Research on demand forecast of vehicle turnover equipment based on GM(1,1)-BP combined model

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Abstract. According to the historical data characteristics of vehicle turnover equipment demand, a GM (1,1) - BP combined model is established. Firstly, GM (1,1) model is used to forecast the historical data of vehicle turnover equipment demand. On this basis, BP neural network is introduced to correct the residual of the prediction. It optimizes the forecasting method of vehicle turnover equipment demand, makes up the deficiency of single model, and enhances the accuracy of vehicle turnover equipment demand forecasting.

1. Introduction
With the rapid development of logistics equipment construction in our army, a large number of new technologies, new materials, new processes and new achievements have been adopted in vehicle equipment. It is required that packaging structure and storage method must conform to the structural characteristics and physical and chemical characteristics of equipment, and there are higher standards and requirements for equipment storage technology and materials, storage management and implementation methods, which undoubtedly pose severe challenges to the scientific storage of equipment. For catering to the request of the development goals of our army logistics equipment, we should strengthen the storage technology, storage material, storage management and the storage standardization work in the future, make up for the shortcomings of storage principles, preparation, implementation and inspection in equipment storage management, highlight the research of the conducting storage materials, heat storage materials, flame retardant storage material, explosion-proof storage material, electromagnetic storage materials, three storage materials and multifunctional protective storage materials, and study field storage technology and combinatorial storage technology actively and deeply to ensure combat effectiveness and efficiency for storage, so as to provide strong theories, technologies and systems for the vehicle equipment storage.

Vehicle equipment storage is an important content of the equipment management, however, the basic conditions of vehicle equipment storage in our army are limited, the technical products are scarce, the management mode is backward, and the environment faced by the storage is extremely harsh, which should be paid great attention to. According to the characteristics of the present vehicle equipment construction, the task of vehicle equipment storage is likely to be put forward at any time. The quality of vehicle equipment storage is directly related to whether the vehicle can manage well, drive well and go far, and whether it can effectively play its combat effectiveness. Therefore, in order to further the study of storage and protection technology, extend the service life of vehicle equipment, keep vehicle equipment intact rate, first of all, this topic analyzed the corrosion damage situations of our army vehicles and equipment and the basic form of vehicles and equipment corrosion, summarized
the corrosion damage, and then it analyzed the typical natural environment faced by vehicle equipment, researched the action mechanism of typical environmental factors on different materials of vehicle equipment. Qualitative analysis and research are carried out to explore the influence of natural environmental factors on the corrosion of vehicle equipment, and to explore the corrosion mechanism of vehicle equipment. According to the vehicle equipment failure mechanism, reasonable storage method and protection technology are scientifically determined. This topic selected advanced and efficient materials for storage and protection, and designed simple and practical technical scheme of storage and protection devices to provide advanced and practical, simple structure and high cost-effectiveness technical means for the storage and protection of our army vehicle equipment.

This paper mainly studies the irreparable equipment in vehicle turnover equipment. This kind of equipment is in great demand, has certain historical data, is complex in type and low in key, for its faulty parts generally replaced immediately and it is difficult to predict because of the influence of many uncontrollable factors. Aim at the characteristic of this kind of equipment requirements, we put forward a new method which is based on the Grey Model (GM: Grey Model) and the error Back Propagation (BP: Back Propagation) neural network combination model to forecast the demand of vehicle turnover equipment. GM (1,1) model needs fewer sample data and has high prediction accuracy for linear relationship. Meanwhile, BP neural network has good non-linear dynamic characteristics and adaptive ability, and can accurately predict the non-linear relationship among them [2]. Therefore, firstly, GM (1,1) model is used to preliminarily forecast the equipment demand data of the army over the years, and then BP neural network is used to modify and improve the residual of the grey prediction model. It effectively overcomes the shortcomings of GM (1,1) model and BP neural network model, greatly improves the prediction accuracy, and achieves the relatively optimal demand forecasting effect.

