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Urban Traffic Volume Forecast Based on BP Neural Network: A Case Study of Xiamen City

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ABSTRACT

From the perspective of transportation nature, urban comprehensive traffic management can be divided into two types: passenger traffic and freight traffic. In order to improve the efficiency of urban overall planning, it is very important to make reliable predictions of passenger traffic and freight volume of the city. With the continuous development of the social economy, the limitations of traditional traffic volume prediction methods have gradually emerged. By analyzing the problems of traditional regression prediction in traffic forecasting, a BP neural network based on polynomial regression is used to predict the city's traffic volume, and the model is tested against the known data of Xiamen City in 2000-2017. The model selects the total import and export volume, the permanent residents of the region, the added value of the tertiary industry, the income of the urban population, and the income of the rural population as the influencing factors of the urban traffic volume. At the same time, the model is solved by MATLAB software. The results show that the neural network can be used to predict urban traffic volume. It provides a reference for the realization of urban comprehensive traffic planning and management.

KEYWORDS: polynomial regression, BP neural network, traffic volume prediction, comprehensive traffic planning management

1. INTRODUCTION

Transportation is one of the important supporting factors for economic development. Good traffic conditions and road network layout will promote the optimization of industrial structure, the development of regional advantages and the development of regional logistics, and also bring a large increase in investment and the convenience of residents. The healthy and rapid development of the transportation industry is of great significance to the rational distribution of national economy, the coordination of regional economic development and the optimization of resource allocation and productive force distribution. Traffic forecasting is one of the core issues in the field of transportation planning and management research.It is also an important part of transportation planning and decision analysis. Therefore, it is very important to choose a method that can accurately predict traffic volume. The influence factors of traffic volume and the development trend of highway freight volume and passenger volume will change greatly in different periods, leading to the randomness and non-linearity of the historical data of highway traffic volume. Howeverÿthe traditional forecasting methods, such as average growth rate method, elastic coefficient method and regression analysis method, are relatively simple. In addition, the data is required to meet certain statistical rules, and it cannot meet the needs of practice development when dealing with the problem of nonlinear traffic volume prediction. Some of these prediction methods are based on historical data of traffic volume, and the other part is based on some variables related to traffic volume. However, the relationship between traffic volume and other variables is not always linear. Therefore, the traditional regression analysis has the disadvantage of large error in the prediction of traffic volume. And the traditional prediction method needs a lot of work in the prediction process, and BP neural network is a mature theory of recent development. The theory is combined with other algorithms to make corrections, which makes the results more accurate and reliable. Based on the previous research. Through learning, new prediction theories and methods are proposed, and the traffic volume is predicted reliably and quickly under the premise of possessing historical data.

In this paper, polynomial regression is applied to the time-based linear prediction of traffic volume related variables, and then the nonlinear problem in the prediction process is solved by using BP neural network. On the other hand, this paper will construct a BP neural network prediction model with different hidden layer nodes for passenger traffic and freight volume, and compare and analyze the prediction results to obtain a traffic volume prediction neural network model with less error, and finally predict the future traffic volume. Also, based on the passenger traffic and freight volume of Xiamen City from 2000 to 2017, BP neural network prediction model is used to predict the traffic volume from 2018 to 2020.

