Research on Logistics Demand Forecasting Model of Truck Broker Based on PSO - BPNN

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Abstract

National policies encourage the development of the truck broker logistics based on the Internet platform. Accurate data forecasting is an effective way to improve the logistics demand market. Based on the BP neural network prediction model based on particle swarm optimization, economic data of Multiple factors are accurate, and the truck broker demand forecasting index system is established. The global search ability of particle swarm and the self-learning ability of BP neural network are used to compensate for parameter initialization sensitivity and training. In the example, the comparison between the combined model and the single BP neural network model shows that the combined model predicts better data accuracy and is suitable for short-term forecasting of the truck broker demand market.

Keywords

Truck Broker,demand forecast,particle swarm optimization,BP neural network.

1. Introduction

The General Office of the State Council in 2015 encourage the development of the truck broker relying on the Internet platform to mark the formal recognition and support the truck broker enterprises in China [1], and allowing the truck broker to union with other transportation business in the next year [2]. The truck broker is generally a type of light asset investment that doesn't engage in specific transportation operations, but only engages the search and distribution of cargo sources, the choice of transportation modes, and the planning of logistics transportation lines[3]. The low-cost truck broker's transportation has realized the transformation of logistics enterprises from heavy assets to light assets. At present, logistics and industry have some problems, such as decentralized resources, low vehicle utilization rate, and information asymmetry. If the required logistics information cannot be aggregated on one platform for effective processing, an information island will be formed, and it is difficult to achieve global optimal configuration of resources. Therefore, accurate forecasting information can provide decision-making basis for the track broker' scientific development of enterprise market planning and rational allocation of logistics resources, and also guarantee the logistics supply and dispatch.

At present, scholars have begun research in this field. L.Y. Chang established a truck broker transport resource organization optimization model with opportunity constraints to optimize the matching of transport resources, supply and transportation routes, and designed a hybrid intelligent algorithm for particle subgroups and neural networks to solve the problem and scientifically organize the capacity reducing transportation costs[3]. Subsequently, the PCA-AHP of the vehicle-free carrier partner selection model was established, and the principal component analysis (PCA) of the vehicle-free carrier partner selection index system for multiple indicators was carried out, and the quality of transportation service was determined to affect the truck broker selection partner. The key factor is to provide a basis for decision-making for the rational choice of allies[4]. T.Zhou conducted a comprehensive analysis of various factors affecting regional logistics demand, and used radial basis function neural networks to construct a nonlinear prediction model for regional logistics demand[5]. W Wei combined the ant colony optimization algorithm with BP neural network to prove that the research of AM automated logistics information system neural network has better nonlinear function method and potential feedback dynamic data processing ability. Its parameter convergence is fast and adaptive, and the prediction accuracy is high[6]. J.Tian combined adaptive and floating-point coding genetic algorithms with neural networks to accurately predict urban logistics demand with high accuracy and fast convergence speed[7]. Theoretical research and practice have shown that predictive models with multiple method combinations have higher prediction accuracy than single predictive models.

This paper intends to predict the logistics demand of the truck broker. In order to overcome the shortcomings that is the assumptions of single prediction methods, the paper uses the particle swarm optimization algorithm to optimize the BP neural network. Firstly, establish a vehicle-related carrier logistics demand indicator system, collect relevant data of Shaanxi regional economy, and use a single BP neural network method and particle swarm optimization algorithm to optimize the BP neural network method, the date is some economic data of Shaanxi Province from 2007 to 2016. The forecast results of Amount of cargo and cargo turnover are compared with the actual data. Finally, the better model is used to make short-term forecast of logistics demand about Shaanxi Province in the next few years, providing effective data reference for logistics enterprises under the government and the truck broker mode.

2. Indicator establishment

2.1 Demand quantity selection

The scale of logistics demand can reflect the development of logistics industry and the supply of logistics services. For the track broker, the amount of logistics demand is important data that enterprise decision-makers must master. In this paper, the statistical data of cargo transportation volume and cargo turnover is used as the measurement index of logistics demand, that is the data of the carrier-free carrier logistics demand in the article selects the relevant data of Shaanxi Province for nearly seventeen years, and the demand vector Z contains the freight volume Z1 and cargo turnover Z2 two analogy indicators.

2.2 Selection of multi-factor economic indicators

There is a great correlation between regional logistics demand and regional economic level[8]. There are many economic factors affecting regional logistics demand. Due to the limitation of statistical data acquisition, this paper selects 11 economic indicators to constitute the component of factor vector X. A more representative view is that the macro aspect mainly includes three major parts: economic scale, industrial structure, and economic spatial layout[9]. According to the different meanings selected by each indicator, the establishment of the indicator system is shown in Table1.

