Fault diagnosis of low-speed heavy-duty rolling bearings based on acoustic emission and CEEMDAN energy entropy

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ABSTRACT

To address the limitations of conventional vibration analysis in detecting faults in low-speed heavy-duty rolling bearings, this paper employs acoustic emission technology to capture fault-related information during their operation. Subsequently, the gathered acoustic emission signals are decomposed using the CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) algorithm. By incorporating the correlation coefficient and variance contribution rate, a sensitive IMF (Intrinsic Mode Function) component is selected, and its energy entropy is calculated as the extracted fault feature. This feature is then fed into a neural network for accurate fault classification. To validate the effectiveness of this approach, a simulation test platform for low-speed heavy-duty bearing detection was established. Experimental results demonstrate that this method achieves high accuracy and promising outcomes in addressing the fault identification challenges of low-speed heavy-duty rolling bearings.

Keywords: Bearing fault diagnosis, acoustic emission, CEEMDAN, energy entropy, BP neural networks

1. INTRODUCTION

The vibration signals emitted by low-speed heavy-duty rolling bearings exhibit distinct characteristics such as low frequency, short duration, and minimal energy. However, existing bearing fault diagnosis research primarily focuses on bearings operating under medium to high speeds (exceeding 100 rpm), light loads, and constant rotational speeds[1]. Thus, developing a fault diagnosis method tailored specifically for low-speed heavy-duty rolling bearings, leveraging current technologies, has emerged as a crucial research priority.

Low-speed heavy-duty bearings operate at sluggish speeds and under significant loads, making them less sensitive to fault-induced vibrations that are often masked by environmental noise. When employing traditional vibration analysis methods for fault diagnosis, the following challenges arise[2-4]:

(1) The extremely low bearing speed results in a vibration signal frequency that closely resembles ambient noise frequencies. Standard high-pass filters tend to eliminate signals below 3 Hz, significantly compromising the spectrum analysis's effectiveness.

(2) The extended interval between fault pulse impacts renders the shock pulse method ineffective in accurately detecting fault signals.

(3) The fault point generates feeble impact energy with a low frequency, insufficient to evoke a significant impact response.

The vibration analysis method, a mature and widely adopted technique for fault detection in rotating machinery, has proven effective in assessing the integrity of medium to high-speed rotating equipment. However, its applicability to low-speed rotating machinery operating below 100 rpm poses significant challenges, and it becomes ineffective at ultra-low speeds. This is due to the difficulty in accurately distinguishing the normal operating frequency of low-speed machinery, as well as the lack of significant changes in vibration signals when components fail. To address this limitation, this paper proposes employing acoustic emission technology, which offers high resolution for low-frequency signals, to capture fault signals in low-speed heavy-duty rolling bearings. By utilizing the CEEMDAN algorithm, we can effectively extract fault characteristics from the complex, non-stationary, and nonlinear signals. Finally, a BP neural network is utilized for fault classification, aiming to accumulate valuable experience in exploring fault diagnosis technology for low-speed heavy-duty rolling bearings.

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2. THEORETICAL MODELS

2.1 Fundamentals of acoustic emission technology

At the inception of rolling bearing faults, the lattice structure within the metal undergoes an elastic transition from a low-energy state to a high-energy state. When the elastic stress of these lattices reaches a critical threshold, they shift to an adjacent low-energy state, achieving a new stable condition. During this lattice state transition, a portion of the strain energy is released in the form of transient elastic waves, leading to the phenomenon of acoustic emission (AE). Due to their unique operating environment, ultra-low speed rolling bearings are subjected to significant impact or alternating loads during operation. Over time, this can lead to fatigue, pitting, cracks, and wear faults in the bearings. As the bearing operates, the faulty component rubs and collides with other parts, generating AE signals. The generation and propagation of bearing faults are accompanied by corresponding AE signals, which encode information about the specific fault. Different fault types produce distinct AE signals, enabling us to diagnose various fault types by processing and analyzing the captured AE signals using various signal processing techniques.