2. LITERATURE REVIEW

Research on the theoretical system of traffic flow prediction is of great academic value and practical significance to improve traffic congestion. For many years, traffic managers have focused on improving the reliability of traffic information prediction. The history of traffic volume prediction can be traced back to the early 20th century. In the early 1970s, The "four-stage method" has been developed in a mature way, and it has been playing a leading role in traffic demand forecasting. In the late 1980s, with the application of microcomputers, many new methods and traffic planning software were gradually applied to the field of traffic planning. Che-Chiang Hsu, Chia-Yon Chen[1] proposed a new technique to combine the residual correction of the GM(1,1) model with the signal estimation of the neural network to improve the GM(1,1) model and It is applied to Taiwan's energy demand forecast; Deng-Yiv Chiu, Chin-Ching Lin [2] combines grey theory, genetic BP neural network, and BS option pricing theory to explore the internal mechanisms of guarantees in financial markets; Bao Rong Chang, Hsiu Fen Tsai [3] used support vector regression to improve the control and environmental parameters of the GM(1,1) model, proposed the SVRGM model, and reduced the over-fitting of the GM(1,1) model for predicting time series. The effect, considering the advantages of the GARCH model in solving the volatility agglomeration effect, establishing a combined model of the GARCH model and the SVRGM model, and using the BP neural network to determine the combined weight, experiments show that the combined model better solves the problems of over-fitting and volatility agglomeration; T.Y. Pai, S.H. Chuang, H.H. Ho[4] et al. used online control parameters to predict suspended solids and chemical oxygen demand in industrial wastewater respectively by using GM(1,N) model, RGM(1,1) model and neural network, and compared the advantages and disadvantages of the model. Vythouucas[5] adopted artificial neural network algorithm in traffic prediction, which pioneered the forecast of traffic artificial neural network. Thierry[6] made use of artificial neural network to predict short-term traffic volume and achieved certain results. Corinne[7] first established a traffic flow prediction model based on the principle of artificial neural network and used virtual data to verify the effectiveness of the model. In the same year, Haibo[8] used the prediction method of dynamic sequential learning model to predict traffic volume, which proved that this method was more accurate than the traditional method. In 2005, G.Karlaflis[9] proposed a new neural network optimization method in Transportation Research Part C. In 2008, Coskun Hamzacebi[10] adopted an improved BP neural network model in traffic volume prediction, and the study on the prediction of traffic volume using BP neural network is more in-depth.

The accuracy of traffic volume prediction is closely related to urban comprehensive traffic management. Only traffic management personnel can accurately grasp the development trend of urban traffic, and then correctly formulate relevant traffic management policies, integrating from people, vehicles, roads and environment. Consider to improve the urban traffic management system to the greatest extent and enhance the role of urban transportation.

3. FORECAST METHOD ANALYSIS

3.1 Polynomial regression

Polynomial regression involves only two variables, namely, time as the independent variable X, and other variables related to the traffic volume as the dependent variable Y. For example, the total import and export of foreign trade, the permanent population in the region, the added value of the tertiary industry. The regression model is to find a polynomial relationship between X and Y, this function relationship can generally be represented by Y=AX^2+BX+C. The values of A, B, and C can be determined from the sample data using the least squares method or other methods. After A, B, and C are determined, each time there is a value of X, a Y value can be obtained according to the function relationship.

The reliability and error of regression equation can be tested by significance test and error calculation. Polynomial regression can reveal the quantitative relationship between related variables and time. Therefore, the corresponding variables can be calculated according to the predicted years.

3.2 BP neural network analysis

BP neural network is a multi-layer feedforward neural network with error back propagation. According to statistics, 80%-90% of neural network models adopt BP network or its variant, which is the most common in neural network system. A network structure consists of an input layer, an implicit layer and an output layer. Its information processing capability mainly comes from the multiple composite functions of the nonlinear output function, and the network structure is relatively simple and easy to implement. The process is as follows: The external information is passed from the input layer to the neural network, a processing method of the input layer is selected, and the result is passed to the hidden layer. According to different problems, the required complexity of the neural network is different, that is, the hidden layer in the middle processing system is different, and the hidden layer can be divided into a single hidden layer and multiple hidden layers. The information processed by the input layer is passed to the hidden layer, further processed by the hidden layer and the resulting information is finally processed by the output layer and the result is output. If the resulting output does not match the expected output, the error is reversed, propagated forward by the output layer, and the network connection weights and thresholds of the output layer, hidden layer, and input layer are updated. Repeat the forward propagation calculation output and the reverse error to adjust until the output value meets the desired output, or a certain number of times.

