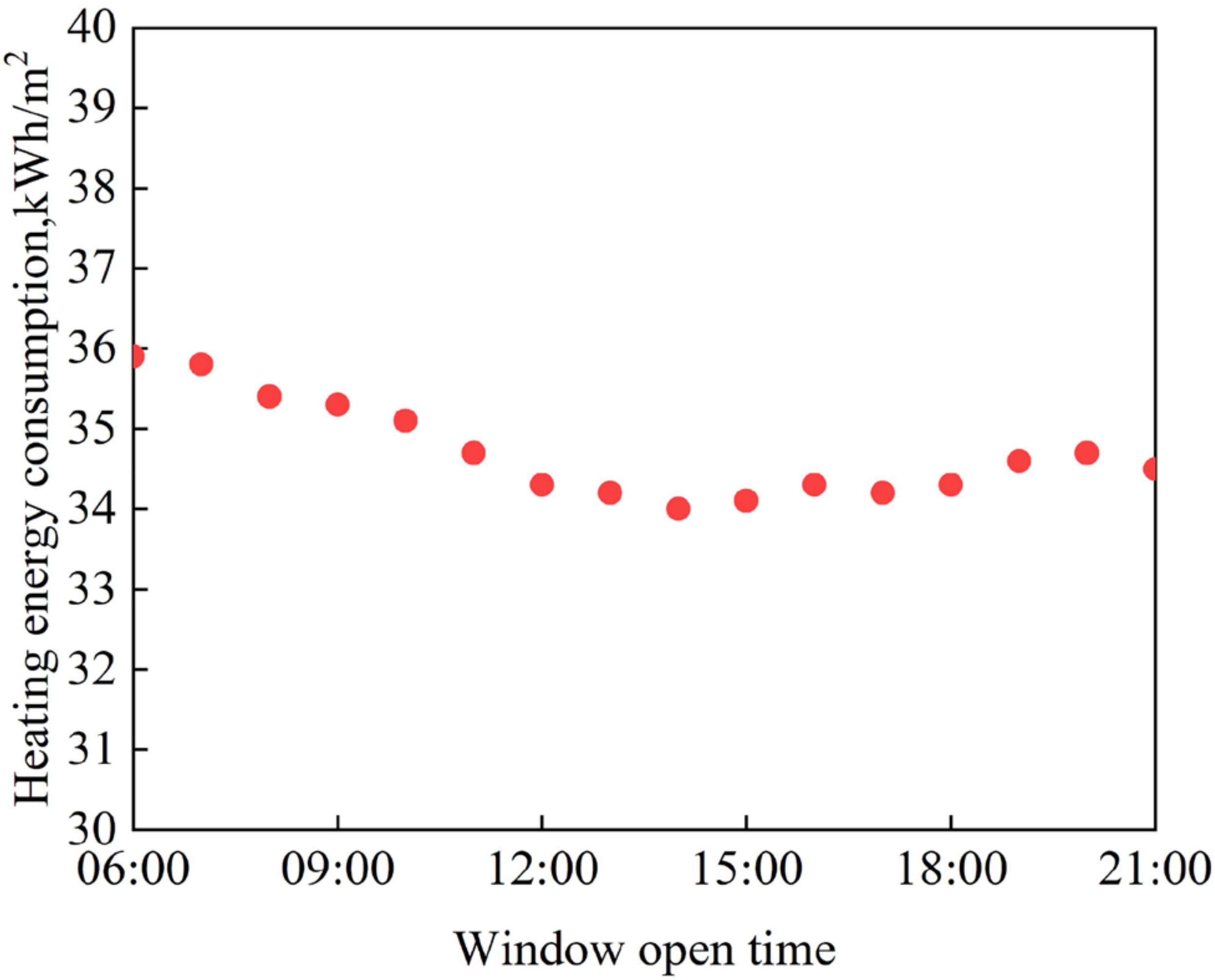


Fig. 17. Heating energy consumption for different window-open time.

