Prediction and Optimization Performance Models for Poor Information Sample Prediction Problems

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Abstract: The prediction process often runs with small samples and under-sufficient information. To target this problem, we propose a performance comparison study that combines prediction and optimization algorithms based on experimental data analysis. Through a large number of prediction and optimization experiments, the accuracy and stability of the prediction method and the correction ability of the optimization method are studied. First, five traditional single-item prediction methods are used to process small samples with under-sufficient information, and the standard deviation method is used to assign weights on the five methods for combined forecasting. The accuracy of the prediction results is ranked. The mean and variance of the rankings reflect the accuracy and stability of the prediction method. Second, the error elimination prediction optimization method is proposed. To make, the prediction results are corrected by error elimination optimization method (EEOM), Markov optimization and two-layer optimization separately to obtain more accurate prediction results. The degree improvement and decline are used to reflect the correction ability of the optimization method. The results show that the accuracy and stability of combined prediction are the best in the prediction methods, and the correction ability of error elimination optimization is the best in the optimization methods. The combination of the two methods can well solve the problem of prediction with small samples and under-sufficient information. Finally, the accuracy of the combination of the combined prediction and the error elimination optimization is verified by predicting the number of unsafe events in civil aviation in a certain year.

Key words: small sample and poor information; prediction method performance; optimization method performance; combined prediction; error elimination optimization model; Markov optimization

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0 Introduction

Managers often predict the future trends based on small samples and poor information. In order to achieve the expected prediction effect, it is particularly important to select appropriate forecasting methods, and to optimize the predict results if necessary. This paper focuses on the problems of information prediction with small samples.

The problem of poor sample information is characterized by a lack of information and a small number of samples. Lei et al. [1] established the GM(1,1) model of time-interval prediction for soft foundation settlement by using the grey theory, modified it with GM(1,1) model of residual error, and compared the results with the logarithmic curve estimation method. The results showed that the model was more accurate and more consistent with the reality. Chen et al.[2] used the grey fuzzy dynamic model to predict the production of municipal solid waste based on limited samples, and the prediction precision was higher than that of the traditional grey dynamic model. Bruno et al.[3] studied the coastal dynamics with the method of polynomial prediction

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and compared it with linear regression prediction. The result showed that polynomial prediction model is more suitable for this problem. Using the time series neural network method and the rolling weight adjustment method, Yang et al.[4] predicted the wind speed, and the precision of the prediction results was higher than that of the time series prediction method. Barbounis et al.[5] used the prediction model of local recurrent neural network with internal dynamics to study on the wind speed prediction problem. The simulation results showed that this model had better performance than other network models. Niu et al.[6] used the support vector machine (SVM) method to predict short-term load based on data mining, and the prediction results showed that this method had higher prediction precision than the ordinary back propagation (BP) neural network model. Muzaffar et al.[7] used a special recursive neural network, the long and short term memory network, to predict short-term loads. Compared with the traditional root mean square error (RMSE) and mean absolute percentage error (MAPE) methods, the prediction precision was higher and could be further improved. Dudek[8] proposed a single predictive variable linear regression prediction method to predict short-term power load, and compared the performance of the proposed method with autoregressive integrated moving average model (ARIMA), exponential smoothing model, neural network model and other models, confirming the high-precision capability of the method. Li et al.[9] used an adaptive exponential smoothing model to predict the short-term travel time of urban arterial street, and the model could deal with almost all kinds of traffic conditions. Combining with the Markov madel, Pourmousavi et al.[10] used the artificial neural network prediction method to predict the wind speed, which improved the prediction precision.