Table 1 the track broker forecasting indicator system

Forecast indicator name	Unit	Code	Indicator meaning
Total output value	hundred million RMB	X1	Reflecting the scale of the economy affects
GDP per capita	Yuan	X2	

			the scale of demand
First production value	hundred million RMB	X3	Reflect the impact of economic structure on the scale of demand
Second production value	hundred million RMB	X4	
Third production value	hundred million RMB	X5	
Household consumption level	Yuan	X6	Regional trade and business circulation are important components of demand
Total fixed asset investment	hundred million RMB	X7	
Total import and export	Thousands of dollars	X8	
Total retail sales of consumer goods	hundred million RMB	X9	
Commodity retail price index	/	X10	
Total population	Ten thousand of people	X11	
Freight volume	Ten thousand of tons	Z1	Reflect the scale of demand
Turnover	hundred million tons	Z2	

Note: The total import and export volume is divided according to the domestic destination and source of goods; the retail price index of goods is based on the price of the previous year. The index (=100) is calculated.

2.3 Establishment of indicator system

The establishment of the truck broker demand forecasting index system is the cornerstone of the research and is a reliable basis for evaluating whether the research work is targeted. Taking into account the accuracy of the research work and the actual feasibility, the establishment of the indicators follows the principles of comprehensiveness, uniform measurement, operability, independence, etc., and builds the following vehicle-free carrier demand forecasting index system. After determining the indicator system, collect relevant economic data of its ten indicators from 2000 to 2016 in Shaanxi Province. The indicator data of the article are all from the website of the National Bureau of Statistics of the People's Republic of China to ensure the reliability of the data source,see Table 2.

Table 2 Statistical data of relevant indicator systems in Shaanxi Province from 2000 to 2016

Years	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	Z1	Z2
2000	1804.00	4968	258.22	782.58	763.20	2210	653.67	2387540	607.6	98.3	3644	29201	573.00
2001	2010.62	5506	263.63	878.82	868.17	2857	773.43	2647470	665.1	99.1	3653	31364	676.30
2002	2253.39	6145	282.21	1007.56	963.62	3093	915.35	2784130	728.2	98.6	3662	33540	776.90
2003	2587.72	7028	302.66	1221.17	1063.89	3335	1200.68	3554700	853.2	100.5	3672	34961	849.10
2004	3175.58	8587	387.88	1553.10	1234.60	3733	1508.89	4556870	966.5	102.5	3681	37961	963.50
2005	3933.72	9899	435.77	1951.36	1546.59	4182	1882.18	6149314	1331.3	100.1	3690	41551	1028.80
2006	4743.61	11762	484.81	2452.44	1806.36	4742	2480.69	6922389	1542.4	101.8	3699	44217	1081.70
2007	5757.29	15546	592.63	2986.46	2178.20	5480	3415.02	8235942	1837.3	104.9	3708	49175	1191.10
2008	7314.58	19700	753.72	3861.12	2699.74	6483	4614.42	10455863	2317.1	106.9	3718	83493	2027.05

2009	8169.80	21947	789.64	4236.42	3143.74	7154	6246.90	8672997	2699.7	99.9	3727	92557	2218.55
2011	12512.30	33464	1220.90	6935.59	4355.81	10053	9431.08	14083481	3900.6	104.8	3743	120908	2824.67
2012	14453.68	38564	1370.16	8073.87	5009.65	11852	12044.50	15189728	4581.6	102.3	3753	136727	3192.14
2013	16205.45	43117	1460.97	8912.34	5832.14	13206	14884.15	20219749	5245.0	101.8	3764	141579	3200.56
2014	17689.94	46929	1564.94	9577.24	6547.76	14812	17191.92	27688331	5918.7	100.7	3775	157012	3521.46
2015	18021.86	47626	1597.63	9082.13	7342.10	15363	18582.24	29877091	6578.1	99.8	3793	140900	3263.52
2016	19399.59	51015	1693.85	9490.72	8215.02	16657	20825.25	29468674	7367.6	100.3	3813	149046	3444.92

Source: National Bureau of Statistics of the People's Republic of China, http://www.stats.gov.cn/

3. PSO-BPNN model construction

3.1 The basic principles of the model

The Back-Propagation Neural Network (BPNN) is a multi-stage acyclic network trained by the error back propagation algorithm proposed by the group of scientists led by Rume-lhart and McCelland. It is one of the most widely used neural network models[10], but the model constructed by the BP neural network may fall into a local minimum and cannot ensure convergence to the global minimum. However, if the particle swarm optimization algorithm using the mean square error index as the fitness value trains the weight of the BP neural network, the convergence speed will be faster, and the local extremum can be avoided. The use of bio-intelligent algorithms to optimize the initial parameters and network structure of neural network optimization is a better method[11], which makes the model show more effective prediction results. Compared with other algorithms, the particle swarm optimization algorithm is simpler to operate and has better global optimization ability[12]. The optimization of BP neural network has obvious advantages. Therefore, this paper selects the combination method of particle swarm optimization algorithm to optimize BP neural network training.

