Study on Civil Aviation Unsafe Incident Prediction Based on Markov Optimization

Fei Lu, Wenya Li(✉), Zhaoning Zhang, and Kexuan Liu

Civil Aviation University of China, Tianjin 300300, China
lufei315@126.com, liwenya522@163.com

Abstract. The civil aviation safety management system requires accurate prediction of the future safety status, but there are often many uncertain factors in the occurrence of air traffic insecurity events. In order to study its development trend and strengthen the accurate analysis and prediction of unsafe events, a combined forecasting model based on Markov correction process is proposed. Firstly, apply the grey system theory to construct a GM (1, 1) model. Then, based on the grey prediction model and the exponential smoothing method, combination forecasting model is established. And according to the standard deviation of the prediction result, the weight is determined to correct the data. Finally, combined with the Markov method, the probability transfer matrix is determined and the results are optimized. Based on the statistics of civil aviation insecure events in the past ten years, the prediction accuracy of the optimized model is significantly higher than that of the single gray prediction model or the exponential smoothing prediction model, which verifies the effectiveness of the method.

Keywords: Unsafe event · Gray model · Combination forecast · Markov optimization

1 Introduction

The Civil Aviation Safety Management System (SMS) requires the collection and analysis of safety information to construct a safety management mechanism based on risk early warning management and feedback control [1]. In recent years, with the increasing flight flow, the absolute value of civil aviation unsafe incidents has also increased. Therefore, how to prevent and control the occurrence of civil aviation unsafe incidents becomes more and more important.

With regard to the study of civil aviation unsafe events, the current commonly used prediction methods include regression analysis and prediction, BP neural network method and saturation growth trend prediction. Wang, Liu [2] analyzed the gray correlation degree of civil aviation accident signs and their influencing factors also used the model to analyze the measured statistical data of the 2001–2004 accident signs. Luo et al. [3] predicted the number of accidents in the next three years by establishing a gray prediction model of the number of accidents. Shi et al. based on the grey topological prediction theory method to predict the year and month of the number of deaths within a certain threshold range by establishing a time series model group corresponding to

S. Liu and G. Yang (Eds.): ADHIP 2018, LNICST 279, pp. 524–534, 2019.
https://doi.org/10.1007/978-3-030-19086-6_58

different thresholds [4]. Outside the country, Fullwood et al. [5] used linear regression to predict aviation safety trends based on accident data in relevant air service difficulties reports. McCann [6] of the American Aeronautical Meteorological Center used neural networks to predict aircraft icing at different intensities. GARRIDO established an Ordered Profit model for predicting the severity of traffic accidents [7].

In summary, it can be found that the above prediction methods often require a large amount of data to obtain a stable and long-term development trend, and do not consider that the actual development trend is often fluctuating. The grey system mainly studies the uncertain system of “small sample and poor information” [8]; the exponential smoothing rule takes into account the whole-term data, and assigns different weights according to the distance of the data. And the Markov prediction is applicable to the prediction of long term and random fluctuation of data series.

Therefore, the author will use gray prediction to reveal the time series development trend of civil aviation unsafe events, and combine the exponential smoothing method to correct the results and establish a combined forecasting model. Based on this, the Markov theory is used to determine the state transition probability to obtain the Markov optimization prediction model that meets the development characteristics of civil aviation unsafe events, which can significantly improve the prediction effect.

2 The Combined Forecasting Model

There are many influencing factors in air traffic insecurity events, and a considerable part of them are difficult to describe in quantitative form. For the distribution of air traffic insecurity events, different predictors will have different understandings, and different prediction methods will be used. So, it is necessary to use a variety of quantitative prediction methods, a combination of qualitative and quantitative methods to predict, in order to increase the accuracy of the prediction issues.

2.1 The Grey Prediction Model

The gray system analysis method is to identify the similarity or dissimilarity between the development factors of the system factors, that is, to analyze the correlation degree, and to seek the law of system change by generating the original data. The generated data sequence has strong regularity, which can be used to establish the corresponding differential equation model to predict the future development trend and future state of the thing, the so-called gray prediction.