Although these prediction methods can achieve the purpose of prediction and the optimization model can effectively improve the prediction precision, they are only suitable for specific research problems. For different prediction problems, it is necessary to re-select the prediction methods. Therefore, this paper studies the prediction problem of poor information events with small samples. We establish the combined prediction model based on the prediction error, and the optimization model of prediction results, as well as analyze the performance of the prediction model and optimization model. In order to test and verify the performance of the model, we conduct a large number of prediction experiments to assess the accuracy and stability of the prediction method and the correction ability of the optimization model. Varieties of different samples are used in the prediction experiment to ensure the universality of the prediction samples and the generality of the prediction model and the optimization model.

1 Combinatorial Prediction Model and Optimization Model

1.1 Combinatorial prediction model

Combinatorial prediction method is a prediction method that comprehensively analyzes and combines the results of different methods for the same problem. The purpose of combinatorial prediction is to improve the prediction precision as much as possible by synthetically utilizing the information provided by different methods. In the developing period of event, it is often difficult for a single prediction model to fit closely to the frequent fluctuations. Compared with the single prediction model, the combinatorial prediction model can obtain a better prediction result than that of any single prediction model, reduce the systematic error of prediction, and significantly improve the prediction effect.

The combinatorial prediction is shown as

$$\begin{cases} \sum_{i=1}^{n} w_i = 1 \\ w_i = \dfrac{1}{q-1} \dfrac{\sum s_i - s_i}{\sum s_i} \\ y = \sum w_i \times y_i \end{cases} \tag{1}$$

where y is the result of combination prediction, y_i the prediction result of the ith traditional single prediction method, w_i the weight coefficient of the ith traditional single prediction method, s_i the standard deviation of the prediction result of the ith traditional single prediction method, and q the number of traditional single prediction methods.

1.2 Error elimination optimization model

In any case, there are always errors in the result of predictions. The prediction error cannot be completely eliminated by any kind of optimization model. Therefore, the error elimination refers to reducing the overall error of the predictions as much as possible to a level that is accepted by the forecaster. Error elimination is defined as reducing the average prediction error to an acceptable level. Based on this definition, a new prediction result optimization model is established and named as error elimination optimization model (EEOM). The model is described as follows.

The initial predicted value is processed as

$$\begin{cases} r_k^{(0)} = \dfrac{\hat{y}_k^{(0)} - y_k^{(0)}}{y_k^{(0)}} \\ \bar{r}^{(0)} = \sum\limits_{k=1}^{K} \dfrac{r_k^{(0)}}{K} \end{cases} \tag{2}$$

where $r_k^{(0)}$ is the relative error of the initial predicted value, $\hat{y}_k^{(0)}$ the initial prediction result; $y_k^{(0)}$ the true value, $\bar{r}^{(0)}$ the overall average error level of the initial prediction result, and K the number of data of the sample.

The acceptable average prediction error level is ε. If $\left|\bar{r}^{(0)}\right| \leqslant \varepsilon$, the prediction result $y = \sum w_i \times y_i$; other wise the iteration is given as

$$\begin{cases} \hat{y}^{(l)} = \hat{y}^{(l-1)}(1 - \bar{r}^{(l-1)}) \\ \bar{r}^{(l)} = \sum\limits_{k=1}^{K} \dfrac{r_k^{(l)}}{K} \\ \hat{y}_k^{(l)} = \hat{y}_k^{(l-1)}(1 - \bar{r}^{(l-1)}) \\ r_k^{(l)} = \dfrac{\hat{y}_k^{(l)} - \hat{y}_k^{(l-1)}}{\hat{y}_k^{(l-1)}} \end{cases} \tag{3}$$

where $\hat{y}^{(l)}$ the optimized value of the predicted result after the lth iteration, $l = 1, 2, 3, \cdots, n$, $\bar{r}^{(l)}$ the overall average error level after the optimization of the lth iteration, $r_k^{(l)}$ the prediction error of the kth data of the sample after the lth optimization iteration, $k = 1, 2, 3, \cdots, K$, and $\hat{y}_k^{(l)}$ the optimization result of the prediction value of the k-th sample data after the lth optimization iteration. When $\left|\bar{r}^{(l)}\right| \leqslant \varepsilon$, the iteration ends, and the prediction optimization result is shown as

$$\hat{y}^{(l)} = \hat{y}^{(l-1)}(1 - \bar{r}^{(l-1)}) \tag{4}$$

1.3 Markov optimization model

Markov optimization studies the transfer law between states according to the division of data states to predict the future trend of the system[11].

