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A Scheme for Charging Load Prediction of EV Based on Fuzzy Theory

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Abstract. With the development of the electric vehicle industry, the increasing charging load of electric vehicles has brought enormous pressure to urban distribution networks, affecting their safety and efficiency. Therefore, the power system needs a better load forecasting model to predict the load value more accurately. Considering that traditional electric vehicle charging load prediction models still have many shortcomings, this article uses fuzzy theory to deal with uncertain influencing factors and combines fuzzy clustering method to analyze the charging habits of local residents. In order to make the power load prediction results more effective and reliable, this paper proposes a fuzzy neural network prediction model that takes into account user habits. The key influencing factors are fuzzy processed, and the fuzzy c-means clustering method is introduced for mining. The law of charging time for most car owners is analyzed. The superiority of the prediction model incorporating fuzzy theory was verified through comparative experiments. The accuracy of the final time-sharing prediction is above 90%.

Keywords. Load forecasting, fuzzy logic, neural network

1 Introduction

In recent years, with the continuous deterioration of the ecological environment, energy issues have become an urgent problem to be solved, in this context, the rapid rise of the development of electric vehicles, gradually replacing traditional fuel vehicles. In 2021, the production and sales of electric vehicles in China both exceeded 2million, and the output reached 1.148 million, a year-on-year increase of 43.7%; The sales volume reached 1.183 million units, a year-on-year increase of 59.5%. It is estimated that by 2025, China's electric vehicle market will exceed 5million vehicles/year, accounting for more than 30% of the global market share and more than 80% of new energy vehicles. The rising charging load of electric vehicles puts a burden on urban power grids. Large-scale electric vehicle charging will increase transformer losses, increase line losses, and

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cause the reliability of the system to decline. In addition, the charging behavior of EV users presents discontinuity and randomness in time and space, which brings uncertainty to load prediction. The prediction of electric vehicle charging load has become a research direction that attracts much attention.

Machine learning methods have become an important tool in EV charging load forecasting[1-4], Zhang,J.Et al. [5] used a combination of multi-channel convolutional neural network and temporal convolutional network to predict the load, making the prediction result more accurate. But machine learning methods are faced with overfitting, underfitting and other problems.

Therefore, Wang Hailing et al. [6] adopted Monte Carlo method for demand analysis to improve the accuracy of prediction, but Monte Carlo method also has problems such as result deviation and complicated calculation.

Another approach is to use fuzzy theory. The advantage of fuzzy theory is that it can deal with fuzzy and uncertain information effectively, In the case of small amount of data, using fuzzification can integrate uncertainty into the prediction model, so as to improve the accuracy of prediction. Kwang-HoKim et al. [7] used a fuzzy expert system to consider the effects of temperature and holidays on load and modify the load prediction results of artificial neural network. Jin Shichen [8] of Qingdao University entered temperature factors into the deep neural network model as inputs after fuzziness of membership function. However, the existing fuzzy theory prediction methods do not deal with the uncertainty factors well. In this paper, a new prediction method is proposed, which fuzzizes the key influencing factors. At the same time, the fuzzy clustering method is used to analyze the charging habits of users, and a neural network prediction model based on fuzzy theory is established to improve the accuracy of prediction.

2 Fuzzy-theory-based EV Charging Load Prediction Model

This section ascribes how to build a Fuzzy-Theory-based EV charging load prediction model.

A *Data pro-processing and fuzziness*

The prediction model needs to preprocess the original data before data input. In addition, because the data set has multiple dimensions, a normalization operation is required before load forecasting can be performed[9].In this paper, the method of maximum and minimum normalization is used for data normalization:

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where x is the original data, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the original data, respectively, and x_{scaled} is the normalized data value.

In this paper, The fuzzy theory is used to describe the factors that affect the charging load, such as temperature and humidity[10].

Fuzzy set is used to contain uncertain and fuzzy members. All members in the set have membership degree to represent the relationship between the member and the set.Triangular membership function is used to describe the degree to which a variable's value belongs to a fuzzy set. The expression of triangle membership function is:

$$f(x,a,b,c)=\begin{cases}0\ ,x<a\\ \dfrac{x-a}{b-a},a\le x<b\\ \dfrac{c-x}{c-b},b\le x<c\\ 0\ ,x\ge c\end{cases} \tag{2}$$

Where a,b,c represents the coordinates of triangle vertices in different intervals, a,c determines the feet of the triangle, and b determines the peaks of the triangle.

Temperature and humidity are selected as the environmental factors of EV charging load prediction, and they are fuzzy and brought into the neural network. Taking temperature data as an example, there is a membership degree for each temperature data corresponding to each temperature segment. Fig.1 shows the membership function distribution of temperature data.

