Prediction Technology of Payment Terminal State Based on Grey Model

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Abstract. This article analyzes the characteristics of power payment terminal operation. Grey model theory is used to predict the change trend and specific values of the multi-dimensional status information of the equipment. Firstly, the correlation analysis method is used to extract the core data with lower correlation degree from the massive state data. Secondly, the development trend of the data is predicted by the gray prediction model. Finally, the effectiveness of the gray model is verified by actual field data.

1. Introduction
With the continuous development of sensor technology and data transmission technology, condition-based maintenance strategies based on equipment condition monitoring have begun to become possible. In order to reduce the loss, extend the normal working time of the equipment, and realize the trouble-free operation of the equipment, it is necessary to estimate the remaining normal working time of the equipment in combination with the equipment status data and select the optimal equipment maintenance time. The early warning technology of equipment failure is a comprehensive technology that integrates machinery, computer, automation, communication, control and other disciplines. Its core lies in accurate prediction and evaluation of equipment operating status, and provides timely and accurate data support for equipment maintenance personnel.

According to statistical rules, equipment failures can be divided into two categories, namely, gradual failures and occasional failures. Occasional failure can occur at any period in the equipment life cycle, and the timing of occurrence is basically irregular, and it is difficult to predict in advance [1-3]. Gradual failures mainly occur during the expiration period of consumption loss, caused by equipment aging, wear, etc.

Before a gradual failure occurs, there are usually more obvious signs that accompany it, such as increased vibration, noise, abnormal temperature, and electromagnetic indicators outside the normal fluctuation range. It is easier to capture with a suitable sensor. Grasp the signal characteristics of the equipment and predict possible failures in advance, which is helpful for equipment maintenance personnel to make a suitable maintenance plan.

2. Grey Theory
In the objective world, people often divide the factors into different systems through the mutual restriction and interrelationship of factors. The information grasped in the system is distinguished by the shade of color. If the meaning of each factor in the system is clear. The interrelationship between the factors is clear. It shows that the system hierarchy is clear, and the system functions are well understood. Then the above system is called the white system. Conversely, if the system information is
completely unknown, it is called a black system. The gray system is a system between the above two systems. It has both some known information and some unknown information [4-6]. The structure and function of the system are not completely known as systems with incomplete information. Incomplete information generally refers to: the system factors are not completely clear, the relationship between the factors is not completely clear, the system structure is not completely clear, and the principle of system action is not completely clear.

Due to the diversity of cognitive perspectives, there is almost no white system in real research. Because of the limited cognition ability, people's understanding of the objective world is not deep enough, and the black box system also exists in a large number of natural social life and is not known to people. Therefore, most of the common systems can be regarded as gray systems, which have important meanings to people's production and life.

The theoretical basis of gray system is system theory, and gray system is mainly used as the theoretical research object [7-9]. This theory absorbs the ideological theories and research methods of disciplines such as information science, mathematics, and computer science. Then the grey system theory analyzes, studies and evaluates the system goals. Therefore, it is highly comprehensive and practical.

Next, build a model of the electricity payment terminal.

Among the key components of the payment terminal, the state information, such as equipment temperature, vibration, and stress, is randomly distributed. However, this kind of irregularly distributed information is closely related to the current operating state of the equipment. Therefore, these known irregular information can be converted into regular sequence information, which can meet the gray system modeling conditions.

In this article, the operating status of a payment terminal can be regarded as a gray system. Collect known information such as temperature and vibration through various measuring instruments such as sensors. Then the acquired measurement information is analyzed. This information is used to understand the current and future operating status of the equipment, and to guide the maintenance of the equipment and subsequent maintenance.

For the equipment in normal operation, its gray characteristics are mainly manifested in:

1. The parameters affecting equipment failure are not clear.
2. The relationship between the various parameters of equipment operation and the relationship between parameters and faults is not clear.
3. The quantitative relationship between operating parameters and failure categories is not clear.
4. The cause of the fluctuation of each parameter and how the failure occurred are not clear.

The basic form of the gray model is $GM(n, m)$, where $n$ represents the order, $m$ represents the number of variables based on time [7].

Generally, the higher the order selected by the model, the more complicated the meaning of the model established. The model calculation is also difficult, but the prediction accuracy does not increase. $GM(1, m)$ model is suitable for establishing the state model of the system, which can reflect the relationship between the various variables in the model. Therefore, $GM(n, m)$ is usually used as the modeling basis of high-level models. Although the $GM(1, m)$ model reflects the changing law of $x_t$, $x_{t-1}$ at each moment depends on the value of other variables at this moment. If the predicted value of other variables other than $x_t$ is not output, the predicted value of $x_t$ cannot be obtained. But when $N = 1$, that is, $GM(1, 1)$ does not have this phenomenon. In order to ensure the rapid response and accuracy of the equipment failure prediction model mentioned in this article, the chosen gray model is $GM(1, 1)$. The modeling and solving process is as follows.

Sort the original data in the order of formation time to form the original sequence $X^{(0)}$.

