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Annual Variation Characteristics of Air Conditioning Operating Behavior and Its Impact on Model Application in Office Buildings

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Abstract: Air conditioning (AC) is an important component of building energy consumption. Reducing building AC energy consumption has attracted significant research interest worldwide. Studies have shown that the AC control behavior of users is a key factor affecting building AC energy consumption; however, the existing research on the dynamic laws for the AC control behavioral changes of users over a long period is limited. Therefore, taking a typical open office as an example, this study collected measured data spanning different years, and explored the temporal variation characteristics of AC operating behavior in office buildings. Based on a dynamic model framework constructed with a three-parameter Weibull function and a time superposition function, this study conducted modeling and analysis of dynamic AC operating behaviors in the same open-plan office across different years. First, the AC operating behavioral model was trained in parallel using field measurement data from different years to quantitatively analyze the patterns and extent of changes in occupants' AC operating behaviors. Subsequently, AC operating data from a fixed year was used as a test set to examine the impact of behavior changes on the prediction accuracy of the AC operating behavioral model through indicators such as open rate, on–off profiles, confusion matrices, and open rate under different time periods/temperatures. Results indicate that, due to behavioral changes, the maximum difference in the probability of AC opening under the same temperature can reach 96.8%. These behavior changes occur not only in varying intensity but also function as influencing factors. If behavior changes are ignored, prediction accuracy for AC open rates decreases by approximately 15%. This study reveals a method for dynamically adjusting the AC operating behavior model and improving its accuracy, which can significantly improve the accuracy of AC operating behavior modeling, the practical application effect of the behavior model, and reduce the energy consumption and carbon emissions of buildings.

Keywords: air-conditioning operating behavior prediction; behavior change; office building

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1. Introduction

Building energy conservation has attracted increasing attention worldwide in the context of climate change and carbon emission reduction [1]. Public buildings are an important component of building energy consumption, and reducing their energy consumption intensity has always been an important energy conservation topic [2]. Office buildings are one of the important components, and their annual energy consumption accounts for approximately one-third of all public buildings [3,4]. Therefore, studying the energy consumption operation mechanisms of office buildings and methods for reducing energy consumption is highly significant.

Air conditioning (AC) accounts for approximately 40–60% of all operating energy consumption in office buildings [5] and is an important way to implement energy conservation and emission reduction strategies [6,7]. Achieving the maximum reduction of AC energy consumption while meeting the reasonable energy consumption needs of users is an important task currently being explored. Measures such as increasing the utilization rate of renewable energy, improving the efficiency of heat exchangers at the AC terminals, and applying energy-saving enclosure structures can effectively reduce AC energy consumption and provide energy-saving benefits. In addition, indoor occupants being energy users directly affect the intensity and time distribution of energy use, and their important role in reducing building energy consumption cannot be ignored [8,9]. Occupant behavior, like other factors such as building size, meteorological conditions, and construction technology, are crucial to AC energy consumption. Occupant behaviors affecting building energy consumption can be categorized into two main types: one is the occupant behavior of operating equipment, and the other is the occupant presence in the room [10–12]. Different AC operating behaviors lead to different building AC energy consumption levels under the same building envelope, meteorological parameters, and AC system performance [13]. Existing studies have shown that the AC energy consumption in buildings can be reduced by 7~52.5% when AC operating behavior is deeply understood and occupant-centric AC control methods are applied [14,15]. Accurately considering the impact of occupant behavior on actual AC usage patterns is necessary to conduct an in-depth analysis of AC operation and energy consumption [16]. Therefore, many scholars have conducted relevant studies recently on AC operating behavior and its models.

AC operating behavior research focuses on the control actions of occupants such as opening, closing, and temperature adjustment of AC equipment [17,18]. Turning the AC on and off directly affects the final state of the AC equipment and determines the duration of the cooling loads [19]. Monitoring the behavior parameters of occupants and other environmental data and selecting the influencing factors related to the AC operating behavior as the model input is necessary when establishing the AC operating model. Based on previous studies, the factors affecting AC switching can be divided into two categories: environmental and non-environmental factors [20]. Environmental factors include outdoor temperature, indoor temperature, and indoor thermal comfort, whereas non-environmental factors include the time of day, occupant age, and gender. In the process of tracing the causes of AC operating behavior, mathematical methods such as correlation analysis [21] and causal inference analysis [22] are often used to quantitatively characterize the relationship between external variables and occupants' actions. Mun et al. [23] proposed that the temperature is the main environmental factor affecting the opening of ACs. Regarding the correlation between outdoor and indoor temperatures and the opening of ACs, some scholars believe that the opening of ACs is directly affected by the indoor temperature, whereas others believe that the role of outdoor temperature cannot be ignored.

The quantitative characterization of AC operating behavior based on measured data is a key aspect in studying AC operating behavior. The main methods include logistic regression [24–27], the Weibull function [25,28], and the time discrete model based on the Markov chain and Monte Carlo method [29]. Machine learning has also developed into one important method for modeling occupant behavior in recent years because it can efficiently use multiple factors and multiple historical data as inputs to occupant behavior models. This includes the use of decision tree [30], XGBoost [31], and other models to predict AC operating behavior. Among them, the logistic regression function has a better fitting effect on the AC operating behavior, and the time discrete model based on the Markov chain is more widely used [32]. Du et al. [24] used logistic regression to establish a prediction model for the AC operating behavior of a typical residence in Chongqing and established a quantitative relationship between the indoor temperature and the AC on–off state. Ren et al. [25] conducted a questionnaire survey of residents in six cities and established an AC operating behavior model based on the Weibull function according to the indoor temperature and events. Jian et al. [33] proposed a framework for simulating random AC operating behavior by combining measured data with a logistic regression function. Mun et al. [23] compared the accuracy of AC operating prediction under different machine learning algorithms. The prediction methods of binary logistic regression, random forest, and support vector machine models were compared. The results showed that the random forest algorithm provided the best prediction performance. However, more research is needed to model the AC operating behavior in office buildings [27,34]. In addition, some scholars have pointed out that environmental parameters at past moments will also affect the air-conditioning status at the current moment [35,36].

