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Article

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Energy Reports

Provided in Cooperation with:

Elsevier

Suggested Citation: Tian, Ying; Yu, Junqi; Zhao, Anjun (2020) : Predictive model of energy consumption for office building by using improved GWO-BP, Energy Reports, ISSN 2352-4847, Elsevier, Amsterdam, Vol. 6, pp. 620-627, <https://doi.org/10.1016/j.egy.2020.03.003>

This Version is available at:

<https://hdl.handle.net/10419/244063>

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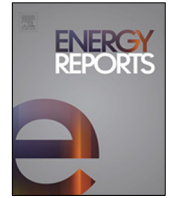
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Research Paper

Predictive model of energy consumption for office building by using improved GWO-BP

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ARTICLE INFO

Article history:

Received 12 November 2019

Received in revised form 28 January 2020

Accepted 3 March 2020

Available online xxxx

Keywords:

Building electrical load prediction

BP neural network

Fuzzy C-means clustering algorithm

Grey wolf optimizer algorithm

ABSTRACT

Building energy data analysis is a major branch of smart city development research. The usual back propagation neural network model for building energy prediction has problems of unclear physical significance, poor data generalization and low fitting accuracy. Therefore, a composite prediction model of building power consumption based on FCM-GWO-BP neural network was proposed. According to the similar statistical distribution characteristics of data, the fuzzy C-means clustering algorithm (FCM) was used to cluster the historical power consumption data. BP neural network prediction model was established for different categories to reduce the impact of relevant noise in the sample data on the modeling accuracy. Then, according to the train and test data sets of each category, the corresponding grey wolf algorithm was established to optimize the error back propagation neural network prediction model (GWO-BP). The experimental results showed that compared with the sample prediction accuracy index root mean square percentage error (RMSPE), the GWO-BP neural network after FCM clustering was reduced by about 0.225 compared with the BP model, and was reduced by about 0.135 compared with the GWO-BP model, so its prediction accuracy was improved by 75% at most. Respectively, the mean absolute percentage error (MAPE) was reduced by 14.41% and 6.48%. It can be seen that this model has strong generalization ability, better prediction accuracy and reliability, and absolutely can meet the needs of practical engineering.

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1. Introduction

With the continuous progress of urbanization, the construction of smart city has gradually attracted extensive attention (Lytras and Visvizi, 2018). As the focus of smart city, intelligent energy system refers to through the analysis and integration of information and data resources to avoid resource waste. The software core technologies of smart city construction include big data, internet of things, cloud computing, intelligent algorithm and others (Visvizi and Lytras, 2018b; Chui et al., 2018).

Many scholars have studied the key problems of building energy consumption in intelligent energy system, and successfully solved the problems of energy consumption characteristic analysis, energy consumption influencing factor analysis, energy coordination optimization and so on (Kim et al., 2019a; Yang et al., 2018; Xu et al., 2017b). At present, the energy consumption of building is larger, and the data format is more diverse, and the

data level is constantly improved. As a result, the development of intelligent energy system is facing a bottleneck, and it is in urgent need of a more generalized and robust prediction method to support the system (Visvizi and Lytras, 2018a; Wu et al., 2018).

The main research methods of building energy consumption include building model simulation and data-driven in the moment. Firstly, common building energy simulation software is TRNSYS (Al-Saadi and Zhai, 2015; Safa et al., 2015), ECO-TECT (Peng, 2016; Amani, 2018) and EnergyPlus (Yu et al., 2015; Fumo et al., 2010). Currently, simulation method in real building energy consumption prediction is inefficiency. On the one hand, modeling the building is time consuming, and the model need to be continuously improved according to the results of operation for more precise prediction; on the other hand, the building model is difficult to provide accurate real-time control strategy for operation stage in the design phase; meanwhile, the professional demand of establishing a model of parameter settings for modelers is fairly higher (Fumo and Rafe Biswas, 2015). Therefore, the traditional simulation software program is not appropriate to be used for the actual management of the system. As for data-driven, mainly methods include multiple linear regression (MLR) (Catalina et al., 2013), support vector

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machine (SVM) (Shine et al., 2019), auto regression (AR) and other models (Bourdeau et al., 2019). The MLR model is highly non-linear in terms of multivariable factors that affect building energy consumption, so the prediction accuracy is relatively low. The SVM model requires a large amount of data for model training, so the absence of variables has a large impact on the model effect, and the robustness is not high. The input variable of AR model is only the historical data of building energy consumption without considering other factors, so the prediction accuracy is difficult to meet the actual requirements. In recent years, with the rapid development of Artificial Intelligence, BP (Back Propagation) neural network has been widely applied in dynamic prediction of building energy consumption due to its prominent non-linear mapping, self-adaptation, fault tolerance and other characteristics (Biswas et al., 2016; Daut et al., 2017; Liu et al., 2016; Xu et al., 2017a). However, BP neural network has some defects such as local optimization, irrelevant to physical meaning, strong dependence on training data and slow convergence speed, which hinder its application in practical engineering. Some researchers adopt grey wolf optimization (GWO) to optimize the BP neural network's global search capability, which can greatly avoid trapping in local best solution (Esmail et al., 2018; Shi et al., 2017). However, due to poor correlation between model input variables and output variables, and high redundancy and coupling relationship between variables, the defects of poor prediction accuracy of the model have not been well solved (Daut et al., 2017).

