Prediction of Railway Passenger Traffic Volume based on Grey BP Neural Network

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Abstract – **Railway passenger volume is an important basis for railway operation organization. Predicting railway passenger volume plays a key role in overall construction planning of railway. In order to make a better plan for future railway construction in China, improve the utilization ratio of railway and development of national economy, this paper combines the gray prediction model with the BP neural network model to predict railway passenger volume. Make preliminary prediction based on the railway passenger volume from 2008 to 2016 by using the gray prediction model, consider the continuity of passenger transportation demand, the data of next two years are combined and input into BP neural network for prediction, then obtain the railway passenger volume of the corresponding year, and the average relative error of the predicted results is 0.74%. The example proves that the prediction accuracy and speed of the grey BP neural network combination model are higher than that of the single gray prediction model, it is an effective nonlinear railway passenger volume prediction method and can assist the railway overall planning.**

Keywords – **Railway Passenger Flow, Passenger Volume Prediction, Grey BP Neural Network Model, Nonlinear Series, Combination Model.**

I. INTRODUCTION

Railway passenger volume prediction is one of the important foundations and main bases of railway transport organization, which is a quantitative indicator reflecting the service of the transport industry to the national economy and people lives and also an important reference for the formulation of railway operation plans [1]. At present, the qualitative prediction of railway passenger volume mainly uses Delphi method [2], and the quantitative prediction mainly uses gray prediction, RBF neural network model, exponential smoothing method, Markov analysis method, regression analysis method, elastic coefficient method and other methods [3] - [6]. Generally speaking, there are many influencing factors of the railway passenger volume, and some data are difficult to collect. The model with higher data requirements is not dominant in the prediction railway passenger volume. The gray forecasting model can predict based on a small amount of data, directly avoids the complex relationship between parameters [7], but the railway passenger traffic presents nonlinear characteristics due to environmental impact, yet the gray prediction model are poor for nonlinear data fitting. In response to this situation, some scholars have combined the gray prediction model with other algorithms, but most are direct combinations, which ignores the defects of the gray prediction model and accumulates errors. Artificial neural networks can easily handle complex nonlinear problems while avoiding the problem of regression selection. Therefore, this paper optimizes the gray prediction model, and uses the gray BP neural network combined with the BP neural network in the artificial neural network to predict the railway passenger volume.

II. THE ESTABLISHMENT & SOLUTION OF THE GREY PREDICTION MODEL

A. *Principle of Gray Prediction Model*

The gray system was proposed by Deng Julong [8], it refers to the system in which part of information in the

system is known and partially unknown [9]. The gray prediction model is a prediction method based on the gray system theory to establish mathematical models and make predictions through a small amount of incomplete information. Commonly used gray prediction models include series prediction, catastro- -phe and outlier prediction, seasonal catastrophe and outlier prediction, topology prediction, and system prediction. The gray prediction model requires less modeling information, it is convenient in operation, high modeling precision, and has wide application in various prediction fields. It is also an effective tool for dealing with small sample prediction problems. The GM (1, 1) model is used in this paper. The GM (1, 1) model represents a differential equation model of 1 order and 1 variable.

B. *Establishment and Solution of Gray Prediction Model*

Set the original data sequence as:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots x^{(0)}(N)\}$$

Wherein, $X^{(0)}$ is initial data set sequence, and $x^{(0)}(1)$ is initial data. [10]

Then the original sequence is accumulated to generate the accumulated data sequence.

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots x^{(1)}(N)\}$$

Wherein, $X^{(1)}$ is the set sequence of accumulation of the original data, and $x^{(1)}(1)$ is the result of the accumulation of the original data. It is known that $X^{(1)}$ meets the following formula: $\frac{dX^{(1)}}{dt} + aX^{(1)} = \mu$

In which, a is constant, μ is known grey number of development, and it is endogenous control gray number, and a constant input to the system.

Then establish matrix B,y based on accumulated data sequences:

$$B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(1)] & 1 \\ -\frac{1}{2}[x^{(1)}(3) + x^{(1)}(2)] & 1 \\ \vdots & 1 \\ -\frac{1}{2}[x^{(1)}(N) + x^{(1)}(N-1)] & 1 \end{bmatrix} y = (x^{(0)}(2), x^{(1)}(3), \cdots x^{(0)}(N))^T$$

Calculate $(B^T B)^{-1}$, and by least square method, it can gain: $\hat{s} = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix} = (B^T B)^{-1} B^T y$

Wherein $\hat{a}$, $\hat{u}$ are estimated values to be solved.

