Demand Forecast of Weapon Equipment Spare Parts Based on Improved Gray-Markov Model

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***Abstract*—The demand for spare parts of weapons and equipment is time-varying and random. It is difficult to predict the demand for spare parts. Therefore, on the basis of gray GM(1,1), a state transition probability matrix based on improved state division is used to establish a demand forecast model for weapon equipment and spare parts. The model not only considers the characteristics of the GM(1,1) model's strong handling of monotonic sequences, but also extracts the characteristics of random fluctuation response of data through the transformation of the state transition probability matrix, avoiding the phenomenon of the worst prediction results when the maximum probability state is not the actual state. It is proved through experiments that the prediction result based on the improved gray-Markov model is superior to the traditional model and the classic gray-Markov prediction model, and the accuracy of the improved model is about 1.46 times higher than that of the gray model.**

Keywords-Grey Theory; Markov Model; Spare Parts Forecast

I. INTRODUCTION

Weaponry is composed of many parts, and these parts need to be repaired and replaced during use. In order to shorten the short interval between the repairs of weaponry and equipment, increase normal working hours, reserve a reasonable number of spare parts for replacement at any time. Weaponry spare parts are effective measures to improve the availability of weaponry and equipment, reduce life cycle costs, and ensure the effectiveness of combat effectiveness on time [1]. In the issue of spare parts support, the prediction of spare parts demand is an important means to promote "precision support", and is also one of the key and difficult points in the research of equipment comprehensive support.

There are many reasons for the occurrence of spare parts demand. In addition to the reliability rules of weapons and equipment itself, the use of equipment, repair strategies and maintenance methods will affect the number and time of spare parts demand. Spare parts demand shows randomness and fluctuation Therefore, equipment managers urgently need to find a method to predict the random demand for repair spare parts.

At present, there are many technologies for demand planning, forecasting and decision-making, mainly including time series forecasting models, regression analysis methods, support vector machines, neural networks, gray forecasting and decision making, Markov forecasting, Combined optimization decision-making, and their Between each other. Among them, the method based on the time series prediction model requires a large amount of historical data, and the data must not have periodic changes or mutations. Neural network-based spare parts demand prediction method requires a large number of statistical samples, and the prediction results are highly subjective and random. These factors greatly limit the application of artificial intelligence methods [2]. Therefore, how to improve the prediction accuracy of the demand for spare parts for weapons and equipment is an important link for effectively guaranteeing the supply of spare parts for our military equipment.

The gray prediction model is suitable for solving the problems of small samples, poor information and uncertainty. It has less calculation and is convenient and practical. It has a good prediction effect for short-term prediction, but it has a poor fit for long-term prediction and volatile data series. The Markov theory describes the influence of random factors and the internal laws of transition between states through the state transition probability, which can effectively make up for the deficiencies of the gray model [3]. To this end, this paper proposes to predict the demand for spare parts for weapons and equipment based on an improved gray Markov model, in order to effectively improve the prediction accuracy of random volatility data and broaden the application range of gray theory.

II. RESEARCH STATUS OF SPARE PARTS DEMAND MANAGEMENT

With the development and progress of economic globalization and science and technology, people have higher requirements for product quality and production efficiency, and there are more and more complex equipment in industrial production. In the process of using complex equipment, failures will inevitably occur due to factors such as maintenance damage, wear, corrosion, and expiration of life. In order to restore the normal operation of the equipment in time, minimize the economic loss caused by equipment failure or shutdown. [4] Companies generally purchase and store a certain number of accessories in advance, which are called spare parts. Spare parts, as support materials for the daily maintenance and emergency handling of equipment, are an important factor in ensuring the normal operation of complex equipment. Accurate and timely spare parts supply can ensure the continuity of production operations of the enterprise. Spare parts are an important material basis for equipment support work. Spare parts management Work has become an important part of equipment support work. Spare parts planning is affected by spare parts demand, so an effective spare parts demand forecasting model will provide an important basis for spare parts management decision making, and it is also the basis for quickly responding to changes in customer needs and improving corporate service levels.

