Advances in Artificial Intelligence, Big Data and Algorithms
G. Grigoras and P. Lorenz (Eds.)

doi:10.3233/FAIA230824

Equipment Spare Parts Demand Forecasting and Ordering Decision Based on Holt and MPG

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Abstract: By extracting the historical usage data of equipment spare parts in the equipment management platform, using Holt method to predict the demand of spare parts, and using MPG method, we can develop reasonable ordering strategy for the demand prediction of spare parts, and provide guarantee for the development of scientific spare parts reserve optimization strategy, and provide scientific decision basis for the improvement of equipment maintenance and guarantee effectiveness.

Keywords: Equipment Spare Parts Demand; Forecasting; Holt; MPG

1 Introduction

In the management of weapon and equipment maintenance, the forecast of maintenance spare parts requirements is the basis of maintenance spare parts inventory management, which is a very important part of spare parts management. An accurate forecast of spare parts requirements has an important impact on the development of spare parts inventory strategies and the construction of inventory models [1], and is the basis for ordering decisions.

Liu Deng Yi [2] used principal component analysis to reduce the dimensionality of the characteristic variables and used a biased estimation method represented by ridge regression for demand forecasting of aircraft spare parts. Huang Guoxing et al [3] applied the random forest regression principle to the field of spare parts demand forecasting for naval components and constructed a random forest-based forecasting model. Wang Lili et al [4] proposed a method of aircraft spare parts demand forecasting based on hierarchical time-assigned coloring Petri nets, and built a spare parts demand forecasting model based on aircraft sortie rate. He Congliang [5] based on an improved neural network ordnance emergency maintenance spare parts demand forecasting model, using the fitting ability of the powerful nonlinear function of the neural network model, decomposed the intermittent type of spare parts demand into two steps, and derived the ordnance spare parts demand forecasting results. Liu, H. et al [6] established a spare parts demand forecasting model for the k/n(G) system and gave the spare parts demand characteristics. Dong Snapshot et al [7] proposed a follow-up spare parts combination forecasting method based on fuzzy soft sets and Bayes. Yunjing Zhang et al [8] constructed a Markov chain model to mine the pattern of spare parts demand in peacetime from the historical data of spare parts demand, and designed a Markov chain

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transfer probability adjustment strategy for wartime spare parts demand based on the change of combat intensity for simulating the pattern of wartime spare parts demand. QiuLijun et al [9] introduced the support vector machine (SVM) regression theory into the field of spare parts demand prediction, proposed a support vector machine based spare parts demand prediction method, and gave specific steps and evaluation indexes for the accuracy of demand prediction results. Dong Snapdragon et al [10] proposed a method of subsequent spare parts exponential smoothing prediction based on rough set theory correction for the problem of large errors in subsequent spare parts demand prediction. Chen Ding et al [11] established a repairable spare parts demand prediction model based on the gray generation and extinction process, and studied the memorylessness based on the gray generation and extinction process and the conditions for the existence of steady-state solutions of the prediction model. Liu Liu et al [12] applied the method to predict the consumption quantity of equipment spare parts under small sample data conditions based on the analysis of the principle of partial least squares regression method. XuFei et al [13] applied rough set theory and hierarchical analysis to add correction factors to the GM(1, 1) prediction model, and proposed an improved GM(1, 1) prediction model to improve the prediction accuracy. Zhao Jianzhong et al [14] introduced probability weighted moments into a new method for modeling the life distribution of missile equipment to overcome the problem of large bias in statistical estimation based on classical moments with small sample size.At present, big data technology has been widely researched and applied to provide a new way for the prediction of equipment spare parts [15-17]. With various equipment management platforms built and put into operation, a large number of equipment maintenance, security, management and other related historical data unified on the platform to provide equipment information services for users at all levels, this study extracts the historical use data of a type of spare parts for a type of equipment accumulated by the equipment management platform, using Holt method, predicts the demand for spare parts, and further uses MPG method to develop a reasonable ordering strategy.

