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Prediction of Energy Demand of Customer Microgrid Based on Multi-Level Fuzzy Evaluation Model

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Abstract. In order to improve the accuracy of customer microgrid energy demand forecasting, this paper conducts an in-depth study on the prediction of customer microgrid energy demand based on a multi-level fuzzy evaluation model. Firstly, a multi-level fuzzy evaluation index system was constructed, the multi-level fuzzy evaluation indicators were clarified, and the correlation characteristics, interactive characteristics and data dimension characteristics of customer energy consumption data were analyzed. Then, according to the principle of multi-level fuzzy evaluation method, the factor set and the evaluation set are clarified, and the multi-level fuzzy relationship is induced by the multi-level fuzzy mapping, the fuzzy matrix is obtained, and the identification parameters are processed to complete the prediction of the customer's microgrid energy demand. The simulation results show that the overall prediction accuracy of the proposed model is high, the prediction time is short, and the practicability is strong.

Key words. Multi-level Fuzzy Evaluation Model, Micro-grids, Energy Demand, Prediction

1. Introduction

In recent years, the rapid development of various fields in China has promoted China's economic development at the same time, but also caused the use of energy resources to gradually tighten, therefore, China put forward energy conservation and environmental protection policies [1], hoping to fundamentally solve the problem of energy waste, and the main core of energy waste is that demand and supply are equal, rather than supply is greater than demand. Grid power is the main energy source in the current public life and work [2], and the energy demand forecast of customer microgrids is the main part of maintaining the high-quality development of the power grid. With the rapid development of science and technology, intelligent technology and information technology are widely used in the power grid industry, and the management of microgrids is gradually refined, and the accurate and long-term prediction of microgrid energy demand is very important for the fine management of microgrids [3]. With the development of intelligence and informatization of the power grid system, the power grid management has gradually changed to the horizontal interconnection mode, predicting the energy demand of the customer's microgrid, and focusing on the balance of supply and demand of the microgrid, providing a basis for the energy consumption and energy supply of the power grid system. Therefore, this paper conducts in-depth research on the energy demand forecasting of customer microgrids to achieve the purpose of energy demand forecasting [4].

2. Related Work

At present, many relevant experts and scholars have conducted research on the energy demand prediction of customer microgrids, and put forward some research results. An energy demand forecasting model of a customer microgrid based on a neural network is proposed, and the energy demand of the customer microgrid is analyzed through neural network [5], so as to obtain an effective microgrid energy demand prediction model, and the relevant data of the demand forecast sample are collected according to the acquisition method of customer energy consumption data, and the relevant data obtained are normalized to extract the effective customer energy demand data source. Experimental results show that the neural network-based customer microgrid energy demand forecasting model can effectively reduce the energy demand forecasting time, but does not improve the accuracy of microgrid energy demand forecasting. In order to improve the accuracy of customer microgrid energy demand forecasting, the advantages of neural network and grey prediction method are analyzed, and then the gray neural network customer microgrid energy demand forecasting method is proposed. After the grey model and the neural network are used to predict the energy demand, the rough set theory is given, the weighting coefficient is clarified, and finally the prediction value is obtained by combining the energy demand forecasting results [6]. Experimental results show that the proposed method has certain feasibility and can effectively improve the accuracy of the energy demand prediction of customers' microgrids, but the method has the problem that the overall process is relatively complex. An optimization algorithm based on parallelized parameters was proposed to improve the training efficiency of the prediction model. A parallel algorithm of genetic algorithm and particle swarm optimization is proposed to optimize the combinatorial vector machine. The correlation vector is used to predict the energy demand of the microgrid [7], the evaluation parameters of the energy demand forecast of the microgrid are calculated through the demand forecasting results, the evaluation parameters are input into the evaluation model, the weight coefficient of the energy demand prediction index of the microgrid is clarified by the entropy method, and the data are verified by a simulation experiment, and the experimental results show that the method has good scalability compared with the single method, but the accuracy of the overall microgrid energy demand prediction is low [8].

3. Forecast and Analysis of Energy Demand of Customer Microgrid

A. Construct a Multi-level Fuzzy Evaluation Index System

The relative ratio method is used to measure each evaluation index through the standard value, and the actual index value is compared with the standard value to obtain the individual index of the index value, and the weighted average of the individual index is used to obtain the comprehensive evaluation index [9].