This paper proposed a composite model of power prediction based on fuzzy C-means clustering and grey wolf optimized back propagation neural network. In view of the strong coupling and non-linear characteristics of the sample data of building power consumption, the sample data is divided into several categories by fuzzy C-means clustering method, so as to reduce the impact of the correlation of the data itself on the modeling accuracy. On the basis of obtaining all kinds of sample data, the corresponding BP neural network model is distributed and constructed. At the same time, the grey wolf algorithm with global optimization ability was used to optimize the parameters of the error back propagation neural network, so as to avoid the blindness of artificial parameter selection and improve the prediction accuracy of the model. By using the actual operation data of an office building in Xi'an, the prediction results show that the prediction accuracy of the FCM-GWO-BP model proposed in this paper is much higher than that of the traditional prediction model in accuracy, and it can meet the actual application requirements of the project.

2. Composite model of building power consumption prediction for office buildings

2.1. Fuzzy C-means clustering algorithm

As a typical clustering method, fuzzy C-means (FCM) has been successfully applied in data analysis, image segmentation and other fields (Qiu et al., 2017).

FCM algorithm is an unsupervised pattern recognition method, and its core idea is to determine the membership degree of each data point by using the objective function, and then achieve the goal of automatic data classification of samples (Zhao and Zheng, 2017).

A sample is $X = \{x_1, x_2, \dots, x_n\}$, and clustering number is c . Where X can be divided into class c and can be presented as the fuzzy matrix $U = (u_{ik})_{c \times n}$; u_{ik} is the signal, and sample i belongs to the first k class membership. Meanwhile u_{ik} is supposed to

meet the following conditions:

$$\begin{cases} \sum_{i=1}^c u_{ik} = 1, 1 \leq k \leq n \\ 0 \leq u_{ik} \leq 1, 1 \leq k \leq n \\ \sum_{k=1}^n u_{ik} > 0, 1 \leq i \leq c \end{cases} \quad (1)$$

FCM algorithm finds the optimal solution by gradient descent, which is to make the objective function reach the minimum value. The iterative steps of clustering algorithm are as follows (Wen and Wang, 2018):

Step 1: Determine the number of clusters c , the weight index m ; randomly generate the clustering center matrix $Z(0)$; make the number of iterations $l = 0$.

Step 2: Use Eq. (2) to calculate the membership matrix $U(l+1)$, and modify the clustering center $Z(l+1)$.

$$\begin{cases} z_i^{(l+1)} = \frac{\sum_{k=1}^n (u_{ik}^{(l)})^m x_k}{\sum_{k=1}^n (u_{ik}^{(l)})^m} \\ u_{ik}^{(l+1)} = \left[\sum_{j=1}^n \left(\frac{d_{jk}^{(l)}}{d_{jk}^{(l+1)}} \right)^{\frac{2}{m-1}} \right]^{-1} \end{cases} \quad (2)$$

where, l is the number of iterations, and m is the weighted index.

Step 3: For a given threshold $\varepsilon > 0$, the algorithm terminates when the target function $J(ml) - J(ml+1) \leq \varepsilon$. Otherwise, the iteration returns to Step 2.

2.2. GWO-BP neural network algorithm

Back propagation algorithm is one of the most effective multi-layer neural network learning methods. Its main characteristics are that though adjusting forward transmission of signals, backward propagation of errors and continuous adjustment of network connection values can make the final output of the network as close as possible to the expected output, so as to achieve the training purpose (Daut et al., 2017).

Grey wolf optimizer (GWO) is a new swarm intelligence optimization algorithm proposed by Mirjailili et al. in 2014. Its core is to optimize the dynamic process of parameter by simulating the hunting process of grey wolves, such as finding, surrounding and attacking prey (Hatta et al., 2018).