The demand for spare parts is very special. In most cases, the demand for spare parts occurs in uncertain and irregular time intervals, and the quantity is also unstable and changeable. Strictly speaking, demand is usually divided into: slow-moving spare parts, intermittent demand spare parts. The consumption of spare parts is extremely special. Some spare parts consume a large amount, while some spare parts consume a small amount, and have not even been consumed in a few years. This greatly increases the difficulty of accurately predicting the consumption of spare parts. In fact, in addition to conventional methods for forecasting spare parts, it is more important to study forecasting methods for uncertain or intermittent demand. Spare parts demand forecasting is a very important part of equipment management, and it is the basis of inventory management. Accurately planning the supply of spare parts can reduce the huge budget spent on spare parts, supply the required spare parts in time, improve the availability of equipment and the completeness of weapons and equipment, ensure that the equipment can complete production tasks and normal operations on time, and guarantee weapons and equipment In military exercises and battles, fighters will not be missed. On the other hand, accurate demand forecasting will have a very important impact on the formulation of spare parts inventory strategies and the construction of inventory models [5].

In many complex equipment companies, spare parts inventory management has not attracted enough attention. In general: On the one hand, there are generally backward spare parts inventory management methods, improper inventory management methods, difficult spare parts search, and excessive backlog of a large number of unimportant spare parts, resulting in high inventory costs of enterprises; on the other hand, some spare parts Inventory will not be able to meet equipment maintenance or customer demand changes. The shortage of key spare parts may cause equipment delays in maintenance or even shutdown accidents occasionally. Inventory issues increasingly become a bottleneck restricting the survival and development of complex equipment companies. For companies, the most important issue is how to use inventory management strategy and inventory management system optimization to greatly reduce the amount of inventory funds occupied by spare parts, and then increase Capital turnover and corporate economic benefits.

III. THEORETICAL OVERVIEW OF GREY SYSTEM AND MARKOV CHAIN

A. *Basic concepts of gray system*

The naming of the gray system is different from the naming methods of other systems, it is named according to the degree of mastery of the information. The completely unknown information is represented by "black", this system is called the black system, and the information that is clearly grasped is represented by "white", this system is called the white system. According to this law, it is clear that "gray" is in the middle ground, and our grasp of this part of information is in a state of "ambiguity". This system is called the gray system.

The most widely used grey system in the field of forecasting is the GM(1,1) model. Due to its small sample data, simple calculation and other advantages, it has been widely used in various fields such as society, economy, ecology, agriculture, etc., especially in the case of small samples, poor information and uncertain systems and lack of data, it has also been successful. Application, which determines that the GM(1,1) model in the gray system occupies an important position in the fields of prediction and decision-making. In order to expand the scope of application and prediction accuracy of the GM(1,1) model, many scholars have done a lot of theoretical research. These studies mainly focus on: processing the original data, constructing the background value in the GM(1,1) model, discussing the method of determining the initial value in the GM(1,1) model, combining the gray system theory and other theoretical models Combine. Among them, there are two types of concepts in optimized combination forecasting. One is a forecasting method that selects appropriate weights for the weighted average of the forecast results obtained from several forecasting methods. The key is to determine the weighting coefficient of each individual forecasting method. Compare in several prediction methods, choose the prediction model with the best fit or the smallest standard deviation as the best model for prediction. Combination forecasting is to play its role when a single forecasting model cannot completely describe the changing law of the forecast.

B. *Basic principles of the gray system*

Using the information currently available to explore and predict unknown information is the most important theory of the gray system, which is the process from "grey" to "white" until the research purpose is achieved. The basic principles of the gray system are:

1) *Principle of difference information*

"Difference" is information, and all information must be different. Saying "thing A is different from thing B" means that A has special information that B does not, which is the so-called difference. The basic way people understand the world is to observe the differences of different things in the objective world.

2) *The principle of non-uniqueness of solution*

When the information is not fully grasped, the solution obtained for it is uncertain and non-unique. This is caused by the incompleteness of the gray system information and cannot be avoided.

3) *Principle of least information*

How to use the least information that has been mastered to maximize the effect is an important feature of the gray system to study unknown information.

4) *Cognitive basis principle*

Information is the basis of cognition. All cognition must be based on the information you have.

5) *New information priority principle*

The new information has priority in cognition, and its use value is greater than the old information.

6) *The principle of immortality*

Incomplete information and uncertainty are universal. Information is completely relative and temporary. The completeness of information is specific to a specific environment, and the objective environment is constantly changing, which will also be accompanied by the emergence of new uncertainties.

