Application research of grey prediction model in rocket launcher fault prediction

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Abstract. This paper puts forward the importance of artillery equipment failure prediction, introduces the basic principles of grey prediction modeling, and finds the traditional GM (grey model) (1,1) deficiency. Aiming at this deficiency, the GM(1,1) model is improved based on residual correction and adaptive learning. The fault prediction of a rocket launcher automatic leveling system is taken as an application example, and the grey prediction GM(1,1) is compared and analyzed. Basic model and improved prediction of GM(1,1) model. The analysis shows that the improved GM(1, 1) grey prediction method improves the prediction accuracy and achieves a faster convergence speed, which indicates that the model is feasible and effective, and can provide an effective technical basis for the rocket gun automatic leveling system fault prediction.

1. Introduction
With the application of a many high and new technologies in artillery equipment, the degree of integration, digitization and intelligence has continued to increase. However, due to various factors such as maintenance methods and capabilities, its maintenance work is still mainly based on the passive maintenance mode of the artillery system failure. With the further improvement of the safety and reliability requirements of artillery equipment, it is necessary to take a scientific method before the system shows signs of failure, accurately predict the failures that may occur in a short period of time, and give a treatment method for possible failures or how to prevent the occurrence of these failures to ensure that the system is always in a good technical state during the execution of combat missions. This prediction of the "health" state of the system changes the traditional passive maintenance mode to the active maintenance mode, which can predict the health status and failure risk of the artillery equipment system in advance, thereby reducing the failure rate of the equipment system and improving the reliability of the artillery equipment And maintainability, reducing the full life cost of artillery equipment. However, due to the fast equipment update speed, the system is more complex, historical data is lacking, there are fewer data samples that can be used for fault prediction, and the available feature parameters are limited. Traditional time series prediction methods, regression analysis prediction methods, mathematical model prediction methods, etc. exist certain disadvantages [1].

Grey system theory is based on the characteristics and performance of the system with little data and poor information. It can find rules from cluttered, limited, and discrete data, build a grey system model, effectively solve conventional system predictions, and have simple operations and high accuracy easy to test. Therefore, the grey theory can be applied to the fault prediction of artillery
equipment, and the grey model is established through limited data to highlight the regularity of the grey amount [2-3], thereby predicting the state of the artillery system.

In this paper, the rocket launcher automatic leveling system is regarded as a grey system. By establishing a grey prediction model and improving prediction methods based on residual correction and adaptive learning, the state of the rocket launcher automatic leveling system is predicted.

2. Grey prediction model

2.1. Grey prediction principle

Grey theory is a new method to study the problem of less data and information uncertainty. It was proposed by Professor Deng Julong of Huazhong University of Science and Technology (now Huazhong University of Science and Technology) in 1982 [1-3]. It takes “small samples” and “poor information” uncertain systems with known and unknown information as research objects. It generates and develops some known information and advances valuable information in order to achieve system operation behavior, correct description and effective monitoring of evolution laws. The core idea is to treat any random process as a grey process that changes in a certain space-time area. All random variables are regarded as grey variables, and the data is processed through generative transformation. Data for research. The grey theory emphasizes that by studying the known information of the irregular system, extracting and digging valuable information, and then using the known information to reveal the unknown information, so that the system is constantly “whitening”.

The grey prediction is to establish a grey differential equation according to the law of system development, and solve the differential equation coefficients through data sample fitting, thereby establishing a grey prediction model, which effectively solves problems that are not easily solved by conventional prediction methods. In fact, the grey prediction model is generally used for short-term failure prediction. It can also get better prediction results when there are few sample data [4-5].

2.2. Grey GM (1,1) model

The model built in the grey system is called the grey model. The model builds a differential equation based on a sequence of raw data. There are many forms of grey prediction models. Among them, the most widely used and most representative is the GM (1,1) prediction model for time series modeling, which is especially suitable for the prediction of dynamic systems [6]. This model is based on the non-negative initial data sequence of the dynamic system. After the exchange between the difference equation and the differential equation, the discrete data sequence is used to establish a continuous dynamic differential equation. Give more accurate predictions of the development of the data.