The algorithm divides the wolves into the optimal grey wolf, the second-best grey wolf, the third best grey wolf and the remaining grey wolf. The highest ranking optimal grey wolf has two partial, one male and one female, which is responsible for decision-making and leading the whole wolf pack in the process of hunting and seeking for the best. Behaviors at each level need to be strictly subject to the leadership at the higher level, so as to carry out group optimization. Research shows that the grey wolf algorithm is obviously superior to the traditional evolutionary strategy, genetic algorithm, particle swarm optimization algorithm and other intelligent algorithms in global optimization (Xu and Ding, 2017).

Therefore, GWO is selected in this paper to optimize the weights and thresholds of BP neural network. The main mathematical model of the algorithm is described below.

Step 1: Surround. The first step of grey wolf hunting is to lock the target and surround. Its mathematical formulas are as follows:

$$D = |C \cdot X_p(t) - X(t)| \quad (3)$$

$$X(t+1) = X_p(t) - A \cdot D \quad (4)$$

where, t is the current iteration number; $X_p(t)$ is the location of prey of the current t generation; $X(t)$ represents the current

position of t generation grey wolf individuals; both A and C are vector coefficients, whose specific values can be obtained from the formulas (Mirjalili et al., 2014):

$$A = 2a \cdot r_1 - a \quad (5)$$

$$C = 2 \cdot r_2 \quad (6)$$

In the above formulas, the value of a decreases linearly from 2 to 0 as the number of iterations increases, while r_1 and r_2 are random vectors in the interval of $[0, 1]$.

Step 2: Hunt. After the encirclement, the wolf will be guided by the optimal grey wolf, the sub-optimal grey wolf, and the third superior grey wolf for position updating, and the mathematical model is as follow:

$$D_\alpha = |C_1 \cdot X_\alpha| \quad (7)$$

$$D_\beta = |C_2 \cdot X_\beta| \quad (8)$$

$$D_\delta = |C_1 \cdot X_\delta| \quad (9)$$

$$X_1 = X_\alpha - A_1(D_\alpha) \quad (10)$$

$$X_2 = X_\beta - A_2(D_\beta) \quad (11)$$

$$X_3 = X_\delta - A_3(D_\delta) \quad (12)$$

$$X_{(t+1)} = \frac{X_1 + X_2 + X_3}{3} \quad (13)$$

In the above formulas, $X_{(t+1)}$ is the updated position of grey wolf individual (namely the optimal solution vector).

Step 3: Attack. The last step of grey wolf optimization is to capture the target, that is, to obtain the optimal solution. The optimal solution is obtained mainly by decreasing the value of a , and the wolf will realize the attack on the prey when the value of A gets any value in the interval of $[-2a, 2a]$ and $|A| \leq 1$ (Kutaiba et al., 2018).

2.3. GWO-BP algorithm for fuzzy C-means clustering optimization

GWO-BP with fuzzy C-means clustering optimization is a group intelligence algorithm which can obtain the global optimal solution while selecting the mode, and can improve the convergence speed and precision. The core of GWO-BP algorithm is to take the weight and threshold of BP neural network as the grey wolf location information $X(t)$, and updating the location is equal to updating the weight and threshold of BP neural network, so as to find the global optimal.

Considering the timeliness and interference of building energy consumption, this paper firstly conducts sample identification through data clustering, and then established BP neural network prediction model for different types of samples. In order to avoid trapping in local optimum, the back propagation algorithms are finally modified by grey wolf optimization algorithm. The structure diagram of the composite prediction model is shown in Fig. 1. The BP model assigns the weighting matrix and threshold of hidden layer neurons between the input layer and hidden layer by random, which containing a large number of variable parameters and the parameter variables are difficult to control and the result is not stable. The GWO algorithm has the advantages of less parameters and stronger global search ability. After introducing grey wolf optimization algorithm, punishment factor and kernel parameters of BP neural network can be dynamic optimized because the GWO-BP algorithm can effectively extract the optimum matrix connection weights and threshold in order to achieve a better and relatively stable prediction effect. The GWO bionic algorithm mimics wolf predation and solves similar dynamic non-numerical optimization problems.

3. Case analysis

3.1. Introduction to office buildings

The data used is from a comprehensive office building in Xi'an. The office building has 44 floors above ground and 3 underground floors, with a total construction area of 300 000 m² (including 300 000 m² air conditioning heating area). The building is a concrete shear wall structure with solid clay bricks for the external walls. The glass is low-E, which is the energy saving and environmental protection new-type. The shape coefficient of the whole office complex is 0.8. Units in the office building have irregular working hours on weekdays and weekends, and irregular overtime work on weekdays and weekends. Therefore, typical sample modeling cannot be carried out simply according to the regular work schedule in the modeling process, and clustering method should be adopted to improve the accuracy of the model.

