Research on short-term energy consumption control method of green building based on peak density optimization

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Abstract: In order to improve the short-term energy consumption control effect of green buildings and shorten the control time, this paper proposes a short-term energy consumption control method of green buildings based on density peak optimization. Firstly, the research status of green building energy consumption control is analyzed, and the short-term energy consumption data information of green building is obtained; Secondly, the definition of peak density algorithm is given, the short-term energy consumption control model of green building is constructed, and the initial cluster center of the short-term energy consumption model of green building is selected to calculate the probability density of the short-term energy consumption control model of green building; Finally, the adaptive genetic algorithm is used to control the short-term energy consumption of green buildings. The experimental results show that the research method can achieve good prediction accuracy in each season, and the short-term energy consumption control time of green buildings is only 3.2 seconds, indicating that the research method can effectively improve energy consumption control efficiency, shorten the short-term energy consumption control time of green buildings, and verify the superiority of the research method. At the same time, it indicates that the research method has certain application value in short-term energy consumption control of green buildings, and can provide a theoretical basis and data support for the field of short-term energy consumption control of green buildings.
Key Words: Peak density optimization; Probability density; Cluster center; Adaptive genetic algorithm

1. Introduction

Clean and renewable energy has been widely used. However, fossil energy is still widely used. However, the use of this energy produces polluting gases, which need to be treated qualitatively with prevention and control measures, especially in the construction industry [1]. According to statistics, in 2016, China's total building energy consumption reached 899 million tons of standard coal, accounting for 20.62% of the total national energy consumption, including 346 million tons of standard coal for public buildings, accounting for 38.53% of the total building energy consumption. Therefore, energy conservation and emission reduction in the construction industry is the focus at this stage. In the past practice of building energy conservation, many effective measures have been applied and achieved good energy conservation results. Therefore, building energy consumption needs to be carefully managed [2-3]. Fine management of building energy consumption is an important development direction of building energy conservation in the future. Building energy consumption data research provides a basis for energy conservation and emission reduction. The data mining depth of the national building energy consumption monitoring platform is low. This is because of data problems and outliers, which leads to the low quality of the data and restricts the application of the building energy consumption data. At the same time, machine learning is applied to this field, but because of the diversity of building types and different operating characteristics, the prediction effect of this algorithm is poor.

Therefore, many scholars have put forward the working method of energy consumption prediction taking a certain type of building as an example. For example, Wenninger Simon et al. proposed the use of QLattice for interpretable long-term building energy consumption prediction [4]. Most studies only focus on prediction performance, without considering the potential of interpretable AI. In order to fill this gap, a new QLattice algorithm was designed to the data set of more than 25000 German buildings to predict the annual building energy performance, and the importance of variables was analyzed, and put forward the appropriate application, so as to achieve building energy consumption control. This method has higher load forecasting accuracy, but it takes longer to shorten the control time. Bevilacqua Piero proposed the effectiveness of green roofs in reducing building energy consumption across different climates [5], this study provides a comprehensive literature review, summarizes the relevant research results of green roof energy conservation, provides appropriate answers to the energy efficiency problems of such solutions, and quantitatively reports the results obtained under different climatic conditions. This method can achieve better energy-saving effect, but the short-term energy consumption control effect of the building is not good. Pan Yue et al. proposed a data-driven estimation of building energy consumption with multi-source heterogeneous data [6], this method learns heterogeneous data to calculate building energy consumption. It belongs to the Cat Boost model of integrated learning, which has advantages in processing category variables and generating reliable results. Its purpose is to assess the intensity of energy used described nonlinear relationships, and achieve building energy consumption control. But the control efficiency of short-term building energy consumption is low.

In response to the above issues, this article proposes a short-term energy consumption control method for green buildings based on density peak optimization, hoping that it can improve the accuracy of prediction and shorten the short-term energy consumption control time.

2. Acquisition of short-term energy consumption data information of green buildings

2.1 Research status

People gradually pay attention to building energy consumption [7-9] and make predictions [10-13], but the prediction accuracy of this method is low, to solve this problem, people have improved the traditional prediction algorithm, and achieved some results, such as machine learning optimization.