C. *Grey prediction model*

The gray prediction model uses GM (1,1) modeling on the known information to find the simulated value, and then predicts the unknown information. This determines the change range of the gray forecast object, and its range must be bounded and related to time. As the core model of grey prediction, GM(1,1) model is widely used in practical research. The establishment of the model is based on the data in the time series. Through this model, the law of data change is analyzed, and the internal relationship is analyzed from the external relationship of various factors to find the hidden law, thereby generating the corresponding data sequence, and performing differential equation modeling. Forecast the development trend of things.

Predicting the gray system is to mine and discover the development laws of the system by processing the original data and establishing the gray model, so as to predict the future state of the system. Since the gray system contains both known information and unknown information, its prediction is the prediction of the gray process that is related to time and changes in a certain direction. Although the laws shown by some gray processes are random and disorderly, their essence is bounded, orderly, and potentially regular. There are four main types of gray system forecasts:

a) Sequence prediction: refers to the prediction of the behavior of the system variables in the future. After the qualitative analysis of the data series, the appropriate sequence operator is selected, and the gray model is established based on the number sequence after the operation of the operator. The accuracy of the model It can be used to predict after inspection.

b) Catastrophe prediction: refers to the prediction of the abnormal value of the gray system, that is, the prediction of the time when a given gray number occurs, so as to provide guidance for the work of relevant departments.

c) System prediction: refers to the prediction of multiple variables in the system together, which is mainly used to predict the relationship between system variables and reveal the development and changes of the system.

d) Topological prediction: also called waveform prediction. When the original data fluctuates greatly, the gray model is used to predict the waveform of future behavior data.

D. Markov process

Markov process has great significance in stochastic process and is widely used in biology, physics and other sciences. The definition of Markov chain was first proposed in the early nineteenth century, and then people began to study and explore a random process with no aftereffect. Ineffectiveness means that the state of the future is only related to the present and not related to the past. Markov has made great contributions to probability theory, number theory, and differential equations[6]. During 1906-1912, he proposed and studied Markov chains. His research results are of great help to probability theory. The random process he studied is called Markov process.

Markov processes are continuous or discrete according to their state and time parameters, and are divided into three categories

1) Time and state are both discrete Markov processes, called Markov chains.

2) The Markov process with continuous time and discrete state is called continuous-time Markov chain.

3) Time and state are continuous, which is called Markov process.

The research object of Markov model is mainly the state of the system and the transition between states. The main purpose of establishing Markov model for calculation analysis is to predict the possible state of variables in the future by analyzing the current state and change trend of system variables, and then provide corresponding theoretical basis for decision-making.

The steps of using Markov process to predict include:

Step1 Reasonably divide the state. When the sample has less data, the number of states should be as small as possible, so that each state contains more data, which can more objectively reflect the transfer law between each state;

Step2 Calculate the transition probability between each state in the Markov process of the system, and determine the corresponding state transition matrix;

Step3 According to the initial state of the system and the transition probability matrix to predict the state in the future.

IV. IMPROVED GRAY MARKOV MODEL

A. Gray model

Grey system theory was first proposed by our famous scholar Professor Deng Julong in 1982. It is a theory of gray system modeling, prediction, analysis, control and decision-making. Grey prediction method is a new type of nonlinear prediction technology in the late 1990s, which is a method system based on sequence operators and gray sequence production. The gray prediction model uses accumulation, accumulation or step ratio generation techniques, and uses differential fitting to directly convert the time series into a first-order univariate constant coefficient differential equation. According to the principle of continuity of prediction, the gray theory can be used to get more Accurate prediction results [7]. For data with relatively short data series, less information, and less regularity, data that meets the characteristics of poor information systems, the gray model can show superiority and advanced. The gray model is usually divided into a first-order single-variable model and a first-order Combined model. The model is used in this paper.

