A Bearing Life Prediction Method of Improving Smooth Degree and the Background Value

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Abstract. Bearings, as a component in many complex weapons, can be used to reduce friction to improve the efficiency of equipment. Bearing CV value can quantify the working performance of bearings, which can act as a reference standard for staff to evaluate the working condition of bearings. According to the known data, the real CV value of the bearing is calculated in this paper. In order to improve the smoothing ratio, the data is processed by the idea of data transformation and the background value is optimized by the new formula. The two improve the GM (1,1) model and simulate the predicted bearing CV and calculate the moment of failure by this model, which is compared with the traditional GM (1,1) and the improved GM (1,1) by cumulative method in terms of error and accuracy. It is verified that the average relative error and the model prediction accuracy of the model prediction life are 0.0185 and 98.15% respectively after the improvement of the stability and background value. Therefore, this method has certain practical value in engineering, and is more effective than the cumulative GM (1,1) model.

1. Introduction

Bearings are present in most weaponry, for example, the trunnion section of the launcher arm of a missile launcher requires bearings to rotate, and many small and medium sized motors use bearings [1]. One disadvantage, however, is that these bearings often fail, causing damage and eventual failure [2]. Reference 3 takes the rolling bearing as an example. It is mentioned that the defects of the inner and outer rings will make the metal in contact surface flake off and form pits on the bearing surface, and the impact of the rolling body on the racetrack on one or both sides will cause various pollutants such as external viscosity and particles to enter between the rolling body and the racetrack, leading to wear or scratch, etc.[3]. Using the maximum likelihood estimation method, the CV values of the bearings are calculated to quantify their operating conditions, and an algorithm is designed based on the original GM (1,1) method to predict the CV values by reducing the smoothing ratio of the original data series and optimizing the background value calculation method. In addition, in terms of relative error and prediction accuracy, this paper accordingly compares the former with the improved GM (1,1) model based on the cumulative method.

2. Calculation method of bearing's real confidential value

In fact, the CV value, also known as the performance

evaluation index [4], can be seen as a dichotomous probability, so you can generally use the CV (Confidential Value) as a measure of rolling bearing failure. CV value can quantify the rolling bearing failure degree, its value range between 0 and 1, where 0 is the rolling bearing complete failure state, 1 is the best working performance state (where less than or equal to 0.05 is taken to mean that the rolling bearing is no longer capable of operating), then the CV value is expressed as follows [5]:

$$CV = P_i(cv_i = 1 | x_i) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)}} \quad (1)$$

Where, x is the k -dimensional column vector, β_0 is the regression intercept, and β_i is the regression coefficient.

In this paper, bearing data from the University of Cincinnati was chosen to test the accuracy of the performance of three prediction methods[6]. First, the CV is calculated for the entire operating cycle of the rolling bearing, which has 984 moments of sampling for this bearing type, with a 10-min interval between each of the sampling moments, and the rolling bearing CV is then calculated according to the method of maximum likelihood estimation.

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$$\begin{matrix} X_1 & X_2 & \cdots & X_{984} \\ x_{11} & x_{12} & \cdots & x_{1,984} \\ x_{21} & x_{22} & \cdots & x_{2,984} \\ \vdots & \vdots & \ddots & \vdots \\ x_{20480,1} & x_{20480,2} & \cdots & x_{20480,984} \\ \downarrow & \downarrow & \cdots & \downarrow \\ cv_1 & cv_2 & \cdots & cv_{984} \end{matrix} \quad (2)$$

$$\begin{cases} \frac{\partial \ln L}{\partial \beta_0} = 0 \\ \vdots \\ \frac{\partial \ln L}{\partial \beta_{984}} = 0 \end{cases} \quad (4)$$

It can solve out β_0 to β_{984} with formula (4), it means that it can get all the 984 CV values of the whole bearing working cycle, as Fig.1.

$$\ln L = \sum_{i=1}^n [cv_i \ln \frac{e^{\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + L + \beta_{984} x_{i,984}}}{1 + e^{\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + L + \beta_{984} x_{i,984}}} + (1 - cv_i) \ln \frac{1}{e^{\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + L + \beta_{984} x_{i,984}}}] \quad (3)$$

If $\ln L = 0$, we can get:

