Use of Back Propagation Artificial Neural Network to Predict Passenger Volume of Beijing Subway

Xiaoqing Zhang, Zhili Liu, Lan Li
MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology
Beijing Jiaotong University
Beijing, China
liuzl@bjtu.edu.cn;13120933@bjtu.edu.cn;13120861@bjtu.edu.cn

***Abstract*—This paper analyze different aspects of factors that affecting passenger volume of Beijing subway, then select fifteen key factors from four aspects: internal structure of the urban rail transit system, urban demographic features, economic development and urban transport structure. Firstly, SPSS software is used to examine the multicollinearity among all the variables and then we remove three factors that are of strong multicollinearity with others. Finally, B-P artificial neural network model is established based on the remainder of factors to predict passenger volume of Beijing subway for the next few years. The results show that the average relative error of the past twenty year is 5.56%.**

Keywords-passenger volume prediction of Beijing subway; SPSS; B-P artificial neural network

I. INTRODUCTION

With the accelerated pace of urbanization, motorization and modernization, the development of transportation in Beijing faces similar problems with other international metropolis like New York, Tokyo, Seoul and so on. Rapid growth of private cars, traffic congestion and severe haze are three serious problems remain to solve. In order to change this situation, *Transportation development and construction planning of the twelfth Five-Year period* were published by Beijing municipal government to accelerate the construction of rail transit and make sure the rail transportation become backbone of urban public passenger transport system.

Urban rail transit plays a key role in guiding and supporting optimization and adjustment of urban spatial structure. Priority to the development of urban public transport systems, efficiency improvement and raise of modal share of public transport are essential to ease problems of urban gridlock and air and noise pollution caused by the use of private cars. The accuracy of prediction has a direct impact on relevant departments to formulate long-term planning, improve the operational efficiency of urban rail transit system, develop a reasonable ticket fare and increase operating income system.

Because of the relevance of the subject and its direct connection with the quality of life, this study aims to contribute to providing a reliable method to predict subway passenger volume. In Section 2, we collect related data of the past twenty years and process preliminarily by SPSS software. In Section 3, we present the whole B-P artificial neural network prediction process. The results are presented in Section 4. Finally, conclusions are drawn in Section 5.

II. ANALYSIS OF FACTORS AND DATA COLLECTION

A. Analysis of various factors

By analyzing the level of urban development in Beijing as well as the current transport structure, we select factors that having influence on Beijing subway passenger volume from the following four aspects:

1) *Internal structure of the urban rail transit system:* the number of subway lines, length of subway lines, the number of subway vehicles.

2) *Competing transport modes and their structures:* the number of public buses, the number of bus lines, length of bus lines, bus passenger volume, the number of taxis, taxi passenger volume, the number of bicycle.

3) *Urban demographic features:* urban and suburban resident population, employed population, floating population.

4) *Income and expenditure situation:* per capita income, per capita transportation and communication expenditure.

B. Data collection

We collect data from Beijing statistical yearbooks of recent years as well as other information from Beijing Traffic Management Bureau and some relevant departments. There is a total of 20 years of data from year 1993 to 2012. They are shown in Table Ⅳ and Table Ⅴ.

C. Analysis of multicollinearity

During the process of practical forecasting, the dependent variable is subject to the combined effect of many factors and it needs to be explained by a plurality of independent variables, however, multicollinearity may exist between them and they cannot be allowed to enter the model totally, therefore we are to analyze them first and remove factors which are of strong multicollinearity with others.

We use SPSS regression analysis to exclude variables whose regression coefficients are not significant during the

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significant test in each aspect. Here the dependent variable is subway passenger volume, variables are selected respectively from the four aspects, the method we choose is backward selection and the results are shown in Table I, it can be seen that twelve variables remain eventually.

TABLE I. REMOVED FACTORS

Aspect	Removed variables
Internal structure of the urban rail transit system	Length of subway lines
Competing transport modes and their structures	Length of bus lines
Urban demographic features	Employed population
Income and expenditure situation	None

III. B-P NEURAL NETWORK PREDICTING PROCESS

B-P model is a forward multilayer back-propagation neural network learning algorithm and it has become the most important and widely used learning algorithm that training feedforward neural network nowadays. The neural network can preferably solve the nonlinear problem. In this paper, we will use the neural network tool kit provided by Matlab 2014 and establish a three-layer B-P artificial neural network model to forecast passenger volume of Beijing subway for the next five years.

