Research on the Application of Three Exponential Smoothing Models in Spare Parts Consumption Prediction

Jian Ren; Kun Li; Qiuhong Tan; Feng Guo *

Naval Aviation University Qingdao Branch,Qingdao，266041，China

Corresponding author: tanqiuhong_614@163.com

Abstract. In response to the problem of large data storage capacity and limited prediction in recent years in the moving average method, this article uses three exponential smoothing methods to establish a primary exponential smoothing model, a secondary exponential smoothing model, and a tertiary exponential smoothing model to predict spare parts consumption, and analyzes the application effect of the model through numerical examples. The numerical examples show that the three exponential smoothing models can effectively solve the problem of moving average method in spare parts consumption prediction, and the proposed research method has certain promotion and application value.

Keywords: Exponential Smoothing; Consumption Prediction; Spare Parts; Time Series

1 Overview

At present, some literature often uses the moving average method to predict the time series of spare parts consumption. However, although the moving average method is simple and feasible, it has some shortcomings: firstly, it stores a large amount of data. Every time the moving average is calculated, it is necessary to store the latest N observations, which can be inconvenient when frequent predictions are needed; The second is that the moving average method only considers the latest N-period data, while it does not consider data before the t-N period at all. However, in practical situations, observations from different periods contain different amounts of information. A more practical approach is to consider the observations from each period and weight them in chronological order [1-6]. The exponential smoothing method can eliminate random fluctuations in historical statistical sequences, identify the main development trends, and not only does not require storing a lot of historical data, but also considers the importance of each period of data, while using all historical data [7-11]. Therefore, this article attempts to use the first exponential smoothing method, second exponential smoothing method, and third exponential smoothing method for the application research of spare parts consumption prediction.

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2 Three Exponential Smoothing Models

2.1 One time exponential smoothing model

- $y_1, y_2, \ldots, y_t$ $y_1, y_2, \ldots, y_t$:Time series observations;
- α :Weighting coefficient

The first exponential smoothing value is:

$$S_t^{(1)} = \alpha y_t + (1-\alpha) S_{t-1}^{(1)} \tag{1}$$

The predicted value of one exponential smoothing is:

$$\hat{y}_{t+1} = S_t^{(1)} \tag{2}$$

2.2 Quadratic exponential smoothing model

The primary and secondary exponential smoothing values are:

$$\begin{aligned} S_t^{(1)} &= \alpha y_t + \left(1-\alpha\right) S_{t-1}^{(1)} \\ S_t^{(2)} &= \alpha S_t^{(1)} + \left(1-\alpha\right) S_{t-1}^{(2)} \end{aligned} \tag{3}$$

The predicted values for quadratic exponential smoothing are:

$$\hat{y}_{t+T} = a_t + b_t T, (T = 1, 2, 3, \ldots) \tag{4}$$

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

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

2.3 Cubic exponential smoothing model

The first, second, and third exponential smoothing values are:

$$\begin{aligned} S_t^{(1)} &= \alpha y_t + \left(1-\alpha\right) S_{t-1}^{(1)} \\ S_t^{(2)} &= \alpha S_t^{(1)} + \left(1-\alpha\right) S_{t-1}^{(2)} \\ S_t^{(3)} &= \alpha S_t^{(2)} + \left(1-\alpha\right) S_{t-1}^{(3)} \end{aligned} \tag{5}$$

The predicted values for cubic exponential smoothing are:

$$\hat{y}_{t+T} = a_t + b_t T + c_t T^2 \tag{6}$$

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

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

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

3 Model application

The consumption of a certain spare part for 20 consecutive quarters is shown in Table 1. Try using the exponential smoothing method to predict the consumption for the 21st and 22nd quarters.