The literature review revealed that when describing AC operating behavior, most studies mainly focus on the AC switch data of a specific year when establishing the model. Furthermore, studies investigating the dynamic laws of changes in occupant behavior over a longer period are limited [37]. However, owing to the influence of the environment and the composition of occupants, changes in occupant behavior in buildings are very common. Notably, changes in the composition of occupants are more common in office buildings, and changes in the AC operating behaviors of occupants are more likely to occur, compared with residential buildings where occupant turnover is less frequent. Therefore, identifying the changing rules of occupant behavior in office spaces based on actual data, analyzing the influence of behavioral changes on the accuracy of the AC operating behavior model, and studying technical methods for dynamically adjusting models are necessary.

Based on the above analysis, this study used the AC operating behavior data from an office space in Nanjing to study the changing patterns of occupant behavior. Based on the investigation and analysis of indoor environmental parameters and occupant behavior data in the summer over two years, this study proposed a model framework for AC operating behavior and constructed an action-based AC operating behavior model based on the Markov chain time discrete model. The fitting functions of the influencing factors and the probability of turning the ACs on and off were established, and the changing patterns and degree of AC operating behavior over time were explored based on the year. The method of dynamically adjusting the AC operating behavior model to improve the model accuracy was revealed through different combinations of data training sets and test sets. The research outputs have a positive significance for increasing the accuracy of AC operating behavior models, improving the practical application effects of behavior models, and reducing the actual energy consumption of buildings.

2. Materials and Methods

2.1. Technical Approach

The technical approach used in this study is illustrated in Figure 1. This study first establishes a model framework for AC operating behavior, followed by parallel training of the model using data from 2016 and 2018 to explore the dynamic patterns of AC operating behavior over time.

1. Data survey and testing

The dataset used in this study was collected from an open-plan office at a university in Nanjing, China. Basic information about the indoor occupants, their daily routines, and environmental parameters was recorded using questionnaires and field surveys. Additionally, the influence of indoor and outdoor environmental factors on AC operating behavior was analyzed. Subsequently, this study employed models, such as Weibull function and time superposition function, to quantitatively characterize the probabilistic relationship between environmental variables and AC switch actions. Moreover, a random AC operating behavior model was constructed using a time-discrete function based on the Markov chain.

2. Model training

Based on the constructed model framework, this study further analyzes the dynamic patterns of AC operating behavior over time. The probability functions within the AC operating behavior model framework were trained in parallel using base data from 2016 and 2018, thereby constructing an AC operating behavior model based on data from the same office across different years. The two generated AC operating behavior models were then simultaneously applied to predict the AC operating behavior in 2018, and the results were compared with the actual behavior characteristics of 2018.

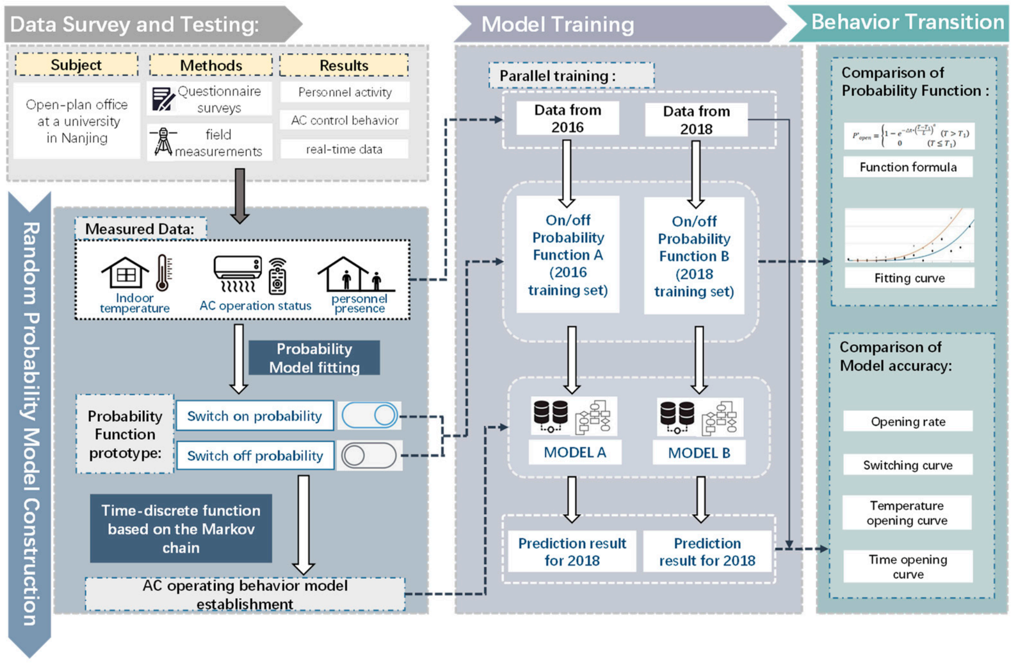


Figure 1. Technical Approach.

3. Behavior transition analysis

Considering the stochastic nature of AC operating behavior, the model was compared and validated using the results of 100 simulations against the actual AC switching status in the model validation phase. The validation metrics included the switching rate, confusion matrix, switch curve, and variation curve of the AC switch probability with outdoor temperature and time of day. By comparing the differences in the AC switch probability functions under different training datasets and examining the model accuracy, this study explores the extent to which behavioral changes affect the predictive analysis of AC operating behavior and analyzes how to dynamically adjust the AC operating behavior model under the influence of behavioral changes, thereby improving the prediction accuracy and optimizing the practical application of the behavior model.

2.2. Field Measurement and Survey

Figure 2 shows the office and testing instruments used in this study. The test site is located on the west side of the first floor of a three-story office building in Nanjing, Jiangsu Province, China. The floor plan is shown in Figure 2A. The central area is an open-plan office space surrounded by several offices. Because these surrounding offices are generally enclosed, the data source for this study was the open-plan office area, as indicated by the shaded region. The open-plan office covers an area of approximately 110 m^2 (excluding the lobby). Four cabinet-type split ACs are located at the four corners of the room, and the ventilation system is a combination of natural and mechanical ventilation. Approximately 20 individuals, primarily architectural graduate students and professionals, occupy this office regularly.

Measurement points were arranged within the study area, as shown in Figure 2A. The numbers in the figure represent the measurement point distribution, and the labels “a/b” next to the points indicate the device codes. Points 1–3 recorded the distribution of occupants (using infrared motion sensors), points 4–5 measured the outdoor temperature and humidity, and points 6–9 recorded the indoor temperature and on/off status of the ACs. The measurement period spanned from 20 August to 30 September 2016, and from 29 June to 20 August 2018. All devices recorded data at 5-min intervals, and the height of the measurement instruments from the ground was approximately 0.75 m. The data logger used in the tests is shown in Figure 2B. The HOBO Occupancy/Light Logger has a detection radius of 12 m, with a horizontal detection range of 102° (±51°) and a vertical range of 92° (±46°). The temperature and humidity recorder (WSZY-1) offers a resolution of 0.1 °C for temperature and 0.1% RH for humidity.