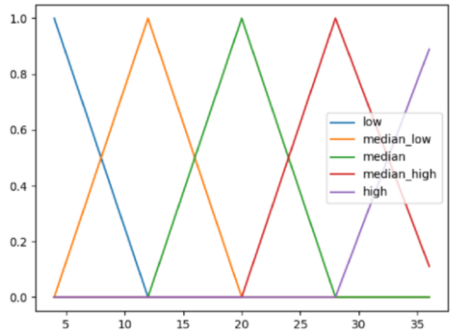

Fig.1 Temperature data belongs to degree function distribution

B *Fuzzy clustering method*

Clustering method can improve the learning efficiency and accuracy of the prediction model by placing similar points in the same class. In load prediction, clustering method can be used to analyze users' charging behaviors and habits. [11].

In this paper, the fuzzy C-value clustering method is used to divide the data set into several fuzzy subsets. Fuzzy C-means clustering is an iterative algorithm, its ultimate goal is to minimize the loss function:

$$J_m=\sum_{i=1}^{N}\sum_{j=1}^{C}u_{ji}{}^{m}\left\|x_i-c_j\right\|^2 \tag{3}$$

Where N represents the number of data points, C represents the number of cluster centers, $u_{ji}{}^{m}$ represents the i th data point pair and the j th cluster center, m is the ambiguity coefficient that controls the degree of ambiguity in the clustering process. The larger the m value, the more ambiguous the data division and the value of m is usually between 1.5 and 2.5. The smaller the loss function, the better the clustering effect.

The constraints of the fuzzy C-means algorithm are:

$$\sum_{i}^{N}\mu_{ij}=1,\ \ \mu_{ij}\in[0,1] \tag{4}$$

The detailed flow of the fuzzy C-means clustering algorithm is as follows:

(1) Initialization operation. Firstly, a cluster center vector $\vec{C}=[c_1,c_2,c_3,\cdots,c_j]$

and a membership function matrix U_{ij} are randomly initialized. The membership matrix dimension is $N \times C$, and the elements in the membership matrix are represented by μ_{ij}.

(2) Update membership function. Membership function update is based on the location of the current cluster center, for the i th data point, its membership function is:

$$\mu_{ij} = 1 \Bigg/ \sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_j - c_k \right\|} \right)^{\frac{2}{m-1}} \tag{5}$$

(3) Update the cluster center. The updated membership function matrix is used to recalculate the location of the cluster center, and the membership function value is used to represent the weight of each data point in the cluster.The clustering center update formula is as follows:

$$C_j = \sum_{i=1}^{N} \mu_{ij}{}^{m} \cdot x_i \Bigg/ \sum_{i=1}^{N} \mu_{ij}{}^{m} \tag{6}$$

(4) Determine whether the algorithm converges. If it does not, steps two and three are repeated until the algorithm converges.The termination condition of the fuzzy C-mean obtained from the above is:

$$max_{ij} \left| \mu_{ij}{}^{k+1} - \mu_{ij}{}^{k} \right| < \varepsilon \tag{7}$$

Where ε is the threshold of convergence, the termination condition requires that the change of every element is less than this threshold. To ensure the effectiveness of clustering, ε should be taken as a very small value.

Once convergence is reached, the algorithm terminates, and the final clustering center and membership function value represent the fuzzy clustering solution.Each point can be assigned to several clusters according to their membership function values. In short, the fuzzy c-means algorithm can optimize the clustering effect by adjusting the membership function matrix and clustering center for many times.

The quality of clustering results is the highest when the number of clusters is 2, which is determined by the fuzzy fraction coefficient method[12].Therefore, cluster analysis was carried out on the three data of load value, day and hour, and the cluster number was set to 2, representing the two categories of peak and trough respectively, and the clustering result as shown in the Fig.2 was finally obtained.

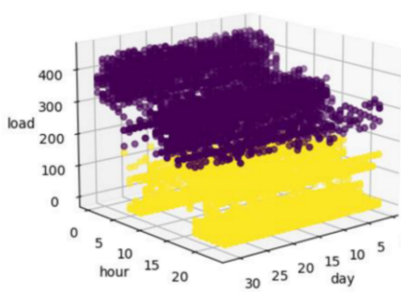

Fig.2 Clustering results

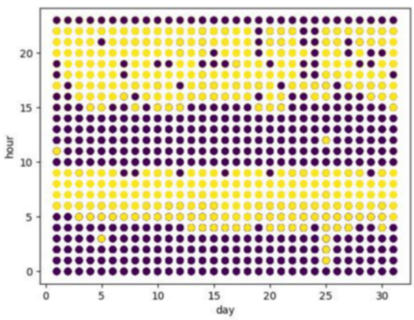

Fig.3 Day and hour clustering results

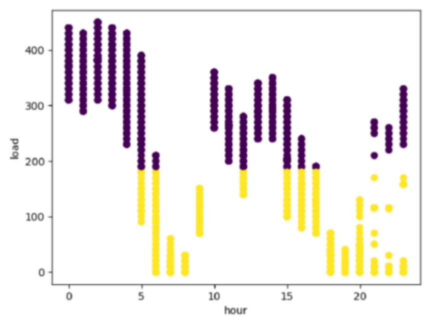

Fig.4 Hour and load clustering results

Fig.3 and Fig.4 show the clustering results from the two dimensions of day and hour and load value and hour respectively. It can be seen that on most days, 23~4 and 10~15 are the peak hours for charging. The duration of the peak period is about five hours.