Acoustic emission detection technology is a comprehensive approach that encompasses the detection, recording, and analysis of AE signals to deduce their sources using specialized instruments[5]. The elastic waves emanating from acoustic emission sources propagate through the material, ultimately reaching its surface and inducing surface displacements. These displacements are detected by acoustic emission sensors, which transform the material's mechanical vibrations into electrical signals. These signals are then amplified, processed, and recorded for further analysis. Acoustic emission is a ubiquitous physical phenomenon, occurring when most materials undergo deformation or fracture. Generally, the frequency range of AE signals varies depending on the material and the mechanism of AE generation, spanning the spectrum from infrasound to ultrasonic frequencies.

The AE signal generated by rolling bearing faults is a high-frequency signal, typically ranging from tens to hundreds of kilohertz, exhibiting rapid attenuation during propagation. As the signal originating from the fault source traverses one or more contact surfaces, it undergoes refraction, reflection, and scattering, leading to a certain degree of attenuation[6,7]. This complex process results in the final AE signal exhibiting intricate characteristics. Given that different parts and fault types yield distinct AE signal profiles, the processing and analysis of these signals offer a means to identify and evaluate the operational status of low-speed rolling bearings.

2.2 Feature extraction utilizing CEEMDAN energy entropy

Empirical Mode Decomposition (EMD) is a nonlinear and nonstationary signal processing method prevalent in mechanical fault diagnosis. It adaptively decomposes intricate multi-component signals into single-component Intrinsic Mode Functions (IMFs). To mitigate modal aliasing, Ensemble Empirical Mode Decomposition (EEMD) introduces Gaussian white noise of the same amplitude into the signal under analysis and performs multiple EMD decompositions, leveraging the uniform distribution properties of white noise. However, as the white noise added during the decomposition cannot be completely canceled out, EEMD suffers from suboptimal decomposition completeness. Building upon EEMD, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) further incorporates adaptive white noise at each decomposition stage. By calculating the unique residual signal for each IMF, CEEMDAN achieves nearly zero reconstruction error with a relatively small average number of IMF[8]. This decomposition process exhibits integrity, effectively resolving the modal aliasing issues of EMD and the decomposition completeness limitations of EEMD.

Suppose $E_j(\cdot)$ is the jth modal component obtained after decomposition of a given signal $x[n]$, ε_i represents the Gaussian white noise satisfying $N(0,1)$ for each decomposition insertion, $i = 1, \dots, I$ represents the number of sets, μ_j represents the standard deviation of Gaussian white noise, $\overline{IMF_k}$ represents the k-th mode obtained after decomposition, $r_k[n]$ represents the k-th residual, $k = 1, \dots, K$, there, The CEEMDAN decomposition result of the signal $x[n]$ can be represented:

$$x[n] = R[n] + \sum_{k=1}^{K} \overline{IMF_k} \tag{1}$$

Among the series of IMF components derived from the CEEMDAN decomposition of rolling bearing AE signals, only a select few are typically sensitive to bearing faults and carry significant fault information. Conversely, other components may be spurious or misleading. Consequently, the precise selection of these fault-sensitive IMF components is crucial. It not only helps eliminate false or noise components unrelated to bearing fault information but also accentuates the features of valuable components. This step holds significant importance in the accurate extraction of fault characteristics[9].

In this paper, we adopt a method that combines the correlation coefficient and variance contribution rate to identify the sensitive IMF component. Specifically, we calculate the correlation coefficient between the IMF component and the original AE signal, as well as its variance contribution to the original signal, as outlined below:

$$p_i = \frac{1}{N}\sum_{i=1}^{N} x(i)h(i+\tau) \tag{2}$$

where p_i is the correlation coefficient between the i-th order IMF component and the original AE signal, N is the time series length, and τ is the time interval.

$$q_i = \frac{(x_i - E)^2}{k\sigma^2} \tag{3}$$

where q_i is the variance contribution of the intrinsic modal component to the original AE signal, E and σ are the mean and standard deviation of the original AE signal, and k is the number of sampling sequences.

Therefore, sensitive IMF components containing bearing critical fault characteristic information can be selected based on two indicators: correlation coefficient p_i and variance contribution q_i.

