ISSN: 2414-1895 DOI: 10.6919/ICJE.202109_7(9).0048

Optimizing BP Neural Network Prediction Model based on WOA

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Abstract

Aiming at the problem that the (Back Propagation, BP) neural network converges too slowly in the prediction and is easy to fall into the local optimum, this paper proposes to use the (Whale Optimization Algorithm, WOA) to optimize the BP neural network. WOA is to find the optimal solution through the hunting behavior of bionic whales to "drive" and "round up". According to the characteristics of the algorithm, WOA is used in the BP neural network to optimize the weights and thresholds of the network, thereby improving the accuracy of the prediction model. The experimental results show that compared with the original BP neural network, WOA-BP has obvious accuracy and convergence. Advantage.

Keywords

Whale Swarm Algorithm; Neural Network; Bionic Optimization; Predictive Model.

1. Introduction

In the late 1960s, Bryson and others first proposed the idea of Back Propagation (BP). Scientists later applied it to neural networks, and with the development of the times, it was gradually applied in various research fields. Among them, the use of inverse neural networks for prediction is very popular. In various industries where prediction is applied, its prediction Accuracy is closely related to economic benefits and is a key factor in measuring a predictive model. Early prediction methods include exponential smoothing method, regression analysis method, time series method and grey system method. In the literature [1], the time series method is used to predict the power load and finally achieved good results. With the rapid development of artificial intelligence technology, more and more scholars use artificial neural networks in predictive models, and have higher accuracy than earlier predictive models [2-5]. Artificial Neural Network (ANN) is inspired by human brain neurons when transmitting and processing information, so to a certain extent, some similar characteristics of human brain neurons-parallel processing and plasticity in processing nonlinear complex function models, Especially in the engineering and economic fields, it has high practicability. When using artificial neural networks, although they have good accuracy, as neural networks, their own shortcomings (easy to fall into local optimal solutions and slow convergence during prediction) will affect the accuracy of the model in the prediction, selection and prediction A neural network that is suitable for things and setting reasonable parameters can compensate for the above shortcomings to a certain extent; in addition, for neural networks, the selection and training of weights and thresholds between neurons is also one of the important factors that directly affect the accuracy of the prediction model. one. Literature [6-7] uses the BP algorithm for load forecasting, and the BP neural network takes the square error of the model as the target. Therefore, it is inevitable that the neural network has slow convergence speed, easy to fall into the local optimal solution, the number of layers and the number of neurons does not have accurate guidance, and can only use experience to continuously try and other shortcomings, which will affect the model's performance. Forecast accuracy.

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The principle of Whale Optimization Algorithm (WOA) is an algorithm proposed based on the daily activities of whales. The sub-algorithm has the advantages of low space complexity and fast convergence. It is an emerging intelligent optimization algorithm and has been applied to varying degrees in many fields [8-9]. Previously, there were similar uses of intelligent optimization algorithms to optimize neural networks, such as: particle swarm algorithm to predict power load, genetic algorithm to optimize neural networks. However, most optimization algorithms have the disadvantage of slow convergence and easy to fall into local optimal solutions. For example, the particle swarm algorithm cannot always maintain the function of particle diversity in the update of the particle's position, which makes it too singular in evolution.

In order to improve the prediction accuracy of the BP neural network, this paper proposes to use WOA to optimize the threshold and weight of the neural network. Using the easy-to-convergence feature of WOA, when the neural network is constantly searching for errors in the reverse direction, WOA continues to iterate to find the optimal solution. This improves the accuracy of the BP neural network. The experimental results prove the effectiveness of the algorithm in the BP neural network prediction model.

2. WOA-BP prediction model

2.1 BP neural network

BP neural network, as a forward multi-layer reverse error network, is usually composed of layers: input, implicit, and output. Each layer is composed of multiple parallel neurons [10]. BP neural network simulates the process of brain neurons processing signals. Each layer is connected by neurons, and neurons in the same layer are not connected. Although the BP neural network has a simple structure, when multiple neurons are clustered together, it can represent a nonlinear model, which can exert powerful functions. Take the commonly used three-layer BP neural network as an example, as shown in Figure 2