The particle swarm optimization (PSO) algorithm is a group adaptive search algorithm. The basic idea is that it is inspired by the bird group to seek food, and cooperates to find the best value through information sharing between individuals[13]. In the PSO algorithm, a group of random particles is initialized first, and then each particle is updated by tracking the individual optimal solution and the global optimal solution until the optimal solution is found.

3.2 Steps of the model

The process of the truck broker logistics demand forecasting based on PSO-BP neural network is divided into the following steps:

(1) Standardization of sample data. Considering the active range of the BP neural network training function, all the data are normalized into this interval, and the magnitude difference between different orders of data between different dimensions is eliminated. The input data normalization method formula is as follows:

$$XX(i,j)=\frac{X(i,j)-X_{\min(j)}}{X_{\max(j)}-X_{\min(j)}} \tag{1}$$

Among them, the maximum value of the sample data is the minimum value of the sample data.

(2) Establishment of BP neural network. The structure of the BP neural network is divided into three layers: the input layer, the hidden layer, and the output layer. Input data from $X2\Lambda\ X12$, output data $Z1, Z2$;

(3) Set the parameters, weights and thresholds of the network. Set the acceleration factor c_1, c_2 and the weight threshold, the velocity of the particle group particles, the maximum speed $v_{\max}$ and the minimum speed $v_{\min}$.

(4) Update the individual extremum and global extremum of the particle. If the current fitness of the individual particles is better than the individual extremum before the iteration, the update of the individual extremum is performed $p_i(t) = X_i(t)$; Otherwise, all individual extreme values with the best fitness are global optimal.

(5) Iterative optimization. Calculate the global extremum, reach the maximum number of iterations when the network error reaches the set accuracy requirement, and then jump to the next step; otherwise, jump to step 3 to perform the optimal update of the individual and the group until the number of iterations reaches the preset maximum. Excellent. The mean square error is used as the fitness function of the particle:

$$fitness = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M}(y_{ij} - \overline{y_{ij}})^2 \tag{2}$$

N is the number of samples trained, M is the particle dimension, is the ideal output value of the first sample, and is the actual output value of the first sample.

(6) Get the optimal solution, and give the initial weight and threshold to the network for prediction. Forecast experimental data of output freight volume and cargo turnover.

4. Simulation and numerical analysis

4.1 Training of PSO-BPNN model

The PSO-optimized BPNN model was simulated using MATLAB R2015b software to verify the validity of the model. The number of input layer nodes is 11, and the number of hidden layer neurons is 15, see Fig. 1.

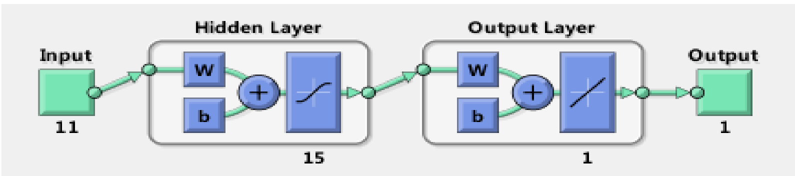

Fig.1 PSO-BPNN model structure

The PSO-BPNN model was trained on 11 sets of sample data from 2000 to 2016 in Shaanxi Province, and the freight volume Z1 and cargo turnover Z2 of the 10 groups from 2007 to 2016 were predicted. Figure 4-2 shows the fitness curve of the cargo volume Z1 and the cargo turnover Z2 in the process of optimizing the BP neural network weight and threshold. The horizontal axis is the training frequency of the model and the vertical axis is the network training error.In the iterative process of the PSO algorithm, the fitness value of the particles changes significantly, and the error is continuously reduced. The cargo quantity Z1 is iterated to 95 times, and the sample value of the test is reduced to 0.036; the cargo turnover amount Z2 is iterated to 22 times, and the square of the error of the test sample is reduced to 0.065.