Record the original sequence as

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\}$$

(1)

The superscript represents the number of accumulations, then the first-order accumulation generation sequence is

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)\}$$

(2)

among them

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1, 2, \ldots, n$$

(3)

Then the grey differential equation is

$$x^{(0)}(k) + az^{(1)}(k) = b$$

(4)

The whitening equation of equation (4) is the whitened GM (1,1) model:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b$$

(5)
Among them: a is the development coefficient; b is the amount of grey effect, and \(x^{(1)}\) is the background value generated by the original mean \(x^{(0)}\) next to the mean.

\[
x^{(0)}(k + 1) = 0.5x^{(0)}(k) + 0.5x^{(0)}(k - 1), \quad k = 2, 3 \cdots n
\]

(6)

According to the least square method, solve the development coefficient \(a\) and the ash interaction amount \(b\):

\[
[a, b]' = (B'B)^{-1}B'Y
\]

(7)

\[
B = \begin{bmatrix}
-Z^{(1)}(2) & 1 \\
-Z^{(1)}(3) & 1 \\
\vdots & \vdots \\
-Z^{(1)}(10) & 1
\end{bmatrix}, \quad Y = \begin{bmatrix}
x^{(0)}(2) \\
x^{(0)}(3) \\
\vdots \\
x^{(0)}(10)
\end{bmatrix}
\]

(8)

The solution of the whitening equation (5) is also called the periodic response function, and the expression is

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

(9)

The solution of the whitening equation (4) is

\[
\hat{x}^{(0)}(k + 1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-at} + \frac{b}{a}, \quad k = 1, 2, 3 \cdots n
\]

(10)

Inversely accumulate the reduction sequence to get the model fitted value or predicted value

\[
\hat{x}^{(0)}(k + 1) = \hat{x}^{(0)}(k + 1)\hat{x}^{(0)}(k), \quad k = 1, 2, 3 \cdots n
\]

(11)

3. Improvement of grey GM (1, 1) model

3.1. Deficiencies of the traditional GM (1, 1) model

In the grey prediction, the solution of the differential equation of the grey model will directly affect the final prediction accuracy. The traditional grey model only uses the initial value of the actual sample as the initial condition when solving the parameters \(a\) and \(b\), and uses the least square method to directly solve. Because the relationship between the initial value and the predicted value of the actual sample is uncertain, it is too one-sided to use this value as the initial condition, and there are many factors affecting the system, so that its calculation results cannot reflect the changing trend of future values. In addition, the background value of the GM (1,1) model in the basic principles of grey modeling is constructed using the immediate mean value. When the development coefficient \(a\) is small, that is, the sequence changes slowly, the prediction accuracy is high; but when the development coefficient \(a\) increases to a certain level, after this value, satisfactory prediction results cannot be achieved.

In view of this, an improved Euler algorithm is introduced to solve the GM (1,1) model, that is, iterative method is used when solving differential equations, and iteration is performed according to the results of the previous step, instead of just referring to the initial sample value. For each iteration, a trapezoidal formula is used to correct the calculated value. At the same time, an equal-dimensional innovation GM (1,1) model with self-updating function and residual correction method are applied to improve prediction accuracy.

3.2. Isodimensional innovation GM (1, 1) model

The accuracy of grey predictions is based on reliable historical data. The points closer to the origin data are more affected by historical data, the change trend is more consistent, and the prediction accuracy is higher; For points farther away from the origin data, new random factors will appear over time, which will cause large deviations in predicted values. Therefore, in the process of establishing a prediction model, new information entering the system is placed into \(x^{(0)}\) at any time, and old information is deleted at the same time, and the prediction accuracy is guaranteed through the metabolic process. The GM (1,1) model based on equal dimension and new information improves the
prediction accuracy by continuously updating the data while maintaining the model dimension unchanged.