Establish time response equation by known conditions to calculate $\hat{x}^{(1)}(i)$:

$$\hat{x}(k + 1) = \left[x^{(1)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$$

Then conduct descending reduction

$$x^{(0)}(i) = x(i) - \hat{x}(i - 1)(i = 2,3, \cdots N)$$

Thus, the reduction value is gained.

III. BP NEURAL NETWORK PREDICTION MODEL

A. *Model principle*

The BP neural network was proposed by researchers led by Rinehart and McClelland in 1986. It is a multilayer feed-forward neural network trained by error back propagation algorithm derived from an artificial neural network. The BP neural network deals with nonlinear problems by simulating the functional structure of the biological nervous system. It is often used for data classification and prediction model construction, and can better fit multi-input and multi-output data. The BP neural network is a hierarchical neural network with three or more layers [11], which is generally composed of input layer, implicit layer, and output layer. The basic unit is neuron. The neuron receives the input information, the implicit layer processes data, and the output layer outputs data. The BP neural network uses supervised training to compare the output results with the real data, so that the error is forwarded to adjust the weight of the nodes in the transmission to reduce the error, and finally reach the training goal [12].

B. *Model Establishment and Solution*

The working steps of the BP neural network prediction model are as follows:

(1) Acceptance and processing of input information

Input information to the BP neural network and assign corresponding initial weights:

$$A = \{a_1, a_2, a_3 \cdots a_n\}; W = \{w_1, w_2, w_3 \cdots w_n\}$$

Wherein, a_n is the input information, A is the input information set, w_n is the initial weight, and W is the initial weight set.

Multiplication of input information with corresponding weights, then fusion to form new information: $p_j = \sum w_{ij} a_i$

Wherein, p_j is the new information after fusion, a_i is input information, and w_{ij} is the initial weight.

(2) Formation of output information

When the information p_j after the fusion is greater than the threshold θ of the implicit layer, the BP neural network will collect the information p_j through the conversion function f, and convert to form the output information y_j.

$$y_j = f(\sum w_{ij} a_i - \theta)$$

In the formula, the threshold θ is used to correct the deviation of the information after fusion of the neural network, and the value is generally [0, 1].

(3) Reverse transmission of error

The neural network corrects the weight w_{ij} by calculating the difference between the output value w_{ij} and the predicted output $y_j{'}$, and performs recalculation using the adaptive momentum gradient descent method.

The difference between the output value of the m-th sample and the predicted output value is: $\lambda_m = y'_{jm} - y_{jm}$

The weight between the implicit layer and the output layer is corrected to:

$$w_{ij}^k = w_{ij}^{k-1} + \gamma \times g(\lambda_m)$$

In the formula, w_{ij}^k is the k-th corrected weight between the i-th neuron in the anterior layer and the j-th neuron in the posterior layer, γ is the momentum factor and g is the gradient error correction function [13]

IV. COMBINATION MODEL OF GRAY BP NEURAL NETWORK

The gray prediction model requires less data and can perform predictive analysis under the condition of "small data and poor information". At the same time, because the accumulation weakens the randomness of the original data, the original data can show certain rules, but the traditional gray prediction is not accurate for long-term prediction, and deviates from the original data, and its law to the original data is not obvious.

BP neural network has a good curve fitting ability for complex nonlinear systems. It can locally approximate the network, and approach any nonlinear mapping infinitely as long as it has enough implicit layers and hidden nodes. It has strong fault tolerance and excellent adaptability [14], but it requires higher sample data for training. The sample data must have certain representativeness and typicality. Otherwise, it will affect the ubiquity of the neural network. At the same time, the single BP neural network has poor generalization and has certain influence on the prediction result [15].