As shown in Figure 18, the window-open duration has a more pronounced effect on the heating energy consumption. Similarly, linear fitting of heating energy consumption per unit area for different window-open duration times yielded an R^2 of 0.999, indicating that heating energy consumption shows a good linear growth trend with increasing window-open duration time. For every additional 5-min window-open duration, heating energy consumption increases by 5.6%. The average window-opening duration for the occupants of this passive house was 8 and 23 min on weekdays and weekends, respectively; the resulting heating energy consumption is 37.1 and 44.8 kWh/(m^2·a), respectively, a difference of 17.2%.

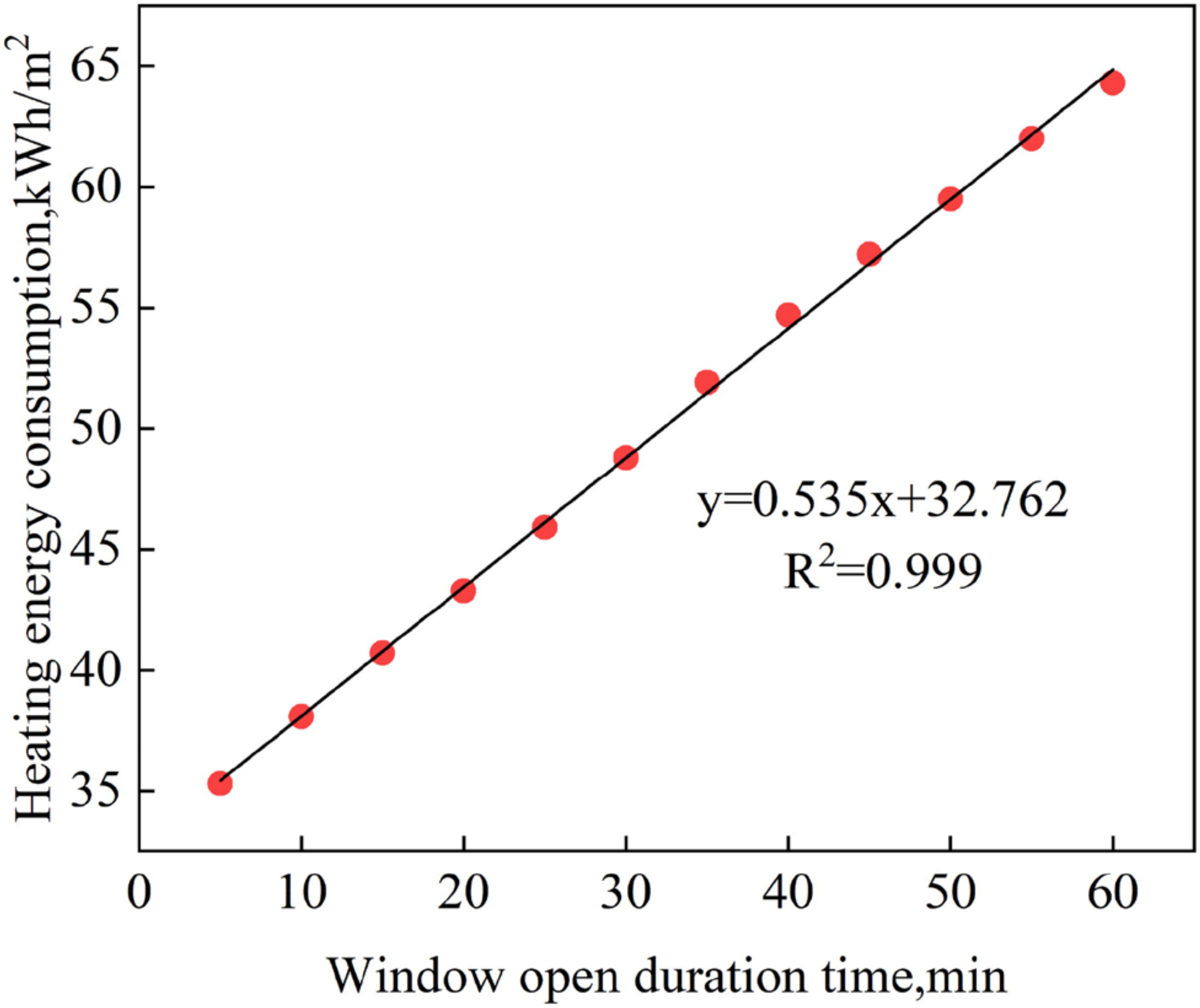


Fig. 18. Linear fitting results of heating energy consumption with window-open duration time.