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}.$$  \hfill (1)

Accumulating the original sequence, we get
\[ x^{(i)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, 3, \ldots, n \]  
(2)

\( x^{(i)} \) is the 1-AGO sequence of \( x^{(0)} \).

\[ x^{(0)} + ax^{(i)}(k) = b \]  
(3)

is the original form of \( GM(1, 1) \).

\[ x^{(0)}(k) + az^{(i)}(k) = b \]  
(4)

is the basic form of \( GM(1, 1) \).

where \( z^{(0)}(k) = \frac{1}{2}(x^{(0)}(k) + x^{(0)}(k-1)), k = 2, 3, \ldots, n \).

After deduction, the time response sequence of (4) is

\[ x^{(0)}(k+1) = \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a}, k = 1, 2, \ldots, n . \]  
(5)

The predicted value is

\[ \hat{x}^{(0)}(k+1) = \hat{x}^{(0)}(k+1) - \hat{z}^{(0)}(k) = \left( 1 - e^{-a} \right) \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-ak}, k = 1, 2, \ldots, n . \]  
(6)

The parameter \(-a\) becomes the development coefficient of the gray model, reflecting the development trend of \( \hat{x}^{(0)} \) and \( \hat{z}^{(0)} \). The parameter \( b \) is called the gray action amount. The gray effect in the \( GM(1, 1) \) model is the data mined from the output sequence, which reflects the relationship between data changes.

3. \( GM(1, 1) \) Accuracy

After the model is built, the accuracy of the model should be tested by appropriate methods to determine whether the model is consistent with the actual situation.

Suppose the original data at the \( k \)-th moment is \( x^{(0)}(k) \), and the predicted value after modeling is \( \hat{x}^{(0)}(k) \), then the residual value at the \( k \)-th moment is

\[ q(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) . \]  
(7)

The relative residual value is

\[ \epsilon(k) = q(k)/x^{(0)}(k) . \]  
(8)

In practical application, different permissible relative error values can be determined according to the actual requirements.

Correlation test is the test quantity to judge the degree of correlation between the predicted series and the actual series, which reflects the degree of trend coincidence between the two. When calculating the degree of relevance, mathematical methods must be used to standardize the new series and the original series. The correlation calculation process is as follows. The calculated correlation degree generally needs to be greater than 0.6 to meet the requirements.

1) Calculate the correlation coefficient of the sequence

\[ \xi_i(k) = \gamma \left( x^{(i)}(k), \hat{x}^{(i)}(k) \right) = \min_{\|a, m\|} \max_{\|s, \gamma\|} \left| x_0(k) - x_i(k) \right| + \xi \cdot \max_{\|s, \gamma\|} \max_{\|s, \gamma\|} \left| x_0(k) - x_i(k) \right| . \]  
(9)

where \( \xi = 0.5 \).

2) Calculate correlation degree

\[ \gamma = \frac{1}{n} \sum_{i=1}^{n} \xi_i(k) . \]  
(10)

The content of the posterior error test is based on the size of the residual \( |q(k)| \) to examine the probability of the point with the smaller residual (prediction error) and the size of the indicators related to the residual variance.
where \( n \) is the number of data in the original data column, and the average value of the original data \( X^{(0)} \) is \( x(\text{mean}) \).

\[
x(\text{mean}) = \frac{1}{n} \sum_{k=1}^{n} x^{(0)}(k),
\]

(11)

where \( n-1 \) is the number of data in the residual sequence, and the average value of the residual sequence \( q(k) \) is \( q(\text{mean}) \).

\[
q(\text{mean}) = \frac{1}{n-1} \sum_{k=2}^{n} q(k),
\]

(12)

where the variance of the original data column \( X^{(0)}(k) \) is \( S_i^2 \).

\[
S_i^2 = \frac{1}{n} \sum_{k=1}^{n} [x^{(0)}(k) - x(\text{mean})]^2,
\]

(13)

where the variance of the residual sequence \( q(k) \) is \( S_q^2 \).

\[
S_q^2 = \frac{1}{n-1} \sum_{k=2}^{n} [q(k) - q(\text{mean})]^2,
\]

(14)

where the posterior difference ratio is \( C \).

\[
C = \frac{S_q^2}{S_i^2},
\]

(15)

where the small error frequency is \( P \).

\[
P = P\left\{ |q(k) - q(\text{mean})| < 0.6745S_i \right\},
\]

(16)

The accuracy of the grey model was evaluated by combining the values of \( P \) and \( C \), as shown in Table 1.

| Model accuracy level | \( P \) | \( C \) |
|----------------------|-------|-------|
| Good                | > 0.95 | < 0.3 |
| Qualified           | > 0.81 | < 0.55|
| Poor                | < 0.71 | > 0.65|

Compared with common statistic evaluation indicators, the gray model test adopts relatively vague standards, such as good, qualified, bad, to measure the pros and cons of the model. Such an evaluation system does not involve the influence of certain specific statistical distribution assumptions used in the model. It determines the degree of influence between the child factor and the parent factor in terms of data relevance. It does not give an absolute acceptance or rejection conclusion, which is more suitable for practical applications. Although the grey model includes consideration of the discreteness of the original data and the discreteness of the residual series, it also considers the fit of small probability events. However, this degree of integration is also limited. Even if a comprehensive evaluation method is used to evaluate the pros and cons of model performance, it is difficult to fully reflect the objective reality.

