Research on Forecast Model and Algorithm of Train Passenger Sending Volume

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***Abstract*—The forecast of the passenger volume of the railway station is to analyze the development trend of passenger traffic in the future. Correctly predicting the passenger volume will help to develop the local regional economy, rationally allocate resources and reduce operating costs. Although the gray prediction model is widely used in many fields, the smoothness of the original data sequence has a very important influence on the accuracy of the gray prediction model. In addition, many raw data sequences have low smoothness in practical applications, so the gray The field of use of predictive models is limited. A gray GM(1,1) model based on polynomial function transformation is proposed, and the model is applied to the prediction of train passenger volume in 2010-2013. The prediction results show that the prediction accuracy of the model is significantly higher than that. The prediction results of the GM(1,1) model have certain application value.**

Keywords- Polynomial Function, Grey Prediction Model, Train Passenger Volume

I. INTRODUCTION

The train passenger volume prediction is a dynamic analysis of the development trend of railway transportation. Scientifically and accurately predicting the passenger transmission volume of the railway station is not only the basis of the special planning for railway passenger transportation, but also the premise for formulating various traffic layouts, which helps to accurately grasp The overall trend of railway passenger transport development, promote the optimal allocation of railway transportation resources, give full play to the maximum efficiency of railway transportation, and the scientific and timeliness of government decision-making will also be greatly improved, which is of great significance for the establishment of an integrated transportation system. However, the passenger volume of the railway station is a relatively complex relationship that is affected by many factors. To accurately predict it, it is necessary to collect a large amount of data and information, and modeling is difficult.

There are many technical methods used in the prediction of passenger traffic at home and abroad: one is extrapolation prediction; the other is causal prediction. There are four-stage method, Kalman filtrate method, neural network model and multiple linear regression model belonging to causal prediction method. There are gray model, time series model, discrete prediction model with periodic fluctuation term and grey neural network model. For example, Li Li[1] used the improved four-stage passenger flow forecasting method to predict the trend passenger traffic, transfer passenger traffic, and induced passenger traffic. Meng Ge, Wu Zhong-dong[2] used fuzzy support vector regression machine to predict train passenger traffic. Jia Jun-fang, Sun Yun-hua, Liu Hua[3] used the gray GM (1,1) prediction model to predict the passenger traffic of the intercity train plan with the Shanghai-Nanjing line as the background. The grey prediction model has a better prediction effect on the uncertainty system, and the number of samples in the modeling process does not need to be too much, the distribution law of the sample does not need to be too good, and the calculation amount is small. However, the shortcomings of the prediction results are monotonic, which makes the application of the gray prediction model receive certain restrictions. In order to avoid this kind of malpractice, this paper fits the polynomial function to the fluctuation of the passenger flow of the train passenger. The polynomial function is used to transform the original data and then bring it into the gray GM (1,1) model, and the prediction result is subjected to the polynomial function. The gray GM(1,1) model based on the polynomial function transformation of the corresponding prediction result is used to predict the transmission volume of the train passengers.

II. GREY PREDICTION SYSTEM OVERVIEW

A. Establishment of GM(1,1) model, Accuracy test and scope of application

The grey prediction system modeling method is a new target research direction in the prediction theory system. It is a very common method for the study of "small sample" and "uncertainty". There are many about the existence of reality. The grey uncertainty prediction problem has played a big role, and its practicability and effectiveness have been fully tested in practice. The grey prediction model uses a small amount of valid data (usually more than 4) and gray uncertainty data to perform the cumulative generation of sequences to predict the future development trend of the system. Normally, the non-negative sequence $X^{(0)}$ does not have regularity, but the sequence $X^{(1)}$ generated by the accumulation is generally monotonically increasing, as shown in FIG. 1.

