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Research Article

A Bearing Performance Degradation Modeling Method Based on EMD-SVD and Fuzzy Neural Network

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Bearing performance degradation assessment has great significance to condition-based maintenance (CBM). A novel degradation modeling method based on EMD-SVD and fuzzy neural network (FNN) was proposed to identify and evaluate the degradation process of bearings in the whole life cycle accurately. Firstly, the vibration signals of bearings in known states were decomposed by empirical mode decomposition (EMD) to obtain the intrinsic mode functions (IMFs) containing feature information. Then, the selected key IMFs which contain the main features were decomposed by singular value decomposition (SVD). And the decomposed results were used as the training samples of FNN. At last, the output results of the tested data were normalized to the health index (HI) through learning and training of FNN, and then the performance degradation degree could be described by the distance between the test sample and the normal one. According to the case study, this modeling method could evaluate the performance degradation of bearings effectively and identify the early fault features accurately. This method also provided an important maintenance strategy for the CBM of bearings.

1. Introduction

Bearings not only play a significant role but also have a high failure rate in mechanical equipment. The performance degradation of bearings often affects the lifetime of the whole mechanical system. If we can accurately evaluate the degradation state of bearings in the whole life cycle, discover the incipient fault in time, and make proper maintenance strategies, in that way, we can effectively avoid and prevent the occurrence of cascading failures, which is of great significance in economy and safety [1].

In recent years, in order to reduce the costs and time of maintenance, CBM has become the main maintenance strategy of modern industry. Vibration signal monitoring and analysis is more appropriate and effective way to monitor the running state of bearings because there is abundant information which contains the health condition of bearings in the signals [2, 3]. Hence, many fault diagnosis methods based on fault-feature extraction of vibration signals and pattern recognition technology have been proposed. On this basis, because fault diagnosis cannot reflect the degenerative trend of bearings, performance degradation assessment is more effective than fault diagnosis in realizing the CBM, which receives more and more attention [4]. There are two vital challenges needed to be studied constantly in the process of performance degradation assessment [5]. The first one is selecting a fault-feature extraction method which can reflect the running state of bearings from the vibration signals. Another challenge is establishing an intelligent and excellent performance degradation model [6–11]. Many experts and scholars have done a lot of research on the above two aspects. Pan et al. [12] proposed a modeling method based on wavelet packet decomposition and fuzzy mean clustering to evaluate the degradation process of bearings. Firstly, normal signals and fault signals were decomposed by wavelet packet, and then each node energy was taken as the characteristic matrix which was used as the training samples of fuzzy c-means. Finally, the degradation degree could be reflected by degradation indicator. Zhou et al. [13] proposed a degradation assessment method based on wavelet entropy and support vector data description (SVDD) to establish the degradation model of bearings. Firstly, the SVDD model was

trained by the energy entropy of vibration signal decomposed by wavelet packet in normal state, and then the relative distance between the energy entropy of test sample to the hypersphere was taken as the quantitative index of bearing degradation assessment. Because the vibration signals of bearings were nonstationary, the above fault-feature extraction method, the wavelet packet, did not fundamentally overcome the shortcomings of Fourier transform, and the decomposition process is not self-adaptive [14]. Zhou et al. [14] proposed a new method based on EMD and logistic regression to evaluate the degradation process of bearings. The energy of intrinsic mode functions (IMFs) was taken as the eigenvector, and then the logistic regression model was established with the eigenvectors in normal state and fault state. Finally, the index of degradation assessment after obtaining the regression parameters was calculated, and it can reflect the degenerative trend of bearings. Ali et al. [15] used the energy entropy of each IMF as the eigenvector for the training of artificial neural network (ANN) to detect the severity of the fault and then realized the quantitative description of the degenerative process of bearings. Although the above method overcomes the shortcomings of wavelet packet decomposition, there also exists modal mixing in the EMD process because of noise or intermittent signals, which will make the fault-feature extraction unstable and inaccurate. Singular value is the inherent feature of a matrix; it has scale invariance and rotation invariance. The singular value changes little when the elements change slightly. Therefore, SVD based on traditional EMD can solve this problem effectively [16]. As an important intelligent information processing method, FNN has strong self-learning and direct data processing ability, so it is more suitable for structural knowledge expression, which can realize arbitrary nonlinear mapping with arbitrary precision [17]. In addition, due to the function of fuzzy logic, FNN could get better division among the different degradation stages, so it has unique advantages in revealing the trend of gradual change of performance. Based on the above discussion, a novel degradation modeling method based on EMD-SVD and FNN was proposed. The case study in this paper showed that the new proposed method could compensate for the shortcomings of previous research effectively, and it could also identify the incipient fault features accurately.

This paper is organized as follows. In Section 2, the methodology which includes some related algorithms and the new proposed bearing performance degradation modeling method was introduced. In Section 3, two cases with different fault types were conducted to validate the effectiveness of the new proposed method. And Section 4 presented the conclusion of the whole paper.

2. Methodology

In this section, some related algorithms which include EMD algorithm, SVD algorithm, FNN algorithm, and the selection criterion of IMF were introduced. Based on these algorithms, a new bearing performance degradation modeling method was proposed.