2. Overview and construction of GM (1,1) model

2.1. Overview of GM (1,1) model

Grey forecasting method is a method to discover and grasp the development law of the system and make a scientific quantitative forecasting of the future state of the system through the processing of original data and the establishment of grey model [3]. GM (1, 1) model is the earliest and most commonly used model in the grey forecasting model. The model is compatible with the relevant properties of differential, difference and exponential, so its properties are not unique, that is, grey; the parameter variables in the model can be adjusted and changed, not determined, that is, grey. The GM (1,1) model has a good forecasting effect on the uncertain system of "small sample" and "poor information", and its principle is easy to understand, the operation method is very simple and has the test property [4].

2.2. Construction of GM (1,1) model

2.2.1. Accumulative generation operation. The cumulative generation operation plays an important role in the construction of the whole grey prediction model and is the basis of the model construction. The trend of grey accumulation in the system can be observed through the operation of cumulative generation, so as to obtain the mathematical characteristics and variation rules implied in the original data sequence[5]. Suppose the original non-negative data sequence \( X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \). By cumulating \( X^{(0)} \) to generate a new data sequence \( X^{(i)} = (x^{(i)}(1), x^{(i)}(2), \ldots, x^{(i)}(n)) \), among them:

\[
x^{(i)}(t) = \sum_{j=1}^{t} x^{(0)}(i), \quad t = 1, 2, \ldots, n
\]

(1)

2.2.2. Fitting of differential equation. The first order differential equation of GM (1,1) is as follows:
\[ \frac{dx}{dt} + ax = b \]  

(2)

\[ \frac{dx}{dt} \]

represents the rate of change of variable \( x \), and \( a \) and \( b \) are parameters.

The differential equation is fitted by a series of numbers generated by one-time accumulation, that is:

\[ \frac{dx^{(i)}}{dt} + ax^{(i)} = b \]  

(3)

Since formula (3) contains only one variable \( x \), \( a \) and \( b \) are parameters to be determined. Therefore, it is supposed that:

\[ \hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} \]  

(4)

In the formula, \( \hat{a} \) is the parameter vector to be determined.

Since both \( a \) and \( b \) are parameters to be determined, formula (3) can be expressed by a linear combination of \( \frac{dx^{(i)}}{dt} \) and background \( \beta \), that is:

\[ \alpha^{(i)}[x^{(i)}(t+1)] + a\beta^{(i)}(t+1) = b \]  

(5)

In the formula:

\[ \alpha^{(i)}[x^{(i)}(t+1)] = x^{(0)}(t+1) \]  

(6)

\[ \beta^{(i)}(t+1) = \frac{1}{2}[x^{(i)}(t) + x^{(i)}(t+1)] \]  

(7)

So, according to the formulas (5), (6) and (7), the following conclusions can be obtained:

When \( t = 1 \), \( x^{(0)}(2) = a\left(-\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] \right) + b ; \)

When \( t = 2 \), \( x^{(0)}(3) = a\left(-\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] \right) + b ; \)

\vdots

When \( t = n \), \( x^{(0)}(n) = a\left(-\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)] \right) + b ; \)

Introduce the following symbols:

\[ X_0 = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \quad X = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] \\ \vdots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)] \end{bmatrix}, \quad E = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \]

There are:
\[ X_0 = a\beta + bE = \begin{bmatrix} \beta \\ E \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \beta \\ E \end{bmatrix} \hat{a} \]  

where \( B = \begin{bmatrix} \beta \\ E \end{bmatrix} \), that is:

\[
B = \begin{bmatrix}
-\frac{1}{2}x^{(1)}(1) + x^{(1)}(2) \\
-\frac{1}{2}x^{(1)}(2) + x^{(1)}(3) \\
\vdots \\
-\frac{1}{2}x^{(1)}(n-1) + x^{(1)}(n)
\end{bmatrix} 
\]

The there is \( X_0 = B\hat{a} \), according to the least square method, we get:

\[
\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T X_0 
\]  

In the formula, \( B^T \) is the transformation matrix of matrix \( B \).

