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Dynamic Prediction Method for Valuable Spare Parts Demand in Weaponry Equipment Based on Data Perception

Weiyi Wu* **Yunxian Jia** **Yangyang Zhang** **Bin Liu**

Shijiazhuang Campus, Army Engineering University, Shijiazhuang, Hebei, 050003, China

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ABSTRACT

Missile is an important weapon system of the army. The spare parts of missile equipment are significant effect on military operations. In order to improve the mission completion rate of missile equipment in wartime, this paper introduces data sensing method to forecast the demand of valuable spare parts of missile equipment dynamically. Firstly, the information related to valuable spare parts of missile equipment was obtained by data sensing, and the sample size was determined by Bernoulli uniform sampling probability. Secondly, according to the data quality of multi-source and multi-modal, the data requirement for dynamic demand prediction of valuable spare parts of missile equipment was obtained. Finally, according to the characteristics of the spare parts, the life of the spare parts was predicted, realizing the dynamic prediction of the demand for valuable spare parts of missile equipment. The results show that the demand of valuable spare parts of missile equipment can be predicted dynamically by using this method, the accuracy is higher than 95%, and the real-time performance is more excellent.

1. Introduction

Spare parts are the material basis in the support resources of surface-to-air missile weapons and equipment. The allocation and ordering of spare parts are very important for the support of weapons and equipment and directly affect the integrity of equipment and the combat effectiveness of troops. A military missile equipment consists of about 3 million to 6 million parts, including a large number of valuable parts [1]. The supply support of such a large number of valuable spare parts is an important link of combat effectiveness producation, so it is necessary to study and discuss the demand forecasting method of valuable spare parts of missile equipment based on data management and analysis technology. This paper studies the dynamic prediction method of intermittent mechanical spare parts demand based on data perception, and applies the data sensing method to the dynamic prediction of missile equipment valuable spare parts demand, which can improve the scientific rationality of missile equipment maintenance spare parts inventory.

2. Demand Data Perception Method Based on Data Quality

The valuable spare parts of missile equipment possess intermittent characteristics. The dynamic fault information of valuable spare parts can be obtained effectively through data sensing method, and the demand prediction can be realized using the fault information.

**Corresponding Author:*
Weiyi Wu,
Shijiazhuang Campus, Army Engineering University, Shijiazhuang, Hebei, 050003, China;
Email: weiyi1019@163.com

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2.1 Data Acquisition

When collecting large-scale data, in order to truly reflect the fault information of missile equipment, the sensing area is usually divided into several disjoint sub regions, and the data are collected in each sub area to reflect the change of the whole perception area.

The missile equipment fault information Z is divided into K disjoint sub regions, which are expressed as $Z=\{z_1,z_2,\cdots,z_K\}$. Due to the large number of sub regions, if the heterogeneous data sources of each sub region all send their sensing data to the data processing center for upper level applications, the data transmission volume is too large, and finally a large number of data distortion is caused by data congestion [7,8]. In the process of data acquisition, the data quality information reflects the accuracy, integrity and consistency of the data. The higher the data quality is, the more reliable the decision-making results can be obtained by using these data. The main idea of the algorithm is as follows.

According to the accuracy requirements $\varepsilon(\varepsilon \geq 0)$ and $\delta(0 \leq \delta \leq 1)$ given by users, the Bernoulli uniform sampling algorithm is used to perform (ε,δ)-approximation on the multi-source and multi-modal data quality of the overall perception data [9], and the sampling probability p required by the users is obtained. Finally, in order to save the network resources as much as possible, pK data sources are selected for data transmission.

Supposing the start time of K disjoint sub regions is $t_s t_s$, and its multi-source, multimodal data set is $S=\{D_{t_s}^{(1)},D_{t_s}^{(2)},\cdots,D_{t_s}^{(K)}\}$, and the corresponding data quality set is $DQ=\{q_1,q_2,\cdots,q_k\}$. Each multi-source and multi-modal data quality information includes accuracy, integrity and consistency. Then the data quality information of the whole missile equipment fault information area is the weighted average value of the each sub region data quality [10]:

$$Avg(DQ)=\sum_{i=1}^{K} w_i q_i \Big/ \sum_{i=1}^{K} w_i \tag{1}$$

where $W_Z=\{w_1,w_2,\cdots,w_K\}$ are the weights of the K sub regions. The weight of each sub region is usually unchanged, or the small change of the weight has little influence on the weight sum, so the weight sum is regarded as a constant.