4.2 Comparison of model effects

In order to test the validity of the proposed model, this paper compares the BP neural network model and the PSO-BPNN model demand forecast results. The input of the model is the Shaanxi logistics demand data after standardization. Based on the PSO-BPNN prediction model, the MATLAB platform is used to establish an input layer with 11 neurons, the hidden layer has 15 neurons, and the output layer has 1 neuron. The model, and calculate the prediction results; a single BP neural network model is also tested by MATLAB simulation, and the prediction results are obtained. Fig.2 to Fig.5 below are comparison charts of the prediction results of the two models.

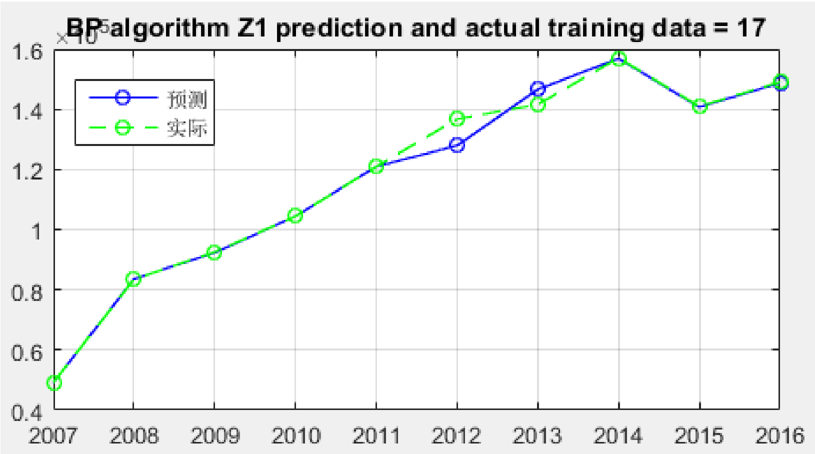

Fig.2 Comparison of predicted and actual values of BP algorithm Z1

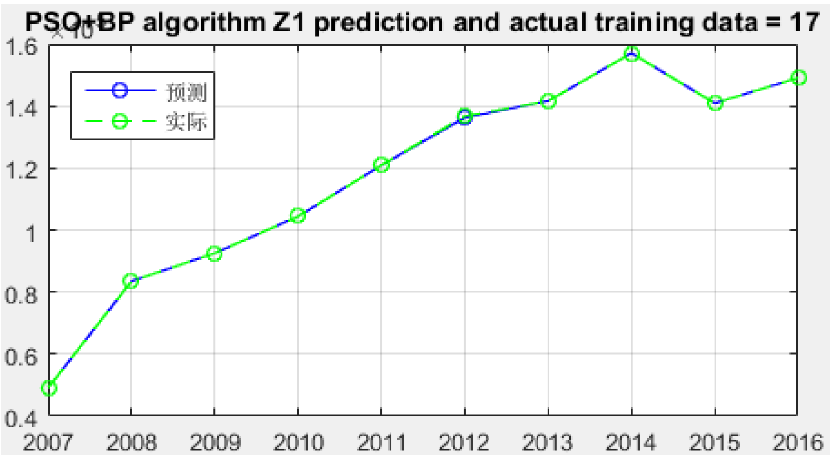

Fig.3 Comparison of predicted and actual values of Z1 PSO-BP algorithm

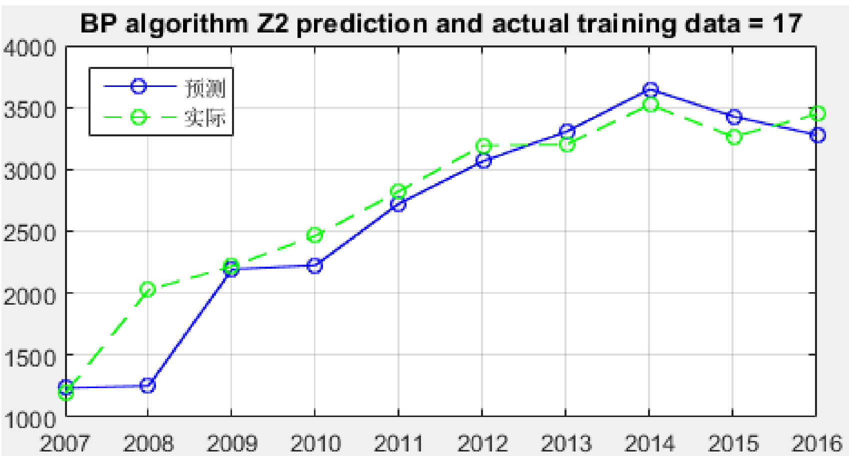

Fig. 4 Comparison of predicted and actual values of BP algorithm Z2

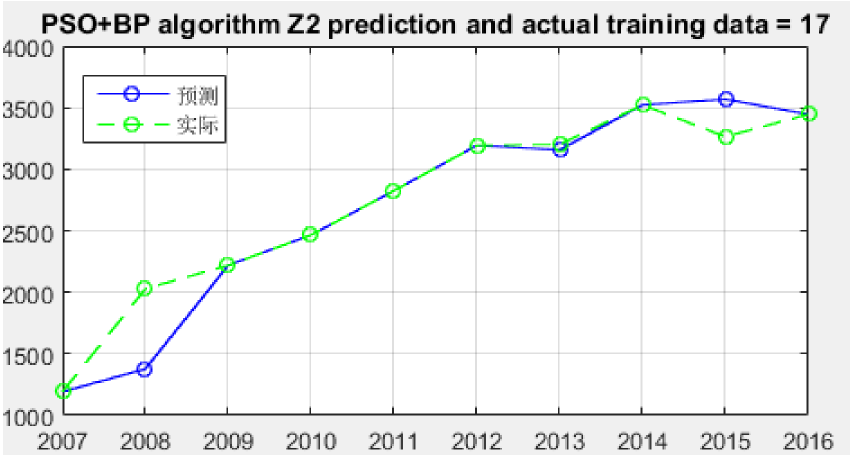

Fig.5 Comparison of predicted and actual values of Z2 PSO-BP algorithm

It can be seen intuitively from the broken line chart that the predicted value of the PSO-BP model is closer to the actual value. Therefore, the PSO-BPNN prediction model has a better ability to predict the demand for car-free carrier logistics. The PSO-BP algorithm prediction and actual correlation coefficient, prediction and actual mean square error are significantly smaller than the BP algorithm's prediction and actual correlation coefficient, prediction and actual mean square error. This shows that the PSO-BP combination algorithm is more accurate than the single BP algorithm.

4.3 Short-term prediction of the demand for car-free carriers using PSO-BP neural network

The particle swarm optimization BP neural network algorithm is used to predict the logistics demand of Shaanxi Province in the next few years. The model is implemented under MATLAB R2015b. Firstly, the PSO-BP model is established by using the parameters set above, and the raw data in the table is used to predict the freight volume and cargo turnover. Then, a three-level neural network is established, and the original data in Table 2-2 is optimized by using PSO to optimize the BP neural network. As an input to the model, Z1 and Z2 serve as outputs. Finally, the prediction results are optimized according to the weights,see Table 3.

Table 4-3 Forecast of Car Carrier Carrier Demand in Shaanxi Province from 2017 to 2020

Years	2017	2018	2019	2020
Freight volume / tons	163056	174306	181627	183453