The prediction of building energy consumption has made remarkable progress after decades of development. The widely used methods include engineering simplified prediction method, etc. The engineering simplified prediction method is the empirical value of building energy consumption level summarized based on a large number of engineering practices. This method can be used to predict in the early stage of building design. it is also the most widely used in practice, but the corresponding poor prediction accuracy of this method can not support more in-depth research due to the convenience of Engineering simplified prediction method. The density peak algorithm realizes the control of building energy consumption by mining historical data. The simulation prediction can be carried out according to the historical data of energy consumption, increased replicability. The big data related to building historical energy consumption has been fully reserved with the application recording means, this provides data for forecasting and can promote development.

Energy consumption data prediction is a branch of data mining. Data mining has formed seven universal processes after the research of many scholars, and scholars improved the process.it can be seen that data mining of energy consumption needs three main tasks through the investigation and analysis of relevant research: data selection and processing, model establishment and matching, result analysis and application. However, the prediction of building energy consumption needs further optimization.

2.2 Building energy consumption data information acquisition

The actual operation data of short-term energy consumption of green buildings are obtained through investigation. The building is located in M City, with a building area of 42000m^2. It is a comprehensive green building, including accommodation and catering functions. The main energy consumption places of the building during the day are the hall and banquet hall according to the investigation, and the main energy consumption places at night are the guest rooms. The building's equipment operates 24 hours a day. The building has an energy consumption detection system, which can obtain more reliable hourly data of building total energy consumption [14]. Select the hourly data of the building's total energy consumption in July 2021 as the sample for descriptive statistics. See Table 1 for details.

Table 1 Description and statistics of hourly total energy consumption data of green buildings in M City

Describe statistical parameters	Value
Total data	744
Average	702.2
Standard deviation	276.8
Minimum value	0
Lower quartile	578.6
Median	776.4
Upper quartile	848.1
Maximum	2474.3
Number of missing values	16
0 value quantity	17

The box diagram can be used to quickly and conveniently judge whether there are abnormal values in the data. Figure 1 is a box diagram drawn by using the hourly total energy consumption data of the building. It can be seen that there are many outliers on both sides of the dotted line, which indicates that there are a large number of outliers in the data set, which need to be further processed [15].

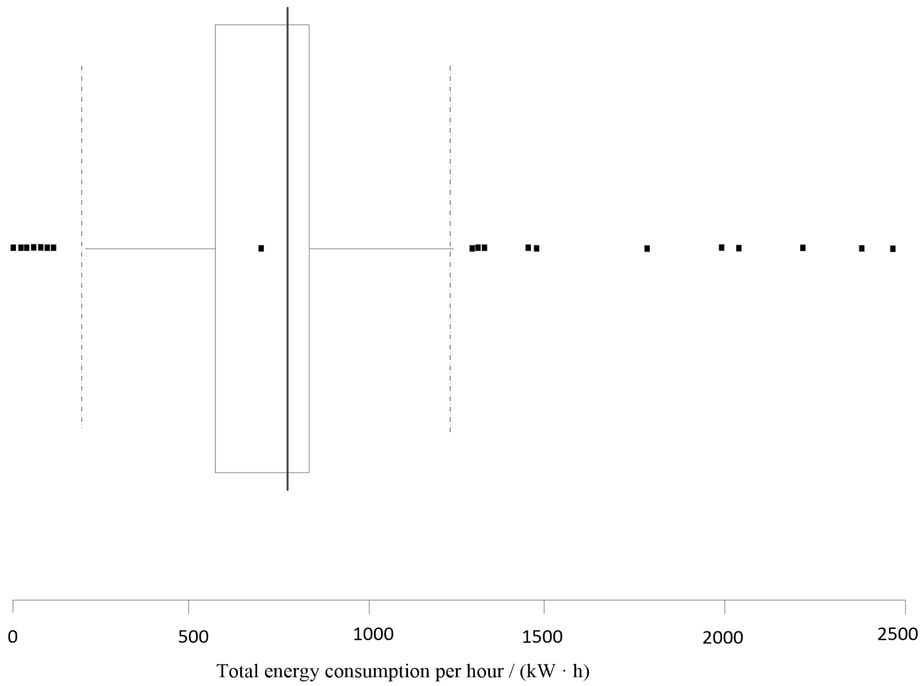

Fig. 1 Diagram of data box

3 Short term energy consumption control of green buildings

3.1 Density peak algorithm

The core of the density peak algorithm is the description of the distribution of data points, which is described as follows:

DPC algorithm gives different density calculation methods for different types of data points. For discrete data, use the truncation function, as shown in formulas (1) to (2).