2.1. EMD Algorithm. EMD is a smoothing process, which can decompose a complex, nonstationary signal into a number of IMF. Each IMF's frequency and composition are different and the decomposition process is self-adaptive, so EMD is very suitable for dealing with nonstationary bearing vibration signals. In the process of EMD, each IMF component must satisfy the two following conditions: (1) the number of the extreme points and the zero points should be equal or not more than one; (2) the mean of the maximum and minimum of extreme points is zero at any point in the signal curve [16, 18, 19]. So, for the signal $X(t)$, its equation of EMD can be expressed as

$$X(t) = \sum_{i=1}^{n} C_i(t) + r(t). \tag{1}$$

In this equation, $C_i(t)$ represents the IMF components and $r(t)$ is the residual component, and it represents the average trend of the signal. And the process of EMD is shown in Figure 1.

However, when the noises or intermittent signals appear in the vibration signal, there also exists modal mixing in EMD, which will make the fault-feature extraction unstable and inaccurate. SVD can enhance the resilience of fault-feature matrix obtained by EMD through the way of matrix operation, which contributes to extracting the substantive features under the condition of noises or intermittent signals mixing accurately. Especially in practical problems, we often choose the effective IMF components which contain the main fault-feature information from all of the IMF components to analyze further. Therefore, the selection of effective components from all of the IMF components for SVD is also the key step of fault-feature extraction in this paper.

2.2. Select the Key IMF Components Using CorAA. In this paper, we introduced the concept of correlation analysis algorithm (CorAA) to analyze the correlation between the original signal and each IMF, which helped to select the key IMF components [20]. The correlation coefficient can directly judge the correlation degree between each IMF component and the original signal. That is to say, the greater the correlation coefficient, the more feature information the IMF component contains, and it can be identified as the key IMF component for further analysis. Given the original signal $X(t)$, and the IMFs $C_i(t)$, the CorAA process can be expressed as follows:

(1) The calculation of covariance ($C_{xy}(i)$):

$$\begin{aligned} C_{xy}(i) &= E\left\{\left[X(t) - u_X\right]\left[C_i(t) - u_{C_i}\right]\right\} \\ &= \lim_{T \longrightarrow \infty} \frac{1}{T} \int_0^T \\ &\quad \cdot \left\{\left[X(t) - u_X\right]\left[C_i(t) - u_{C_i}\right]\right\} dt. \end{aligned} \tag{2}$$

In equation (2), $C_{xy}(i)$ represents the covariance of $X(t)$ and the IMF components $C_i(t)$, $i = 1, 2, 3, \ldots, N$; N is the total number of IMFs. And

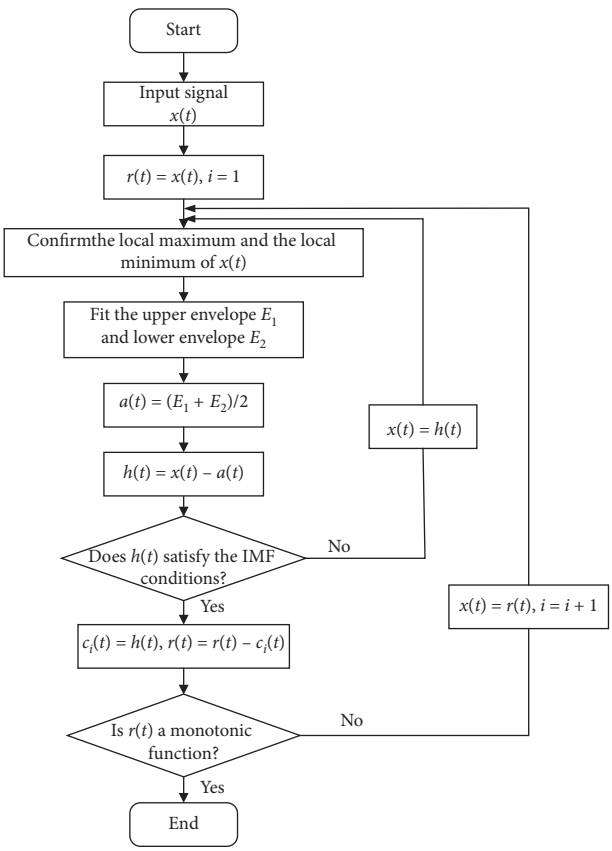

Figure 1: The flow chart of EMD.

u_X and u_C denote the mean value of $X(t)$ and $C_i(t)$ separately.

(2) The calculation of correlation coefficient ($p_{XC}(i)$):

$$p_{XC}(i) = \frac{C_{XC}(i)}{\sigma_X \sigma_{C_i}}. \tag{3}$$

In equation (3), $p_{XC}(i)$ represents the correlation between $X(t)$ and $C_i(t)$. σ_X and σ_{C_i} represents the standard variance of $X(t)$ and $C_i(t)$ separately. The larger $p_{XC}(i)$ is, the more correlative the IMF is.

