

Rolling Bearing Fault Diagnosis Based on FMD Optimized by an Objective Function

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ABSTRACT: *Aiming at the problems of unstable FMD mode screening and insufficient fault-sensitive mode recognition ability, a composite objective function based on CK and EE is proposed. The objective function uses the correlation kurtosis to characterize the strength of the periodic impact characteristics in the mode, and the energy entropy index to reflect the signal complexity and the degree of dispersion of the energy distribution. Through the synergistic effect of the two, the fault impact information can be highlighted and the interference of noise and unrelated complex components can be suppressed. Secondly, in order to reduce the dependence of key parameter selection on experience, this paper introduces the joint optimization strategy of INFO and MOPSO optimization algorithm to adaptively optimize the decomposition parameters. The experimental results show that the proposed method can accurately extract the fault sensitive modes of rolling bearings, reduce the influence of noise and irrelevant components on the diagnosis results, and has good applicability and stability for rolling bearing faults.*

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I. INTRODUCTION

Rotating machinery is widely used in the chemical, electric power, metallurgical, and mechanical manufacturing industries. Faults in rotating machinery may lead to local damage, substantial economic losses, and even casualties. A large body of research has shown that bearing faults account for approximately 30% of all rotating machinery faults[1][2][3]. Bearings are critical components in various machines and industrial equipment, serving to support rotating shafts and reduce friction [4]. Accordingly, various bearing faults frequently occur during operation. If such faults cannot be detected and addressed in a timely manner, the reliability of mechanical equipment will be significantly reduced, its production functions may be lost, and economic losses amounting to millions or even tens of millions may be incurred; in severe cases, catastrophic accidents involving equipment destruction and loss of life may occur [5][6][7][8].

Huang E. et al. [9]proposed the Empirical Mode Decomposition (EMD) method. EMD is an adaptive signal processing technique that can effectively analyze nonlinear and non-stationary signals. However, problems such as end effects and mode mixing may adversely affect the accuracy of the analysis results[10][11]. On the basis of EMD, Konstantin Dragomiretskiy et al. [12] proposed Variational Mode Decomposition (VMD). VMD is a non-recursive signal processing method that decomposes a time series into several Intrinsic Mode Functions (IMFs) with limited bandwidth, and then obtains the optimal result for each mode through iterative updating. Although VMD can achieve signal decomposition, some modes still contain considerable noise and invalid components, making fault features insufficiently prominent[13][14].

To address the above issues, Feature Mode Decomposition was proposed by Miao YH in 2023 [15]. Based on the concept of deconvolution, FMD decomposes vibration signals by constructing an adaptive finite impulse response (FIR) filter bank, and optimizes the filter parameters with the objective of maximizing correlated kurtosis. However, the decomposition performance of FMD is highly sensitive to parameter settings. To solve this problem, Xiaolan Yan et al. [16]proposed a bearing fault diagnosis method based on Parameter-Optimized Feature Mode Decomposition (POFMD). By combining the Particle Swarm Optimization (PSO) algorithm with the FMD algorithm, this method enables adaptive signal decomposition without prior knowledge and exhibits strong robustness against noise interference.

To overcome the limitations of insufficient sensitivity to transient features in early weak impulsive faults and compound faults, the tendency of fault information to become dispersed, and the need for manual parameter setting, this paper proposes an improved FMD method based on multi-objective optimization. In this method, correlated kurtosis and energy entropy are collaboratively optimized, and the parameters in the objective function are adaptively tuned using the Weighted Mean of Vectors (INFO) algorithm and the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. Through both simulation and experimental analyses of rolling bearing signals, the effectiveness and superiority of the proposed method in the diagnosis of

early weak faults in rolling bearings are verified.

II. The principle of FMD

FMD is developed based on the concept of deconvolution. By constructing an adaptive finite impulse response (FIR) filter bank, it decomposes vibration signals and optimizes the filter parameters with the objective of maximizing correlation kurtosis [17]. Based on this principle, FMD employs an adaptive FIR filter bank to decompose the signal into different modes. This method can more effectively enhance periodic impulsive components, thereby making fault features more prominent. In addition, it exhibits superior signal decomposition capability, particularly showing significant advantages over VMD in terms of denoising performance and frequency separation [18]. The main procedure of FMD is summarized as follows:

(1) Parameter initialization: The number of modes K , filter length L , delay parameter or period range, and iteration termination conditions need to be specified. Meanwhile, the FIR filter coefficients corresponding to each mode are initialized.

(2) Signal filtering and mode extraction: The existing filter bank is used to perform convolution on the original signal, thereby obtaining the corresponding modal components.

(3) Period estimation: Each modal signal is analyzed, for example through autocorrelation analysis or envelope analysis, in order to estimate the corresponding impulsive period T .

(4) Objective function construction (correlation kurtosis): Correlation kurtosis (CK) is taken as the optimization objective, on the basis of which an evaluation function capable of reflecting periodic impulsive characteristics is established.

$$CK_M(T) = \frac{\sum_{n=1}^N (\prod_{m=0}^M y(n-mT))^2}{(\sum_{n=1}^N y^2(n))^{M+1}} \quad (1)$$

In the formula : T is the fault shock cycle ; m is the displacement order ; CK is the objective function.