1) The original data sequence required for the design of spare parts for weapons and equipment is:

$$X^{(0)}=\{X^{(0)}(1),X^{(0)}(2),\cdots,X^{(0)}(n)\} \quad (1)$$

among them: $x^{(0)}(k)>0, k=1,2,\cdots,n$。

2) Accumulate the original sequence once:

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

among them: $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)(k=1,2\cdots,n)$

3) Generate a sequence of immediate means:

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

among them: $z^{(1)}(k)=\frac{1}{2}\left[x^{(1)}(k)-x^{(1)}(k-1)\right]$

4) Establish model whitening equation:

$$\frac{dz^{(1)}}{dx}+az^{(1)}=b \quad (4)$$

Among them:a and b are undetermined parameters.

5) The gray equation of the model is:

$$x^{(1)}(k)+az^{(1)}(k)=b \quad (5)$$

6) The corresponding time response equation is:

$$x^{(1)}(k+1)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-at}+\frac{b}{a} \quad (6)$$

7) The least square estimates of parameters a and b are:

$$A=\begin{bmatrix}a\\b\end{bmatrix}=\left(B^TB\right)^{-1}B^TY \quad (7)$$

$$B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & 1\\ -z^{(1)}(n) & 1\end{bmatrix} \qquad Y=\begin{bmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(n)\end{bmatrix}$$

8) Reducing the prediction results to the prediction sequence:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \quad (8)$$

among them: $k=1,2,\cdots,n-1$

It can be seen from the above that the model predicts the original sequence after one accumulation. Because the one-time accumulation sequence is monotonic, the model is suitable for predicting the data of the exponential change law, and the prediction error is large for random volatility data.

The GM(1,1) forecasting model occupies an important position in the grey system theory. The starting point of the model research is to explore valuable information in its own time series and explore the law of the research content without considering the impact of the research content. The gray system prediction model takes a small amount of data information as the research object. Its research characteristics are simple calculation, simple principle and high prediction accuracy. The model has good prediction accuracy for modeling small amounts of information, but the prediction accuracy for irregularly changed and fluctuating data will be greatly reduced, so the gray prediction model does not have high prediction results for any data. The Markov chain prediction model is different from the gray system model. It makes up for the shortcomings of the gray prediction model and can study data with large volatility. Its model requires the prediction object to have Markov properties. In this chapter, the two models are reasonably combined to form a gray Markov prediction model. The GM(1,1) model is used to characterize the trend of the original data sequence, and the Markov prediction model is applied to the simulated data obtained by the GM(1,1) model. The length of the ruler is selected and the shortness of the inch is compensated to improve the accuracy.

B. Grey Markov model

According to the gray system theory, the gray mean model and the Markov model are fused, and the gray Markov model is used to predict the demand for weapon equipment and spare parts. Specifically, the gray mean model is used to predict the future demand for weapon equipment and spare parts [8]. The state transition matrix determines the possible state of future spare parts, and finally corrects the prediction result based on the ratio between the predicted value and the actual value, so as to realize accurate prediction of weapon equipment spare parts. After determining the state division and state transition matrix, the general gray Markov model uses the maximum value of the current transition probability as the next transition value [9]~[11]. This method ignores the possibility of other transition probabilities and based on the last state. For prediction, it is easy to be affected by randomness, which makes the prediction accuracy low, so the gray Markov model is improved.

The modeling idea of the gray-Markov combination model is to first establish a gray prediction model to obtain a prediction sequence, and then use the relative difference sequence of the prediction sequence and the actual sequence to divide the state space, find the interval of the predicted value, and follow the prediction [12]. The interval modifies the results of the model prediction, increases the credibility of the prediction, calculates the transition probability matrix from the point where the original data sequence falls into each state, and estimates the future change trend based on the state transition probability matrix.

Calculate the state transition probability matrix and obtain the predicted value according to the gray model $\hat{x}^{(0)}(k)(k=1,2,\cdots n)$ .Using the curve as a reference, it is divided into several bar regions parallel to the trend curve, and each region constitutes a state. In this way, a non-stationary random sequence that matches the characteristic points of the Markov chain is divided into n states. Any state is

$$\otimes_i = [\otimes_{1i}, \otimes_{2i}] \tag{9}$$

among them: $\otimes_{1i} = \hat{x}^{(0)}(k) + A_i$, $\otimes_{2i} = \hat{x}^{(0)}(k) + B_i$

The state transition probability is:

$$p_{ij}(k) = \frac{M_{ij(k)}}{M_i}, i = 1,2\cdots,n \tag{10}$$

In the formula: $M_{ij}(k)$ is the number of original data that state $\otimes_i$ transfers to state l after $\otimes_j$ steps; M_i is the number of original data in state $\otimes_i$.