(3) Select the key IMF components:

After calculating the correlation coefficient, we selected the key IMF components according to the order of the calculated values, and the total number of key IMFs could be confirmed as we needed.

2.3. SVD Algorithm. SVD is an important orthogonalization method of matrix decomposition in linear algebra. For a real matrix, $A_{m\times n}$, whose rank is r, if there exist two orthonormal matrices, U and W, and another diagonal matrix D, they satisfy the following equation:

$$\begin{aligned} A_{m\times n} &= U_{m\times m} D_{m\times n} W_{n\times n}^T = \sum_i^r \delta_i u_i w_i^T U^T U \\ &= E_{m\times m} W^T W = E_{n\times n}. \end{aligned} \tag{4}$$

The equation (4) is called the singular value decomposition of the real matrix $A_{m\times n}$.

In this equation, $U_{m\times m} = [u_1, u_2, \ldots, u_m]$, $D_{m\times n} = \begin{bmatrix} \Delta_{r\times r} & 0 \\ 0 & 0 \end{bmatrix}$, $\Delta_{r\times r} = \mathrm{diag}(\delta_1, \delta_2, \ldots, \delta_r)$, $W_{n\times n} = [w_1, w_2, \ldots, w_n]$, $r = \min(m, n)$, and $\delta_i (i = 1, 2, \ldots, r)$ is the singular values of the real matrix $A_{m\times n}$. $\delta_i = \sqrt{\lambda_i}, \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_r \geq 0$ is the eigenvalues of $A^T A$. Under the restrictions of $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_r \geq 0$, the singular value of the matrix $(\delta_1, \delta_2, \ldots, \delta_r)$ is unique [21]. The singular value has the following two features: (1) the singular values of matrices have a better stability; (2) the singular values also have both proportion invariance and rotation invariance. Therefore, singular values can reflect the features of eigenvectors very well [16]. So, SVD based on EMD can make up for the deficiency of traditional EMD by the means of matrix operation, which makes the fault-feature extraction more stable in the vibration signals.

2.4. FNN Algorithm. FNN is an important intelligent information processing method, which combines the advantages of fuzzy logic and neural network well. Therefore, the FNN not only has strong self-learning ability to deal with data directly but also has strong ability of structural knowledge expression, so it can realize arbitrary nonlinear mapping with arbitrary precision easily [16]. Figure 2 shows the general structure of FNN.

The fault feature itself is discrete; although it reflects the fault type of bearings, it cannot directly describe the degradation performance process. In this paper, the main function of FNN is to reflect the mapping relationship between the fault features to HI and then realize the establishment of degradation model. In the FNN model, the first layer is called the input layer. Each node of this layer corresponds to an input constant. In this paper, the number of nodes in the input layer is consistent with the number of key IMF components decomposed by EMD. The function of the input layer is to transmit the input signal to the next one without any transformation; the second layer is called the quantization input layer, whose function is to fuzzify the input variables; the third layer is called the hidden layer, which is used to realize the mapping between the fuzzy value of the input variables and the output variables; the fourth layer is the quantization output layer, whose function is outputting the fuzzy value; and the fifth layer is the weighted output layer, which makes the output results to express clearly [17]. In this paper, the training sample of FNN was composed of singular values obtained from EMD-SVD. And the test sample came from the singular values of the measured signal.

2.5. A Bearing Performance Degradation Modeling Method Based on EMD-SVD and FNN. On the basis of the above theory, the bearing performance degradation modeling method based on EMD-SVD and FNN is shown in Figure 3.

The specific modeling steps were as follows:

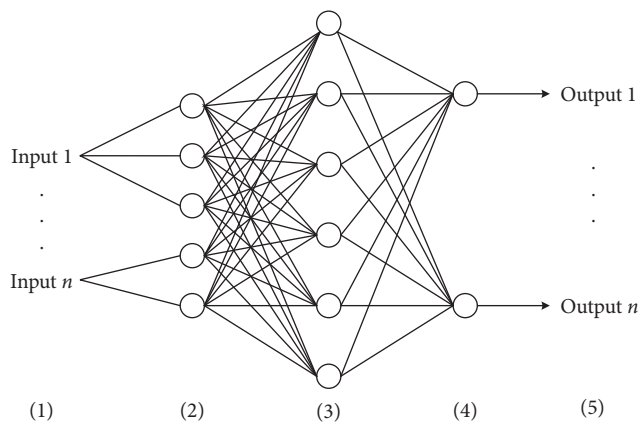

Figure 2: Structure diagram of FNN.

(1) Extract the fault features based on EMD-SVD: firstly, pick up 10 groups of vibration signals in normal state and fault state, respectively, from the test data for establishing the training samples. Secondly, wavelet threshold denoising could be used to remove interference components in order to improve the accuracy of feature extraction. Then, decompose the above vibration signals separately, and n IMF components with different characteristic scales were obtained, $c_1, c_2, \ldots, c_n$, which were used to compose the initial eigenvector matrix. Finally, the key IMF components in the initial eigenvector matrix were decomposed to generate singular value matrix by SVD. And the singular value $\delta = [\delta_1, \delta_2, \ldots, \delta_n]$ $\delta_1 \geq \delta_2 \geq \cdots \geq \delta_n$ was obtained.