(5) Filter updating: Under the criterion of maximizing correlation kurtosis, iterative optimization methods, such as gradient-based updating or analytical solutions, are employed to update the FIR filter coefficients corresponding to each mode, so that the filter output can gradually enhance the periodic impulsive features.

$$\max_{f_k} \frac{\sum_{n=1}^N (\prod_{m=0}^M y_k(n-mT))^2}{(\sum_{n=1}^N y_k^2(n))^{M+1}} \quad (2)$$

In the formula : f_k is the k th filter coefficient vector.

(6) Mode updating and reconstruction: The updated filters are used to re-extract the modal components, and the characteristic indices of each mode are correspondingly updated.

$$\mathbf{p}^{(i)} = \sum_{m=0}^M \mathbf{X}_{mT} \left[\prod_{j=0}^M \mathbf{y}_{jT}^{(i)} \right]^2 \mathbf{y}_{mT}^{(i)} \quad (3)$$

In the formula : $\mathbf{y}_{jT}^{(i)}$ is the output vector corresponding to the jT delay in the second iteration.

(7) Convergence determination: It is determined whether the termination conditions are satisfied, such as reaching the maximum number of iterations or the change in the objective function falling below a predefined threshold. If not, the procedure returns to Step (3) for further iteration; otherwise, it proceeds to the next step.

(8) Mode selection and output: According to correlation kurtosis or other auxiliary indicators, the obtained modes are ranked and screened, and the fault-sensitive modes are extracted as the input for subsequent fault diagnosis. The FMD decomposition process is shown in Figure 1.

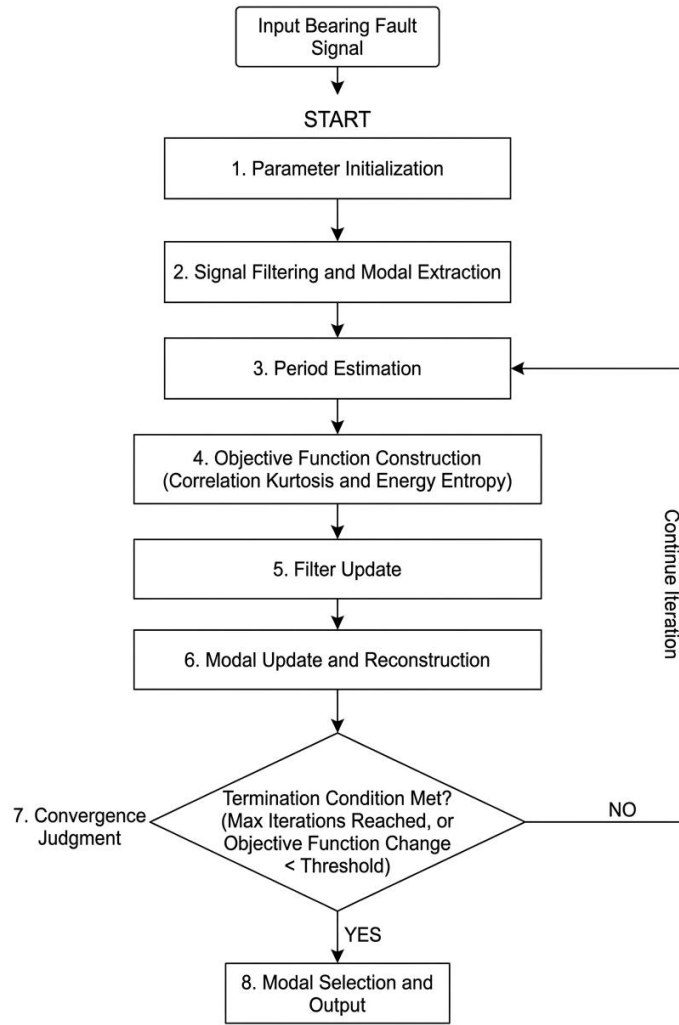


Fig. 1 FMD decomposition flow chart

III. FMD composite objective function optimization design

Ideally, a fault-sensitive mode should satisfy two requirements simultaneously. First, the mode should contain pronounced periodic impulsive features so as to reflect the regular vibration response induced by local defects in rolling bearings. Second, the overall modal complexity should be relatively low, with concentrated energy and minimal interference from noise and other irrelevant components. Therefore, it is necessary to select a composite indicator that comprehensively addresses these two aspects.

To demonstrate the rationality of the objective function adopted in this paper, several representative indicators are selected for comparison. Specifically, kurtosis, CREST Factor (CREST F), Impulse Factor (IF), Clearance Factor (CF), Correlation Coefficient (CC), and Correlated Kurtosis (CK) are used to highlight periodic impulsive characteristics, whereas information Entropy (E), Sample Entropy (SampEn), Permutation Entropy (PE), Energy Entropy (EE), and Spectral Entropy (SE) are employed to reflect the internal energy distribution characteristics of the modes.

