Research on early warning of rolling bearing wear failure based on empirical mode decomposition

Peng Wang

Department of Electronic Information Engineering,
Xi'an Technological University,
Xi'an 710021, China
Email: 24566357@qq.com

Di Li

Center for Project Management of Equipment Development,
Department of PLA Army,
Beijing, 10072, China
Email: 5876634@qq.com

Ningchao Zhang*

Department of Electronic Information Engineering,
Xi'an Technological University,
Xi'an 710021, China
Email: ningchaoz@mls.sinanet.com
*Corresponding author

Abstract: In order to solve the problems of low precision and long time-consuming of traditional methods, this paper designs a rolling bearing wear fault early warning method based on empirical mode decomposition (EMD). Based on the wear reason of rolling bearing, the acceleration sensor is used to collect its vibration signal, and the EMD algorithm is used to stabilise the signal to obtain multi-scale signal. Each multi-scale signal is decomposed into sub-band to get multi-scale sub-band signal, then the multi-scale sub-band sample entropy is obtained, and the optimisation function of local preserving projection algorithm is constructed to obtain the eigenvalue and eigenvector of wear failure fault, and finally the fault early warning is realised. The simulation results show that the signal denoising effect of this method is good, the early warning accuracy is always above 94%, and the average alarm time is close to 0.27 s.

Keywords: empirical mode decomposition; EMD; rolling bearing; wear failure; fault warning; local preserving projection algorithm.

Reference to this paper should be made as follows: Wang, P., Li, D. and Zhang, N. (2021) 'Research on early warning of rolling bearing wear failure based on empirical mode decomposition', *Int. J. Materials and Product Technology*, Vol. 63, Nos. 1/2, pp.72–85.

Biographical notes: Peng Wang received his PhD in School of Mechanical and Electrical Engineering from the Northwestern Polytechnical University in 2013. He is an Associate Professor in the College of Electronic Information

Engineering of Xi'an Technological University. His research interests include photoelectric measurement technology, machine vision inspection systems, and image processing.

Di Li is an Associate Professor in the Center for Project Management of Equipment Development, Department of PLA Army. His research interests include optoelectronic measurement technology and system and project management.

Ningchao Zhang received his PhD in School of Physical Science and Technology from the Southwest Jiaotong University in 2014. He is currently a Lecturer in the College of Electronic Information Engineering of Xi'an Technological University. His research interests include electromagnetic radiation measurement technology and intelligent information processing.

1 Introduction

In practice, due to the heavy task of mechanical equipment and the bad working environment of some equipment, the failure rate of rolling bearing is greatly improved (Wang and Zhou, 2020). In different types of mechanical equipment components, rolling bearing is the most widely used, but also the most critical, and is one of the easily damaged parts. According to the relevant survey data, more than 30% of the mechanical equipment using rolling bearings at this stage are caused by rolling bearings. Once the mechanical equipment fails, the work efficiency will be reduced, and the life safety of workers may be threatened. Therefore, it is necessary to conduct in-depth study on the wear failure of mechanical equipment rolling bearings (Wang et al., 2017).

At present, there are many researches on the early warning methods of wear failure of rolling bearings, and some research results have been achieved, and they have been further promoted in practice. For example, Jiang et al. (2019) proposed a kind of early warning method for wear failure of mechanical equipment rolling bearing based on oil monitoring information. Based on the aviation test data, the wear dataset of rolling bearing of mechanical equipment is obtained. On this basis, multi-parameter correlation analysis is used to reduce the dataset, and the parameters of the reduced dataset are tested by fitting regression and normal distribution. The obtained data are used as the criteria of wear failure warning, and the warning results of rolling bearing wear failure are output. However, in the process of rolling bearing wear failure warning using this method, due to the long data processing time, the early warning time is increased. In Wei et al. (2018), the wear failure early warning method of mechanical equipment rolling bearing based on big data mining is proposed. First, according to the working principle of heavy machinery rolling bearings, the bearing pedestal is used as the basis of modelling. According to the modelling results, the failure process is analysed and the fault characteristic values are calculated. On this basis, the early warning of wear failure is realised by monitoring the change of fault signal and characteristic value. However, due to some errors in the modelling process and a large number of noise in the fault signal, the accuracy of fault warning for wear failure of rolling bearing is reduced. In Liu et al. (2020), an early warning method for wear failure of rolling bearing based on principal component analysis and neural network is proposed. In this method, expert method is used to design the failure index of rolling bearing, and principal component analysis is used to analyse the correlation of the failure index. According to the processing results, the research data are preprocessed and the multiple principal components obtained are taken as the foundation of BP neural network construction. Through setting activation function and model training, the rolling bearing wear loss effect is output. However, there is a lot of noise in the research data used in this method, so the early warning of wear failure of rolling bearing is greatly reduced.