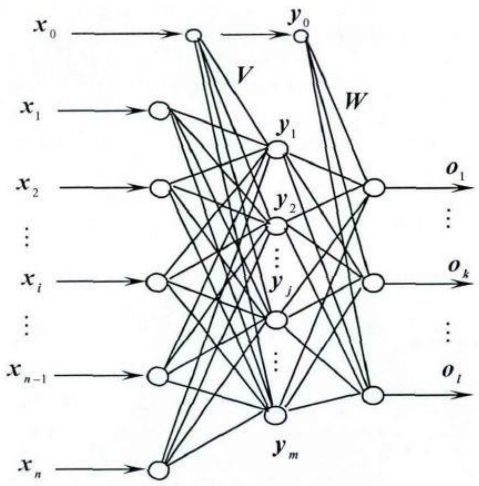

Figure 1. Three-layer neural network

The BP neural network is mainly divided into two steps: the network error is obtained through the forward propagation of the data and the reverse adjustment through the error data [11] The forward transfer refers to the input data of the input layer, which is calculated by the hidden layer, and finally passed to the output layer. It is not the final output data. If the data meets the given standard during this process, the transfer ends, otherwise it will turn to reverse error transfer. Error refers to the error data that occurs during the forward transmission and the input data is continuously transmitted backwards, and the weight of the neural network is continuously adjusted by feedback, and the final output value that meets the regulations is obtained by correcting the weight. During training, the BP neural network continuously adjusts the data through the forward transfer operation and the reverse transfer error to adjust the alternate process. Constantly make network corrections, and finally make

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the final forecast data highly close to the expected data, and stop computing when the accuracy set by the forecast is met.

2.2 Whale Optimization Algorithm

Whale algorithm is an algorithm proposed based on the habits and behaviors of whales. Whales are a group of animals with high intelligence. They will cooperate with each other when hunting to continuously chase and round up their prey. In the algorithm, the position of the whale can be regarded as a feasible solution. In whale hunting, each whale will have two behaviors: surround its prey, and the whale will move towards other whales. It can be seen that when a suitable feasible solution is found, the whole will approach this feasible solution: the other is a bubble net., The whale makes a continuous circular swim and continuously sprays bubbles to drive away its prey. In each swim, the whales randomly choose these two behaviors.

2.2.1 Bracketing mode

This model shows that the school of whales is moving towards the best position of the whale. It can be seen as searching around the local optimal solution. The mathematical formula is as follows:

$$D = |CX^*(t) - X(t)| \tag{1}$$

$$X(t+1) = X^*(t) - AD \tag{2}$$

Where t in formula (1) represents the current number of iterations, in formula (1) and (2), A and C represent coefficients, $X^*(t)$represents the optimal whale position, X(t) is the current whale position, and A and C can be obtained by this formula:

$$A = 2ar_1 - a \tag{3}$$

$$C = 2r_2 \tag{4}$$

$$a = 2 - \frac{2t}{T_{MAX}} \tag{5}$$

Among them, r1 and r2 are random numbers between (0,1), a is an adaptive value that linearly decreases as the number of iterations increases, and T_MAX is the set maximum number of iterations.

2.2.2 Hunting mode

This mode is a hunting behavior of whales, which continuously swim towards their prey through their own rotating motion, which can be regarded as a random movement when they do not find the optimal position. The mathematical formula is as follows:

$$X(t+1) = X^*(t) + D_P e^{bl} cos(2\pi l) \tag{6}$$

As in the above formula (6), $D_P = |X^*(t) - X(t)|$ represents the distance between the whale and the prey at this time, $X^*(t)$ is the best position so far, and b is a constant, The function is to define the shape of its own spiral movement, l is a random number between (-1,1). In the algorithm, while moving itself, it must constantly narrow the search range. The probability P is used to determine which state the whale is in. The decision is as follows:

$$X(t+1) = \begin{Bmatrix} X^*(t) - AD, P \\ X^*(t) + D_p e^{bl} cso(2\pi l), 1-p \end{Bmatrix} \tag{7}$$

For the whale swarm algorithm, when in the encircling mode, it is impossible to determine whether it is the optimal position at this time. Blind movement can easily cause the algorithm to fall into the optimal solution. In this regard, the algorithm adds a judgment mechanism to the encircling mode and uses the A variable in the mode to determine. Since A is constantly fluctuating, when |A<1|, the whale chooses to move to the best individual. When |A≥1|, choose random free movement. As shown in the following formula

$$D = |CX_{rand} - Xt| \tag{8}$$

$$X(t+1) = X_{rand} - AD \tag{9}$$

Among them, X_rand means randomly selecting the whale position, when |A≥1|, means selecting a random position to move, so as to enhance the global optimization ability of the algorithm.

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2.3 Algorithm test

This paper selects 6 kinds of commonly used test functions similar to the Whale Swarm Algorithm to test and compare the Whale Swarm Algorithm. The purpose is to test the algorithm's optimization ability and convergence.

