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Application of a Combined Model to Spare Parts Consumption Prediction

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Abstract: Spare parts consumption prediction lays a foundation for spare parts support. This paper combines the exponential smoothing method with a grey model, and establishes a combined model. The combined model solves the problem of spare parts consumption prediction. The example indicates that the combined model is much more accurate than a single model.

Keywords: Combined model; exponential smoothing method; grey model; spare parts consumption.

1. INTRODUCTION

The spare parts consumption is the categories and the amounts of spare parts used to maintain the specific amount of equipments at the specific states under specific times and conditions. Nearly all the segments about spare parts include acquisition, storage, supplying and management have close connections with the analysis of the spare parts consumption information. We can project reasonable spare parts support scheme and enhance the scientific lever of spare parts support work only if we master the law of spare parts consumption.

Many scholars have made scientific researches on spare parts consumption prediction. Zhao Jianzhong improves on search mode of APSO and weighted method of least squares support vector machine. Then the consumption forecasting model of missile spare parts is established based on RS, EW and WLS-SVM with APSO, and realization process is analyzed. The example results show that the combinatorial forecasting model has better forecast precision and important applied value in the course of consumption forecasting of missile spare parts [1]. Ni Xiancun uses the concept of the repair degree and improves the proportional hazards model based on general renewal process. The parameter value is estimated by analyzing failure data and then the number rotables are calculated based on Monte Carlo simulation. An example is given and the results of various maintenance policies with and without considering covariates are compared and analyzed. Result s show that the model has a larger practical value [2]. Li Dawei uses the initial spare parts scheme as prior information and proposes the regulate method of spare parts in incipient operation based on the Bayes method. Finally , the simulation example shows that the method proposed is feasibility. Comparing with classical method, the method proposed can improve the accuracy of spare parts consumption estimation and has good steadiness. So the more rational spare parts scheme can be formed [3].

In spare parts consumption predicting practice, there are not enough historical data to be used to forecast by variety of reasons, and the small sample data of spare parts consumption are the only available information. The traditional forecasting methods produce little effect on small sample data. Therefore, a combined model for spare parts consumption prediction based on exponential smoothing method and grey model is developed to avoid the limitations of single prediction method, utilize all the information , and improve the prediction of spare parts precision consumption. This combined model works well with small sample data.

2. MODELING

2.1 Exponential Smoothing Method

The exponential smoothing method has some specific models such as the single exponential smoothing model, the double exponential smoothing model and the cubic exponential smoothing model [4,5]. The single exponential smoothing model could be used when the time series are stable, and the trend shows a horizontal direction. The double exponential smoothing model could be used when the time series shows a linear direction. The cubic exponential smoothing model could be used when the time series shows a non-linear direction.

(1) The formula of single exponential smoothing is $S_t^{(1)} = \alpha x_t + (1-\alpha)S_{t-1}^{(1)}$ and the prediction model of single

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exponential smoothing is $\hat{x}_{t+1} = S_t^{(1)} = \alpha x_t + (1-\alpha)\hat{x}_t$.

(2) The formula of double exponential smoothing is $S_t^{(2)} = \alpha S_t^{(1)} + (1-\alpha)S_{t-1}^{(2)}$ and the prediction model of double exponential smoothing is $\hat{x}_{t+T} = a_t + b_t T$, where

$$a_t = 2S_t^{(1)} - S_t^{(2)} \ , \ b_t = \frac{\alpha}{1-\alpha}\left(S_t^{(1)} - S_t^{(2)}\right).$$

(3) The formula of cubic exponential smoothing is $S_t^{(3)} = \alpha S_t^{(2)} + (1-\alpha)S_{t-1}^{(3)}$ and the prediction model of cubic exponential smoothing is $\hat{x}_{t+T} = a_t + b_t T + \frac{1}{2}c_t T^2$, where

$$a_t = 3S_t^{(1)} - 3S_t^{(2)} + S_t^{(3)} ,$$

$$b_t = \frac{\alpha}{2(1-\alpha)^2}\left[(6-5\alpha)S_t^{(1)} - 2(5-4\alpha)S_t^{(2)} + (4-3\alpha)S_t^{(3)}\right],$$

$$c_t = \frac{\alpha^2}{(1-\alpha)^2}\left[S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}\right].$$