For each prediction method, the relative values of the original sequence and the prediction sequence are calculated as

$$C = \frac{y_k^{(0)}}{\hat{y}_k^{(0)}} \times 100\% \tag{5}$$

where $y_k^{(0)}$ is the value of the original sequence value, and $\hat{y}_k^{(0)}$ the predicted sequence value.

The relative values of predicted results are divided into n kinds of states that are denoted as $E_1, E_2, \cdots, E_n$. The interval of each state is $[e_{is}, e_{ir}]$ $(i = 1, 2, \cdots, n)$, where e_{is} is the minimum value of the interval, and e_{ir} the maximum value of the interval. Each relative value C is distributed in one of the states E_i. The probability of transferring from state $E_i (i = 1, 2, \cdots, n)$ to another state $E_j (j = 1, 2, \cdots, n)$ is P_{ij}, which is called state transfer probability. The calculation of P_{ij} is as

$$P_{ij} = \frac{C_{ij}}{C_i} \tag{6}$$

where C_i is the total number of occurrences of state E_i and C_{ij} the number of transfer from state E_i to E_j. Then the state transition probability matrix $\boldsymbol{P}$ is shown as

$$\boldsymbol{P} = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{pmatrix} \tag{7}$$

By using the state transition probability matrix $\boldsymbol{P}$, the possible future states and trends can be predicted from the current states. The relative value E_i can be obtained from the matrix $\boldsymbol{P}$ and the predicted result of the prediction model. The median value e_i of the relative value state interval $[e_{is}, e_{ir}]$ that is, the relative value of state E_i, is used as the optimization coefficient of the predicted result. Then the optimization result $y$can be calculated as

$$\begin{cases} y = \hat{y}_k^{(0)} \times e_i \\ e_i = \dfrac{1}{2}(e_{is} + e_{ir}) \end{cases} \tag{8}$$

2 Performance Analysis of Prediction Models and Optimization Models

2.1 Performance of prediction models

2.1.1 Evaluation principle

A variety of prediction models, including the combinatorial prediction model, are used to conduct prediction experiments, and the prediction precision of the prediction results of each prediction model is calculated as

$$\varepsilon_{ij}^{(l)}=1-\left|\frac{\hat{y}_{ij}^{(l)}-y_j^{(l)}}{y_j^{(l)}}\right| \tag{9}$$

where $\varepsilon_{ij}^{(l)}$ is the prediction precision of the ith prediction model for the jth item of event l, $y_j^{(l)}$ the statistical true value of the jth item of event l, $\hat{y}_{ij}^{(l)}$ the value predicted by using the ith prediction model of jth item of experiment l.

According to the prediction results of each experiment, the prediction models are ranked according to the order of prediction precisions from high to low. After a large number of experiments, the mean and variance of the ranking of each prediction method are calculated. The mean of the ranking reflects the accuracy of the method, and the variance determines the stability of the method. The accuracy and stability of a prediction model can reflect the advantages and disadvantages of the model.

2.1.2 Verification analysis

This paper uses historical data to predict the number of unsafe accidents of civil aviation, take-off and landing flights, turnover of passenger traffic, total mail volume, etc. in five years, involving 150 prediction experiments, each of which involves six prediction models. In the combinatorial prediction model, the weight of each single prediction model is determined by the standard deviation of its prediction result. Through the establishment and application of the prediction model, the prediction precision ranking of each prediction model is shown in Table 1.

The ranking data in Table 1 can be used to calculate the rank mean and variance of each prediction method. The results are shown in Table 2.

