Research on Bearing Life Prediction Method Based on EMD and Gray Model

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Abstract. In order to predict the residual life of bearing based on practical signals, the Empirical Mode Decomposition (EMD) is proposed and it is used to decompose the signal and filter out the invalid frequency components in the signal. The root means square (RMS) values of the pre-processed life cycle data samples were calculated. It is used to describe the health status of bearings and form a list degradation characteristic quantity. Then the list is used to train the Grey Model. The characteristic quantity trend is estimated by the trained Grey Model. It is verified by testbed and engineering practice. The results show that this method can predict bearing life effectively and with high precision.

1. Introduction

In engineering practice, the service life and design life of bearings are greatly different under the influence of operating conditions\textsuperscript{[1]}. At the same time, the bearing is one of the key components that affect the health and life of the coal machine equipment. Therefore, the prediction of bearing life is of great significance. It is also one of the focuses of coal machine maintenance personnel.

Bearing life prediction technology is mainly divided into three categories: life prediction method based on the failure model, the prediction method based on probability statistics and data-driven prediction method. The life prediction method based on the failure model is based on physical mechanisms such as fatigue accumulation damage\textsuperscript{[2-5]}, such as the L-P model, Paris fatigue life prediction model, I-H model, Z model, T model, etc. The method is based on an accurate description of the failure mechanism of coal-bearing. However, in engineering practice, it is difficult to accurately describe its failure mechanism and establish an accurate model. The probabilistic statistical prediction method is to estimate the statistical life of bearings\textsuperscript{[6-8]} based on probability, such as the proportional failure rate model, Bayesian statistical model, three-parameter Weibull model, etc. The data-driven prediction method mainly uses state data to predict bearing life. Extraction can describe the bearing's full life cycle process characteristic quantity as the degradation characteristic quantity, and estimate the bearing's remaining life by predicting the changing trend of the degradation characteristic quantity through the prediction model\textsuperscript{[9-12]}, such as BP neural network model, MK-LSSVM prediction model, SVM prediction model, etc. Based on the probability model and data-driven method, on the one hand, it overcomes the limitation of
establishing an accurate mathematical model for bearing life prediction; On the other hand, it is restricted by whether the sample is complete and accurate. If the sample is not complete and accurate, it cannot make an accurate prediction.

Grey Models (GM) can be used to establish prediction models with a small amount of incomplete information, which has been widely used in hydrologic prediction, geotechnical engineering, and fault diagnosis. This paper introduces a grey model to predict the bearing life of the coal machine. To some extent, it overcomes the limitation of the accuracy and completeness of the sample.

In engineering application practice, time domain and frequency domain indexes are usually selected as degradation characteristic quantities for bearing life prediction [13]. However, the characteristics such as time-domain index and frequency domain index are affected by the specific working environment of coal machine equipment (dust, noise, impact vibration, etc.), and thus affect the accuracy of bearing life prediction.

Therefore, this paper proposes a set of bearing life prediction methods to realize the prediction of bearing life. First of all, Empirical Mode Decomposition (EMD) method for the input vibration signal filtering processing, remove the invalid components in the signal. Then, the signal eigenvalue root means square is extracted as the degenerate eigenvalue. The gray model is used as the life prediction model, and the degradation characteristic quantity is input to realize the prediction of bearing life. This method is applied to the field maintenance of coal machine equipment, and the result is satisfactory.

2. EMD Filter and GM Prediction Model

2.1 EMD Filtering

Empirical Mode decomposition (EMD) hypothesis [14]: Any signal can be decomposed into a number of Intrinsic Mode Functions (IMF) plus a trend item. The basic mode component must satisfy the following two conditions:

1. In the signal, the number of extreme points \( N_e \) (including maximum points and minimum points) and the number of zero-crossing points \( N_z \) must be equal or at most nearly one.

\[
(N_z - 1) \leq N_e \leq (N_z + 1)
\]  

2. At any time point, the mean value of the upper envelope determined by the local maximum \( f_{\text{max}}(t) \) and the lower envelope determined by the local minimum \( f_{\text{min}}(t) \) is zero.

\[
(f_{\text{max}}(t_i) + f_{\text{min}}(t_i))/2 = 0, \quad t_i \in [t_a, t_b]
\]

The EMD decomposition process of a signal can be described as follows:

1. Determine all local extreme points of time series \( x(t) \), and then connect all maximum points and all minimum points with a curve respectively to obtain the upper and lower envelope. The mean of the upper and lower envelopments is denoted as \( m(t) \).

2. By subtracting the mean value of the envelope from the original time series \( x(t) \), \( h(t) = x(t) - m(t) \). Two conditions of whether the basic mode component is satisfied are obtained. If
not, repeat the first step as the data to be processed until it is a basic mode component \( f_1(t) \), marked: \( h_1(t) \).

