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RESEARCH PAPER

Forecasting Technology of National-Wide Civil Aviation Traffic

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Abstract: The long-term forecasting of national-wide civil aviation traffic provides basis for the airspace project planning. A gray combination forecasting model is put forward based on the GM (1, 1) forecast model and least squares principle. With the historical data analysis of the national-wide air traffic from the year 1985 to 2008, the forecasting applicability is examined with three different methods, such as the time series forecasting, regression forecasting and neural-network forecasting. After analyzing the characteristics of Chinese national-wide civil aviation traffic data and contrasting forecasting result, the gray combined forecasting model produces the best effect among these forecasting models.

Key Words: air transportation; air traffic volume; long-term forecasting; grey forecasting; combined forecasting; forecasting model

1 Introduction

The long-term forecasting data of national air traffic can provide decision-making supportive information for the civil aviation management departments to amend the airspace structure and the design airspace programming. It can also offer a quantitative basis to improve the hardware and software environment and make the traffic flow in the air traffic network more reasonable on the macro picture.

Relative forecasting researches at home and abroad in the civil aviation field are summarized as follows. Grubb *et al*.[1,2] adopted the Holt-Winters method. They conducted a long-term forecasting on the passenger transportation volume in UK and a short-term forecasting of the traffic flow in Beijing Capital International Airport respectively. Profillidis[3] used the fuzzy linear regression method to forecast the traffic demand in the airport of Greece Rhodes. Fan *et al*.[4] made a flight forecasting for the airlines based on the C-means clustering method. Chen[5] carried out a regression forecasting of the international and domestic passenger transportation and turnover volume based on GDP economy indexes. Wei and Feng[6] adopted the support vector regression method to forecast the passenger volume. Zhao and Guo[7] forecasted the air traffic flow in eastern China with consideration of the effect of random factors. Devoto *et al*.[8] applied the multiple linear regression method and the ARIMA method to forecast the traffic demand of three airports in Sadin, Italy. Wang and Xia[9] forecasted the dynamics of the flight under real time by the BP neural network. Cheng *et al*.[10,11] made a real time forecasting of air traffic volume with the neural network and the statistical analyze model. Meng and Yang[12] vaguely processed the undetermined factors in regression forecasting and then forecasted the civil aviation passenger volume by the neural network. Blinova[13] adopted the neural network to forecast the passenger flow in Russia. Zhang and Guo[14] used the GM (1, N) model and made a short-term forecasting of annual traffic flow in the Capital Airport of China with consideration of the effect of regional GDP.

Through the above-mentioned results, it can be found that the long-term forecasting for the air traffic is still lacked both at home and abroad. Thus, the current paper introduces a long-term forecasting model based on the data characteristics of the air traffic flow in China. It also discusses the adaptability of the widely-used forecasting methods.

2 Grey combined forecasting model

The principle of the grey combined forecasting model is as follows. First, it introduces a first-order weakening operator so

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as to get a first-order buffer sequence; then it uses the first n data, second n data, ···, and the last n data in the raw data to weaken the data and establishes GM (1, 1) forecasting models respectively; at last it makes a combined forecasting based on the several established GM (1, 1) models. This paper uses the least square principle to determine the weight value in the combined model.

2.1 Data weakening

Equation (1) is used to weaken evenly the buffer operator AWBO, $x(k)$ is the original sequence, and $x^{(0)}(k)$ is the time data sequence after weaken processing.

$$x^{(0)}(k)=\frac{1}{n-k+1}[x(k)+x(k+1)+\cdots+x(n)];k=1,2,\cdots,n \tag{1}$$

2.2 GM (1, 1) model

The time data sequence after weaken processing is $X^{(0)}=(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$, and their accumulated generation sequence is $X^{(1)}=(x^{(1)}(1), x^{(1)}(2),\ldots, x^{(1)}(n))$. Among this sequence,

$$x^{(1)}(i)=\sum_{l=1}^{i}x^{(0)}(l), \qquad i=1,\cdots,n \tag{2}$$

And the whitening differential equation of GM (1, 1) model should be:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b \tag{3}$$

In Eq. (3), a and b are the parameters that are going to be identified, then make

$$Y=\begin{bmatrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots\\x^{(0)}(n)\end{bmatrix},$$

$$B=\begin{bmatrix}-\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2)) & 1\\-\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3)) & 1\\\vdots & \vdots\\-\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n)) & 1\end{bmatrix} \tag{4}$$

Then based on the least square, the parameter sequence in the grey differential Eq. (3) should meet Eq. (5), therefore the value of a and b can be calculated.

$$\begin{bmatrix}a\\b\end{bmatrix}=(B^TB)^{-1}B^TY \tag{5}$$

GM (1, 1) diversion time responding and return function should be:

$$x^{(1)}(t+1)=(x^{(0)}(1)-\frac{b}{a})e^{-at}+\frac{b}{a} \tag{6}$$

$$x^{(0)}(t+1)=x^{(1)}(t+1)-x^{(1)}(t) \qquad t=1,2,\cdots,n \tag{7}$$

2.3 Result testing

Forecasting result can be usually tested by forecasting precision indexes[16]. The commonly used indexes include the relative deviation ε and the mean relative deviation $\overline{\varepsilon}$, which are shown in Eqs. (8) and (9).

$$\varepsilon=\frac{X-\hat{X}}{X}\cdot 100\% \tag{8}$$

X is the actual value while, $\hat{X}$ is the estimated value

$$\left|\overline{\varepsilon}\right|=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i-\hat{X}_i}{X_i}\right|\cdot 100\% \tag{9}$$

n is the amount of samples

2.4 Least square estimation

Assume the relationship between the fitted value $\hat{Y}$ of dependent variable and the independent variable X is linear, then an Eq. (10) can be

$$\hat{Y}=c+dX \tag{10}$$

In order to minimize the error between the observed and the fitted values, partial derivatives are made to a and b; therefore Eq. (11) is minimized.

$$F(c,d)=\sum(Y-\hat{Y})^2=\sum(Y-c-dX)^2 \tag{11}$$

$$\frac{\partial F}{\partial c}=-2\sum(Y-c-dX) \tag{12}$$

$$\frac{\partial F}{\partial d}=-2\sum(XY-c-dX^2) \tag{13}$$

The necessary condition for $F(c, d)$ having a minimized value is that the value of Eqs. (12) and (13) are 0, thus the solution is :

$$\begin{cases}d=\dfrac{\sum XY-n\overline{X}\overline{Y}}{\sum X^2-n\overline{X}^2}\\c=\overline{Y}-d\overline{X}\end{cases} \tag{14}$$

Including that, $\overline{X}$ and $\overline{Y}$ are the mean value of independent values and observed values.

3 Long-term forecasting of national civil aviation traffic

The short-term forecasting of civil aviation traffic usually means the forecasting is less than 1 year; the middle-term forecasting usually indicates the forecasting is between 2 and 5 years; and the long-term forecasting is usually more than 5 years[17]. This paper uses the raw data of landing and takeoff flights between 1985 and 2002 and makes a fitting so as to forecast the future 6 years' traffic volume between 2003 and 2008. It also studies the long-term forecasting adaptability of the grey combined forecasting model and three other commonly used forecasting methods (time sequence forecasting, regression forecasting and neural network forecasting) on civil aviation traffic volume.

3.1 Grey combined forecasting

Table 1 shows the history data of air traffic in national civil aviation, and the weakening data are derived from Eq. (1).