4. The Operating State of Payment Terminal is Predicted Based on Grey Model

This article applies the aforementioned data processing and modeling methods. The operating state of the core components inside a certain group of power payment terminals is selected for data prediction. After correlation analysis, the index data after screening is shown in Table 2.

| Payment Terminal | Indicators | Unit | 9:00 | 10:00 | 11:00 | 12:00 |
|------------------|------------|------|------|-------|-------|-------|
| Terminal 1       | Amplitude  | mm   | 3.5  | 2.9   | 3.6   | 3.4   |
|                  | Temperature| ℃    | 38.2 | 37.5  | 36.3  | 35.8  |
| Terminal 2       | Amplitude  | mm   | 3.1  | 3.2   | 2.6   | 3.0   |
|                  | Temperature| ℃    | 36.3 | 35.9  | 36.9  | 38.7  |
| Terminal 3       | Amplitude  | mm   | 3.8  | 3.6   | 3.2   | 3.1   |
|                  | Temperature| ℃    | 35.6 | 38.6  | 39.2  | 39.1  |
The state data at each time point is input into the model as the original training data of the gray model. Predict the state at the next moment. The collected actual values and predicted values of equipment operating status are summarized in the same table for analysis as shown in Table 3.

### Table 3. The prediction results of payment terminal

| Payment Terminal | Indicators | 13:00 | 14:00 | 15:00 | 16:00 | \( P \) | \( C \) |
|------------------|------------|-------|-------|-------|-------|-------|-------|
| **Amplitude**    |            |       |       |       |       |       |       |
| Terminal 1       |            |       |       |       |       |       |       |
| Predictive value | 3.6        | 2.7   | 2.8   | 2.6   | 0.36982 | 1     |
| Actual value     | 3.4        | 2.8   | 2.6   | 3.5   |         |       |
| Residual value   | 0.2        | -0.1  | 0.2   | 0.1   |         |       |
| **Temperature**  |            |       |       |       |       |       |       |
| Predictive value | 36.5       | 38.2  | 37.3  | 35.4  | 0.43928 | 1     |
| Actual value     | 36.4       | 38.2  | 37.1  | 35.5  |         |       |
| Residual value   | 0.1        | 0     | 0.2   | -0.1  |         |       |
| Terminal 2       |            |       |       |       |       |       |       |
| Predictive value | 3.3        | 2.9   | 3.4   | 3.6   | 0.35823 | 1     |
| Actual value     | 3.2        | 3.1   | 3.3   | 3.6   |         |       |
| Residual value   | 0.1        | -0.2  | 0.1   | 0     |         |       |
| **Temperature**  |            |       |       |       |       |       |       |
| Predictive value | 37.5       | 38.1  | 35.8  | 36.9  | 0.27836 | 1     |
| Actual value     | 37.5       | 38.2  | 35.7  | 36.9  |         |       |
| Residual value   | 0          | -0.1  | 0.1   | 0     |         |       |
| Terminal 3       |            |       |       |       |       |       |       |
| Predictive value | 3.4        | 2.6   | 3.0   | 3.3   | 0.53682 | 1     |
| Actual value     | 3.5        | 2.6   | 2.8   | 3.0   |         |       |
| Residual value   | -0.1       | 0     | 0.2   | 0.3   |         |       |
| **Temperature**  |            |       |       |       |       |       |       |
| Predictive value | 38.1       | 38.9  | 36.4  | 39.0  | 0.83643 | 1     |
| Actual value     | 37.9       | 38.6  | 36.4  | 39.2  |         |       |
| Residual value   | 0.2        | 0.3   | 0     | -0.2  |         |       |

From the table, it can be seen that the \( GM(1, 1) \) model has a better predictive effect on the internal components of the payment terminal. The ratio of the posterior difference calculated in each dimension is less than 0.5, and the frequency of small errors is all 1, indicating that the gray model built for the internal components of the payment terminal has better accuracy. The internal operating status of the core components can be estimated, which improves the operating reliability of the equipment.

### 5. Conclusion

This article mainly introduces the dynamic prediction method for the state data of the power payment terminal equipment. First, the correlation analysis method is used to screen and reduce high-dimensional variables, and the core equipment state parameters are extracted from massive data through correlation analysis. Then, the gray system model \( GM(1, 1) \) is used to predict the trend of equipment status data. Finally, we take the actual operating data of the payment terminal as an
example, and use the established $GM(1, 1)$ model to predict the operating data at the next moment. The results show that the established prediction model can accurately predict its operating trend.

Acknowledgements
This paper is supported by “State grid science and technology project (2020YF-49).”

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