### 2.2.3. The determination of prediction equation

Solve the first-order differential equation fitted above, and the corresponding time response function is obtained as follows:

\[
\hat{x}^{(1)}(t + 1) = (x^{(0)}(1) - \frac{b}{a})e^{-at} + \frac{b}{a}, \quad t = 1, 2, \ldots, n 
\]  

Among them, the parameter \( b \) is grey action, determined by the original data, reflecting the data change rule. \(-a\) is the development coefficient, reflecting the development trend of \( \hat{x}^{(1)} \) and \( \hat{x}^{(1)} \).

By deriving and restoring the above time response functions, the GM (1,1) model prediction equation is obtained as follows:

\[
\hat{x}^{(0)}(t + 1) = -a \begin{bmatrix} x^{(0)}(1) - \frac{b}{a} \end{bmatrix} e^{-at}, \quad t = 1, 2, \ldots, n 
\]  

### 2.2.4. The determination of residual sequence

The accuracy of GM (1,1) model is checked. If it does not meet the requirements, the established model can be modified by residual sequence to improve its prediction accuracy. According to the prediction equation of GM (1,1) model, the residual sequence is obtained as follows:

\[
r(t) = x^{(0)}(t) - \hat{x}^{(0)}(t), \quad t = 1, 2, \ldots, n 
\]  

In it, \( x^{(0)}(t) \) is the actual demand of the original data, \( \hat{x}^{(0)}(t) \) is the predictive value of \( x^{(0)}(t) \).

### 3. Residual correction of GM (1,1) model based on BP neural network

#### 3.1. The BP neural network

3.1.1. The structure of BP network. Multi-level feedforward neural network based on BP algorithm (abbreviated as BP network) is currently the most widely used neural network in the world. In theory, it can map any complex non-linear relationship. Its structure is simple and its application is strong, so it can be used to predict complex non-linear systems [6]. The composition of the BP network generally includes input layer, hidden layer and output layer, the structure is shown in Figure 1. In the BP neural network, input vector \( X \) has \( n \) elements, \( X = (x_1, x_2, \ldots, x_n)^T \), if \( x_0 \) is added, a threshold can be introduced for hidden layer neurons. The output vector of the hidden layer is
\( Y, Y = (y_1, y_2, \cdots, y_j, \cdots, y_m)^T \), if \( y_0 \) is added, a threshold can be introduced for the output layer neurons. The input vector of output layer is \( Z, Z = (z_1, z_2, \cdots, z_k, \cdots, z_l)^T \). The weight matrix between the input layer and the hidden layer is represented by \( V, V = (v_1, v_2, \cdots, v_j, \cdots, v_n)^T \), where \( v_j \) is the corresponding weight vector of the \( j \) neuron in the hidden layer; The weight matrix between the hidden layer and the input layer is represented by \( W, W = (w_1, w_2, \cdots, w_k, \cdots, w_l)^T \), where \( w_k \) is the corresponding weight vector of the \( k \) neuron in the output layer.

![Figure 1. BP network with hidden layer.](image)

Mathematical relationships among the layers are as follows:

For the output layer, there are:

\[
z_k = f(u_k) = f\left(\sum_{j=0}^{m} w_{jk} y_j\right), \quad (k = 1, 2, \cdots, l) \quad (13)
\]

For the hidden layer, there are:

\[
y_j = f(u_j) = f\left(\sum_{i=0}^{n} v_{ij} x_i\right), \quad (j = 1, 2, \cdots, m) \quad (14)
\]

In the formula, all transfer functions \( f(x) \) adopt Sigmoid functions:

\[
f(x) = \frac{1}{1 + e^{-x}} \quad (15)
\]

3.1.2. The learning process of BP network. The learning process of BP network can be divided into two phases:

First, the forward propagation phase of a signal: When forward propagation occurs, input samples are transferred from the input layer to the output layer after being processed layer by layer by the hidden layer. If the actual output and desired output of output layer is not consistent, it will be transferred to the back propagation phase of the error.

