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Rolling Bearing Fault Diagnosis Using Adaptive Variational Mode Extraction Based on Harmonic Coherence Factor Under Strong Noise

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Abstract

To address the challenge where early fault signals of rolling bearings are easily submerged by strong noise, and fault features are difficult to extract under harsh working conditions, this paper proposes an adaptive fault diagnosis method termed HCF-IAPO-VME. Firstly, a novel harmonic coherence factor (HCF) is constructed to simultaneously evaluate the intensity of periodic impulse features and the consistency of harmonic structures without relying on prior fault frequency information. Secondly, the Improved Arctic Puffin Optimization (IAPO) algorithm is adopted, and HCF is taken as the fitness function to adaptively determine the optimal parameters of variational mode extraction (VME). Different from conventional VME and optimization-based methods that depend on prior fault frequencies and single-feature metrics, the proposed method achieves adaptive parameter optimization and reliable weak fault extraction under heavy-noise conditions. Subsequently, the optimized VME is used to extract fault-related modes, and envelope demodulation is applied to identify fault characteristic frequencies. Simulation signals and two public experimental datasets are used to verify the performance of the proposed approach. Quantitative and qualitative comparisons with VMD, FK and AVME are carried out using the fault feature coefficient (FFC), kurtosis, signal-to-noise ratio (SNR) and envelope entropy (EE). The results show that HCF-IAPO-VME can effectively suppress strong noise interference and accurately extract weak early fault features in rolling bearings.

Keywords: rolling bearings; fault diagnosis; variational mode extraction; improved arctic puffin optimization; sparsity index

1. Introduction

Serving as core components of rotary machinery, rolling bearings determine the overall reliability and operational safety of mechanical systems. Accordingly, early fault detection for rolling bearings is critical for avoiding equipment failures and reducing maintenance costs [1–4]. However, measured vibration signals are inevitably contaminated by inherent structural vibrations of bearings, which heavily obscure faint incipient fault impulses. According to the dynamic model from Lynagh et al. [5], such interferences originate from four primary sources: the variable compliance effect originating from periodic fluctuations in ball–race contact stiffness, roughness of rolling contact surfaces, assembly-induced eccentricity and rotor imbalance, and periodic vibrations associated with cage movement. These inherent vibrations produce dense sidebands that overlap fault



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characteristic frequencies, posing great obstacles to direct feature extraction. Therefore, separating weak fault signatures from signals remains a key technical bottleneck in bearing fault diagnosis [6–8].

In recent years, adaptive signal decomposition techniques have been widely adopted for fault diagnosis of rotating machinery. Among them, Variational Mode Decomposition (VMD) [9] exhibits higher decomposition accuracy than Local Mean Decomposition (LMD) [10], Empirical Mode Decomposition (EMD) [11], and Ensemble Empirical Mode Decomposition (EEMD) [12]. VMD has a solid theoretical foundation and can effectively mitigate mode mixing, thus becoming a mainstream signal processing tool for fault diagnosis. Nevertheless, the decomposition capability of VMD is susceptible to the penalty coefficient, modal quantity, and initial central frequency. To choose suitable initial parameters and improve VMD's decomposition capability, many in-depth studies have been carried out. For instance, Ma et al. [13] proposed a scale-space and spectrum segmentation-based approach to estimate the mode number, enabling incipient fault feature extraction, though this scheme only addresses mode number selection while ignoring the penalty factor. Li et al. [14] determined mode numbers using energy-loss coefficients and derived an empirical formula for adaptive identification of the penalty factor. Gu et al. [15] adopted the minimum average envelope entropy as the fitness function and applied Grey Wolf Optimization to obtain optimal VMD parameters. Li et al. [16] developed an adaptive energy-constrained VMD method based on spectrum segmentation to realize automatic optimization of key parameters.

Beyond the aforementioned general decomposition algorithms, Vafaei and Rahnejat developed two targeted analytical approaches tailored for high-speed spindle bearing vibration diagnosis. Vafaei et al. presented an ARMA spectral analysis algorithm featuring outstanding frequency resolution [17]. Compared with conventional FFT, this method effectively eliminates sideband artifacts and separately isolates vibration components from the cage, rolling elements, inner race and outer race. Based on the ARMA spectral framework, Vafaei and Rahnejat further proposed the IRR-WD approach [18], which integrates repeatable runout averaging with wavelet decomposition. The IRR-WD technique enables clear separation between synchronous imbalance vibration and asynchronous bearing fault components, alongside quantitative amplitude quantification for individual vibration sources. Nevertheless, both algorithms rely on manually predefined frequency bands. Their performance degrades sharply for heavy-noise signals without prior knowledge of fault characteristic frequencies.

Though the optimized VMD, ARMA and IRR-WD methods can deliver acceptable diagnostic accuracy under mild noise environments, they have common bottlenecks. On the one hand, existing VMD optimization neglects spectral aliasing interference caused by residual signals, which distorts extracted fault modal components. On the other hand, ARMA and IRR-WD cannot update parameters adaptively without prior fault-frequency information. More importantly, neither type of method adopts a quantitative evaluation index customized for bearing periodic impulse features to guide adaptive decomposition.

To address the residual signal interference limitation of VMD algorithms, Nazari et al. [19] developed variational mode extraction (VME) within the VMD framework. VME fully considers the spectral overlap between the residual signals and the target mode and outperforms VMD in terms of decomposition accuracy and computational speed [20]. Nevertheless, VME performance is controlled by two preset parameters: the penalty coefficient for modal-bandwidth adjustment and the initial central frequency for spectrum localization. To obtain the optimal parameter combination and further enhance decomposition accuracy, Li et al. [21] presented a method that adaptively determines VME's initial center frequency based on the convergence trend of VMD, thereby strengthening fault feature extraction.

Pang et al. [22] proposed an iterative VME approach, which uses the residual dominant frequency from the last decomposition as the new initial center frequency and optimizes both center frequency and penalty factor dynamically. Liu et al. [23] developed an adaptive window fusion strategy based on logarithmic cyclic diagrams and correlation coefficients to determine the optimal parameters of VME.

However, most existing optimized VME methods rely on prior fault frequency knowledge or single statistical indicators while neglecting the inherent harmonic consistency of periodic fault impulses, thereby yielding poor robustness and generalization performance under strong noise conditions. Furthermore, conventional optimization strategies lack effective adaptive parameter tuning capability for low-signal-to-noise scenarios, making it difficult to stably extract weak fault features under severe background interference. To overcome the above limitations, a sparsity index is constructed to eliminate dependence on prior theoretical fault frequencies and comprehensively assess the intensity of periodic impulse features and the consistency of harmonic structures. Meanwhile, Improved Arctic Puffin Optimization (IAPO) is introduced in this work. The proposed method takes the sparsity index as the fitness function; IAPO searches for optimal VME parameters adaptively, realizing accurate fault feature extraction under strong noise environments.

The structure and main content are arranged as follows. Section 1 reviews research progress on fault feature extraction for rolling bearings. Section 2 elaborates fundamental theoretical principles. Section 3 presents the proposed sparsity index and verifies its fault-feature sensitivity. Section 4 uses simulated fault signals to test the IAPO algorithm and overall method performance. Section 5 validates the approach via measured experimental datasets. Section 6 concludes the major findings and proposes prospective research prospects.

The main innovations are as follows:

- (1) A parameter-adaptive VME scheme is developed for efficient extraction of fault features in rolling bearings.
- (2) A novel evaluation index is constructed, which features high sensitivity to bearing fault characteristics and strong robustness against noise.
- (3) The IAPO algorithm is integrated with the proposed index and is employed to adaptively optimize VME parameters, thus improving extraction accuracy for incipient fault features under heavy-noise backgrounds.

2. Method Construction

2.1. Variational Mode Extraction (VME)

Compared with the traditional VMD method, VME extracts only the target mode, thereby effectively reducing computational complexity. In the VME algorithm, the input signal consists of the target mode and the residual component, as illustrated in Equation (1):

$$f(t) = u_d(t) + f_r(t) \quad (1)$$

The target mode is centered at its characteristic frequency, which is obtainable through the minimization of J_1 :

$$J_1 = \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_d(t) \right] e^{-j\omega_d t} \right\|_2^2 \quad (2)$$

where ω_d is the central frequency of $u_d(t)$, δ stands for the Dirac delta function, and $*$ refers to the convolution calculation.

Simultaneously, it is necessary to reduce the overlapping spectrum of residual signals and objective modal components, which can be achieved by minimizing J_2 :

$$J_2 = \|\beta(t) * f_r(t)\|_2^2 \quad (3)$$

where $\beta(t)$ represents the impulse response of the selected filter.

$$\hat{\beta}(\omega) = \frac{1}{\alpha(\omega - \omega_d^n)^2} \quad (4)$$

where ω denotes frequency.

In summary, by decomposing the bearing vibration signal into the target mode and residual signal, the fault mode extraction problem is converted into a constrained minimization problem, as shown in Equation (5):

$$\begin{aligned} & \min_{u_d, \omega_d, f_r} \{ \alpha J_1 + J_2 \} \\ \text{s.t. } & u_d(t) + f_r(t) = f(t) \end{aligned} \quad (5)$$

where α stands for the penalty factor.

To achieve efficient extraction of target modes, the constrained optimization problem in Equation (5) is converted into an unconstrained counterpart via quadratic penalty terms and Lagrange multipliers. The corresponding augmented Lagrangian function is defined as:

$$\begin{aligned} L(u_d, \omega_d, \lambda) = & \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_d(t) \right] e^{-j\omega_d t} \right\|_2^2 + \\ & \|\beta(t) * f_r(t)\|_2^2 + \|f(t) - (u_d(t) + f_r(t))\|_2^2 + \\ & \langle \lambda(t), f(t) - (u_d(t) + f_r(t)) \rangle \end{aligned} \quad (6)$$

where λ represents the Lagrange multiplier.