Table 1. Calculation of Consumption and First, Second, and Third Order Exponential Smoothing Values

t	y_t	$S_0^{(1)}$	$S_0^{(2)}$	$S_0^{(3)}$	a_t	b_t	c_t	$\hat{y}_t$	$\hat{y}_t - y_t$	$(\hat{y}_t - y_t)^2$
0	12	13.50	13.50	13.50	13.50	0.00	0.00			
1	15	14.25	13.88	13.69	14.81	0.84	0.09	13.50	-1.50	2.25
2	17	15.63	14.75	14.22	16.84	1.73	0.17	15.75	-1.25	1.56
3	20	17.81	16.28	15.25	19.84	2.78	0.25	18.75	-1.25	1.56
4	22	19.91	18.09	16.67	22.11	2.79	0.20	22.88	0.88	0.77
5	18	18.95	18.52	17.60	18.89	-0.81	-0.25	25.09	7.09	50.32
6	30	24.48	21.50	19.55	28.48	5.54	0.51	17.83	-12.17	148.15
7	32	28.24	24.87	22.21	32.32	5.14	0.35	34.53	2.53	6.41
8	52	40.12	32.49	27.35	50.23	13.83	1.24	37.81	-14.19	201.29
9	55	47.56	40.03	33.69	56.29	10.52	0.60	65.30	10.30	106.07
10	71	59.28	49.65	41.67	70.55	13.74	0.82	67.41	-3.59	12.92
11	78	68.64	59.15	50.41	78.89	11.38	0.38	85.11	7.11	50.56
12	86	77.32	68.23	59.32	86.58	9.52	0.09	90.65	4.65	21.61
13	103	90.16	79.20	69.26	102.15	13.53	0.51	96.19	-6.81	46.36
14	110	100.08	89.64	79.45	110.77	11.07	0.13	116.19	6.19	38.30
15	123	111.54	100.59	90.02	122.87	11.90	0.19	121.97	-1.03	1.06
16	131	121.27	110.93	100.47	131.50	10.05	-0.06	134.96	3.96	15.71
17	150	135.63	123.28	111.88	148.94	14.72	0.47	141.49	-8.51	72.40
18	166	150.82	137.05	124.46	165.77	16.72	0.59	164.14	-1.86	3.48
19	183	166.91	151.98	138.22	183.01	17.86	0.59	183.08	0.08	0.01
20								201.45	$\frac{1}{19}\sum_{t=1}^{19}(\hat{y}_t - y_t)^2$	41.09
21								221.07		

Solution:

According to research findings, the quadratic exponential smoothing method is generally suitable for predicting time series of linear trends, the cubic exponential smoothing method is generally suitable for predicting time series of upward trends of quadratic curves, and the other methods generally use the first-order exponential smoothing method [12-17]. Therefore, this article intends to first draw up a scatter plot, analyze the trend of the time series, and then select an appropriate exponential smoothing model and smoothing coefficient for prediction. The specific methods are as follows:

Firstly, draw a scatter plot (as shown in Figure 1). From this graph, it can be seen that the overall annual consumption shows a quadratic curve upward trend, so a cubic exponential smoothing model can be used for prediction.

Then, by observing the trend of the time series, it can be seen that there is a certain upward trend, so let $\alpha = 0.5$. The initial values of the first, second, and third smoothing values $S_0^{(1)}, S_0^{(2)}, S_0^{(3)}$ are taken as the mean of the first two terms of the time series, namely:

