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Research on Prediction Model of Daily Charging Demand Based on WOA-BP

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Abstract: *With the rise of new energy vehicles, the coverage of charging piles is becoming more and more extensive, so it is necessary to study the charging demand. In this paper, a charging demand prediction model is constructed by using the BP neural network based on the whale optimization algorithm, and an empirical study is carried out by taking a charging pile in Shanghai as an example. The research results show that the MAPE of the WOA-BP neural network is about 7.65% lower than that of the BP neural network, which shows that WOA-BPNN model is more suitable for the prediction of charging demand and its prediction results can provide a certain decision-making basis for the allocation and deployment of charging piles in the future.*

Keywords: *WOA-BP neural network; charge amount; prediction*

1. Preface

With the development of science and technology, a new round of industrial transformation is sweeping the world, and automobiles are closely related to intelligence, information, energy and other related technologies. The research, development, popularization and promotion of new energy vehicles have gradually become the strategic planning orientation of various countries. Also, the pollution problem is becoming more and more obvious. As a powerful tool for building a green and low-carbon society, new energy vehicles will become the main development direction of the automotive industry in the future. In the "Action Plan for Carbon Dioxide Peaking Before 2030", the State Council proposed to promote new energy vehicles on a large scale and promote the electrification of public service vehicles. It is expected that by 2030, the proportion of new energy and clean energy-powered vehicles will reach 40% left and right [1]. With the rapid development of new energy vehicles, the coverage and demand of charging piles have gradually increased. As of December 2021, the number of charging infrastructure nationwide has reached 2.617 million [2]. In order to further understand the needs of residents, and to more effectively allocate and deploy the number and coverage of charging piles, it is crucial to study the use of charging equipment and charging needs.

At present, many domestic and foreign scholars have carried out related research on new energy vehicles from a macro or micro perspective. From a macro perspective, Xin et al.[3]analyzed the relevant factors such as the number of new energy vehicles in Jiangxi Province, vehicle types, etc., so as to predict the demand for charging facilities and put forward suggestions. In order to understand the charging demand, Li et al. [4] modeled and predicted the charging demand by analyzing the usage characteristics of electric vehicles in different scenarios based on the distribution of population density, combined with the number of motor vehicles and the number of new energy vehicles, the results show that the predicted results are in good agreement with the actual ones. Zhou et al. [5] analyzed and studied the development trend and layout concept of urban charging facilities, combined with multi-angle and multi-methods. Taking Quanjiao County, Chuzhou City, Anhui Province as an example, they analyzed the planning and layout of charging facilities. It shows that in order to improve the construction and spatial layout of charging facilities, its demand forecasting and planning layout methods can provide corresponding technical support. Cai [6] established an LSTM model when studying the charging capacity prediction problem of a single pile group. By comparing with the model results of traditional time series models such as ARIMA and SARIMA, it was found that the LSTM model improved the prediction accuracy.

To sum up, the current research on the charging demand of new energy vehicles mainly starts from the perspective of influencing factors, and there are still few relevant prediction studies, and the accuracy

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of prediction-related models still needs to be improved. Therefore, this paper uses the BP neural network method to build a new energy vehicle charging capacity prediction model, and in order to make up for the randomness of the initial weight of the BP neural network, the whale optimization algorithm is used to further improve, in order to provide a basis for the prediction of future charging demand.

2. Model approach

2.1. BP neural network

The BP neural network is a network model that firstly propagates the information forward, and then backpropagates the error, and the two are interleaved to achieve the preset accuracy. Nowadays, neural networks are widely used and are often used for function fitting, prediction and classification, and have achieved good results. However, there are still some problems in the application process. For example, when initializing the connection weights of each layer before starting training, the BP neural network will randomly assign a value between [0, 1], However, the assignment of this randomness often leads to a slower convergence rate of the model, and is prone to problems such as falling into a local minimum. Therefore, when using BP neural network, the selection of network parameters is very important.

2.2. Whale Optimization Algorithm

Whale optimization algorithm (WOA) is a heuristic intelligent optimization algorithm proposed by Australian scholar Mirjalili [6] in 2016. The algorithm simulates the entire predation process of humpback whales, including three stages: surrounding the prey, attacking the bubble net, and searching for prey.

2.2.1. Surrounding the prey

In this step, since the individual location of each whale cannot be known in advance, the location of the whale needs to be updated according to the current location of the prey, so as to lock the encirclement.

$$D = |C \cdot X_P(t) - X(t)| \tag{1}$$

In this formula: $X_P(t)$ is the position of the optimal individual; $X(t)$ is the position of the current individual; t is the current iteration number; C is the disturbance to the prey; D is the update step size when surrounded.