Because the above method does not consider the noise in the collected signal, the accuracy of fault alarm is low. Therefore, in order to improve the accuracy and reduce the time of the early warning, a new early warning method based on EMD is proposed.

2 Design of early warning method for wear failure of rolling bearing

2.1 *Analysis of wear reasons of rolling bearing*

Before the design of the early warning method of rolling bearing wear failure, it is necessary to analyse the reasons of rolling bearing wear, and design the early warning method of rolling bearing wear failure, so that the method has multiple advantages such as high early warning accuracy and short warning time.

The specific structure is shown in Figure 1.

1. *Outer ring:* the outer ring mainly has the function of supporting roller and steel ball. Generally, it is installed on the bearing pedestal or shell.
2. *Inner ring:* the inner ring usually moves with the shaft and is generally mounted on the shaft (Yuan et al., 2017).
3. *Bearing retainer:* the main function of the cage is to separate the rolling elements according to a certain distance, and each rolling element is separated by an equal distance, so the load of each rolling element is the same.
4. *Rolling element (steel ball or roller):* the bearing capacity of a rolling element is usually related to its size and mass (Xu, 2017).

In the process of mechanical equipment being put into use, there are many reasons for rolling bearing failure, such as corrosion, insufficient lubrication and assembly error. Therefore, different failure modes will appear, such as wear failure, corrosion failure, etc. The process of wear failure of rolling bearing of mechanical equipment can be generally divided into three stages, as shown in Figure 2.

Generally, according to the wear principle, the wear of rolling bearing is divided into the following parts.

2.1.1 *Adhesive wear*

The oil film generated by lubricating oil will be cracked due to high temperature, which will cause adhesion on the contact peak point on the surface of rolling bearing. However, with the decrease of temperature, the adhesion point at the contact peak point will gradually fracture. This process is repeated all the time, and this process is called sticking therefore, the severity of adhesive wear is related to the fracture location of adhesion point (Xu et al., 2018; Xia and Lin, 2019).

Figure 1 Rolling bearing structure (see online version for colours)

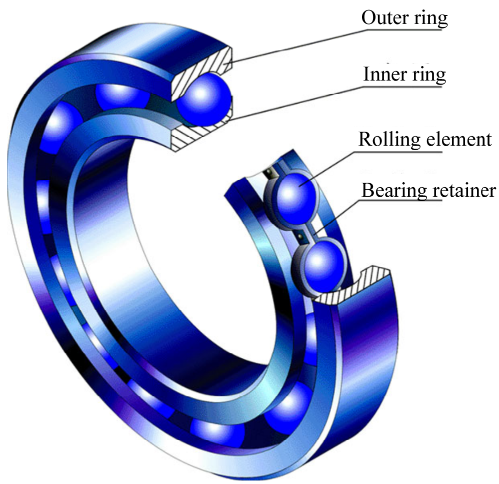
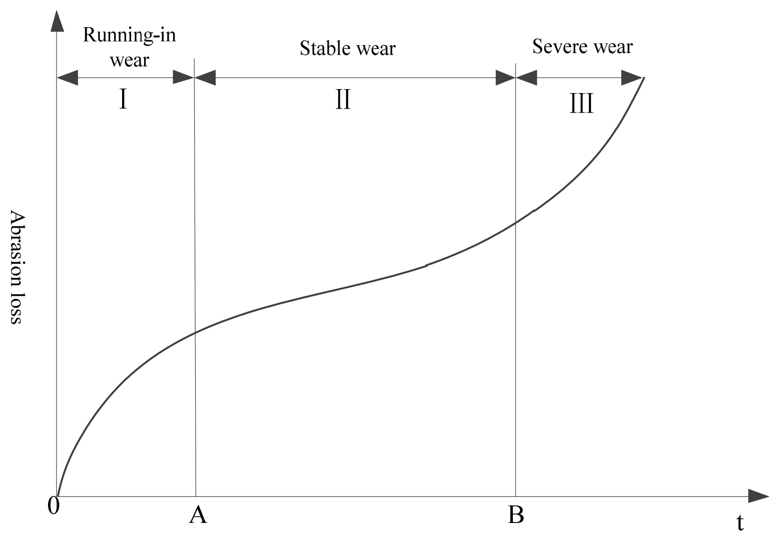


Figure 2 Wear process curve



2.1.2 Fatigue wear

No matter what kind of friction state the rolling bearing surface is, there must be a kind of alternating stress. Under the action of this stress, the rolling bearing surface will crack due to fatigue, and then the lubricating oil will enter into the crack through extrusion, which will cause the crack to expand and finally fall off. Therefore, there will be a kind of pit of different sizes on the rolling bearing surface wear is called fatigue wear (Ma et al., 2020; Hao and Hu, 2020). The influence of the viscosity of the lubricating oil on the fatigue wear of the rolling bearing is shown in Table 1.