The office building in this paper has been put into use for a long time. At the same time, the building is equipped with an energy consumption monitoring platform and the system operates normally, which can realize real-time data collection of outdoor temperature and humidity, air conditioning supply and return water temperature, flow rate and energy consumption. It can ensure the reliability and authenticity of data. Fig. 2 shows the annual energy consumption of lighting socket, air conditioner, power and special power in office buildings. It can be known that lighting socket accounts for the largest proportion of electricity consumption, and the energy consumption of the other three items is basically flat. This is mainly due to the Clause 6.4.3 GB50189-2015 requires public buildings should be in accordance with the item of lighting, air conditioning, electric power, special power socket for power monitoring and measurement. And if the end of the air conditioning system separate metering electricity, air conditioning system at the end of electricity shall be calculated in the lighting and socket items, including 220 V fan, indoor air terminal (fan coil units, VAV, and so on), as well as split air conditioning, etc.

3.2. Construct the sample set

3.2.1. Selection of input and output parameters

In the first step of predictive modeling, relevant data should be obtained, and the input and output data involved in modeling should be preprocessed to obtain an accurate and applicable sample set (Hosseini, 2014).

In view of the non-linear complexity of building energy consumption system, the main factors affecting power consumption are generally divided into four major characteristics: equipment, personnel, weather and building, including building structure and materials, personnel density, temperature, humidity and so on (Fumo, 2014).

The output parameters of the model are selected from the actual operation data of an office building in Xi'an for a whole year. General component is the power of office building lighting socket electricity, air conditioning, power electricity utilization and special, at the same time each category has different characteristics and the corresponding significantly influence factors. Considering the office building has the characteristic of strong regularity, the input parameters of the model are comprehensively evaluated, and the input parameters are finally selected as follows on the basis of literature research (Erkoreka et al., 2016; Chen and Lee, 2019; Kim et al., 2019b):

- (1) Outdoor meteorological parameters: outdoor daily average temperature T ; daily average moisture content W ; daily average relative humidity RH ; total solar radiation R .
- (2) Historical energy consumption data: previous daily energy consumption Q_{t-1} ; energy consumption on the same day of the

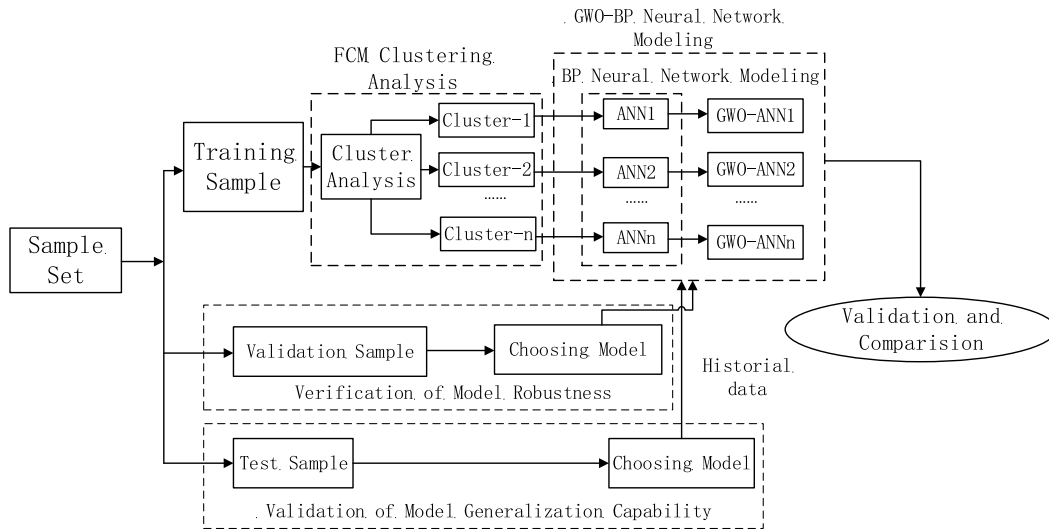


Fig. 1. Structure of composite prediction model.

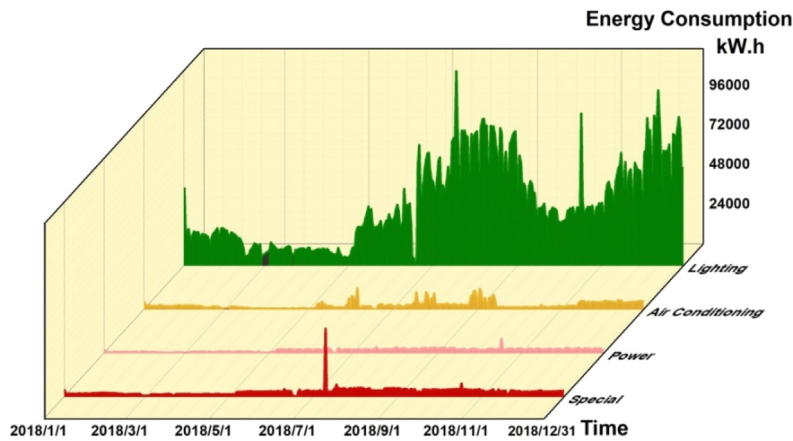


Fig. 2. Office building power consumption variation.

previous week Q_{w-1} ; energy consumption of the same day and month in the previous month Q_{m-1} .
 (3) Working day: setting the data as 1 if it is the working day; otherwise setting the data as 0.