To verify the superiority of the selected indicators in evaluating the fault characteristic information of rolling bearings, a simulated signal is constructed as follows:

$$f(t)=f_1(t)+f_2(t)+f_3(t) \quad (4)$$

$$f_1(t)=\sum_k e^{-1000(t-kT_p)} \sin(2\pi \cdot 2000(t-kT_p)) \quad (5)$$

$$f_2(t)=0.025 \sin(2\pi \cdot 7t+\pi/6) \quad (6)$$

$$f_3(t)=0.025 \sin (2\pi \cdot 14t-\pi/3) \tag{7}$$

$$f'(t)=f(t)+n(t) \tag{8}$$

Where $f'(t)$ denotes the simulated fault signal, which is composed of $f_1(t)$, $f_2(t)$, $f_3(t)$, and $n(t)$, where $n(t)$ represents Gaussian white noise with the signal-to-noise ratio (SNR) set to -3 , -5 , -8 , and -10 dB. The sampling duration is set to 1 s, and the sampling frequency is 2000 Hz. The time-domain waveform of the simulated fault signal is shown in Figure 2. The fault signal is then decomposed, and the comparison results of different evaluation indices under different SNR conditions are obtained, as shown in Figures 3 and 4.

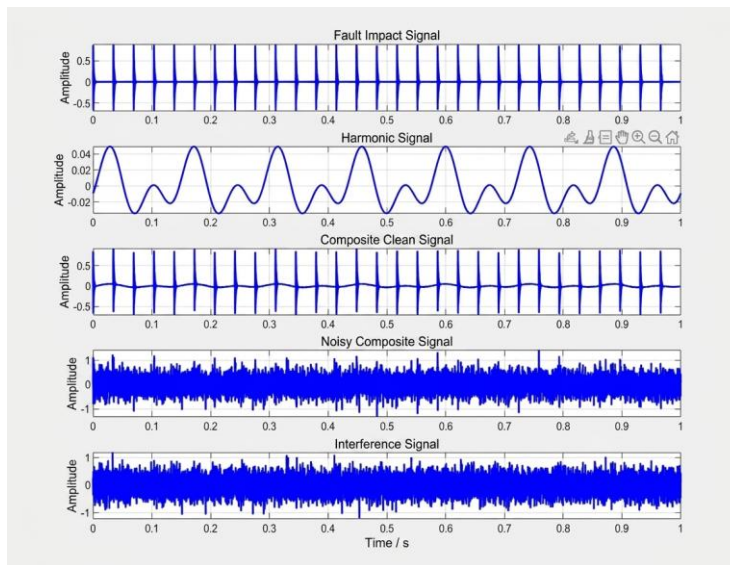


Fig.2 Time domain waveform of simulated fault signal

As shown in Fig. 3, the six indicators exhibit significantly different responses under different signal-to-noise ratios. Although kurtosis, crest factor, impulse factor, and margin factor can reflect impact characteristics to some extent and are simple to calculate, they are highly sensitive to noise and random large-amplitude impulses, resulting in large fluctuations and poor stability under different signal-to-noise ratio conditions. Consequently, their sensitivity to periodic fault impact signals of rolling bearings is reduced. In contrast, the correlation coefficient and correlated kurtosis show better stability and higher sensitivity to periodic fault impacts. The correlation coefficient reflects the overall similarity between the mode and the original signal, but it is less effective in characterizing the periodicity of fault impacts. Correlated kurtosis, by incorporating periodic information into conventional kurtosis, can not only characterize the intensity of impulsive components but also highlight the periodic pattern of fault impacts, making it more targeted for rolling bearing fault feature characterization.

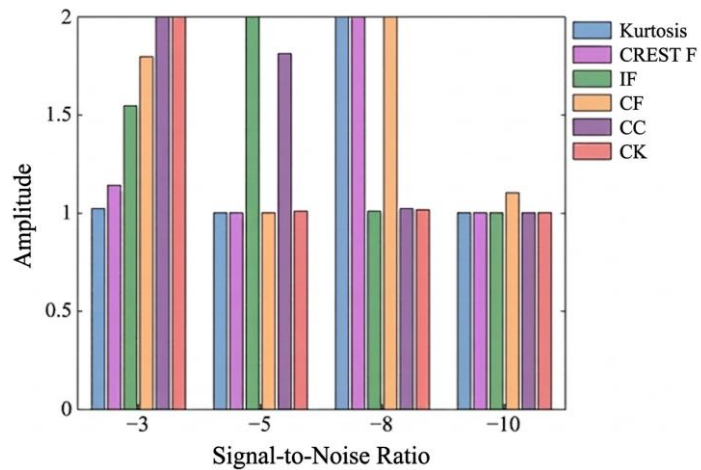


Fig. 3 Calculation results of six periodic objective functions under different signal-to-noise ratios

As illustrated in Fig. 4, different entropy measures show distinct response characteristics as the noise level changes. Among them, energy entropy remains relatively stable and corresponds well to the concentration of effective features within the mode. Information entropy can describe the variation in overall signal uncertainty, but it is not sufficiently sensitive to local energy concentration. Sample entropy reflects sequence complexity to a certain extent, yet its dependence on parameters such as embedding dimension and tolerance limits its engineering applicability. Permutation entropy and spectral entropy are useful for describing dynamic disorder and frequency-domain complexity, respectively, but they are less direct in indicating fault energy concentration. Therefore, correlated kurtosis and energy entropy characterize mode quality from the perspectives of fault impact enhancement and signal complexity constraint, respectively, and their complementarity better satisfies the requirements of FMD mode quality evaluation for distinct periodic impacts, feature concentration, and complexity constraint.