Second, the back propagation of the error: error back propagation is that the output error is retransmitted to the input layer layer by layer in some form through the hidden layer, and the error is allocated to all the units in each layer, so as to obtain the error signal of each layer unit, which is the
basis for correcting the weight of each unit [7].

The process of constant weight adjustment is the learning and training process of the neural network, which is carried out until the output error of the neural network is reduced to an acceptable level, or until the pre-set learning times.

The algorithm of BP network adopts $\sigma$ learning rule, which is often called error gradient descent algorithm. The process of learning is to compare the actual output with the expected output value, in which the connection weight and threshold are modified by the error value of the actual output and the corresponding expected output, so that the two are as close as possible until the required accuracy is achieved [8]. The specific algorithm flow is shown in Figure 2.

3.2. Construction of GM (1,1) -BP combination model

The key of GM (1,1) model is to accumulate and generate the original data series, so as to reduce the error caused by the randomness of the original data. On this basis, a first-order differential equation is obtained, and then the prediction equation is determined by solving and restoring the equation. However, due to the complexity of the factors affecting the demand for vehicle turnaround equipment, the corresponding distribution law can not be expressed by a certain distribution, which has strong discreteness and non-linearity. Therefore, using GM (1,1) model alone can only predict the linear characteristics of historical data, but can not extract the non-linear characteristics of vehicle turnover equipment demand, so it is difficult to predict accurately. In this paper, a GM (1,1) -BP combined model is proposed. Firstly, GM (1,1) model is used to forecast the demand of vehicle turnaround
equipment. Then the residual of GM (1,1) model in the first step is corrected by BP neural network. This takes into account the non-linear characteristics of the factors affecting the demand of vehicle turnaround equipment as well as the linear characteristics. The residual correction results are combined with the prediction results of the first GM (1,1) model to obtain the forecast value of vehicle turnaround equipment demand of the combined model. The algorithm flow chart of the combined model is shown in Figure 3.

![Algorithm Flow Chart](image)

Figure 3. The algorithm flow chart of the combined model.

According to the prediction equation of the first step GM (1,1) model, the residual sequence of vehicle turnover equipment demand is as follows:  

\[ r(t) = x(t) - \hat{x}(t), t = 1, 2, \ldots, n. \]

In order to facilitate calculation, the residual sequence of demand is normalized [9]. The formula is as follows:

\[ r'(t) = [r(t) - s]/(k - s) \]

Among it:

\[
\begin{align*}
    s &= \left[9r(t)_{\text{min}} - r(t)_{\text{max}}\right]/8 \\
    k &= \left[9r(t)_{\text{max}} - r(t)_{\text{min}}\right]/8
\end{align*}
\]  

In the formula, \( r(t)_{\text{max}} \) and \( r(t)_{\text{min}} \) respectively represent the maximum and minimum values in the demand residual sequence.

The error gradient descent algorithm is used to train the residual output of GM (1,1) model prediction equation. Finally, the simulation function \( \text{sim} \) is used to simulate the BP network. The specific call form is:

\[ z(t) = \text{sim}(\text{net}, r'(t)) \]

In the formula, \( z(t) \) is the network output, \( \text{net} \) is the object of training, \( r'(t) \) is the network input.

Then, the sum of the corrected and adjusted residual by BP neural network and GM (1,1) model predicted values is the final predicted value of vehicle turnover equipment demand:

\[ X'(t) = \hat{x}(t) + z(t) \]

In the formula, \( \hat{x}(t) \) represents the predicted value obtained by GM (1,1) model and \( z(t) \) represents the residual value corrected by BP neural network.

For the vehicle turnover equipment demand forecasting studied in this paper, there is only one residual of each training input and output, that is, the number of neurons \( m \) and \( n \) in the input and output layers are both 1. The number of neurons in the hidden layer \( l \) can be determined by the following formula [10]:

\[ l = \sqrt{m + n + q} \]
In the formula, \( q \) takes \([0,10]\) as a constant, and the calculation accuracy and times will increase as the value of \( q \) increases.