A. *Modeling idea of B-P artificial neural network*

Firstly, we see all the intricate factors that having influence on passenger volume of Beijing subway as a big system, then draw multilevel hierarchical structure according to the direct or indirect relationships of the elements in this system to describe the relationship between various elements.

The twelve variables constitute the input layer of the B-P artificial neural network, four aspects form the hidden layer and subway passenger volume is the output layer. Finally we establish a three-layer B-P artificial neural network model. As shown in Fig. 1.

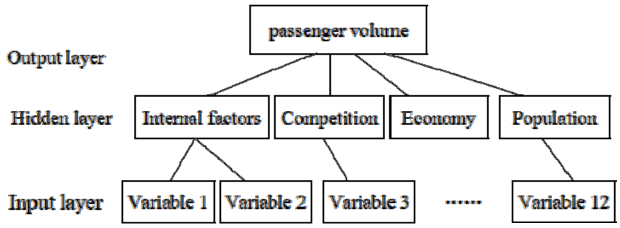

Figure 1. Structure of the prediction model.

B. *Numerical fitting process*

In this model we assume that the subway passenger volume is related with twelve variables, corresponding predictions of the twelve variables need to be obtained before predicting the subway passenger volume in the next five years. In order to ensure the accuracy of the predictions, we adopt the fitting function rather than a single linear regression method or the growth rate method, because deviation of the fitting function is smaller than other methods. The software we use is Matlab 2014 and the following is an example of the fitting process of subway vehicles number.

Firstly, draw a scatter plot of the data;

Secondly, draw fitting curves of different degrees based on the scatter plot;

Thirdly, compare the three main curves shown in Fig.2, here we choose 4th degree polynomial because it fits the scatter plot well.

The fitting function of the variable : The number of subway vehicles is

$$y_8 = 0.059x^4 - 1.3x^3 + 10x^2 - 3.1x + 310$$

We can also obtain fitting functions of the other eleven variables according to this method.

- The number of public buses:
  $y_1 = 0.0071x^4 - 0.36x^3 + 5.8x^2 - 23x + 70$
- The number of bus lines:
  $y_2 = 0.5x^2 + 16x + 200$
- Bus passenger volume:
  $y_3 = 0.0046x^4 + 0.16x^3 - 7.8x^2 + 190x + 2600$
- The number of taxis:
  $y_4 = 0.35x^3 - 13x^2 + 150x + 55$
- Taxi passenger volume:
  $y_5 = 19x + 370$
- The number of bicycle:
  $y_6 = 0.57x^2 + 25x + 690$
- The number of subway lines:
  $y_7 = 0.0054x^3 - 0.12x^2 + 0.72x + 0.92$
- Urban and suburban resident population:
  $y_9 = 1.8x^2 + 3.4x + 820$
- Floating population:
  $y_{10} = 0.75x^2 + 2.3x + 160$
- Per capita income:
  $y_{11} = 0.6x^2 + 2.9x + 26$
- Per capita transportation and communication expenditure:
  $y_{12} = -0.78x^3 + 34x^2 - 230x + 510$

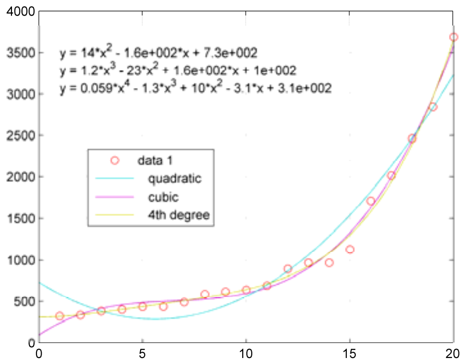

Figure 2. Fitting function.

C. Prediction process

1) Read sample data: Reads the input and output data of twenty samples we have collected as well as the twelve fitting functions from a text file, it will establish a B-P artificial neural network with twelve input variables, four hidden layer nodes, one forecasting target, B-P algorithm is then used to train the network and the computer will generate a nonlinear mapping model internally about the original data and relevant indexes. Use this model to forecast subway passenger volume.

