Prediction of Air Cargo Volume Based on Grey-periodic Extensional Combinatorial Model

She-miao FENG
Management School, Guangzhou Civil Aviation College, Guangzhou, China

Keywords: Aviation logistics, Grey theory, Gray-periodic extensional combinatorial model.

Abstract. Aviation logistics volume changes over time is an obvious regularity. According to the characteristics of aviation logistics volume data, on the basis of common GM(1,1) model and by means of establishing residual error periodic extensional model, the paper extracts predominant period and reconstruct a new data sequence, it can well overcome the contradiction between the growth tendency and the periodic fluctuation of seasonal products sales. Applying the method, a typical simulation study was carried out to illustrate its validity. Is is found that the model can greatly increased the accuracy of aviation logistics volume predication.

Introduction

Aviation logistics is an important part of China's comprehensive logistics system. Along with the gradually changes of industrial structure and consumption structure, the proportion of high value-added goods logistics is increasing [1,2]. Therefore, it is necessary to predict the aviation logistics accurately and discover its change rules, and then take appropriate measures to guide the development of aviation logistics, and it is also important basis for government departments and other decision-making organization to formulate development strategies and plans [3,4]. Aviation logistics industry is obviously different from highway, railway, water transport in terms of economic and technology, and aviation logistics market has a short development history, so the prediction and research of aviation logistics is still at the exploratory stage [5]. However, under the influence of various complexity and uncertainty factors, the development law of aviation logistics industry have not been fully understood, so it is very difficult to obtain a model which can accurately predict the aviation logistics systems [6,7]. According to the existing research, it is found that aviation logistics varies obviously with the time or seasons [8, 9].This paper uses the grey theory, taking into account the time cycle factors, the grey-periodic extensional combinatorial model is established to forecast air through put. The research results show that this method than the average gray GM (1, 1) model has higher prediction accuracy.

Grey-periodic Extensional Combinatorial Model

Considering the technical characteristics of air transport, the air logistics system is under the joint influence of human activities (political, economic, social and cultural) and natural environment (weather, meteorology and safety environment), so it can be regarded as a typical grey system. Grey system theory takes the uncertain system with "known part of information and unknown part of information" as the research object, and extracts valuable information based on the analysis and mining of "part" of known information, so as to realize the understanding and induction of system operation rules [10].

On the basis of GM(1,1) model, the grey-periodic extensional combinatorial model is established for residual sequence as residual compensation of grey GM(1,1) model. The prediction steps with the model are as follows:

First, the data sequence is established according to the historical data of air traffic flow $\left\{x^{(0)}(k)\right\}$, $x^{(0)}(k) \geq 0; k=1, 2, ..., n$, and the GM (1,1) model of the sequence is established according to the data sequence:
\[ \hat{x}(k) = (x(1) - b/a) e^{-a(k-1)} + b/a \]  

(1)

And then the residual sequence \( x'(k) \):

\[ x'(k) = x^{(0)}(k) - \hat{x}(k) \]  

(2)

The mean generation function of residual sequence is established: 
\[ \bar{x}_m(i) = \left( \sum_{j=0}^{n-1} x(i + jm) \right) / n '\]

Where, \( i = 1, 2, ..., m, 1 \leq m \leq M \), \( n \) is sample sequence length, \( n' \) is the largest integer less than \( n / m \), \( M \) is the largest integer less than \( n / 2 \). On this basis, the mean generation function matrix 
\[ \begin{bmatrix} \bar{x}_1(1) & \bar{x}_2(1) & \bar{x}_3(1) & ... & \bar{x}_M(1) \\ \bar{x}_1(2) & \bar{x}_2(2) & \bar{x}_3(2) & ... & \bar{x}_M(2) \\ \bar{x}_3(3) & ... & \bar{x}_M(3) \\ \vdots & \ddots & \ddots \end{bmatrix}. \]

The mean generation function \( \bar{x}_m(i) \) is periodized: 
\[ f_m(k) = \bar{x}_m(k), \quad k = i \left( \text{mod}(m) \right) \]

Where, \( k = 1, 2, ..., n \), \( f_m(k) \) is congruence; \( f_m(k) \) is extension of the mean generation function.