2.2 Bernoulli Uniform Sampling Probability Determination

In order to obtain the accurate demand for valuable spare parts of missile equipment, it is necessary to determine the specific value of the data sample. In this paper, Bernoulli uniform sampling probability method is used to calculate the appropriate sample size.

Assuming that $\overline{I}$ is the estimated value of the actual demand I for valuable spare parts. For any actual probability $\varepsilon(\varepsilon \geq 0)$ of missile spare parts failure and the sensor sensing failure probability $\delta(0 \leq \delta \leq 1)$, if the missile spare parts demand meet $\Pr\left(\left|\overline{I}-I\right| I \geq \varepsilon\right) \leq \delta$, then the $\hat{I}$ is called approximate estimation of I, where $\Pr(X)$ is the occurrence probability of event X. The specific process is shown in the following figure:

If the sampling probability of data quality information set DQ is p, then the approximate value of multi-source and multimodal data quality is as follows:

$$Avg\left(\overline{DQ}\right)=\frac{\sum_{i=1}^{K} w_i q_i \cdot x_i}{p\sum_{i=1}^{K} w_i} \tag{2}$$

where the binary random variable x_i indicates whether the missile fault data information in the sub area z_i is extracted, and the extracted value is 1, otherwise it is 0. That is, random variables x_i obey two-point distribution, and $\Pr(x_i=1)=p$. In addition, the x_i of different regions are independent. The sensing fault data of missile equipment is $E(x_i)=p$, and its binomial distribution variance is $E(x_i)'=p(1-p)$.

The unbiased estimation $Avg\left(\overline{DQ}\right)$ of missile spare parts data quality information set can be obtained through Bernoulli uniform sampling [11-13]:

$$E\left(Avg\left(\overline{DQ}\right)\right)=Avg(DQ) \tag{3}$$

According to the definition of $Avg\left(\overline{DQ}\right)$:

$$E\left(Avg\left(\overline{DQ}\right)\right)=E\left(\sum_{i=1}^{K} w_i q_i \times x \Big/ p\sum_{i=1}^{K} w_i\right) \tag{4}$$

Since the the x_i of sub regions are independent, so:

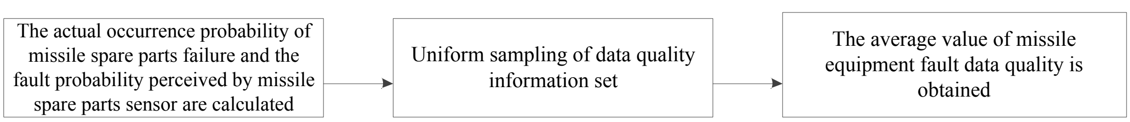

Figure 1. Quality average value solution of missile equipment fault data.

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$$
\begin{aligned}
E\left(Avg\left(\overline{DQ}\right)\right) &= \left(\sum_{i=1}^{K} w_i q_i / p\sum_{i=1}^{K} w_i\right) E\left(x_i\right) \\
&= \left(\sum_{i=1}^{K} w_i q_i / p\sum_{i=1}^{K} w_i\right)\cdot p = Avg\left(DQ\right)
\end{aligned} \tag{5}
$$

$Avg\left(\overline{DQ}\right)$ is unbiased estimation of data quality accurate weighted mean $Avg\left(DQ\right)$. According to the central limit theorem, when the sample size is greater than or equal to 30, $Avg\left(\overline{DQ}\right)$ obeys the normal distribution, and the expectation is $E\left(Avg\left(\overline{DQ}\right)\right) = Avg\left(DQ\right)$ and the variance is $Var\left(Avg\left(\overline{DQ}\right)\right)$. In the environment of large-scale sensor network, when sampling the service data obtained by sensor, the required sample size will be far greater than 30 under very low precision requirements. So it is true that $Avg\left(\overline{DQ}\right)$ obey approximate normal distribution. At this condition, $E\left(Avg\left(\overline{DQ}\right)\right)$ is the appropriate sample size of valuable spare parts for missile equipment.