Table 1 Effect of lubricant viscosity on fatigue wear of rolling bearing

Oils	*Temperature/°C*	*Viscosity/(mm/s)*	*Contact fatigue stress/MPa*	*Transfer power/kW*
Spindle oil	20	116	450	4.9
Machine oil	20	757	600	8.8
	82	84	430	4.5
Cylinder oil	57	303	490	5.0
	45	757	550	7.4

According to Table 1, the viscosity of lubricating oil of rolling bearing is positively correlated with contact fatigue stress and transmission power.

2.1.3 Abrasive wear

In the process of rolling bearing work, the bulge of the surface and the hard particles outside will scratch the surface, and even more will cause surface falling off. This process is called abrasive wear, and the main forms are mainly divided into micro cutting, extrusion peeling and fatigue failure.

2.1.4 Corrosion and wear

The metal of rolling bearing will wear out due to chemical or electrochemical reaction with surrounding medium. This wear process is called corrosion wear (Duan et al., 2020; Zhang et al., 2017).

2.1.5 Fretting wear

Figure 3 shows the specific fretting wear mechanism.

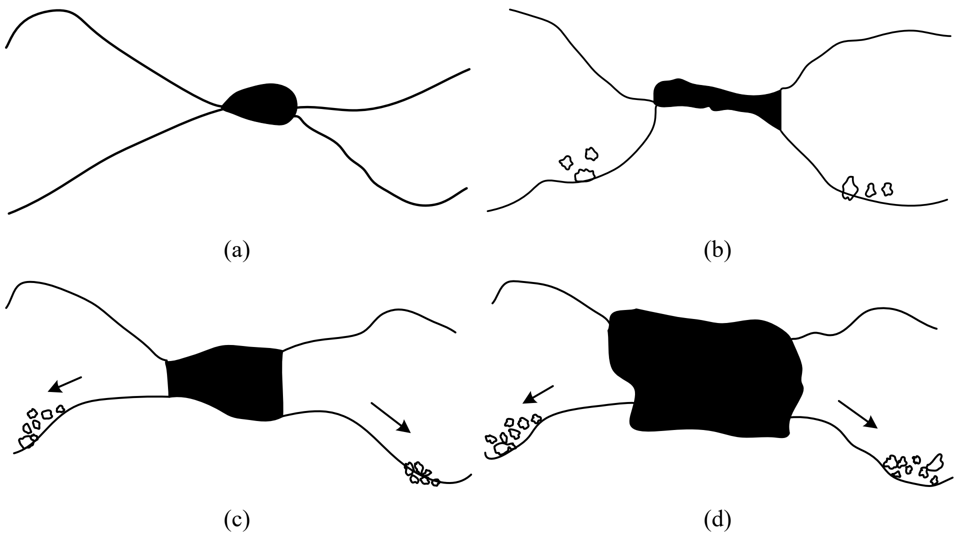
Figure 3(a) shows that under the action of vibration, abrasive particles will be produced due to adhesion and accumulate in the adjacent concave valley; Figure 3(b) under the action of friction, the convex surface of the rolling bearing will gradually flatten out, so that the abrasive particles generated will remain between the contact surfaces; Figure 3(c) shows that under the continuous grinding effect of abrasive particles on the contact surface, more abrasive particles will be generated Figure 3(d) shows that pockmarks will be produced under the action of larger abrasive particles (Chen et al., 2017).

2.1.6 Erosion wear

Erosion wear refers to that the hard materials or particles contained in flowing gas and liquid will cause wear on the surface of rolling bearing (Fu et al., 2017; Guo and Wang, 2019).

To sum up, the above analysis of rolling bearing wear causes, and need to be based on the analysis results, in order to achieve rolling bearing wear failure early warning.

Figure 3 Fretting wear mechanism



2.2 Early warning of rolling bearing wear failure based on EMD

On the basis of the above analysis, this paper introduces EMD and designs a new early warning method of rolling bearing wear failure.