(2) Establish the performance degradation model by FNN: the singular values obtained in the previous step were treated as the training samples of FNN. We chose a group of vibration signals whose time span is 0.1 s as the test samples every 10 minutes. And we also did the same treatment to those signals by EMD-SVD in order to obtain their singular values. After determining the training samples and test data of FNN, the performance state of bearings could be expressed as the normalized HI ($0 < \mathrm{HI} < 1$). Because HI indicates the integrity of bearing performance, we can continuously and quantitatively evaluate the bearing degradation performance according to the output HI. The closer the HI is to 1, the better the bearing performance is, while the closer the HI is to 0, the worse the bearing performance is.

3. Case Study

In this section, we used the test data from the Intelligent Maintenance Systems (IMS) to evaluate the degradation process of bearing 1 in the first run-to-failure test and bearing 3 in the second run-to-failure test, respectively, which verified the rationality of the proposed method. Bearings 1 and 3 ultimately failed due to different fault types.

3.1. Experiment Setup. The test data in this paper were obtained from the bearing run-to-failure test of the NSF I/UCR Center for Intelligent Maintenance Systems (IMS) [22]. The test device diagram is shown in Figure 4. And the structural parameters of the bearings are shown in Table 1. In this test, the rotational speed was kept at 2000 rpm, and a 6000 lb radial load was added to the bearings and the shaft. Two PCB 353B33 high sensitivity acceleration sensors were installed on each bearing, and the sampling frequency was 20 kHz. In order to describe the deterioration state, the vibration signal of 0.1 s time slice was collected and analyzed every 10 minutes.

3.2. Performance Degradation Model of Bearing 1

3.2.1. Feature Extraction Based on EMD-SVD. The first test-to-failure experiment lasted for about 163 hours when the outer race defect occurred in bearing 1. 10 groups of vibration signals in normal state and fault state were separately selected from the test data in order to establish training samples. Before the feature extraction of EMD-SVD, the original vibration signals should be pretreated by wavelet threshold denoising to improve the accuracy. The time-domain diagram of vibration signals and IMFs obtained by EMD in normal state and fault state is shown in Figure 5 (take one group of the vibration signals in normal state and fault state separately as an example).

Figures 5(a) and 5(b) show the time-domain diagrams of the vibration signals and IMF components decomposed by EMD in normal and fault state, respectively. Then, we calculated the correlation coefficient to select the key IMF components. The calculation results are shown in Table 2.

From Table 2, we could find that the correlation coefficient values of IMF components 1, 2, 3, 4, 5, and 6 were larger than the others in normal state or fault state. Therefore, the first 6-order IMF components could be identified as the key IMFs and were used to generate the initial vector matrix. Then, by decomposing the initial vector matrix by SVD further, the results of each 10 groups of test data are shown in Table 3 ($\delta_1 - \delta_6$ are singular values).

The singular values of different IMF components corresponded to the changes of energy in different frequency bands [21]. It was obtained in Table 3 that the singular value matrix changed correspondingly with the increase of the bearing fault degree. The singular value of each component in fault state was larger than that in normal state, but it did not increase linearly with the increase of bearing fault degree.

3.2.2. Establishing the Performance Degradation Model. After the fault-feature extraction of EMD-SVD, the performance state of bearing could be expressed as the normalized HI ($0 < \mathrm{HI} < 1$) by FNN. So, each 0.1 s time slice signal would be output as HI, and then the performance degradation curve is shown in Figure 6 by analyzing all of the time slices signals collected from the test data.

The abscissa axis of the performance degradation curve represented the number of time slices picked up from the

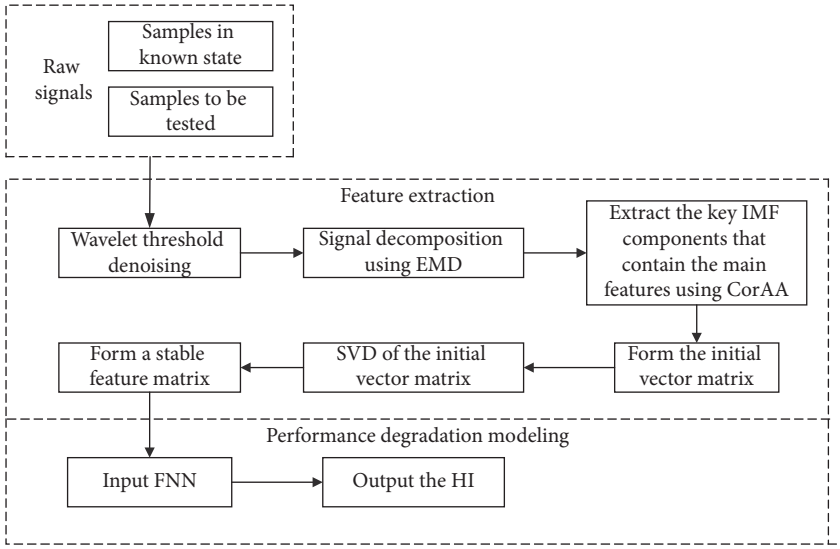

Figure 3: The bearing performance degradation modeling method based on EMD-SVD and FNN.