Simulation of this passive house based on the occupants' actual window-opening behavior yields a heating energy consumption of 38.0 kWh/(m^2·a), and the occupants' window-opening behavior increases the heating energy consumption of this passive house by 37.7%. For occupants who habitually open windows, it is recommended to ventilate the room at 14:00 every day to reduce the window-open duration.

Comparison with other literature reports

D'Oca et al. (2014) discussed the impact of thermostat and window-opening behavior on building energy consumption. They found that the energy consumption of dwellings simulating occupant control (window-opening and heating setpoint adjustment) with probabilistic functions was 61% higher than for fixed schedules.

The window-opening model obtained was then used to replace the fixed occupant window-opening schedule to obtain the building heating energy consumption, as shown in Figure 19. The heating energy consumption obtained from the probabilistic model based on window opening is 57.4 kWh/(m^2·a), a 26.3% increase compared to that obtained from the simulation using a fixed schedule.

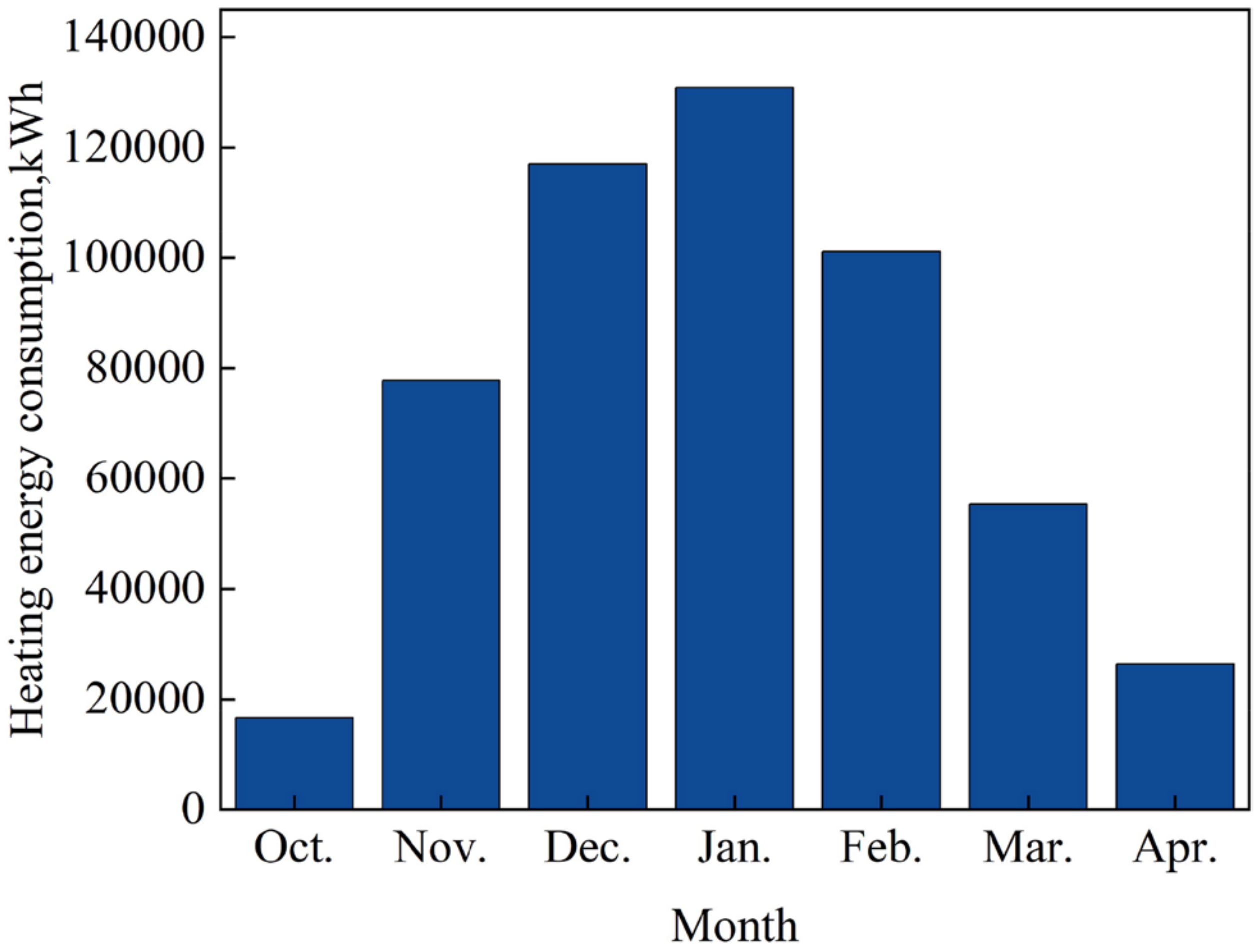
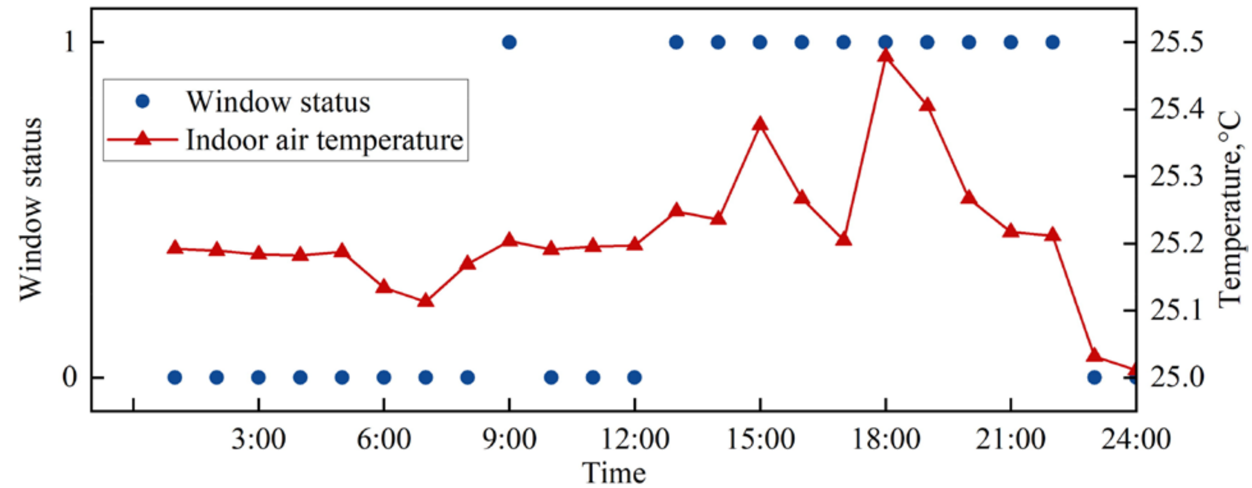
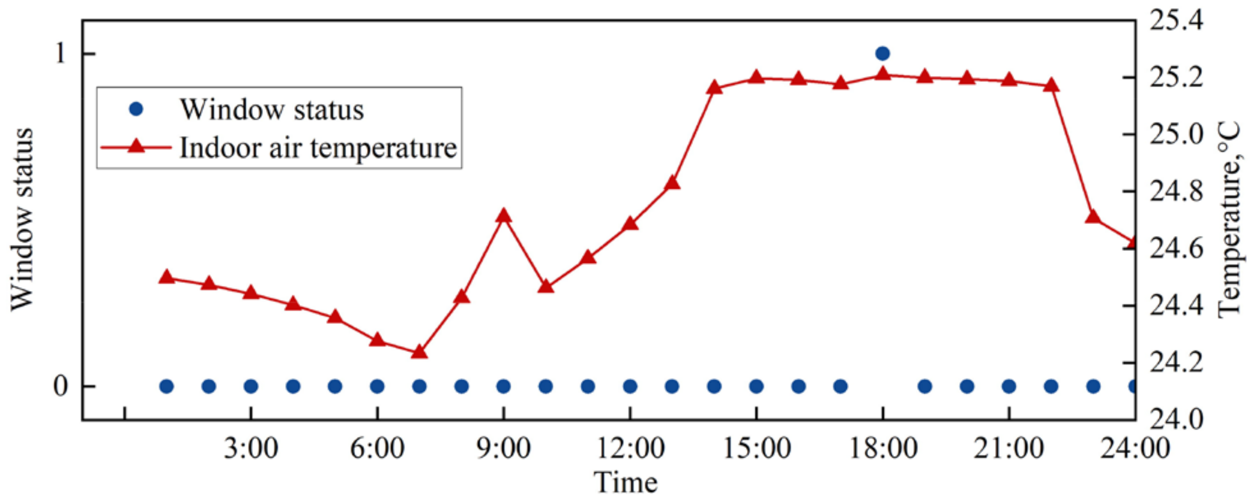