$$\rho_i = \sum_{j \neq i} \chi(d(i,j) - d_c) \tag{1}$$

$$\chi(x) = \begin{cases} 1, & x < 0 \\ 0 & x \geq 0 \end{cases} \tag{2}$$

Where, d_c is the truncation distance, which is specified by the user. Gaussian function is used for non discrete data, as shown in formula (3).

$$\rho_i = \sum_{j \neq i} e^{-(\frac{d_{ij}}{d_c})^2} \tag{3}$$

The core of DPC algorithm is to select the cluster center, calculate the density ρ of each data point through formula (1) ~ formula (2) or formula (3), and then calculate the distance δ between each data point and the nearest data point with higher density.

$$\delta_i = \min_{j:\rho_j > \rho_i} d(i,j) \tag{4}$$

For the data point o_i with the maximum local density, where $\delta_i = \max_j d(i,j)$.

Generate Decision Diagram, as shown in Figure 2, is the distribution of a group of data points. Through formulas (1) to (4), the local density ρ and relative distance δ of each data point can be calculated, and then the decision diagram shown in Figure 3 can be obtained.

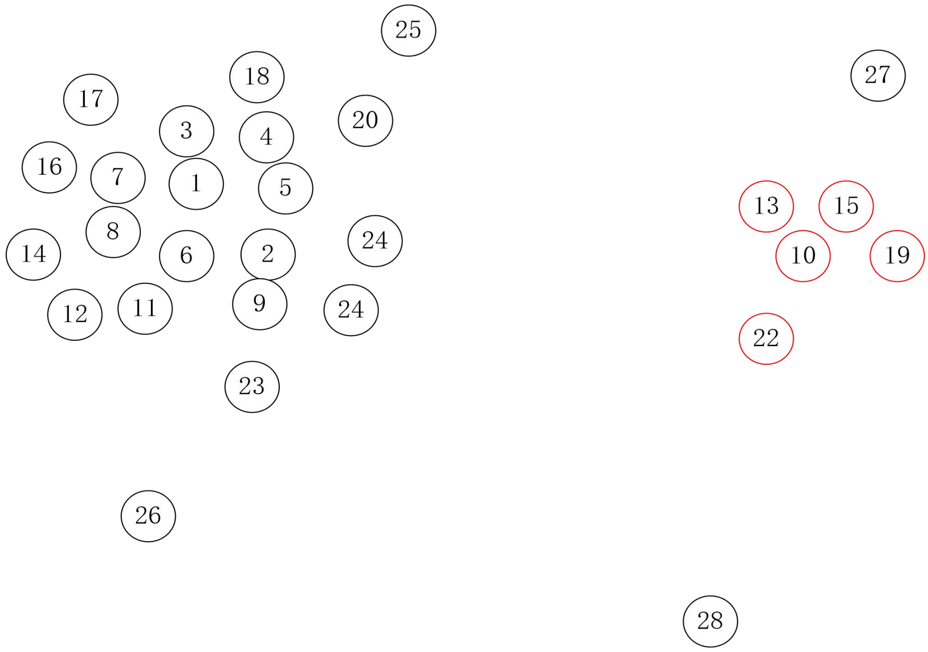

Fig.2 Distribution of data points

We can see that ① and ⑩ are selected as clustering centers according to figure 3, and then compared with figure 2, which is consistent with the distribution of data. After selecting the cluster center, the next step is to allocate each data point.