Figure.1 The real CV value of entire life cycle

3. Prediction method of bearing's real confidential value

So far, the most extensive and direct method to predict the data sequence is to use the grey GM (1,1) model for calculation. The GM (1,1) modified models commonly used include the GM (1,1) model with improved metabolism, GM (1,1) model with optimized combination of intelligent functions, GM (1,1) model with coupled trigonometric function transformation, etc. However, after comparison with the real value, the average relative error of these models is still some way from the ideal value. In view of this, the GM (1,1) model with improved smoothness and optimized background value is compared with the original GM (1,1) model and the GM (1,1) model with improved accumulation method, and the relative error and multiple indexes of prediction accuracy are analyzed.

3.1 Principle of improved GM (1,1) prediction model with cumulative method

When predicting CV values, it adopts the model of GM (1,1) based on cumulative method, the cumulative method is a method of fitting, it combines with the original GM (1,1) model can improve the performance of the prediction model [7].

Calculating the background values,

$$\begin{aligned} \text{and } x^{(1)}(i) &= \sum_{j=1}^i x^{(0)}(j), (i = 2, 3, \dots, n) : \\ z^{(1)}(i) &= \frac{x^{(1)}(i-1) + x^{(1)}(i)}{2} \end{aligned} \quad (5)$$

The equation set consists of first-order operator and second-order operator can solve the prediction parameters a and u :

$$\begin{cases} \sum_{i=2}^n x^{(0)}(i) + a \sum_{i=2}^n z^{(1)}(i) = u(n-1) \\ \sum_{i=2}^n (n-i+1)x^{(0)}(i) + a \sum_{i=2}^n (n-i+1)z^{(1)}(i) = u \frac{n(n-1)}{2} \end{cases} \quad (6)$$

We can get:

$$\begin{cases} a = \frac{\frac{n(n-1)}{2} \sum_{i=2}^n x^{(0)}(i) - (n-1) \sum_{i=2}^n z^{(1)}(i)}{\left| -\frac{n(n-1)}{2} \sum_{i=2}^n z^{(1)}(i) + (n-1) \sum_{i=2}^n z^{(1)}(i) \right|} \\ u = \frac{\sum_{i=2}^n z^{(1)}(i) \sum_{i=2}^n x^{(0)}(i) - \sum_{i=2}^n z^{(1)}(i) \sum_{i=2}^n z^{(1)}(i)}{\left| -\frac{n(n-1)}{2} \sum_{i=2}^n z^{(1)}(i) + (n-1) \sum_{i=2}^n z^{(1)}(i) \right|} \end{cases} \quad (7)$$

Substitute a and u in grey equation of GM (1,1) model, it can get the CV value prediction formula:

$$\hat{x}^{(0)}(i) = \frac{2(2-a)^{i-2}(u - ax^{(0)}(i))}{(a+2)^{i-1}} \quad (8)$$

3.2 The prediction method of bearing life after improving the smoothness and background value

3.2.1 Improvement of smoothness

It can be assumed that there are data sequences, then the ratio between the sum of the KTH data $x(k)$ and the first $k-1$ data in the whole sequence is called the data smoothness ratio [8], which can reflect the smoothness of the change of the whole data sequence, which is

$$\rho(k) = \frac{x(k)}{\sum_{i=1}^{k-1} x(i)} \quad (9)$$

Where, $k = 2, 3, \dots, n$. The smaller the value of $\rho(k)$, the more stable the data sequence.

To reduce the value of $\rho(k)$, this paper proposes an improved data processing method of $\frac{x_i}{(\ln i)^c}$, where $i = 2, 3, \dots, k-1$ and c is a constant greater than 0. The feasibility of the improved method of $\frac{x_i}{(\ln i)^c}$ is proved below.

$$\because i < k$$

$$\therefore \ln i < \ln k$$

$$\therefore \frac{1}{\ln k} < \frac{1}{\ln i}$$

Sum up both sides of the inequality,

$$\begin{aligned} \text{then } \frac{x_k}{(\ln k)^c} \cdot \sum_{i=2}^{k-1} x_i &< x_k \cdot \sum_{i=2}^{k-1} \frac{x_i}{(\ln i)^c} \\ \therefore \frac{x_k}{(\ln k)^c} &< \frac{x_k}{\sum_{i=2}^{k-1} \frac{x_i}{(\ln i)^c}} \end{aligned} \quad (10)$$

Therefore, Equation (18) proves that $\frac{x_i}{(\ln i)^c}$ transformation can optimize the smoothness of the whole data sequence.