4. Reliability test of GM (1,1) -BP combined model

According to the system reliability theory, the reliability of GM (1,1)-BP combined model is tested [11]. The specific methods are as follows:

According to the expression of residuals, the mean of residuals can be obtained as follows:

\[
\bar{z} = \frac{1}{n} \sum_{i=1}^{n} z(t) / n
\]

(21)

Then, the variance of the residual is:

\[
S_1^2 = \frac{1}{n} \sum_{i=1}^{n} [z(t) - \bar{z}]^2
\]

(22)

The variance of the original data is as follows:

\[
S_2^2 = \frac{1}{n} \sum_{i=1}^{n} [x^{(0)}(t) - \frac{1}{n} \sum_{i=1}^{n} x^{(0)}(t)]^2
\]

(23)

The standard deviation ratio is:

\[
C = \frac{S_1}{S_2}
\]

(24)

The small error probability of the combined model is:

\[
P = P \{ |z(t) - \bar{z}| < 0.6745S_1 \}
\]

(25)

According to the size of \( P \) and \( C \), the reliability level of the combined model is determined [12].

The specific relationship is shown in Table 1.

| Table 1. Relation of \( P \), \( C \) values and reliability level. |
|---------------------------------------------------------------|
| **Level of reliability** | **Good** | **Qualification** | **Reluctance** | **Disqualification** |
|--------------------------|----------|------------------|----------------|---------------------|
| \( P \)                  | >0.95    | >0.8             | >0.7           | \( \leq 0.7 \)      |
| \( C \)                  | <0.35    | <0.45            | <0.65          | \( \geq 0.65 \)     |

5. Case verification

This paper combines the field investigation and data collection of the equipment warehouse directly under XX theatre, takes the wiper of the unit's main transport vehicle XXX as the research object, collects the demand data of the 9 years since XXXX when it was equipped with mounted troops, and takes it as the data sample.

Firstly, GM (1,1) model is used to forecast the demand. The actual demand from the 10th to 14th years is compared with the forecast value. The concrete results are shown in Figure 4.
Figure 4. Comparison of actual and predicted demand of wiper for XXX transport vehicle.

From Figure 4, we can see that the demand sample is more discrete, and the demand for wipers of this model is more stochastic and volatile. The data predicted by GM (1,1) model alone show a linear law generally, which deviates greatly from the actual demand. Then, the residual sequence of GM (1,1) model prediction is modified by BP neural network, and the final prediction result of GM (1,1) - BP combined model is obtained by accumulating with the preliminary prediction value, as shown in Figure 5.

Figure 5. Comparison of actual and predicted demand of revised wiper for XXX transport vehicle.

Compare the residual sequence predicted by GM (1, 1) model with that revised by the BP neural network, as shown in Figure 6. It can be directly reflected from the figure that, through the correction of BP neural network, the prediction error is reduced and the prediction accuracy is improved. Therefore, the prediction effect of GM (1,1)-BP combined model is better than that of single GM (1,1) prediction model, which can effectively improve the prediction accuracy of vehicle turnover equipment demand.
According to the reliability theory in chapter 3, the reliability of GM (1,1)-BP combined model is tested and analyzed, and the specific results are shown in Table 2.

Table 2. The reliability test results.

| Varieties of equipment | Mean value of error | P  | C  | Level of reliability |
|------------------------|---------------------|----|----|----------------------|
| Wiper                  | 1.93                | 0.86 | 0.08 | Good                |

6. Conclusion

By constructing GM (1,1)-BP combined model, the residual sequence of GM (1,1) model prediction results is corrected by using the nonlinear dynamic characteristics and strong robustness of BP neural network, which effectively avoids the defects of single prediction model. This not only takes into account the non-linear characteristics of the influencing factors of vehicle turnover equipment demand, but also takes into account the linear characteristics, so that the demand forecasting of vehicle turnover equipment has reached a high accuracy, which provides a certain reference for the demand forecasting of military vehicle turnover equipment.

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