$S_t^{(1)}$, $S_t^{(2)}$ and $S_t^{(3)}$ refer to the t^{th} 1-3 order exponential smoothing predictive value respectively, and $S_{t-1}^{(1)}$, $S_{t-1}^{(2)}$ and $S_{t-1}^{(3)}$ refer to the $(t-1)^{th}$ 1-3 order exponential smoothing predictive value, x_t and $\hat{x}_t$ are the t^{th} actual value and estimated value, T is the number of time points from initial to the predict target time point, and α is a smoothing coefficient $(0 < \alpha < 1)$.

2.2 Grey Model

The scope of application of a grey model is the situation when the changes of spare parts consumption data are close to exponential function. The time series based on the spare parts consumption data collected is

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\} \quad x^{(0)}(i) \ge 0, \quad i = 1,2,\cdots,n .$$

After accumulative operations, the new time series is

$$x^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right\},$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \ k = 1,2,\cdots,n$.

The mean sequence of $x^{(1)}$ is noted as $z^{(1)}$ [6], which is

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) ,$$

$$z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)\right\}.$$

The grey model is

$$x^{(0)}(k) + az^{(1)}(k) = b ,$$

where a and b are grey coefficients.

The estimated values of a and b are acquired by the least square method. Because of

$$B = \begin{bmatrix} -z^{(1)}(2) & -z^{(1)}(3) & \cdots & -z^{(1)}(n) \\ 1 & 1 & \cdots & 1 \end{bmatrix}^T ,$$

$$y_N = \left[x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right]^T ,$$

we have $P = [a,b]^T = \left(B^T B\right)^{-1} B^T y_N$.

The whitening response result of the grey model is

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

and the prediction model of original series $\hat{x}^{(0)}$ can be gained by regressive operations.

The reference values of accuracy indicators about the grey model such as relative error, ratio of standard deviation and small error probability are listed in Table **1**.

When the test grade is above 2nd, we can apply this model directly. When the test grade is below 2nd, this model can not be used to predict unless some modifications are applied to the model till it can pass the test.

Table 1. Accuracy Indicators of the Grey Model

Grade	Relative Error Δ	Ratio of Standard Deviation C	Small Error Probability p
One	0.01	0.35	0.90
Two	0.05	0.50	0.80
Three	0.10	0.65	0.70
Four	0.20	0.80	0.60

2.3 Combined Model

Based on the exponential smoothing method and the grey model, we can establish the combined model

$$\begin{cases} \hat{x}_t = \sum_{i=1}^{2} w_i(f_{ti} + \alpha\varepsilon_{ti}) \quad t = 1,2,\cdots,n \text{ and } 0 \le \alpha \le 1 \\ \sum_{i=1}^{2} w_i = 1 \end{cases}$$

where w_1 and w_2 are weight values, and f_{t1} , f_{t2} and $\hat{x}_t$ denote the predictive values of the exponential smoothing method, the grey model and the combined model respectively. Assuming that the predictive error drifts around a fixing value, $\alpha\sum_{i=1}^{m} w_i\varepsilon_{ti}$ can be denoted as the constant a , then $\hat{x}_t = a + \sum_{i=1}^{2} w_i f_{ti}$, $t = 1,2,\cdots,n$. Actually, a is the weighted average value of each single prediction model.

3. APPLICATION

Given the consumption data of a specific kind of spare parts in 2010-2014, the detailed data list in Table **2**. Assuming that the amount of this kind of equipment is constant, predict the spare parts consumption amount of this equipment in 2015.