Accurate extraction of fault characteristics serves as a fundamental prerequisite for identifying bearing fault modes. As various types of faults arise in rolling bearings, the frequency distribution of their Acoustic Emission (AE) signals undergoes changes, leading to alterations in the energy distribution. Notably, most of the energy tends to concentrate within the resonance frequency band, significantly reducing the randomness of the energy distribution. Entropy, a measure of uncertainty, encapsulates information distribution in the form of probability and can quantify the unevenness of a system's attribute distribution. By integrating energy and entropy, energy entropy emerges as an effective approach for extracting mechanical fault features, widely adopted in fault diagnosis, including wavelet energy entropy and EMD energy entropy. Consequently, this paper introduces the concept of CEEMDAN energy entropy to quantify and analyze the characteristic information of bearing faults[10,11].

Using CEEMDAN algorithm to obtain k IMF components and one residual quantity for the collected AE signals, as shown in equation (1), without considering the residual amount, the energy of each IMF component is calculated, expressed by E_k, and the set $E = \{E_1, E_2, \dots, E_K\}$ characterizes the energy distribution of the AE signal. Define CEEMDAN energy entropy as:

$$H = -\sum_{\mathrm{k}=1}^{K} \frac{E_k}{\sum E_k} lg \frac{E_k}{\sum E_k} \tag{4}$$

Based on the above theory, the feature extraction process based on CEEMDAN energy entropy can be shown as follows:

(1) CEEMDAN decomposition: based on the CEEMDAN algorithm, the original AE signal of the collected low-speed heavy-duty rolling bearings is decomposed to obtain a series of IMF components;

(2) Sensitive IMF components extraction: according to equations (2) and (3), we calculate the correlation coefficient between the IMF components of each order and the original AE signal and the variance contribution rate to the original signal, and extract the sensitive IMF components that can reflect the fault information of low-speed heavy-duty rolling bearings;

(3) Energy entropy calculation: we calculate the energy entropy of each sensitive IMF component according to equation (4), which is used as a characteristic parameter for fault diagnosis;

(4) Fault diagnosis: it is input to the classifier for fault classification according to the obtained energy entropy characteristic parameters.

2.3 BP neural networks

The BP neural network, or Back Propagation Neural Network, is a forward-feed network with an error backpropagation mechanism. In this architecture, the connections between layers of neurons follow a unidirectional forward propagation path. However, when the actual output value differs from the desired target, the error is propagated backwards to each layer of neurons. Based on this error, the network adjusts the weights and thresholds of each layer, ensuring that the prediction result gradually converges towards the desired output value.

The BP neural network comprises an input layer, one or more hidden layers, and an output layer, as schematically depicted in Figure 1. These layers are interconnected via weights and thresholds. During forward propagation, the weighted sum of the inputs is calculated, and this sum is then fed into a specific activation function, such as the Sigmoid function, to generate the output for the next layer:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

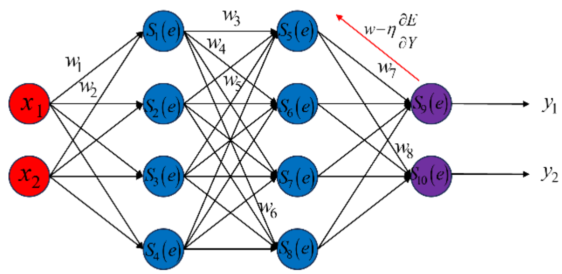

Figure 1. BP neural network feedforward structure diagram.

3. EXPERIMENTAL MODELING AND SIMULATION ANALYSIS

Considering the unique operating requirements of low-speed heavy-duty rolling bearings under specialized working conditions, a scaled simulation test bench was designed and constructed by Simulink, as illustrated in Figure 2. This test bench comprises a motor, rack and pinion system, shaft and bearing assembly, commutator, and swingarm. Utilizing this test setup, experimental data from the rolling bearings were gathered from the test bench. To simulate different bearing defects, the end cover was dismounted and remounted with bearings possessing various flaws. Acoustic emission sensors positioned in the housing and bearing cover captured the emitted signals, which were then collected and stored using a data acquisition card and computer.