3.2.2. Input parameter standardization

As the input data has many categories and different dimensions, it greatly affects the calculation efficiency. Therefore, this paper first normalized the input data, as shown in the following equations:

$$T = \frac{T - T_{min}}{T_{max} - T_{min}} \tag{14}$$

$$W = \frac{W - W_{min}}{W_{max} - W_{min}} \tag{15}$$

$$RH = \frac{RH - RH_{min}}{RH_{max} - RH_{min}} \tag{16}$$

$$R = \frac{R - R_{min}}{R_{max} - R_{min}} \tag{17}$$

In formulas (14)~(17), T_{min} and T_{max} respectively sample of minimum and maximum outdoor air temperature, °C; W_{min} and W_{max} are the minimum and maximum moisture contents of air in the sample respectively, g/kg dry air. RH_{min} and RH_{max} are respective the minimum and maximum values of average relative humidity in the sample, m/s; R_{min} and R_{max} sample the minimum

and maximum of solar radiation, MJ/m². The power consumption and outdoor meteorological parameters can be seen in Fig. 3.

3.3. Consumption prediction for building

3.3.1. Sample data selection

The collected data were preprocessed according to the steps in 3.2.2, and the continuous power consumption records from January to December 2018 (365 records in total) were obtained as sample data.

To improve the robustness of the model, $N_1 = 110$ groups of data were randomly selected as prediction samples, and the remaining $N_2 = 255$ groups were selected as training samples. At the same time, 59 sets of data in January (31 days) and February (28 days) of 2019 were selected for modeling prediction to verify the generalization ability of the model.

In Fig. 3, four seasons were selected to compare the amount of electricity data. On the one hand, it shows that the office building power consumption is larger irregularity. July and October electricity consumption is relatively larger, and it mainly because of cold and heat variability. The office building power consumption is relatively low in January because the building has just been put into using, and some idle office units did not begin to work.

On the other hand, in the input parameters of this office building, the dry-bulb temperature presents a great regularity, with

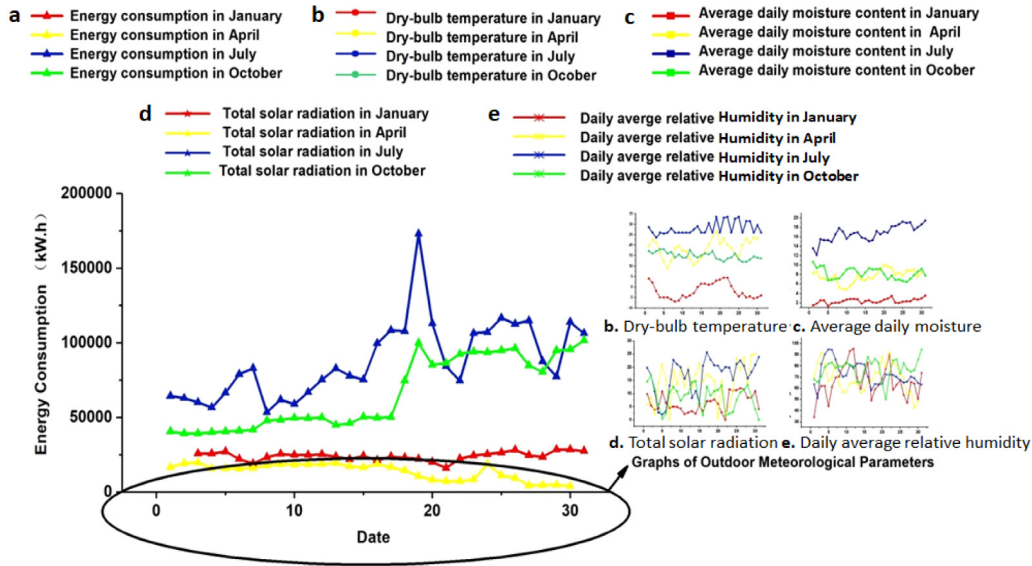


Fig. 3. Power consumption and outdoor meteorological parameters in January, April, July and October 2018.

the highest in July, the lowest in January, and the temperature fluctuation range of April and October are similar.