Cargo turnover / 100 million tons	3761.63	4009.88	4114.14	4257.80

Judging from the forecast results, with the development of the economy, the logistics demand in Shaanxi Province has shown a steady trend in the next few years.

The above experiments show that:

(1) BP neural network model has certain advantages in demand forecasting, and it has self-learning adaptive ability and is widely used. However, it may fall into a local minimum, and it cannot guarantee convergence to the global minimum point, and the operation time is long, and the accuracy of prediction is relatively low.

(2) Using particle swarm optimization to optimize the initial parameters and network structure of neural networks is a better method. The particle swarm optimization algorithm with mean square error index as the fitness value trains the weight of BP neural network, and it will get faster convergence speed, which can avoid the occurrence of local maximum value.

(3) The prediction based on PSO-BPNN model is more accurate than the single BP neural network prediction model. This method has better nonlinear fitting ability and higher prediction accuracy for the truck broker logistics demand forecasting.

5. Conclusion

This paper is used the empirical data of Shaanxi Province to provide a better demand forecasting method for the truck broker, and it provides a decision-making way for scientifically formulating enterprise development planning and rational allocation of enterprise logistics resources, ensuring logistics supply demand and adjusting logistics supply and demand balance. This paper is collected multi-factor economic data of Shaanxi Province for 17 years, and is constructed PSO-BPNN car-free carrier demand forecasting model. Finally, we compare the date with the prediction result of single BP neural network model, which shows that the combined model is more suitable for car-free carrier logistics demand. The quantity is forecasted and has stronger applicability. The final application combination model is for short-term market forecast of the logistics demand of car-free carriers in Shaanxi Province.

Due to the differences in data and the uncertainty of the environment in the macro economy, the article has inevitable defects. The selection of actual indicators has certain limits, and the statistical error of the data causes the model prediction results of the PSO-BP algorithm combination to have certain deviations. If the classification of data statistics can be made more scientific and complete, it will be more conducive to the prediction research of this demand.

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