978-1-7281-2165-9/19/$31.00 ©2019 IEEE
DOI 10.1109/ICMTMA.2019.00182

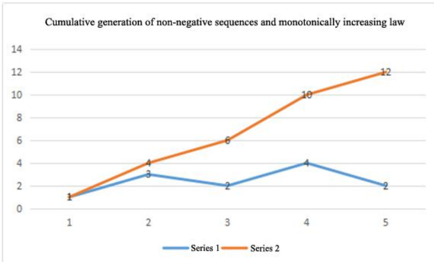

FIG. 1. Cumulative generation of nonnegative sequences and its monotonically increasing law

Establishment of GM(1,1) model

Definition 1 Let $X^{(0)}=(x^{(0)}(1),x^{(0)}(2)\ldots\ldots x^{(0)}(n))$, $X^{(1)}=(x^{(1)}(1),x^{(1)}(2)\ldots\ldots x^{(1)}(n))$,then $x^{(0)}(k)+ax^{(1)}(k)=b,k=1,2,\ldots\ldots n$ is said to be the original form of the GM(1,1) model. In the GM(1,1) model, a is called the development coefficient, and b is called the gray action amount.

Definition 2 Let $X^{(0)}=(x^{(0)}(1),x^{(0)}(2)\ldots\ldots x^{(0)}(n))$ $X^{(1)}=(x^{(1)}(1),x^{(1)}(2)\ldots\ldots x^{(1)}(n))$, , $Z^{(1)}=(z^{(1)}(2),z^{(1)}(3),\ldots\ldots z^{(1)}(n))$, where $z^{(1)}(k)=\frac{1}{2}(x^{(1)}(k)+x^{(1)}(k-1)),k=1,2,\ldots,n$, Let $x^{(0)}(k)+az^{(1)}(k)=b$ be the basic form of the GM(1,1) model.

Professor Deng Ju-long gave a block diagram of GM(1,1) in the References [4], Let $z^{(1)}(k)$ be MEAN, $x^{(0)}(k),x^{(1)}(k)$ is the observable quantity, it is the system behavior, a is the development coefficient, it reflects the development trend of $x^{(0)}(k),x^{(1)}(k)$. If a is negative, the situation is increasing, the larger the absolute value of a , the more the growth Fast; if a is positive, the situation is attenuated, the larger the absolute value of a , the faster the attenuation; b is the input of the system, because b is unobservable and must be calculated, so b is called the gray effect of the system the amount.

Theorem 1

Let $X^{(0)}=(x^{(0)}(1),x^{(0)}(2)\ldots\ldots x^{(0)}(n))$,where $x^{(0)}(k)\ \geq 0$, $k=1,2,\ldots,n$ 1-AGO (one-time accumulation generation) sequence where $x^{(1)}$ is $x^{(0)}$: $X^{(1)}=(x^{(1)}(1),x^{(1)}(2),\ldots\ldots x^{(1)}(n))$ where $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),k=1,2,\ldots\ldots,n$; $Z^{(1)}$ is the immediate averaging sequence of $x^{(1)}$: $Z^{(1)}=(z^{(1)}(2),z^{(1)}(3),\ldots\ldots z^{(1)}(n))$, where $z^{(1)}(k)=\frac{1}{2}(x^{(1)}(k)+x^{(1)}(k-1)),k=1,2,\ldots,n$, $x^{(0)}(k)+az^{(1)}(k)=b$

et $P=(a,b)^T$, $Y=\begin{bmatrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots\\x^{(0)}(n)\end{bmatrix}$, $B=\begin{bmatrix}-z^{(1)}(2)&1\\-z^{(1)}(3)&1\\\vdots&\vdots\\-z^{(1)}(n)&1\end{bmatrix}$

Then the least squares estimation parameter column of the GM(1,1) model $x^{(0)}(k)+az^{(1)}(k)=b$ satisfies

$$P=(B^TB)^{-1}B^TY=\begin{bmatrix}a\\b\end{bmatrix}$$

The GM(1,1) model can be rewritten as

$$x^{(0)}(2)+az^{(1)}(2)=b;$$
$$x^{(0)}(3)+az^{(1)}(3)=b;$$
$$\vdots$$
$$x^{(0)}(3)+az^{(1)}(3)=b;$$