Meanwhile, based on Parseval's theorem, Equation (6) is rearranged, and the frequency-domain form of the augmented Lagrangian function is derived as Equation (8):

$$\|x(t)\|_2^2 = \|\hat{x}(\omega)\|_2^2 \quad (7)$$

where $\hat{x}(\omega)$ denotes the Fourier transform of $x(t)$.

$$\begin{aligned} L(u_d, \omega_d, \lambda) = & \alpha \|j(\omega - \omega_d)[(1 + \text{sgn}(\omega))\hat{u}_d(\omega)]\|_2^2 + \\ & \|\hat{\beta}(\omega)\hat{f}_r(\omega)\|_2^2 + \|\hat{f}(\omega) - (\hat{u}_d(\omega) + \hat{f}_r(\omega))\|_2^2 + \\ & \langle \hat{\lambda}(\omega), \hat{f}(\omega) - (\hat{u}_d(\omega) + \hat{f}_r(\omega)) \rangle \end{aligned} \quad (8)$$

where $\text{sgn}(\cdot)$ denotes the sign function, and $\langle \cdot \rangle$ represents the inner product operation.

The Alternating Direction Method of Multipliers (ADMM) is adopted to address the unconstrained optimization problem of VME. This algorithm decouples the original optimization problem into multiple subproblems for iterative solution. In every iteration step, a single variable is optimized relying on the updated values of the remaining two variables. Through one complete iteration of the three optimization variables and a series of algebraic transformations, the update expression for the target mode is derived as follows:

$$\hat{u}_d^{n+1}(\omega) = \frac{\hat{f}(\omega) + \alpha^2(\omega - \omega_d^{n+1})^4 \hat{u}_d^n(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{\left[1 + \alpha^2(\omega - \omega_d^{n+1})^4\right] \left[1 + 2\alpha(\omega - \omega_d^n)^2\right]} \quad (9)$$

The update expression for center frequency is derived as:

$$\omega_d^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_d^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_d^{n+1}(\omega)|^2 d\omega} \quad (10)$$

The updating formula of the Lagrange multiplier is derived as:

$$\hat{\lambda}^{n+1} = \hat{\lambda}^n + \left[\frac{\hat{f}(\omega) - \hat{u}_d^{n+1}(\omega)}{1 + \alpha^2 (\omega - \omega_d^{n+1})^4} \right] \quad (11)$$

2.2. Bearing Frequencies

According to references [5,17,18], the theoretical characteristic frequencies of rolling bearings are defined as:

Shaft rotational frequency:

$$f_s = \frac{n}{60} \quad (12)$$

Inner-race fault frequency:

$$f_i = \frac{Nf_s}{2} \left(1 + \frac{d \cos \theta}{D} \right) \quad (13)$$

Outer-race fault frequency:

$$f_o = \frac{Nf_s}{2} \left(1 - \frac{d \cos \theta}{D} \right) \quad (14)$$

Rolling-element spin frequency:

$$f_b = \frac{Df_s}{2d} \quad (15)$$

where D denotes the bearing pitch diameter, d is the rolling-element diameter, θ represents the contact angle, N is the number of rolling elements, and n is the spindle rotating speed.

2.3. Traditional Arctic Puffin Optimization (APO)

Arctic Puffin Optimization (APO) [24] is a newly developed swarm intelligence algorithm that simulates the predation and migration behaviors of Arctic puffins. The algorithm includes three main stages: population initialization, position updating, and individual selection.

Although APO shows acceptable performance in some optimization tasks, it still has obvious defects, such as insufficient population diversity, weak local search ability, and unbalanced exploration and exploitation capacities, which limit its performance in parameter optimization of VME.

3. The Proposed HCF-IAPO-VME Method

3.1. Improved Arctic Puffin Optimization

To improve the optimization efficiency of VME algorithm parameters, IAPO is proposed based on the traditional APO. This algorithm overcomes key limitations of the original APO for optimization: insufficient population diversity, poor local exploration capability, and an unbalanced trade-off between convergence speed and optimization precision. By simulating the natural behavioral characteristics of Arctic puffins, such as

group cooperation, precise diving predation, and environmental adaptation, dynamic parameter adjustment, an elite guidance strategy, and an adaptive mutation mechanism are introduced to enhance optimization performance in continuous-space optimization problems. The execution process of the IAPO algorithm includes three stages: initialization, movement, selection and update.

3.1.1. Initialization Stage

Within the bounded search space $[l_j, u_j]$, S Arctic puffin individuals are randomly initialized to construct the initial population matrix P . X_{ij} represents the j -th dimensional position of the i -th puffin individual, and its position in the i -th iteration is formulated as $X_i(t) = [X_{i1}(t), X_{i2}(t), \dots, X_{im}(t)]$.

$$X_{ij} = L_i + rand_j[0, 1] \times (u_j - l_j), \quad i = 1, 2, \dots, S_p, j = 1, 2, \dots, m \quad (16)$$

where $rand_j[0, 1]$ represents a random number generator producing uniformly distributed values over $[0, 1]$ for dimension j , and m stands for the dimensionality of the optimization problem.

The fitness function $f(X_i(t))$ is constructed according to the optimization objective to evaluate the performance of each individual in the initial population. Personal best and global best solutions are updated iteratively based on calculated fitness values.

3.1.2. Movement Stage

In the population updating phase, a differentiated renewal strategy is utilized to separate elite individuals from common individuals. In addition, a dynamic parameter tuning mechanism is embedded to balance global exploration and local exploitation performance.

In matrix P , the top E Arctic puffins with optimal fitness values are picked out as elite individuals, denoted as $X_{elite}^k(t)$ for $k = 1, 2, \dots, E$. Let ρ denote the elite proportion coefficient; then, $E = [\rho S]$.

To achieve a tradeoff between global exploration and local exploitation performance of IAPO, dynamic inertia weight $w(t)$ and adaptive learning factors $c_1(t)$ and $c_2(t)$ are incorporated into the algorithm, defined as:

$$w(t) = w_{\max} \exp(-3t/T_{\max}) + w_{\min}(1 - \exp(-3t/T_{\max})) \quad (17)$$

$$c_1(t) = c_{1,\text{start}} \exp(-2t/T_{\max}) + c_{1,\text{end}}(1 - \exp(-2t/T_{\max})) \quad (18)$$

$$c_2(t) = c_{2,\text{start}} \exp(-2t/T_{\max}) + c_{2,\text{end}}(1 - \exp(-2t/T_{\max})) \quad (19)$$

where t represents the current iteration count. The upper and lower boundaries of the inertia weight are separately defined as $w_{\max}$ and $w_{\min}$, and the maximum iteration number is correspondingly described as $T_{\max}$. Meanwhile, the initial and terminal values of the cognitive coefficient, as well as the starting and ending values of the social coefficient, are defined in sequence as: $c_{1,\text{start}}$, $c_{1,\text{end}}$, $c_{2,\text{start}}$ and $c_{2,\text{end}}$.

The position update of puffin individuals employs distinct strategies for elite and non-elite solutions.

For elite individuals, a local fine-tuning strategy is implemented to enhance local exploitation capability:

$$X_i(t+1) = \begin{cases} X_i(t) + \eta_1(X_{\text{best}}(t) - X_i(t)) + M(0, \sigma^2), & \text{if } r \leq p_1 \\ X_i(t) + \eta_2(X_{\text{elite}}^k(t) - X_i(t)), & \text{otherwise} \end{cases} \quad (20)$$

where $X_{\text{best}}(t)$ denotes the current global best position, $X_{\text{elite}}^k(t)$ denotes the randomly selected elite individual, η_1 and η_2 denote learning step sizes, σ is the standard deviation of

the adaptive Gaussian perturbation, and $r \sim U(0, 1)$ denotes the Gaussian random variable following a standard normal distribution.

$$\sigma = 0.05(1 - t/T_{\max})(u_j - l_j) \quad (21)$$

For non-elite individuals, a velocity update mechanism is adopted to strengthen global exploration capability:

$$V_i(t+1) = w(t)V_i(t) + c_1(t)r_1 \odot (P_i(t) - X_i(t)) + c_2(t)r_2 \odot (G(t) - X_i(t)) \quad (22)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (23)$$

where $V_i(t)$ represents the velocity of the i -th individual, $P_i(t)$ stands for the personal optimal position, $G(t)$ corresponds to the global best coordinate, $r_1, r_2 \in [0, 1]^D$ denotes random vectors, and $\odot$ denotes Hadamard product.

3.1.3. Selection and Update Stage

The updated coordinate of every Arctic puffin is acquired by comparing the fitness metrics of the candidate position $X_i(t+1)$ and the present location $X_i(t)$, which is formulated as:

$$X_i(t+1) = \begin{cases} X_i(t+1), & \text{if } f(X_i(t+1)) < f(X_i(t)) \\ X_i(t), & \text{otherwise} \end{cases} \quad (24)$$

To improve population diversity, an adaptive mutation strategy is incorporated, and an elite-guided global search is executed every five iterations. The elite solutions are utilized to guide the population to explore potential superior regions, as follows:

$$X'_i(t+1) = X_i(t+1) + \nu \cdot N(0, 1) \quad (25)$$

$$X_{\text{search}} = X_{\text{elite}}^k(t) + \varsigma \cdot (u_j - l_j) \odot N(0, 1) \quad (26)$$

where ν denotes the mutation probability, and ς denotes the search radius coefficient.

3.2. Harmonic Coherence Factor (HCF)

3.2.1. HCF Index Construction

Sparsity indices, which quantify the periodic and impulsive components in vibration signals, are widely applied in rotating machinery fault diagnosis [25]. This work constructs a new sparsity indicator to serve as the fitness function. Its capacity to fully depict fault signatures directly governs the decomposition performance of the VME algorithm.

Once localized damage emerges on rolling bearings, the collected vibration signal presents obvious periodic impulse components within the time domain. Following envelope demodulation analysis, the envelope spectrum can distinctly reflect the bearing fault characteristic frequency together with its harmonic components, which indicates that the bearing vibration fault signal possesses second-order cyclostationary characteristics. Therefore, from the frequency-domain perspective of bearing vibration signals, a sparsity index that requires no prior knowledge of theoretical fault frequencies and can comprehensively evaluate the intensity of periodic impulse characteristics and the consistency of harmonic structures is proposed, termed the Harmonic Coherence Factor (HCF).