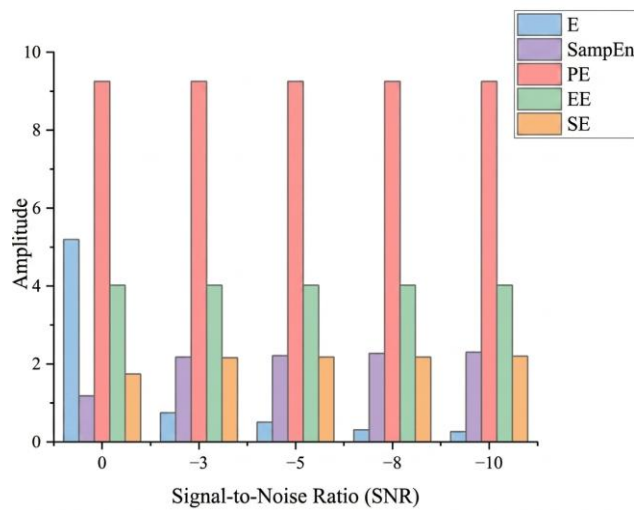


Fig.4 Calculation results of five signal complexity objective functions under different signal-to-noise ratios

IV. MOPSO-INFO-FMD adaptive optimization method

To achieve adaptive optimization of both the composite objective function and the key FMD parameters, an MOPSO-INFO collaborative framework is established. In this framework, the three key parameters of FMD are adaptively searched using the Multi-Objective Particle Swarm Optimization (MOPSO)[19] algorithm and the Weighted Mean of Vectors (INFO)[20] algorithm, thereby reducing the subjectivity of empirical parameter selection and improving the accuracy and stability of fault-sensitive mode extraction.

Construction of MOPSO-INFO optimization model

Since correlated kurtosis and energy entropy characterize different modal states and exhibit an inherent trade-off, a single-objective optimization strategy is insufficient to balance their coordination. Therefore, MOPSO is employed to optimize the weight parameters in the composite objective function. By introducing Pareto dominance and an external archive mechanism into conventional particle swarm optimization, MOPSO can preserve both solution quality and distribution diversity during the multi-objective optimization process, making it suitable for balancing correlated kurtosis enhancement and energy entropy suppression. INFO, as an intelligent optimization algorithm for continuous-space problems, features fast convergence, strong global search capability, and a relatively simple implementation. Through information interaction and differential updating among population individuals, INFO achieves a balance between global exploration and local exploitation, thus reducing the risk of falling into local optima. Given that the FMD parameter space is typically multimodal, nonlinear, and strongly coupled, INFO is well suited for the adaptive search of FMD

parameters. Accordingly, the proposed MOPSO–INFO collaborative optimization algorithm integrates weight optimization and key parameter tuning, enabling the evaluation criteria and decomposition parameters to operate cooperatively. The MOPSO-based weight optimization process (a) and the INFO-based optimization process (b) are illustrated in Fig. 5.