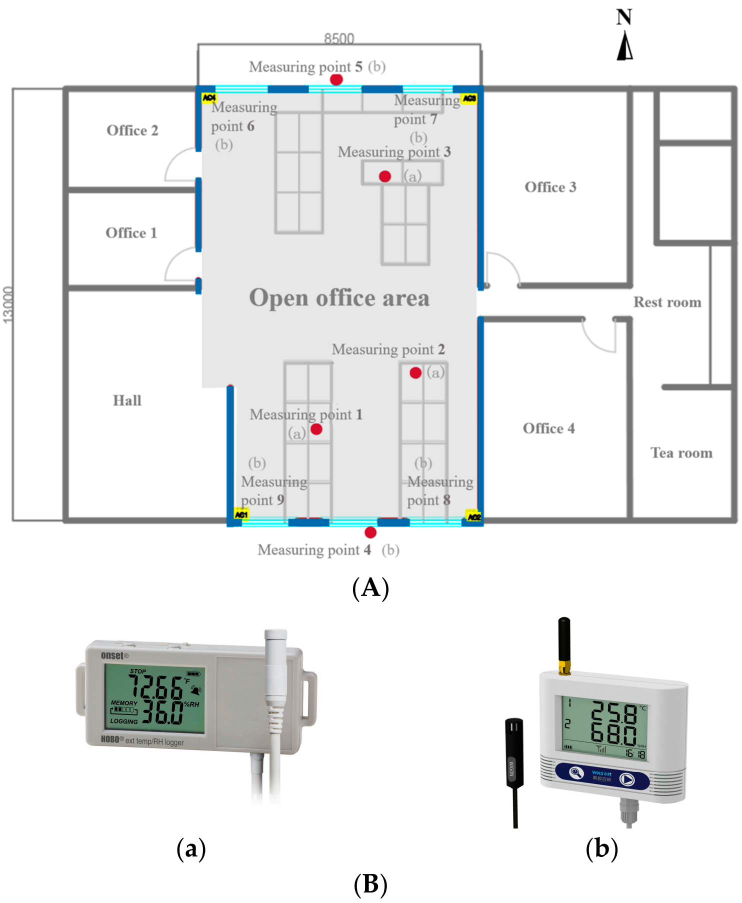


Figure 2. Measurement layout. (**A**) Floor plan of the test object. (**B**) Test instruments: (**a**) HOBO Occupancy/Light Logger, (**b**) temperature and humidity recorder (WSZY-1).

2.3. AC Behavioral Operating Model

2.3.1. AC-On Function

According to existing research results, the indoor temperature, outdoor temperature [23,38,39], and time of day [38] are considered to be three important factors affecting the AC turn-on action. During the analysis of the measured data, it is found that indoor temperature variations were relatively stable compared to outdoor temperature. Part of the indoor temperature data exhibited the same variation trend as outdoor temperature, while another part showed decreases when the AC was on and increases after it was turned off. Quantifying the correlation between variables through correlation coefficients is commonly used to study the connection between variables [40]. This study used the Spearman rank correlation coefficient to determine the correlation between the influencing factors in the environment and the action of turning on the AC. The larger the correlation coefficient, the higher the correlation. According to the measured data, the correlation analysis and time of day and indoor/outdoor temperature calculation with the AC turning on action demonstrated that the turning on action correlated more with outdoor temperature (correlation coefficient of 0.76) but showed a weak correlation with time (correlation coefficient of 0.21) and indoor temperature (correlation coefficient of 0.56). Therefore, this study selected the outdoor temperature as an input parameter of the AC-on function.

This study used the Weibull function to describe the AC turning on action. This function is widely used in linear regression fitting and can use single or multiple independent variables as influencing factors to predict the dependent variable with a binomial distribution. The Weibull model accurately describes the behavior of the AC turning on based on the threshold and scope in the literature [41]. The model simplifies the interaction between behavior and environment into a corresponding relationship under different thresholds. When the environmental parameters reached the threshold requirements, the action judgment function was immediately triggered to determine whether the corresponding action occurred.

This study adopts this function to describe the AC turn-on behavior quantitatively. The formula is shown in Equation (1):

$$P'_{open} = \begin{cases} 1 - e^{-\triangle \mathrm{t} * \left(\frac{T-T_1}{L}\right)^a} & (T > T_1) \\ 0 & (T \leq T_1) \end{cases} \tag{1}$$

where P'_{open} is the probability of turning on the AC; T is the outdoor temperature, °C; T_1 is the threshold value, °C; L is the range of outdoor temperature, °C; $\triangle$t is the time step, min; and a is the coefficient of the formula.

2.3.2. AC-Off Function

The moments at which the AC turning off actions occurred were statistically analyzed based on the measured data. The results showed that 25 out of 30 AC turning off actions in 2016 occurred at the moment people left, while 24 out of 50 AC turning off actions in 2018 occurred at the moment people left. Therefore, other factors affect the turning off of the AC along with people leaving, and further data mining is required.

According to the analysis of the influencing factors, the cumulative impact of time was considered to trigger the AC turning off action. The function describing the AC turning off action is considered a probability function superimposed over time, and the probability of the AC turning off at the current moment is affected by the previous moment. The function prototype is expressed in Equation (2):

$$P'_{close} = \begin{cases} P_1 * (1 - P_1)^{n_1 - 1} & \tau_1 \leq \tau < \tau_2, Y = y \\ P_i * (1 - P_i)^{n_i - 1} * \prod_{k=1}^{i-1} (1 - P_k)^{n_k}, & \tau_2 \leq \tau < \tau_\mathrm{n}, Y = y \\ 0 & (\tau_{i+1} \leq \tau) \; or \; \left(0 \leq \tau < \tau_{i)}, Y = y \right. \end{cases} \tag{2}$$

where P'_{close} is the probability that the AC is turned off at that moment, τ is the current moment, i is the number of time periods with different AC closing probabilities from $\tau_1 \sim \tau$, n_1 is the number of time steps from $\tau_1 \sim \tau$, n_k is the number of time steps from $\tau_{k-1} \sim \tau_k$, n_i is the number of time steps from $\tau_{i-1} \sim \tau$, P_1 is the probability that the AC is turned off during the time period $\tau_1 \sim \tau$, P_i is the probability that the AC is turned off during the time period $\tau_{i-1} \sim \tau_i$, and Y is the year.