Let $X^{(0)}$ be used as a non-negative time series for $GM(1,\ 1)$ model:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2),\ \ldots,\ x^{(0)}(n)) \tag{1}$$

$X^{(1)}$ is the $1 - AGO$ sequence of $X^{(0)}$, i.e.

$$
\begin{aligned}
&X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)); \\
&X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), k = 1, 2, \ldots, n
\end{aligned}
\tag{2}
$$

Let $Z^{(1)}$ be the immediate mean (MEAN) generation sequence of $X^{(1)}$, i.e.

$$
\begin{aligned}
&Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)) \\
&z^{(1)}(k) = 0.5^{x^{(1)}(k)} + 0.5^{x^{(1)}(k-1)}
\end{aligned}
\tag{3}
$$

Then the definition model of GM (1, 1), that is, the gray differential equation model of GM (1, 1) is:

$$
x^{(0)}(k) + az^{(1)}(k) = b \tag{4}
$$

The symbolic meaning of the model GM (1, 1) is: G—Grey, M—Model; (1, 1) –(First order equation, One variable).

In the formula, a is called the development coefficient, and b is the gray amount of action. $\hat{a}$ is set as the parameter vector to be estimated, that is, $\hat{a} = (a, b)^T$, and the least squares estimation parameter column of the above grey differential equation satisfies:

$$
\hat{a} = (B^T B)^{-1} B^T Y_n \tag{5}
$$

In the above formula:

$$
B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \cdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix} \tag{6}
$$

The whitening equation, called the grey differential equation, is also called the shadow equation.

As mentioned above, the basic steps of the grey prediction method are:

(1) Establish a GM (1, 1) prediction model.

From the original sequence $X^{(0)}$, the $1 - $ AGO sequence and the calculated nearest sequence $Z^{(1)}$ is generated. The variable parameter $\hat{\alpha} = (a, b)^T$ is estimated by the least squares method, and the GM (1, 1) model is obtained as a prediction model:

$$
\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{7}
$$

The time response sequence (or time response function) of the prediction model is:

$$\hat{x}^{(1)}(t+1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-at} + \frac{b}{a} \tag{8}$$

Take $x^{(1)}(0) = x^{(0)}(1)$ to get the reduced value:

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t) = (1 - e^{a})\left[x^{(0)}(1) - \frac{b}{a}\right]e^{-at} \tag{9}$$

(2) Test the prediction accuracy

The main purpose of modeling is to predict that in order to improve the prediction accuracy, so we must first ensure that the simulation accuracy is sufficiently high. Therefore, it is necessary to perform a residual test on the above model firstly, and only the model that passes the residual test can be used as a prediction.

Find the residual variance of the actual value and the predicted value separately S_1, S_2:

$$\begin{aligned} S_1 &= \left\{\frac{1}{n}\sum_{k=1}^{n}\left[\bar{x}^{(0)}(t) - \frac{1}{n}\sum_{k=1}^{n}\bar{x}^{(0)}(t)\right]\right\}^{\frac{1}{2}} \\ S_2 &= \left\{\frac{1}{n}\sum_{k=1}^{n}\left[x^{(0)}(t) - \frac{1}{n}\sum_{k=1}^{n}x^{(0)}(t)\right]\right\}^{\frac{1}{2}} \end{aligned} \tag{10}$$

Then calculate the ratio c and the error probability α

$$c = \frac{S_1}{S_2} \tag{11}$$

$$\alpha = p\left\{|\bar{x}^{(0)}(k) - \frac{1}{n}\sum_{k=1}^{n}\bar{x}^{(0)}(k)| < 0.6745S_2\right\} \tag{12}$$

The calculated c and α determine the accuracy of the model based on the gray prediction model accuracy level, as shown in Table 1 below:

Table 1. The accuracy inspection levels of gray prediction model.

Grade	α	c
Excellent	>0.95	<0.35
Good	>0.80	<0.45
Medium	>0.70	<0.50
Bad	≤0.70	≥0.65

2.2 The Grey Prediction Model

The exponential smoothing method is a kind of moving average method, which mainly gives different weights to past observations, and the weight of recent observation is greater than the weight of long-term observations. Mainly used for short- and medium-term forecasts.

Let the time series be $y_1, y_2, \cdots y_t$, then the basic formula for one exponential smoothing is:

$$S_t = \alpha * y_t + (1 - \alpha) * S_t - 1 \tag{13}$$

In the formula:

S_t—Smooth value of time t;
y_t—Actual value of time t
α—Smoothing constant, the value range is [0, 1]

The prediction formula is:

$$y'_{t+1} = \alpha * y_t + (1 - \alpha) * y'_t \tag{14}$$

y'_{t+1}—The predicted value of the time t + 1, that is, the smooth value of the t period S_t
y_t—The actual value of the t period;
y'_t—The predicted value of the t period, that is, the smooth value of the previous period S_{t-1}.