EMD algorithm is used to decompose the collected signal, because this method can select the appropriate basis function to decompose the signal according to the characteristics of the signal, accurately obtain the resolution of the signal in different frequency bands, overcome the uncertainty problem in wavelet decomposition, and has certain adaptability in the field of signal analysis (Sawaqed and Alrayes, 2020), so as to improve the accuracy of fault early warning.

The implementation steps of signal decomposition are as follows:

1 The collected signal $x(t)$ is a local maximum point and a minimum point, and then the upper and lower envelope is formed by cubic spline curve, and its mean value is $m(t)$.

2 The average value of upper and lower envelope lines $m(t)$ and noise component $z(t)$ need to be subtracted from $x(t)$, and the result is expressed as follows:

$$h_1(t) = x(t) - m(t) - z(t) \tag{1}$$

After calculating the above results, it is necessary to judge whether $h_1(t)$ can satisfy the constraint of eigenmode function. If it is not satisfied, it is necessary to take $h_1(t)$ as the original signal and repeat the above process until $h_1(t)$ can constrain the condition and regard it as an eigenmode function (Minhas et al., 2020).

3 According to the above results, it is necessary to subtract $h_1(t)$ from $x(t)$ to obtain the residual signal.

$$r_1(t) = x(t) - h_1(t) \tag{2}$$

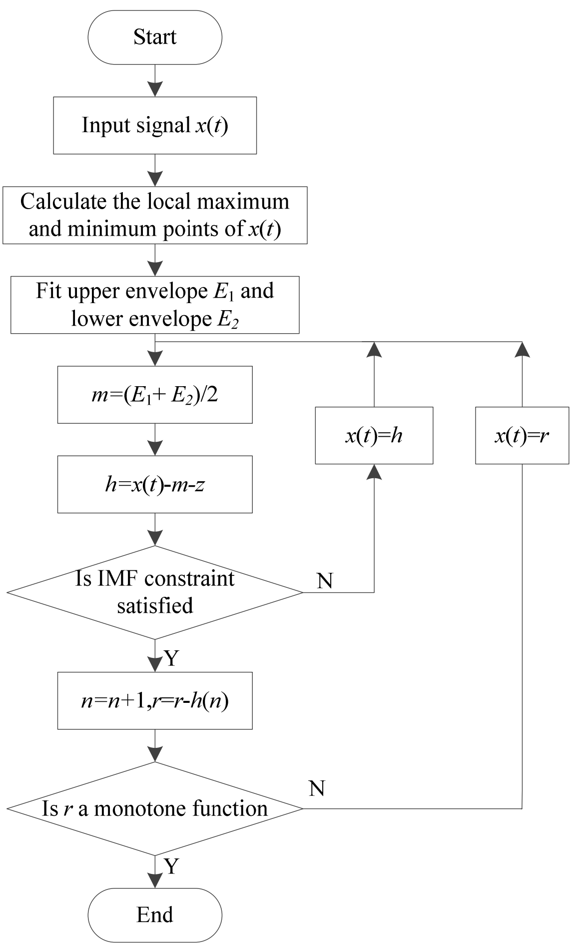
4 In this way, n eigenmode functions are obtained in turn. The residual term is represented by $r_n(t)$, then the original signal is:

$$x(t) = \sum_{i=1}^{n} h_1(t) + r_n(t) \tag{3}$$

The stop conditions of original signal decomposition are: when $r_n(t)$ has no extremum and the function is a monotone function; when $r_n(t)$ is less than the preset minimum value.

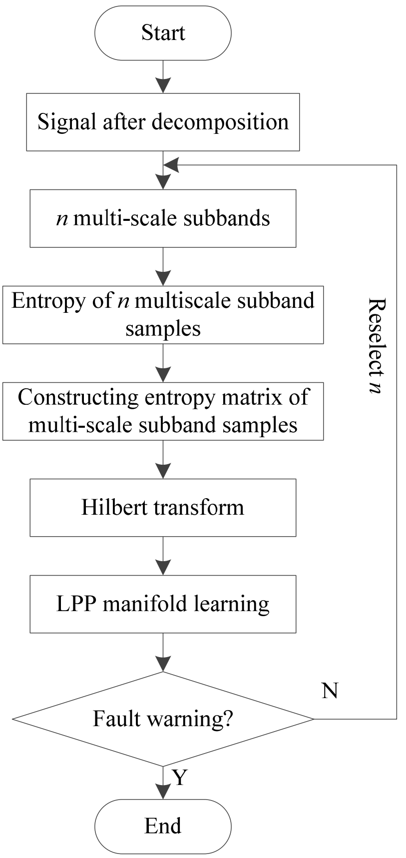
The vibration signal decomposition process based on EMD is shown in Figure 4.