Then extract the advantage cycle. According to the principle of difference equation, the following method is used to determine whether the hidden length of the sequence \( m \) is the period:

For a given confidence level \( \alpha \), if \( F^{(m)} > F_{\alpha} (m-1, n-m) \), Dominant cycle \( m \) exists in \( x(k) \).

Where, \( F^{(m)} = (n-m) S^{(m)}/((m-1)S) \) obeys the F distribution of degree of \( (m-1, n-m) \) freedom. Where 
\[ S^{(m)} = \sum_{i=1}^{m} n_i (\bar{x}_m(i) - \bar{x})^2, \quad \bar{x} = \left( \sum_{i=1}^{n} x(i) \right)/n, \quad n_i = n/i, \]

\[ S = \sum_{i=1}^{m} \sum_{j=1}^{n_i} (x(i + (j-1)m) - \bar{x}_m(i))^2. \]

The continuation function of sequence \( x'(k) \) minus period \( m \) forms a new sequence

\[ x''(k) = x'(k) - f_m(k) \]  

(3)

Then repeat the process of extracting advantage cycle for the new sequence \( x''(k) \) to further extract other advantage cycles. The superposition value of different periods at the same time is denoted as 
\[ f(k) = \sum_{i=1}^{m} f_i(k), \]

and the periodic epitaxial model established by the periodic superposition extrapolation method is obtained. The grey-periodic epitaxial combination model is obtained by using \( \hat{x}(k) \) and \( f(k) \) combination as sequence fitting:

\[ \bar{x}(k) = \hat{x}(k) + f(k) \]  

(4)

Case Analysis

Aviation logistics volume has a specific corresponding meaning. There is no universally recognized definition, the industry generally tends to take air cargo volume as the approximate index of aviation logistics volume. In general, air cargo volume is not equal to aviation logistics volume, but an important part of aviation logistics volume. However, to some extent, air cargo volume determines the business volume of inventory, distribution and other links. Therefore, it is reasonable
to analyze air cargo volume in favor of aviation logistics volume. This paper selects the air cargo volume collection data of a consolidator from 2010 to 2018 as the data source (unit: 100kg), as shown in the following table 1.

Table 1. Air Cargo volume from 2010-2018(Unit: Hundred kilograms).

| quarter | 2010   | 2011   | 2012   | 2013   | 2014   | 2015   | 2016   | 2017   | 2018   |
|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 1       | 50.11  | 60.43  | 65.99  | 74.89  | 85.84  | 98.27  | 85.90  | 127.30 | 128.62 |
| 2       | 43.34  | 68.09  | 72.94  | 81.43  | 96.82  | 103.37 | 103.73 | 136.96 | 136.08 |
| 3       | 58.64  | 72.56  | 80.33  | 91.58  | 105.16 | 102.78 | 120.72 | 142.43 | 141.19 |
| 4       | 64.86  | 71.19  | 83.03  | 93.10  | 106.93 | 97.72  | 132.39 | 150.91 | 145.45 |

It is found that aviation logistics volume increasing continuously in this time. Aviation logistics volume conforms to the overall trend in the development of social economy, but at the end of each year, with relatively obvious cyclical changes, so grey-cycle extension combination model can be applied for fitting of this data.

First of all, the above time series were arranged in time order, and the GM(1,1) model was established to obtain the following function: 

\[ \hat{x}(k+1) = 2133.765423e^{0.027419k} - 2083.655423 \]

Obviously, this model is an exponential model, which reflects that the overall change trend of material flow is increasing. The relative error and residual of fitting are shown in table 2 (serial Numbers 1, 2, 3 and 4 in the table represent the first, second, third and fourth quarters of 2010, and serial Numbers 5, 6, 7 and 8 represent the first, second, third and fourth quarters of 2011, and so on). It can be seen that the average relative error of fitting is 7.09% due to the significant periodicity of the air flow, with low accuracy. In order to improve the fitting accuracy, residual sequence should be considered.