(3) After decomposing the first basic pattern component with the original time series, subtracting the remaining value sequence will be regarded as a new "original sequence", \( s_1(t) = x(t) - f_1(t) \). The above steps will be repeated to extract the second, the third, and the second basic pattern component successively. You end up with the remainder of the original signal \( r_n(t) \).

In the process of EMD decomposition, the fast-changing signal, which is a high-frequency signal, is decomposed first, and then the slowly changing signal is decomposed successively. This feature of EMD decomposition is a filtering process from the perspective of filtering. Different from the traditional filter, the cutoff frequency of this filter is determined by the signal itself, so it is an adaptive filtering process. According to the needs of signal processing, the cut-off order of filter can be determined \[15\], which can be expressed as follows:

\[
X(t) = \sum_{l,h=1}^{l,N} IMF_{l,h}(t) \quad (l,h \in [1,N])
\]  

(3)

Where: \( X(t) \) is the filter signal output by the filter, \( IMF_{l,h}(t) \) is the eigenmode component, and \( N \) is the number of eigenmode components. The band-pass filter, high pass filter, and low-pass filter can be realized with different values of \( l \) and \( h \).

2.2 GM Prediction Model

The Gm prediction model processes the data through correlation analysis to find the law of data change, generates the data series with strong regularity, and then establishes the corresponding differential equation, so as to predict the future development trend.

Assume that the data sequence can be expressed as: \( y = [y(1), y(2), \ldots, y(n)] \), A new data sequence is obtained by accumulating the data once, \( y_n = [y^1(1), y^1(2), \ldots, y^1(n)] \).

Where:

\[
y^1(k) = \sum_{i=0}^{k} y_i
\]  

(4)

The following differential equations is established by using the new data series.

\[
d\frac{y}{dt} + a \cdot y^1 = u
\]  

(5)

Where: \( a \) and \( u \) are the parameter to be estimated. 

let:

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

(6)

The following formula is used to solve the parameter to be estimated \[16\].

\[
\hat{a} = (B^T B)^{-1} B^T y_n
\]  

(7)

Where:

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

(8)

\[
y_n = [y(2), y(3), \ldots, y(n)]
\]  

(9)

The discrete solutions of differential equations can be expressed as follows:

\[
y^1(k+1) = \frac{y(n) - n \cdot u}{a} \cdot e^{-ak} + \frac{n \cdot u}{a} \quad (k = 0, 1, 2, \ldots, n-1)
\]  

(10)
As $\tilde{y}(k+1)$ is the predicted value after accumulation, it is reduced:

$$y(k+1) = \tilde{y}(k+1) - \tilde{y}(k)$$

(11)

3. Bearing life prediction model

3.1 Degradation Feature Selection

The selection of the characteristic quantity of bearing degradation is to determine an index that can reflect the variation law of bearing performance degradation. Many international standards, such as ISO2372, use RMS to describe the deterioration of mechanical equipment performance. It can be seen that RMS can accurately describe the law of mechanical equipment performance decline. Therefore, this paper chooses RMS as the degradation characteristic quantity to describe the decline of bearing life. Since environmental noise and other factors have a great influence on RMS, simple band-pass filtering will weaken the effective frequency component in the signal. EMD filtering method is adopted to filter out the useless components in the signal and retain the effective components to the maximum extent.

3.2 Prediction methods based on EMD and GM models

The specific process of bearing life prediction based on EMD and GM model is as follows:

1. The vibration acceleration signal $x(t)$ of bearing life cycle sample data is extracted at equal time intervals. The data length is $N$, and the number of samples is $m$, to form a data sequence: 

$$\{x_1(t), x_2(t), \ldots, x_m(t)\} \quad (i = 1, 2, \ldots, N)$$

2. EMD filtering method is used to filter the sample data sequence to obtain the new data sequence.

3. The RMS of the new data sequence is calculated to form the degenerate eigenvalue sequence.

4. The obtained degenerate feature sequence is input into the grey model as training samples to establish the grey model.

5. Using the established grey model to predict the next possible value of the degradation feature sequence, the prediction of the one-step is realized, and whether the predicted value is greater than the set threshold value is judged. If it is greater than the set threshold, the prediction is ended. Instead, go to step (6).

6. Add the predicted value of one step forward to the degraded feature quantity sequence, and repeat step (5) to realize the prediction of forward $H$ steps.

After multi-step prediction, the predicted value reached the set bearing life threshold, and the residual life of the bearing was estimated according to the time interval of the sample data.

4. Experimental verification

In order to verify the validity of the algorithm, the experimental data of bearing life-cycle test bench in literature [17] were used to verify the validity of the method.
Figure 2. Life-cycle Test Table for Bearing.