At the same time, the higher the value of the positive index, the better, the lower the value of the inverse index, the better, the index value in the evaluation index system is expressed, and the standard value is expressed, and the treatment formula of the positive index and the inverse index can be obtained as shown in equation (1) and equation (2):

$$H_t = Y_i / Y_m \tag{1}$$

Standardized processing of user demand data, as shown in Formula (2).

$$H_t^{'} = \frac{Y_m}{Y_i} \tag{2}$$

The arithmetic mean method is used to obtain the index of the comprehensive evaluation of multi-level fuzzy evaluation index, which is expressed as follows:

$$I = \sum H_t \cdot Z_i \tag{3}$$

In equation (3), the weights Z_i of the evaluation indicators set in the rating index system are described.

B. Forecast and Analysis of Energy Demand of Microgrids

Although the amount of energy consumption data of the customer's microgrid is relatively large, and the ways of data generation are also different, there is a correlation between each data, and the state of the data is called complex association, and there are two forms of data association, which are weak correlation and strong association. Analyze the characteristics of any effective customer microgrid energy consumption data, and analyze them in turn according to the degree of relevance of the data, so as to lay a good foundation for the calculation of the customer energy demand forecasting model [10].

Data interactivity specifically refers to the interaction behavior between effective customer energy consumption data, and the different transmission methods that can make the data more closely related and helpful in tracking customer energy consumption data in the future.

The business value of data mainly refers to the total energy demand of customers in the relative cycle, part of which is used in the business field, through the analysis of the state of business development, and the trend of customer energy demand can be comprehensively analyzed [11].

The higher the level of the data dimension, the greater the amount of information hidden in the data information, and the data dimension feature can provide prediction data for the energy demand forecasting model, but it will also increase the amount of computation of the energy demand model.

The authenticity of customer energy demand data plays a decisive role in the accuracy of energy demand forecasting models, so the way to obtain customer energy demand data is particularly important. In this paper, the data collection of energy demand of the customer's microgrid is mainly carried out by means of intelligent device detection, system operation data and customer service data [12].

4. Prediction of Energy Demand of Customer Microgrid Based on Multi-level Fuzzy Evaluation Model

A. The Basic Principle of Multi-level Fuzzy Evaluation Method

For the prediction of the energy demand of the customer's microgrid, it is necessary to use the multi-level fuzzy evaluation method, and the qualitative evaluation is used as a quantitative evaluation according to the membership theory of fuzzy mathematics to analyze the energy demand forecast of the customer's microgrid.

Designing a customer's microgrid energy demand forecasting model can be roughly divided into the following steps:
Step 1: Factor set $Q=\left(q_1,q_2,q_3,\cdots,q_n\right)$;
Step 2: Judge the set $W=\left(w_1,w_2,w_3,\cdots,w_n\right)$;
Step 3: One-factor judging $f:Q\to\phi(W)$;

Multi-level fuzzy mapping can induce multi-level fuzzy relations $E_f\in\phi(Q*W)$, which can also be expressed as:

$$E_f=\left(q_i,w_i\right)=f\left(q_i\right)\left(w_i\right)=r_{ij} \tag{4}$$

According to the above multi-level fuzzy relationship equation (4), the multi-level fuzzy matrix is expressed as:

$$E=\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{22} & \cdots & a_{2m} \\ \ldots & \cdots & \ldots.. & \ldots & \cdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nm} \end{bmatrix} \tag{5}$$

In equation (5), the E evaluation matrix representing a multi-level fuzzy single factor is a fuzzy comprehensive decision-making model composed of fuzzy relations.

Step 4: The weights are evaluated and calculated according to the evaluation model of multi-level fuzzy mathematics, so as to obtain the total evaluation results of the customer's microgrid energy demand. According to the maximum degree of membership, the degree of impact of the comprehensive evaluation results on the energy demand of the customer's microgrid is clarified.

B. *Construction of Multi-level Fuzzy Evaluation Model*

The relationship between the energy demand and the influencing factors of the customer microgrid is complex, and the relationship between the energy demand and the influencing factors is described by the prediction model of the energy demand of the customer microgrid. The influencing factor indicators are clarified, and the influencing factor indicators are used as data samples to construct a multi-input support vector regression prediction model for customer microgrid energy demand forecasting.