The individual position update is shown in formula (2):

$$X(t+1) = X_P(t) - A \cdot D \tag{2}$$

The random variables A and C are shown in formulas (3) and (4) respectively:

$$A = 2a \cdot r - a \tag{3}$$

$$C = 2r \tag{4}$$

In the formula: r is a random number between [0, 1]; a is shown in formula (5), representing a linear reduction from 2 to 0; T is the total number of iterations.

$$a = 2 - 2t/T \tag{5}$$

When A is between $[-1,1]$, the algorithm performs a local search, and when $|A| > 1$, the algorithm performs a global search.

2.2.2. Hunting behavior (Local search)

The bubble net attack is a very characteristic hunting strategy of humpback whales, that is, during the predation process, the whale spirals from the sea to the surface of the sea, and at the same time, the bubbles spit out form a cylindrical or tubular bubble net, which surrounds the prey and forces it to the center of the net.

The hunting behavior of whales is summarized as shrinkage and encirclement and spiral update. It is assumed that the probability of the whales choosing the two cases is 50%, the following mathematical model of position update is established:

$$X(t+1) = \begin{cases} X_P(t) - A \cdot D, & p < 0.5 \\ X_P(t) + D' \cdot e^{bl} \cdot \cos(2\pi l) + X_P(t), & p \geq 0.5 \end{cases} \tag{6}$$

Where $D' = X_P(t) - X(t)$ indicates the distance of the n^{th} whale to the best position, b is a constant, l is a random quantity between $[-1, 1]$.

2.2.3. Search for prey (Global search)

In the process of searching and preying, the whale doesn't update its position according to the prey, instead, the position of other whales in the population is randomly selected to replace the prey to update its position, which ensures that the whales can perform a global search at this stage and avoid the defect of falling into local optimum.

$$D = |C \cdot X_{rand}(t) - X(t)| \tag{7}$$

$$X(t+1) = X_{rand}(t) - A \cdot D \tag{8}$$

X_{rand} is the position of a whale randomly selected from the population.

The algorithm has the advantages of simple operation and less adjustment parameters. Using the WOA to optimize the BP neural network can effectively solve the problems of its local optimum and slow convergence. The flow chart of the BP neural network algorithm optimized based on the WOA is shown in Figure 1:

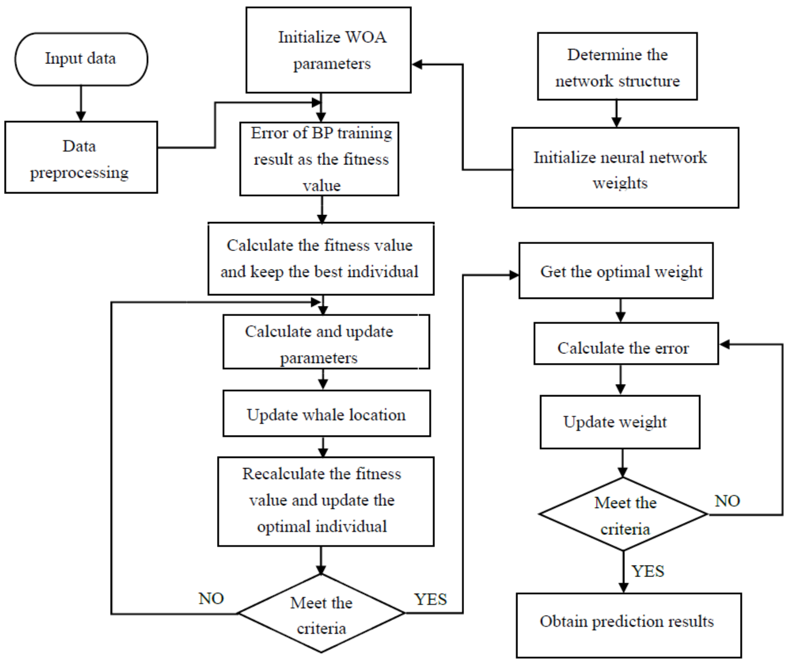

Figure 1: Flow chart of WOA-BPNN.

3. Empirical Analysis

3.1. Data Analysis and Processing

This paper takes the charging demand of a charging pile in Shanghai as an example to study the charging demand prediction model of the charging pile. First, the daily charging capacity of the charging piles is summarized, and considering that there are uncharged vehicles on some days, the data will be found to be irregular, so the data corresponding to the discontinuous time is removed. From this, it can be seen that the data interval is 770 pieces of data from December 27, 2018 to December 03, 2020. The data sequence of daily charging demand after processing is shown in Figure 2 (a).

From the overall fluctuation trend of the charging demand in Figure 2 (a), there is no obvious increase or decrease trend in the charging capacity, and the change is relatively balanced. The reason is that the purchase and use of new energy vehicles by nearby residents are relatively balanced.