C *Fuzzy neural network prediction model*

The fuzzy neural network model proposed in this paper is divided into two parts: fuzzy precursor network and conventional posterior network. The latter part network uses a regular network, which will not be introduced in detail here. The fuzzy precursor network introduces the fuzzy theory, which is divided into four parts, namely the input layer, the fuzzy layer, the fuzzy rule layer and the normalized output layer. The fuzzy precursor network structure is shown in Fig.5.

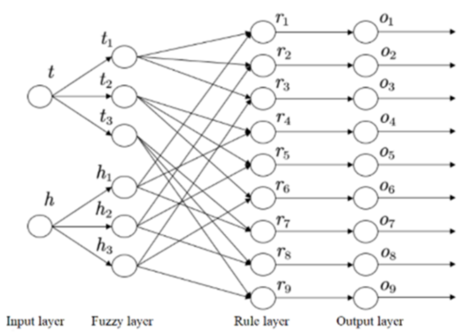

Fig.5 Fuzzy precursor network structure

The input dimension of the input layer is 2, which represents the clear value of temperature and humidity respectively.

The fuzzy layer is called the membership function layer. Each neuron in this layer represents the membership value of temperature or humidity to a certain degree.

The fuzzy rule layer is also called ‘and’ layer, which reflects the and feature in fuzzy reasoning and realizes the fusion of data membership to temperature and humidity.

The output layer of the last layer performs the normalization operation. The output of this layer is connected to the afterproduct network.

In the experiment of this topic, a fuzzy precursor network of 2×10×25×25 is used, the input is a two-dimensional clear value, and the output is 25 fuzzy rule conclusions. By connecting the fuzzy precursor network with the conventional posterior network, the final fuzzy neural network model will be built.

3 Experiment and Discussion

A *Network model construction*

According to the above analysis, the output dimension of the fuzzy precursor network is 25, and these data are used to represent the temperature and humidity status of the data. On this basis, the 28 dimensional data of month, day and hour are added as the input of the subsequent network model. Therefore, the input layer of the conventional consequent network needs 28 nodes, and the number of hidden layers and nodes of the conventional consequent network need to be selected according to the complexity of the problem.

The prediction of the fuzzy neural network can be divided into the following steps:

(1) Clear value blurring.Fuzzy set is designed and membership function is defined.

(2) Fuzzy reasoning. The fuzzy rule base is determined, the nodes of the fuzzy predecessor network rule layer are generated, and the operations required by the rule layer are designed.

(3) The fuzzy precursor network of 2×10×25×25 is constructed, and the input is month, day, and hour, so the input layer of posterior network requires 28 nodes.

(4) Network training. The goal of neural network training is to minimize the loss function and test the trained network using test sets.

This paper uses the charging load data of an EV charging pile in Dongguan, Guangdong Province from September 2020 to August 2021 as the data set. Using the data of day, hour, temperature, humidity and power load at the first 24 points as input, several neural network prediction models were built, The ratio of training set to test set is 8:2.The prediction performance was compared.Root mean square error (RMSE), mean absolute error (MAE) and R2 coefficient were used as measurement standards.

B *Experimental result*

The predictions are as follows:

Build a fully connected network with four hidden layers, update the weights using BP algorithm, and get the predicted values of BP network and fuzzy BP network, as shown in Figure 6. Then a convolutional neural network and a fuzzy convolutional neural network with four one-dimensional convolution layers are constructed. The reason for using one-dimensional convolution is that the input data is in the form of multidimensional vectors. The results are shown in Figure 7.

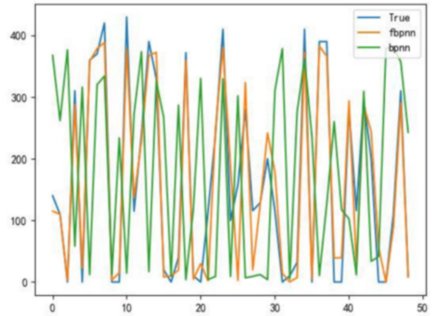

Fig.6 Predicted values of f-bpnn

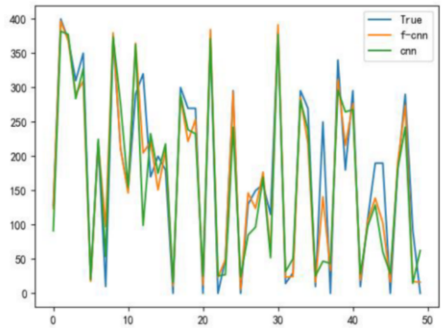

Fig.7 Predicted value of f-cnn

From the above results, it can be concluded that the predicted value of the deep learning model with fuzzy theory is more suitable to the actual value.The final evaluation indicators of each model are shown in Table 1 below.