Although the variance of the prediction results of the exponential prediction model is the lowest

Table 1 Ranking statistics of forecasting methods

Prediction model	No.					
	1	2	3	4	5	6
Exponential prediction model	0	0	0	4	7	14
Grey prediction model	4	1	2	3	13	2
Polynomial prediction model	9	5	6	3	1	1
Logistic curve prediction model	3	6	3	11	2	0
Linear prediction model	0	7	4	4	1	8
Combinatorial prediction model	9	6	10	0	0	0

Table 2 Ranking mean and variance of forecasting methods

Prediction model	Mean	Variance
Exponential prediction model	5.40	0.56
Grey prediction model	4.04	2.52
Polynomial prediction model	2.40	1.92
Logistic curve prediction model	3.12	1.47
Linear prediction model	3.80	2.62
Combinatorial prediction model	2.04	0.76

and the stability is the best, its accuracy is the worst among all the prediction models, so the exponential prediction model cannot be used for prediction in most cases. Although the accuracy of the polynomial prediction is close to that of the combinatorial prediction, its stability is poor; so the polynomial prediction model is not suitable for a general problem. Therefore, through the mean and variance of the ranking of each prediction method in this paper, it can be seen that the combinatorial prediction model can be used as a prediction method for general poor information events, for its accuracy and stability.

2.2 Optimized model performance

The optimization models that are involved in the comparison include EEOM, the Markov optimization model and the two-layer optimization model. The two-layer optimization model combines the error elimination optimization with the Markov optimization. Based on the first optimization model, another optimization model is utilised to further modify the first optimization result.

2.2.1 Evaluation principles

The set of prediction data is $n=\{1, 2, 3, \cdots, N\}$. The set of the optimization model is $m=\{1, 2, 3, \cdots, M\}$. The accuracy of the optimization model is $\varepsilon_m^{(n)}$. The difference $\varepsilon^{(n)}$ between the two optimization models can be expressed as

$$\varepsilon^{(n)}=\varepsilon_i^{(n)}-\varepsilon_j^{(n)} \quad i,j\in m;i\neq j \tag{10}$$

If $\varepsilon^{(n)}$ is positive, the optimization model i has higher precision and better correction performance. Otherwise, it means that the optimization model j has better correction performance. The correction performance of the optimization model refers to the ability that can make the predicted result close to the real value.

The statistical function of times with higher precision of prediction model i than prediction model j is shown as

$$\begin{cases} y_i=\sum_{n=1}^{N}y_i^{(n)} \\ y_i^{(n)}=\begin{cases}1 & \varepsilon^{(n)}>0 \\ 0 & \varepsilon^{(n)}\leqslant 0\end{cases}\end{cases} \tag{11}$$

And the precision difference sequence $\varepsilon^{(n)}$ is processed as

$$\varepsilon^{(n)}=\{\varepsilon^{(1)},\varepsilon^{(2)},\cdots,\varepsilon^{(N)}\}$$
$$\left|\varepsilon^{(1)}\right|\leqslant\left|\varepsilon^{(2)}\right|\leqslant\cdots\leqslant\left|\varepsilon^{(N)}\right| \tag{12}$$

$$\begin{cases}\varepsilon'=\{\varepsilon^{(1)},\cdots,\varepsilon^{([N/3])}\} \\ \varepsilon''=\{\varepsilon^{([N/3]+1)},\cdots,\varepsilon^{([2N/3])}\} \\ \dot{\varepsilon}=\{\varepsilon^{([2N/3+1])},\cdots,\varepsilon^{(N)}\}\end{cases} \tag{13}$$

where ε' is the set with elements of small precision difference, ε'' the set with elements of medium precision difference, $\dot{\varepsilon}$ the set with elements of large precision difference, and [·] the integer operator.

After the optimization of the predicted results by using the optimization model, the precision of the prediction model is usually improved, but occasionally the precision decreases. Therefore, when the precision is used to evaluate the prediction model, the correction ability of the optimization model can also be evaluated by using the degree of precision decline.