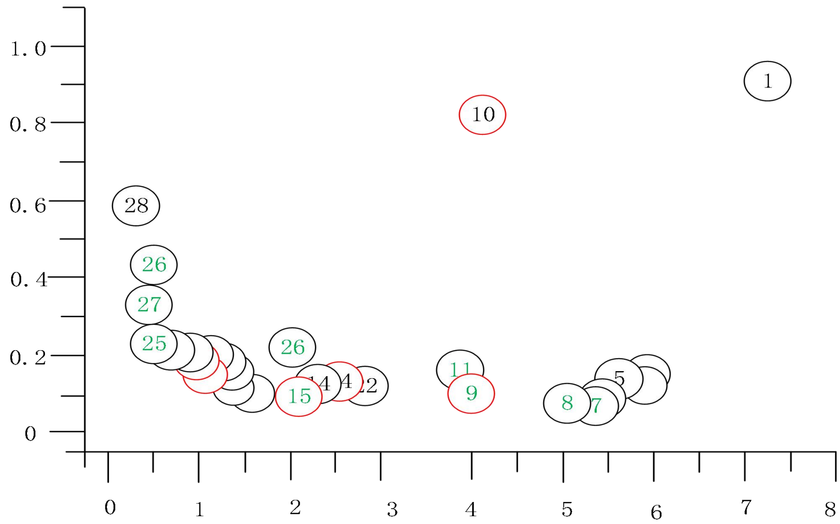

Fig. 3 Clustering decision diagram

This algorithm can identify clusters of any shape, but it needs to manually determine the parameter value of the truncation distance d_c based on experience. If the truncation distance is not ideal, the clustering effect is also poor. In addition, the time complexity is too high when calculating the density of data points, which also leads to the unsatisfactory clustering effect of the algorithm on large-scale data sets and limits its application. At the same time, DPC algorithm can not automatically determine the clustering center, the robustness of data point allocation is low, and it is easy to generate misclassification. In addition, the density peak algorithm can not deal with the clustering of complex data sets such as manifold data sets, which leads to the deficiency of density peak algorithm.

Therefore, this paper optimizes the peak density algorithm to effectively improve the effect of short-term energy consumption control methods for green buildings.

3.2 Initial cluster center selection

First, the initial cluster center is selected.

The DPC algorithm can select the cluster center, but this selection method needs to manually determine the cluster center point, and when facing some manifold data sets, the clustering results are not accurate enough. A new method based on Gaussian distribution in order to automatically select more accurate clustering centers, called gd-dpc algorithm for short.

Normal distribution is a method commonly used for anomaly detection. The mean of data is in the middle, and the data distributed on both sides belong to small probability events. Most of the conventional data points are in the majority in the density peak clustering algorithm, and the data points determined as the density peak points account for a small part. Therefore, this method can be used to obtain the set of data points whose distribution probability is a small probability event in the data set. Because the cluster center point is surrounded by data points with lower density than it, the density of the cluster center point should be greater than the average density of the data points surrounding it, and the points greater than the average density of the data set form another set. We can get the density peak point, that is, the initial cluster center point through the intersection of the two sets.

The formula for calculating the γ value of data points is as follows:

$$\gamma_i = \rho_i \cdot \delta_i \tag{5}$$

μ is the mean value of γ, and the calculation formula is as follows:

$$\mu = \frac{1}{i}\sum_{j=1}^{i}\gamma_j \tag{6}$$

σ^2 is the variance of γ, and the calculation formula is as follows:

$$\sigma^2 = \frac{1}{i}\sum_{j=1}^{i}(\gamma_j - \mu)^2 \tag{7}$$

The probability density $P(\gamma_i)$ of the γ value of the data point is calculated as follows:

$$P(\gamma_i) = \prod_{j=1}^{i}\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(\gamma_j-\mu)^2}{2\sigma^2}\right) \tag{8}$$

Based on the resulting probability density $P(\gamma_i)$ and the given threshold ω to determine whether the data point is an abnormal point, that is a point with a small probability density value. When $P(\gamma_i) < \omega$, the data point is an abnormal point; Otherwise, it is a normal data point. ω is a small constant because the clustering of the entire data set is divided into two steps, and the data points taken in this step need to contain the clustering center, which can ω Expand appropriately to obtain more data points.

The local density of the cluster center should be higher than the average density of the data points in the data set. Accordingly, because the cluster center is surrounded by low-density points, a short-term energy consumption control model for green buildings is established, which is expressed as:

$$\rho = \frac{1}{n}\sum_{i=1}^{n}\rho_i \tag{9}$$

As shown in equation (9), n represents the number of data points. The outliers higher than the mean density are defined as the initial cluster center points and stored in the initial cluster center point set $C(i)$.

3.3 Short term energy consumption control of green buildings

After obtaining the building related information, an adaptive genetic algorithm is used to control the short-term energy consumption of green buildings according to the control principle. The specific algorithm flow is as follows:

Firstly, the parameters of short-term energy consumption control model and encoding controller of green buildings are optimized. The parameters of the short-term energy consumption control model of green buildings to be optimized are mapped to the coding space by using binary coding method through coding [16]. The coding accuracy requirements are shown in equation (10):

$$\frac{(p-q)}{2^m-1}<\sigma \tag{10}$$

Where, P represents the upper limit of the parameters of the short-term energy consumption control model for green buildings, q represents the lower limit of the parameters of the short-term energy consumption control model for green buildings, and m represents the code length of the parameters of the short-term energy consumption control model for green buildings, σ Represents the coding accuracy of short-term energy consumption control model for green buildings[17]. Set encoding precision to $\sigma<0.08$, the code length ≥ 5 can be calculated by equation (10).