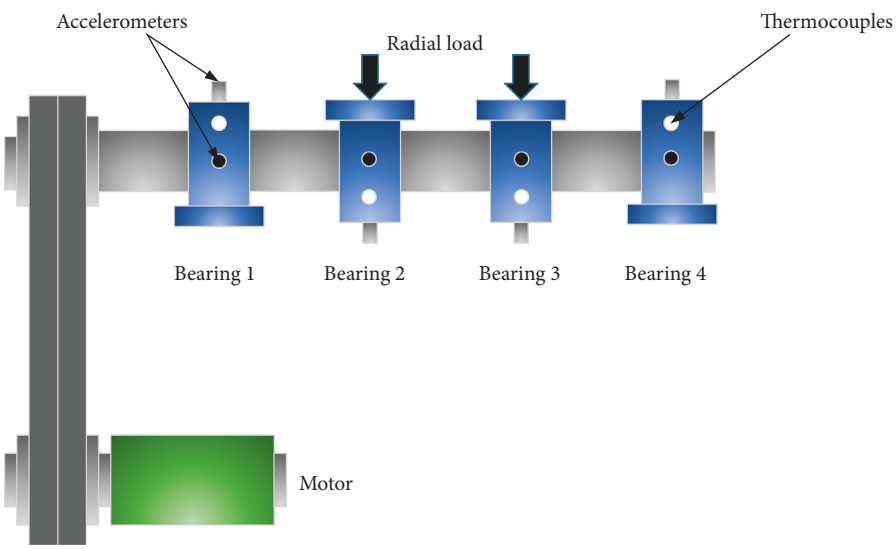

Figure 4: The test device diagram.

Table 1: The structure parameters of bearings.

The designation of bearing	Bearing diameter (mm)	Rolling diameter (mm)	Number of rollings	Contact angle (degree)
ZA2115	71.501	8.407	16	15.17

test data. Because the sampling interval was 10 minutes, the number of time slices multiplied by 10 minutes could be approximately equal to the running time of the bearing, and the ordinate axis indicated the health index, that is to say, it reflected the integrity of bearing performance. From the performance degradation curve, it could be found that the life cycle of bearings experienced through 4 stages which was divided by the red line in the diagram. The first stage was called the stable stage (1st time slice–496th time slice), when the health index was stably around 1, which meant the performance of the bearing remained was in normal state and the integrity was 100%. But at the point of 496th time slice, the early fault features were extracted, so the second stage was the initial performance degradation stage (496th time slice–702nd time slice). At this stage, the HI began to decline slowly which meant that the performance of the bearing began to degenerate. At the 702nd time slice, the HI dropped suddenly, which meant the failure occurred. After that, the HI gradually rose to normal level and there also existed some abrupt fluctuations, mainly because of big spall or the edge of crack smoothed and rounded rapidly after the failure occurred [23, 24]. The third stage was called the deterioration stage (702nd time slice–896th time slice). The fourth stage was called the