Fig. 19. Monthly calculation results based on the window-opening model.

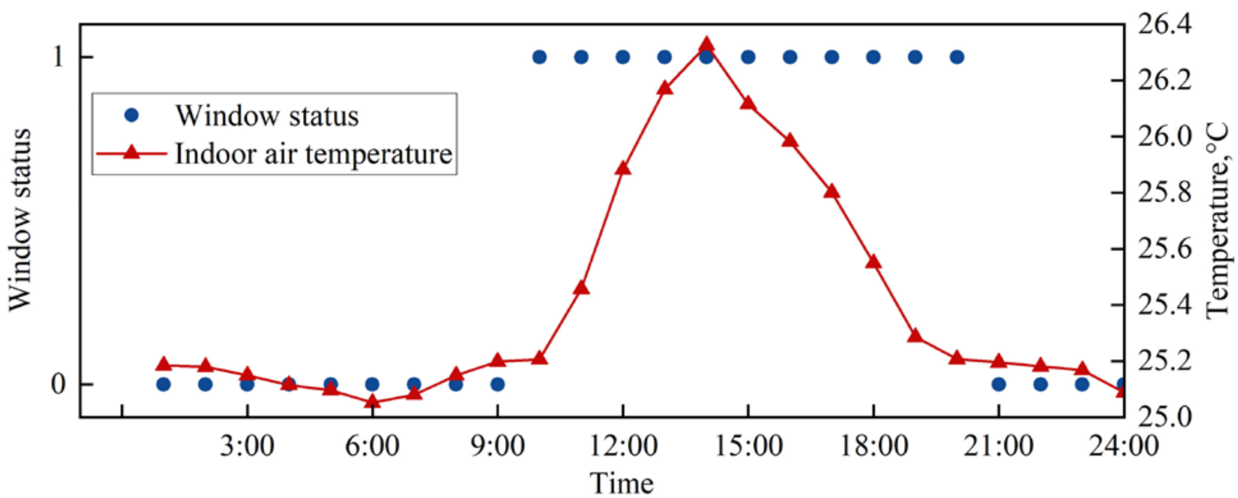
Hawila, Diallo, and Collignan (2023) pointed out through verification that logistic regression models (Nicol 2001; Haldi and Robinson 2008; Haldi and Robinson 2009; Zhang and Barrett 2012; Li et al. 2015; Pan et al. 2018; Pan et al. 2019; Rupp et al. 2021; Sansaniwal, Mathur, and Mathur 2021) overestimate the number of window-opening actions. According to the heating period (Wang, Ji, and Ren 2017), choosing three representative days, window-opening status are shown in Figure 20.



(a) November 20



(b) January 20



(c) March 20

Fig. 20. Window-opening status in different heating period.

The number of window-opening actions predicted at the early heating period (EH) and late heating period (LH) is overestimated. For the entire heating period, the window-opening probability model predicted a total of 1,532 window-opening actions, while the actual was 732. This indicates that the probabilistic model overestimates the occupant window-opening behavior, resulting in high simulated heating energy consumption.

When modeling, more attention should be paid to human behavior regularity. Ding et al. (2021) indicated that machine learning can achieve accurate real-time human behavior predictions and build human behavior models (Shih 2014; Newsham et al. 2017; Wang, Chen, and Hong 2018a). Deng and Chen (2019) used a neural network to build a human behavior model for energy consumption simulations and found the energy consumption error to be less than 13%. Yu et al. (2010) established a prediction model for building energy consumption using a decision tree and achieved an accuracy of 92%. Wang and Ding (2015) used polynomial and Markov-chain Monte Carlo methods to build a human behavior model and predicted computer energy consumption with less than 5% error. Machine learning can better determine the laws of human behavior, make parameter modifications, and achieve high prediction accuracy. Therefore, machine learning is expected to become the main method for human behavior research.