The short-term energy consumption of green buildings can be controlled by using the control parameters according to the control rules. The specific control steps are as follows:

Firstly, input and output of energy consumption control model variables are carried out. The input variables are error E and error velocity V, and the output variables are W [18]. Fuzzy reasoning method is used to make fuzzy decision. The judgment formula is as follows

$$\begin{cases} G=\bigcup_{i=1}^{n} G_i=\bigcup_{i=1}^{n}(A_i\times B_i)\times C_i \\ \gamma_{G_i}=\min\{\lambda_{A_i}(E),\lambda_{B_i}(V),\lambda_{C_i}(W)\} \\ \gamma_c(W)=\max\{\min[\gamma(E,V),\gamma(E,V,W)]\} \end{cases} \tag{11}$$

Where, G represents the control rules of the energy consumption control model, A and B represent the control parameters, $\gamma_c(W)$ represents the membership function value of the control rule G_i input, and C_i represents the corresponding output value obtained. Use equation (11) to make fuzzy decision. After that, the fuzzy output of the energy consumption control model is

$$W=\frac{\sum_i \gamma c_i(W_i)\cdot C_i}{\sum_i \gamma c_i(W_i)} \tag{12}$$

The actual output of the energy consumption control model is shown in equation (13) according to equation (12):

$$\omega=\alpha W+\beta\sum W_i\cdot T_s \tag{13}$$

Where, α represents the scale factor, β represents the integration coefficient and T_s represents the sampling time. the self-adaptive idea is used, a self-organizing adjustment mechanism is constructed to test the error and its change in the response process of the system.

The coding process of membership function and control rule is as follows: genetic algorithm is used to optimize the membership function parameters of each fuzzy subset:

Firstly, 1 ~ 7 are used to represent the input variables and output variables of the energy consumption control model, including 7* 7 Rules in total and 49 membership function parameters to be optimized. Each control rule is encoded with 3-bit binary code, and the length of the control rule coding string is 147 bits. The conditions to be considered are:

① The fuzzy universe of the input variables of the energy consumption control model is normalized. If the direction of the control system is not special, the control rule base has symmetry.

② According to the control rules, adjust them accordingly, reduce the number of control rules to be optimized to 24, reduce the coding length to 72 bits, and uniformly code the control parameters. Then, the fitness function is selected and the commonly used ITAE performance index is used as the objective function of genetic algorithm optimization:

$$L = \int t\left|e\right| dt \tag{14}$$

Equation (14) is the integral of time multiplied by the absolute value of error, which is discretized as shown in equation (15).

$$L = \sum_{i=1}^{k} T\left|e_i\right| \tag{15}$$

Where, T represents the sampling time for collecting the energy consumption value, k represents the sampling times of the energy consumption value, and e_i represents the error of the energy consumption control system during sampling. The larger the individual's fitness, the better. The fitness function is

$$F(x) = \frac{1}{1+NL} \tag{16}$$

Where, N represents the sensitivity control parameter, which is usually taken as 1. the minimum value problem is transformed into the maximum value problem of the fitness function through the above formula.

The genetic operator is used to further optimize the error after the above operations. Firstly, the poor individuals are eliminated, and the two-point crossover method of nonlinear sorting selection is used to crossover the control rules and membership function parameters of the energy consumption control model, so as to increase the diversity of the population and speed up the search speed of the optimal solution; Then, the individuals of the population are recombined to make the population add new individuals and increase the search space for possible solutions. Before the crossover operation, the alleles in the control rule coding string are compared. If the absolute difference is less than 2, the crossover operation is implemented. Otherwise, the genes remain unchanged. After that, the mutation operation is adopted to preserve the diversity of individuals in the population, inhibit the prematurity of individuals in the population, and complete the genetic operation by adaptively adjusting the cross mutation probability. The specific process is as follows:

Let the crossover probability of the population be expressed by j_c and the mutation probability of the population be expressed by j_m, but too large or too small j_c is not conducive to the heredity of the population. j_m too large or too small is not conducive to the emergence of new individuals. Use equation (17) to perform cross mutation operation:

$$ji = \begin{cases} j_i \times \{1/(1 - f_{\min}/f_{\max})\} & (f_{avg}/f_{\max}) > a, (f_{\min}/f_{\max}) > b, j_i < 1 - f_{\min}/f_{\max} \\ j_i & other \end{cases} \quad (17)$$