2) Transfer function: Neighboring layers of the B-P artificial neural network are connected together by a transfer function. In general, the input layer and the hidden layer use the S-type function. There are two common S-type functions to be used, logsig is a logarithmic function that can generate (0, 1) output, while tansig is a tangent function that generate (-1, 1) output, we use tansig as transfer function for testing here because tansig converges faster than logsig. We adopt purelin which is a linear function and can generate the output of any range for the output layer.

3) Data preprocessing: When the input data are between 0 and 1, learning efficiency and convergence speed of the network will be enhanced greatly. As we can see, the largest number we input is no more than 6000, dividing each number in the sample data by 8000. After the conversion, we can ensure that any data is less than 1. In the meanwhile, there left space between 6000 and 8000 to prevent overflow caused by the increase of the forecast data. Set the precision up to 0.0001, take 50 times as learning step and take 80,000 times as the maximum number of iterations. When the precision reaches 0.0001 or the iteration number reached 80000 times, the software will output predictions and draw the fitting chart.

4) Key Code

```
gwwnet=newff(minmax(inputSampledata),[4,1],{'tansig',
'purelin'},'traingdm');
gwwnet.trainParam.show = 50;
gwwnet.trainParam.lr = 0.05;
gwwnet.trainParam.epochs = 80000;
gwwnet.trainParam.goal = 1e-4;
```

IV. RESULTS

The biggest advantage to use the tansig function is its fast convergence speed. Experiments show that the prescribed precision can be achieved within 4-5 million times which is shown in Fig.3. And the fitting curve is shown in Fig.4. Due to the difference between the results of each training result, we have trained the network lots of times and take the every year average prediction as final results. They are shown in Table II.

TABLE II. PREDICTED VALUES FOR THE NEXT FIVE YEARS

Year	2014	2015	2016	2017	2018
Predicted Values (10^6)	3664	4420	5225	6028	6770

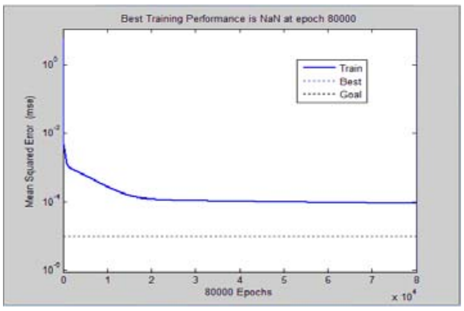

Figure 3. Learning rate of tansig transfer function

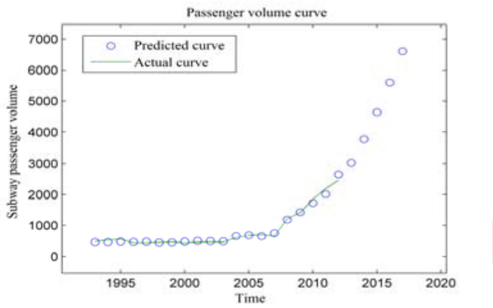

Figure 4. The prediction results of tansig transfer function.

As can be seen from Fig. 3, predicted values obtained by the prediction model are basically close to the actual curve in the past twenty years and the model is well fitted.

We calculate the relative error between predicted values and actual values from year 1993 to 2012, as shown in Table III. The average relative error is 5.56%, which shows that the prescribed precision is relatively high. Results indicate that B-P ANN model is adaptable to the passenger volume prediction and can be adopted as a reference for formulating operational planning of Beijing Subway. From the Predicted values we can see Beijing subway passenger volume increased steadily for the coming years.

V. CONCLUSIONS

The main objective of this article is to provide an improved prediction method to predict passenger volume of Beijing subway, we analyze the factors that influence passenger volume of Beijing subway theoretically at first and selected fifteen factors from four aspects, then used SPSS software to remove factors which are of strong multicollinearity with others, so we establish a three-layer B-P ANN model based on the selected factors to predict the Beijing subway passenger volume for the next five years and ultimately the relative error between the actual and predicted values are calculated. The average value of the relative error is 5.56%, which confirm the feasibility of this method.