2.2.2 Verification analysis

In order to further verify the correction ability of the two-layer optimization model after obtaining a superior optimization model that is get by comparing EEOM with the Markov optimization model, it is also necessary to compare the degree of precision change before and after using the superior model with that of using two-layer optimization model.

(1) EEOM and Markov optimization model

In this paper, 78 optimization experiments are conducted. In each optimization experiment, EEOM and the Markov optimization model are used to optimize the predicted results, and the times of higher precision of the optimization results of the two optimization models are counted seperately. The higher precision of EEOM occurs higher 43 times, and that of the Markov optimization model occurs 35 times.

Comparing the optimization precision of EEOM with that of the Markov optimization model, the optimization precision difference of the two optimization models is divided into three categories: Small difference, large difference and great difference. The interval between the small difference values is [0.000, 0.014), that between the large difference values is [0.014, 0.025), and that between the great difference values is [0.025, 0.205]. After the precision difference is classified, the comparison results of accuracy between EEOM and the Markov optimization model are shown in Table 3.

Table 3 Comparison of higher precision times of EEOM and the Markov optimization model

Difference category	Times when EEOM has higher precision	Times when the Markov optimization model has higher precision
Small difference	11	15
Large difference	15	11
Great difference	17	9
Total	43	35

There are 36 times of EEOM resulting in decline of precision, and 28 times of the Markov optimization model. The precision reduction of the EEOM and the Markov optimization model is shown in Fig.1.

It can be seen from Table 3 that the correction

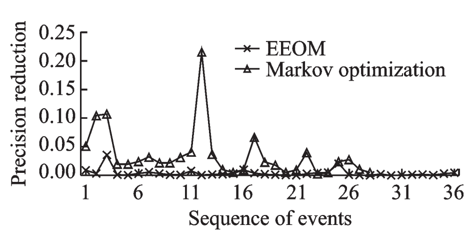

Fig.1 Precision reduction of the EEOM and the Markov optimization

ability of EEOM is better than that of the Markov optimization model. When the accuracy of EEOM is higher than that of the Markov optimization, there are 17 times that the precision of the two methods has a great difference. When the precision of the Markov optimization model is higher than that of EEOM, there are only 9 times that the precision difference is great. It can also be seen from Fig.1 that the stability of EEOM is better than that of the Markov optimization model. Therefore, when performing two-layer optimization, EEOM is the first-layer optimization method.

(2) EEOM and the two-layer optimization model

In this part, 72 optimization experiments are conducted. In each optimization experiment, EEOM and the two-layer optimization model are used to optimize the predicted results, and the times of higher precision of the optimization results after using the two optimization models are counted seperately. The higher precision of EEOM is 35 times, and that of the Markov optimization model is 29 times. The optimization precision of the two models is the same as 8 times.

Comparing the optimization precision of EEOM with that of the two-layer optimization model, the optimization precision difference of the two is divided into three categories: Small difference, large difference and great difference. The interval between the small difference values is [0.000, 0.010), that between the large difference values is [0.010, 0.019), and that between the great difference values is [0.019, 0.340]. After the precision difference is classified, the comparison results of accuracy between EEOM and the two-layer optimization model are shown in Table 4.

Table 4 Comparison of higher precision times of EEOM and the two-layer optimization model

Difference category	Times when EEOM has higher precision	Same	Times when the two-layer optimization model has higher precision
Small difference	7	8	9
Large difference	13	0	11
Great difference	15	0	9
Total	35	8	29

There are 29 times of EEOM resuling in decline of precision, and 27 times of the two-layer optimization model. Precision reduction of EEOM and the two-layer optimization model was shown in Fig.2.