In order to compare the improved algorithm with the original algorithm, the population size, combination rate, memory pool size, search dimension ratio, and dimensional change rate of the two are all set to the same parameters. The horizontal comparison will compare the improved algorithm with the particle swarm algorithm and The ant colony algorithm is set to the same dimension, number of iterations, and population number. The whale algorithm and other bionic algorithms are tested 50 times through MATLAB software and the optimal value (min) and the optimal average value (mean) are obtained. The optimal average value can describe the accuracy of the algorithm. The specific test results are shown in Table 1. Show.

Table 1. Algorithm test results

	CSO	**WOA**	**PSO**	ACO
Schwefel	min:2.9042 mean:0.8562 Iteration:1000	min:1.427e-31 mean:0.7818 Iteration:1000	min:2.13 mean:10.8924 Iteration:1000	min:7.028 mean:40.41 Iteration:1000
Rosenbrock	min:0 mean:1.2407 Iteration:214	min:0 mean:1.0712 Iteration:165	min:0.13 mean:0.957 Iteration:785	min:0 mean:1.341 Iteration:234
Sphere	min:0.874 mean:14.076 Iteration:900	min:0 mean:12.407 Iteration:455	min:16.43 mean:27.607 Iteration:900	min:0.079 mean:2.4507 Iteration:900
Ackley	min:0.352 mean:0.927 Iteration:1000	min:0 mean:0.5869 Iteration: 147	min:2.656 mean:7.5518 Iteration:100	min:4.4e-15 mean:0.8150 Iteration:1000
Griewank	min:0.1542 mean:2.7530 Iteration:974	min:0.0348 mean:2.2451 Iteration:974	min:1.761 mean:3.470 Iteration:974	min:0.0783 mean:2.3540 Iteration:974
Rastrigin	min:134.41 mean:154.246 Iteration:1000	min:4.418e-14 mean:7.0927 Iteration:1000	min:149.9 mean:221.569 Iteration:1000	min:0.914 mean:71.544 Iteration:1000

3. Model testing and comparison

This paper uses the Whale Swarm Algorithm (WOA) to optimize the weights and thresholds of the BP neural network, and establishes a WOA-BP prediction model. By initializing the position of the whale, and constantly comparing the overall optimum in the subsequent iterations, adjust the whale's adaptability to the environment and search for the optimal solution for the best prey. Corresponding to the particle swarm algorithm, the ant colony algorithm reduces operations such as crossover, and has a relatively simple structure and fast convergence speed.

3.1 Relevant parameter design

In order to verify the usefulness of the proposed WOA-BP model, 2000 sets of two-dimensional data and 2000 sets of one-dimensional data were randomly selected through MATLAB. The data set is completely random, and its range is controlled within (0-100). The first 1000 two-dimensional data and the first 1000 one-dimensional data are used as the training data set. The last 100 data are predicted data for testing. In order to achieve a fair comparison effect in the experiment, the relevant parameters of the proposed model and other models are shown in Table 2 below.

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Table 2. Comparison of similar model parameters

Comparison algorithm	BP	WOA-BP	PSO-BP
Population		50	50
Dimension		10	10
Number of iterations		200	1000
Input layer	2	2	2
middle layer	5	5	5
Output layer	1	1	1
Training times	1000	1000	1000

3.2 Error analysis

In order to verify the usefulness of the model proposed in this paper, the original BP neural network model is compared with the PSO-BP model and WOA-BP. In comparison, each model uses its most suitable parameters for multiple tests, obtains more accurate prediction results and compares with the proposed model. The accuracy and error of each model prediction can be clearly seen. Table 3 and Figures 2 and 3 are shown below

Table 3 Compares the predictions of each model

Evaluate the parameters	BP	PSO-BP	WOA-BP
MAE	11.14	7.33	4.42
RMSE	14.23	10.46	8.12
$R^2/\%$	81.55	89.76	95.45