The implementation steps of the three-layer BP network learning algorithm are as follows:

1. Network initialization. Put the input layer to the hidden layer, the ownership value of the hidden layer to the output layer is random number arbitrarily small, and set the initial threshold.
2. Provide training samples. According to the learning rule, the input vector X= ($x_1 \ldots x_m$) and the corresponding output vector D= ($d_1 \ldots d_l$) need to be provided.
3. Calculate output layer by layer from input layer to hidden layer and output layer.
   (1) Suppose for each neuron of the input layer: Input as x_i, the output is $O_i = x_i$ (i=1,2,3…m), i——-the number of neurons in the input layer.
   (2) For each neuron in the hidden layer: the input is
   $x_j' = \sum_{i=1}^{m} w_{ij} O_i - Q_j$,
   the output is
   $O_j = f(x_i)$, (j=1,2,3…n),
   j——-the number of neurons in the hidden layer.
   (3) For each neuron in the output layer: the input is
   $x_j'' = \sum_{j=1}^{n} w_{jk}' O_j' - Q_k'$,
   the output is
   $y_k = g(x_k'')$,(k=1,2,3…L)
   k——- the number of neurons in the output layer.

In the above formula, w_{ij} is the weight between the input layer and the hidden layer. w_{jk}' is the weight between the hidden layer and the output layer, the function f (x) is usually an s-type function, in the meantime, g(x) can be a nonlinear function or a linear function.

4. Adjust the weight. According to the error, adjust the weight layer by layer from the output layer node to the hidden layer node and then to the input layer node.
5. Return 2 and recalculate until the error meets the requirement.

This paper takes the total import and export volume of foreign trade in previous years, the permanent population in the region, the added value of tertiary industry, the per capita income of urban residents and rural residents as the input layer elements, and take passenger and freight volume as the output layer. By selecting different hidden layers to predict passenger and cargo traffic volume, the BP neural network model with the minimum error is obtained. Also this model is used to predict the passenger and freight volume of the year. Figure 1 shows the three-layer BP network structure used to predict traffic volume.

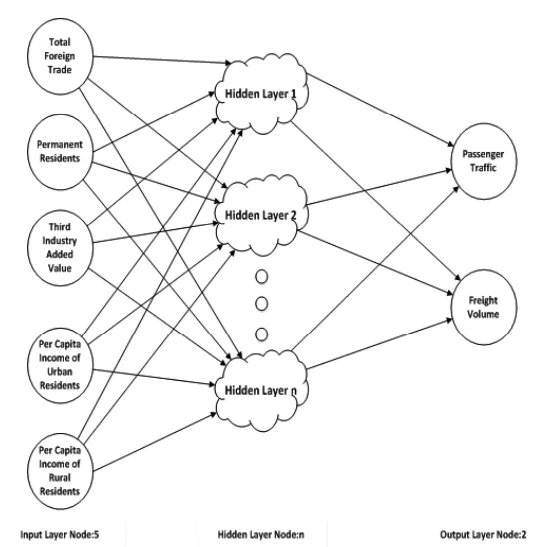

FIG. 1 Structure diagram of BP network for traffic volume prediction

4. EXAMPLE ANALYSIS

This paper takes Xiamen City as the research object and collects data on the traffic volume of Xiamen City from 2000 to 2017. The passenger volume and freight volume are predicted separately by the above methods, and the model is finally solved by using MATLAB. The prediction results are compared with the actual situation to prove the feasibility of the prediction model.

4.1 Data collection

BP neural network prediction model and polynomial regression were applied to Xiamen passenger traffic forecast. The main factors that determine the passenger and freight volume of Xiamen city are the total import and export volume, the permanent resident population, the added value of tertiary industry, the per capita income of urban residents and the per capita income of rural residents. The historical data of passenger and cargo volume and related influencing factors are shown in table 1.