2 Algorithm Model

2.1 Holt's Method

The Holt method [18-19] is a linear exponential smoothing method based on the principle that the exponential smoothing value in any period is a weighted average of the actual observed value in the current period and the exponential smoothing value in the previous period, calculated as.

$$S_t = \alpha Y_t + (1-\alpha)(S_t + b_{t-1}) \tag{1}$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \tag{2}$$

Prediction formula:

$$\hat{Y}_{t+m} = S_t + b_t m \tag{3}$$

where: α is the horizontal smoothing factor, which is the horizontal smoothing parameter, γ is the trend smoothing factor, which controls the effect of trend change, and m is the number of extrapolated periods. Eq. (1) is called the horizontal equation, which uses the trend value of the previous period b_{t-1} to directly correct the smoothed value S_t ,to S_t approximate the latest data value, and Eq. (2) is called the trend equation, which is used to correct the trend value b_t . When using Holt exponential smoothing method for forecasting, the appropriate value of the smoothing factor determines the accuracy of the forecast, and this study uses the stepwise search method to obtain α and γ , so that the sum of squared errors $\Sigma(Y_t - \hat{Y}_t)^2$ is minimized.

The mean relative error was used to test the accuracy of the model:

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\frac{|Y_k - \hat{Y}_k|}{Y_k} \tag{4}$$

The closer the value is to zero, the better the predictive power of the model.

2.2 MPG Method

The MPG method, Maximum Part-period Gain (MPG) [20], is based on the idea that when the demand $D(t)$ of a certain cycle (t) is combined to order together with the t cycle relative to the 1st cycle (the 1st cycle has demand)can save one time order fee(S), However, the inventory maintenance fee for the maintenance ($t-1$) cycle is increased $(t-1)\cdot D(t)\cdot H$ (H is maintain inventory costs for the unit). To save costs, only if the conditions are met:

$$(t-1)\cdot D(t)\cdot H < S \tag{5}$$

In other words, if the increase in inventory maintenance cost due to combined orders is less than the order cost, only then can we implement advance orders, otherwise we cannot combine orders. Since H and S are given constants, the smaller $(t-1)\cdot D(t)$ is, the more economical it is to combine orders, since the inventory maintenance costs will be much less than the ordering costs.

For processing convenience, the conditional Eq. (5) is deformed as:

$$(t-1)\cdot D(t) < \frac{S}{H} \tag{6}$$

Where $(t-1)\cdot D(t)$ is a variable quantity in "spare parts-cycle". Ordering a part 1 cycle in advance is called a "spare part-cycle".

The steps of the MPG method are as follows:

(1) Select the smallest "spare parts-cycle" requirement from the net requirement table;

(2) Combine the corresponding net requirements and order them together with the cycle that has a net requirement before that cycle;

(3) If all the "spare parts-period" values are greater than $\frac{S}{H}$ after the consolidation, it means that the increase in inventory maintenance cost due to the combined order is higher than the order cost, and should be stopped; otherwise, go to step (1).

Total cost calculation formula:

$$C_T = C_R + C_H \tag{7}$$

$$C_R = kS \tag{8}$$

$$C_H = \frac{1}{2} H \Sigma (Q_S + Q_F) \tag{9}$$

Of which: $\boldsymbol{C_T}$ is the total cost; $\boldsymbol{C_R}$ is the total ordering cost; $\boldsymbol{C_H}$ is the total inventory maintenance cost; $\boldsymbol{k}$ is the number of orders placed; $\boldsymbol{S}$ is the one-time order fee; $\boldsymbol{H}$ is the unit maintenance inventory cost; $\boldsymbol{Q_S}$ is the inventory level at the beginning of a cycle; $\boldsymbol{Q_F}$ is the inventory level at the end of a cycle.

3 Demand Forecast and Ordering Decision for a Certain Type of Spare Parts

3.1 Historical Usage Data

In this study, for a certain type of equipment, the maintenance records of the equipment are extracted from the database of the equipment management platform, and the historical data of the equipment using a certain type of key spare parts in each quarter are shown in Table 1.