The average daily moisture content also showed great regularity and was the highest in July, the lowest in January, and fluctuated within the same range in April and October. In comparison, the total solar radiation and relative humidity show greater irregularity. Traditional energy consumption prediction methods fail to combine these physical meaning in practice, resulting in low accuracy and great influence by outliers in power prediction. Therefore, this paper proposes to use FCM-GWO-BP model combined with physical meaning analysis to optimize it, so as to improve prediction accuracy and generalization performance.

3.3.2. Actual modeling

Based on the analysis in the second section, this experiment adopted the three-layer BP neural network structure.

Taking the energy consumption of a lighting socket as an example, FCM clustering algorithm was used to cluster the training samples. From its physical interpretation, the parameters $\varepsilon = 0.000001$, $t_{\max} = 200$, $m = 4$. With reference to 2.1, c was set as 2 to $\sqrt{N_2}$. The results of multiple times of clustering are shown in Fig. 4. It can be seen that clustering it into four categories has the most ideal effect.

At the same time, the information entropy (Kikuta and Takahashi, 2016) of the clustering results is calculated for verification, and the results are shown in Fig. 5, so as to verify the results of multiple clustering.

After clustering into four categories, BP neural network models (ANN_1 , ANN_2 , ANN_3 , ANN_4) were established for four training samples (class A, class B, class C and class D), and all the unclustered sample groups were taken to establish BP neural network model (ANN_0). The number of neurons in the input layer of the neural network is 8; the hidden layer is 17; the output layer is 1; and the training function of the hidden layer is Sigmoid function. The output layer function is a linear function; the training times are 1000; the learning rate is 0.01; and the training target is $1.00E-08$. Forecast 59 set of clustering samples, and determine the type of its offspring into corresponding $ANN_1/ANN_2/ANN_3/ANN_4$ model to forecast, and then get the clustering of predicted $\hat{y}(i)$. As control group, the sample under test into ANN_0 get load forecast $\hat{y}(0)$. The RMSPE values of the corresponding model and the ANN_0 model are compared.

After the system is grouped into 4 categories, a total of 8 groups of input parameters can be obtained. Aiming at the problem that BP neural network is easy to get stuck at locally optimal value, the parameters are optimized by referring to the steps in part 2. The grey wolf optimization algorithm was used to test the samples, and RMSPE values of the $ANN_{i\#}$ model were obtained.

4. Result analysis

4.1. Determination of performance evaluation indexes

Finally, the fitting results are evaluated and verified. Common prediction model error evaluation indexes are:

Δ - absolute error:

$$\Delta = \hat{y}(i) - y(i) \quad (18)$$

δ - relative error:

$$\delta = \frac{\Delta}{y(i)} \times 100\% \quad (19)$$

MAPE- mean absolute percentage error:

$$MAPE = \frac{\sum_{i=0}^N \frac{|y(i) - \hat{y}(i)|}{y(i)}}{N} \times 100\% \quad (20)$$

RMSPE- root mean square percentage error:

$$RMSPE = \frac{\sqrt{\frac{1}{N} \sum_{i=0}^N (y(i) - \hat{y}(i))^2}}{\bar{y}} \quad (21)$$

where N represents the number of samples to be predicted; \bar{y} is sample mean; $y(i)$ and $\hat{y}(i)$ present the real value and the predicted value of the i sample respectively. During the convenience period, the normalized dimensionless value is adopted for power consumption. The prediction accuracy is inversely proportional to the above values.

4.2. Evaluation and verification of the model

4.2.1. Robustness verification of the model

After the prediction model was run for 8 times, it can be seen from Table 1 that after using FCM clustering the average RMSPE of the GWO-BP neural network prediction was reduced by 0.225 compared with the BP model, and was reduced by about 0.135