Given preprocessed vibration signal $x[n]$, the envelope signal is $e[n]$, and the envelope squared signal is $y[n]$:

$$\tilde{e}[n] = e[n] - \frac{1}{N} \sum_{i=1}^N e[i] \quad (27)$$

$$y[n] = \tilde{e}^2[n] \quad (28)$$

The discrete Fourier transform of $y[n]$ is calculated as:

$$Y[k] = \tilde{e}^2[k] \quad (29)$$

where $M = 2^{\lceil \log_2(4N_s) \rceil}$ denotes the next power-of-two length for zero-padding.

The corresponding cyclic frequency axis is given by:

$$f_{\alpha k} = \frac{k f_{\text{samp}}}{M}, k = 0, 1, \dots, \frac{M}{2} \quad (30)$$

The cyclostationarity density function $D(\alpha)$ is derived as:

$$D(f_{\alpha}) = \frac{\frac{1}{N_s^2} |Y(k)|^2}{\sum_{k=0}^{\frac{M}{2}} \frac{1}{N_s^2} |Y(k)|^2 \Delta f_{\alpha}}, k = 0, 1, \dots, \frac{M}{2} \quad (31)$$

$$\Delta f_{\alpha} = \frac{f_{\text{samp}}}{M} \quad (32)$$

where f_{α} denotes the cyclic frequency.

The HCF is designed to quantify the correlation between the observed harmonic energy distribution of fault features and the ideal cyclostationary model, and the dominant cyclic frequency $f_{\alpha \text{max}}$ is determined by:

$$f_{\alpha \text{max}} = \underset{f_{\alpha} \in [f_{\alpha \text{min}}, f_{\text{samp}}/2]}{\operatorname{argmax}} D(f_{\alpha}) \quad (33)$$

where $f_{\alpha \text{min}}$ denotes the minimum valid frequency to reject DC and low-frequency noise, and f_{samp} denotes the sampling frequency.

The HCF is formally defined as:

$$\text{HCF} = \frac{\sum_{k=1}^K D(k \cdot f_{\alpha \text{max}})}{\sum_{k=1}^K \exp(-\frac{(k-1)^2}{2})} \quad (34)$$

where K denotes the harmonic order [26], and $D(k \cdot f_{\alpha \text{max}})$ is the cyclostationarity density at the k -th harmonic; the term $\sum_{k=1}^K \exp(-\frac{(k-1)^2}{2})$ represents the expected energy sum of the ideal cyclostationary model at the harmonic frequencies.

3.2.2. HCF-IAPO-VME Fault Diagnosis Framework

The HCF index is integrated into the VME framework, and the objective function for parameter optimization is constructed as follows:

$$\begin{cases} \operatorname{argmax}_{\gamma_i=(\alpha, f_d)} \text{HCF}_{\gamma_i} \\ \text{s.t. } \alpha \in [100, 4000] \\ f_d \in [0.01 f_{\text{samp}}, 0.49 f_{\text{samp}}] \end{cases} \quad (35)$$

where $\gamma_i = (\alpha, f_d)$ denotes the VME parameter combination, HCF_{γ} is the HCF value of the mode extracted by VME with parameters (α, f_d) , and f_{samp} represents the signal sampling frequency.

According to reference [27], the optimization ranges of α and f_d are determined. The overall diagnosis workflow of the proposed algorithm is displayed in Figure 1, and the detailed operation procedures are described as follows:

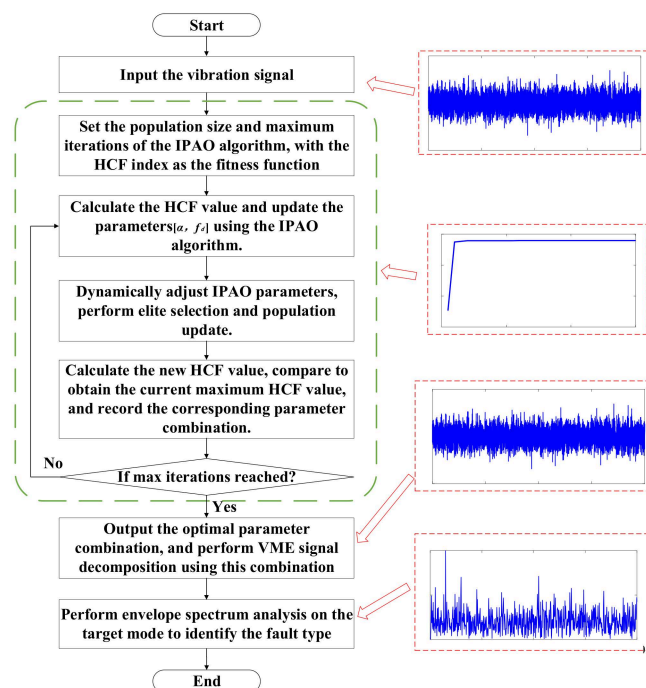


Figure 1. Implementation flow diagram of the HCF-IAPO-VME fault diagnosis approach.

Step 1: Input the vibration signal and the VME parameter optimization range according to Equation (35).

Step 2: Input the IAPO algorithm parameters (population size, $N = 30$; maximum number of iterations, $T_{\max} = 30$).

Step 3: Search for optimal VME parameters; calculate and save HCF values of the mode.

Step 4: Repeat Step 3 if the stopping condition $k \geq K$ is satisfied; terminate the iteration. If not, assign $n = n + 1$ and proceed with the iterative computation.

Step 5: Obtain optimal parameters (α, f_d) .

Step 6: Input optimal parameters into VME to extract target mode.

Step 7: Perform envelope spectrum analysis on the extracted target mode to diagnose the fault.

4. Simulation Verification

4.1. Simulation Signals and Index Sensitivity Analysis

To verify the effectiveness and advantages of the HCF index, four types of simulated signals are established, including periodic fault impulse x_1 , random impulse x_2 , harmonic interference x_3 and Gaussian white noise x_4 . Comparative analyses between HCF and classic metrics (kurtosis, envelope spectrum kurtosis, EE, Gini, Gini Index of the Square Envelope and Spectral Coherence) are carried out. The time-domain waveforms of all simulated signals are plotted in Figure 2.

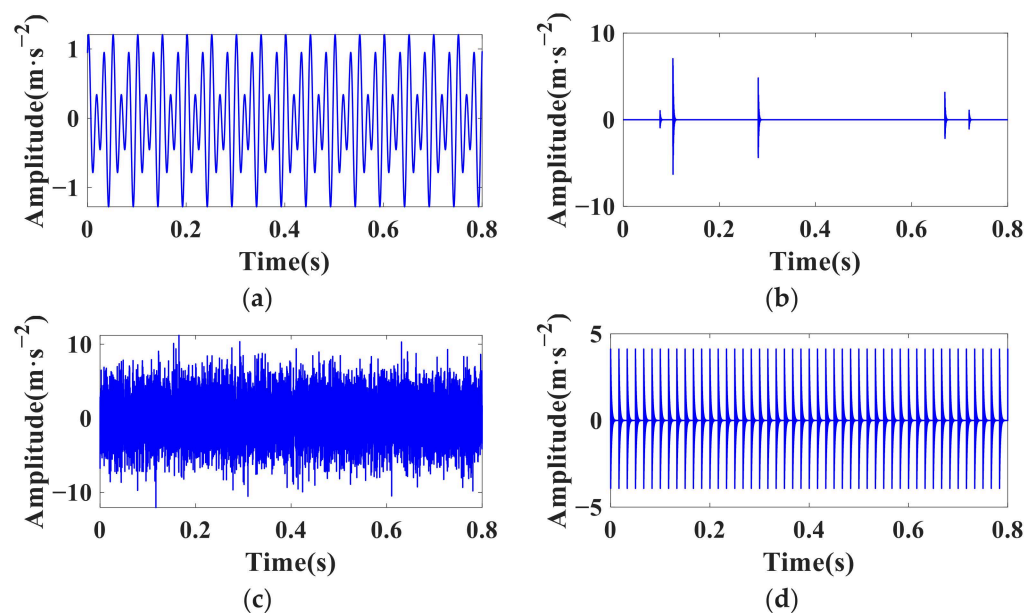


Figure 2. Simulation signals. (a) Harmonic interference; (b) random impulse; (c) Gaussian white noise; (d) periodic fault impulse.

The performance of HCF is compared with conventional indices, namely EE, ESK, K, Gini, GISE and SC, using four typical simulated signals. The results shown in Figure 3 indicate that under harmonic interference, ESK and SC reach the maximum value of 2.00, proving their high sensitivity to harmonic interference; for random impulses, EE, K, Gini and GISE all peak at 2.00, which means they are strongly responsive to random impulses. Under pure Gaussian white noise conditions, SC is 1.46, while the remaining indices keep values close to 1, reflecting excellent noise immunity. Focusing on periodic fault impulses, HCF achieves the highest value of 2.00. Compared with EE (1.18), ESK (1.63), K (1.02), Gini (1.59), GISE (1.70) and SC (1.25), the sensitivity of HCF is 69.49%, 22.70%, 96.08%, 25.79%, 17.65% and 60.00% higher respectively. Meanwhile, HCF is barely affected by harmonic interference, random impulses and Gaussian noise. The comprehensive comparison demonstrates that HCF achieves the best overall performance in terms of sensitivity and anti-interference capability, making it more suitable for fault feature extraction evaluation.

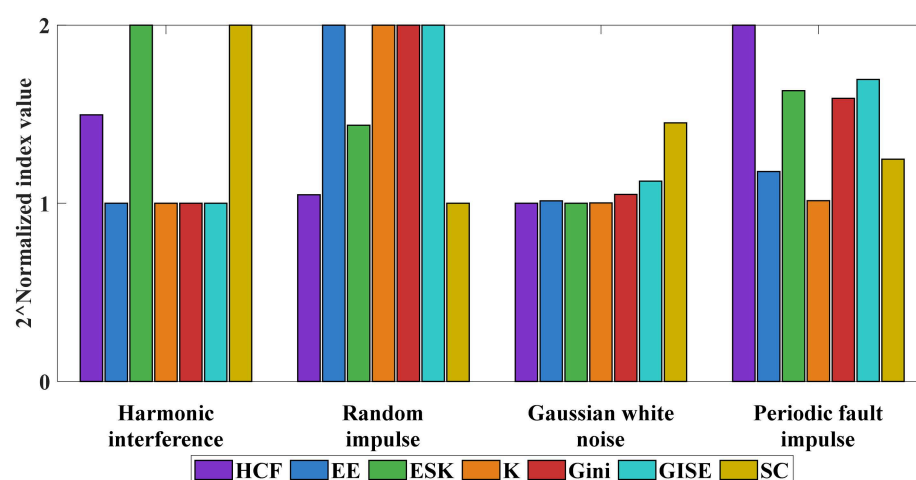


Figure 3. Sensitivity analysis of different indices to various signal types.

