Supply Chain Demand Forecasting Based on WOA-ELM

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Abstract. In the whole supply chain management process, accurate control of supply chain demand is an important part. In order to study supply chain demand with predictability and credibility, an extreme learning machine model based on whale optimization algorithm is proposed. By analyzing the demand of a company for 14 months, the data relationship is constructed from seven influencing factors including cost, seasonal coefficient, sales intensity, market characteristics, number of shoppers, product structure and credit index. After the training of WOA-ELM model data, the average error result is 5.71%, which has a good error effect. It can provide a new idea for supply chain demand forecasting.

Keywords: Supply Chain Management · Supply Chain Demand · WOA-ELM · Hybrid Model

1 Introduction

Supply chain demand is an important factor in supply chain management. Scientific and accurate planning of supply chain demand can make enterprises more efficient in the process of supply chain management, and can better improve the accuracy of logistics decision-making. With the development of economic globalization and the continuous improvement of science and technology, enterprises began to compete in the supply chain and gradually began to use computer methods to predict supply chain demand [6]. Xie et al. uses the genetic algorithm to estimate the developing coefficient and the control variable of the GM(1, 1) model and predicts the demand of every level in the supply chain with this forecasting model. And the accuracy of demand forecasting in the supply chain was improved [7]. Feng et al. uses Petri net to search and recur real-time change rule of the supply chain enterprise needs, and builds the enterprise supply chain collaborative prediction model [1]. Xue et al. proposed a long short-term memory network to predict emergency material demand [8]. But they use a single model to predict the supply chain, and the results are uncertain. Therefore, this study proposes a hybrid model of whale optimization algorithm and extreme learning machine to predict supply chain demand. it combine with cost, seasonal coefficient, sales strength, market characteristics, number of shoppers, product structure and credit index to predict the demand, and compares the prediction results of the ELM model alone. The results show that the average prediction error of the WOA-ELM model is only 5.71%, which is far less than that of the ELM

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model alone. Therefore, the proposed WOA-ELM method can provide a new solution for supply chain demand forecasting.

2 Materials and Methods

2.1 ELM Model

Extreme Learning Machine (ELM) [2] was proposed by Huang et al. Its characteristic is that the weight of nodes in the hidden layer is given randomly or artificially, and does not need to be updated. The learning process only calculates the weight of output. The algorithm includes input layer, hidden layer and output layer. The weights and thresholds are generated randomly, and then the output weights are obtained by solving the equations with the least square method. Compared with other shallow learning systems, such as single Layer perceptron and Support Vector Machine (SVM), traditional ELM has a single implicit layer, which is considered to have advantages in learning speed and generalization ability. ELM does not depend on gradient descent, and its learning speed is faster than the traditional feedforward network such as BP algorithm, which also has good applicability for large and nonlinear samples.

Assuming that the number of neurons in the input layer of the model is n, the number of neurons in the hidden layer is L, and the number of neurons in the output layer is m. Given N different training samples $x_j, j = 1, \ldots, N$ can map the sample to another feature space by activating function $g(a_i, b_i, x_j)$. And for the matrix H obtained by mapping, there is the following expression:

$$H\beta = T \tag{1}$$

$$H = \begin{pmatrix} h(x1) \\ \vdots \\ h(xj) \\ \vdots \\ h(xN) \end{pmatrix} = \begin{pmatrix} g(a1, b1, x1) & \cdots & g(aL, bL, x1) \\ \vdots & \vdots & \vdots \\ g(a1, b1, xj) & \cdots & g(aL, bL, xj) \\ \vdots & \vdots & \vdots \\ g(a1, b1, xN) & \cdots & g(aL, bL, xN) \end{pmatrix} \tag{2}$$

Where, H is the hidden layer output matrix of neural network, t is the output matrix of the network, β is the connection weight matrix between hidden layer nodes and output layer nodes, a_i is a matrix composed of the connection weights of the 1 ~ n node in the input layer and the i node in the hidden layer, $I = 1,\ldots, L$, representing the i hidden layer neurons, b_i is the threshold of the i^{th} hidden layer node.

Optimal output weight $\overset{\wedge}{\beta}$ can be obtained by least square method in new feature space.

$$\overset{\wedge}{\beta} = H^{+}T \tag{3}$$

Where, H^{+} is Moore-Penrose generalized inverse matrix of H.

2.2 WOA

Whale optimization Algorithm (WOA) is a new heuristic optimization algorithm which imitates hunting behaviour of humpback whale. In the WOA, the position of each humpback whale represents a feasible solution. In Marine activity, humpback whales have a special hunting method, a foraging behaviour called bubble-net feeding strategy [5].