Type of experimental bearing LDK UER204, bearing speed 2100 r/min. Sampling frequency 25.6 kHz, sampling time 1.28 s, a sampling interval of 5 min. Limited space, here select two groups of bearing test data for algorithm verification.

| Serial number | The number of samples | Bearing life | Failure site |
|---------------|-----------------------|--------------|--------------|
| Test 1        | 33                    | 161min       | Outer ring   |
| Test 2        | 25                    | 123min       | Outer ring   |

First, the data of test 1 were analyzed. According to the above process, 33 sets of data obtained in experiment 1 were filtered by EMD to extract the RMS of each set of data, and the results were shown in Figure 3.

Figure 3. The trend of variation of RMS in the life cycle of bearing.

It can be seen from Figure 3. that the bearing performance enters into a decline period in 50min ~ 60min, and a relatively stable period in 60min ~ 125min, with some fluctuations. The bearing performance enters into a fast decline period in 125min ~ 161min. Here, the data of 0~125 minutes is taken as the data sample as the degradation characteristic quantity to predict the bearing life.

Firstly, the prediction threshold of the degradation feature is determined. When the degenerate feature of sample 1 reaches 12.7, the bearing fails. When the degradation characteristic quantity of sample 2 reaches 11.4, the bearing fails. At the same time, considering the safety factor of equipment operation, the threshold value of bearing degradation characteristic is set to 10.

Secondly, the prediction samples are pretreated by EMD filtering. The root mean square value is extracted. The degenerate feature quantity is constructed and input into the prediction model. The results are shown in Table 2.

| Serial number | Actual residual life | Methods of this paper | Without EMD filtering |
|---------------|---------------------|-----------------------|-----------------------|

Table 2. Life prediction of the test bearing.
It can be seen from Table 2 that the prediction result obtained by the method in this paper is the closest to the real value and the accuracy is higher. However, the prediction result without EMD filtering deviates from the real value. From the perspective of practical application, if the predicted value obtained by this method is used as the reference standard for equipment maintenance, the bearing has the largest service value and the best economy. According to the prediction results without EMD filter processing, to a certain extent, it leads to "over maintenance" and poor economy. When determining the prediction threshold of the residual life of the bearing, the problem of equipment safety is taken into account. Therefore, the prediction threshold of the residual life of the bearing is jointly determined by the degradation characteristic value of the bearing when it fails and the safety factor of the equipment, thus effectively avoiding the problem of "under maintenance" caused by the predicted value falling to the right of the true value.

5. Engineering Application

5.1 Field Testing
The vibration amplitude of the 4# drive motor of a belt conveyor is significantly larger than that of the other three drive motors. To further clarify the health status of motor 4, the motor was tested. According to the field situation, the measuring points of the 4# drive motor are arranged as shown in Figure 4. The motor speed is 1496r/min, and the shaft end support bearing model is NU322ECM.

![Test system composition](image)

Figure 4. Test system composition.

The testing system consists of a vibration acceleration sensor, data acquisition instrument, workstation, and other equipment. The test lasted 10 days. Five sets of signals are collected every day with a sampling frequency of 4000Hz and a sampling number of 8000. A total of 50 sets of valid data were obtained during the test. During the test, it was found that the vibration amplitude of the shaft end of the motor was significantly higher than that of the tail, and had a small increase trend. Therefore, the vibration of the motor shaft extension is taken as the analysis object.

5.2 Results Analysis
Firstly, the prediction threshold of the degradation feature is determined. Since there is no historical data as a reference, empirical values can be used. The threshold value is usually 5~8 times of the bearing degradation characteristic under normal conditions. Figure 5. Shows that the sample data has a slight increase trend, with the maximum value being 5m/s². Considering the safety factor of large equipment, 20m/s² is used as the prediction threshold of bearing degradation characteristics.

After EMD filtering, RMS features are extracted and input into the GM model to predict the residual life of the motor bearing, as shown in Figure 5. The predicted trend curve accurately depicts the trend change of the root mean square of the sample data. It is predicted that the remaining life of the motor bearing is 28 days.
According to this, the motor will be replaced in the overhaul one month later, and the motor will be disassembled and verified in the repair shop. The results show that there are serious faults in the bearing of the shaft extension end of the motor, so as to meet the replacement standard. The analysis and prediction results are consistent with the actual situation on site.

6. Conclusion
(1) Field application and test-bed experiments show that the accuracy of life prediction of coal machine equipment can be greatly improved by extracting RMS after EMD processing.
(2) Under the condition of incomplete sample data and missing information, the GM prediction model can realize the prediction of residual life of coal machine equipment bearing with high accuracy.
(3) The results of the test-bed test and field application show that this method can effectively predict the life of bearing coal machine equipment and guide the maintenance of equipment in the field.

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