3.2.2 Background value optimization

The background value of grey prediction model is one of the important factors that affect the prediction precision [9]. By bearing the CV value of actual change trend is hard to predict, in order to further reduce the error, in the prediction of model bearing CV value using the following formula instead of the general model of the background value.

$$\begin{aligned} Z^{(1)}(k) &= \frac{X^{(0)}(k)}{\ln X^{(0)}(k) - \ln X^{(0)}(k-1)} \\ &- \frac{X^{(0)}(1) - X^{(0)}(k-1)}{X^{(0)}(k) - X^{(0)}(k-1)} \end{aligned} \quad (11)$$

4. Comparison of simulation results of three prediction models

In the first stage (time 1-700), bearing failure data at time 1-20 were used for training. The second stage (701-900 moments) was trained with data from 701-720 moments. And the third stage (901-984 moments) was trained with

data from 901-910 moments.

The accuracy test methods of general gray prediction model include residual error, posterior error or correlation degree, etc. Here, the residual test method is used to compare the relative error, average relative error and model prediction accuracy index between the improved model $\frac{x_i}{(\ln i)^c}$ and the traditional GM (1,1) model and the GM (1,1) model improved by the cumulative method.

Assume the sequence of residuals $E = X^{(0)} - \hat{X}^{(0)}$, then

$$e(i) = x^{(0)}(i) - \hat{x}^{(0)}(i) \quad (12)$$

Then the residual $\varepsilon(i)$ is

$$\varepsilon(i) = \frac{|e(i)|}{x^{(0)}(i)} \times 100\% \quad (13)$$

So, we can get the average relative error at a certain stage

$$\bar{\varepsilon} = \frac{1}{n} \sum_{i=1}^n |\varepsilon(i)| \quad (14)$$

The prediction accuracy P of the model is $P = (1 - \bar{\varepsilon}) \times 100\%$ (15)

Both the i value of traditional GM (1,1) model and the GM (1,1) model improved by the accumulation method start from 1. However, since the denominator of

the GM (1,1) model improved by $\frac{x_i}{(\ln i)^c}$ cannot be 0,

its i value should start from 2.

It can be seen from Figure. 2 that, when CV value is equal to 0.05, the X-axis coordinate (failure time) corresponding to the traditional GM (1,1) model is about 945 time, while the X-axis coordinate corresponding to the GM (1,1) model improved by the accumulation method is about 953 time. The predicted data and residual curves are shown in Figure 2 and Figure 3. The X-axis coordinate corresponding to the GM (1,1) model

after $\frac{x_i}{(\ln i)^c}$ transformation and background value

optimization is about 940 time, while the X-axis coordinate corresponding to the real CV value of 0.05 is about 937 time. As one time is ten minutes, the remaining working time (min) of the bearing can be calculated according to equation (16).

$$s = 10 \times (x|_{CV=0.05} - n_0) \quad (16)$$

Where, $x|_{CV=0.05}$ is the corresponding x-coordinate value when CV value is 0.05, namely the failure time, and n_0 is the known detection time. It can be seen that the average prediction accuracy of the improved model in the whole working cycle of this type of bearing reaches 98.15%, which is significantly higher than that of the other two prediction models and the prediction results of the model with improved stability and background

value are the closest to the reality.

Figure.2 Predicted results of improved, cumulative and the original GM (1,1)

Figure.3 Relative error among improved, cumulative and the original GM (1,1)

5. Conclusion

In this paper, bearing failure data from the university of Cincinnati, USA were used to test the accuracy of the new prediction model with improved stability and background values, and the results were compared with those of the traditional GM (1,1) model and the GM (1,1) model based on the cumulative method. On this basis, the relative errors and model prediction accuracy for each stage of the three models are calculated. Finally, the conclusion is drawn as follows: the relative error value of the new prediction model is much lower than the latter

two and the prediction accuracy is greatly improved, so it is more practical for the maintenance of weapons and equipment, especially rotating machinery. The value of this improved forecasting method lies in its ability to facilitate the actual operation of the staff.

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