In order to make full use of the advantages of the gray model and the BP neural network, the two models are combined to form a gray BP neural network model. The specific implementation steps are shown in Fig.1 [16].
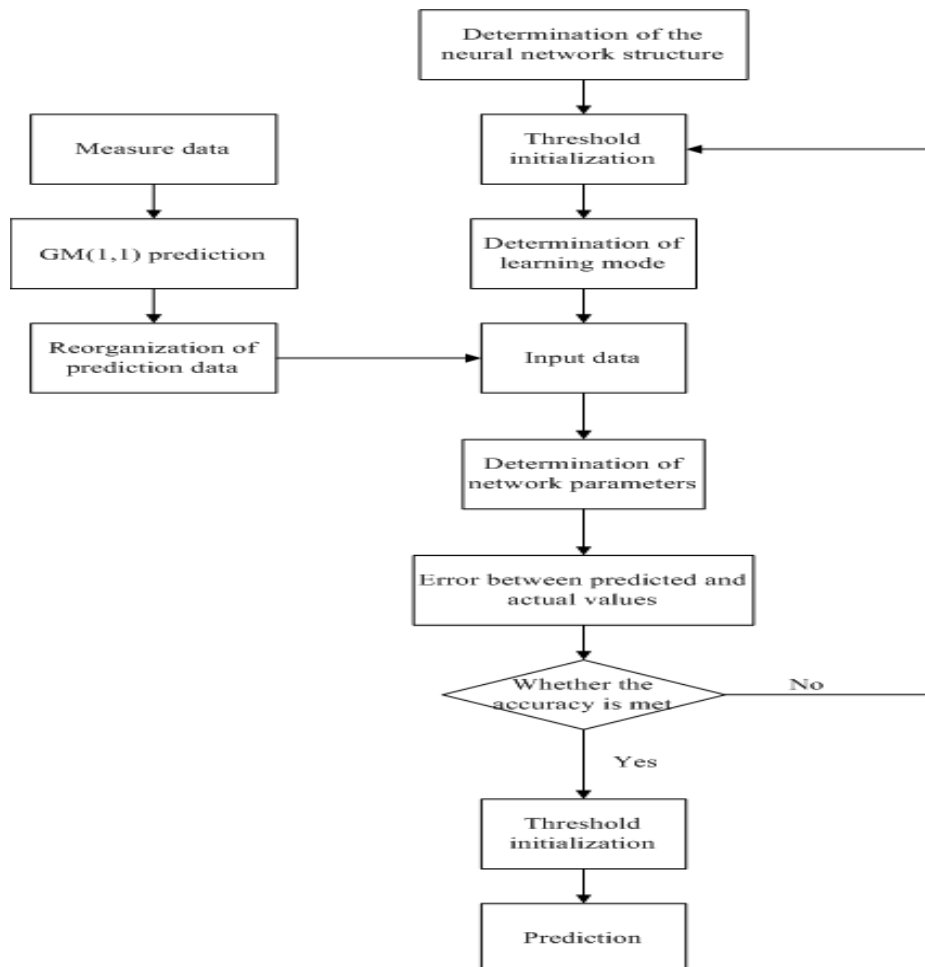

Fig. 1. Prediction process.

V. CASE STUDY

A. *Gray Prediction Model of Railway Passenger Volume in China*

The national railway passenger traffic volume from 2008 to 2017 gained from National Data Network is analyzed by the gray prediction model GM (1, 1). The results are shown in Tab.1 and Fig.2, and the relative error $\overline{E}$, the mean square error ratio C, the small probability error P, and the GM (1, 1) function are obtained at the same time.

Table 1. Actual value of passenger traffic volume in China and prediction value by gray prediction model (*10,000 people).

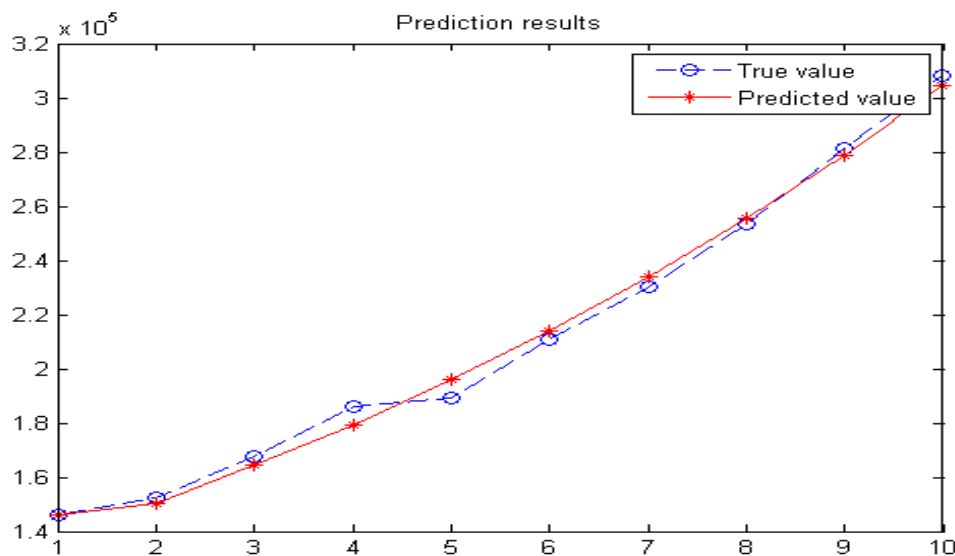| Year	Railway passenger traffic volume	Prediction value by gray prediction model	Relative error
2008	146192.98	146190	0.00%
2009	152451.19	150390	1.35%
2010	167609.02	164250	2.00%
2011	186226.07	179400	3.67%
2012	189336.85	195940	-3.49%
2013	210596.92	214010	-1.62%
2014	230460	233750	-1.43%
2015	253484	255300	-0.72%
2016	281405.23	278850	0.91%
2017	308379.34	304560	1.24%

Fig. 2. Fitting diagram of predicted results and real values.