Where, $i = c, m$. when the conditions $(f_{avg}/f_{\max}) > a$ and $(f_{\min}/f_{\max}) > b$ are met, it is considered that the population of this generation is relatively concentrated. Then j_c and j_m change adaptively according to the degree of concentration. The value range of parameter a is [0.5, 1], the value range of parameter b is [0.2, 0.5], $j_c < 1 - f_{\min}/f_{\max}$, $j_m < 1 - f_{\min}/f_{\max}$ can ensure that the values of j_c and j_m are less than 1.Taking the building energy consumption control parameters as the research object, the above adaptive genetic algorithm is used to optimize the control parameters of the energy consumption control model, and the optimized control parameters are used to implement the optimal energy consumption control for the near zero energy consumption buildings.

It can be seen from this section that the building energy consumption control model based on density peak optimization can accurately complete the building energy consumption control, and it has certain replicability. When the energy consumption control of a certain type of building is completed, if it is necessary to control the energy consumption of another similar building, the model can be applied to the new building energy consumption control by adjusting the input data set of the model and optimizing the super parameters. This feature makes it possible to popularize the building energy consumption control method based on density peak optimization and standardize the workflow.

Historical data is the basis for building short-term energy consumption control model based on density peak optimization. At the same time, various factors in the monitoring and recording process may lead to data anomalies and data missing. Therefore, it is necessary to preprocess the historical data of building energy consumption in the initial stage of the study. It is necessary to analyze the characteristics of building energy consumption data to obtain the energy consumption characteristics of the controlled buildings after the completion of pretreatment [19]. Combining the characteristics of building energy consumption and the applicability of density peak optimization algorithm, the matching of density peak optimization model can be completed, and the algorithm model required for prediction can be selected. After that, on the basis of establishing the prediction model and completing the optimization of model parameters, it is necessary to test the control effect of the building short-term energy consumption control model based on density peak optimization. If the control effect can meet the research needs, the building energy consumption control will be successfully completed; If the control effect can not meet the research needs, it is necessary to re-select the appropriate algorithm model, or re adjust and optimize the algorithm model parameters. After re testing the model control effect and determining that the control results meet the research needs, the building energy consumption control can be completed. Therefore, a universal workflow in the field of building short-term energy consumption control can be proposed, as shown in Figure 4.

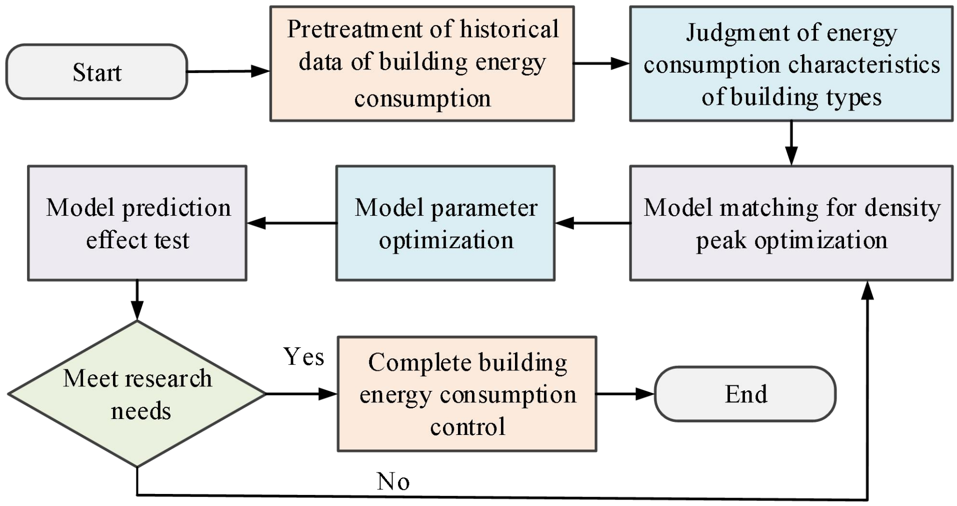

Fig.4 Short term energy consumption control workflow of green buildings based on density peak optimization

4. Experiment

4.1 Experimental Design

This chapter conducts seasonal energy consumption control effect verification experiments on green buildings based on the accuracy of model control results and time cost evaluation methods. This chapter uses the same platform to carry out control experiments on each model in order to ensure the accuracy of control results of each model and the unity of time cost comparison. The models in this paper are written in Python language. The operating system is a 64 bit windows10 system. The hardware environment is Intel (R) core (TM) i7-7700hq CPU @2.80ghz, and the memory is 16.0gb. Through the comparative analysis of the control results, this chapter summarizes the adaptation relationship between different types of buildings and different models.