2.3.3. Running Judgment Logic

Figure 3 shows the judgment logic of the action-based AC operating behavioral model within a time step, where the input parameters are the time of day, outdoor temperature, occupancy state in the room, the AC on/off state of the previous moment, and the output parameter is the AC on/off state of the current moment. When the AC is off at the previous moment, it determines whether an occupant-arrival trigger condition exists. When the trigger condition occurs, a random number is generated for comparison with the calculation result of the AC turning-on function; when the random number is less than or equal to the probability value of the trigger condition, the AC is turned on; otherwise, it enters into the comparison of the next time step until the AC is turned on. If no trigger condition exists, the AC maintains its state at the previous moment. The AC is judged when turned on at the previous moment to see whether the factors that trigger the state change exist—that is, whether a person left and whether the current moment is between 18:00 and 23:00. If the time range condition is satisfied, the AC turning-off function is judged. If the trigger condition of people leaving occurs, the AC status will be output as "off". When a trigger condition does not exist, the AC maintains the on/off status of the previous moment.

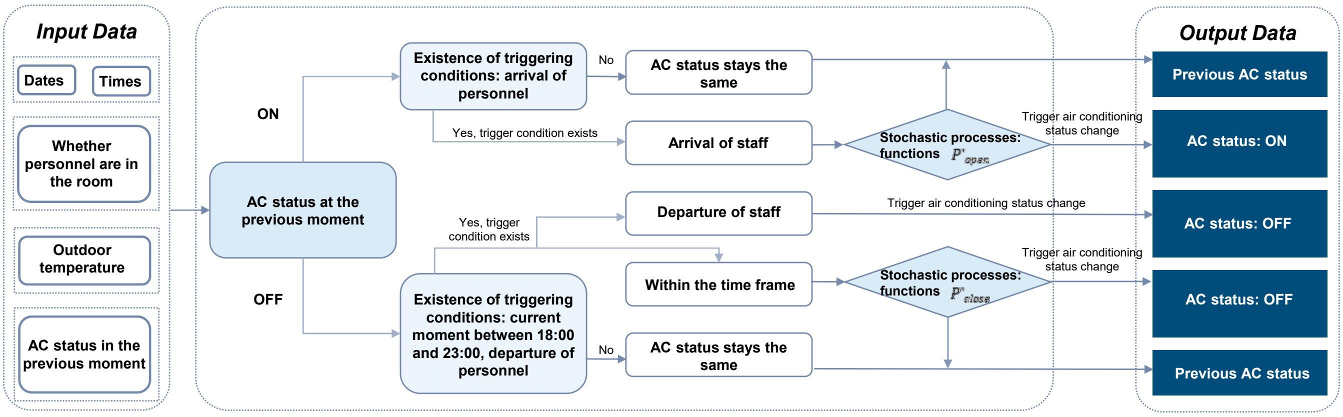


Figure 3. The judgment logic of the AC operating behavior model.

2.4. Model Validation

After discretizing the time, the simulation is performed for each step from the first time point, and after obtaining the AC on–off state at this time point, it proceeds to the next time point until the simulation is completed. Considering the randomness of the model, each simulation process was repeated 100 times, and the statistical values of the 100 simulation results were compared and analyzed with the measured data. The following four indicators were applied in this study when analyzing the simulated and measured data.

1. AC open rate

The AC open rate describes the proportion of AC on hours to the total hours. The open rate is calculated as shown in Equation (3)

$$C = \frac{N_1}{N_2} \tag{3}$$

where C is the open rate; N_1 is the number of time points when the AC is on; and N_2 is the number of time points within the analysis time range.

2. AC on–off profile and confusion matrix

The AC on–off profile is a curve drawn according to the time and on–off status of the AC. A confusion matrix was used to quantitatively describe the consistency between the simulated and measured AC on–off profiles. The confusion matrix categorized the results into four categories, as listed in Table 1. In this study, F1 [42] was used as a comprehensive index to evaluate the accuracy of the AC on–off profile, which is a generalized evaluation index for accuracy calculated as shown in Equation (4).

$$\mathrm{F1} = \frac{2 \times M1S1}{2 \times M1S1 + M0S1 + M1S0} \tag{4}$$

Table 1. Confusion matrix [20].

Model		Actual Measurement	
		1	0
Simulate	1	$M1S1$	$M0S1$
	0	$M1S0$	$M0S0$

3. Temperature/time consistency

Temperature/time consistency is the agreement between the actual AC open rate and the average value of 100 simulations under different outdoor temperatures and times of the day. The absolute error rate S between the actual and simulated curves was calculated using Equation (5) to evaluate the accuracy.

$$\mathrm{S} = \frac{\int_{X_1}^{X_2} \frac{|P_s - P_M|}{P_M} dX}{\mathrm{X}_2 - \mathrm{X}_1} \tag{5}$$

where S is the absolute error rate, $X_1 - X_2$ is the temperature/time range of the analysis, and $P_s,\ P_M$ are the AC open rates obtained from the simulation and measurement, respectively.

3. Results and Analysis

3.1. The Effect of Behavior Changes on AC Operating Behavior Model

3.1.1. AC Turning On Model

The probability of the AC turning on at different outdoor temperatures under the premise that the room is occupied was calculated, and the probability function of the AC turning on was fitted using the least squares method. The relationship between the outdoor temperature and the probability of the AC turning on was then obtained, the fitting curves are shown in Figure 4. The fitting function is shown in Equation (6), and the curve fitting goodness (R^2) obtained based on the 2016 and 2018 data training were 0.88 and 0.93, respectively.

