Freight Volume Forecast of Wuhan City Circle Based on Wavelet Neural Network

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Abstract: Freight system is a complex system with multi factors coupling. The relationship among the factors of freight is staggered, showing strong randomness, uncertainty and nonlinearity. The wavelet neural network combines the self-learning ability of the neural network with the powerful detail feature of the wavelet, which has adaptive resolution and good tolerance.The freight volume of Wuhan city circle and eight important parameters which affect the freight volume taken as the basic data, the annual comprehensive index of the impact factor of the freight volume is obtained through the significant analysis of F statistics. Then a wavelet neural network is constructed with the enhanced flexibility by the introduction of translation factors and of the expansion factors. The parameters are optimized continuously until the whole network reaches the minimum error by training. So the network can extrapolate the future freight volumes. Through the test and analysis of the forecast results, the validity of the wavelet neural network used in the prediction of freight volume is proved.

Introduction

At present, the Wuhan city circle efforts to co-ordinate the development of railway, highway, water, air and other integrated transport mode, to achieve the reasonable allocation of resources and the pilot "two oriented society" construction. The scientific and reasonable forecast of freight volume of Wuhan city circle is beneficial to guide the traffic construction in the region in the region and to carry out the scientific development concept.

Because of the close connection among the goods transportation, the local economy and the enterprises development, the freight volume forecasting is an important issue in the research of freight market and economic development [1]. Freight volume is an important basis for the construction of transportation demand and the guidance of the national economy. Freight volume is the joint action result of two aspects of the economic demand (system external) and transportation system (system interior). From the perspective of external economic system, the traffic volume is influenced by two factors: One is various economic aggregate, such as the scale of economy and infrastructure, etc; the other is various economic configurations, such as the structure of industry and estate. From the perspective of internal transport system, the traffic volume is also influenced

by two factors: One is the transport aggregate; the other is the transport structure. At different stages of national economic development, scale factors and structural factors play different roles and show different forms in growth and change of transport volume. In different stages of the development of national economy, the scale factor and structure factor have different effects on the growth of the freight volume, and the growth of the freight volume also has different performance [2]. At the same time, imbalance of supply and demand in the transportation market exist objectively, the impact of internal and external system on the goods volume is not the identical, which makes the prediction of freight volume has the characteristics of large complexity and nonlinear[3]. Under the condition of market economy, the development of the national economy has a certain cyclical fluctuations, so the national economy on the demand of the freight volume also show some random and volatility. With the traffic market development, the inherent law of the freight demand becomes more complex and changeable [4].

Wavelet neural network based on BP and Morlet

Wavelet neural network has good approximation effect on the nonlinear function. The good localization and multi-resolution learning function of wavelet neuron, make the wavelet neural network has stronger adaptive ability and higher prediction accuracy. The freight volume time series is realized by linear superposing the selected nonlinear wavelet, namely the complex mapping from each parameter to freight volume is realized by the finite term of wavelet series [5,6]. The actual freight volume $y(t)$ can be fitted by the basis of the wavelet $h(a,b,t)$:

$$\hat{f}_t(X) = \sum_{t=1}^{T} w_t h\left[\frac{\sum_{t=1}^{m} u_{ti} x_t(i) - b_t}{a_t}\right] \quad (1)$$

Where $x_t(i)$ is the actual value of the i influence factor of the freight volume at moment t; $X = (x_t(1), x_t(2), \ldots . x_t(m))$, $\hat{f}_t(X)$ is fitting value of time Series C; w_t, b_t and a_t are respectively the weight coefficients, translation factors and scaling factors of wavelet bases; T is the number of wavelet bases; $h(a,b,t) = \frac{1}{\sqrt{|a|}} \bullet h_{basic}\left(\frac{t-b}{a}\right)$, $h(t)$ is called the mother wavelet; t is called the wavelet base.