The specific steps based on the improved gray Markov prediction model are:

Step1: According to the original data $x(k)$, find the coefficient a、b in the gray model, and get the fitting value $\hat{x}(k)$ corresponding to the actual data.

Step2: The range of the relative residual value sequence is obtained from the relative residual value formula.

Step3: According to the actual situation, use the residual formula to divide the relative residual value range into states: $\otimes_1$、$\otimes_2 \cdots, \otimes_L$

Step4: Based on the improved Markov chain state transition probability determination method, the one-step state transition probability matrix is calculated:

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1L} \\ p_{21} & p_{22} & \cdots & p_{2L} \\ \vdots & \vdots & & \vdots \\ p_{L1} & p_{L2} & \cdots & p_{LL} \end{pmatrix} \tag{11}$$

among them: $p_{ij} \geq 0, \sum_{j=1}^{L} p_{ij} = 1$

Suppose a prediction system has $\otimes_1$、$\otimes_2$、$\otimes_3$、$\otimes_4$ four states, the last data in actual data $x(k)$ is in state $\otimes_4$, then the initial distribution is $I^{(0)} = (0 \quad 0 \quad 0 \quad 1)$, and the predicted value of the next data is $I^{(1)} = I^{(0)} \cdot P$, based on which the state interval in which the predicted data is located can be obtained.

The gray Markov model is a model that combines the gray model and the Markov model. Its prediction process is: firstly generate gray according to the original data sequence, determine the parameters of the gray model according to the generated sequence; then use the established gray model Carry out simulation prediction, test the accuracy of the established model according to the predicted value and actual value; then appropriately divide the gray prediction result into several states, establish a Markov model, and predict and modify the state of the gray prediction result. According to the combination of gray model and Markov model, traditional gray Markov model prediction methods mainly include the following two:

Use the Markov process to predict the sign of the gray prediction result residual model. After processing the given time series, a gray model is established, and the residual data series can be obtained by comparing the predicted result of the gray model with the actual value. The absolute value of the residual data sequence is used as the original data, and the gray prediction is performed to obtain the gray residual model. In order to improve the prediction accuracy, the Markov process is used to predict the sign of the residual model at the future time.

Use Markov process to predict the relative error of gray prediction results. Establish a gray model based on the original data series, divide the state of the relative error of the gray prediction result, and predict the state of the relative error of the gray prediction result at the future time according to the current state transition, thereby improving the accuracy of the gray prediction result Sex. The essence of the first combination forecasting method is to correct the gray residual model to improve the accuracy of the forecast; the essence of the second combination forecasting method is to directly correct the gray forecast results, so it is better than the first combination forecasting method. The calculation process is simple.

When the Markov process is used to predict the relative error of the gray results, there are two ways: one is to directly predict the state of the system in the future based on the initial state of the system and the n-step state transition matrix; the other is It is based on the initial state of the system and the one-step state transition matrix to predict the state of the next moment, and then based on the state of the next moment and the one-step state transition matrix to predict the state of the system at a later time. The advantage of the first method is that when predicting the state of the system at any time, the initial state used is known and accurate, and the various states of the system at a certain time are considered, and The probability of overestimation and underestimation is small; the disadvantage is: when predicting the state of the system at a distant time, a multi-step state transition matrix is needed. The calculation process of the multi-step state transition matrix is more complicated, and when the number of steps is large The accuracy of the corresponding matrix cannot be guaranteed. The advantage of the second method is that only one step of the state transition matrix is required for Markov prediction, the calculation process is simple, and when the predicted state is accurate, the prediction result is very ideal; the disadvantage is: when the state of the system at a certain moment When the forecast is inaccurate, the forecast result will have a big deviation, and it will affect the forecast accuracy at subsequent moments. In the following articles, the model corresponding to the first calculation method is called the first gray Markov model, and the model corresponding to the second calculation method is called the second gray Markov model.