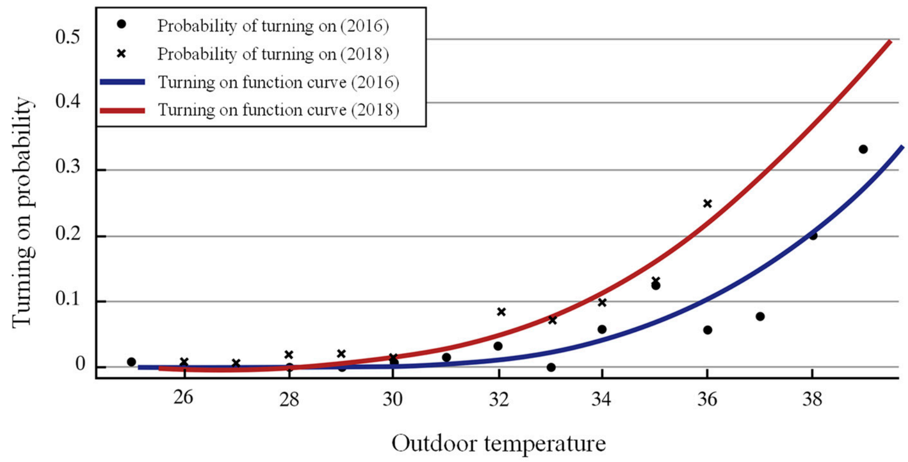


Figure 4. AC turning on probability at different outdoor temperatures.

Comparing the two AC turning-on functions, the temperature threshold and scope of the two results for the two years were the same. However, at the same outdoor temperature, the turning on probability based on the 2018 data was higher than that based on the 2016 data.

$$P\prime_{open} = \begin{cases} \begin{cases} 1 - e^{-5*(\frac{T-25}{25})^{4.70}} & (T > 25, Y = 2016) \\ 0 & (T \leq 25, Y = 2016) \end{cases} \\ \begin{cases} 1 - e^{-5*(\frac{T-25}{25})^{3.63}} & (T > 25, Y = 2018) \\ 0.05 & (T \leq 25, Y = 2018) \end{cases} \end{cases} \tag{6}$$

3.1.2. AC Turning Off Model

Differences in the AC turning off behavior were observed between 2016 and 2018. In 2016, 83% of the AC turning off actions occurred when people left the room. Therefore, the AC turning off action in 2016 can be simplified to relate only to the event of people leaving the room. In 2018, only 48% of AC turning off actions occurred when people left the room.

Further research was conducted on the occurrence patterns of people turning off their ACs in advance in 2018, as shown in Figure 5.

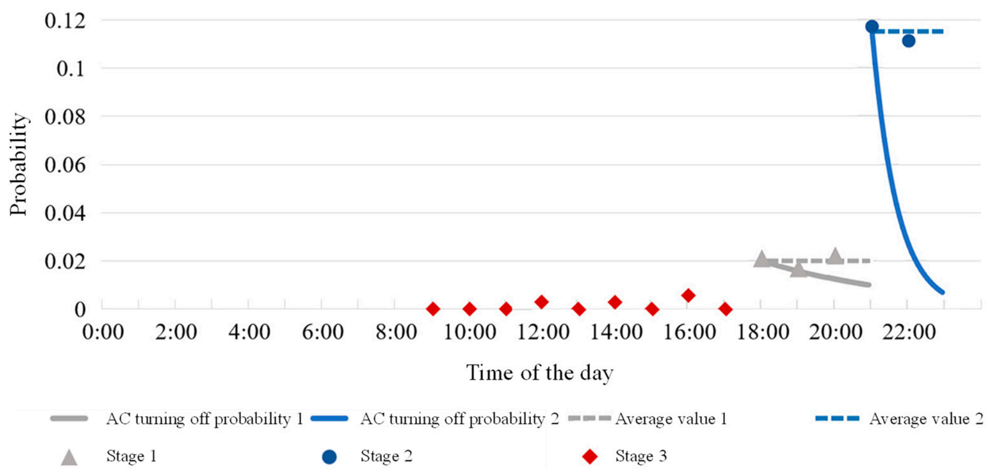


Figure 5. AC turning off probability.

The data points in Figure 5 represent the hourly probabilities. From the values of the AC turning off probability at different hours, it can be found that the AC turning off probability presents three characteristic stages: (1) before 18:00, the probability of the AC turning off at this stage is close to 0; (2) 18:00–20:00, the probability of turning off the AC at this stage is low; and (3) 21:00–22:00, the AC is turned off with a high probability of being triggered. These different stages are represented by different data colors and shapes in Figure 5.

At the same time, the dotted line in Figure 5 represents the average value of the AC turning off probability in the two time periods. According to the average value, the mathematical probability of the AC turning off is divided into two stages with high and low probabilities: the average AC turning off probability is 0.02 from 18:00 to 20:55 and 0.12 from 21:00 to 22:55. The probability of AC turning off at time step τ is the result of multiplying the AC turning off probability of the current step by the AC non-turning off probability of the previous $\tau - 1$ steps. The final AC turning off model in 2018 is shown in Equation (7), and the generated function curves are shown in Figure 5 for AC turning off probabilities 1 and 2, which are indicated by the two solid lines.

$$P\prime_{close} = \left\{ \begin{array}{cc} 0 & (Y = 2016) \\ \left\{ \begin{array}{cc} 0.02 * (1 - 0.02)^{n-1} & (18 \leq \tau < 21, Y = 2018) \\ (1 - 0.02)^{36} * 0.115 * (1 - 0.12)^{n-1} & (21 \leq \tau < 23, Y = 2018) \\ 0 & ((23 \leq \tau \leq 24)\ or\ (0 \leq \tau \leq 17), Y = 2018) \end{array} \right. & \end{array} \right. \quad (7)$$

3.2. The Effect of Behavior Changes on Model Accuracy

3.2.1. AC Open Rate

Figure 6 shows the comparison between the simulated and measured results of the AC open rates of the models for the two years. The calculation results of the two AC operating behavior models are relatively concentrated, and the variance is close to 0. Concurrently, the AC operating behavior model trained based on 2018 data can accurately predict the AC open rate, with an error of only 1.6%. However, when the influence of behavioral change is ignored, the obtained AC operating behavior model achieves an average AC open rate of 0.33, and the prediction error is 17.5% lower than the actual value.

3.2.2. AC On–Off Profile and Confusion Matrix

Figure 7 shows the simulation results of the AC on–off profiles. Considering the visibility of the graph, only ten results are shown on the graph. The solid color blocks in the figure represent the time periods when the AC is turned on. The black blocks are the calculation results obtained from the 2018 training set, the blue blocks are the calculation results obtained from the 2016 training set, and the red blocks are the actual measured AC on–off states. The figure shows that both models can realistically reflect the time-by-time on–off pattern of the AC with no frequent switching. In general, the models for the two years describe the actual AC operating behavior to a certain extent. However, the model results of the 2016 training set show a lower frequency of AC usage than those of the 2018 training set. Therefore, the AC usage habits of indoor occupants changed to some extent from 2016 to 2018. The AC operating behavior described by the model obtained based on the 2016 training set had the characteristics of a lower frequency of usage and a lower probability of the AC turning on.