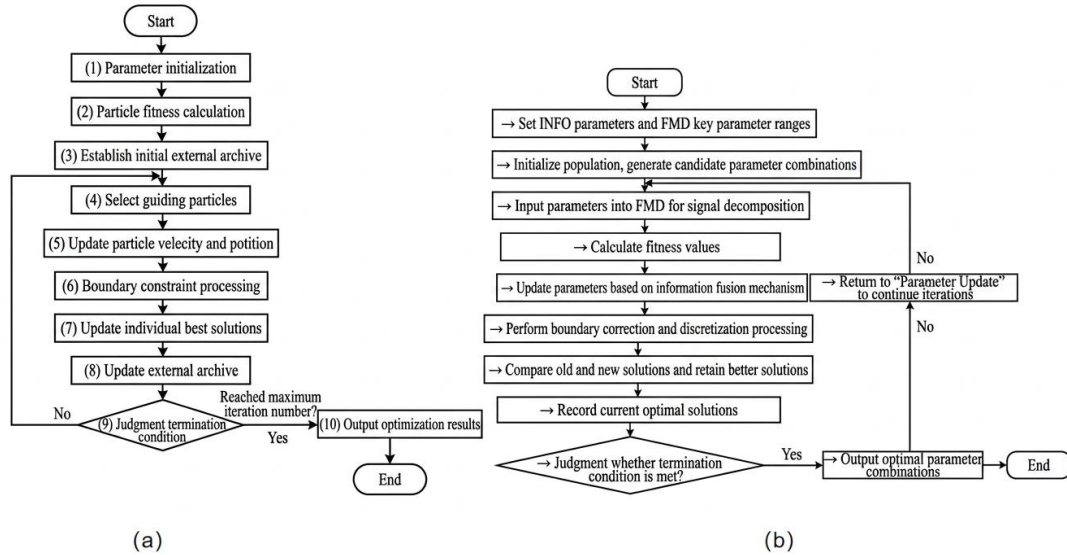


Fig. 5 MOPSO weight optimization (a) and INFO optimization (b) flow chart

MOPSO-INFO-FMD rolling bearing fault diagnosis process

- (1) Vibration signals under different operating conditions are collected from the rolling bearing test rig and stored as one-dimensional time-series vibration data.
- (2) To address the strong influence of decomposition parameters on feature extraction performance, an adaptive optimization strategy combining INFO and MOPSO is adopted for key parameter tuning. MOPSO is first used to search promising regions through particle swarm evolution, and INFO is then employed to perform further optimization in the parameter space by virtue of its strong global search capability, thereby improving optimization accuracy and convergence stability and ultimately obtaining the optimal parameter combination.
- (3) The optimized parameters are introduced into the signal decomposition model to adaptively decompose the original vibration signal into multiple mode components. Then, based on correlation, energy distribution, and comprehensive evaluation indices, the mode components are analyzed and screened to retain effective modes sensitive to fault features while removing redundant modes and irrelevant noise components.
- (4) The selected effective mode components are reconstructed to obtain a signal in which rolling bearing fault information is enhanced.
- (5) Time-domain, frequency-domain, or envelope spectrum analysis is then performed on the reconstructed signal to extract rolling bearing fault features, and the bearing operating condition is identified in combination with the characteristic fault frequencies.
- (6) Finally, according to the extracted features, different bearing states, including normal condition, inner-race fault, outer-race fault, and rolling element fault, can be diagnosed.

Test signal analysis

The data were obtained from the self-collected dataset of Changchun University (CCU). A rolling bearing fault simulation test platform was established, consisting mainly of a hydraulic cylinder, a high-speed motor, a test bench controller, and a speed–torque sensor. In the experiment, an NSK 6007 deep-groove ball bearing was selected as the research object. The sampling frequency was set to 20 kHz, the rotational speed was 3000 r/min, and a radial load of 1000 N was applied together with an inner-race fault to simulate the operating condition of a faulty rolling bearing. The rolling bearing fault simulation test platform is shown in Fig. 6.

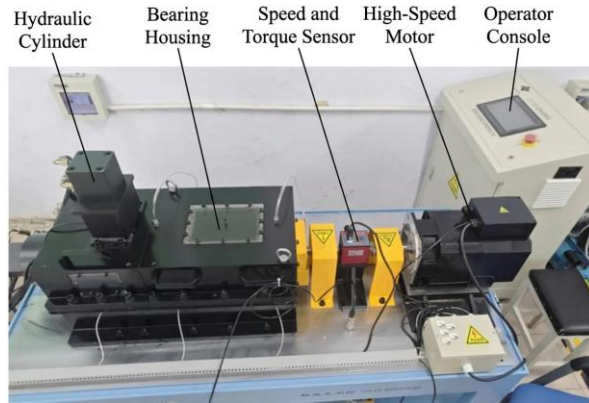


Fig.6 Rolling bearing fault experimental platform

As shown in the time-domain waveform (a) and spectrum (b) of the inner-race fault in Fig. 7, the signal exhibits obvious vibration fluctuations throughout the entire sampling period, with relatively large amplitude variations and certain local impulsive components, indicating that the fault information is already reflected in the original signal. In particular, a distinct spectral peak appears near 2000 Hz, accompanied by multiple frequency components distributed in the adjacent bands, suggesting that the frequency structure of the fault signal is relatively complex.

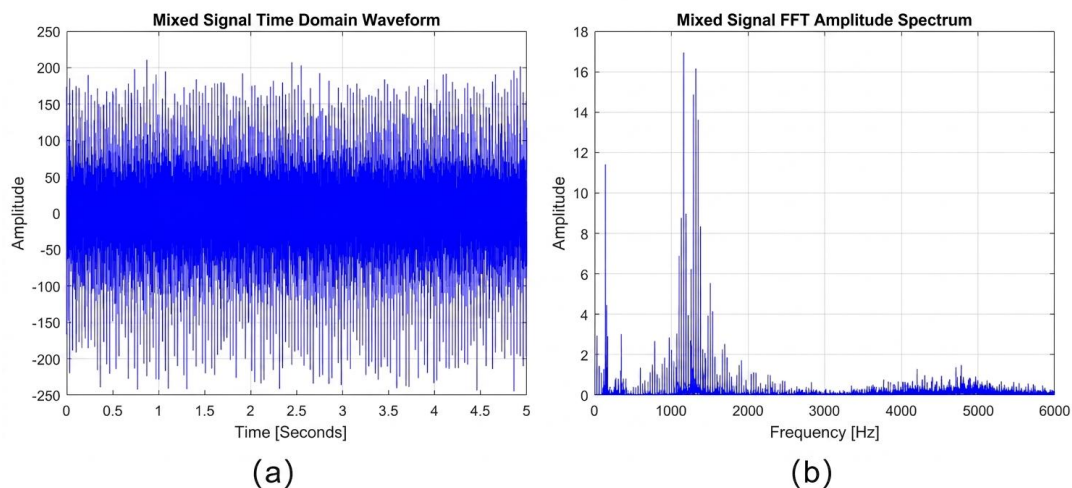


Fig. 7. Time-domain waveform (a) and spectrum (b) of the inner-race fault vibration signal.