Figure 4 Decomposition process of vibration signal



Assume that the failure signals of inner ring, outer ring, ball and cage of rolling bearing are x_1, x_2, x_3 and x_4 respectively; the data matrix of wear failure signal of bearing inner ring, outer ring, ball and cage is represented by X_1, X_2, X_3 and X_4 respectively (Yang et al., 2018; Huang and Zhang, 2020). Since the number of sensors arranged in each experiment is n, the sensors on inner ring, outer ring, ball and cage are represented if the collected signals are represented by A_1, A_2, ..., A_n, B_1, B_2, ..., B_n, C_1, C_2, ..., C_n and D_1, D_2, ..., D_n.

Figure 5 Flow chart of fault warning



The multi-scale sub-band sample entropy of the above signals is obtained.

$$samEn(m, r, D) = -\ln \frac{B^{m+1}(r)}{B^m(r)} \tag{4}$$

where $B^m(r)$ is the multi-scale sub-band signal.

$$B^m(r) = \frac{1}{D-m+1} \sum_{i=1}^{D-m+1} B_i^m(r) \tag{5}$$

where D is the distance between two signals and m is the signal bandwidth.

Then the multi-scale sub-band sample entropy of the four signals is $K_1 = [j_1, j_2, ..., j_n]$, $J_1 = [j_1, j_2, ..., j_n]$, $L_1 = [l_1, l_2, ..., l_n]$ and $F_1 = [f_1, f_2, ..., f_n]$. Then there are:

$$K_1 = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{K_1(\tau)}{t-\tau} d\tau \tag{6}$$

$$J_1 = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{J_1(\tau)}{t-\tau} d\tau \tag{7}$$

$$F_1 = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{F_1(\tau)}{t-\tau} d\tau \tag{8}$$

$$L_1 = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{L_1(\tau)}{t-\tau} d\tau \tag{9}$$

In the above formula, Cauchy principal component is represented by P.

Hilbert transform is applied to K_1, J_1, F_1 and L_1 to calculate the analytic signals KK_1, JJ_1, FF_1 and LL_1, which are respectively expressed by the following formulas:

$$KK_1 = K_1 + id_1 \tag{10}$$

$$JJ_1 = J_1 + ij_1 \tag{11}$$

$$FF_1 = F_1 + if_1 \tag{12}$$

$$LL_1 = L_1 + il_1 \tag{13}$$

On this basis, the local preserving projections (LPP) algorithm is used to reduce the dimension of the analytical signal.

1 The LPP optimisation function can be expressed as follows:

$$\min\left(\sum_{i,j}\left(y_i - y_j\right)^2 S_{i,j}\right) = \min\left(\sum_{i,j}\left(W^T x_i - W^T x_j\right)^2 S_{i,j}\right) \tag{14}$$

In the above formula, x_i and x_j represent two adjacent data points in the high-dimensional space, $W_{i,j}$ represents the similarity matrix between x_i and x_j in the original space, and y_i and y_j correspond to the two data points of x_i and x_j in the reduced dimension space.

2 The similarity matrix is obtained. If x_i is the k nearest neighbour of x_j, then $W_{i,j}$ is expressed as follows:

$$W_{i,j} = \exp - \frac{\left\|x_i - x_j\right\|^2}{t} \tag{15}$$

Otherwise, $W_{i,j} = 0$.

For the optimisation function transformation, we can get the following results:

$$\frac{1}{2} = \left(\sum_{i,j}\left(W^T x_i - W^T x_j\right)^2 S_{i,j}\right) = W^T XLX^T W \tag{16}$$

In the above formula, X is a high dimensional matrix.

Then W can be obtained by the following formula:

$$W = \mu XDX^T \tag{17}$$

In the above formula, D represents the diagonal matrix, and W is mainly composed of the eigenvector $w_1, w_2, ..., w_m$ corresponding to $\mu_1, \mu_2, ..., \mu_m$ composed of the first m eigenvalues.

According to the eigenvalues and eigenvectors of the wear failure fault of rolling bearing, the specific process is shown in Figure 5.

To sum up, EMD algorithm is used to complete the design of early warning method for rolling bearing wear failure. The following needs to test the application effect of this method.