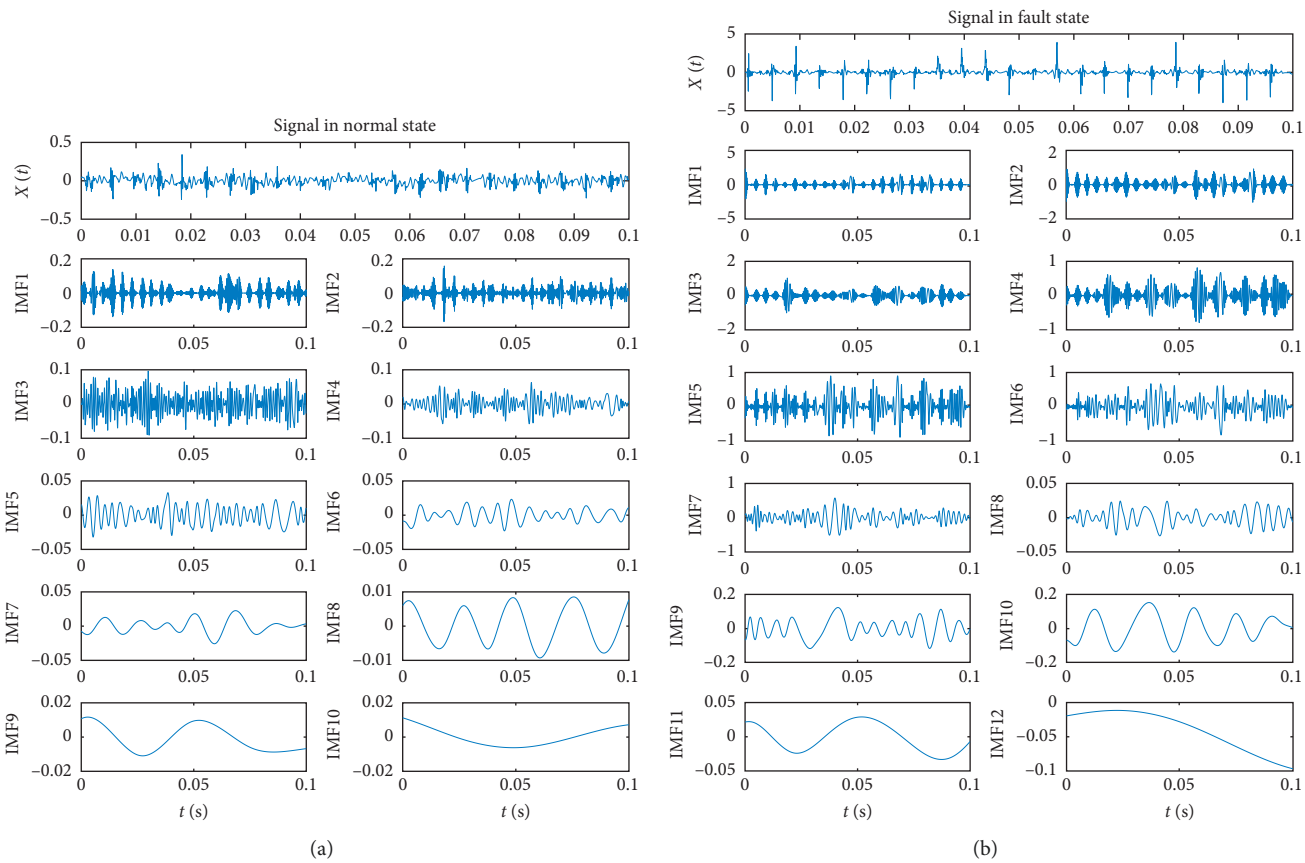

Figure 5: The vibration signals and IMFs obtained by EMD in normal and fault state of bearing 1.

Table 2: The calculation results of the correlation coefficient.

IMF components	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	IMF11	IMF12
Correlation coefficient												
Normal state	0.4167	0.3394	0.5105	0.2787	0.1814	0.2279	0.1227	0.1692	0.0933	0.0579		
Fault state	0.3939	0.2462	0.1819	0.2414	0.2819	0.2453	0.1729	0.0937	0.0783	0.0645	0.0458	0.0224

severe degradation stage (896th time slice to the end), when the performance of the bearing deteriorated sharply until to the state of complete failure.

As shown in Figure 7, the turning point of the initial performance degradation stage was 496th time slice. To verify the accuracy of early fault-feature recognition, the vibration signals before and after 496th time slice were picked up and analyzed through the EMD-PWVD time-frequency method. The analysis result is shown in Figure 8. Through comparative analysis, the following information could be obtained: (1) the frequency distribution of vibration signals after the 496th time slice was shifted from low frequency to high frequency; (2) the energy of vibration signal after the 496th time slice was increased obviously. The above information could prove that the performance of the bearing has changed before and after the turning point, so it fully demonstrated that the modeling method proposed in this paper could accurately identify the early fault features.

In other way, the time-domain features of vibration signals can also reflect the degenerative process of bearings to a certain extent [25]. Therefore, a degradation model with root mean square, average amplitude, and mean square amplitude was also established in this paper, and the result is shown in Figure 8 (curves 1–3 indicated the trend of the root mean square, the average amplitude, and the mean square amplitude, respectively). As could be seen from Figure 8, the degradation curves of the above three time-domain features could describe the degenerative process of bearing performance well, but they could not accurately identify the early fault features in time, which illustrated the innovation and effectiveness of the modeling method proposed in this paper by contrast.

3.3. Performance Degradation Model of Bearing 3. In order to verify the validity of the proposed modeling method, bearing 3 was selected as another research object to establish its performance degradation model. The second test-to-failure

Table 3: Singular value decomposition results of vibration signals in normal and fault state of bearing 1.

State of bearing	Signals	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6
Normal state	Group 1	4.00	3.57	2.96	2.12	2.00	1.47
	Group 2	4.10	3.26	2.65	2.32	1.69	1.13
	Group 3	3.67	3.41	3.03	2.25	2.05	1.32
	Group 4	4.59	3.04	2.52	1.95	1.81	1.13
	Group 5	4.19	2.99	2.80	2.18	1.76	1.27
	Group 6	4.40	3.07	2.78	2.39	1.82	1.26
	Group 7	4.30	3.40	3.01	2.23	2.06	1.43
	Group 8	4.15	3.43	2.76	2.52	1.70	1.19
	Group 9	4.06	3.78	2.51	2.40	1.75	1.34
	Group 10	4.09	3.32	2.52	1.89	1.84	1.30
Fault state	Group 11	11.40	8.30	7.53	6.84	6.37	4.42
	Group12	11.28	8.80	7.64	6.43	5.98	3.19
	Group 13	11.78	7.67	7.36	6.31	5.95	4.61
	Group 14	11.08	7.06	6.19	6.10	5.50	4.47
	Group 15	10.94	8.13	6.43	5.92	5.34	4.07
	Group 16	11.04	8.93	8.02	6.71	5.60	4.84
	Group 17	11.02	7.63	7.50	6.48	5.42	4.64
	Group 18	13.84	10.56	8.75	7.88	5.69	3.44
	Group 19	12.61	10.41	9.56	7.75	6.62	5.16
	Group 20	13.78	9.84	8.51	7.45	5.65	3.76