Table 2. Spare Parts Consumption Amount From 2010 to 2014

Year	2010	2011	2012	2013	2014
Spare Parts Consumption Amount	98	100	104	102	104

(1) Analyzing from Table **2**, we can find that the spare parts consumption data is a random variable changes around a fixing value, thus we adopt the single exponential smoothing method to predict. The value of smoothing coefficient α influences the predicting result. The average relative error reaches minimum when $\alpha = 0.3$ by verification tests. Therefore, the spare parts consumption prediction model is

$$\hat{x}_{t+1} = S_t^{(1)} = 0.3x_t + 0.7\hat{x}_t \quad (t \ge 1)$$

(2) According to those historical consumption data of spare parts listed in Table **2**, the grey model can be established as below:

$$\hat{x}^{(1)}(k+1) = 10363e^{0.0097k} - 10265 \text{ , } k \ge 0$$

After regression operation, the simulation values of original series is

$$\hat{x}^{(0)} = \{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(5)\} = \{98,101,102,102.9,103\}.$$

The accuracy indicators of the grey model are $\Delta = 0.0078 < 0.01$, $C = 0.4681 < 0.5$, and $p = 0.8$. So the precision of this model is 2nd grade, which can be used to predict the next year's spare parts consumption.

(3) After Combining the exponential smoothing method with the grey model, we can obtain the weight coefficient of the exponential smoothing method $w_1 = -0.07$, the weight coefficient of the grey model $w_2 = 1.07$, and the constant $a = -0.03$.

The simulation values of three prediction models are shown in Fig. (**1**), and the comparative analysis of each predictive model is listed in Table **3**.

From the Table **3**, it is obvious that the root-mean-square error of combined model is the minimum error. So the combined prediction model can enhance the predictive precision, and the predictive value of this kind of spare parts is 106 in 2014.

Table 3. Comprehensive Comparison of Three Prediction Models

Year	Actual Value	Simulation Value			Residual Error			Root-Mean-Square Error		
		Exponential Smoothing	Grey Model	Combined Model	Exponential Smoothing	Grey Model	Combined Model	Exponential Smoothing	Grey Model	Combined Model
2010	98	100.7	98.2	97.8	-2.7	-0.2	0.2	1.23	0.54	0.43
2011	100	99.8	101.3	101	0.2	-1.3	-1			
2012	104	99.9	101.9	102.1	4.1	2.1	1.9			
2013	102	101.1	102.9	103	0.9	-0.9	-1			
2014	104	101.4	103.1	104.1	2.6	0.9	-0.1			

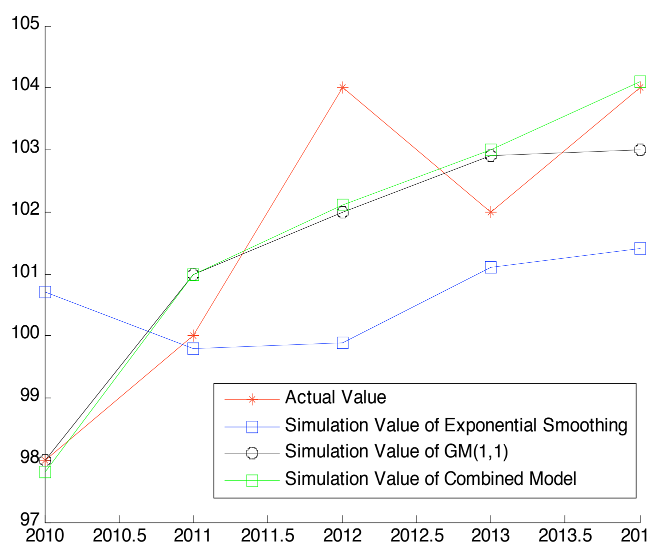

Fig. (1). Simulation Values of Three Prediction models

4. CONCLUSION

The predictive precision of combined model applied to predict the short-term consumption of spare parts can be enhanced effectively by using the information of the exponential smoothing method and the grey model synthetically. The application of this combined model can be extended for long-term prediction, and other single predictive models can be combined aiming at solving different problems. Also, this combined model can be utilized in other predictive fields.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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