TABLE III. THE RELATIVE ERROR BETWEEN THE PREDICTED AND ACTUAL VALUES

Year	Actual Values (10^4)	Predicted Values (10^4)	Relative Error
1993	49110	49110	0.00%
1994	53296	47400	11.06%
1995	55802	49660	11.01%
1996	44414	48140	8.39%
1997	44507	48720	9.47%
1998	46331	46330	0.00%
1999	48223	48220	0.01%
2000	43478	48510	11.57%
2001	46870	50440	7.62%
2002	48242	49270	2.13%
2003	47248	47250	0.00%
2004	60653	65650	8.24%
2005	67976	67980	0.01%
2006	70306	64880	7.72%
2007	65493	74520	13.78%
2008	121660	121700	0.03%
2009	142260	142300	0.03%
2010	184650	174600	5.44%
2011	219280	201800	7.97%
2012	246162	262900	6.80%

As for the convergence speed of B-P ANN is slow AND when a new sample is added in, it would affect the previous studied samples, we need to further explore the practical application of B-P model with other mathematical theory in the future.

In addition, due to the huge subway passenger volume and passenger randomness, a variety of forecasting methods should be combined in order to narrow the gap between the predicted results and the actual values.

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TABLE IV. DATA OF FACTORS FROM YEAR 1993 TO 2012

Year	No. of Public Buses	No. of Bus Lines	Length of Bus Lines (km)	Bus Passenger Volume (10^4)	No. of Taxis	Taxi Passenger Volume (10^4)	No. of Bicycle (10^3)	No. of Subway Lines
1993	4890	266	3491	286268	46022	48770	7360	2
1994	4984	263	4654	299993	56124	55525	7880	2
1995	4984	261	6790	315777	56686	59600	8315	2
1996	6427	266	9484	305433	59493	64895	8708	2
1997	10044	284	12320	346676	59902	65386	9071	2
1998	10382	322	14887	359742	59694	54717	9404	2
1999	12018	377	16512	370131	59485	59111	9678	2
2000	13604	422	15584	348716	62613	59770	9886	2
2001	14803	461	13126	395190	61740	59846	10204	2
2002	16939	502	1576	436652	62848	62848	11019	3
2003	16753	527	16017	376151	62283	62283	11143	4
2004	18451	517	15133	436016	51561	58758	11530	4
2005	18503	574	18214	441871	66000	65000	11917	4

2006	19522	601	18468	389183	66323	64121	12304	4
2007	19395	621	17353	409689	66646	64111	12691	5
2008	21507	648	17857	458081	66646	69000	13078	8
2009	21716	692	18270	516517	66646	68000	13677	9
2010	21548	713	18743	505144	66646	69000	14333	14
2011	21628	749	19460	503272	66646	69600	14499	25
2012	22146	799	19547	515416	66646	69900	14919	26

TABLE V. DATA OF FACTORS FROM YEAR 1993 TO 2012

Year	**Length of Subway Lines （km）**	**No. of Subway Vehicles**	**Subway Passenger Volume (10^4)**	**Urban and Suburban Resident (10^3)**	**Employed Population (10^3)**	**Floating Population (10^3)**	**Per Capita Income**	**Per Capita Transportation Expenditure （yuan）**
1993	40.6	323	49110	6448	6278	1786	3548.0	202.7
1994	40.6	335	53296	7062	6643	1843	5086.0	203.0
1995	40.6	383	55802	7894	6653	1953	6238.0	206.8
1996	40.6	401	44414	8902	6602	2005	7339.0	218.8
1997	40.6	435	44507	10050	6558	2106	7862.0	229.8
1998	40.6	437	46331	11280	6222	2332	10098.2	369.5
1999	53.7	491	48223	12572	6186	2454	10654.8	467.9
2000	54.0	587	43478	13636	6193	2501	12560.3	604.7
2001	54.0	617	46870	13851	6289	2628	13768.8	768.3
2002	75.0	641	48242	14232	6792	2869	13253.3	1271.0
2003	114.0	692	47248	14564	7033	3076	14959.3	1688.1
2004	114.0	892	60653	14927	8541	3268	17116.5	1562.2
2005	114.0	968	67976	15380	8780	3573	19533.3	1943.5
2006	114.0	967	70306	15810	9197	3834	22417.0	2173.0
2007	142.0	1130	65493	16330	9427	4197	24576.0	2689.0
2008	200.0	1714	121660	16950	9809	4651	27678.0	2793.0
2009	201.4	2014	142260	17550	9983	4732	30674.0	2843.0
2010	336.0	2463	184650	19619	10316	7047	33360.0	2933.0
2011	372.0	2850	219280	20186	10697	7422	37124.0	3205.0
2012	442.0	3685	246162	20693	11073	7738	41103.0	3453.0