2.3 Data Acquisition Method Based on Multi-source and Multimodal Data Quality

The calculation steps of data acquisition method based on multi-source and multimodal data quality are as follows:

Input: weight W_Z, data quality $Sup\left(DQ\right)$ and $Inf(DQ)$

Output: Perceptual data set D_s to be transmitted

1) Initialize $W_{\max} = 0$, $Sum\left(W_Z\right) = 0$

2) For each w_i in W_Z Do

3) $Sum\left(W_Z\right) += w_i$

4) If $w_i > W_{\max}$ then

5) $W_{\max} = w_i$

6) Calculate the sampling probability

7) $p = \dfrac{Sup\left(DQ\right)W_{\max}\phi_{\delta/2}^2}{Sup\left(DQ\right)W_{\max}\phi_{\delta/2}^2 + Inf\left(DQ\right)Sum\left(W_Z\right)\varepsilon^2}$

8) For each sensor aera $z_i \in Z$ Do

9) Generate a random number s in range [0,1]

10) If $r < p$ then

11) Send its data D_i to the data center

12) $D_s \leftarrow \left\{D_i\right\}$

13) Return D_s

Firstly, the maximum weight $W_{\max}$ and the weights sum $Sum\left(W_Z\right)$ are obtained based on the weight W_Z of each sub region. After that, the upper bound $Sup\left(DQ\right)$ and the lower bound $Inf\left(DQ\right)$ of data quality are given. Generally, the upper bound is taken as 1, and the lower bound is given by the users according to their specific requirements [14].

After the sampling probability is determined, the data processing center performs Bernoulli uniform sampling in the K sub regions. The specific steps are as follows: The data processing center generates a random number r between [0, 1] for each sub region. If r is less than or equal to the sampling probability p, the perceived data $D_i\left(1 \le i \le K\right)$ of the region is the data needed for dynamic demand prediction of valuable spare parts, otherwise the sensing data in this area is invalid.

3. Results

In order to test the validity of the dynamic prediction method in this paper, the dynamic demand prediction of 12 intermittent key valuable spare parts for an anti-tank missile equipment is simulated based on the Matlab platform. The demand of 12 kinds of missile equipment spare parts from 2013 to 2018 is counted. The statistical results are shown in Table 1.

The historical fault interval is extracted from the maintenance record of 12 valuable spare parts of missile equipment each year. The historical data is shown in Table 2.

In order to obtain accurate spare parts demand, the fault data of missile equipment spare parts are grouped based on the above data. The main shaft of the missile belongs to mechanical wear parts, which is prone to a large number of faults in the running stage. The time between failures usually conforms to Weibull distribution and exponential distribution, and few obey lognormal distribution and normal distribution. In this paper, the scatter diagram of fault data is used to judge its distribution model, and then the parameter solution and fitting verification are carried out. The fault interval time is sorted and grouped within [0, 4200] hours. The number of groups is determined by formula (6).

$$Z_p = 1 + 3.3\,ln\,R \tag{6}$$

The number of non-truncated fault data is 81, and the reliability n of system components is 8. R is the wartime maintenance replacement rate. According to the above formula, the grouping and sorting table is as follows.

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Table 1. Demand data of 12 types of missile equipment spare parts from 2013 to 2018.

Spare part number	2013year/N	2014year/N	2015year/N	2016year/N	2017year/N	2018year/N
1	48	51	53	59	61	65
2	62	68	69	72	76	77
3	56	58	59	61	68	69
4	72	75	76	78	79	81
5	76	78	79	82	83	85
6	49	51	53	58	62	68
7	68	76	79	82	86	91
8	32	35	38	41	48	52
9	66	68	71	72	76	79
10	81	83	86	91	94	95
11	46	48	51	58	62	68
12	52	57	59	61	64	69

Table 2. Failure interval of each spare part.