Table1 traffic volume and major influencing factors in Xiamen from 2000 to 2017

Year	Passenger capacity	Cargo volume	Total import and export volume
2000	0.449	0.2448	594.87
2001	0.498	0.2548	644.24
2002	0.4758	0.2676	883.12
2003	0.444	0.3055	1088.11
2004	0.52	0.3043	1402.58
2005	0.54	0.3612	1664.86
2006	0.58	0.455	1911.26
2007	0.57	0.4582	2318.36
2008	0.64	0.5853	2666.12
2009	0.55	0.8371	2546.14
2010	0.59	1.01	3353.26
2011	0.66	1.19	4124.51
2012	0.69	1.36	4615.33
2013	0.7	1.57	5210.71
2014	0.79	2.35	5179.45
2015	0.87	2.68	5169.09
2016	0.96	2.78	5091.55
2017	1.01	3.03	5816.04

Table 1 Contd...

Data source: official website of Xiamen municipal bureau of statistics

4.2 prediction of traffic volume influencing factors based on polynomialx regression

In the regression model, the total import and export volume, permanent population, added value of tertiary industry, per capita income of urban residents and per capita income of rural residents in Xiamen from 2000 to 2017 were taken. The linear regression models of each factor are obtained respectively, as shown in equation 1-5.

(1) The polynomial regression equation for the total volume of foreign trade imports and exports is:

$$y = 3.1675x^2 - 12388.291x + 12106873.269,$$

$$R^2 = 0.9690$$

(2) The polynomial regression equation for the resident population of Xiamen is:

$$y = 0.2024x^2 - 798.097x + 786922.533,$$

$$R^2 = 0.9216$$

(3) The polynomial regression equation for the added value of the tertiary industry in Xiamen is:

$$y = 7.6607x^2 - 30640.191x + 30637804.185,$$

$$R^2 = 0.9987$$

(4) The polynomial regression equation for the per capita income of urban residents in Xiamen is:

$$y = 60.8887x^2 - 242138.348x + 240730777.608,$$

$$R^2 = 0.987$$

(5) The polynomial regression equation for the per capita income of rural residents in Xiamen is:

$$Y = 47.0208x^2 - 187899.145x + 187719314.69,$$

$$R^2 = 0.9973$$

The R^2 (fitting goodness determination coefficient) of the above polynomial regression is greater than 0.92, showing that these models can explain changes in variables, therefore, it can be used to predict the value of influencing factors of traffic volume in Xiamen in 2018-2020. According to the above polynomial regression equation. The total foreign trade import and export, resident population, added value of the tertiary industry, per capita income of urban residents, and per capita income of rural residents in Xiamen from 2018 to 2020 are shown in Table 2.

Table 2 Predicted factors of traffic influencing factors in Xiamen City from 2018 to 2020

Year	Total foreign trade import and export	Permanent residents	Third industry added value
2018	6388.301	430.184	275
2019	6787.207	444.972	303
2020	7192.448	459.76	333

4.3 Traffic Forecast of Xiamen City Based on BP Neural Network

Based on the reasonable selection of the influencing factors of traffic volume prediction, the general steps of using BP neural network to predict the traffic volume of Xiamen City from 2018 to 2020 using MATLAB software are as follows:

(1) Data input. The sample data of Xiamen passenger traffic and freight volume is predicted to be divided into training samples constituting the training network and test samples used to test the performance of the BP network. Since measurement units differ between factors affecting traffic volumes, data needs to be normalized for comparison purposes.

(2) Training network. Optimize the initial input weights and thresholds of the network through genetic algorithms, According to the difference between the historical data and the predicted value of the passenger volume and freight volume of Xiamen, the network is coordinated, and the output error is calculated by the inverse propagation of the error. When the average error of the system satisfies the given convergence condition, the corresponding error is obtained. Network parameters for the sample pattern set. Training data selected from the traffic volume and traffic volume factors of Xiamen City from 2000 to 2015.