Write the matrix form as follows:

$$\begin{bmatrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots\\x^{(0)}(n)\end{bmatrix}=\begin{bmatrix}-z^{(1)}(2)&1\\-z^{(1)}(3)&1\\\vdots&\vdots\\-z^{(1)}(n)&1\end{bmatrix}\begin{bmatrix}a\\b\end{bmatrix}$$

We have $Y=BP$

In the above-mentioned equations, P is a sequence of parameters to be determined, and Y and B are known quantities, because there are $n-1>2$ equations, and the variables are only a,b , and there is no solution to the equations when incompatible. The least squares solution of the equation is obtained by the least squares method.

Using $-az^{(1)}(k)+b$ instead of $x^{(0)}(k)$ ($k=2,3,\cdots n$), the error sequence is

$\varepsilon=Y-BP$,

To make $\min\|Y-BP\|^2=\min(Y-BP)^T(Y-BP)$

Using the matrix derivation formula $P=(B^TB)^{-1}B^TY=\begin{bmatrix}a\\b\end{bmatrix}$,

Expanding the matrix of parameter identification to get the expression of parameter a,b :

$$a=\frac{\sum_{k=2}^{n}x^{(0)}(k)\sum_{k=2}^{n}z^{(1)}(k)-(n-1)\sum_{k=2}^{n}x^{(0)}(k)z^{(1)}(k)}{(n-1)\sum_{k=2}^{n}(z^{(1)}(k))^2-(\sum_{k=2}^{n}z^{(1)}(k))^2}$$

$$b=\frac{\sum_{k=2}^{n}x^{(0)}(k)\sum_{k=2}^{n}(z^{(1)}(k))^2-\sum_{k=2}^{n}z^{(1)}(k)\sum_{k=2}^{m}z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n}(z^{(1)}(k))^2-\sum_{k=2}^{n}z^{(1)}(k)^2}$$

Definition 3 Let $X^{(0)}$ be a non-negative sequence, $X^{(1)}$ be a 1-AGO sequence of $X^{(0)}$, and $Z^{(1)}$ be the sequence of the nearest mean of $X^{(1)}$, $\begin{bmatrix} a & b \end{bmatrix}^T = (B^TB)^{-1}B^TY$,then $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ is the whitening equation of the GM(1,1) model $x^{(0)}(k) + az^{(1)}(k) = b$, also called the shadow equation.

Theorem 2 Let $P = (B^TB)^{-1}B^TY = \begin{bmatrix} a \\ b \end{bmatrix}$, then

(1) The solution of the whitening equation $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ (also called the time response function) is

$$x^{(1)}(t) = (x^{(1)}(1) - \frac{b}{a})e^{-at} + \frac{b}{a}$$

(2) The time response sequence of the GM(1,1) model $x^{(0)}(k) + az^{(1)}(k) = b$ is

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \quad k = 1, 2, \cdots, n ;$$

(3) Restore value $= (1 - e^a)(x^{(0)(1)} - \frac{b}{a})e^{-ak}$

$, k = 1, 2, \ldots\ldots, n$

Calculate the parameters a and b according to the definition, and substitute the calculation result into the time response function sequence to restore the simulated prediction value.

Test of prediction accuracy of GM(1,1) model

The residual value $\varepsilon^{(0)}(k)$ and the relative error value $q(k)$ between the restored value of the original data and the actual observed value are as follows:

$$\begin{cases} \varepsilon^{(0)}(k) = \hat{x}^{(0)}(k+1) - \hat{x}^{(0)}(k) \\ q(k) = \dfrac{\varepsilon^{(0)}(k)}{\hat{x}^{(0)}(k+1)} \times 100\% \end{cases}$$