Limitation and future work

Due to objective reasons, we only tested four typical families of a representative passive house building in Harbin city, and the test of environmental parameters was limited. In future studies, if conditions permit, the sample size of the test can be expanded, and the factors affecting the window-behavior should be fully considered, not only indoor and outdoor air temperatures, but also air quality, noise, and so on. At the same time, there is a certain randomness in human behavior, so it takes a long time to get a lot of test data to sum up the law of human behavior. In the face of massive data, machine learning may become a better means of research.

Conclusions

In this study, based on field tests of the group, we studied the occupancy and behavioral law of opening windows in a passive house, simulated the energy consumption, and studied the factors influencing the heating energy consumption. The main conclusions are as follows:

1. The heating energy consumption of the passive house under the design condition is 27.6 kWh/(m^2·a), which meets the energy efficiency index of ultra-low-energy buildings. The actual heating energy consumption exceeded the standard limit, possibly owing to high heating temperatures and occupants opening windows.
2. This passive house had excessive indoor air temperatures during the test period, exceeding the upper limit of the winter comfort indoor air temperature range by 78.7%. Window-opening rates for winter are low but vary significantly with time, with the average value on weekends being 2.5 times higher than that on weekdays.
3. The heating energy consumption increases with indoor heating temperature. For every 1 °C increase in indoor heating temperature, heating energy consumption increases by 5.2%.
4. The difference in heating energy consumption caused by the window-open time differences was insignificant. The heating energy consumption increased with the window-open duration. For every additional 5 min of window opening, heating energy consumption increases by 5.6%.
5. The probabilistic model overestimates the occupants' window-opening behavior, resulting in a higher simulated heating energy consumption than that of fixed schedules. When modeling human behavior, more attention should be paid to human behavior regularity. Therefore, machine learning is expected to become the primary method for human behavior research.
6. In the design and operation of a heating system, the difference in the indoor air temperatures of different floors should be considered to avoid overheating on high floors. During the heating period, some occupants keep the windows open; therefore, it is recommended to reasonably deploy the ventilation volume of the fresh-air system.

Hence, the impacts of temperature control and window opening on the heating energy consumption of buildings in severely cold regions cannot be ignored. For nearly zero energy buildings, the role of human behavior should be fully considered in the design and operation.

Authors contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Ya Wu, Zhaojun Wang, and Yuxin Yang. The first draft of the manuscript was written by Ya Wu and all authors commented on previous versions of the manuscript. The language revision was done by Cheuk-ming Mak and Jing Liu. All authors read and approved the final article.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Table 1. Research on human behavior.

Climate zone	Building type	References	Main findings
Severe cold	Residential building	Feng et al. 2016b; Lai et al. 2018a; Lai et al. 2018b; Bian et al. 2023	Water use pattern, window-opening behavior, air-conditioning usage, gas wall-hanging furnace usage
	Office building	Sun et al. 2018	
	—	Zhou et al. 2022	
Cold	Residential building	Ren, Yan, and Wang 2014; Feng et al. 2016b; Yao and Zhao 2017; Lai et al. 2018a; Lai et al. 2018b; Hu et al. 2019a; Yan et al. 2019; Hu et al. 2020; Jin et al. 2020a	Air-conditioning usage, water use pattern, window-opening behavior, occupancy, lighting
	Office building	Zhou et al. 2015; Wang et al. 2016; Zhu et al. 2017; Pan et al. 2018; Yan et al. 2018; Zhou et al. 2018; Jin et al. 2020b	
Hot summer and cold winter	Residential building	Ren, Yan, and Wang 2014; Feng et al. 2016a; An et al. 2017; Cui, Yan, and Chen 2017; Lai et al. 2018a; Lai et al. 2018b; Hu et al. 2019a; Duan et al. 2023	Cooling usage pattern, window-opening behavior, occupancy, lighting, temperature set point, heating behaviors
Temperate	Residential building	Lai et al. 2018a; Lai et al. 2018b	
Hot summer and warm winter	Residential building	Ren, Yan, and Wang 2014; Lai et al. 2018a; Lai et al. 2018b	Window-opening behavior, air-conditioning usage, lighting
	Office building	Zhou et al. 2015; Zhou et al. 2018	
Not mentioned	Residential building	Hu, Yan, and Qian 2019b	Occupancy, cooling usage pattern, occupant horizontal and vertical movement
	Office building	Chen, Hong, and Luo 2017; Sun and Hong 2017b; Wang, Chen, and Hong	

		2018a
	—	Kang et al.
		2022

Table 2. Basic information of test instruments.