2.3 The Grey Prediction Model

In the changing period, it is often difficult to have a single prediction model that fits the reality of frequent fluctuations very closely. So under these circumstances, the combined prediction model may get a better than any independent prediction. The predicted value of the combined prediction model can reduce the systematic error of the prediction and significantly improve the prediction effect.

For the same object, the comprehensive prediction results are calculated by adopting various prediction methods and assigning certain weights to the prediction results.

$$Y = \sum W_i \times Y_i \tag{15}$$

In this formula:

Y—The results of combination forecasting model, that is, the final predicted values after the combined processing;
Y_i—The predicted value obtained by the i^{th} prediction method;
W_i—The non-negative weighting factor given by the i^{th} prediction method, $\sum W_i = 1$

The above weights are determined according to the standard deviation of various prediction methods, and the formula is as follows:

$$W_i = \frac{1}{n-1}\frac{S - S_i}{S} = \frac{1}{n-1}\frac{\sum S_i - S_i}{\sum S_i} \tag{16}$$

Among them:

S_i—The standard deviation of the ith prediction model;
n—The Number of prediction methods

In most cases, for the sake of simplicity of calculation, the weight coefficient can be selected as the equal weight coefficient.

3 The Markov Optimization Model

The Markov process is mainly to study the current state and state transition laws of a running system to predict the state that may occur in the future.

According to the prediction result of the GM (1, 1) model, the relative error between the original sequence and the predicted sequence is calculated, and the state interval is determined according to the relative range of the error.

$$M = \frac{\hat{x}^{(0)}(k)}{x^{(0)}(k)} \times 100\% \tag{17}$$

There are n possible states $E_1, E_2, \cdots E_n$ in the development of an event. The probability that an event starts from a certain state E_i and the next time shifts to another state E_j is called a state transition probability P_{ij}, and the state transition matrix P is:

$$P = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{pmatrix} \tag{18}$$

Through the state transition probability matrix, it is possible to predict the state or trend that may occur in the future by the current initial state.

$$P_{ij} = \frac{M_{ij}}{M_i} \tag{19}$$

The state transition matrix is generally calculated using the principle of the frequency is approximately equal to the probability. Where: M_i is the total number of times the state E_i appears, and M_{ij} is the number of times the state E_i has transitioned to the state E_j.

According to the relative error state E_i measured by the predicted values of the matrix P and the combined prediction method, the median value of the relative error state interval $[e_{is}, e_{ir}]$ corresponding to the state is used as the optimized value of the result:

$$Y = \frac{\hat{x}^{(0)}(k)}{1 \pm \frac{1}{2}[e_{is}, e_{ir}]} \tag{20}$$

When the combined predicted value is larger than the actual value, the denominator plus minus sign takes a positive value, and when it is smaller than the actual value, it takes a negative value, and when the predicted value is more accurate than the actual value, there is no need to correct it.

The Markov optimization prediction modeling process is shown in Fig. 1.