$$S_0^{(1)} = S_0^{(2)} = S_0^{(3)} = \frac{y_1 + y_2}{2} = 13.5$$

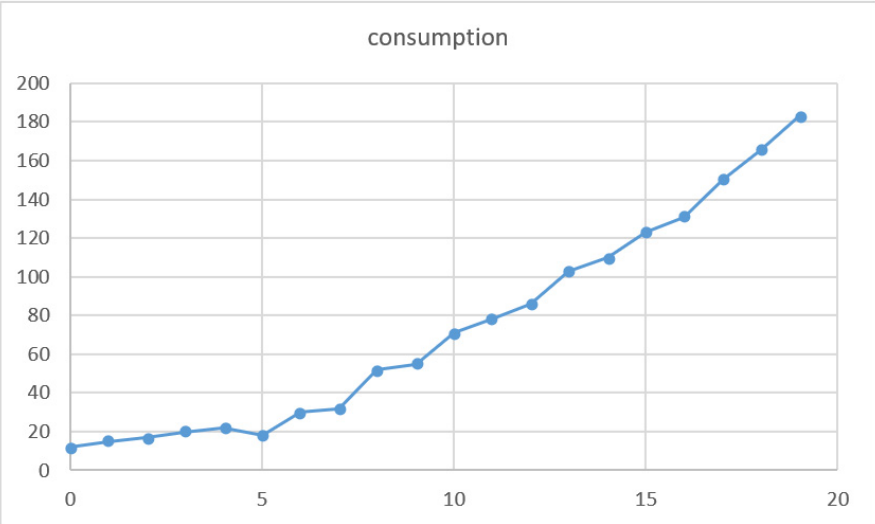

Fig. 1. Scatter Chart of Consumed Items

Secondly, calculate the first smoothing value, second smoothing value, third smoothing value, parameter value, predicted value, error, etc. for each period, as shown in the table above. From this table, the cubic exponential smoothing prediction model can be determined, namely:

$$\hat{y}_{19+T} = 183.01 + 17.86T + 0.59T^2$$

Therefore, the predicted consumption values for the 21st and 22nd quarters are:

$$\hat{y}_{20} = 183.01 + 17.86 \times 1 + 0.59 \times 1^2 \approx 201.45 \approx 201$$

$$\hat{y}_{21} = 183.01 + 17.86 \times 2 + 0.59 \times 2^2 \approx 221.07 \approx 221$$

The variance of the predicted results using the cubic exponential smoothing method is 41.09.

If the first and two times exponential smoothing methods are used for prediction, their variances are 366.12 and 37.03, respectively (as shown in Table 2). Among these three exponential smoothing methods, the prediction accuracy of the quadratic and cubic exponential smoothing methods is relatively close, and much higher than that of the primary exponential smoothing method; The quadratic exponential smoothing method has the highest prediction accuracy among them.

Table 2. Prediction Error of Primary and Secondary Exponential Smoothing Methods

t	y_t	One time exponential smoothing method		Two times exponential smoothing method			
		$\hat{y}_t$	$(\hat{y}_t - y_t)^2$	a_t	b_t	$\hat{y}_t$	$(\hat{y}_t - y_t)^2$
0	12			13.50	0.00		
1	15	13.50	2.25	14.63	0.38	13.50	2.25
2	17	14.25	7.56	16.50	0.88	15.00	4.00
3	20	15.63	19.14	19.34	1.53	17.38	6.89
4	22	17.81	17.54	21.72	1.81	20.88	1.27
5	18	19.91	3.63	19.38	0.43	23.53	30.59
6	30	18.95	122.03	27.45	2.98	19.81	103.79
7	32	24.48	56.60	31.61	3.37	30.43	2.47
8	52	28.24	564.62	47.74	7.63	34.98	289.80
9	55	40.12	221.44	55.09	7.53	55.37	0.14
10	71	47.56	549.45	68.91	9.63	62.63	70.14
11	78	59.28	350.45	78.13	9.49	78.53	0.28
12	86	68.64	301.37	86.41	9.09	87.63	2.65
13	103	77.32	659.47	101.12	10.96	95.49	56.35
14	110	90.16	393.63	110.52	10.44	112.09	4.35
15	123	100.08	525.33	122.49	10.95	120.96	4.15
16	131	111.54	378.69	131.61	10.34	133.44	5.96
17	150	121.27	825.41	147.99	12.35	141.95	64.79
18	166	135.63	922.03	164.59	13.77	160.34	32.03
19	183	150.82	1035.71	181.84	14.93	178.35	21.60
20	$\frac{1}{19}\sum_{t=1}^{19}(\hat{y}_t - y_t)^2$		366.12	$\frac{1}{19}\sum_{t=1}^{19}(\hat{y}_t - y_t)^2$			37.03

4 Summary

Although the one-time exponential smoothing method overcomes two drawbacks of the moving average method, when there is a linear trend in the changes of the time series, there is still a significant lag deviation when using the one-time exponential smoothing method for prediction. The correction method is to perform a second exponential smoothing and establish a linear trend model using the law of lag deviation. Although quadratic exponential smoothing can handle long-term trends with linear changes, quadratic curves or more complex long-term trends require the use of cubic exponential smoothing or higher forms of smoothing to predict. In practical applications, it is advisable to try several methods and choose the one with the highest accuracy for prediction.

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