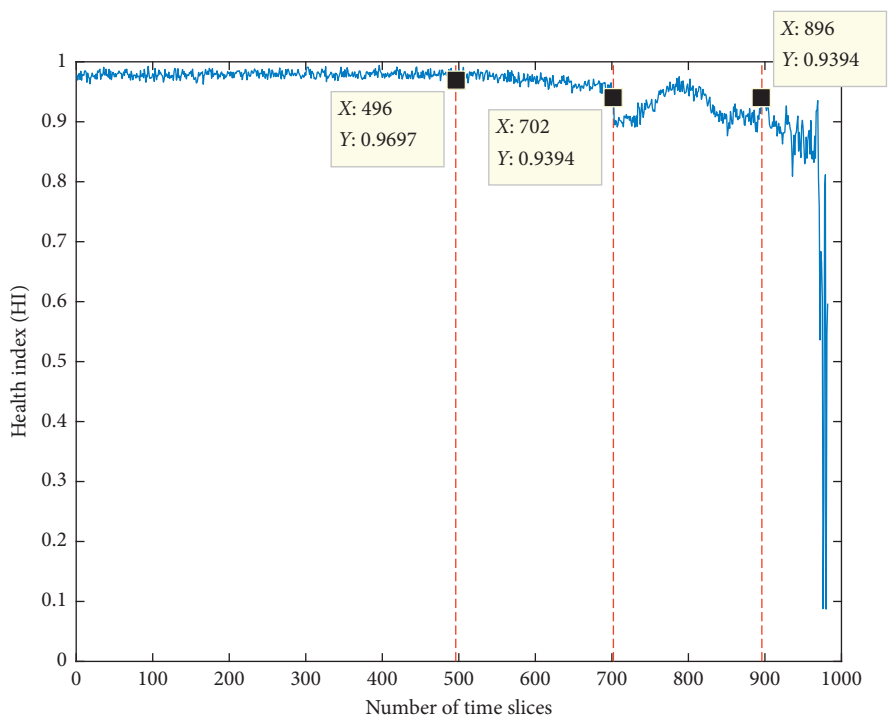

Figure 6: The performance degradation curve in the life cycle of bearing 1.

experiment lasted for about 804 hours when the inner race defect occurred in bearing 3, which had different fault types from bearing 1. The performance degradation model of bearing 3 was established in the same way as bearing 1. And the result is shown in Figure 9.

The performance degradation process of bearing 3 could be divided into 3 stages. From the 1st time slice to the 1976th time slice, it was the stage of normal state. After the 1976th time slice, the HI began to decline slowly which meant that the performance of the bearing began to degenerate. There also existed some abrupt fluctuations in the curve, which had the same reasons as bearing 1. At the 2119th time slice, the HI dropped suddenly, which meant the stage of deep degradation started until the bearing completely lost efficacy.

4. Conclusion

In this paper, a novel bearing performance degradation modeling method based on EMD-SVD and FNN was proposed. The conventional EMD algorithm was optimized

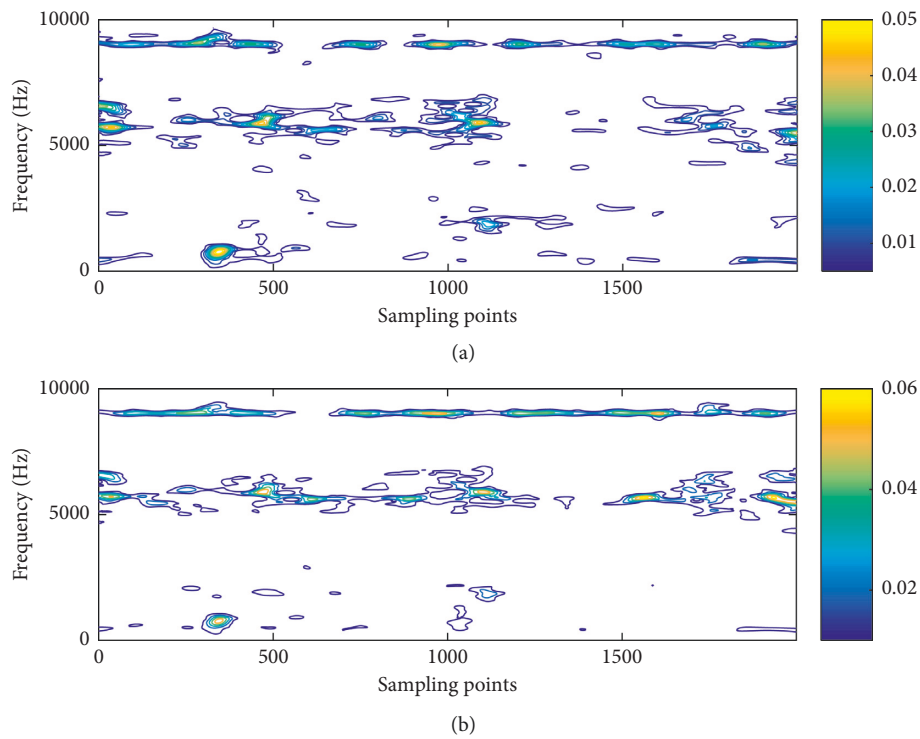

Figure 7: Time-frequency distribution map of EMD-PWVD before and after the turning point. (a) The EMD-PWVD time-frequency distribution of the 495th time slice. (b) The EMD-PWVD time-frequency distribution of the 497th time slice.