Table.1 Analysis of prediction model results

MODEL	RMSE	MAE(KW)	R2
bp-nn	43.9	34.1	0.53
f-bp-nn	43.6	29.7	0.9
cnn	55.7	37.5	0.84
f-cnn	45.6	30.7	0.9

According to Table1,The neural network combined with fuzzy theory has better performance in predicting results.Then, the peak and valley load data are modeled respectively. The fitting diagram of the training set and the fitting diagram of the real data and the predicted data can be obtained, as shown in Fig.8, 9 respectively.

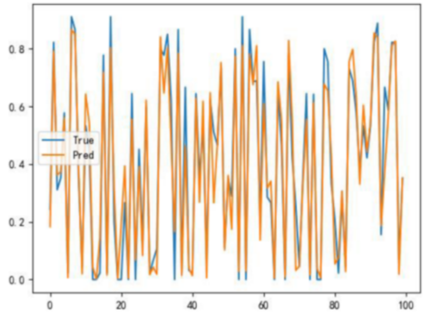

Fig.8 Valley time training set fitting graph

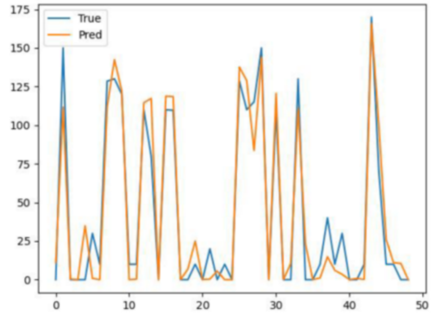

Fig.9 Valley time forecast results

While f-cnn network is used to predict the peak charging load, and the same prediction results were obtained, as shown in Fig.10, 11.

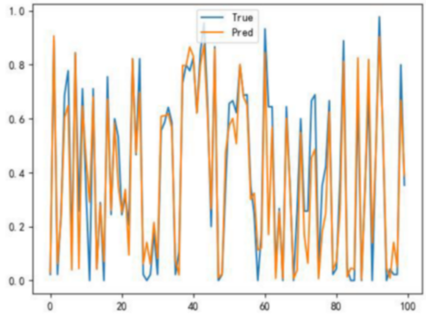

Fig.10 Peak time training set fitting graph

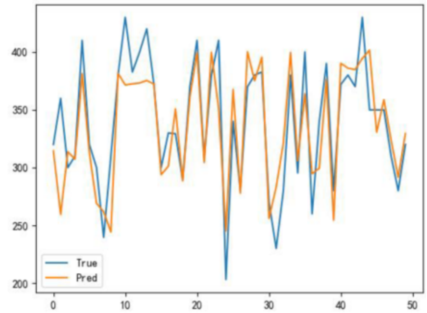

Fig.11 Peak time prediction results

From the fitting degree of the training set, the result of the network prediction is relatively accurate.Two indicators, MAE and RMSE, were used to measure the results, as shown in Table 2 below.

Table.2 Time-sharing load data forecasting results

TIME	RMSE	MAE(KW)
Total period	43.6	29.7
Valley time	30.8	18.9
Peak time	33.7	26.9

When user charging habits are considered, the prediction error is relatively small, and the accuracy rate of the prediction model with fuzzy theory is above 90%, which reflects the effectiveness of the prediction model with fuzzy theory clustering.

4. Conclusion

In this paper, a neural network forecasting model based on fuzzy theory is established, and a solution to the uncertainty factors in load forecasting is proposed.In this paper, the fuzzy theory is introduced into the data prediction, and the two types of data, temperature and humidity, are fuzzy processed. The charging habits of car owners are also taken into account. The fuzzy C-means clustering method is used to classify the data set into two types: valley time and peak time, so as to improve the accuracy of prediction. And the fuzzified temperature and humidity data, along with daily and hourly data, were used as inputs to the neural network model, optimizing the prediction performance of the model.In this paper, the neural network with fuzzy theory is compared with the network without fuzzy theory, and the effectiveness of fuzzy theory for improving the accuracy of load prediction is proved.Finally, this paper uses f-bp-nn network to make time-sharing prediction of real data set. The results show that the neural network prediction model with fuzzy theory can better deal with uncertain data and has good performance.

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