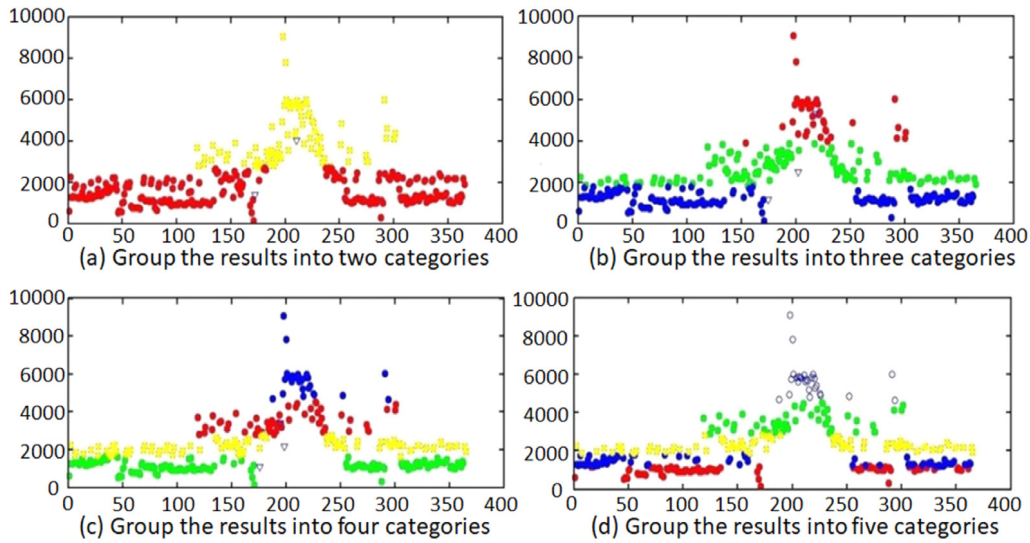


Fig. 4. MATLAB conducted multiple FCM tests.

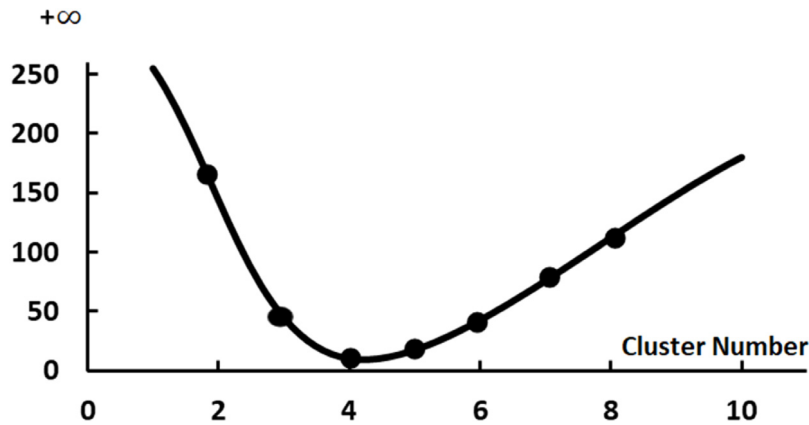


Fig. 5. The change trend of information entropy with the clustering number.

Table 1
Comparison of RMSPE of each model.

	RMSPE ₀	RMSPE _i	RMSPE _{i*}
Training set	0.298	0.208	0.073
Testing set	0.213	0.183	0.141

compared with the pure GWO-BP model. The result indicating that the prediction accuracy of the neural network after clustering was significantly improved, with a maximum increase of 75%. The reason for this is that the neural network interference after clustering is less and more targeted. The RMSPE values of ANN₀, ANN_i and ANN_{i*} were calculated according to the steps in the second section, as shown in Table 1. The calculation results of RMSPE in both test set and training set were better than GWO-BP and better than BP model.

4.2.2. Model generalization verification

A total of 59 groups of data in January (31 days) and February (28 days) of 2019 were substituted for modeling and prediction. The modeling and prediction were carried out according to the steps in Section 2. The results are shown in Fig. 6.

Fig. 6 is calculated to predict the error Δ, as shown, the absolute error of BP model in January of 2019 comes to 1293 kW h; GWO-BP comes absolute error is up to 764 kW h. The GWO-BP optimized by fuzzy C-means clustering algorithm is the minimum

absolute error, and is only 509 kW h. In January 2019, the RMSPE of FCM-GWO-BP model reached 5.04%, and the model optimized with parameters reduced by 14.13% and 7.22% respectively. In February 2019, the RMSPE of FCM-GWO-BP model reached 5.45%, which was 12.17% lower than that of the model without clustering, and 8.15% lower than that of the model without grey wolf algorithm for parameter optimization.

The reason for the increasing in accuracy is that different working data can improve the generalization ability of the model. The more different working days, the more precise model selection, the performance of the algorithm will be stronger. It is worth noting that optimization GWO-BP algorithm belongs to the building energy consumption prediction method of data driven.

The actual new building has to be put into use for a while, and we have to get the run data of the building over a period of time firstly. Then, we can use the algorithm to forecast for on-line optimization by computer, in order to guide the real energy scheduling.