Table 1. Historical usage records of a certain type of spare parts

year	quarter	use (pieces)
2019	1	1446
2019	2	1634
2019	3	1946
2019	4	2307
2020	1	2547
2020	2	2744
2020	3	2906
2020	4	3173
2021	1	3347
2021	2	3428
2021	3	3538
2021	4	3698

3.2 Spare Parts Demand Forecasting

Using Holt method, the stepwise search method was used to obtain α =0.9, γ =0.1, and the historical usage data was predicted, and the results are shown in Table 2.

Table 2. Prediction results of historical usage records for a certain type of spare parts

year	quarter	use (pieces)	Predicted values	Relative error(%)
2019	1	1446	1634	13.00%
2019	2	1634	1642	0.49%
2019	3	1946	1792	7.91%
2019	4	2307	2097	9.10%
2020	1	2547	2480	2.63%
2020	2	2744	2759	0.55%
2020	3	2906	2970	2.20%
2020	4	3173	3132	1.29%
2021	1	3347	3384	1.11%
2021	2	3428	3568	4.08%
2021	3	3538	3647	3.08%
2021	4	3698	3734	0.97%

count: $MAPE = 3.87\%$

It shows that the model has a good prediction capability.

Using Holt's method, the demand for spare parts for each quarter of 2022 is predicted based on the historical data of using a certain type of spare parts for this equipment, and the prediction results are shown in Table 3 and Figure 1

Table 3. Demand forecast for a certain type of spare parts

year	quarter	Predicted values
2022	1	3873
2022	2	4041
2022	3	4209
2022	4	4377

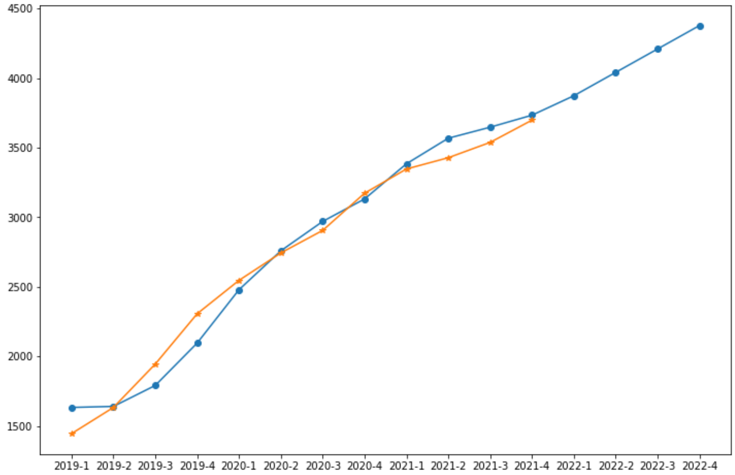

Figure 1. Predicted effect of a type of spare parts

3.3 Spare Parts Ordering Scheme

It is known that the ordering cost of the spare parts S = 1000000 yuan and the unit maintenance inventory cost H = 100 yuan, using the MPG method, the ordering scheme and inventory changes are calculated as shown in Table 4.

Table 4. Table of ordering scheme and stock changes for a certain type of spare parts

year	quarter	Forecast demand (piece)	combined order(piece)	quarter-beginning inventory(piece)	quarter-end inventory(piece)
2022	1	3873	7914	7914	4041
2022	2	4041	0	4041	0
2022	3	4209	8586	8586	4377
2022	4	4377	0	4377	0

Calculate the total cost of consolidated ordering:

$$C_T = 3666800(\text{Yuan})$$

Total cost without consolidated ordering:

$$C_T' = 4825000(\text{Yuan})$$

The cost saving is 1158,200 yuan, with a saving ratio of about 24%, which is relatively obvious.

In practice, it is necessary to fully consider factors such as safety stock of spare parts and errors in long-time forecasting in order to meet the demand of maintenance guarantee.

4 Conclusion

By extracting the historical usage data of equipment spare parts in the equipment management platform, using Holt method to predict the demand of spare parts, and using MPG method to develop reasonable ordering strategy, it is conducive to the reasonable and effective implementation of various tasks such as equipment raising, stockpiling and supplying, which can provide guarantee for the development of scientific spare parts stockpile optimization strategy and improve the equipment maintenance guarantee efficiency, which is of great significance.

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