Instrument name	Test parameters	Measuring range	Measuring accuracy
Temperature and humidity self-recording logger	Air temperature	40–100 °C	±0.5 °C
	Relative humidity	0–100%	±3%
PIR sensor	Indoor situation	—	—
Intelligent displacement recorder	Window status	—	—

Table 3. Basic information of test households.

Number	Floor	Age (years)	Gender	Career
Household 1	7	78	Woman	Retired elderly
Household 2	9	40	Man	Office worker
		40	Woman	Office worker
		11	Woman	Student
Household 3	11	42	Man	Office worker
		42	Woman	Office worker
		12	Man	Student
Household 4	11	62	Woman	Retired elderly
		35	Man	Office worker
		35	Woman	Office worker
		3	Woman	Student

Table 4. Thermal performance parameters of the enclosure structure.

Enclosure structure	Area, m^2	Heat transfer coefficient, $W/(m^2 \cdot K)$	Thickness of insulation layer, mm	Thermal insulation materials
Roof	892	0.1	300	Graphite polystyrene board, EPSλ = 0.03 $W/(m \cdot k)$
Exterior wall	4468	0.13	300	Graphite polystyrene board, EPSλ = 0.03 $W/(m \cdot k)$
Exterior door	9	1.0	—	Triple glass, double low-e, filled with argon gas
Exterior window	1405	0.8	—	Triple glass, double low-e, filled with argon gas
Basement floor	752	0.1	300	Graphite polystyrene board, EPSλ = 0.03 $W/(m \cdot k)$

Table 5. Indoor heat.

		Schedule		
		Weekdays	Weekends	
Internal heat source	Heat gain	Person	100 W/person	Based on the field tests
		Refrigerator	150 W	Always on
		Lighting	5 W/m2	According to the personal schedule
		TV	60 W	According to the personal schedule

Table 6. Indoor thermal and humidity environment parameters statistics table.

NO.	Indoor air temperature, ℃			Indoor relative humidity, %		
	Average	Maximum	Minimum	Average	Maximum	Minimum
Household 1	24.3	28.6	14	57.3	75.7	31.1
Household 2	24.1	26.8	15.8	65.1	90.3	32.0
Household 3	25.8	29.7	18.7	52.8	68.4	15.8
Household 4	27.3	29.3	25.2	52.1	65.1	28.6

Table 7. Calculation results of heating energy consumption at different indoor heating temperatures.

	Heating energy consumption, kWh						
Indoor heating temperature	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.
16 ℃	1333.09	22886.69	56639.51	67380.71	47644.68	8872.86	3026.91
17 ℃	1333.03	25550.93	58915.92	69768.23	49726.40	9605.52	2970.61
18 ℃	1332.95	28450.99	61159.07	72120.07	51801.08	10925.51	2934.63
19 ℃	1332.86	31363.15	63472.23	74546.55	53889.35	12563.42	3115.08
20 ℃	1435.07	34337.53	65729.05	76902.80	55946.47	14610.90	3836.07
21 ℃	1824.83	36999.59	68142.79	79363.84	58128.70	16916.59	5084.70
22 ℃	2783.54	39246.09	70592.13	81893.30	60352.47	19349.56	6668.49
23 ℃	4055.99	41548.75	73119.36	84503.78	62633.40	21885.17	8204.95
24 ℃	5388.11	43953.99	75766.51	87210.35	64948.68	24470.98	9844.50
25 ℃	6657.26	46487.47	78559.19	90108.99	67305.54	27144.46	11627.38
26 ℃	7905.31	49244.13	81614.65	93370.45	69910.48	30011.23	13572.24