For the inner-race fault, MOPSO-INFO is employed to optimize the weight parameters and key decomposition parameters of the composite objective function-based FMD. As shown in Figs. 8 and 9, the parameter search points are widely distributed within the predefined range, whereas the final convergence points are concentrated in locally optimal regions. This indicates that MOPSO can balance global exploration and local convergence during the search process, thereby improving the reliability of parameter selection. Under INFO optimization, the accuracy corresponding to the three parameters gradually increases with the number of iterations and becomes stable in the later stage, reaching approximately 98.5% to 98.9%. These results demonstrate that the MOPSO-INFO collaborative optimization method also maintains strong search capability and convergence performance on the second test-rig dataset. The accuracy curve for the inner-race fault rises rapidly in the early stage and gradually stabilizes at a relatively high level, indicating that the obtained optimization results are reliable and stable.

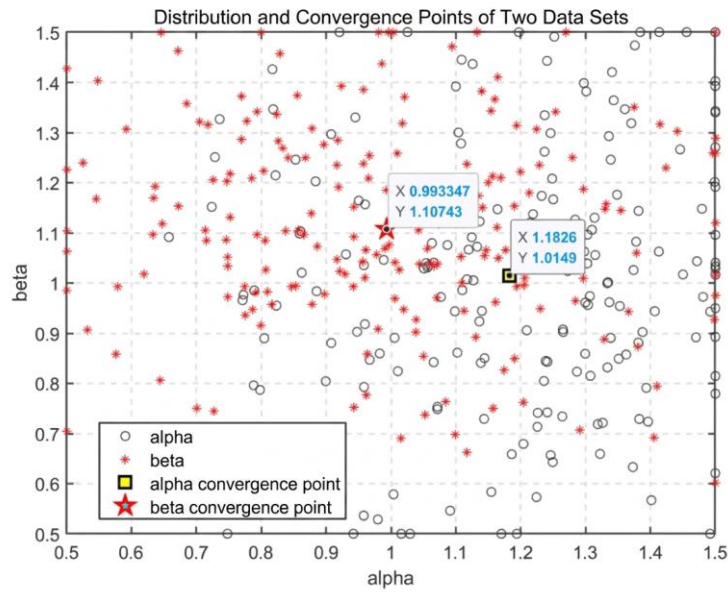


Fig. 8. MOPSO convergence point distribution.

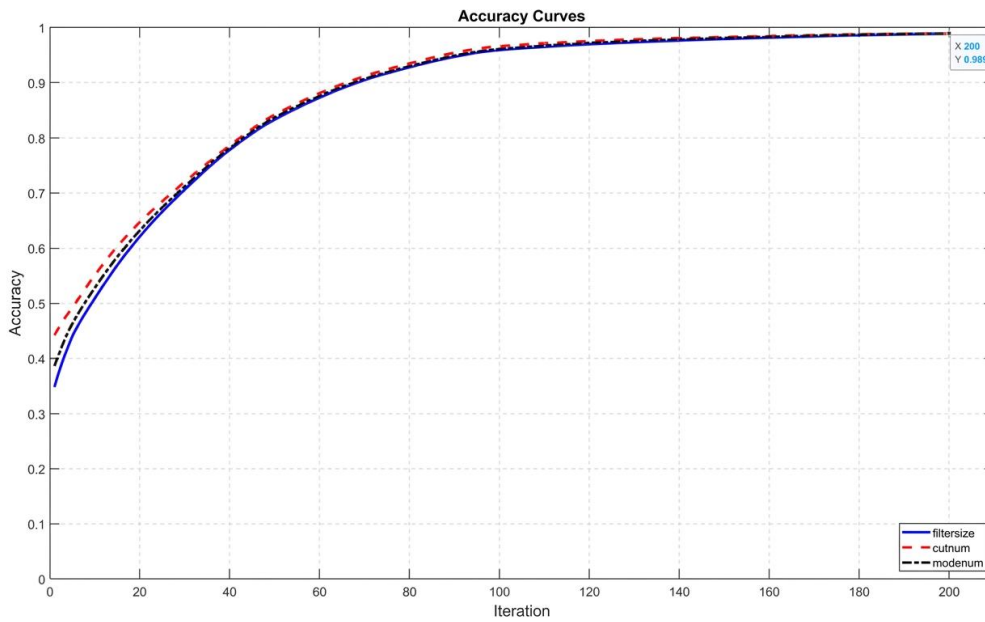


Fig. 9. INFO accuracy convergence curve.