4.2 Experimental index

4.2.1 Model accuracy evaluation

The commonly used evaluation parameters for the accuracy evaluation of the control model are MAPE (mean absolute percent error) and RMSE (root mean square error). These two parameters can be used to measure the deviation between the predicted value and the real value, so as to reflect the accuracy of the model. Therefore, this paper introduces MAPE and RMSE parameters as the evaluation parameters of model accuracy. The calculation formulas of MAPE and RMSE are as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{x_i' - x_i}{x_i}\right| \times 100\% \tag{18}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i' - x_i)^2}{N}} \tag{19}$$

As shown in equation (19), N represents the number of samples, Where, x_i represents real value of hourly energy consumption data, kW·h; x_i' represents predicted value of hourly energy consumption data, kW · h; n represents number of data.

4.2.2 Model time cost evaluation

It is also necessary to evaluate the time spent in its modeling process and simulation process in addition to the accuracy evaluation of building energy consumption control model, so as to select the control model with the lowest time cost. Different researchers have different time to build the same energy consumption model due to the difference of modeling level. At the same time, some studies show that more than 80% of the workload of building energy consumption modeling based on historical data is occupied by data preprocessing. The complexity of model building and data preprocessing is affected by the dimension of model input parameters. Therefore, the input parameter dimension can be used to simplify the complexity of the modeling process of the control model, that is, the time cost of modeling. For the time cost measurement in the simulation process of energy consumption control model, the program can directly record the time from the beginning of training to the end of control, and judge the time cost of the model prediction process by the length of time.

4.3 Experimental Result

4.3.1 Short term energy consumption control accuracy of different green buildings

According to the six evaluation indicators of land saving and outdoor environment, energy saving and energy utilization, water saving and water resource utilization, material saving and material resource utilization, indoor environmental quality, operation management and comprehensive performance of the whole life cycle, green buildings are divided into three grades. The order from low to high is one star, two stars and three stars. The higher the star, the better the energy saving. Select a research method and conduct energy consumption control accuracy testing experiments based on three levels of green building historical data. Select 4 sets of historical data for each level, and the model accuracy results are shown in Figure 5.

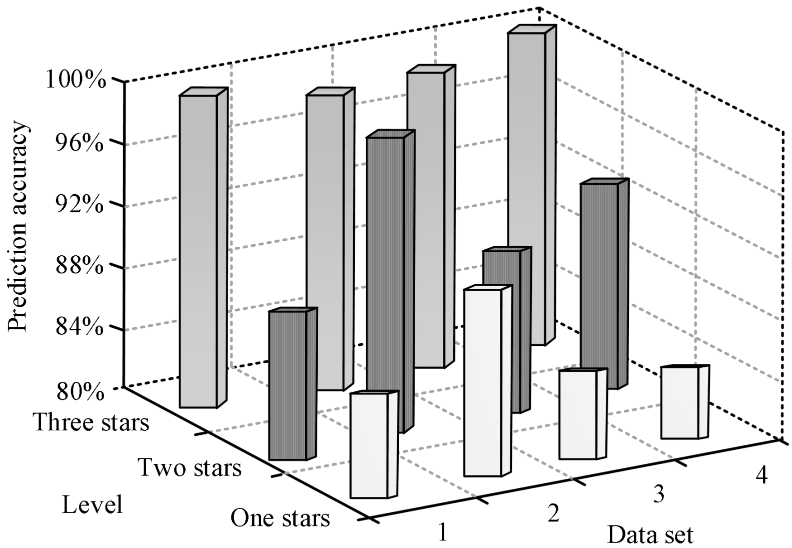

Fig.5 Short term energy consumption control accuracy of different levels of green models

As shown in Figure 5, as the level of green building star rating increases, the accuracy of its energy consumption model also increases. Among them, the highest accuracy of one star green building is 89.23%, and the average accuracy is 84.17%; The highest accuracy of the two-star green building is 94.72%, with an average accuracy of 86.46%; The highest accuracy of the two-star green building is 98.58%, with an average accuracy of 96.31%. Overall, the research model showed better accuracy in higher star ratings, with evaluation accuracy of all three star ratings exceeding 80%, indicating that the research model has certain applicability in short-term energy consumption control of green buildings.