The multi-level fuzzy evaluation standard is used to predict the energy demand, and the influencing factors of the input are assumed to be multi-level fuzzy mapping to the high-dimensional feature space $r_1,r_2,\cdots,r_d\lambda\left(r_1\right),\lambda\left(r_2\right),\cdots,\lambda\left(r_2\right)$. The criterion of multi-level fuzzy evaluation can be clarified, and the nonlinear model can be transformed into a regression model with linear feature space, as shown in equation (6).

$$g\left(r_j\right)=\chi^T\lambda\left(r_j\right)+a \tag{6}$$

In equation (6), the identification parameters that need to be processed are obtained by combining χa equation (5) with equation (6) with the identification parameters of the energy demand forecasting model representing the customer's microgrid.

$$T|g|=\sum_{E}^{i=1}z\left(e_i\right)+\chi \tag{7}$$

In equation (7), the empirical risk value of the prediction model is represented, the loss function of the prediction model is described, and the confidence risk of the prediction model is described $T|g|z\left(e_i\right)\chi$.

In order to facilitate the solution of the multi-level fuzzy evaluation model, the above formula is transformed into a duality problem, and the nonlinear function is obtained. The parameters corresponding to the support vector machine, the set of input data vectors and output vectors are taken as the main parameters of the multi-level fuzzy evaluation model, and the energy demand prediction model of the customer's microgrid can be obtained.

C. *Implementation of the Customer's Microgrid Energy Demand Forecasting Model*

The implementation process of the customer's microgrid energy demand forecasting model is shown in Figure 1.

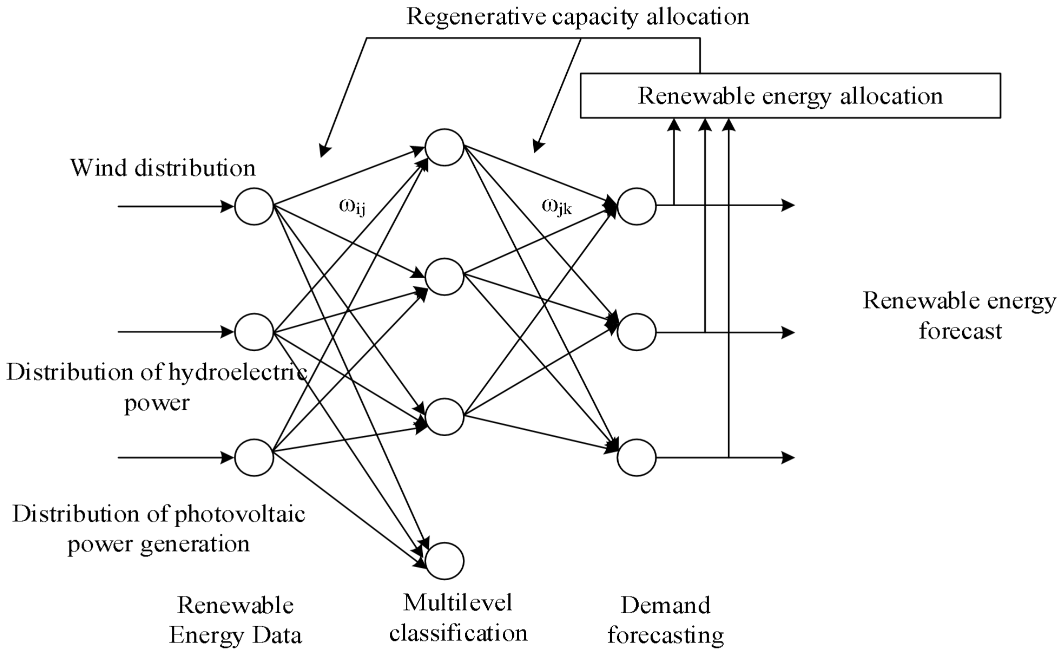

Figure 1. Forecasting Process for User Microgrid Demand

Detailed implementation steps:

The training sample set of the customer's microgrid energy demand data is analyzed, and the membership function is clarified by the multi-level fuzzy evaluation method;

The membership function converts the training samples of the given customer microgrid energy demand data into a multi-level fuzzy dataset;

construct a multi-set fuzzy vector energy demand prediction model;

Output the final forecast value of the customer's microgrid energy demand.