3 Simulation experiment

3.1 Experimental scheme design

The main purpose of this paper is to verify the effectiveness of the method, and design the experiment. The specific experimental scheme is as follows:

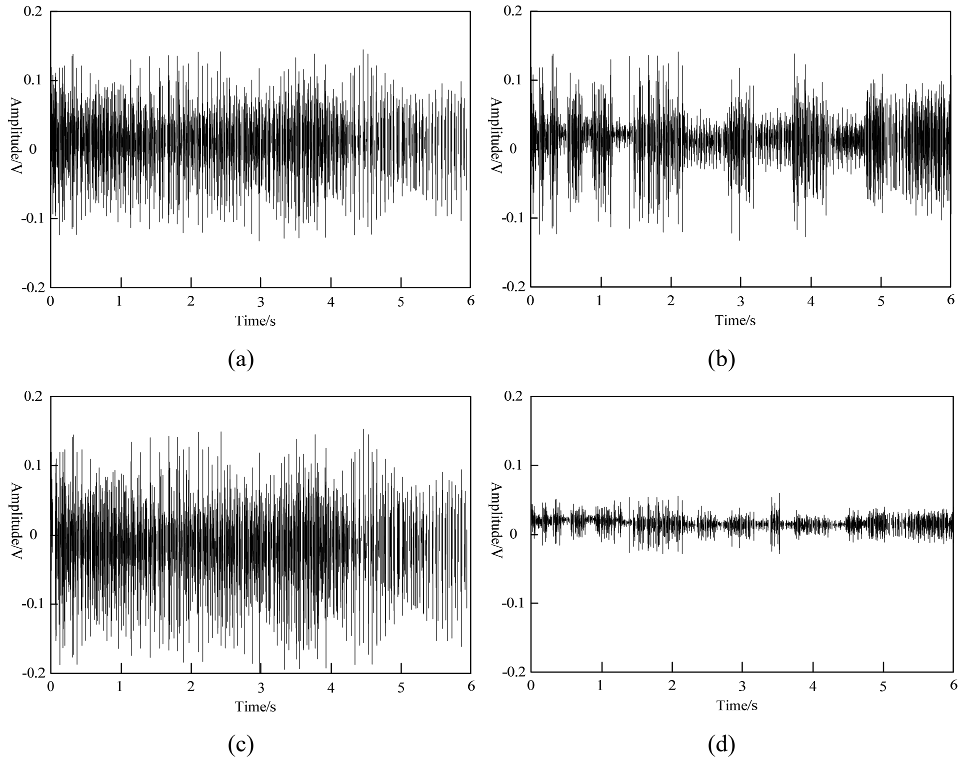
1. *Experimental environment:* the experiment is carried out in the simulation environment. The hardware environment of the experiment is Windows 10 system, the processor is 3.6 GHz computer, and the simulation tool is Matlab 2010b.
2. *Experimental data:* all data used in this paper are from large rolling bearing processing plants. The number of parameter samples is 1,024 and the parameter sampling period is 0.5 s.
3. *Experimental methods:* select the Jiang et al. (2019) based on oil monitoring information of mechanical equipment rolling bearing wear failure early warning method, Wei et al. (2018) based on big data mining mechanical equipment rolling bearing wear failure early warning method, Liu et al. (2020) based on principal component and neural network rolling bearing wear failure early warning method, and this paper designed based on EMD mechanical equipment The early warning method of wear failure of rolling bearing is used as the experimental method.
4. *Experimental index:* signal noise, early warning precision and early warning time are used as evaluation indexes. The smaller the noise component in the signal, the less the influence on the accuracy of early warning results. The higher the early warning precision, the higher the possibility of accurate early warning. The shorter the warning time, the higher the efficiency and the better the practical application effect.

3.2 Analysis of experimental results

3.2.1 Signal noise comparison

The four methods of mechanical equipment rolling bearing wear failure signal noise situation is shown in Figure 6.

Figure 6 Signal noise comparison, (a) Jiang et al. (2019) method (b) Wei et al. (2018) method (c) Liu et al. (2020) method (d) the method of this paper