4.2. Simulation Signal Establishment

To verify the performance of the HCF-IAPO-VME method for incipient defect diagnosis of rolling bearings, a simulated signal model corresponding to outer-raceway faults is formulated as below:

$$\begin{cases} x(t) = x_1(t) + x_2(t) + x_3(t) + n(t) \\ x_1(t) = \sum_{i=1}^I A_i s_j(t - iT_a) \\ x_2(t) = \sum_{z=1}^Z R_z s_z(t - zT_c) \\ x_3(t) = \sum_{h=1}^H P_h \sin(2\pi f_h t + \varphi_h) \\ n(t) = -3randn(1, N_s) \end{cases} \quad (36)$$

where $x_1(t)$ denotes the periodic impulsive component induced by the local fault of the outer race, $x_2(t)$ denotes random impulsive interference, $x_3(t)$ represents the non-fault harmonic component, and $n(t)$ stands for Gaussian white noise.

For $x_1(t)$, A_i denotes the amplitude of periodic fault impulses ($\max = 5$), and $T_a = 1/f_o$ denotes the time interval between consecutive impulses, with f_o being the outer-race fault characteristic frequency. For $x_2(t)$, R_z denotes the amplitude of random impulses ($\max = 10$), and I and Z represent the number of periodic and random impulses, respectively. For $x_3(t)$, P_h , f_h , and φ_h , H stand for the amplitude, frequency, phase and number of harmonics, respectively; N_s denotes the sample size, and $s(t)$ is the impulse response function of the bearing system.

$$s(t) = e^{-\beta_n t} \sin(2\pi f_n t) \quad (37)$$

where f_n is the system's natural frequency, and β_n is the damping ratio.

In the simulation experiment, the sampling frequency is configured as 12,000 Hz with a total sampling length of 10,240 points, and all other relevant parameters are summarized in Table 1. The time-domain waveform and envelope spectrum of the constructed outer-race fault simulation signal are presented in Figure 4.

Table 1. Parameters for constructing simulated signal.

Parameter	$x_1(t)$			$x_2(t)$			$x_3(t)$				
	f_a	β_{n1}	f_{n1}	β_{n2}	f_{n2}	P_1	f_1	φ_1	P_2	f_2	φ_2
Value	60	600	4000	860	5000	0.5	40	$\pi/6$	0.8	60	$\pi/3$

As shown in Figure 4a, periodic impulses induced by local outer-race defects are fully buried in heavy noise and miscellaneous interferences. Fault signatures cannot be identified in the time-domain waveform. Figure 4b presents disordered spectral lines in the envelope spectrum. The main peak deviates significantly from the theoretical outer-race fault characteristic frequency, so the outer-race fault cannot be detected. These results reveal that direct time-domain analysis and conventional envelope demodulation fail to extract faint fault features from simulation signals corrupted by strong noise.

The simulated signal is processed using the HCF-IAPO-VME. Figure 5a shows the fitness value convergence curve. Figure 5b presents the spectrum of the extracted fault mode, where the center frequency of the resonant band matches the preset parameter ($f_{n1} = 4000$) in the simulation model. Figure 5c presents the time-domain waveform of the fault mode extracted with optimal VME parameters. In contrast to the waveform in

Figure 4a, background noise is well suppressed, periodic impulsive signatures are greatly amplified, and the effective frequency band is compressed. As illustrated in Figure 5d, the envelope spectrum of the target mode clearly exhibits the theoretical fault frequency f_o and its harmonics up to $6f_o$. These spectral components present sharp peaks with prominent amplitudes. The simulation results verify that the HCF-IAPO-VME method possesses outstanding noise-suppression capability and can accurately extract faint bearing fault signatures buried under heavy-noise interference.

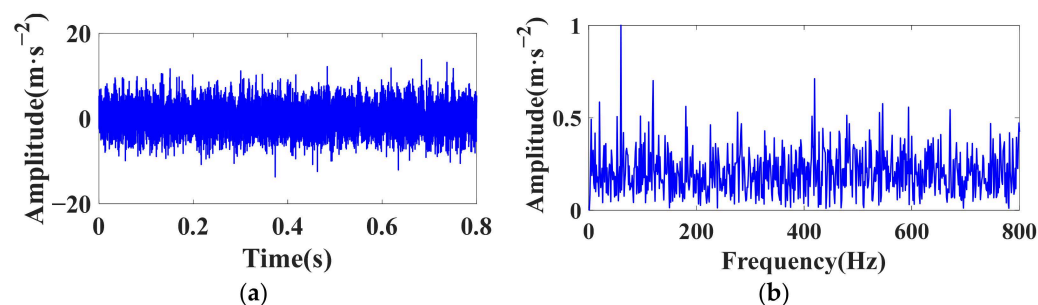


Figure 4. Simulated bearing fault signal. (a) Time-domain signal; (b) envelope spectrum.

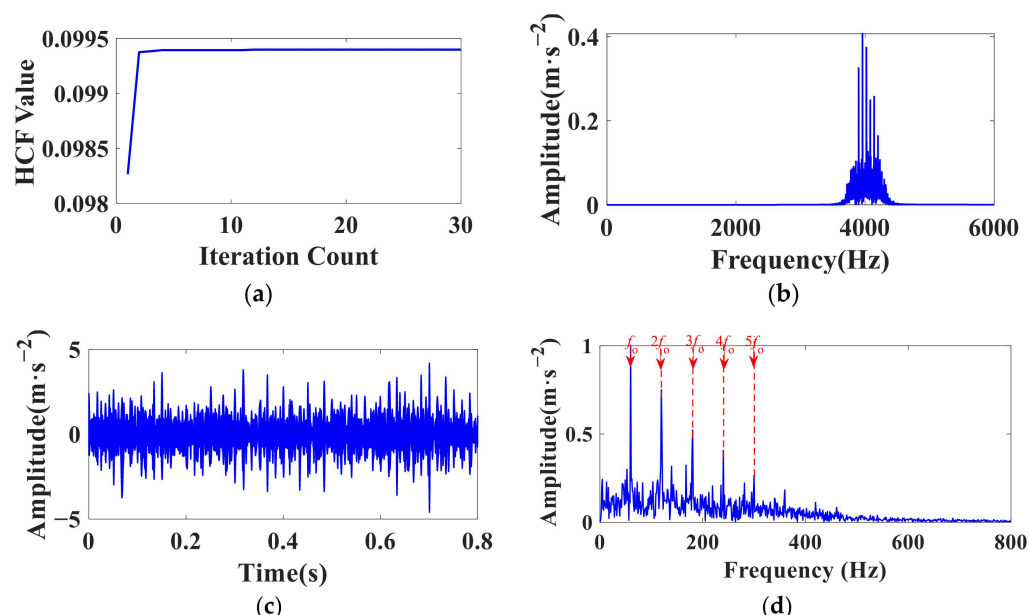


Figure 5. Analysis results of the simulated signal based on HCF-IAPO-VME. (a) Iterative curve of fitness value; (b) spectrum of the extracted mode; (c) extracted mode; (d) envelope spectrum.

4.3. Comparison of Different Optimization Algorithms

To validate the superiority of the IAPO algorithm for incipient fault signals, a comparative study is conducted with five state-of-the-art optimization algorithms: the Whale Migration Algorithm (WMA) [28], the Grey Wolf Optimizer (GWO) [29], the Genetic Algorithm (GA), the Sparrow Search Algorithm (SSA) [30] and APO. For a fair comparison, all algorithms are integrated with VME using the same HCF as the fitness function, and the average convergence curves over 10 independent runs are presented in Figure 6. Experimental results reveal that the IAPO algorithm completes convergence at the 14th iteration, and its optimal fitness value reaches 0.0993976, WMA converges at the 11th iteration with 0.0993973, GWO and GA converge at the 24th and 26th iterations respectively with 0.0993976, SSA converges at the 25th iteration with 0.0993972, and APO achieves 0.0993754. It is demonstrated that IAPO achieves the highest convergence accuracy with the fastest convergence speed when optimizing VME parameters. Compared with other algorithms,

IAPO converges significantly faster under the same accuracy, avoids local optima effectively, and exhibits superior global search capability.

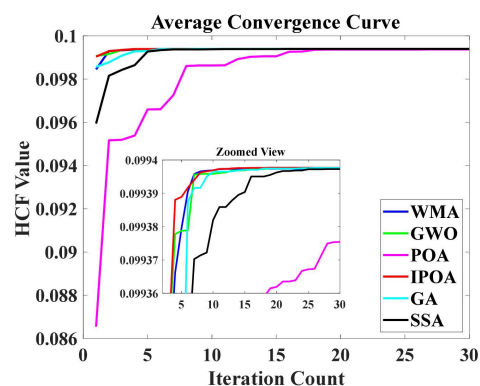


Figure 6. Performance comparison of different intelligent optimization algorithms.

4.4. Robustness Analysis Under Different Noise Levels

To evaluate the anti-noise performance of the proposed HCF-IAPO-VME approach, Gaussian white noise with varied intensities is superimposed on the simulated bearing fault signal, where the signal-to-noise ratio (SNR) varies from -5 dB to -17 dB. HCF-IAPO-VME is employed to process signals under various noise levels, and the results are illustrated in Figure 7.