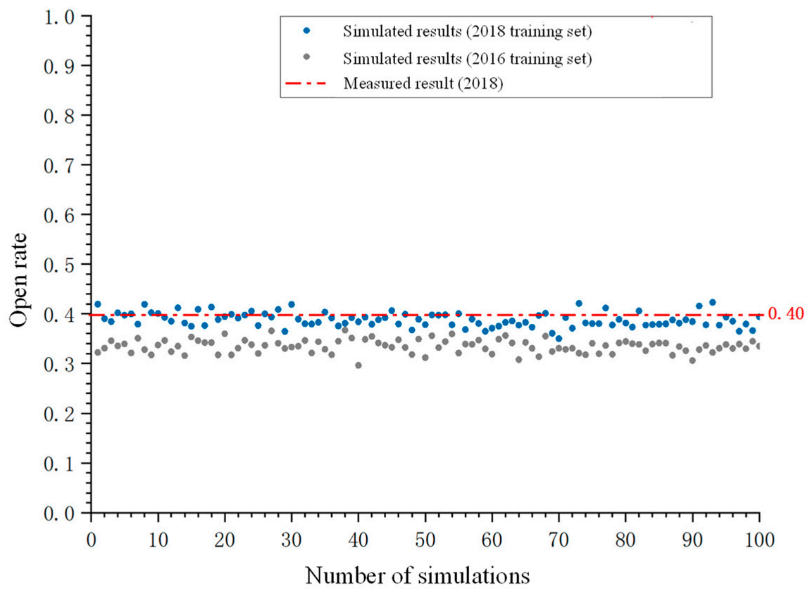


Figure 6. Result of the open rates.

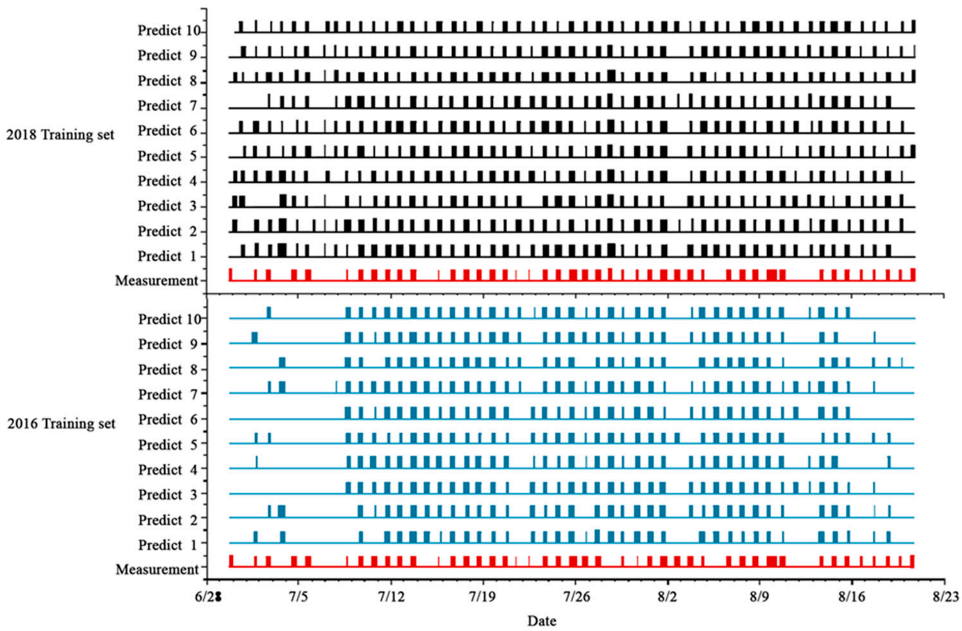


Figure 7. Result of AC on–off profile.

Further quantitative analysis of the 100 simulation results was performed using the confusion matrix, as shown in Figure 8, and the accuracy of the results was evaluated using the F1 value. The horizontal and vertical axes in Figure 8 represent the simulated and measured results of the AC on and off states, respectively, and the radius of the arc represents the proportion of different results. The blue semicircles indicate that the measured results were consistent with the simulation results, whereas the pink semicircles indicate the opposite. The F1 value of the AC operating behavior model trained based on 2016 data was 0.70, whereas the F1 value of the AC operating behavior model trained based on 2018 data was 0.76. Therefore, an 8% improvement in the on–off profile accuracy can be achieved when considering the behavioral variation.

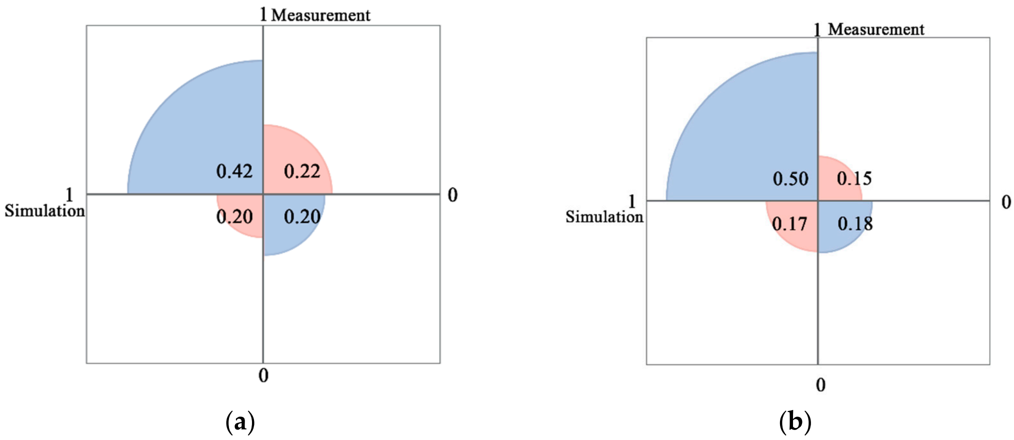


Figure 8. Confusion matrix. (**a**) 2016 training set; (**b**) 2018 training set.