(3) Model evaluation. After the connection weight and threshold are determined, the network performance is tested and evaluated by the test sample to obtain the final BP network prediction model. This paper will select the traffic volume data of Xiamen City in 2016 and 2017 as the data for inspection and evaluation.

(4) Taking the forecasting index data of the sample as the input of the BP forecasting model, using the trained network to perform simulation output, and renormalizing the network output, that is, obtaining the forecasted traffic volume of Xiamen city in the forecast year.

4.3.1 BP data preprocessing

In the multi-dimensional input sample, some variables have large changes and some variables have large differences, which may lead to non-convergence of the network. In addition, the activation function of the neural network model adopts sigmoid function, whose output is between [-1,1] or [0,1]. Therefore, before the system identification, the original calculated data should be preprocessed to make it more suitable for the training of neural network. After the training, the output data should be reversely normalized to restore the data characteristics. The simulation results show that the data after normalization is more conducive to the learning of neural network, so the original input and target data are preprocessed by normalization in this paper. The data of main traffic influencing factors of Xiamen after normalization is shown in table 3.

Table 3 Data of main traffic influencing factors in the normalized Xiamen city

Year	Passenger capacity	Cargo volume	Total import and export volume
2000	-0.96	-1.01	-1.00
2001	-0.81	-1.00	-0.98
2002	-0.88	-1.01	-0.89
2003	-0.99	-0.95	-0.81
2004	-0.73	-0.95	-0.69
2005	-0.66	-0.92	-0.59
2006	-0.53	-0.87	-0.50
2007	-0.56	-0.84	-0.34
2008	-0.31	-0.77	-0.21
2009	-0.61	-0.58	-0.25
2010	-0.48	-0.45	0.06
2011	-0.24	-0.32	0.35
2012	-0.13	-0.22	0.54
2013	-0.11	-0.05	0.77
2014	0.21	0.51	0.76
2015	0.50	0.74	0.75

4.3.2 BP network structure design

The structural design of BP network includes the determination of network input and output vectors and the number of nodes, the selection of network layers, the determination of the number of nodes in hidden layers, the selection of transfer functions between layers, and the range of network connection weights and thresholds.

(1) Number of input and output nodes. This paper selects five influencing factors related to the traffic volume of Xiamen as the input vector, and the passenger traffic and freight volume are the target output of the network. So the input node of the network is 5, and the output node of the network is 2.

(2) Number of network layers. It has been proved theoretically that networks with a bias and at least one hidden layer plus one linear output layer can approximate any rational function. Increasing the number of layers can further reduce the error and improve the accuracy, and can also complicate the network, thereby increasing the training time of the training weight of the network. However, the reduction of error and the improvement of accuracy can also be achieved by increasing the number of neurons in the hidden layer. On the other hand, the training effect is also easier to observe and adjust than increasing the number of layers. So in general, we should consider increasing the number of neurons in the hidden layer first. This paper adopts the network structure of an intermediate hidden layer and debugs the neural network with the minimum error by setting different number of hidden layer nodes.

(3) Add noise. Since statistical data still has a certain gap compared with real data, noise is added to the input layer to improve the robustness of the training data. What is added here is a randomly generated noise with a strength of 0.01.

4.3.3 Training Neural Networks

By changing the number of nodes in hidden layer of neural network, the neural network with different precision is obtained. In this paper, the traffic volume and its influencing factors data of Xiamen City from 2000 to 2015 are used as training data, and the neural network with 5-10 hidden nodes is used for training. The six neural networks were used to predict the traffic volume of Xiamen city in 2016 and 2017, and the data with the smallest average error was compared with the real statistical value. The node number of neural network hidden layer corresponding to the data was the node number of neural network hidden layer finally determined in this paper. The training results are shown in table 4.