The most important work is to determine the network parameters w_t, u_{ti}, b_t and a_t, which makes the sequence $\hat{f}_t(X)$ and $y(t)$ fit the best. The parameters w_t, u_{ti}, b_t and a_t can be optimized by the least mean square error energy function:

$$E = \frac{1}{2}\sum_{t=1}^{N}(\hat{f}_t(X) - Y(t))^2 \quad (2)$$

Where N is the total number of data sampling points. Type (1) using the Morlet wavelet function:

$$h(t)=\cos(1.75t)\exp\left(1-\frac{t^2}{2}\right) \quad (3)$$

The specific algorithms of the network are as follows: [7]:

(1)Initialization of network parameters: the scaling factor a_t, the translation factor b_t of wavelet, and the network connection weights u_{ti} and w_t are given the random initial value;

(2)Input learning sample $x_t(i)$ and corresponding expected output y_i;

(3) Self-learning: the output of the network is calculated using the current network parameters and type (1):

(4) Calculate the instantaneous gradient vector:

$$d_{wt}=\frac{\partial E}{\partial w_t}=-\sum_{t=1}^{N}(\hat{y}_t-y_t)h\left[\frac{\sum_{t=1}^{m}u_{ti}x_t(i)-b_t}{a_t}\right] \quad (4)$$

$$d_{at}=\frac{\partial E}{\partial a_t}=-\sum_{t=1}^{N}(\hat{y}_t-y_t)w_t\frac{\partial h}{\partial a_t} \quad (5)$$

$$d_{at}=\frac{\partial E}{\partial b_t}=-\sum_{t=1}^{N}(\hat{y}_t-y_t)w_t\frac{\partial h}{\partial b_t} \quad (6)$$

$$d_{u_{ti}}=\frac{\partial E}{\partial u_{ti}}=-\sum_{t=1}^{N}(\hat{y}_t-y_t)w_t\frac{\partial h}{\partial x'_t}x_t(i) \quad (7)$$

Among them: $a_t=\sum_{t=1}^{m}u_{ti}x_t(i)$, $t_n^{'}=\frac{x_t^{'}-b_t}{a_t}$

$$\frac{\partial h}{\partial x_t^{'}}=-\cos(1.75t_n^{'})\exp\left(-\frac{t_n^{'}}{2}\right)\frac{t_n^{'}}{a_t}-1.75\sin(1.75t_n^{'})\exp\left(-\frac{t_n^{2}}{2}\right)\frac{1}{a_t} \quad (8)$$

$$\frac{\partial h}{\partial a_t}=\cos(1.75t_n^{'})\exp\left(-\frac{t_n^{'}}{2}\right)\frac{t_n^{'}}{a_t}+1.75\sin(1.75t_n^{'})\exp\left(-\frac{t_n^{2}}{2}\right)\frac{t_n^{'}}{a_t} \quad (9)$$

$$\frac{\partial h}{\partial b_t}=\cos(1.75t_n^{'})\exp\left(-\frac{t_n^{'}}{2}\right)\frac{t_n^{'}}{a_t}+1.75\sin(1.75t_n^{'})\exp\left(-\frac{t_n^{2}}{2}\right)\frac{1}{a_t} \quad (10)$$

(5) Error back propagation：

$$\Delta w_t=-h\frac{\partial E}{\partial w_t^{old}}+a\Delta w_t^{old} \quad (11)$$

$$\Delta u_{ti}=-h\frac{\partial E}{\partial u_{ti}^{old}}+a\Delta u_{ti}^{old} \quad (12)$$

$$\Delta a_t = -h \frac{\partial E}{\partial a_t^{old}} + a\Delta a_t^{old} \quad (13)$$

$$\Delta b_t = -h \frac{\partial E}{\partial b_t^{old}} + a\Delta b_t^{old} \quad (14)$$

Modifying network parameters w_t, u_{ti}, b_t and a_t。

$$w_t^{new} = w_t^{old} + \Delta w_t \quad (15)$$

$$u_{ti}^{new} = u_{ti}^{old} + \Delta u_{ti} \quad (16)$$

$$a_t^{new} = a_t^{old} + \Delta a_t \quad (17)$$

$$b_t^{new} = b_t^{old} + \Delta b_t \quad (18)$$

(6) When the error function value is less than a predetermined value, the network stop learning, otherwise return step (2).