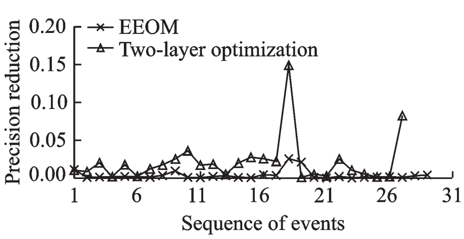

Fig.2 Precision reduction of EEOM and the two-layer optimization

It can be seen from Table 4 that the times when the optimization precision of the two-layer optimization model is higher than that of EEOM is few. And the times of great difference of the two-layer optimization is lesser than that of EEOM. In the experiment, times when EEOM has higher precision is 15, while that for the two-layer optimization model is only 9. In addition, it is can be seen from Fig.2 that the stability of EEOM is better than that of the two-layer optimization model. The optimization stability will reduce while using the Markov optimization model after using EEOM. Therefore, after using EEOM, it is not necessary to carry out the two-layer optimization.

In this paper, a lot of prediction and optimization experiments are conducted to analyze the performance of prediction models and optimization models. It can be found that the stability of the polynomial prediction model is low, the precision of the exponential prediction model is poor, and the precisions and stabilitiec of the grey prediction, the linear prediction and the logistic curve prediction are bad. It also can be found that the correction ability of the Markov optimization model and the two-layer optimization model are poorer than that of EEOM. Therefore, in order to solve the prediction problem of poor information events with small samples, the combinatorial prediction model with good precision and stability can be used to predict , and EEOM with good correction ability can be used to optimize the prediction results.

3 Prediction and Optimization Examples

By inquiring the Civil Aviation Administration of China (CAAC) production bulletin, the data of CAAC unsafe events from 2000 to 2017 can be obtained, as shown in Table 5. The data from 2000 to 2016 are used as forecast data, and the data of 2017 are validation data. The results of this prediction and optimization example can further verify the above conclusions.

Table 5 Data sample

Year	Unsafe event	Year	Unsafe event
2000	93	2009	161
2001	103	2010	221
2002	116	2011	230
2003	100	2012	295
2004	106	2013	302
2005	116	2014	324
2006	117	2015	394
2007	116	2016	541
2008	120	2017	597

The exponential forecast model, the grey prediction model, the polynomial prediction model, the logistic curve prediction model and the linear regression prediction model are used to obtain the predicted results. According to Eq.(1), the weight of the single prediction model involved in the combinatorial prediction model are calculated to establish the combinatorial prediction model. Further, the predicted result of the combinatorial prediction model is obtained. According to Eq.(9), the prediction precisions of the six prediction models are calculated. The comparison of the predicted results and the prediction precisions of the six prediction models are shown in Fig.3.

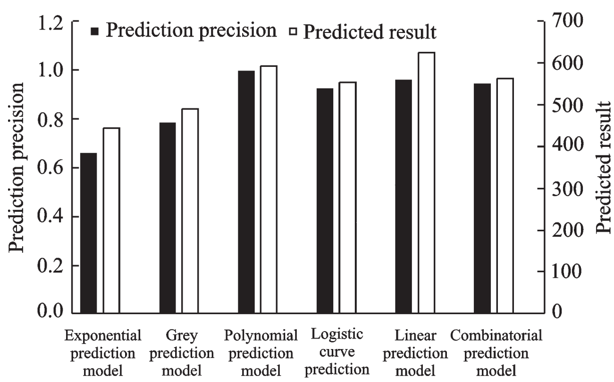

Fig. 3 Predicted result and prediction precision

EEOM, the Markov optimization model and the two-layer optimization model are used to optimize the predicted results that are obtained by the exponential forecast model, the grey prediction model, the polynomial prediction model, the logistic curve prediction model, the linear regression prediction model and the combinatorial prediction model. Then, the optimization precision of each optimization model is calculated. The optimized results and the optimization precisions are shown in Table 6.