3.2.3. Open Rate Under Different Outdoor Temperatures

Figure 9 shows the measured and simulated probabilities of the AC-on state at different outdoor temperatures. The difference between the results of the AC operating model obtained from the 2016 training set and the measured results was generally greater than that of the model obtained from the 2018 training set. Figure 9a shows that when ignoring the influence of behavioral change, the AC operating behavior model deviates significantly from the measured data in the low outdoor temperature zone between 24 °C and 28 °C. When the temperature was below 28 °C, the model-predicted open rate obtained from the 2016 training set was below 0.3, and the probability of opening increased as the temperature increased. Conversely, the measured open rate ranged from 0.3 to 1.0 in this outdoor temperature range and changed negatively with the outdoor temperature. The model obtained from the 2018 training set was consistent with the measured trends and exhibited good accuracy.

From the calculation results of the absolute error rate S, the result of the AC operating behavior model trained based on the 2018 data was 0.09, whereas that of the AC operating behavior model obtained based on the 2016 data was 0.39, and the difference between the two was approximately four times. The open rate profile under different outdoor temperatures and the absolute error rate S generally reflect the changes in the habits of AC users, especially in low-temperature conditions, and the behavioral change in AC usage is more obvious.

3.2.4. Open Rate Under Different Times of the Day

Figure 10 shows a comparison of the measured and simulated probabilities of the AC-on state at different times of the day. As shown in Figure 10a, when the influence of behavioral changes was ignored, the model obtained from the training data in 2016 showed a large difference in time distribution from the actual measurement. Taking 18:00 as the dividing point, the AC shows a lower open rate when turned on and a higher open rate when turned off. Therefore, when the influence of behavioral changes was ignored, the predicted AC on–off states exhibited delayed on and off phenomena over time. The model obtained from the 2018 training set exhibited a similar phenomenon when considering the changes in the behavior of occupants; however, the open rate values showed smaller differences, and the time when the open rate intersects was also earlier. The simulated and measured results intersected at 13:00, and a more accurate opening rate was observed after 19:00.

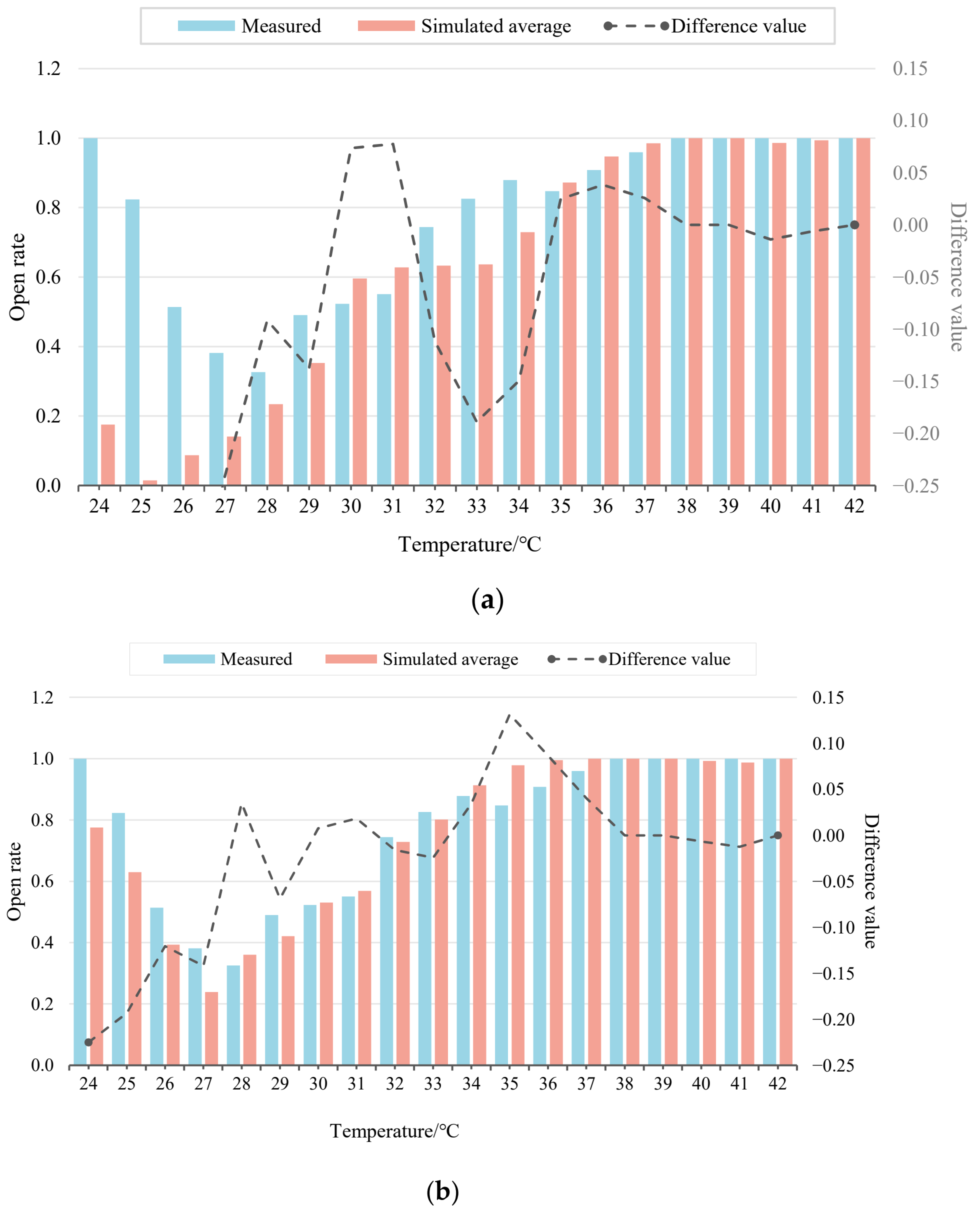
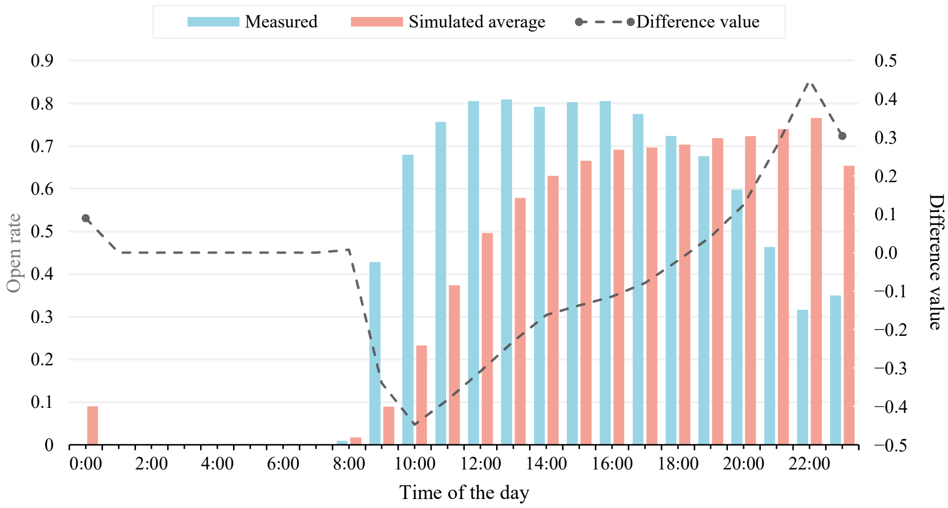
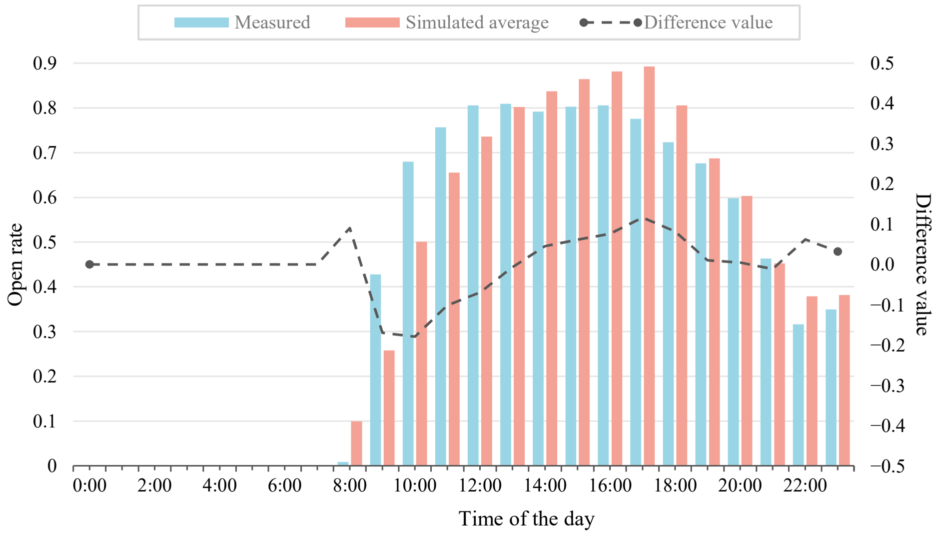