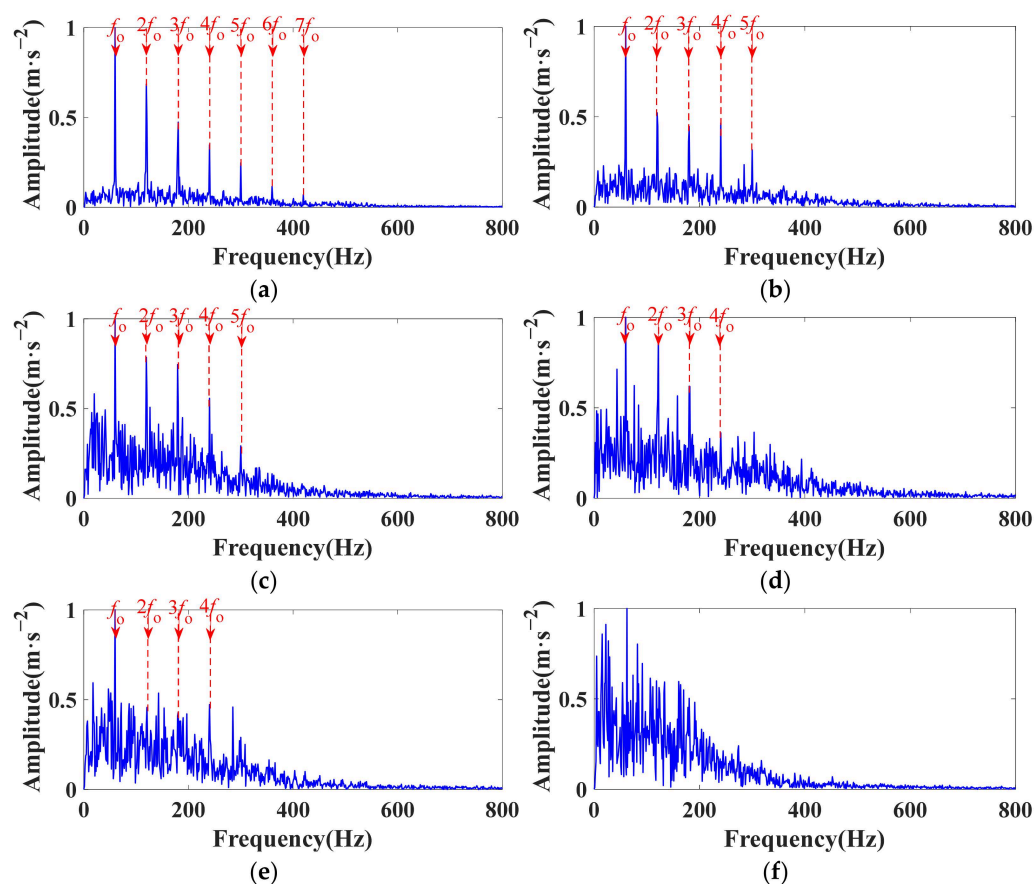


Figure 7. Envelope spectra of the proposed HCF-IAPO-VME method under different noise levels. (a) SNR = -5 dB; (b) SNR = -10 dB; (c) SNR = -12 dB; (d) SNR = -14 dB; (e) SNR = -16 dB; (f) SNR = -17 dB.

At SNR = −5 dB, the proposed method can accurately extract the fault characteristic frequency f_o and its relevant harmonics up to $7f_o$, with sharp spectral peaks significantly higher than the noise floor. As the noise intensity increases to −10 dB and −12 dB, the number of identifiable harmonics gradually decreases, but the fundamental frequency f_o and its main low-order harmonics remain clearly visible. Even at SNRs of −14 dB and −16 dB, f_o and its first several harmonics can still be reliably distinguished from the background noise, enabling effective fault diagnosis. As the SNR decreases further to −17 dB, fault-related characteristics are entirely overwhelmed by background noise, and no clear fault-related spectral lines can be observed.

These results verify the strong noise robustness of HCF-IAPO-VME. It maintains effective fault feature extraction performance under severe noise conditions, with a verified anti-noise boundary of −16 dB for the tested signal.

4.5. Comparison with Existing Methods

To further validate the effectiveness of the proposed HCF-IAPO-VME method in extracting rolling bearing fault features under strong noise interference, the simulated signals are processed using three advanced methods for comparison: variational mode decomposition (VMD), fast kurtogram (FK), and adaptive variational mode extraction (AVME) [23]. The results are presented in Figure 8.

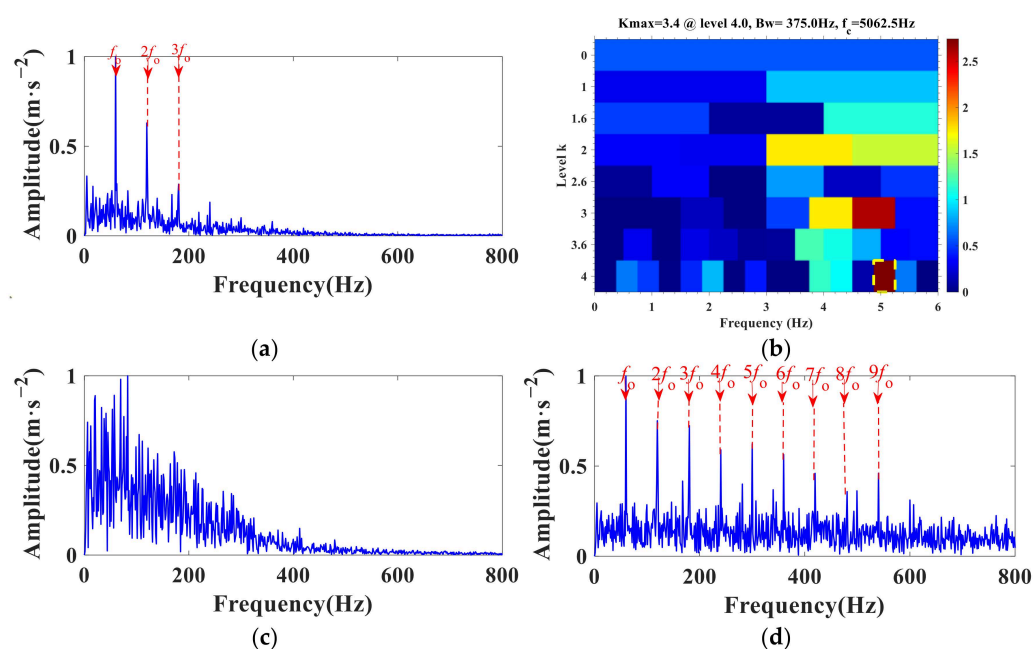


Figure 8. Processing results of simulated signal. (a) Envelope spectrum of VMD; (b) kurtogram of FK; (c) envelope spectrum of FK; (d) envelope spectrum of AVME.

In Figure 8a, clear fault characteristic frequency and its multiple harmonics can be observed in the envelope spectrum obtained by VMD. This indicates that VMD can effectively separate fault-related components from heavy background noise. As for the FK algorithm, the kurtogram in Figure 8b is utilized to locate the optimal resonant frequency band in advance, and Figure 8c presents the envelope spectrum of narrowband signals filtered within this band. Even though the best frequency range is successfully selected, the outer-race fault characteristic frequency f_o and its harmonics cannot be clearly identified. This result proves the weak anti-interference capability of FK, which restricts its capacity to identify fault signatures under high-noise environments. In contrast, the envelope spectrum from AVME in Figure 8d produces sharp peaks corresponding to the theoretical fault characteristic frequency f_o and $2f_o$ to $9f_o$. Reliable fault diagnosis can therefore be

realized. These outcomes show that AVME can suppress noise interference and extract fault information to a certain extent.

In summary, the proposed HCF-IAPO-VME, VMD and AVME can all effectively extract fault features submerged in strong noise. However, the proposed HCF-IAPO-VME method achieves sharper spectral peaks, more complete harmonic components, and a higher signal-to-noise ratio, demonstrating stronger robustness under complex interference conditions.

5. Experimental Validation

To further verify the performance of the proposed HCF-IAPO-VME algorithm, vibration data collected from several public datasets are analyzed in this section.

5.1. CWRU Bearing Dataset

The drive-end bearing vibration records from the Case Western Reserve University (CWRU) bearing database are selected to carry out experimental tests. The motor rotation speed is fixed at 1797 r/min, and the bearing geometric specifications are summarized in Table 2 [31]. Based on the listed parameters, the theoretical inner-race fault characteristic frequency is computed as 162.19 Hz, while the sampling frequency of the collected vibration signal is set to 48,000 Hz.

Table 2. Structural parameters of the bearing.

Bearing Pitch Diameter (mm)	Ball Diameter (mm)	Number of Rolling Elements	Contact Angle (°)
39.04	7.94	9	0

To mimic severe conditions with intense background noise, Gaussian white noise corresponding to an SNR of -8 dB is superimposed onto the original CWRU bearing signal. Figure 9 presents the time-domain waveform and envelope spectrum of the inner-race fault signal mixed with noise. It is obvious that heavy noise completely covers all valid impulse features in the time-domain curve, and the envelope spectrum exhibits disordered spectral lines, with no distinct spectral peaks corresponding to the fault characteristic frequency being directly identifiable.

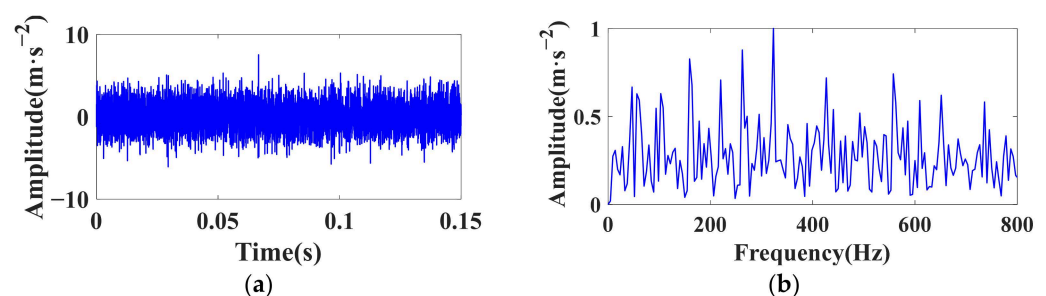


Figure 9. Noisy inner-race vibration signal. (a) Time-domain signal; (b) envelope spectrum.