Time response sequence for GM(1,1) model $x^{(0)}(k) + az^{(1)}(k) = b$

For the detection of the prediction accuracy of $\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}$, there are the following methods:

$$\bar{x}^{(0)} = \frac{1}{M}\sum_{i=1}^{M} x^{(0)}(k)$$

$$s_1{}^2 = \frac{1}{M}\sum_{i=1}^{M}\left[x^{(0)}(k) - \bar{x}^{(0)}\right]^2$$

$$\bar{\varepsilon}^{(0)} = \frac{1}{M-1}\sum_{i=2}^{M} \varepsilon^{(0)}(k)$$

$$s_2{}^2 = \frac{1}{M-1}\sum_{i=2}^{M}\left[\varepsilon^{(0)}(k) - \bar{\varepsilon}^{(0)}\right]^2$$

Then calculate the variance and small probability error:

$$p = \left\{\left|\varepsilon^{(0)}(k) - \bar{\varepsilon}^{(0)}\right| < 0.6745 s_1\right\}$$

After the grey system prediction model is established, it is necessary to pass the test to test whether the model is justified. Only the prediction of the model by these tests can reduce the error. The model accuracy inspection specifications are shown in Tables 1 and 2.

Table 1. Model accuracy test

Grade accuracy	Relative error	Correlation	Mean variance ratio C	Small probability error P
Level 1	0.01	0.90	0.35	0.95
Level 2	0.05	0.80	0.50	0.80
Level 3	0.10	0.70	0.65	0.70
Level 4	0.20	0.60	0.80	0.60

Table 2. Gray prediction accuracy test level standard

Test indicator / Accuracy level	p	c
good	> 0.95	> 0.35
qualified	> 0.80	> 0.50
reluctantly	> 0.70	> 0.65
unqualified	≤ 0.70	≤ 0.65

If both p and c are within the allowable range, then the predicted value can be calculated. Otherwise, the residual response sequence $\left\{\varepsilon^{(0)}(k)\right\}_{k-2}^{M}$ needs to be analyzed to correct the time response function corresponding to the differential equation formula. The frequently used correction method has a residual sequence. Modeling and periodic analysis[5].

Scope of the GM(1,1) model

The application of the GM(1,1) model is not arbitrary. The size of the development coefficient a limits the scope of application of GM(1,1). The GM(1,1) model must be simulated and predicted according to the size limit of a. Error analysis, if the GM (1,1) model is forcibly predicted, the prediction accuracy must be very low, and the obtained prediction data has no reference meaning, and it has no practical significance.

III. GM(1,1) MODEL BASED ON POLYNOMIAL FUNCTION TRANSFORMATION

GM(1,1) modeling process based on polynomial function $y = ax^4 + bx^3 + cx^2 + dx + e$

A. The original sequence of sequences is

$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \ldots x^{(0)}(k), k = 1, 2, \ldots n\right\}$, where $x^{(0)}(i) > 0$.

B. For the original series, a polynomial function is used for function transformation. Let

$y = a\left[x^{(0)}\right]^4 + b\left[x^{(0)}\right]^3 + c\left[x^{(0)}\right]^2 + dx^{(0)} + e$, in order to make GM(1,1) have a better simulation effect, map the value of $x^{(0)}$ to a monotonically increasing sequence $y^{(0)}$. Considering the original sequence $x_k^{(0)} > 0(k = 1,2,\cdots,M)$, it is necessary to initialize the logarithm $x^{(0)}$, as follows:

First use the formula $\hat{x}_k^{(0)} = x_k^{(0)} - C$ to change the $x^{(0)}$ to get $\hat{x}_k^{(0)}$, so that the smoothness of the sequence $y^{(0)}$ will increase, where $k = 1,2,\cdots,M$, C is a constant greater than zero; Let $\hat{x}_k^{(1)} = \hat{x}_k^{(0)} / M$, where $M = \max_k \left|\hat{x}_k^{(0)}\right|$ ($k = 1,2,\cdots,M$); then use the transform to get a new sequence $y^{(0)} = \{y_k^{(0)} | k = 1,2,\cdots,M\}$. According to the diversity of $y_k^{(0)}$ values, use the formula $y = a\left[x^{(0)}\right]^4 + b\left[x^{(0)}\right]^3 + c\left[x^{(0)}\right]^2 + dx^{(0)} + e$ to make $y^{(0)}$ increase monotonically.