It can be seen from Table 6 that the two combinations, to use the combinatorial prediction model

Table 6 Optimization results and precision

Prediction model	Optimized results of EEOM	Optimization precision of EEOM	Optimized results of Markov optimization model	Optimization precision of Markov optimization model	Optimized results of two-layer optimization model	Optimization precision of two-layer optimization model
Exponential prediction model	512.80	0.84	506.16	0.82	507.67	0.82
Grey prediction model	556.89	0.93	469.90	0.73	470.57	0.73
Polynomial prediction model	587.16	0.98	672.35	0.89	672.30	0.89
Logistic curve prediction model	613.99	0.97	503.51	0.81	512.68	0.84
Linear prediction model	626.95	0.95	618.57	0.97	746.07	0.80
Combinatorial prediction model	591.62	0.99	593.87	0.99	588.67	0.98

to predict and then the Markov optimization model to optimize, and to use the combinatorial prediction model to predict and then EEOM to optimize, have the same high accuracy. But from the previous 300 prediction experiments and optimization experiments, it can be found that using the combinatorial prediction model to predict first and then using EEOM to optimize has the highest accuracy and stability. The correction ability of EEOM is the best among the optimize models analyzed in this paper. Therefore, the combinatorial prediction model and EEOM are suitable for solving the small sample and poor information prediction problem.

4 Conclusions

Several prediction and optimization experiments are conducted to analyze the performance of prediction models and optimization models.

This paper randomly selected 25 events containing small sample and poor information to carry out 150 prediction experiments by six prediction models. It can be found from the experiments that the stability of the polynomial prediction model is low, the precision of the exponential prediction model is poor, and the grey prediction, the linear prediction and the logistic curve prediction have bad precision. The combinatorial prediction model is superior to other prediction models at both the stability and the prediction accuracy.

One hundred and fifty optimization experiments are conducted in this paper to analyze the performance of the optimization models. It can be found from the optimization experiments that the correction ability of the Markov optimization model and the two-layer optimization model are poorer than EEOM. EEOM has both high stability and good correction ability. It can also be found that the precision can not be further improved by using the Markov optimization model after EEOM. Therefore, EEOM proposed in this paper is suitable for the optimization of predicted results of small sample and poor information events.

Therefore, in order to solve the prediction problem of poor information events with small samples, the combinatorial prediction model with good precision and stability can be used to predict and EEOM with good correction ability can be used to optimize the prediction results.

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Author contributions Dr. **LU Fei** designed this study, including prediction and optimization models and wrote the manuscript. Prof. **SUN Ruishan** contributed to the design of prediction and optimization models, and the experiments. Mr. **CHEN Zichen** conducted the prediction and optimization experiments, gleaned the data of the experiments and analyzed the results. Ms. **CHEN Huiyu** and Ms. **WANG Xiaomin** helped to glean the data of the experiments, organized the prediction and optimization examples and proofread the manuscript. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

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信息匮乏事件预测及优化方法性能研究

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摘要：为找到更适用于贫乏样本信息预测问题的预测方法及优化方法，提出基于实验数据解析的方法性能对比研究，通过大量预测实验与优化实验，研究预测方法的准确性、稳定性以及优化方法的修正性。研究中分别使用5种传统单项预测方法对贫乏样本信息预测问题进行预测，并运用标准差法对这5种方法分配权重，进行组合预测。对预测结果的精度进行排名，排名的均值和方差体现了预测方法的准确性与稳定性；同时研究提出了误差消除预测优化方法，对预测结果分别使用误差消除优化、马尔科夫优化及对优化结果进一步修正的双层优化，并使用精度的提升与下降程度来反映优化方法的修正性。结果表明，预测方法中组合预测的准确性与稳定性最好，优化方法中误差消除优化的修正性最佳，二者结合可达到贫乏样本信息事件的预测需求。研究最后通过对民航某一年不安全事件数进行预测，验证了组合预测与误差消除优化结合的精确性。

关键词：贫乏样本信息；预测方法性能；优化方法性能；组合预测；误差消除优化模型；马尔科夫优化