Table 2. Fitting results of GM(1,1) prediction model.

|        | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    |
|--------|------|------|------|------|------|------|------|------|------|
| original value | 50.11| 43.34| 58.64| 64.86| 60.43| 68.09| 72.56| 71.19| 65.99|
| fitted value    | 50.11| 59.32| 60.96| 62.66| 64.4  | 66.19| 68.03| 69.92| 71.86|
| residuals       | 0    | 15.98| 2.32 | -2.2 | 3.97  | -1.9 | -4.53| -1.27| 5.87 |
| relative error %| 0    | 36.85| 3.96 | -3.39| 6.57  | -2.79| -6.24| -1.78| 8.9  |
| original value  | 72.94| 80.33| 83.03| 74.89| 81.43 | 91.58| 93.1 | 85.84| 96.82|
| fitted value    | 73.86| 75.92| 78.03| 80.19| 82.45 | 84.72| 87.07| 89.49| 91.98|
| residuals       | 0.92 | -4.41| -5   | 5.31 | 0.99  | -6.86| -6.03| 3.65 | -4.84|
| relative error %| 1.26 | -5.49| -6.03| 7.08 | 1.22  | -7.49| -6.47| 4.25 | -4.5 |
| original value  | 105.16| 106.93| 98.27| 103.37| 102.78| 97.72| 85.9 | 103.73| 120.72|
| fitted value    | 94.54| 97.16| 99.87| 102.64| 105.49| 108.4| 111.4| 114.54| 117.72|
| residuals       | -10.62| -9.76| 1.59 | -0.73| 2.71  | 10.71| 25.54| 10.81| -2.99|
| relative error %| -10.1| -9.13| 1.62 | -0.7 | 2.64  | 10.96| 29.73| 10.42| -2.48|
| original value  | 132.39| 127.3 | 136.9 | 142.43| 150.91| 128.6 | 136.1 | 141.19| 145.49|
| fitted value    | 120.99| 124.36| 127.8 | 131.37| 135.02| 138.8 | 142.6 | 146.59| 150.67|
| residuals       | -11.39| -2.94| -9.14 | -11.06| -15.89| 10.15| 6.55  | 5.41 | 5.22 |
| relative error %| -8.6 | -2.31| -6.68 | -7.76| -10.53| 7.89 | 4.82  | 3.83 | 3.59 |

The residual sequence \( x(k) \) was established for the above residual data, and the dominant period \( m = 4 \) was extracted, \( F^{(4)} = 16.12 > F_{0.05(3,32)} = 2.90 \).
The periodic epitaxial prediction model established by the periodic superposition extrapolation method is \( f(k) = f_{0}(k) \). Mean generation function \( \bar{x}_{1}(1) = 5.914 \), \( \bar{x}_{2}(2) = 2.071 \), \( \bar{x}_{3}(3) = 1.394 \), \( \bar{x}_{4}(4) = 3.957 \). Superposition to generate gray-periodic epitaxial combination model: 
\[
\hat{f}(k+1) = 2133.765423e^{0.027419k} - 2083.655423 + f(k);
\]
The fitting results of the model are shown in table 3.

|      | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| original value | 50.11 | 43.34 | 58.64 | 64.86 | 60.43 | 68.09 | 72.56 | 71.19 | 65.99 |
| fitted value  | 44.21 | 57.25 | 64.29 | 66.62 | 64.12 | 71.37 | 73.88 | 65.96 |
| residuals    | -11.78 | 32.09 | 9.65  | 2.71  | -3.20 | -5.83 | -1.64 | 3.77  |
| relative error % | 0.05 |

|      | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| original value | 72.94 | 80.33 | 83.03 | 74.89 | 81.43 | 91.58 | 93.1 | 85.84 | 96.82 |
| fitted value  | 71.79 | 79.26 | 81.99 | 74.29 | 80.38 | 88.06 | 91.03 | 83.59 | 89.91 |
| residuals    | -1.151 | -1.073 | -1.043 | -0.604 | -1.051 | -3.523 | -2.073 | -2.254 | -6.911 |
| relative error % | -7.14 |

|      | 19  | 20  | 21  | 22  | 23  | 24  | 25  | 26  | 27  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| original value | 105.16 | 106.93 | 98.27 | 103.37 | 102.78 | 97.72 | 85.9 | 103.73 | 120.72 |
| fitted value  | 97.88 | 101.12 | 93.97 | 100.56 | 108.83 | 112.39 | 105.54 | 112.47 | 121.06 |
| residuals    | -7.28 | -5.81 | -4.30 | -2.81 | 6.05  | 14.67 | 19.64 | 8.74  |
| relative error % | 0.34 |