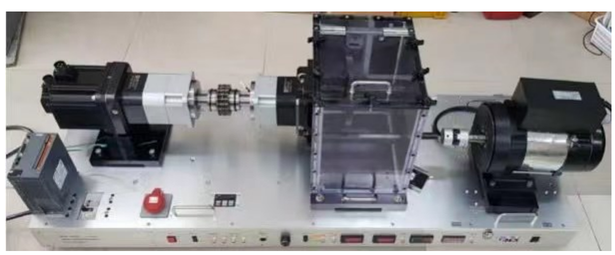

Figure 2. Low-speed heavy-duty rolling bearing acoustic emission acquisition simulation test bench.

Utilizing EDM and wire EDM technology, single-point defects and geometric imperfections were precisely created on the inner ring and rolling elements of the rolling bearing test specimens to mimic pitting corrosion and crack faults. The fault conditions examined include a fault-free state, pitting fault in the inner ring, pitting fault in the rolling element, crack fault in the inner ring, and crack fault in the rolling element. To analyze these fault states, the CEEMDAN algorithm was employed to decompose the acoustic emission (AE) signals collected from the rolling bearing test body in its normal state, as well as during the various fault conditions. This decomposition process yielded the 8th-order IMF (Intrinsic Mode Function) component and associated margins. Specifically, the results of the rolling element pitting corrosion fault decomposition are depicted in Figure 3.

As evident from the CEEMDAN decomposition, the IMF components contain certain low-amplitude components. Direct analysis of all IMF components can pose challenges in isolating meaningful characteristic information pertinent to bearing faults. Hence, the pivotal step in feature extraction lies in the selection of sensitive IMF components.

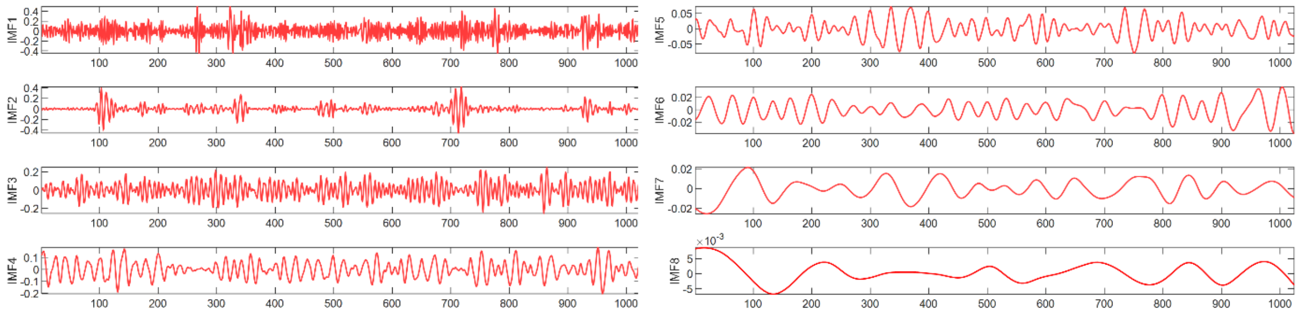

Figure 3. CEEMDAN decomposition results of rolling element pitting fault.

Subsequently, the correlation coefficient and variance contribution rate between the IMF components and the original signal were calculated for various conditions, including the normal state of the rolling bearing test body, inner ring pitting corrosion fault, rolling element pitting corrosion fault, inner ring crack fault, and rolling element crack fault. Specifically, the correlation coefficient and variance contribution rate pertaining to the rolling element pitting fault are depicted in Figure 4.

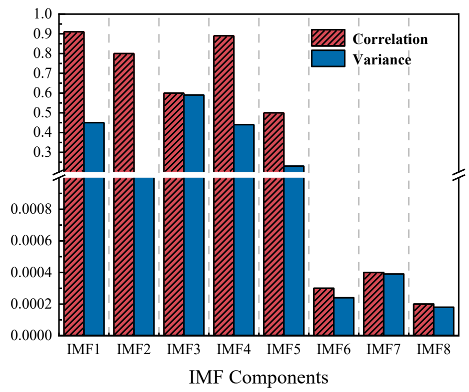

Figure 4. Correlation coefficient and variance contribution rate of IMF components of rolling element pitting faults.

Obviously, the correlation coefficient and variance contribution rate of the IMF components of the first 4th order are large, that is, they have a strong correlation with the original AE signal and contain the main fault information, so the IMF components of the first 4th order can be selected as sensitive IMF components.