Case application

Significant test. To ensure data adequacy, this paper collected the actual data of Wuhan city circle in 1995 - 2014 (20 years), including GDP, the output value of second industry (including industrial and construction), the length of railway transportation line, the length of highway transportation route, the rate of highway transportation route, the number of railway freight cars, the quantity of the goods, the quantity of cargo ship and the freight volume. Data are from Hubei Province Statistical yearbook.

According to the variance analysis of single factor, the 8 characteristic factors affecting the freight volume and the data of the freight volume data are analyzed. The results are shown in Table 1.

Table 1 The significant analysis results of the impact factors of freight volume

The impact factors	F-value	P-value
GDP	119.1074	2.29E-09
The second industry	103.6583	6.77E-09
the length of railway transportation line	57.4978	5.21E-07
the number of railway freight cars	81.53663	4.19E-08
the quantity of the goods	85.2309	3.01E-08
the quantity of cargo ship	68.0612	1.58E-07
the length of highway transportation route	110.3165	4.17E-09
the rate of highway transportation route	60.3218	3.73E-07

The effect of significant factors in table 1 will to be judged. First, to judge according to the F-measure: if F≥F0.05=4.41, the conclusion is significant at levelα=0.05, and vice versa. Second, to judge according to the P-measure: The conclusion is very significant when P-value≤0.01, significant when 0.01<P-value≤0.05,not significant when otherwise. From table 1 we can see that the impact of the 8 characteristics are very significant for the freight volume, so it is reasonable for they are taken as the main factors affecting the freight volume [8].

The comprehensive index of the impact factor of the freight volume. The raw data is normalized to [0, 1] interval, which can make the data of the 8 factors and the freight volume consistent. Finally, the forecast results are anti-normalized. By the normalized data of the factors of each factor and F-measure, annual comprehensive index of the impact factor of the freight volume is calculated as follow:

$$S = \sum_{n=1}^{8} a * F \qquad (19)$$

Where S is the comprehensive index of the impact factor of the freight volume; a is the normalized data for each factor; F is F-measure of each factor. F-measure is equivalent to the weight in the comprehensive index of the impact factor.

Taking the comprehensive index of the impact factor Wuhan city circle t as the input data of the wavelet neural network, as its output data, the wavelet neural network is trained repeatedly until the error reaches the setting standards.

Training method and results. For how to arrange the training of wavelet neural network, it is natural to think that the impact factor of input and the actual freight volume output take the same years, but this is a mistake. Because the impact factor of input is unknown when doing extrapolation forecast, the model cannot be applied. Therefore, this paper takes the training method is: the synthesis index of the freight volume influence factor in the above year is taken as the input, and s actual freight volume of the following year is taken as the expected output. In particular, the wavelet neural network is constructed and trained with the input data in 1995~2011 and the output data in1996~2012. When the error reaches the setting range, the training is completed.

The number of hidden layer nodes is determined to be 10 by testing and comparison. The fitting results after training are shown in Figure 1, which show that the fitting results (using the club) and the actual volume of freight (using the broken line) are quite consistent, and the absolute value of the maximum relative error is 0.87%. In the first half of the years, the actual amount of freight presents the "abnormal" phenomenon of decline, resulting in the difficulty of fitting and the fitting error slightly larger in the figure. In the latter half of the years, the fitting accuracy of the freight volume is better. The reason is that the actual freight volume of the latter half of the years is mainly on the rise, then the regularity is better and the fitting is less difficult.