The optimal weight parameters and FMD parameters obtained by MOPSO-INFO are then introduced into FMD for inner-race fault decomposition, and the results are shown in Fig. 10. Under the optimal parameter setting, the fault signal is decomposed into three mode components. As can be seen from the time-domain waveforms in Fig. 10, the modes exhibit clear differences in waveform morphology, indicating that the different components in the original complex signal have been effectively separated. Among them, the fault-related information is mainly concentrated in the dominant mode, whereas the remaining modes are characterized more by random fluctuations, suggesting that mode mixing has been significantly suppressed. Furthermore, by substituting the NSK 6007 deep-groove ball bearing data into Eq. (9), the inner-race fault frequency can be calculated as 320 Hz.

$$BPFO = \frac{Z}{2} f_r \left(1 - \frac{d}{D_p} \cos \theta \right) \quad (9)$$

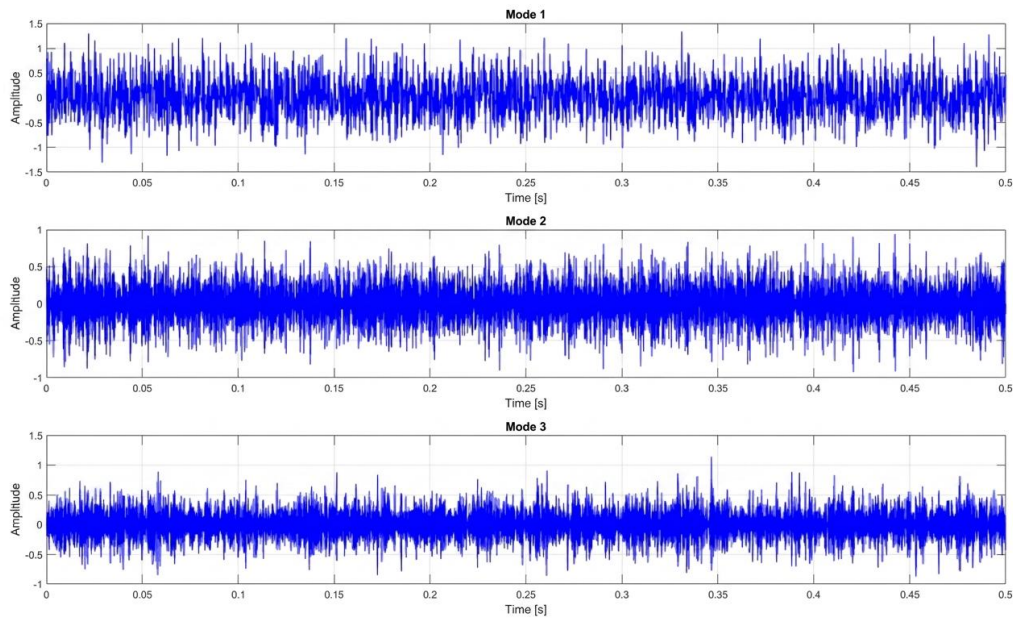


Fig. 10 MOPSO-INFO-FMD inner ring fault mode time domain waveform diagram

Combined with the Hilbert envelope spectra in Fig. 11, the main sensitive mode exhibits distinct characteristic peaks accompanied by several harmonic components at 320 Hz, indicating that the periodic fault impact information in the original signal has been effectively enhanced after decomposition. The mode corresponding to the inner-race fault shows more prominent characteristic peaks and a clearer harmonic structure, demonstrating that the fault features have been well extracted. In contrast, the envelope spectra of the remaining modes display more dispersed energy distributions without obvious regular peaks, suggesting that they contain mainly background noise or information unrelated to the fault.