5. Experimental Results

In order to verify the effectiveness of the multi-level fuzzy prediction of customer microgrid energy demand proposed in this paper, the customer microgrid of a development zone in a city was selected as the research object, and the simulation experiment was carried out in the Matlab simulation environment, and the short-term, medium- and long-term customer energy demand of the region was predicted by combining the evaluation indicators of a development zone in a city and a development zone. Figure 2 illustrates the operation process of the customer's microgrid energy demand forecasting experiment.

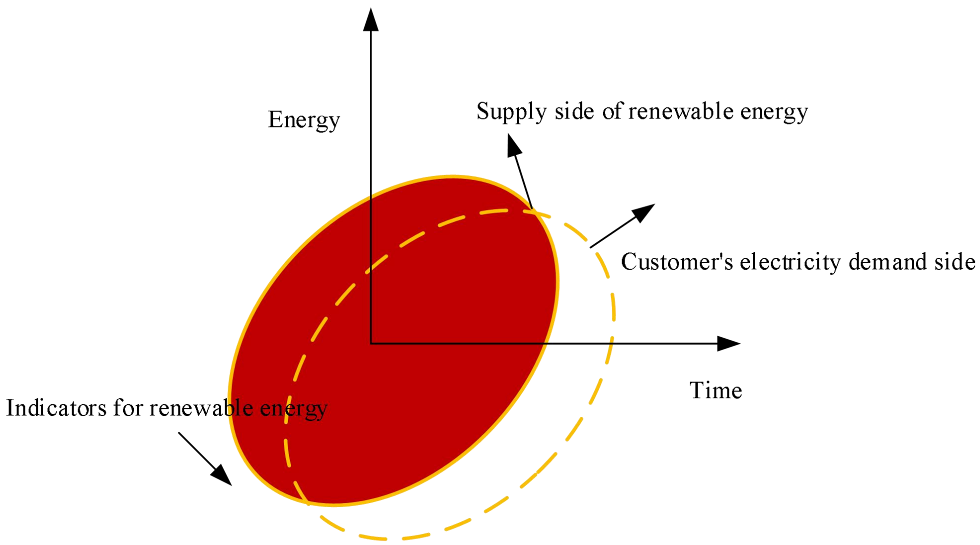

Figure 2. The Energy Demand Forecasting of Customer Microgrid

In order to verify the comprehensive performance of the prediction of the proposed model, the multi-level fuzzy evaluation model proposed in this paper is used for short-term prediction with neural network and gray evaluation model, due to a large amount of data, this paper only focuses on the energy consumption data in the first five hours of October 7, and the comparison results are shown in Table 1.

Table 1. Comparison of Short-term Energy Demand Forecasting Accuracy of Customer Microgrids of Different Models

MOMENT	MULTI-LEVEL FUZZY EVALUATION MODEL/%.	NEURAL NETWORK MODEL/%.	GREY EVALUATION MODEL/%
1:00	99.23	98.13	91.01
2:00	99.15	98.24	90.35
3:00	99.34	98.03	89.32
4:00	99.43	98.46	90.35
5:00	99.28	98.09	89.75

It can be seen from Table 1 that the prediction model proposed in this paper effectively predicts the energy demand of the customer's microgrid, and the five-hour prediction accuracy has been stable at more than 99%, while the other two prediction models can also predict the energy demand of the customer's microgrid, but the overall prediction accuracy remains at about 89%~98%, and the prediction accuracy of the multi-level fuzzy evaluation model proposed in this paper is better than that of the other two prediction models, which shows that the prediction model proposed in this paper can accurately predict the short-term energy demand of the customer's microgrid.

In order to show the prediction performance of the multi-level fuzzy evaluation proposed in this paper, Figure 3 shows the comparison results of the proposed model with the neural network model and the gray evaluation model.