CEEMDAN decomposition was carried out on AE signals in five different states: normal state, inner ring pitting fault, rolling element pitting fault, inner ring crack fault and rolling element crack fault, and the energy entropy of the sensitive IMF component IMF1-IMF4 was extracted as the main feature, and some of the results are shown in Table 1.

Table 1. CEEMDAN energy entropy feature extraction results.

Fault type	IMF1	IMF2	IMF3	IMF4
Normal	0.3467	0.3654	0.3798	0.1623
Inner ring pitting fault	0.2468	0.1764	0.3457	0.1401
Rolling element pitting fault	0.3365	0.1167	0.2457	0.1003
Inner ring crack fault	0.2647	0.2483	0.3028	0.0284
Rolling element crack fault	0.2574	0.3670	0.0487	0.3786

Based on Matlab 2019a software, a BP neural network classification model for low-speed heavy-duty rolling bearing fault diagnosis was constructed, and the sensitive IMF energy entropy decomposed by AE signal CEEMDAN in five different states of bearing was input into the model as feature vectors for fault diagnosis, the training error was set to 0.001, the maximum number of iterations was set to 1000, and the activation function used the Sigmoid function.

To validate the advantages of the CEEMDAN energy entropy approach, we performed an integrated empirical mode decomposition (EEMD) on the gathered AE signal samples. This analysis yielded a sensitive IMF component energy entropy feature vector, which served as an input for the BP neural network to facilitate identification and classification. A comparative analysis was conducted to assess the fault diagnosis performance of both methods. In this experimental setup, 60 sample data sets were gathered for each of the five states, totaling 300 data sets. Out of these, 30 data sets from each state were randomly chosen, amounting to 150 sets, and used as training samples for the BP neural network. The remaining 150 data sets served as test sets for the recognition and classification tasks. Each experiment was replicated 10 times. Figure 5 displays the test results of these 10 iterations, comparing the performance of the sensitive IMF component energy entropy decomposed by EEMD and CEEMDAN when used as eigenvectors for the BP neural network. Additionally, Table 2 provides the average accuracy statistics for the prediction outcomes of both methods.

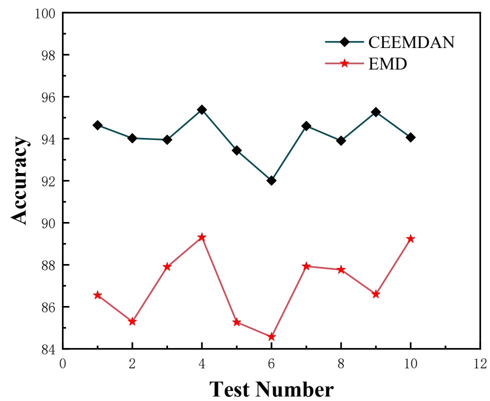

Figure 5. BP neural network fault diagnosis test results.

Table 2. Comparison of fault diagnosis results.

Fault diagnosis model	Average diagnostic recognition accuracy
EEMD energy entropy-BPNN	87.13%
CEEMDAN energy entropy-BPNN	94.13%

From Table 2, it can be concluded that the average recognition accuracy of low-speed heavy-duty rolling bearing fault mode recognition based on CEEMDAN energy entropy-BPNN model is 94.13%, which is higher than that of EEMD energy entropy-BPNN model. It can be seen that the former has a better diagnostic effect and can meet the diagnostic requirements for the fault mode of low-speed rolling bearings

4. CONCLUSIONS

In this paper, we investigate the fault diagnosis method for low-speed heavy-duty rolling bearings utilizing acoustic emission (AE) and CEEMDAN energy entropy. We elaborate on the algorithm theory concisely and establish an AE simulation test platform. Through a comparative experiment, we analyze two algorithm models: CEEMDAN energy entropy-BPNN and EEMD energy entropy-BPNN. Our findings reveal that the CEEMDAN energy entropy method introduced in this paper significantly enhances the fault diagnosis and recognition rate compared to the latter. We apply this approach to fault identification in low-speed heavy-duty rolling bearings, and experiments demonstrate its effectiveness.

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