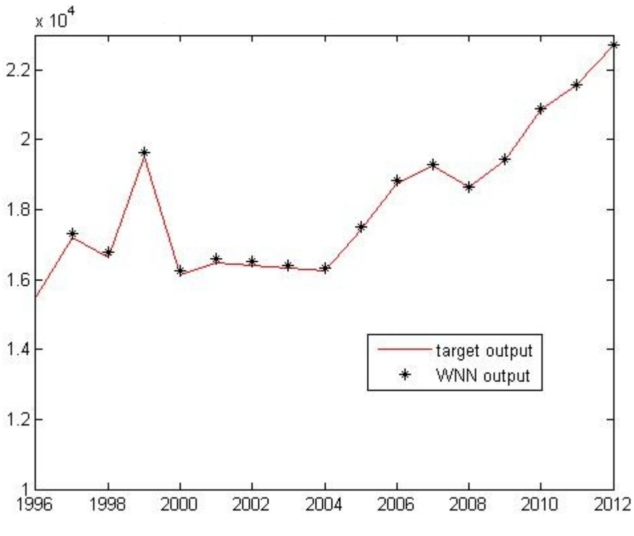

Figure 1 The target sequence after training and the actual output sequence

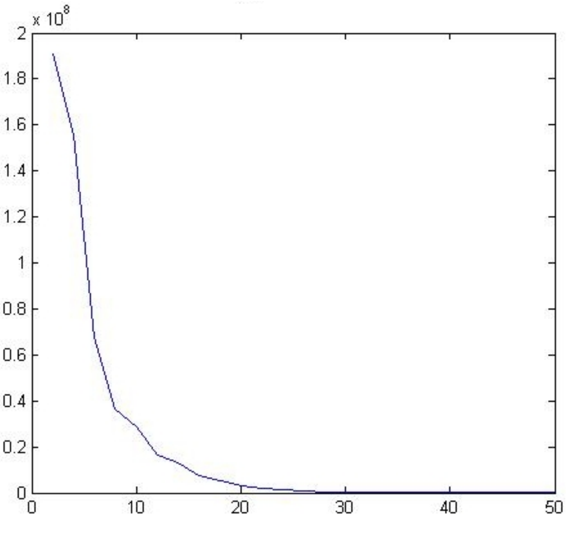

Figure 2 The error down diagram

Figure 2 is a schematic diagram of the error in the training process, in which the horizontal

coordinate represents the network training step number, and the longitudinal coordinate represents the network training error. From Figure 2, the network error has become almost 0 after training 30 times.

Network test. The trained network needs to be tested to determine whether it can be put into actual application. The test data used here are comprehensive index of the impact factor of freight volume in 2012~2013 years, forecast freight volume in 2013~2014 years. Then the forecasted freight volume is compared with the actual freight volume to test whether the forecast error can meet the requirements. Calculation results and relative errors are shown in table 2.

Table 2 calculating results and relative errors of the sample extrapolation

Years	2013	2014
Actual value (million tons)	23145	23658
Forecast value (million tons)	23329.11	24154.17
Relative error (%)	0.7955	2.097

Table 2 shows that the forecast value of the network is very close to the actual value, and the error meets the requirement of the precision, so the network has good generalization ability. The error shows that the actual value is less than the forecast value. The reason is that the industry and construction downturn in recent years, steel and cement and other large raw material demand reduction, which results in the growth rate of the actual freight rate decreasing.

Forecast of future freight volume. Next to forecast freight volume of the years after the original data. Continue to use the above model, taking the comprehensive index of the impact of factors in 2014 as input data to get the 2015 freight volume, which is 252769600 tons. The accuracy of the results will be tested in the future.

To predict the amount of freight in 2016, the above process will be a little change. Using the input data in 1995~2012 and the output data in 1997~2014 to construct a wavelet neural network and train it, namely the corresponding relationship is the output data later than the input data 2 years. Then taking the input data in 2014 to predict the amount of freight in 2016, which is 254095300 tons.

Conclusion

The freight volume is forecasted by using wavelet neural network based on the analysis of the impact factors and characteristics of freight volume. the annual comprehensive index of the impact factor of the Wuhan city circle taken as the input, the corresponding actual freight volume taken as the output of the wavelet network, then train the network using a sufficient number of samples. The time-frequency localization of wavelet and the self-learning function of neural network are exploited in the model of wavelet neural network through weighted calculation and repeated training on the inner pro duct of wavelet basis and input vectors After continuous learning and testing to achieve higher accuracy, it can be used in combination forecasting [6,9].The effect of this method is proved through the application of mentioned example.

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