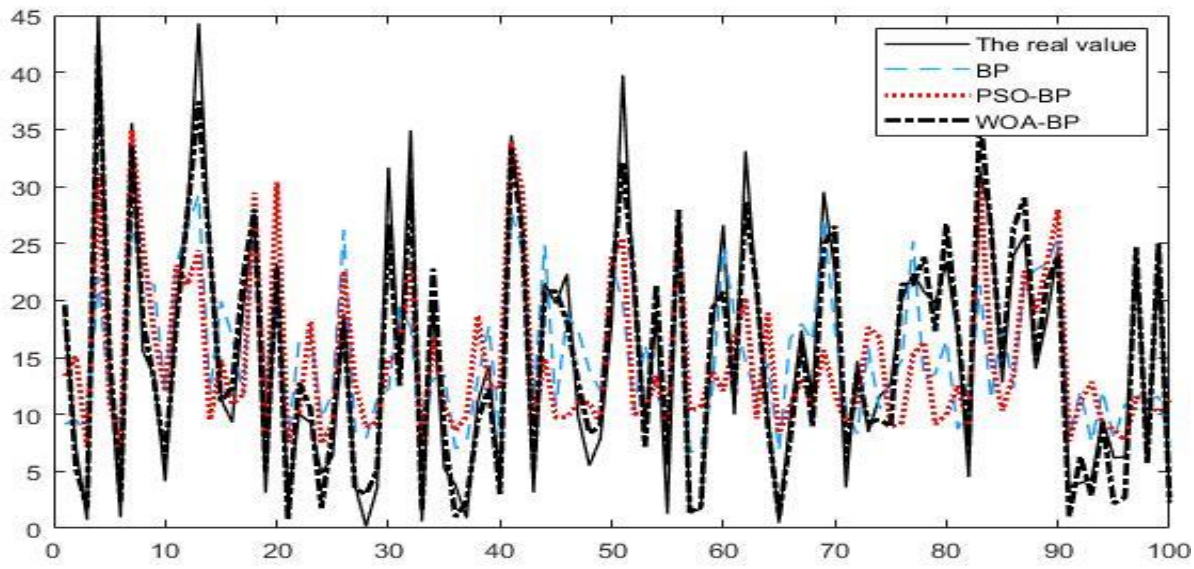

Figure 2. Compares the prediction models

As can be seen from Figures 2, 3 and 3, the WOA-BP model proposed in this paper has the smallest error and the best fit with the real values in the forecasting process. The proposed model achieves the best prediction accuracy, and the prediction error is the smallest of several models. Among them, MAE is 4.42 and RMSE is 8.12 are smaller than other models. R-2. was 95.45 percent higher than traditional BP's 81.55 percent and PSO-BP's 89.76 percent, respectively, up 13.9 percent and 5.69 percent. This shows the feasibility of the proposed WOA-BP model in the forecast.

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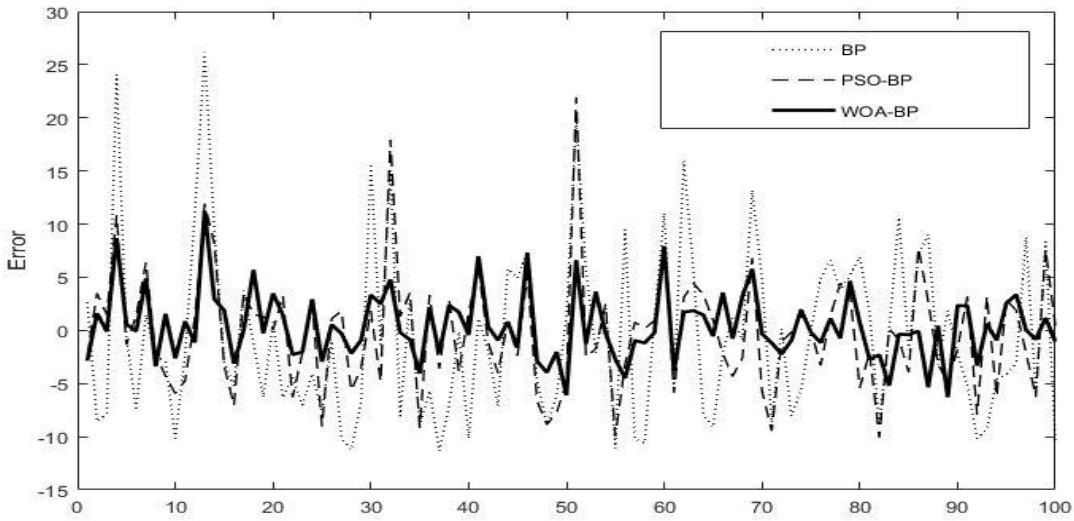

Figure 3. The error ratio of each model

4. Conclusion

In this paper, WOA optimizes the BP neural network prediction model, optimizes the neural network by optimizing the neural network with the general BP neural network and particle group algorithm, and draws the following conclusions after the setting and multiple experiments of the same parameters and analysis: 1. The model proposed in this paper, the structure is simple and effective to reduce the difficulty of prediction and improve the accuracy of prediction. 2. According to the shortcomings of the traditional BP neural network, the threshold and weight of the neural network are optimized by the whale population intelligent optimization algorithm, which makes BP neural network not easy to fall into the optimal solution, and it is not easy to converge prematurely. The experimental results prove the feasibility of the prediction model proposed in this paper.

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