The noisy inner-race vibration signal is processed by HCF-IAPO-VME, in which the HCF index is adopted as the fitness criterion to guide the IAPO algorithm for optimal parameter search. The optimized parameters are input into VME to extract the target fault mode. Envelope spectrum analysis is then performed on the extracted mode; the processing outcomes are displayed in Figure 10. The time-domain waveform of the extracted mode shows distinct periodic impulse characteristics, demonstrating effective enhancement of weak fault features. Compared with the noisy raw envelope spectrum in Figure 9b, the envelope spectrum in Figure 10b achieves significant noise suppression with sharp and

well-defined spectral lines. The theoretical inner ring fault characteristic frequency f_i , together with its harmonic components $2f_i$ and $4f_i$, can be accurately extracted, enabling clear and accurate diagnosis of inner-race defects.

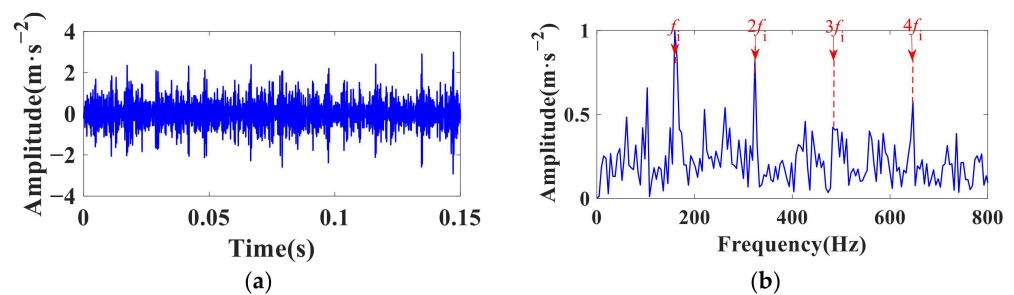


Figure 10. Processing results of inner-race vibration signal by HCF-IAPO-VME. (a) Time-domain signal; (b) envelope spectrum.

The vibration waveform in Figure 9a is separately processed by VMD, FK and AVME, and comparative analysis results are given in Figure 11. In Figure 11a, the main spectral peak in the envelope spectrum matches well with the theoretical inner-race fault characteristic frequency f_i ; this verifies that VMD can extract valid fault characteristics. For the FK approach, the kurtogram in Figure 11b is adopted to select the optimal resonant frequency band, whose center frequency is 5250 Hz and bandwidth is 1500 Hz. Nevertheless, the corresponding envelope spectrum in Figure 11c fails to exhibit prominent spectral peaks consistent with the theoretical fault frequency f_i ; valid fault detection therefore cannot be realized. By contrast, the envelope spectrum obtained by AVME in Figure 11d displays two distinct spectral peaks corresponding to the inner-race fault characteristic frequency f_i and its harmonic component $2f_i$, enabling basic fault diagnosis. Nevertheless, compared with the proposed HCF-IAPO-VME, its spectral peaks are less prominent and fewer harmonics can be identified, which reflects weaker fault feature extraction capability.

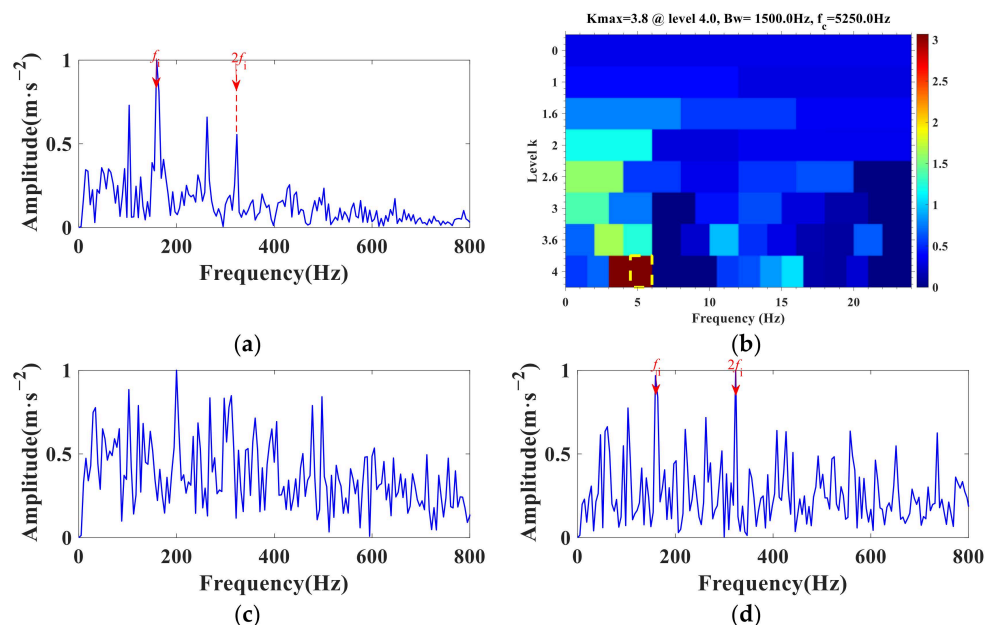


Figure 11. Processing results of inner-race vibration signal. (a) Envelope spectrum of VMD; (b) kurtogram of FK; (c) envelope spectrum of FK; (d) envelope spectrum of AVME.

In summary, FK cannot extract fault features accurately for the inner-race signal under heavy-noise conditions. VMD, AVME and HCF-IAPO-VME can effectively separate

fault features in strong-noise environments. Among these methods, HCF-IAPO-VME can identify more harmonic components and achieve better fault diagnosis performance.

5.2. BJTU-RAO Bogie Test Dataset

The BJTU-RAO database is collected from a scaled subway bogie experimental platform. The axle box bearing is model HRB 352213, and the reduction gearbox adopts helical gears with 16 driving teeth and 107 driven teeth [32].

Select vibration data of outer ring and rolling-element faults under a motor rotational frequency of 40 Hz and zero external load for subsequent analysis. According to the structural parameters listed in Table 3, the theoretical characteristic frequency of outer-race defects is computed as 48.28 Hz, while the theoretical fault frequency of rolling elements equals 18.93 Hz. The sampling frequency of all collected vibration signals is set to 64 kHz.

Table 3. Theoretical bearing fault frequencies.

Bearing Model	Rotational Frequency f	
	Outer-Race	Rolling-Element
HRB 352213	$8.071 * f$	$3.164 * f$

The raw outer-race vibration signal is analyzed, and the results are shown in Figure 12. The time-domain waveform is heavily contaminated by noise spikes. The envelope spectrum shows no distinct spectral lines related to outer-race faults.

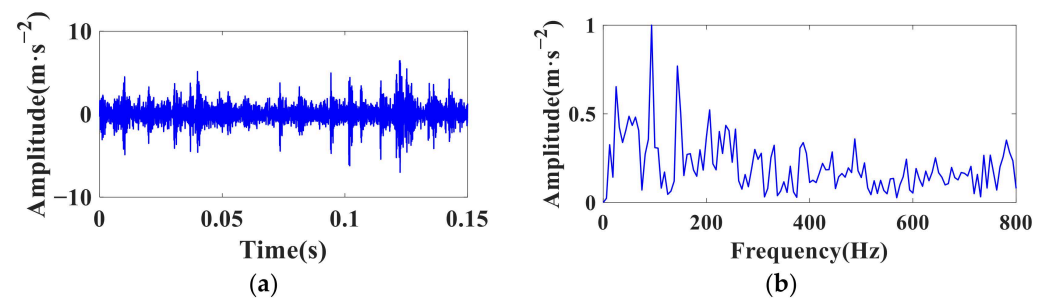


Figure 12. Raw outer-race vibration signal. (a) Time-domain signal; (b) envelope spectrum.

The raw outer-race vibration signal is processed via HCF-IAPO-VME, as depicted in Figure 13. The time-domain waveform exhibits distinct periodic impulse characteristics, with noise artifacts effectively suppressed. Correspondingly, the envelope spectrum presents sharp, high-amplitude spectral lines free of interference, and the theoretical outer-race fault frequency f_o and its harmonics $2f_o$ to $5f_o$ can be clearly identified, confirming the occurrence of an outer-race fault. Results verify that HCF-IAPO-VME successfully extracts fault features buried in complex vibrations under strong noise and achieves accurate diagnosis of bearing outer-race faults, thus demonstrating its effectiveness and superiority in practical fault diagnosis applications.

To further illustrate the excellent performance of HCF-IAPO-VME for outer-race bearing fault diagnosis, the vibration signal in Figure 12a is processed by VMD, FK and AVME respectively. In Figure 14a, the envelope spectrum obtained by VMD successfully captures the outer-race fault characteristic frequency f_o as well as its harmonics $2f_o$ to $3f_o$; this proves that VMD can extract valid fault information. As for the FK approach, the kurtogram in Figure 14b is utilized to locate the optimal resonant frequency band; the filtered narrowband signal adopts a center frequency of 26,000 Hz with a bandwidth of 4000 Hz. Nevertheless, the corresponding envelope spectrum in Figure 14c shows no distinct fault-frequency components, so effective fault discrimination cannot be achieved.

In contrast, the envelope spectrum generated by AVME in Figure 14d delivers relatively prominent spectral peaks, enabling accurate identification of the theoretical fault frequency f_o and its corresponding harmonics $2f_o$ to $5f_o$.

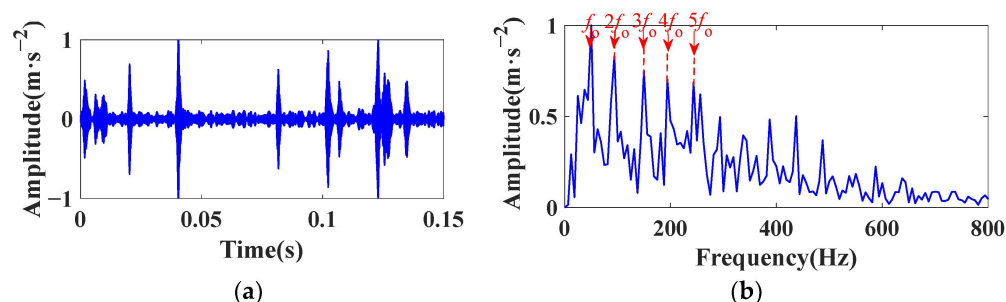


Figure 13. Processing results of raw outer-race vibration signal by HCF-IAPO-VME. (a) Time-domain signal; (b) envelope spectrum.