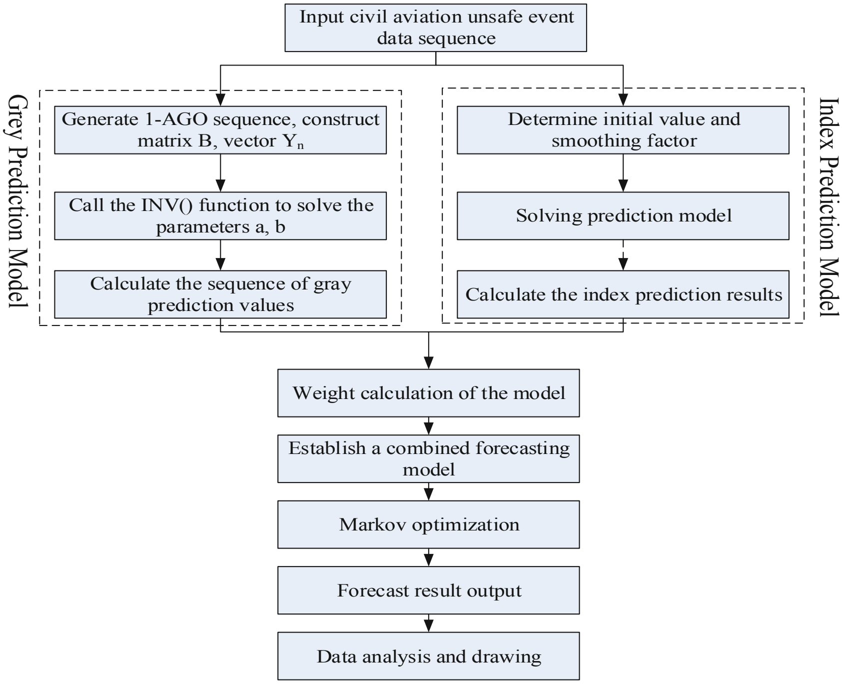

Fig. 1. The predict process of Markov optimization model

4 The Case Analysis

According to civil aviation unsafe event statistics [9], data from 2000 to 2012 can be obtained, as shown in Table 2 below. Based on the original data, the program was written using MATLAB, and the GM (1, 1) and exponential smoothing prediction models were established respectively to fit the number of unsafe events from 2000 to 2012. The number of unsafe events in the next three years was predicted.

Table 2. Actual values

Years	Number of events	Years	Number of events
2000	93	2007	116
2001	103	2008	120
2002	116	2009	159
2003	100	2010	119
2004	106	2011	230
2005	116	2012	295
2006	117	–	–

The cumulative number of gray GM (1, 1) prediction model $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$, find: $a = -0.0432$, $b = 91.8082$, then the prediction formula of the gray prediction model is:

$$\hat{x}^{(1)}(t+1) = 2218.19e^{0.0432t} - 2125.19$$

By calculating the variance ratio and error probability, the grey prediction can be used to predict civil aviation unsafe events, but the accuracy is limited.

Then use exponential smoothing to make predictions. Since the data of exponential smoothing model predicts less than 15, so the initial value is:

$$S_1^{(1)} = S_1^{(2)} = S_1^{(3)} = \frac{y_1 + y_2 + y_3}{3} = 104$$

In the model, the selection of the smoothing factor has a critical impact on the accuracy of the prediction. The larger the value of α, the larger the proportion of y_t in the prediction, the larger the correction, the greater the impact of recent changes in the time series, and the greater the likelihood of interference. Therefore, the impact of the two aspects on the prediction results, the exponential smoothing coefficient $\alpha = 0.5$. The prediction results of civil aviation insecurity events from 2000 to 2012 are shown in Table 3 through the determination of relevant parameters.

Table 3. Prediction results of each model

Years	Grey prediction	Index forecast	Combination forecast
2000	93.00	93.00	93
2001	97.92	98.00	97.98
2002	102.24	107.00	105.57
2003	106.75	103.50	104.48
2004	111.46	104.75	106.76
2005	116.38	110.38	112.18
2006	121.52	113.69	116.04

(*continued*)

Table 3. (*continued*)

Years	Grey prediction	Index forecast	Combination forecast
2007	126.88	114.84	118.45
2008	132.48	117.42	121.94
2009	138.32	139.21	138.94
2010	144.43	180.11	169.40
2011	150.80	205.05	188.78
2012	157.45	250.03	222.25

Based on the formula (16), it can be determined that the results of the gray prediction and the exponential prediction take the weights of 0.3 and 0.7, respectively, to calculate the prediction result of the combined model.

Since civil aviation insecurity events have a certain randomness, direct prediction using a single prediction method cannot obtain ideal prediction values. The combined prediction method is used for weighting and then prediction. It can be found that the combined prediction model is better than the single model prediction. The relative error comparison of the three prediction results is shown in Fig. 2.

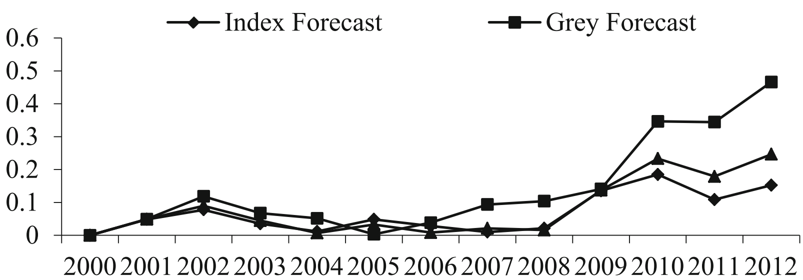

Fig. 2. Relative error comparisons

The state space is divided according to the relative error between the predicted result and the actual value. The number of state divisions is related to the number of samples and the error range of the fitting. Too many samples require more samples. If they are too small, the state difference is not obvious, and the meaning of fluctuation adjustment is lost. Usually 3-5 states are appropriate. According to the principle of equal probability and Markov application experience [10], the division status is shown in Table 4.