The improved gray Markov model is a reasonable combination of the first and second gray Markov models, that is, two calculation methods are used to predict the corresponding values of the system parameters at the future time, and then the two results are calculated. Calculate the average value. The improved gray Markov model is optimized for Markov process prediction, so the gray modeling part and The GM(1,1) model is consistent, but the difference is the correction effect of the Markov process on the gray prediction results. The specific steps for the establishment of the improved gray Markov model mainly include: firstly generate gray for the prediction sequence, obtain the parameters of the gray model according to the generated data sequence, determine the gray model and make predictions; then divide the relative error of the gray prediction results State, determine the state transition of the Markov process; then according to the calculation method of the first gray Markov model and the second gray Markov model to obtain the corresponding correction value of the gray prediction result, so as to obtain the improved gray The predicted value of the Markov model.

V. CASE ANALYSIS

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

A. *Experiment Verification*

Taking the consumption of a spare part of a certain type of self-propelled artillery of the Military Machinery Maintenance Institute as an example, Table I. is the historical data of the consumption of a certain spare part during the continuous service of a certain type of self-propelled artillery of 2016~2019 for 3 years, with the serial number of the spare part as the horizontal axis, and the demand for spare parts For the vertical axis, the improved gray Markov model is used to predict the future demand for spare parts.

TABLE I. HISTORICAL DATA OF SPARE PARTS CONSUMPTION OF A CERTAIN EQUIPMENT

Serial number	1	2	3	4	5	6	7	8
Number of spare parts	20	14	18	9	10	11	6	5

The following data is used as a sample, and the improved gray-Markov model and other models are used to predict the number of spare parts for the eighth time, and a comparative analysis is made.

Using the improved gray-Markov model to predict the demand for spare parts:

From the above data can be obtained

$$X^{(0)} = \{20,14,18,9,10,11,6,5\}$$

It can be obtained by smoothing the historical data of the demand for spare parts of weapons and equipment

$$\lambda_X = \{1.4268,0.7778,2.0000,0.9000,0.9091,1.8333,1.2000\}$$

Therefore, $X^{(0)}$ needs to be exchanged for translation. Take $c = 32.5$, after calculation, we can get

$$Y^{(0)} = \{52.5,46.5,50.5,41.5,42.5,43.5,38.5,37.9\}$$

$$\lambda_Y = \{1.1290,0.9208,1.2169,0.9765,0.9770,1.1299,1.0267\}$$

So, the $Y^{(0)}$ sequence can be operated with the gray model, and finally subtract c to obtain $\hat{X}^{(0)}$

Using Equation 2 to do an accumulation generator for we can get

$$Y^{(1)} = \{52.5,99,149.5,191,233.5,277.5,315.5,353\}$$

The sequence is generated by using the immediate mean for ,which can be obtained according to Equation 3.

$$Z^{(1)} = \{75.75,124.25,170.25,212.25,255.25,296.25,234.25\}$$

Establish prediction equations according to formulas 4, 5, and 6

$$\hat{y}^{(1)}(k) = -1216.14 \times e^{-0.0405412(k-1)} + 1268.64$$

Find the reduction value according to equations 7 and 8

$$\hat{Y}^{(0)} = \{52.5,48.3176,46.398,44.5545,42.7844,41.0845,39.4522,37.8848\}$$

$$X^{(0)} = \{20.0000,15.8176,13.8980,12.0545,10.2844,6.9522,5.3848\}$$

Through the prediction of the gray model, you can get the fitted figure of the simulated value and the actual value after data processing as shown in Figure 1.

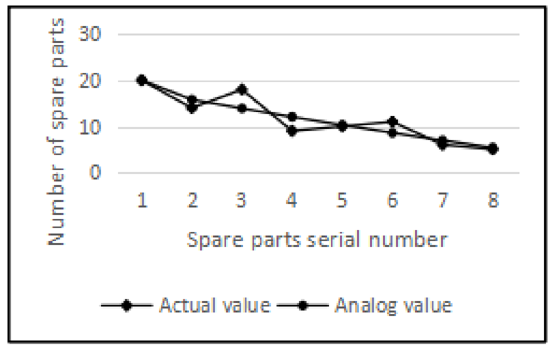

Figure 1. Fitting diagram of simulated value and actual value

Obtain the relative residual sequence according to Equation 9

$$\varepsilon^{(0)} = \{-12.9831,22.7892,-33.9394,-2.8437,21.9588,-15.8705,-7.6955\}$$