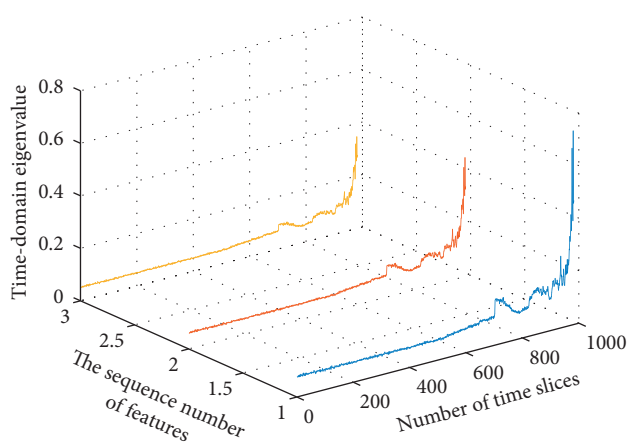

Figure 8: Three kinds of time-domain degradation curves.

by SVD through the way of matrix operation. So, the method of EMD-SVD was used to extract feature vectors, and the test data in normal state and fault state were used as training samples, and then the performance degradation assessment model was built by FNN. The HI ($0 < \mathrm{HI} < 1$) was defined by the distance between the tested sample to the normal one, and its higher value meant better performance. According to the case study, the following characteristics of this proposed method could be concluded:

(1) Only the vibration signals in normal state and fault state were needed to establish this model, and the range of HI is from 0 to 1, which could better reveal the performance degradation trend of bearings.

(2) By comparing the degradation indicators such as root mean square, average amplitude, and mean square amplitude, the method proposed in this paper could accurately identify the initial fault features in an earlier time point.

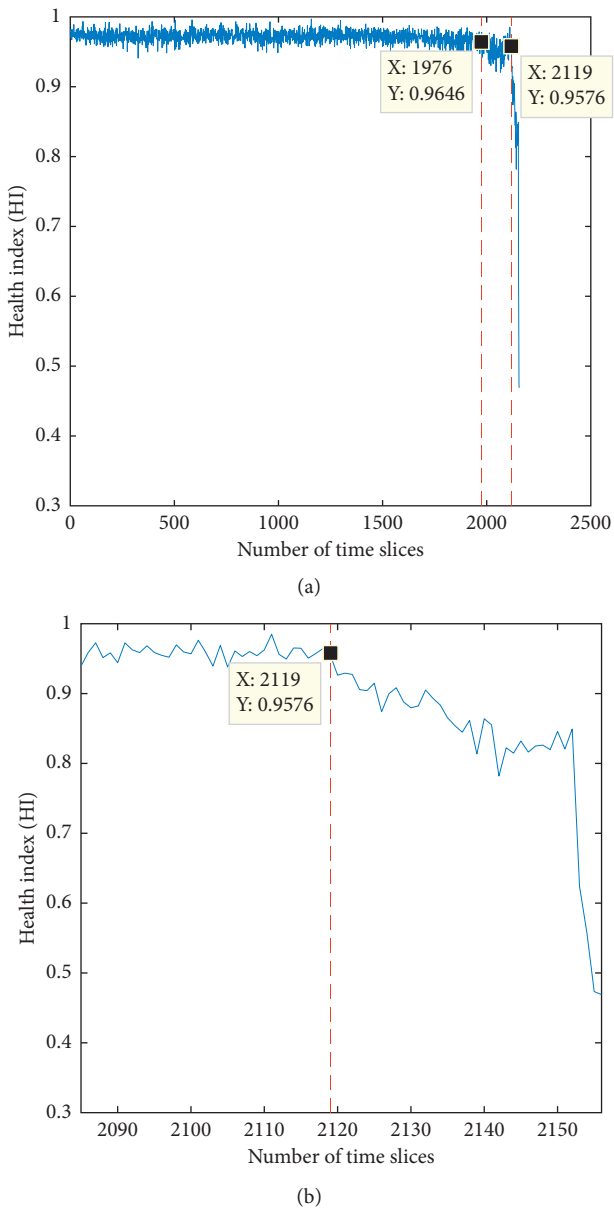

Figure 9: (a) Performance degradation model in the life cycle of bearing 3. (b) The local enlargement of degradation curve.

(3) The new performance degradation model has high accuracy and strong versatility, which contributes to the application in CBM greatly.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Jingbo Gai provided the main idea of the study; Yifan Hu analyzed the experiment and completed the paper; and Junxian Shen helped to programme in some problems.

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