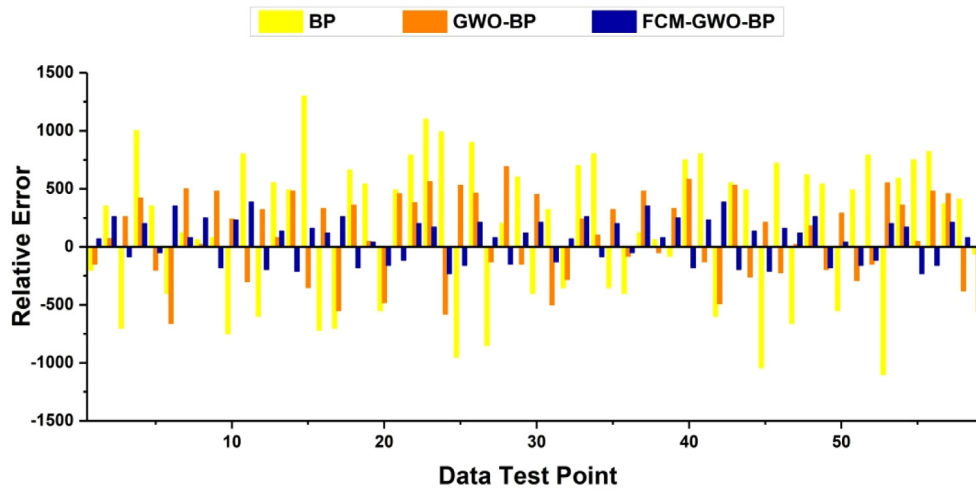
To determine the cluster number of c for building cluster processing, the cluster number shall be determined according to the clustering formula in FCM. The data characteristics of buildings are different, and the number of cluster c is inconsistent. However, according to formula (2), the optimal number of clusters can be calculated through historical data.

In the case study, the average value was calculated after 8 operations, and the MAPE results were shown in Table 2. It can

Table 2

FCM-GWO-BP prediction method was compared with MAPE.

Time	Actual value/kW h	Prediction/kW h (Average)					
		BP model		GWO-BP model		FCM-GWO-BP model	
		Prediction	MAPE (%)	Prediction	MAPE (%)	Prediction	MAPE (%)
January	94815.4	76449.7	19.37	82906.6	12.56	89372.9	5.74
February	74803.3	59737.9	20.14	66500.2	11.10	71100.6	4.95
Average	84809.4	68093.8	19.76	74703.4	11.83	80236.8	5.35

**Fig. 6.** Histogram of absolute error between the predicted values of the two models and the actual values of building electricity consumption.

be seen that the MAPE in February 2019 was as low as 4.95%, which was 6.42% lower than the GWO-BP model without fuzzy C-means clustering optimization and 15.19% lower than the simple BP model.

The results of mean absolute percentage error in January 2019 also show that fuzzy C-means clustering can greatly improve the accuracy of prediction. It can be concluded that the generalization of FCM-GWO-BP neural network method is better than that of GWO-BP and BP prediction method.

5. Conclusion

The construction of the new smart city is driven by data. The mining of collected data and information, and the prediction and diagnosis of building energy consumption are hot topics in the current smart city research. However, due to the increasing amount of energy consumption data and more complex types, an effective energy consumption forecasting model is urgently needed to guide energy consumption.

Aiming at this problem, the paper established a building power consumption prediction method based on FCM-GWO-BP, and studied the power consumption prediction of an office building in Xi'an, Shaanxi province. The main works contain:

(1) Compared with the traditional neural network prediction method, the FCM clustering method is used to carry out unsupervised learning division of the training data set, and the classification prediction model is established for different building energy consumption samples to eliminate the noise in the sample data. The model results show that compared with the pure model, the prediction accuracy is improved by 75%, and the influence of correlation on the prediction performance of the model is reduced.

(2) GWO algorithm is adopted to optimize the parameters of BP neural network to avoid the blindness of parameter selection. The prediction effect of the optimal model constructed based on the sample data of FCM clustering analysis and GWO optimization

parameters is better than that of BP and GWO-BP models. The MAPE of the model is reduced by 14.41% and 6.48% by using the test monthly data set (January and February 2019), which proves that the model has enhanced generalization ability and obtained better prediction accuracy and reliability.

Faced with smart city, the improved GWO-BP modeling was proposed in this paper to analyze and predict the energy consumption of buildings. The novel way can improve the accuracy of prediction, so it is convenient to realize the advance dispatching of power system, and reduce the energy waste in the process of power transmission, and lay a foundation for the construction of self-regulating smart cities.

Declaration of competing interest

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

CRedit authorship contribution statement

Tian Ying: Data curation, Writing - original draft preparation. **Yu Junqi:** Supervision. **Zhao Anjun:** Software, Validation.

Foundation item:

Key Technologies and Demonstration of Green Building Energy Consumption Management Analysis Platform Based on Big Data (2017ZDL-SF-16-5); New Generation Intelligent Building Platform Techniques (2017YFC0704100); Research on Building Energy Intelligent Supervision System for Smart Cities (17JF015).

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