To divide the state, the upper and lower limits of the state are

$$\begin{cases} \Theta_{\min} = \min(\varepsilon^{(0)}) - 0.05 \times \left|\max(\varepsilon^{(0)}) - \min(\varepsilon^{(0)})\right| \\ \Theta_{\max} = \max(\varepsilon^{(0)}) - 0.05 \times \left|\max(\varepsilon^{(0)}) - \min(\varepsilon^{(0)})\right| \end{cases}$$

The range of the residual error is expanded by 5% above and below, calculated

$$\Theta = (-36.7758,25.6256)$$

The interval between the cells in the state is taken to be equal, and the number of states is sequentially selected from 2 to be calculated. The maximum value is the sequence length. From this, 7 sets of trial calculation results can be obtained.

Calculate the one-step state transition probability matrix according to Equation 12

$$P = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0.08 & 0.42 & 0 & 0.5 \\ 0 & 0 & 0.3249 & 0.6751 \\ 0.5 & 0.5 & 0 & 0 \end{bmatrix}$$

(1) Use the state transition probability matrix to obtain the prediction results, as shown in Table II

TABLE II. FORECAST RESULTS

Raw data	**Model calculation data**	**Raw data**	**Model calculation data**
20.0000	20.0000	10.0000	10.5184
14.0000	15.8176	11.0000	10.4467
18.0000	16.9127	6.0000	6.1321
9.0000	10.6324	5.0000	6.5528
Predict three numbers	3.4219	2.4896	1.2732

The state transition probability matrix is used to predict the consumption of spare parts for a certain equipment spare part in the future time period, but its accuracy and accuracy need to be calculated using error analysis formulas, and compared with other gray models or classic gray-Markov models.

B. *Model comparison*

Average error calculation：

$$\bar{E} = \frac{\sum_{k=2}^{n} |e(k)|}{n-1} \tag{12}$$

First, according to the average error calculation formula, calculate the average error of the model when different states are divided. As shown in Table Ⅲ, it can be seen that when the number of states is 4, the accuracy of the model is the highest.

TABLE III. MODEL AVERAGE ERROR UNDER DIFFERENT STATE DIVISION

Number of states	**Model mean error**	**Number of states**	**Model mean error**
2	15.9536%	6	Undesirable
3	13.7272%	7	Undesirable
4	11.5191%	8	Undesirable
5	Undesirable	—	—

Second, the classic gray-Markov model is used for prediction, and the prediction accuracy is compared, as listed in Table Ⅳ.

TABLE IV. FORECAST ACCURACY OBTAINED BY USING DIFFERENT MODELS

GM(1,1)model	**Number of states**	**Classic model**	**Improve the model**
16.8686%	2	15.9536%	15.9536%
	3	**13.7272%**	13.7272%
	4	Undesirable	11.5191%
	5	Undesirable	Undesirable
	6	Undesirable	Undesirable

When the number of state divisions is 2, 3, the accuracy of the improved model is about 1.06 times and 1.23 times higher than that of the model, which is the same as the accuracy of the classic gray Markov prediction model. When the number of state divisions is 4, the accuracy of the improved model is about 1.46 times higher than that of the model, and the classical Markov prediction model cannot achieve the prediction effect because it cannot build a successful Markov chain state transition probability matrix. As the number of state divisions increases, the average accuracy of the improved gray Markov model is on the rise. The improved model supports more number of state divisions, so it is better than the classic gray Markov prediction model. The application environment of the gray prediction method is relatively loose. It does not need to determine whether the data changes follow the same type of distribution. It does not require large sample statistics to make predictions. It has certain application prospects.

VI. CONCLUSION

In the field of spare parts support for weapons and equipment, forecasting has always been a relatively difficult problem. Due to the time-varying and random characteristics of weapon equipment spare parts demand, this paper proposes to predict the demand of weapon equipment spare parts based on the improved gray-Markov prediction method. By comparing the prediction results, the modified model is superior to the traditional gray model and classic the gray-Markov model has high prediction accuracy and provides a reliable scientific basis for the evaluation of weapon equipment reliability and the maintenance of its equipment.

ACKNOWLEDGMENT

This work is supported by the Shanxi Natural Science Basic Research Project (2019JM-603) for its fund support.

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