3.3. Improved GM (1,1) model
In order to improve the prediction accuracy of the GM (1,1) model, in addition to improving the Euler algorithm, an isodimensional innovation forecast is applied, and the residuals of the original and real data are used to modify the GM (1,1) prediction model. According to the traditional After the GM (1,1) method is used to obtain the predicted sequence, the residual sequence can be obtained by operating with the real value:

\[ q^{(0)} = \{ q^{(0)}(1), q^{(0)}(2), q^{(0)}(3), \ldots, q^{(0)}(n) \} \]  

(12)

Positively sequence the residuals:

\[ q^{(0)} = \text{abs} \left\{ \min \{ q^{(0)}(1), q^{(0)}(2), q^{(0)}(3), \ldots, q^{(0)}(n) \} \right\} + \left\{ q^{(0)}(1), q^{(0)}(2), q^{(0)}(3), \ldots, q^{(0)}(n) \right\} + \gamma \]

(13)

P is a normal number, and the residual sequence is converted into a positive sequence by the above formula. Establish a GM (1,1) model for the grey residual sequence, and get the prediction sequence:

\[ \hat{q}^{(0)}(k+1) = (1-e^{-h}) \left[ q^{(0)}(1) - \frac{b}{a_e} \right] + \left( 1-e^{-h} \right) \left[ q^{(0)}(1) - \frac{b}{a_e} \right] e^{-\gamma k}, \quad k = 1, 2, 3, \ldots \]

(14)

In the equation, \( a_e \) and \( b_e \) are the GM (1,1) parameters of the residual sequence. The modified model prediction algorithm:

\[ \hat{x}^{(0)}(k+1) = (1-e^{-h}) \left[ x^{(0)}(1) - \frac{b}{a_e} \right] e^{-(k-1)} + \left( 1-e^{-h} \right) \left[ x^{(0)}(1) - \frac{b}{a_e} \right] e^{-\gamma k}, \quad k = 2, 3, \ldots \]

(15)

4. Grey forecast application case analysis
For rocket launchers, the automatic leveling system is an important guarantee for the execution of combat missions. As the working time accumulates, the automatic leveling system will experience performance degradation or malfunction, which will affect the combat performance of the rocket launcher equipment. In order to improve the reliability and maintainability of the automatic leveling system, not only regular inspections are required, but also the failure prediction of the automatic leveling system is required. The research shows that the number of iterations required by the automatic leveling system in its leveling control process can reflect the system's fault trend, and its law conforms to the exponential distribution. Therefore, this section uses grey theory to perform the number of iterations of the automatic leveling control process of the rocket launcher system prediction.

4.1. Data sampling
Through the internal data logger of a certain rocket launcher, 12 sets of measurement data are obtained, as shown in table 1. The first 10 sets of data are used as the original data to establish the basic prediction model, and the latter 2 sets of data are used to test the improved grey model prediction effect. The GM (1,1) basic model and the improved GM (1,1) model were used to predict the original data.

4.2. Establishment of grey forecasting model and implementation in MATLAB
For the rocket artillery automatic leveling system, the GM (1,1) basic model and the improved GM (1,1) model are used to predict the obtained raw data. The prediction steps are as follows: first perform the GM (1,1) basic model prediction on the original sequence \( \{5,6,8,7,9,11,14,17,20,25,28,34\} \). The results are shown in table 2. The prediction results in table 2 are subjected to difference processing with the original data to obtain the residual sequence \( \{0.8533, 0.4568, 0.3877, 0.2871, 0.4872, 0.1156, 1.0556\} \) for the new GM (1,1) basic model prediction. For the final prediction results, see table 3 shows the process shown in figure 1.
Table 1. Leveling times measurement data.

| Detection time | t | 2t | 3t | 4t | 5t | 6t | 7t | 8t | 9t | 10t | 11t | 12t |
|----------------|---|----|----|----|----|----|----|----|----|-----|-----|-----|
| Leveling times | 5 | 6  | 8  | 7  | 9  | 11 | 14 | 17 | 20 | 25  | 28  | 34  |