Figure 9. Open rate under different outdoor temperatures. (**a**) 2016 training set; (**b**) 2018 training set.

In addition, quantitative calculations revealed that the model trained based on the 2018 data had an absolute error rate S of 0.10, whereas the value was 0.41 for the model trained based on the 2016 data. Based on the influence of behavioral changes, the time for turning the AC on and off by people in the office generally increased, and the open rate profile under different times of the day obtained by the model of the 2016 training set lagged to some extent.



(**a**)



(**b**)

Figure 10. Open rate at different times of the day. (**a**) 2016 training set; (**b**) 2018 training set.

4. Discussion

In studying the annual variation characteristics of AC operating behavior in office buildings, several insights emerge regarding how occupancy patterns, environmental factors, and behavioral trends influence energy use over time. One significant observation is the variability in AC usage based on temporal shifts, such as changes in outdoor temperature, and individual comfort preferences. These factors reveal a dynamic, rather than static, approach to cooling consumption analysis, where AC usage does not follow a uniform pattern but rather adapts based on specific conditions and time-based trends.

This study underscores the importance of time-sensitive behavioral models to better predict AC usage patterns, as behavioral changes can significantly affect energy predictions and, consequently, energy efficiency strategies. For instance, seasonal shifts and daily occupancy patterns were found to impact not only the frequency of AC usage but also the duration and timing of AC operation. The findings suggest that ignoring these temporal factors in AC operating behavior could lead to over- or underestimation of energy consumption, which affects both model accuracy and the effectiveness of energy-saving measures.

In addition, it should be pointed out that the data used in this study comes from 2016 and 2018, which was 6 to 8 years ago. This period was specifically chosen because office usage was not impacted by the pandemic, making it a more accurate reflection of typical office occupancy patterns and AC operating behavior. Additionally, it should be noted that factors like climate variation also have an impact on the occupant behavior change. Further research could enhance this understanding by examining the influence of specific events, such as peak occupancy hours, seasonal transitions, or temperature spikes, on AC operating behaviors. In addition, data from different seasons and multiple years can be continuously collected to account for both seasonal and long-term shifts in occupancy behavior, allowing for a more thorough understanding of these dynamics. Meanwhile, incorporating more detailed behavioral data over longer periods and introducing more advanced, complex models, such as those utilizing machine learning or deep learning, can enhance the accuracy of AC operating behavior models, thereby contributing to more sustainable office environments and reducing operational costs.

5. Conclusions

Currently, research on AC operating behavior lacks relevant theories and methods in the time dimension, with limited analysis on the changes in energy use patterns caused by dynamic temporal shifts. Therefore, this study explores AC operating behavior from a time perspective, with a particular focus on the role of time in influencing AC operating behavior patterns. The main conclusion of this research includes:

1. Variability in AC turning on behavior: The likelihood of turning on the AC varies over time. With consistent thresholds and influencing factors, the probability of AC turning on at a given outdoor temperature can differ by as much as 96.8%.
2. Changes in AC turning off behavior: Over time, the patterns of turning off the AC also shift. These changes are reflected not only in the intensity of likelihood but also in the influencing factors. For example, the relationship between turning off the AC and people leaving, though initially strong, eventually shows a stronger correlation with specific times of day.
3. Impact on Model Accuracy: Ignoring behavioral changes significantly impacts the accuracy of the AC operating behavior model. In this study, the prediction accuracy of the opening rate, F1 score, and temperature/time absolute error rate decreased by 15.9%, 8%, and 30%, respectively.

Additionally, the study shows that while AC operating behavior shifts over time, a consistent functional form and logical framework can describe these patterns across different periods. Updating the model with data that reflects behavioral changes can effectively enhance prediction accuracy and practical model performance, improving building service quality, and reducing operational energy consumption and carbon emissions.

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