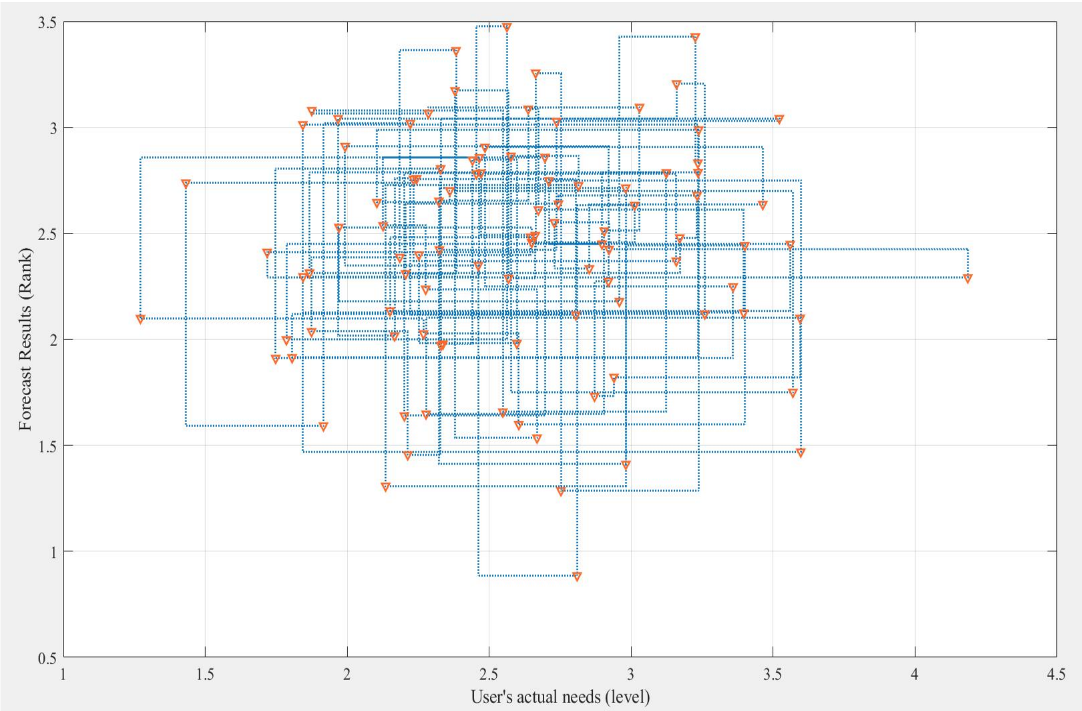

Figure 3. Forecasting Results of Long-term Customer Energy Demand in Different Models

The accuracy of the energy demand forecasting of different forecasting models is analyzed by comparing the energy demand forecast of the region from October 7 to 11, 2018 with the actual energy consumption from October 7 to 11, 2018, and the analysis results are shown in Figure 4.