According to the calculation results, the relative error = 0.0018 < 1, the mean square deviation ratio = 0.0056 < 0.35, and the small probability error = 1 > 0.95. The above results prove that the model has high prediction accuracy and can continue BP neural network analysis. The functional relationship obtained by the gray prediction model is:

$$\hat{X}^{(1)}(k + 1) = 1630841e^{0.7939k} - 1484600$$

B. *Gray BP Neural Network Prediction of National Railway Passenger Traffic Volume*

Since the passenger demand has a certain continuity, that is, the data of the previous year is related to the data of the next year, the data of the previous two years is used to predict the data of the next year [17]. The specific combination of the input data is shown in Tab. 2.

Table 2. Neural network input data (*10,000 people).

Year	2010	2011	2012	2013
Input value	146190	150390	164250	179400
	150390	164250	179400	195940
Expected output	167609	186226.07	189336.85	210596.92

Year	2014	2015	2016	2017
Input value	195940	214010	233750	255300
	214010	233750	255300	278850
Expected output	230460	253484	281405.23	

The first 6 sets of data are trained as training samples, the 7th set of data is used as the test sample to test the prediction accuracy of the network, the 8th set of data is used to predict the total national railway passenger volume in 2017 [18], and the BP neural network is set to three layers, the number of neurons in the input layer is 2, and the number of neurons in the output layer is 1. Neurons in the implicit layer are defined according to Kolmogorov theorem: A three-layer network with n input units, 2n+1 intermediate units, and m output units can accurately represent any mapping, and at the same time optimize the intermediate layer capacity and training time, so it is determined as 5. The transfer function of the implicit layer uses the S-type transfer function, the output layer uses the linear transfer function purelin, and the rest of the functions are default. The maximum number of training sessions is 10,000, the learning rate is 0.05, and the minimum expected error is 0.00001. The specific prediction results are shown in Tab.3.

Table 3. Actual Value of China Railway Passenger Volume and Prediction Value by Gray BP Neural Network (*10,000 people).

Year	Railway passenger volume	Prediction Value of Gray Prediction Model GM(1,1)	Relative error	Prediction Value of Gray BP Neural Network	Relative error
2008	146192.98	146190	0.00%		
2009	152451.19	150390	1.35%		
2010	167609.02	164250	2.00%	167620	-0.01%
2011	186226.07	179400	3.67%	183750	1.33%
2012	189336.85	195940	-3.49%	194120	-2.53%
2013	210596.92	214010	-1.62%	208860	0.82%
2014	230460	233750	-1.43%	228970	0.65%
2015	253484	255300	-0.72%	254180	-0.27%

Year	Railway passenger volume	Prediction Value of Gray Prediction Model GM(1,1)	Relative error	Prediction Value of Gray BP Neural Network	Relative error
2016	281405.23	278850	0.91%	281950	-0.19%
2017	308379.34	304560	1.24%	308050	0.11%

It can be seen from the analysis of Figure 3 and Table 3 above that the results of the combined model prediction through debugging parameters meet the error requirements, and the overall fit is good, and the relative error is less than 3%. Through the data fitting results from 2008 to 2016, the fitting accuracy of the combined model is higher than that of using the gray prediction model alone. The prediction accuracy in 2017 is also higher than that predicted by the gray prediction model alone. It is proved that this model is suitable for railway passenger volume prediction.

VI. CONCLUSION

In this paper, a gray BP neural network model combining gray prediction model and BP neural network is established to predict railway passenger traffic volume. The cases prove that the BP neural network can analyze the laws in a small amount of data processed by the gray prediction, and use its advantage of nonlinear prediction to predict the railway passenger traffic volume. The model effectively improves the accuracy of prediction and has strong fault tolerance. It can be applied to the prediction of railway passenger traffic volume and contribute to the overall planning and construction of the railway. At the same time, the model can also be applied to various types of studies with less amount of data, more overlap and complex non-linear relationship, and unclear inherent law. Since there are many environmental factors affecting railway passenger volume, more accurate prediction needs to be further studied.

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AUTHOR'S PROFILE

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