As a swarm optimization algorithm, it has the advantages of simple operation, few parameters to adjust and strong ability to jump out of local optimum.

It is divided into three stages:

Step1: Encircling prey

Because the prey position is uncertain, the WOA algorithm first assumes that the current best candidate solution is the target prey position or the closest prey position, and then updates its position continuously. This behavior is expressed by the following equations:

$$D = \left|CX^{*}(t) - X(t)\right| \tag{4}$$

$$X(t+1) = X^{*}(t) - AD \tag{5}$$

Where, D is the bounding step, $X(t + 1)$ is the position vector of the solution after the next iteration, $X^{*}(t)$ is the position vector of the current optimal solution, $X(t)$ is the position vector of the current solution, t is the current iteration number, A and C are random coefficient vectors, update $X^{*}(t)$ whenever a better solution appears in the iteration.

A and C are derived from the following formulas:

$$\begin{cases} A = 2ar - a \\ a = 2 - \frac{2t}{t_{\max}} \end{cases} \tag{6}$$

$$C = 2r \tag{7}$$

Where, a is the control parameter and decreases linearly from 2 to 0 during the iteration, $t_{\max}$ is the maximum number of generations, r is a random vector of [0, 1].

Step 2: Bubble-net- attacking method

Case i) Contraction surround mechanism. The new individual position can be defined in any position between the current whale individual and the best whale individual, see formula (5).

Case ii) Spiral update location. Calculate the distance between whales and prey and build equations:

$$X(t+1) = D' e^{bl} \cos(2\pi l) + X^{*}(t) \tag{8}$$

Where, $D' = |X^{*}(t) - X(t)|$, b is a constant, the shape of the logarithmic spiral is defined, l is the random number of [−1,1].

This model takes 0.5 as the cut-off point, and determines the mode of whale feeding by generating a random probability P of 0~1. When $|A|<1$ and probability $P < 0.5$, select *Case i*); when $|A|<1$ and probability $P > 0.5$, select *Case ii*) to update position.

Step3: Searching prey

When $|A|>1$, enter the random search phase, randomly select the whale to update the location. When the maximum number of iterations is reached, the algorithm terminates. The mathematical model of random search is as follows:

$$D = |CX_{rand} - X(t)| \tag{9}$$

$$X(t+1) = X_{rand} - AD \tag{10}$$

Where, X_{rand} is a random position vector, and A determines whether the humpback whale enters a random search state.

2.3 WOA-ELM Model

In order to make ELM model have better prediction effect, this paper introduces WOA optimization algorithm to optimize it and constructs WOA-ELM hybrid model [4]. Firstly, the original data are normalized, and then the number of nodes and the number of parameters to be optimized in the ELM network are set to initialize the number of whales and the fitness value of the population. The whale algorithm is used to iteratively optimize the parameters. Finally, the individual corresponding to the minimum fitness value is the optimal solution. This optimal parameter is assigned to the ELM network, and the ELM network is trained and applied to the supply chain demand forecast.

(1) Data normalization

Since the collected sample data have a large range of changes, and the activation function is very flat outside (0, 1) and the discrimination is too small, it is necessary to process the input data first, and use the map minmax function in MATLAB software to normalize it to [0, 1]. The formula is as follows:

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{11}$$

Where, x is the input value of a feature of the sample, $x_{\min}$ the minimum value of the input value in the sample, $x_{\max}$ the maximum input value in the sample, y is the normalized output value.

(2) Setting model parameters

Step1: ELM network parameters: According to the input data characteristics, the number of nodes in the hidden layer of ELM model is set to be 6, so the parameter Z to be optimized is calculated according to the following formula:

$$Z = nL + m \tag{12}$$

Step2: Parameters of the whale optimization algorithm: set the lower and upper bounds of the algorithm $[-1, 1]$, the maximum number of iterations is 300, the number of whales is 30, and initialize the location of each whale.

(3) Iterative optimization

After calculating the fitness value of all individuals according to the misjudgment rate in the training process, the optimal individual is selected, and then the position of the optimal individual is updated according to the minimum fitness value. Continuously optimize until the misjudgment rate is lower than the set value or the maximum number of iterations is reached.

(4) Supply chain demand forecasting

The optimal weights and thresholds of the output are assigned to the ELM model to predict the supply chain demand.

3 Results and Discussion

3.1 Data Analysis

This study refers to the data in reference [3], and uses 14 sets of data from 7 influencing factors of a company's electronic products, including cost, seasonal coefficient, sales intensity, market characteristics, number of stores, product structure and credit index to construct the relationship between them and supply chain demand, as shown in Table 1.