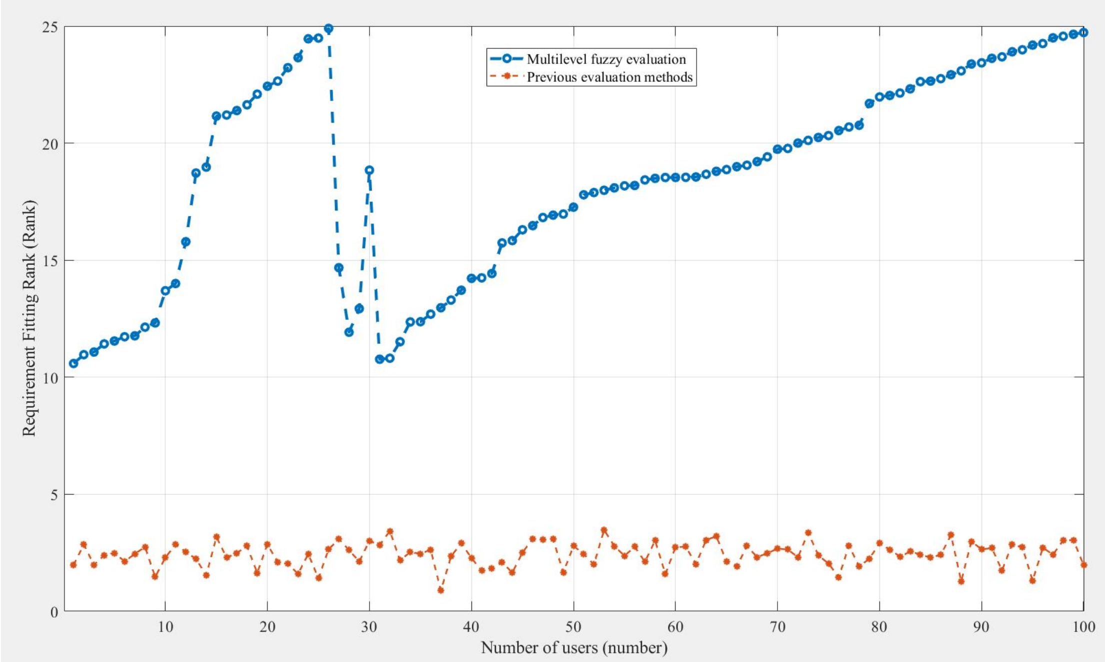

Figure 4. Comparison of the Accuracy of Long-term Customer Energy Demand Forecasting in Different Models

The analysis of Figures 3 and Figure 4 shows that the accuracy of the multi-level fuzzy evaluation model proposed in this paper is higher than 99% in predicting the energy demand of customer microgrids in the region, while the accuracy of the other two models is significantly lower than that of the multi-level fuzzy evaluation prediction model proposed in this paper.

In order to test the comprehensive performance of the proposed model in predicting long-term energy demand, the multi-level fuzzy evaluation model proposed in this paper is used to predict the energy demand of customer microgrids in the region from January to May 2018, and the prediction results of the proposed model are compared with the actual energy consumption, and Table 2 shows the comparison of the long-term prediction results of the proposed model with the other two prediction models.

Table 2. Comparison of the Energy Demand Forecasting Results of Long-term Customer Microgrids of Different Models

MONTH	MULTI-LEVEL FUZZY RATING MODEL		NEURAL NETWORK MODEL		GREY EVALUATION MODEL	
	Forecast results/kW.h	Prediction error/%	Forecast results/kW.h	Prediction error/%	Forecast results/kW.h	Prediction error/%
January	13523.60	99.03	13305.29	96.21	13254.80	95.32
February	14511.63	99.12	14103.98	95.35	14249.90	95.13
March	13426.61	99.24	13553.94	93.21	13529.19	94.21
April	13640.21	99.35	13102.34	91.32	13315.69	95.32
May	12865.32	99.54	12740.09	93.14	12590.78	91.32

As can be seen from Table 2, the multi-level fuzzy evaluation model proposed in this paper can predict the long-term customer microgrid energy demand in the region from January to May 2018, and the prediction accuracy is maintained at more than 99%, although the prediction accuracy of the neural network model is better than that of the gray evaluation model, the prediction accuracy of the two models is lower than that of the model proposed in this paper, which shows that the model proposed in this paper can not only predict the energy demand of customer microgrids, but also effectively improve the prediction accuracy. Table 3 shows the comparison of the time forecast time of customer microgrid energy demand for the three models.

Table 3. Comparison of the Prediction Time of Microgrid Energy Demand of Customers in Different Models

NUMBER OF EXPERIMENTS/TIMES	FORECAST TIME/MIN		
	MULTI-LEVEL FUZZY EVALUATION MODEL	NEURAL NETWORK MODEL	GREY EVALUATION MODEL
1	3.11	5.31	8.56
2	3.09	6.62	8.96
3	3.15	7.92	8.54
4	3.23	6.63	8.67
5	3.43	7.98	8.88

It can be seen from Table 3 that the prediction time of the multi-level fuzzy rating model proposed in this paper is less than 4 minutes through five experiments, while the prediction time of the five experiments using the neural network model fluctuates greatly, fluctuating up and down within 5~7 minutes, and the prediction time of the energy demand using the gray evaluation model is more than 8 minutes.

6. Conclusion

The prediction of the energy demand of the customer microgrid is an important analysis of the energy demand analysis technology of the microgrid, and the accurate prediction and analysis of the energy demand is the main condition for maintaining the stable operation of the microgrid. Combined with the above-detailed analysis, the multi-level fuzzy evaluation model can meet the criteria of specifying energy demand forecasting, and the multi-level fuzzy evaluation model designed in this paper has higher prediction accuracy and faster prediction efficiency than the other two energy demand forecasting models, which is very suitable for application in actual production and life, and has important reference significance for microgrid prediction.

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