Table 2. Leveling times data sheet.

| k  | actual value | $x^{(0)}$ | $x^{(1)}$ | $z^{(1)}$ | $\hat{x}^{(1)}(k)$ | $\hat{x}^{(0)}(k)$ | $\hat{x}^{(o)}(k)$ | $E^{(0)}$ | q(0) |
|----|--------------|------------|------------|-----------|-------------------|-------------------|-------------------|--------|------|
| 1  | 5            | 5          | 5          |           |                   |                   |                   |        |      |
| 2  | 6            | 6          | 11         | 8         | 51.7188           |                   |                   |        |      |
| 3  | 8            | 8          | 19         | 15        | 58.1544           | 6.4356            |                   |        |      |
| 4  | 7            | 7          | 26         | 22.5      | 65.9250           | 7.7706            | 7.8533            | 0.8533 |      |
| 5  | 9            | 9          | 35         | 30.5      | 75.3075           | 9.3825            | 9.4568            | 0.4568 |      |
| 6  | 11           | 11         | 46         | 40.5      | 86.6362           | 11.3287           | 11.3877           | 0.3877 |      |
| 7  | 14           | 14         | 60         | 53        | 100.3150          | 13.6788           | 13.7129           | 0.2871 |      |
| 8  | 17           | 17         | 77         | 68.5      | 116.8313          | 16.5163           | 16.5128           | 0.4872 |      |
| 9  | 20           | 20         | 97         | 87        | 136.7736          | 19.9423           | 19.8844           | 0.1156 |      |
| 10 | 25           | 25         | 122        | 109.5     | 160.8528          | 24.0792           | 23.9444           | 1.0556 |      |
| 11 | 28           | 29.074     | 151.074    | 136.537   | 189.9268          | 29.0740           | 28.8334           | 0.029  |      |
| 12 | 34           | 34.7206    | 185.7946   | 161.1658  | 34.7206           | 34.7206           |                   |        |      |

Prediction parameter: $a=-0.1858$, $b=3.999311t$ forecast: 28.8334t forecast: 34.7206

Table 3. Forecast result data comparison table.

| k  | Actual value | Predictive value | Accuracy | Predictive value | Accuracy |
|----|--------------|------------------|----------|------------------|----------|
| 11 | 28           | 28.8334          | 0.029    | 28.4124          | 0.014    |
| 12 | 34           | 34.7206          | 0.021    | 34.3846          | 0.011    |

4.3. Analysis of prediction results

As can be seen from table 2, the prediction result of the conventional GM (1,1) model is that the predicted value of the leveling times at 11t is 28.8334, and the predicted value of the leveling times at 12t is 34.7206. The prediction result of the improved GM (1,1) model is that the predicted value of the leveling times at 11t is 28.4124, and the predicted value of the leveling times at 12t is 34.3846. Although the measurement data is limited, the prediction ability of the grey theory is very good. The prediction accuracy of the improved GM (1,1) model is less than 1.5%, which is much higher than that of the traditional GM (1,1) model. It is very suitable for forecasting the fault trend of artillery equipment.
5. Conclusion
In this paper, the importance of artillery equipment fault prediction is introduced, the basic principles of grey prediction modeling are introduced, and the traditional grey GM (1, 1) model is found to be insufficient. In view of this deficiency, the GM (1, 1) model is improved based on residual correction and adaptive learning. Taking the fault prediction of a certain rocket launcher auto-leveling system as an application example, the grey prediction GM (1, 1) is compared and analyzed. The prediction effect of the basic model and the improved GM (1, 1) model. The analysis shows that the improved GM (1, 1) grey prediction method improves the prediction accuracy and achieves a fast convergence speed, which shows that the model is feasible and effective, and can provide an effective technical basis for the fault prediction of the rocket launcher automatic leveling system.

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