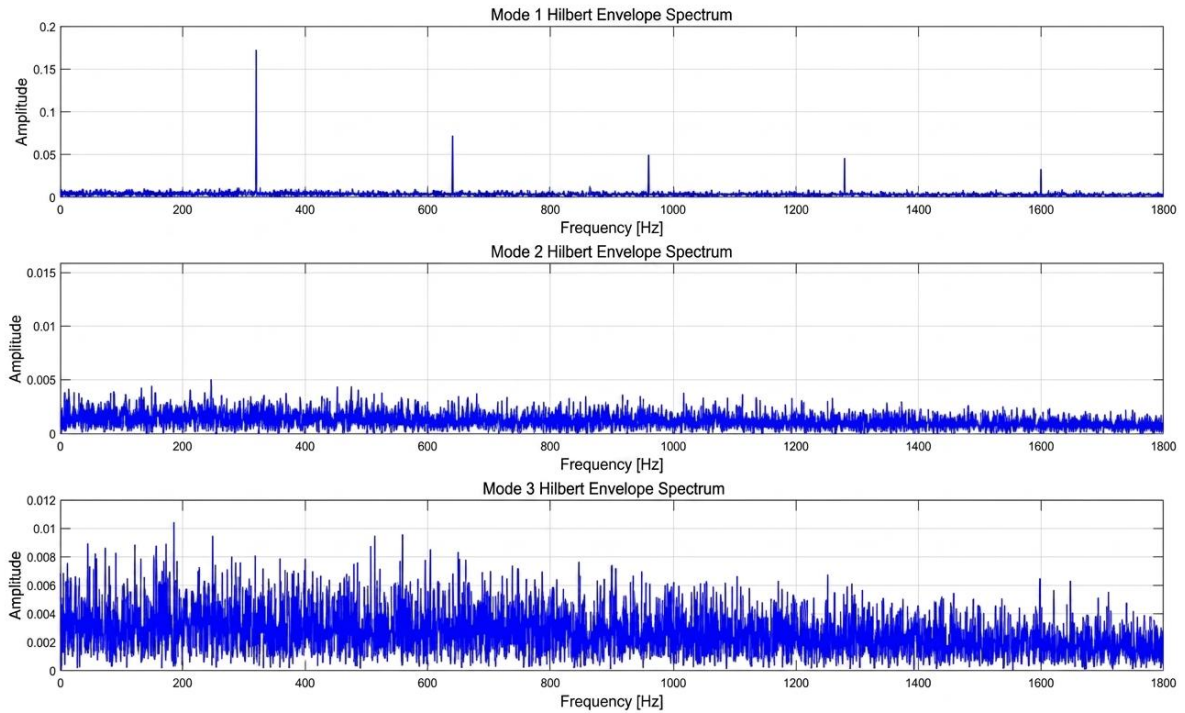


Fig. 11 Hilbert envelope spectrum of MOPSO-INFO-FMD inner ring fault

To verify the effectiveness of the decomposition results, the correlation coefficients of the three output modes are calculated, as shown in Fig. 12. According to the modal correlation coefficient heat map in Fig. 12, except for the diagonal elements equal to 1, the correlation coefficients among the remaining modes are all close

to 0, indicating that there is essentially no significant information redundancy or component overlap between different modes. This demonstrates that the different components in the signal have been clearly separated after the optimized decomposition, further confirming that the proposed method still achieves good modal decomposition performance on the test-rig data.

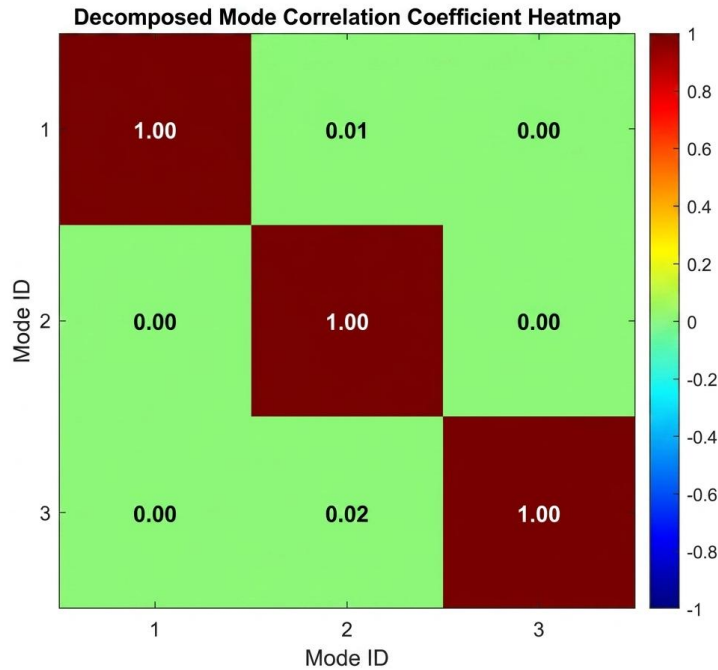


Fig. 12 Thermal diagram of modal correlation coefficient

By comprehensively analyzing the original time-domain waveform, original spectrum, accuracy convergence curves, parameter distribution and convergence points, modal time-domain decomposition results, modal correlation coefficient heat map, and Hilbert envelope spectra, it can be seen that the proposed method can also stably accomplish parameter optimization, mode decomposition, and fault feature extraction on the second test-rig dataset. The optimized parameters exhibit good convergence, the decomposed modes show strong independence, and the fault-sensitive mode can clearly reveal the characteristic fault frequency and its harmonic components. These results indicate that the proposed method has strong fault feature extraction capability and can provide a reliable basis for subsequent fault identification and condition assessment.

V. Conclusion

This study investigates feature extraction and identification for rolling bearing fault diagnosis, with particular emphasis on the problems of weak fault characteristics under complex operating conditions, complicated signal components, strong dependence on empirical parameter setting, and difficulty in mode selection. The main contributions are summarized as follows:

(1) To address the strong parameter dependence in the decomposition process and the unstable fault feature extraction performance, a composite objective function based on correlated kurtosis and entropy measures is constructed, and a joint INFO–MOPSO optimization strategy is introduced. The objective function is analyzed from two perspectives: fault impact enhancement and complex component suppression. By simultaneously emphasizing periodic impulsive features and constraining noise interference, it provides a clearer optimization direction for sensitive mode extraction. The collaborative optimization improves the efficiency of key parameter selection and decomposition performance, while reducing reliance on empirical settings and enhancing the adaptability of the algorithm under different fault types and experimental conditions.

(2) The proposed method is further validated using inner-race fault data. The results show that, after parameter optimization and improved decomposition, the diagnostic accuracy exceeds 98%. The original complex signal can be decomposed into independent mode components, indicating clear decomposition results and effective suppression of mode mixing. Moreover, the Hilbert envelope spectrum of the main sensitive mode demonstrates that the fault impact information is significantly enhanced after decomposition. These findings confirm that the proposed method can accurately identify the fault-sensitive mode and effectively extract rolling bearing fault features.

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