Table 1. Supply chain demand and influencing factor index.

Month	Cost	Seasonal coefficient	Sales strength	Market characteristics	Number of shoppers	Product structure	Credit index	Demand
1	1299	0.561	1	0.98	4805	0.15	0.99	37
2	1499	0.834	0.8	0.95	4340	0.14	0.98	55
3	1499	1.122	0.8	0.96	4020	0.14	0.95	74
4	1499	1.061	0.8	0.9	3968	0.11	0.88	70
5	1499	1.258	0.8	0.96	3451	0.13	0.88	83
6	999	1.455	0.9	0.94	4080	0.14	0.85	96
7	999	1.365	0.9	0.89	4495	0.13	0.87	90
8	1499	1.441	0.4	0.85	4371	0.14	0.9	95
9	1499	1.274	0.4	0.75	3750	0.12	0.81	84
10	1499	1.319	0.3	0.79	4154	0.13	0.77	87
11	1299	1.381	0.3	0.77	4247	0.11	0.79	91
12	1299	0.94	0.1	0.75	3906	0.12	0.74	62
13	1299	0.743	0.1	0.75	3627	0.14	0.69	49
14	1299	0.622	0.1	0.68	3286	0.14	0.71	41

Table 2. The descriptive statistical results and coefficients of variation

--	Cost	Seasonal coefficient	Sales strength	Market characteristics	Number of shoppers	Product structure	Credit index
Sample size	14	14	14	14	14	14	14
Maximum	1499	1.455	1	0.98	4805	0.15	0.99
Minimum	999	0.561	0.1	0.68	3286	0.11	0.69
Average	1356.143	1.098	0.55	0.851	4035.714	0.131	0.844
Standard deviation	178.516	0.309	0.337	0.101	415.345	0.012	0.096
Median	1399	1.19	0.6	0.87	4050	0.135	0.86
Variance	31868.132	0.095	0.113	0.01	172511.143	0	0.009
Kurtosis	0.438	−1.126	−1.764	−1.527	−0.198	−0.61	−0.979
Partial degrees	−1.13	−0.558	−0.169	−0.213	−0.108	−0.6	−0.054
Coefficient of variation (CV)	0.132	0.281	0.612	0.118	0.103	0.094	0.114

The descriptive statistical results of Cost, Seasonal coefficient, Sales strength, Market characteristics, Number of shoppers, Product structure and Credit index are shown in Table 2, including sample size, maximum and minimum statistics. It can accurately grasp the overall situation of the quantitative data. It can be seen from Table 2 that the coefficients of variation of Cost, Market characteristics, Number of shoppers, Product structure and Credit index are all less than 0.15, indicating that the probability of abnormal values in them is small. The coefficient of variation of Seasonal coefficient and Sales strength is greater than 0.15, but their data distribution is uniform (as seen in Fig. 1 and Fig. 2). Therefore, it can also be shown that the probability of abnormal values is small. Thus, The impact indicators are comprehensive and have reference value.

The correlation between the factors is shown in Fig. 3. As can be seen from Fig. 3, only 5 pairs of variable combination correlation coefficient is greater than 0.5, most of the variable combination correlation coefficient is less than 0.5. Therefore, it can indicate that the correlation between the selected influencing factors is weak, and the influence between the two is small. Therefore, analysis can be done without dimension reduction.

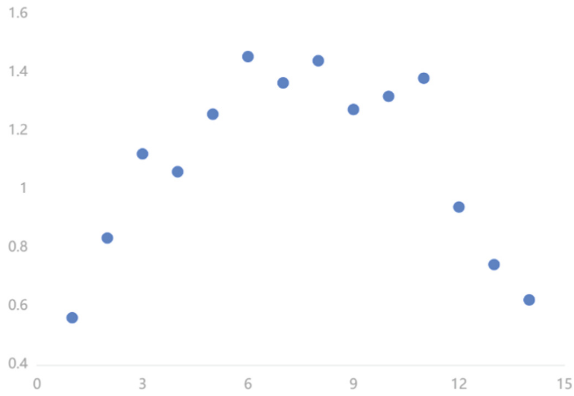

Fig. 1. Distribution of Seasonal Coefficient (Figures drawn by author)