Through the Tables 2 and 3 can determine the state transition of civil aviation unsafe events from 2000 to 2012, as shown in Table 5.

Table 4. State division criteria

Status	1/M
Overestimate E1	[0.92, 0.98]
Normal E2	[0.98, 1.04]
Underestimate E3	[1.04, 1.1.10]
Extremely underestimated E4	[1.10, 1.34]

Table 5. Markov state of prediction results

Years	1/M	Status	Years	1/M	Status
2000	1	E2	2007	0.979280906	E1
2001	1.05127046	E3	2008	0.98410359	E2
2002	1.098767136	E3	2009	1.158737825	E4
2003	0.957155792	E1	2010	1.304594027	E4
2004	0.992841612	E2	2011	1.218374352	E4
2005	1.034078595	E2	2012	1.327311825	E4
2006	1.008304204	E2	–	–	–

According to the state transition probability definition and the representation of the state transition probability matrix, the four state transition cases are statistically obtained. Then the state transition probability matrix of the prediction can be obtained as follows:

$$P = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1/5 & 2/5 & 1/5 & 1/5 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

The number of civil aviation unsafe events in 2013–2015 is predicted and the predicted value is compared with the actual value. According to the Markov optimization model principle, state predictions for several years after the original data can be obtained. Taking 2012 as an example, the state interval in 2012 is E4, that is, the state probability vector X (2012) is (0 0 0 1).

According to formula (20), the prediction results from 2013 to 2015 can be calculated separately, as shown in Table 6.

Table 6. Forecast results from 2013 to 2015

Years	Combination prediction model prediction results	Combination prediction model precision	Markov optimization prediction results	Markov optimization precision
2013	242.5285985	295.8848902	0.80307483	0.979751292
2014	261.5000643	319.0300784	0.807098964	0.984660736
2015	296.6698071	361.9371647	0.752969054	0.918622245

Comparing the combined prediction model with the Markov optimized prediction results, it can be found that the prediction results and precision of the Markov optimized model are significantly improved.

5 Conclusions

In this paper, gray prediction and exponential smoothing prediction are used to predict civil aviation unsafe events. The weighted distribution of the two prediction results is used to establish a combined prediction model. Finally, the Markov process is used to optimize the results. The analysis shows that the prediction accuracy of 2013–2015 is as high as 98.0%, 98.5% and 91.9% respectively, which indicates that the model makes better use of the information of different single models and is suitable for the prediction of civil aviation unsafe events. At the same time, the model has high operability and strong practicability, which can provide a basis for the establishment of civil aviation unsafe incident prevention and control and safety management system.

Acknowledgements. The authors were supported by the National Natural Science Foundation of China (No. 71701202).

References

1. Jia, G., Wang, H.: Study on the composition and operation process of the risk management system of the air traffic safety. J. WUT (Inf. Manage. Eng.) **30**(5), 827–830 (2008)
2. Wang, Y., Liu, X.: Grey relation analysis and grey model for civil aviation accidents forecasting. J. Saf. Environ. **6**(6), 127–130 (2006)
3. Luo, F., Xiong, W.: The grey forecasting for signs of civil aviation accidents. Value Eng. **27**(1), 1–3 (2008)
4. Shi, Y., Lin, Y., Zou, Y., et al.: The prediction model on Chinese traffic deaths based on the grey topology. Math. Pract. Theory **43**(20), 1–3 (2008)
5. Fullwood, R.R., Hall, R.E., Martinez-Guridi, G.: Relating aviation service difficulty reports to accident data for safety trend prediction. Reliab. Eng. Syst. Saf. **60**(1), 83–87 (1998)
6. McCann, D.W.: NNICE-a neural network aircraft icing algorithm. Environ. Model Softw. **10**(10), 1335–1342 (2005)
7. Rui, G., Bastos, A., Almeida, A.D., et al.: Prediction of road accident severity using the ordered probit model. Transp. Res. Procedia **3**, 214–223 (2014)
8. Deng, J.: Gray Control System. Huazhong University of Science and Technology Press, Wuhan (1993)
9. The aviation safety office of CAAC.: Statistical analysis of civil aviation incidents of China. China Academy of Civil Aviation Science and Technology (2015)
10. Suo, F., Wang, S.: Prediction and application study of architecture accidents based on optimization combination. Shanxi Architect. **33**(19), 20–21 (2007)