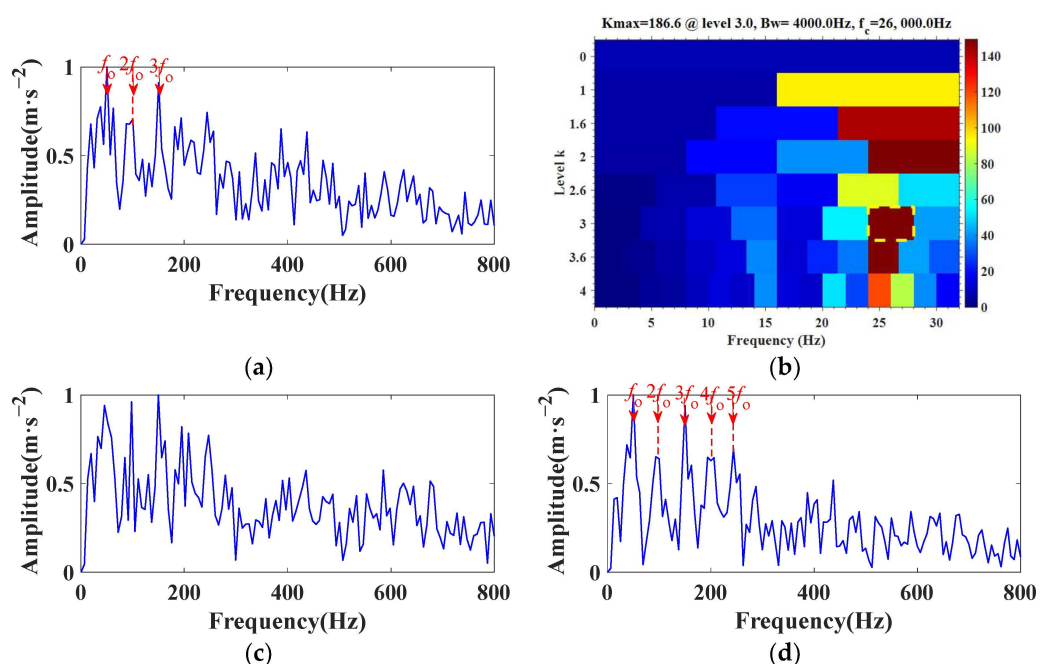


Figure 14. Processing results of raw outer-race vibration signal. (a) Envelope spectrum of VMD; (b) kurtogram of FK; (c) envelope spectrum of FK; (d) envelope spectrum of AVME.

The comparison confirms that HCF-IAPO-VME outperforms VMD, FK, and AVME in extracting fault features submerged by strong noise, achieving better decomposition performance and higher diagnostic accuracy for outer-race vibration signals.

As illustrated in Figure 15, the raw rolling-element vibration signal is severely contaminated by noise, masking periodic fault impulses. Its envelope spectrum contains no spectral lines matching the theoretical rolling-element fault characteristic frequency f_b , preventing direct fault diagnosis.

The vibration signal in Figure 15a is processed by HCF-IAPO-VME. In Figure 16a, the time-domain waveform exhibits a substantial reduction in noise amplitude, demonstrating strong denoising capability. The envelope spectrum in Figure 16b presents distinct spectral lines with prominent amplitudes. Spectral components matching theoretical rolling-element fault frequencies f_b , $2f_b$, $3f_b$, and $4f_b$ are clearly visible, enabling direct diagnosis of a rolling-element fault. These results further confirm the effectiveness and high accuracy of HCF-IAPO-VME for rolling-element fault-feature extraction under heavy-noise conditions.

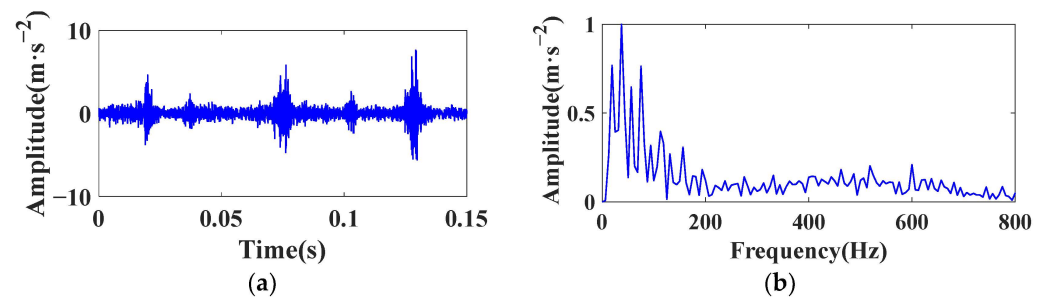


Figure 15. Original vibration signal of the rolling element. (a) Time-domain signal; (b) envelope spectrum.

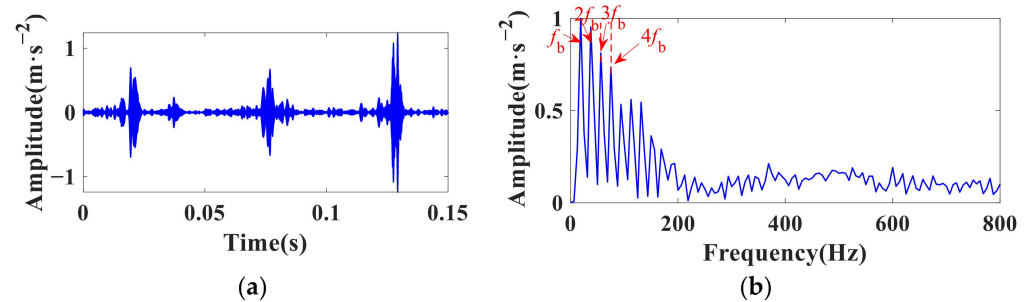


Figure 16. Processing results of original rolling-element vibration signal by HCF-IAPO-VME. (a) Time-domain signal; (b) envelope spectrum.

To further demonstrate the prominent advantages of the proposed HCF-IAPO-VME for rolling-element fault identification, the vibration waveform in Figure 15a is analyzed by VMD, FK and AVME respectively, and all comparison outcomes are visualized in Figure 17. In Figure 17a, the envelope spectrum decomposed by VMD fails to produce distinct spectral peaks matching the theoretical rolling-element fault characteristic frequency, which reveals that VMD is unable to extract effective fault signatures from this measurement signal. For the FK algorithm, the kurtogram in Figure 17b locates the optimal resonant frequency band, whose central frequency is 22,666.7 Hz, and bandwidth equals 2666.7 Hz. However, the main spectral component in the corresponding envelope spectrum (Figure 17c) still deviates from the theoretical fault frequency, resulting in the failure to obtain valid fault information and demonstrating the ineffectiveness of FK in processing this signal. As shown in Figure 17d, the envelope spectrum obtained by AVME also has no obvious peaks aligned with the theoretical rolling-element fault frequency, indicating that AVME cannot achieve stable extraction of fault characteristics under such severe noise interference.

Comprehensive comparison results show that, compared with VMD, FK, and AVME, the proposed HCF-IAPO-VME can effectively analyze rolling-element vibration signals; it accurately extracts fault features submerged in strong noise and achieves reliable rolling-element fault diagnosis. These results further verify the superiority and engineering applicability of the proposed method.

An outer-race fault simulation signal is constructed, and analyses are performed using inner-race vibration signals from the CWRU dataset, as well as outer-race and rolling-element vibration signals from the BJTU-RAO dataset. The results demonstrate that HCF-based IAPO-VME can accurately extract rolling bearing fault features under interference from complex components. Meanwhile, compared with the SEGI index used in VMD and the K index employed in FK, the HCF index can effectively avoid interference caused by complex noise and other signal components.

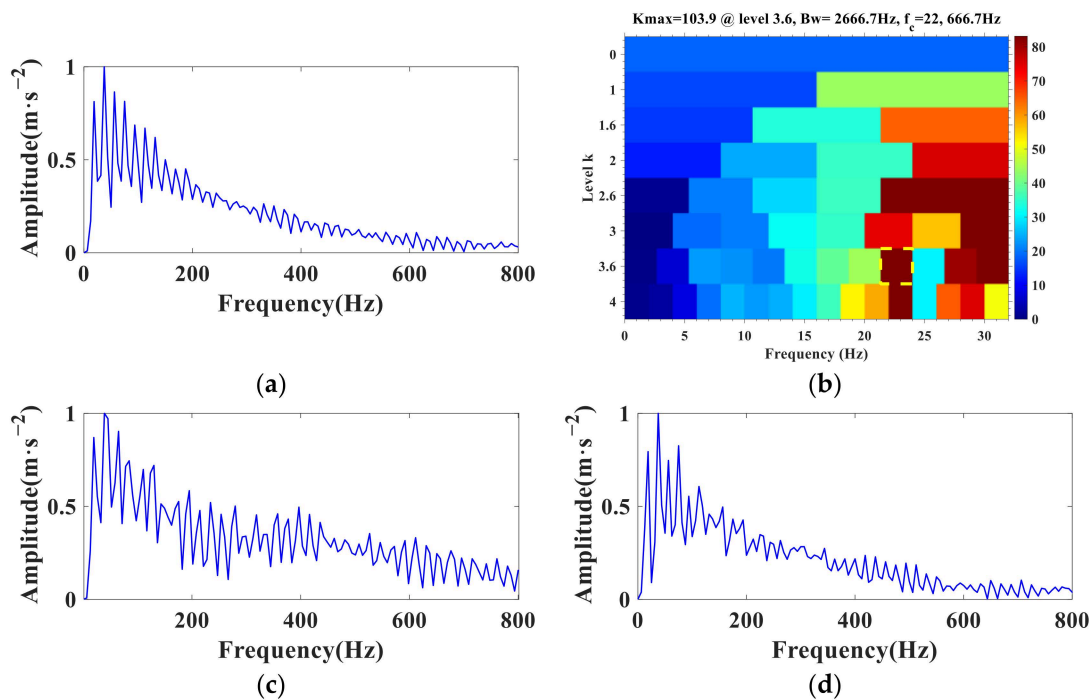


Figure 17. Processing results of raw rolling-element vibration signal. (a) Envelope spectrum of VMD; (b) kurtogram of FK; (c) envelope spectrum of FK; (d) envelope spectrum of AVME.