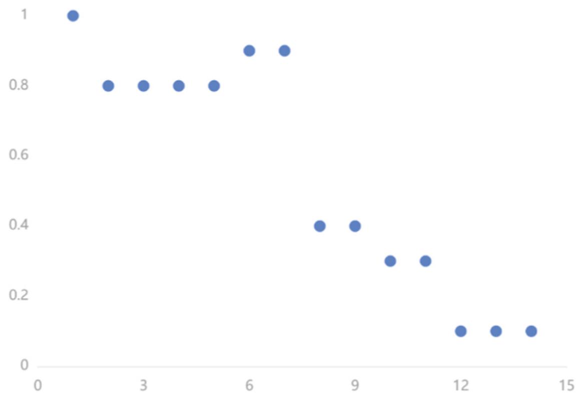

Fig. 2. Distribution of Sales Strength (Figures drawn by author)

3.2 Analysis of Effect

The WOA-ELM model of supply chain demand forecast is established through the relevant steps in Sect. 2.2, and it is realized by MATLAB program. In order to ensure the training effect of the model, the samples of the previous 10 months are used as the training set, and the 11–14th months are used as the test set. ELM model and WOA-ELM model are used to predict supply chain demand. The prediction results are shown in Fig. 4–5. By comparing Fig. 4 and Fig. 5, it is clear that the prediction results of WOA-ELM model are closer to the real results. Therefore, the prediction effect of WOA-ELM model is better than that of ELM model alone.

Error analysis of the prediction results, as shown in Table 3. It can be seen that the average error of ELM model is 16.63%. However, after using WOA to optimize ELM, the average error is reduced to 5.71%. The maximum error is 9.76%, the minimum error is only 1.61%, and the error is less than 10%.

Fig. 3. Data correlation coefficient (Figures drawn by author)

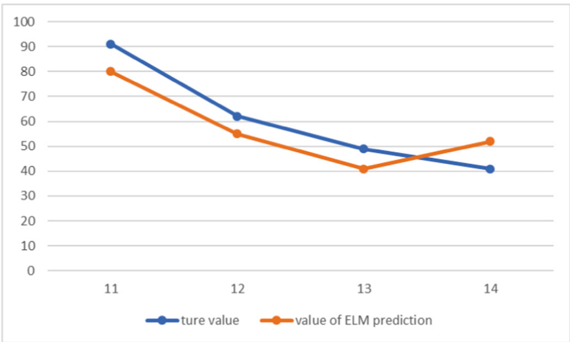

Fig. 4. Comparison of ELM model results and real values (Figures drawn by authors)

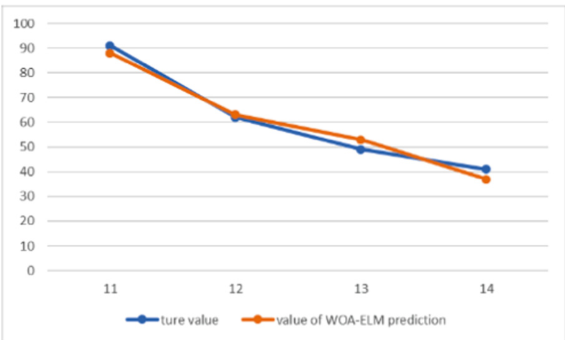

Fig. 5. Comparison of WOA-ELM model results and real values (Figures drawn by authors)

Table 3. ELM and WOA-ELM prediction results and error.

Month	Ture value	Value of ELM prediction	Error	Value of WOA-ELM prediction	Error
11	91	80	12.09%	88	3.30%
12	62	55	11.29%	63	1.61%
13	49	41	16.33%	53	8.16%
14	41	52	26.83%	37	9.76%
average error		16.63%		5.71%	

By comparison, the WOA-ELM model established in this study has stronger learning ability, stronger generalization ability and higher recognition accuracy than the ELM model without optimization, which can be effectively applied to the prediction task of supply chain demand.

4 Conclusions

This paper establishes the ELM model based on the WOA, and realizes the prediction of supply chain demand by feature extraction of supply chain data. The advantages of this model are verified by comparing the results of the single ELM model was adopted and WOA-ELM model. The main conclusions are as follows:

1) Using WOA to optimize ELM overcomes the disadvantages of overfitting or underfitting caused by improper manual parameter adjustment.
2) Using WOA-ELM to predict supply chain demand, the average error is only 5.71%, indicating that this method can effectively predict supply chain demand, so as to control demand.
3) By comparing the results of WOA-ELM and a single ELM model, it can be found that the error of the optimized model is less than that of only a single model. Thus, it is a good attempt to use an optimization algorithm to effectively improve the accuracy of the model. In the next step, more optimization algorithms will be used to optimize the model to improve the accuracy of prediction.

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