Spare part number	Time between failures
1	756.5,1025.3,1125.6,925.3,1125.5,1025.6,1142.6,1326.8,1425.9,1042.6,1125.6,1042.6,836.5,912.5
2	835.6,905.2,912.5,1025.6,1125.6,963.5,1124.5,1134.5,1241.5,1052.6,1325.1,1254.6,915.2
3	948.5,985.6,1056.6,1125.4,1264.5,935.5,846.5,923.5,1235.6,1325.5,1154.6,1234.5,1354.5,942.3,879.6,845.6,1125.6
4	1052.6,1125.3,1264.5,1325.4,1025.4,1059.5,1134.6,1425.9,945.5,1352.4,1254.6,1954.6,876.5,905.6
5	912.5,1054.6,1129.5,1325.4,942.6,984.5,986.5,1025.4,1165.8,1241.2,1305.6,1254.2,1326.8,945.2,948.6,1058.5,1157.6
6	1025.6,1152.4,1305.8,978.5,962.5,1025.6,1254.6,1305.2,987.5,996.5,1251.2,1325.6,945.5,1254.3,1052.6,1321.2,978.5,864.5,894.5,1025.6,1124.6
7	945.5,1056.2,1354.6,1052.6,1364.5,1125.6,1254.6,1356.5,1428.2,1243.6,1352.3,985.6,845.6,1024.5,1125.6,1325.5,945.2,845.6,795.6,1025.6
8	1025.6,1125.6,1245.6,1254.6,1285.6,1297.5,1246.5,1325.1,1154.2,1536.2,1052.6,1024.5,985.6,1034.2,1065.5,1289.5,1294.5,1234.2,1185.6,1145.6,1085.6,1125.4
9	985.6,894.52,1025.6,1254.6,1325.6,1058.6,1125.5,1245.6,1352.5,1024.6,985.6,998.65,1024.5,1054.3,1156.3,1284.6,1325.6,1152.6,1285,6,1045.2,1326.5,1205.3,986.5
10	1025.3,1125.4,1264.5,1305.3,1264.5,1305.6,1325.6,1156.5,985.6,975.6,1125.5,1234.5,1265.2,1352.6,1242.6,1325.2,1425.3,1025.6
11	952.6,976.5,1025.3,1156.5,1215.6,1305.8,1164.5,1265.5,1305.2,984.5,1058.6,1152.6,1245.6,1325.2,985.6,994.5,1025.6,1152.6,1143.5, 1253.6,1246.5,1352.6,1025.6
12	1025.6,1125.6,1165.5,1325.4,952.6,945.3,865.6,786.5,1025.6,1152.4,1168.5,1262.3,1254.3,1325.3,1152.3,1085.3,1125.3,1231.2,1302.5

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Table 4. Fault interval time sorting table.

Upper limit	Lower limit	Value in the group	Frequency number	Frequency	Accumulation
0	600	300	21	0.2593	0.2593
600	1200	600	16	0.1975	0.4568
1200	1800	9000	10	0.1235	0.5802
1800	2400	1200	9	0.1111	0.6914
2400	3000	1500	8	0.0988	0.7901
3000	3600	1800	8	0.0988	0.8889
3600	4200	2100	7	0.0864	0.9753
4200	4800	2400	2	0.0247	1.0000

The observation value $K(t)$ of probability density is calculated as follows:

$$K(t) = \frac{M_i}{M \cdot \Delta t} \tag{7}$$

where M_i is the number of fault intervals in each group, M is the total number of fault intervals, Δt is the group spacing. Through the Matlab simulation calculation of the data, the dynamic prediction results of the demand for 12 valuable spare parts in 2019 are obtained. Compared with wavelet analysis method and GM method, the results are shown in Figure 1.

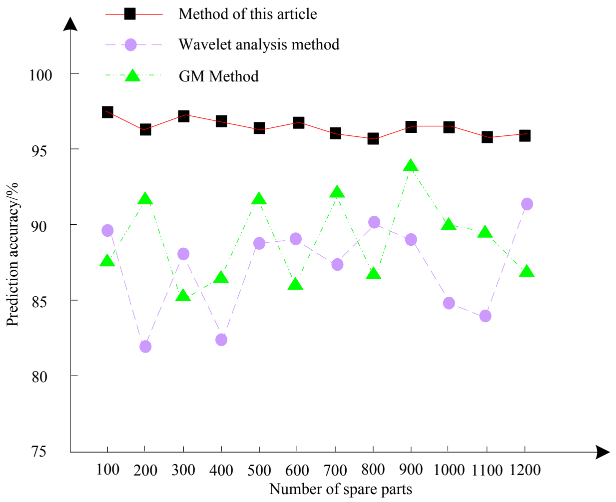

Figure 1. Comparison of prediction accuracy of different methods.