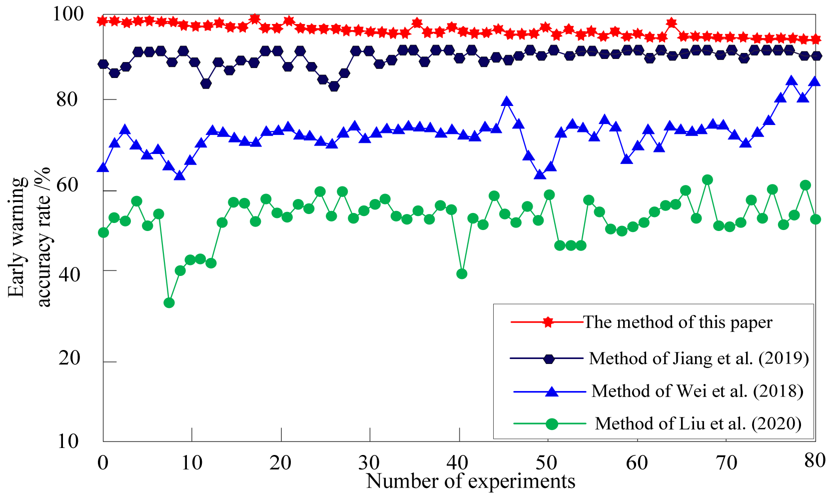
After analysing the above results, the noise amplitude of the method in Jiang et al. (2019) is between –1.2 V–1.5 V, that of the method in Wei et al. (2018) is –1.2 V–1.3 V, and that of the method in Liu et al. (2020) is –1.9 V–1.5 V, compared with the literature method, the signal noise amplitude of this method is about 0, which is the lowest among the three methods. Therefore, using this method for mechanical equipment rolling bearing wear failure warning can get better early warning results.

3.2.2 Comparison of early warning accuracy

The comparison of early warning accuracy of the four methods is shown in Figure 7.

After analysing the above results, the accuracy rate of early warning for wear failure of rolling bearing in Jiang et al. (2019) fluctuates in the range of 82%–92%, that of Wei et al. (2018) fluctuates in the range of 62%–89%, and that of Liu et al. (2020) fluctuates in the range of 34%–63%, which is the lowest among the four methods, while the early warning accuracy of this method is accurate The failure rate of this kind of rolling bearing can always achieve 94% failure rate in heavy machinery.

Figure 7 Comparison of early warning accuracy (see online version for colours)



3.2.3 Comparison of early warning time

Table 2 shows the time consumption comparison of the four methods.

Table 2 Comparison results of early warning time (s)

Number of experiments	*Jiang et al. (2019) method*	*Wei et al. (2018) method*	*Liu et al. (2020) method*	*The method of this paper*
10	7.63	4.32	1.96	0.12
20	6.83	4.78	2.31	0.23
30	8.56	3.21	2.54	0.25
40	7.85	3.86	2.64	0.28
50	7.96	3.64	2.87	0.31
60	6.88	3.47	2.95	0.34
70	7.52	4.24	3.01	0.29
80	6.31	3.85	2.98	0.30
Mean value	7.44	3.92	2.66	0.27

After analysing the above results, the average time-consuming of rolling bearing wear failure warning based on Jiang et al. (2019) is 7.44 s, that of Wei et al. (2018) is 3.92 s, that of Liu et al. (2020) is 2.66 s, and that of this method is 0.27 s, which is the lowest among the four methods.

To sum up, the signal denoising effect of this method is good, the accuracy of early warning is more than 94%, and the early warning accuracy is high. The average time consumption of early warning of rolling bearing wear failure is 0.27 s, which shows the advantages of the rolling bearing wear failure early warning method based on EMD.

4 Conclusions

Bearing is the most widely used and easily damaged component in the industrial production process. It is of great significance to carry out accurate fault warning for bearing. Therefore, based on the early warning of rolling bearing wear, this paper puts forward a new wear early warning method. The simulation results show that the signal denoising effect of this method is good, the early warning accuracy is more than 94%, the early warning accuracy is high, and the average early warning time of moving bearing wear failure is 0.27 s, which shows that this method has good application effect.

On the basis of in-depth study of the basic theoretical knowledge, although this paper has achieved relatively satisfactory research results at this stage, but due to the influence of time and energy and other factors, it still needs to be further improved and improved. The follow-up will focus on the following aspects of the content of research:

1 At the present stage, the method still has high complexity. In the follow-up research process, we focus on how to reduce the complexity of research.

2 The current simulation experiment has certain limitations, and due to the time constraints, no more parameters are included in the experiment. In the future, a lot of time will be used to further verify the performance of the whole method.

Acknowledgements

This work was supported by Natural Science Foundation of Shaanxi Science and Technology Department under Grant No. 2019GY-075, Scientific Research Plan Projects of Shannxi Provincial Education Department, Grant No. 20JK0688.

References

Chen, D.N., Zhang, Y.D., Yao, C.Y., Lai, B.W. and Lu, S.J. (2017) 'Fault diagnosis of rolling bearings based on parameter optimized MPE and FCM', *Bearing*, Vol. 52, No. 5, pp.33–38.