4.3.2 Prediction of short-term building energy consumption model

The building energy consumption control model with three algorithms is applied to carry out energy consumption control experiments based on the historical data. In the experiment, the hourly total energy consumption data of buildings in July in summer, December in winter and March in transition season in the green building data recording cycles well as the corresponding time and meteorological parameters, and they selected as training sets to control the hourly total energy consumption in the next week, and the control values of the three models (density peak optimization, reference [5] method and reference [6] method) are compared with the real value (total) The control results of winter and transitional seasons are shown in Table 2.

Table 2Control results of green building energy consumption model

Control model	Control object	MAPE (%)	RMSE	Input parameter dimension
Density peak optimization	Total energy consumption per hour in summer	2.62	6.72	8
Reference [5] method	Total energy consumption per hour in summer	9.96	22.91	1
Reference [6] method	Total energy consumption per hour in summer	13.41	25.74	1
Density peak optimization	Total energy consumption per hour in winter	2.29	4.63	8
Reference [5] method	Total energy consumption per hour in winter	9.11	15.64	1
Reference [6] method	Total energy consumption per hour in winter	12.08	18.96	1
Density peak optimization	Total hourly energy consumption in transition season	2.47	4.78	8
Reference [5] method	Total hourly energy consumption in transition season	9.59	16.05	1
Reference [6] method	Total hourly energy consumption in transition season	11.38	17.68	1

As can be seen from Table 2, their energy consumption has not only obvious difference between day and night for green buildings, but also obvious difference between working days and non-working days. For summer, the error of the research method is significantly lower than that of references [5] and [6], with a MAPE of only 2.62% and an RMSE of only 6.72, while the RMSE of reference [6] is as high as 25.74; For winter, the error of the research method is significantly lower than that of references [5] and [6], with a MAPE of only 2.29% and an RMSE of only 4.63; For the transitional season, the error of the research method is significantly lower than that of references [5] and [6], with a MAPE of only 2.47% and an RMSE of only 4.78; Overall, the MAPE of the research method in different seasons was lower than 3%, and the RMSE was lower than 5, indicating that it has a good error effect. It can be seen from the control results that the single factor control model of reference [5] method and reference [6] method has poor control accuracy, while the multi factor control model based on density peak optimization has achieved good control accuracy in each season, and can achieve good control effect.

4.3.3 Short term energy consumption control time for green buildings

Reference [5] method, reference [6] method and the method in this paper are used to verify the effect of short-term energy consumption control, the results shown in Table 3.

Table 3Short term energy consumption control time for green buildings

Built-up area/m^2	Short term energy consumption control time for green buildings /s		
	Reference [5] method	Reference [6] method	Paper method
100	12.8	18.5	0.2
200	18.2	28.5	0.8
300	28.5	33.6	1.5
400	38.9	58.9	2.1
500	68.3	82.8	2.9
600	98.1	129.3	3.2

According to the analysis of Table 3, when the green building area is 100m^2, the control time of green building in reference [5] method is 12.8s, the control time of green building in reference [6] method is 18.5s, and the control time of green building in this method is 0.2S; When the green building area is 300m^2, the control time of green building in reference [5] method is 28.5s, the control time of green building in reference [6] method is 33.6s, and the control time of green building in this method is 1.5s. When the green building area is 600m^2, the control time of green building in reference [5] method is 98.1s, the control time of green building in reference [6] method is 129.3s, and the control time of green building in this method is 3.2s. This method has low short-term energy consumption control time of green buildings, which shows that this method has high short-term energy consumption control effect of green buildings.

5 Conclusion

This paper presents a short-term energy consumption control method for green buildings based on peak density optimization. The short-term energy consumption data of green buildings is collected, the initial cluster center of the model of green buildings is selected, calculate the probability density of the control model of green buildings, and the adaptive genetic algorithm is used to control the short-term energy consumption of green buildings. The experimental results show that:

1) The multi factor prediction model based on peak density optimization has achieved good prediction accuracy in each season, and can achieve good prediction results.

2) When the green building area is 600 m^2, the short-term energy consumption control time of green building in this method is 3.2 s. It shows that the short-term energy consumption control effect of this method is high.

However, there are still shortcomings in this study, as the selection of test datasets is too single, resulting in a lack of universality of experimental results. In future research, more diverse datasets will be selected for experiments.

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