Table 4 BP neural network training results

Number of layers	5	6	7	8	9	10
2016 passenger forecast data	1.02	1.01	0.98	0.99	1.02	1.01
2016 passenger actual data	0.96	0.96	0.96	0.96	0.96	0.96
Error	0.0625	0.052083	0.020833	0.03125	0.0625	0.052083
2016 Freight forecast data	3.13	3.05	3.01	3.08	3.05	3.11
2016 Actual shipping data	2.78	2.78	2.78	2.78	2.78	2.78
Error	0.125899	0.097122	0.082734	0.107914	0.097122	0.118705
2017 passenger forecast data	1.06	1.03	1	1.02	1.05	1.02
2017 passenger actual data	1.01	1.01	1.01	1.01	1.01	1.01
Error	0.049505	0.019802	0.009901	0.009901	0.039604	0.009901
2017 Freight forecast data	3.49	3.39	3.41	3.55	3.42	3.43
2017 Actual shipping data	3.03	3.03	3.03	3.03	3.03	3.03
Error	0.151815	0.118812	0.125413	0.171617	0.128713	0.132013
total mean error	**0.09743**	**0.071955**	**0.05972**	**0.08017**	**0.081985**	**0.078176**

According to the test results, when the number of hidden layer nodes of the neural network is 7, the error between the passenger traffic and freight volume forecast data and the actual data of Xiamen in 2016 and 2017 is the smallest, so the number of hidden layer nodes is selected in this paper. Prediction was performed for a BP neural network of 7.

4.3.4 Prediction based on BP neural network

The above content has been screened out the best BP neural network according to the principle of minimum average error, namely the BP neural network when the hidden layer node is 7. The value of influencing factors of traffic volume in Xiamen city in 2018-2020 obtained from the input table 2 of the same neural network after training is used. The final forecast data is shown in table 5.

Table 5 Predicted traffic volume of Xiamen City from 2018 to 2020 based on BP neural network

Year	passenger volume	volume of freight traffic
2018	1.038	3.157
2019	1.051	3.252
2020	1.055	3.309

According to table 5, the predicted results using BP neural network are 103.8 million passengers and 315.7 million tons of cargo in 2018. In 2019, 105.1 million passengers and 3.252 tons of cargo were transported. In 2020, 105.5 million passengers and 330.9 million tons of cargo were transported. The predicted results show that the passenger and freight volume of Xiamen in 2018-2020 is increasing year by year, which is in line with the actual development of Xiamen.

5. CONCLUSION

In this paper, a method for urban traffic volume prediction is introduced by combining polynomial regression with BP neural network, and the feasibility of the model is tested with the actual traffic volume in Xiamen city. The final result proves that: 1) Polynomial regression is used to predict the traffic influencing factors with time as a single independent variable. The fitting degree is higher, and R^2 (goodness of goodness of judgment) is greater than 0.92, so the polynomial obtained by regression is obtained. It can accurately represent the law of the dependent variable changing with time. 2) BP neural network prediction model has strong parallel processing and nonlinear processing ability, and can train a specific neural network with all the data summarized. In this paper, different nodes of hidden layer are trained respectively to obtain the neural network with the minimum error, which is used to predict the traffic volume of Xiamen city. The forecast results show that Xiamen's passenger traffic in 2018-2020 is 103.8 million passengers, 105.1 million passengers, and 105.5 million passenger trips respectively; Xiamen's cargo volume in 2018-2020 is 315.7 million tons, 325.2 million tons, and 330.9 million tons respectively. The forecast results show that the traffic volume in Xiamen will continue to rise, which is related to the rapid economic development of Xiamen in recent years. In particular, the development of Xiamen Port has played a key role in the growth of Xiamen's traffic volume. However, the BP neural network is sensitive to the initial weight selection, and the initial value changes will affect the convergence speed and accuracy of the network. From the above analysis, the urban traffic volume prediction model based on BP neural network can be used to predict the traffic volume of the city. Therefore, it is possible to grasp the development trend of urban traffic as a whole and have practical significance for the management of integrated traffic.

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