Duan, H.L., Guang, J., Guo, H.Y., Guo, M.C. and Xu, L. (2020) 'Reliability analysis and optimization design of rolling bearing wear of the centrifugal clarifier', *Modular Machine Tool & Automatic Manufacturing Technique*, Vol. 54, No. 4, pp.93–95+99.

Fu, Y., Jia, L., Qin, Y. and Yang, J. (2017) 'Roller bearing fault diagnosis method based on LMD-CM-PCA', *Zhendong Ceshi Yu Zhenduan/Journal of Vibration, Measurement and Diagnosis*, Vol. 37, No. 2, pp.249–255.

Guo, T. and Wang, T.C. (2019) 'The research and development of high-speed EMU bogie bearing fault monitoring system', *Audio Engineering*, Vol. 43, No. 4, pp.64–67.

Hao, J.H. and Hu, Y. (2020) 'Research on bearing fault diagnosis and warning based on XGBoost and autoregressive algorithm', *Modular Machine Tool & Automatic Manufacturing Technique*, Vol. 52, No. 2, pp.145–147+162.

Huang, W. and Zhang, Z.F. (2020) 'Early warning of combustion chamber faults based on multivariate state estimation', *Turbine Technology*, Vol. 62, No. 1, pp.38–42.

Jiang, X.F., Zong, Y. and Ruan, S.J. (2019) 'Research on early warning method of bearing wear fault based on oil monitoring information', *Machine Tool and Hydraulic*, Vol. 22, No. 6, pp.1–7.

Liu, G., Zhao, J., Zhang, X. et al. (2020) 'Early warning method of rolling bearing wear failure based on principal component analysis and neural network', *Mechanical Strength*, Vol. 16, No. 4, pp.799–804.

Ma, B., Su, F.J., Zhao, Y. and Cai, W.D. (2020) 'A mechanical fault early warning method based on infinite student's t-mixture model clustering', *Journal of Beijing University of Chemical Technology (Natural Science Edition)*, Vol. 15, No. 4, pp.74–80.

Minhas, A.S., Sharma, N., Singh, G., Kankar, P.K. and Singh, S. (2020) 'Improvement in classification accuracy and computational speed in bearing fault diagnosis using multiscale fuzzy entropy', *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 42, No. 11, pp.1–21.

Sawaqed, L.S. and Alrayes, A.M. (2020) 'Bearing fault diagnostic using machine learning algorithms', *Progress in Artificial Intelligence*, Vol. 9, No. 4, pp.341–350.

Wang, C. and Zhou, J.L. (2020) 'Early warning of coal mine machinery wear fault based on oil wear particle monitoring', *Plant Maintenance Engineering*, Vol. 47, No. 9, pp.149–152.

Wang, S.S., Guo, H., Lei, J.Z. and Zhang, Y.Z. (2017) 'Status and prospect for failure analysis on wear of rolling bearings in China', *Bearing*, Vol. 15, No. 10, pp.58–63.

Wei, X., Li, B. and Zhang, F. (2018) 'Early warning method of mechanical equipment rolling bearing wear failure based on big data mining', *Journal of Xi'an Jiaotong University*, Vol. 52, No. 6, pp.84–90.

Xia, X.J. and Lin, H. (2019) 'Research on health warning for rolling bearing of CNC machine tool based on self-learning SOM and ARMA algorithm', *Journal of Chinese Computer Systems*, Vol. 40, No. 1, pp.217–222.

Xu, Y. (2017) 'Rolling element bearing fault prediction based on grey sequential extreme learning machine', *Computer Measurement & Control*, Vol. 25, No. 7, pp.63–65, pp.69–83.

Xu, Z.L., Xu, G., Li, J. and Qiao, Y.H. (2018) 'Fault period impact characteristic extraction of rolling bearings based on maximum correlated kurtosis deconvolution', *China Measurement & Testing Technology*, Vol. 44, No. 5, pp.31–36.

Yang, Y., Fu, P. and He, Y. (2018) 'Bearing fault automatic classification based on deep learning', *IEEE Access*, Vol. 47, No. 6, pp.71540–71554.

Yuan, H., Wang, X., Sun, X. and Li, H.P. (2017) 'Compressive sensing-based feature extraction for bearing fault diagnosis using a heuristic neural network', *Measurement Science and Technology*, Vol. 28, No. 6, pp.65–79.

Zhang, L.J., Rong, Y.L., Liu, K. and Zhang, B. (2017) 'State pre-warning and optimization for rotating-machinery maintenance', *Journal of University of Science and Technology Beijing*, Vol. 39, No. 7, pp.1094–1100.