(3) By taking the sequence $y^{(0)}$ as the original data into the GM(1,1) model, the estimated value $\hat{y}_{k+1}^{(0)}$ can be obtained, and then the inverse transformation of the inverse function and the inverse transformation of the inverse function are performed to obtain the observed value $\hat{y}_{k+1}^{(0)}$ ($k = 1,2,\cdots,M$) of the sequence $x^{(0)}$ at each moment.

IV. RESEARCH ON FORECAST AND ALGORITHM OF PASSENGER VOLUME TRANSMISSION IN BENGBU RAILWAY STATION

A. Data Sources

Based on the number of passengers sent by Bengbu Railway Station, the grey prediction model is applied. From 2005 to 2013, the data collection of passengers from Bengbu Railway Station was carried out for 9 consecutive years, and the passenger volume of 9 years was obtained. The passenger volume of the first 5 years was used as a training sample, and the passenger volume of the last 4 years was used as a test. For comparison objects, the specific data is shown in Table 3.

Table 3. Bengbu Station 2005-2013 passenger volume data statistics table

years	2005	2006	2007	2008	2009	2010	2011	2012	2013
Passenger volume	444	487	506	546	568	592	553	494	482

B. Model calculation and analysis

The GM(1,1) model based on polynomial function transformation proposed in this paper is used to predict the passenger volume from 2009 to 2013. The results are shown in Table 4:

Table 4. Bengbu Station 2010-2013 passenger volume forecast results

years	Passenger volume	GM(1,1) model			Polynomial function transformation type GM(1,1) model		
		Forecast value (million)	Residual value (million)	Relative error(%)	Forecast value (million)	Residual value (million)	Relative error(%)
2010	592	582	10	1.689	595	-3	-0.506
2011	553	539	14	2.531	551	2	0.362
2012	494	467	27	5.466	493	1	0.202
2013	482	443	39	8.091	483	-1	-0.207

From Table 4, the following conclusions can be drawn: the prediction results using the GM(1,1) model are not only large, but the error is an increasing trend, but the GM(1,1) using the polynomial function transformation type is used. The error value of the prediction result of the model is relatively small; the prediction result obtained by the traditional GM(1,1) after polynomial function transformation is closest to the real value.

V. CONCLUSIONS

It can be seen from the above table that the proposed method has better accuracy, is closest to the true value, and the relative error and mean square error ratio are smaller than the proposed method in References [6]. The results show that the method not only has GM (1,1) The advantages in predicting nonlinear data, while improving the GM(1,1) model, and using polynomial function transformation after processing the original data, greatly improving the accuracy of prediction. The error is reduced, and the prediction field and scope of the gray prediction model are broadened, which has certain practical value.

ACKNOWLEDGEMENTS

This work is supported by General Project of Natural Science Research in Anhui Province (Grant No. 113052015KJ06), Key Project of Natural Science Research in Anhui Province (Grant No. KJ2017A854).

REFERENCES

[1] L. Li., “Traffic Volume Forecast for Ji'nan-Qingdao High-Speed Railway.”. Railway Transport and Economy, 2016, no.9, pp.45-49.

[2] G. Meng, Zh.D. Wu., “Application of FSVR in prediction of single train railway passenger capacity.” Journal of University of Jinan(Science and Technology), 2015, no.5, pp.382-388.

[3] J.F. Jia, W.H. Sun., Liu Hua. "Traffic Volume Forecast and Evaluation of Intercity Passenger Train Operation." Journal of Beijing Jiaotong University, 2004, no.6, pp.95-98.

[4] J.L. Deng., "Gray theory basis." Huazhong University of Science & Technology Press, 2002, pp.57-86.

[5] S.F. Liu, N.M. Xie., "Grey System Theory and Its Application." Science Press, 2008, pp.171-203.

[6] Q. Li., "Further extension of the grey prediction model." Systems Engineering-Theory & Practice, 1993, vol. 13, no.1, pp.64-66.