6. Quantitative Evaluation

To comprehensively and objectively evaluate the fault feature extraction performance of the proposed HCF-IAPO-VME, four quantitative indicators are adopted for comparison: fault feature coefficient (FFC) [33], kurtosis (K), output signal-to-noise Ratio (SNR), and envelope entropy (EE). FFC measures the energy proportion of effective fault components; K reflects the impulsiveness of fault features; SNR represents the noise suppression effect; and EE describes the sparsity and clarity of extracted fault modes. Generally, a superior diagnostic method is expected to achieve higher FFC, higher kurtosis (stable and non-abnormal), higher SNR, and lower envelope entropy. The complete expression of FFC is given by:

$$FFC = \frac{A^2(f_{\text{fault}}) + A^2(2f_{\text{fault}}) + A^2(3f_{\text{fault}})}{\sum A^2(f)} \quad (38)$$

where f_{fault} denotes the fault characteristic frequency; $A(f_{\text{fault}})$ denotes the spectral amplitude corresponding to the fault characteristic frequency within the envelope spectrum; and $A^2(f)$ refers to the total amplitude summation of all frequency components contained in the envelope spectrum.

Four evaluation metrics, including FFC, K, SNR and EE, are adopted to quantitatively assess the signals processed by HCF-IAPO-VME, VMD, FK and AVME, covering simulated signals, inner-race, outer-race and rolling-element fault signals. The results are listed in Table 4.

FFC quantifies the prominence of fault characteristic components, and a higher FFC value corresponds to more salient fault features. K is sensitive to impact components, whereas excessive K usually indicates severe noise interference and unstable decomposition performance. A higher SNR means better noise-suppression performance, and lower envelope entropy corresponds to more concentrated fault feature information.

Table 4. Quantitative comparison of different methods under four indicators.

Signal Type	Method	FFC	K	SNR (dB)	EE
Simulated Signal	HCF-IAPO-VME	0.1094	3.8540	2.0847	0.9817
	VMD	0.1415	3.6412	1.9941	0.9809
	FK	0.0026	3.8525	2.2148	0.9839
	AVME	0.0420	3.6071	2.7256	0.9829
Test Inner-Race	HCF-IAPO-VME	0.0349	3.9042	1.9906	0.9812
	VMD	0.0574	3.8429	1.6956	0.9805
	FK	0.0037	3.7035	1.9071	0.9844
	AVME	0.0047	3.0752	4.9199	0.9844
Test Outer-Race	HCF-IAPO-VME	0.1160	18.0672	−1.0886	0.9473
	VMD	0.0676	105.7520	−3.4118	0.9280
	FK	0.0479	197.5492	−3.5356	0.9350
	AVME	0.0579	121.5710	40.0000 *	0.9421
Test Rolling-Element	HCF-IAPO-VME	0.3426	29.2809	−2.8389	0.9175
	VMD	0.2383	96.5430	−6.9094	0.8421
	FK	0.1198	130.5128	−4.2641	0.9062
	AVME	0.1851	103.2693	40.0000 *	0.9059

* Note: Abnormal value caused by overfitting.

For simulated and measured inner-race fault signals, HCF-IAPO-VME maintains a moderate K value close to the normal distribution level, avoiding the abnormal sharp fluctuation observed in VMD, FK and AVME. Meanwhile, it achieves competitive FFC and SNR values as well as reasonable EE, demonstrating stable feature enhancement and noise suppression performance under moderate noise interference.

Under more complex outer-race and rolling-element fault conditions with heavy background noise, the proposed method obtains obviously higher FFC than the comparative methods. By contrast, VMD, FK and AVME exhibit abnormally high kurtosis induced by noise distortion, while the kurtosis of HCF-IAPO-VME is much lower. In addition, HCF-IAPO-VME maintains a reasonable negative SNR under strong noise, whereas AVME presents an anomalously fixed SNR of 40.0000, which cannot reflect the real noise environment objectively. Moreover, HCF-IAPO-VME obtains lower EE, indicating more concentrated and prominent fault feature information.

In general, compared with VMD, FK and AVME, the proposed HCF-IAPO-VME achieves higher fault feature contribution, more reasonable K, superior noise adaptability and lower EE under various working conditions. The quantitative results further confirm that HCF-IAPO-VME possesses remarkable advantages in extracting faint fault signatures and resisting intense noise interference in rolling bearing fault diagnosis.

To intuitively compare the performance of different algorithms, FFC values of all comparative approaches are plotted in the histogram in Figure 18. The results intuitively demonstrate that the proposed HCF-IAPO-VME has prominent strengths in extracting valid fault characteristics under heavy-noise interference. For outer-race and rolling-element fault samples, HCF-IAPO-VME achieves much higher FFC than VMD, FK and AVME. For the simulated signal and CWRU inner-race fault dataset, VMD obtains slightly higher FFC, but the proposed method still outperforms FK and AVME in diagnosis performance. By comparison, FK obtains extremely low FFC indicators under all experimental scenarios, which demonstrates its poor capability to identify weak fault features.

Combined with the comprehensive analysis of the four quantitative indicators, it is verified that HCF-IAPO-VME has superior performance in weak fault feature extraction, noise robustness, and diagnostic stability compared with the other three methods.

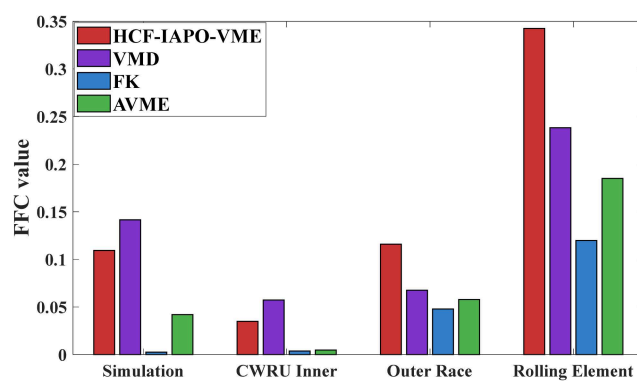


Figure 18. FFC values of different methods under various fault signals.

7. Conclusions

In this paper, an adaptive fault diagnosis framework, HCF-IAPO-VME, is proposed for rolling bearings under heavy-noise conditions. It combines the harmonic coherence factor, Improved Arctic Puffin Optimization (IAPO), and variational mode extraction (VME). The main conclusions are summarized as follows:

- (1) HCF can simultaneously characterize the intensity of periodic impulses and the consistency of harmonic structures. Compared with K, ESK and EE, HCF has the highest sensitivity to periodic fault impulses. It is less susceptible to random impulses, harmonic interference and noise. Therefore, HCF is more suitable as an evaluation index for bearing fault-feature extraction.
- (2) IAPO introduces dynamic parameter adjustment, elite guidance and an adaptive mutation mechanism, which effectively improve population diversity and global search ability. With HCF adopted as the fitness function, IAPO can rapidly converge to the optimal VME parameter combination; it achieves higher convergence precision and faster convergence speed compared with WMA, GWO, GA, SSA and conventional APO.
- (3) HCF-IAPO-VME realizes adaptive optimization of VME parameters. Simulation signals and experimental data from the CWRU and BJTU-RAO datasets verify that the proposed method can extract fault signatures buried in heavy background noise and clearly identify the fault characteristic frequencies and more harmonic components.
- (4) Quantitative evaluation based on FFC, K, SNR, and EE shows that HCF-IAPO-VME achieves higher FFC values, more stable K, a more realistic SNR, and lower EE. Compared with VMD, FK and AVME, the proposed method achieves remarkably superior performance in extracting subtle fault characteristics, suppressing noise interference and maintaining stable diagnosis results.

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Data Availability Statement: The original vibration data analyzed in this study are openly available in public datasets (CWRU bearing dataset and Bogie Test Dataset) as described in references [31,32].

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

A_i	amplitude of periodic fault impulses
$c_1(t)$, $c_2(t)$	adaptive learning factors
d	rolling-element diameter
D	bearing pitch diameter
f_s	shaft rotational frequency
f_i	inner-race fault frequency
f_o	outer-race fault frequency
f_b	rolling-element spin frequency
f_{samp}	sampling frequency
f_α	cyclic frequency
f_n	system natural frequency
f_s	shaft rotational frequency
f_h	harmonic frequency
$G(t)$	global best coordinate
H	number of harmonics
HCF_γ	HCF value of the mode extracted
I	number of periodic fault impulses
K	harmonic order
m	dimensionality of optimization problem
M	next power-of-two length for zero-padding
n	spindle rotating speed
$n(t)$	Gaussian white noise
N	number of rolling elements
N_s	sample size
P_h	harmonic amplitude
$P_i(t)$	personal optimal position
R_z	amplitude of random impulses
$\text{sgn}(\cdot)$	sign function
$s(t)$	impulse response function of bearing system
t	current iteration count
T_a	time interval between consecutive impulses
$V_i(t)$	velocity of the i -th individual
$w(t)$	dynamic inertia weight
$x_1(t)$	periodic impulsive component
$x_2(t)$	random impulsive interference
$x_3(t)$	non-fault harmonic component
X_{ij}	j -th dimensional position of the i -th puffin individual
$X_i(t)$	present location
$X_{\text{best}}(t)$	current global best position
$X_{\text{elite}}^k(t)$	randomly selected elite individual
$\hat{x}(\omega)$	Fourier transform
Z	number of random impulses
α	penalty factor
$\beta(t)$	impulse response of selected filter
β_n	damping ratio
σ	standard deviation of adaptive Gaussian perturbation
ω_d	central frequency
δ	Dirac delta function
θ	contact angle
λ	Lagrange multiplier
ν	mutation probability
ζ	search radius coefficient

η_1, η_2	learning step sizes
ρ	elite proportion coefficient
φ_h	phase
$\odot$	Hadamard product
$\langle \cdot \rangle$	inner product operation

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