|      | 28  | 29  | 30  | 31  | 32  | 33  | 34  | 35  | 36  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| original value | 132.39 | 127.3 | 136.96 | 142.43 | 150.91 | 128.62 | 136.08 | 141.19 | 145.49 |
| fitted value  | 124.95 | 118.46 | 125.75 | 134.71 | 138.98 | 132.87 | 140.56 | 149.93 | 154.63 |
| residuals    | -7.44 | -8.84 | -11.21 | -7.72 | -11.93 | 4.25  | 4.48  | 8.74  |
| relative error % | 9.14 |

|      | 37  | 38  | 39  | 40  | 41  | 42  | 43  | 44  | 45  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| original value | 132.39 | 127.3 | 136.96 | 142.43 | 150.91 | 128.62 | 136.08 | 141.19 | 145.49 |
| fitted value  | 124.95 | 118.46 | 125.75 | 134.71 | 138.98 | 132.87 | 140.56 | 149.93 | 154.63 |
| residuals    | -7.44 | -8.84 | -11.21 | -7.72 | -11.93 | 4.25  | 4.48  | 8.74  |
| relative error % | 9.14 |

By comparing the results in table 3 and table 2, it can be found that the average relative error of fitting obtained by the grey periodic extensional combinatorial prediction model is 5.81%, which significantly improves the accuracy, indicating that the grey periodic epitaxy prediction model has a good application effect in the prediction of aviation material flow. The comparison of fitting results is shown in figure 1 as follows:
Conclusions

Grey-periodic extensional combinatorial model is used to fit the aviation logistics volume in this paper, it is found that this method can improve the accuracy of aviation logistics volume forecast. It has good application effect and proved by an example. Based on the analysis of the model, there can be thought of this method can provide new ideas for aviation logistics volume forecast. However, aviation logistics volume is influenced by various natural, social and economic activities, China's aviation logistics, especially the international aviation logistics, is also restricted by various factors. As time goes by, internal and external conditions associated with historical data will produce various changes. Therefore, it is not completely accurate to extrapolate future changes from historical data alone, so it is necessary to analyze the development trend of aviation logistics volume in combination with the change of economic environment in the future. Decision makers must grasp the trend of aviation logistics volume more comprehensively and accurately, only in this way can decision-making be more scientific.

References

[1] Wei Wen-xuan. Throughput Forecasting of Zhengzhou Air Harbor Based on RBF Neural Network[J]. Logistics Technology, 2014, 33(15):182-184.
[2] Peng Ding-gui, Lin Yan-jing. Forecast Study on Airfreight Volume of Fujian Province Based on Grey-Markov Model[J]. Logistics Engineering and Management, 2014, 36(2):54-55.
[3] Fu Peng-hua, Bao Fu-guang, Li Jin. Research on the Air Cargo Forecast Based On Combination Forecast Model[J]. Shanghai Management Science, 2012, 34(2):48-52.
[4] Zhu Zhi-yu, LIU Yan. Combination Forecast of Air Cargo Volume in China Based on Time Sequence Model[J]. Journal of Xi'an Aeronautical University, 2017, 35(05):65-70.
[5] Feng She-miao. Long-Term Prediction of Civil Aviation Freight Volume Based on Grey Verhulst Model[J]. Journal of East China Jiaotong University, 2013, 30(3):61-64.
[6] You Qing-shan, Xu Hai-wen, Lei Kai-hong. Gray dynamic model based on compressed sensing and its application to prediction of air cargo volume[J]. Journal of Chengdu University of Technology (Science & Technology Edition), 2014, 41(5):651-656.
[7] You Cling-shang, Lei Kai-hong, Xu Hai-wen. Sparse Recovery Model of Air Cargo Volume[J]. Mathematics in Practice and Theory, 2015, 45(2):113-122.
[8] Liu Si-feng, Guo Tian-bang, Dang Yao-guo. Grey system theory and its application[M]. Beijing: Science press, 2004:195-198.
[9] Tsung-Yu Chou, Gin-Shuh Liang, Tzeu-Chen Han. Application of fuzzy regression on air cargo volume forecast[J]. Quality & Quantity. 2013, Vol. 47 (2):897-908.
[10] Zhu Qian, Liao Zhi-gao, Zhang Feng-yi. Air Cargo Demand Forecast of Guangxi Based on Clustering Algorithm and ANFIS[J]. Journal of Wuhan University of Technology, 2015, 37(08):37-41.