The prediction accuracy is transformed into the accuracy rate of spare parts fault identification. If the spare parts that have faults are identified, they need to be replaced, and then the prediction accuracy rate of valuable spare parts demand will become high.

According to the experimental results in Figure 1, the method accuracy is different for different spare parts numbers. When the number of spare parts is 100, the prediction accuracy of wavelet analysis method is 87%, that of GM method is 89%, and that of this proposed method is 97%. When the number of spare parts increases to 800, the prediction accuracy of wavelet analysis method is 90%, that of GM method is 86%, and that of this proposed method is 96%. The prediction accuracy of the method proposed in this paper is high, and it can accurately predict the demand of valuable spare parts for missile equipment.

The prediction time of the valuable spare parts demand of 12 intermittent missile equipment is dynamically predicted with this method, and the results are compared with wavelet analysis method and GM method, shown in Figure 2.

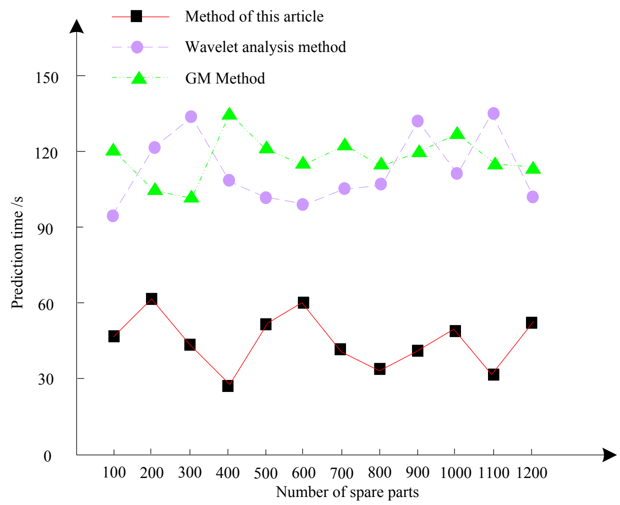

Figure 2. Comparison of prediction time of different methods.

According to the experimental results in Figure 2, when the number of spare parts is 200, the prediction time of wavelet analysis method is 120 s, that of GM method is 110 s, and that of the method in this paper is 60 s. When the number of spare parts increases to 1200, the prediction time of wavelet analysis method is 115 s, that of GM method is 110 s, and that of the method in this paper is 58 s. The prediction time of the method proposed in this paper is short and the prediction efficiency is high. The experimental results verify the real-time performance of the proposed method.

4. Discussions

Missile equipment is a complex electromechanical system. Fault prediction and inventory control of maintenance spare parts are the key factors affecting the combat effectiveness of missile equipment. The data sensing method is applied to the dynamic prediction of intermittent mechanical spare parts demand. This paper forecasts the demand of valuable spare parts of missile equipment

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based on data perception method. The main conclusions are as follows:

(1) In this paper, the new method is used to study the demand law of spare parts design and the simplified workload, and the demand forecast in the spare parts management is mainly studied.

(2) Due to the lack of data samples, the simulation of equipment use and maintenance process is proposed to obtain fitting samples. The method to determine the sample size makes the simulation process universal, which can effectively avoid multiple parameter estimation and hypothesis testing, and reduce the sampling difficulty of complex probability distribution. The research designs the definite time interval combining with specific problems, and obtains excellent results.

(3) The research results in this paper can be applied to the optimal allocation of spare parts in the ground to air system. According to the actual problems, the relevant parameters of spare parts demand prediction can be obtained, and the optimal inventory optimization result can be obtained by using data sensing method to solve the demand of missile spare parts dynamically.

5. Conclusions

In the dynamic prediction of the demand of valuable spare parts, the method based on data perception is introduced to forecast the demand of valuable spare parts dynamically. The basic data of dynamic prediction of the demand for valuable spare parts is obtained by data perception method based on data quality, and the sample size of valuable spare parts is determined by Bernoulli uniform sampling probability. According to the material characteristics of spare parts, the life prediction of missile equipment valuable spare parts is realized. Finally, valuable spare parts are taken as experimental objects to test the effectiveness of the dynamic prediction method. The results show that the method can be applied to the dynamic prediction of valuable spare parts of actual missile equipment, and provide the basis for the integrated support of missile equipment.

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