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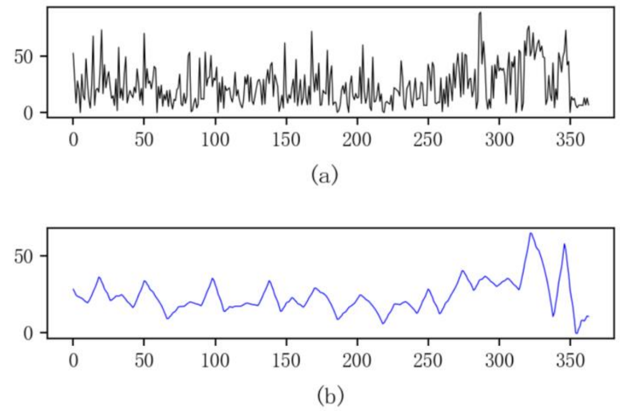

Figure 2: (a) Raw noisy data (b) Data after Wavelet Denoise.

Since time series data is affected by measurement errors, human factors and other factors, moreover, such data will be affected by weather, holidays and the like during the monitoring, collection and transmission process, so there is a certain amount of noise in the data. In order to improve the accuracy of prediction, the original data is first subjected to wavelet denoise, and the image of the data after noise reduction is shown in Figure 2 (b).

3.2. Model Construction

The 362 sets of complete data are divided according to 3:1, that is, the first 270 days in the data are the training set, and the last 92 days of data are used as the test set to construct the model.

In order to study the accuracy of the WOA-BP model and the traditional BP neural network for the prediction of the charging capacity, the parameters of the neural network model are set as follows: the number of input layers is 3, the number of output layers is 1, the number of iterations is set to 100, and the learning rate is 0.1, and the target error is 0.00001; the parameters of the WOA model are set as: the race scale is 20, and the maximum number of evolutions is 20.

3.3. Analysis of model results

This section uses the WOA-P neural network model to train and fit the daily charging requirements of the charging pile, and compares it with the prediction results of the traditional BP neural network. Figure 3 shows the result comparison. As shown in Figure 3, the WOA-BP neural network prediction is more accurate, and the predicted value obtained is closer to the real value, but no matter which model it is, the accuracy of the prediction will decrease over time, especially when the data has large fluctuations, such as the period from the end of June to the end of July 2020, the errors of both models are relatively obvious.

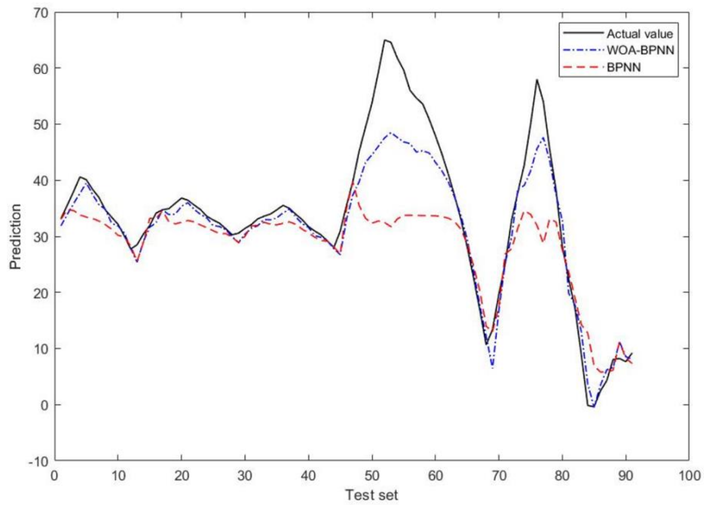

Figure 3: Comparison of actual value, BPNN predicted value and WOA-BPNN predicted value.

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In order to study the prediction accuracy of the two models more accurately and intuitively, for this regression problem, this paper selects the root mean square error (RMSE) and the mean absolute percentage error (MAPE) as the evaluation indicators. The smaller the value of the two indicators, the better the prediction effect of the model. By calculating the prediction results of the BP neural network and the WOA-BP neural network in the test set, the error evaluation index results are obtained as shown in Table 1. It can be seen that the prediction accuracy of the WOA-BP neural network is significantly higher than that of the BP neural network.

Table 1: Comparison of prediction errors.

Model	RMSE	MAPE
BP neural network	10.3384	16.6967%
WOA-BP neural network	4.8016	9.0420%

4. Conclusion

Aiming at the prediction accuracy of the daily charging demand of charging piles, this paper proposes a neural network based on the whale optimization algorithm to study the prediction model, and takes a charging pile in Shanghai as an example to compare it with the prediction results of the basic neural network. The results show that the MAPE of the WOA-BP neural network is about 7.65% lower than that of the BP neural network, even if the neural network using the optimization algorithm has better prediction results, indicating that the model can provide a certain reference for the use of charging piles in the future.

However, the research in this paper is still insufficient, and other factors affecting the daily charging demand of charging piles are not considered, such as: different time intervals, regional locations, etc. Therefore, further research will be carried out in this area in the later stage.

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