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Rolling Bearing Fault Feature Extraction Based on Adaptive Hybrid Black-Winged Kite Optimized VME and SMHD

Guanghe Zhu ^{1,*}, Jiaqi Wang ² and Haijun Zhang ¹ ¹ College of Computer Science and Technology, Xinjiang Normal University, Urumqi 830017, China; zhjlp@163.com² School of Mechanical Engineering, Xinjiang University, Urumqi 830017, China; wjq@stu.xju.edu.cn

* Correspondence: 107622012010088@xjnu.edu.cn

Abstract

Rolling bearing fault features are often weak and easily affected by noise and interference. To improve fault feature extraction performance, this paper proposes an AHBKA-VME-SMHD method. First, the black-winged kite algorithm is improved by opposition-based learning, a Gompertz-based adaptive step size strategy, and an NGO-inspired random displacement strategy. Then, the improved algorithm is used to optimize the penalty factor and desired mode center frequency of VME, guided by a composite fitness function combining Higuchi fractal dimension and energy concentration index. Finally, SMHD is applied to enhance periodic impulsive components, and envelope spectrum analysis is used to identify fault characteristic frequencies. The proposed method is validated using simulated signals and two real-world bearing datasets, namely the CWRU and XJTU-SY datasets. The results show that the proposed method extracts clearer fault-related harmonics than the comparison methods. In addition, it obtains higher kurtosis and Gini index values and lower envelope spectrum entropy values, demonstrating its effectiveness for rolling bearing fault feature extraction.

Keywords: bearing fault diagnosis; adaptive hybrid black-winged kite algorithm; variational mode extraction; sparse maximum harmonics-to-noise ratio deconvolution

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1. Introduction

Rolling bearings are key components in rotating machinery, and their health condition directly affects the safety and reliability of mechanical equipment. When localized defects occur, periodic impulsive components are usually generated in vibration signals. However, these weak fault impulses are often submerged by background noise, random shocks, and harmonic interference, making accurate fault feature extraction difficult [1,2]. Therefore, extracting weak fault features from complex vibration signals is important for condition monitoring and fault diagnosis [3].

Adaptive signal decomposition methods have been widely used for bearing fault diagnosis. Empirical mode decomposition (EMD) and local mean decomposition (LMD) can process nonlinear and non-stationary signals, but they may suffer from mode mixing, endpoint effects, or false components [4,5]. Variational mode decomposition (VMD) has a solid variational framework, but its performance depends strongly on the preset mode number and penalty factor [6,7]. To avoid the difficulty of determining the mode number in

VMD, variational mode extraction (VME) was proposed to extract only one desired mode from the analyzed signal, showing higher efficiency and stronger targeting ability [8,9]. However, VME is still affected by the penalty factor and the desired mode center frequency. Improper parameter settings may lead to mode distortion, insufficient noise suppression, or incomplete extraction of fault-related components.

To reduce the dependence on empirical parameter selection, intelligent optimization algorithms have been introduced into VME-based fault feature extraction to improve diagnostic performance. For example, particle swarm optimization (PSO) [10], Archimedes optimization algorithm (AOA) [11], and black widow optimization algorithm (BWOA) [12] have been used to optimize the key parameters of VME. The black-winged kite algorithm (BKA) is a recently proposed meta-heuristic optimization algorithm with a simple structure, few control parameters, and good search ability [13]. In this study, BKA was selected as the basic optimizer because each fitness evaluation requires VME decomposition and fault-feature calculation, resulting in a relatively high computational cost. The concise update mechanism of BKA can help reduce unnecessary objective-function calls and computational burden. Nevertheless, the original BKA still has limitations in population diversity, adaptive search control, and local optimum avoidance, which may affect the accuracy and efficiency of VME parameter optimization.

In addition, optimized VME may still retain residual noise and interference components, especially under strong noise conditions. Deconvolution techniques are effective for enhancing periodic impulses. Minimum entropy deconvolution (MED), maximum correlated kurtosis deconvolution (MCKD), and multipoint optimal minimum entropy deconvolution (MOMEDA) have been widely used for fault impulse enhancement [14–16]. However, these methods are usually sensitive to parameter settings and noise interference. Sparse maximum harmonics-to-noise ratio deconvolution (SMHD) combines signal sparsity and harmonic characteristics, and enhances periodic impulses by maximizing the harmonics-to-noise ratio [17,18]. Therefore, SMHD is suitable for further enhancing the fault-related components extracted by VME.

Based on the above analysis, this paper proposes a rolling bearing fault feature extraction method based on adaptive hybrid black-winged kite optimized VME and SMHD, namely AHBKA-VME-SMHD. First, opposition-based learning, a Gompertz-based adaptive step size strategy, and a northern goshawk optimization (NGO)-inspired random displacement strategy are introduced into BKA to improve population diversity, search adaptability, and local optimum avoidance ability. Then, the adaptive hybrid black-winged kite algorithm (AHBKA) is used to optimize the penalty factor and desired mode center frequency of VME. A composite fitness function combining the Higuchi fractal dimension (HFD) and energy concentration index (ECI) is constructed to evaluate both signal complexity and fault-related energy concentration. Finally, SMHD is applied to the VME-extracted mode to further enhance periodic impulsive components, and envelope spectrum analysis is used to identify fault characteristic frequencies and their harmonics.

The main contributions of this paper are as follows:

1. An adaptive hybrid black-winged kite algorithm is proposed by introducing opposition-based learning, Gompertz-based adaptive step size adjustment, and an NGO-inspired random displacement strategy into BKA.
2. AHBKA is used to adaptively optimize the key parameters of VME, namely the penalty factor and the desired mode center frequency.
3. A composite fitness function combining HFD and ECI is constructed to guide VME parameter optimization from both signal complexity and fault-frequency energy concentration perspectives.

4. An AHBKA-VME-SMHD fault feature extraction framework is established and verified using benchmark functions, simulated signals, and two public bearing datasets, namely the Case Western Reserve University (CWRU) dataset and the Xi'an Jiaotong University-Sumyoung (XJTU-SY) dataset.

The remainder of this paper is organized as follows. Section 2 introduces the related theories of BKA, VME, and SMHD. Section 3 presents the proposed AHBKA-VME-SMHD method. Section 4 analyzes the optimization performance of AHBKA and simulated bearing fault signals. Section 5 verifies the proposed method using experimental bearing datasets. Finally, Section 6 concludes this paper.

2. Related Theories

2.1. Black-Winged Kite Algorithm (BKA)

The Black-winged Kite Algorithm (BKA) is a recently proposed nature-inspired meta-heuristic optimization algorithm that simulates the predation and migration behaviors of black-winged kites. In BKA, each black-winged kite represents a candidate solution in the search space, and the prey or leader represents the current global optimal solution. The algorithm mainly consists of three stages: population initialization, attacking behavior, and migration behavior. The attacking behavior is used for local exploitation around promising regions, whereas the migration behavior enhances global exploration and helps the population escape from local optima. Owing to its simple structure, few adjustable parameters, and high convergence accuracy, BKA is suitable for solving parameter optimization problems in signal processing and fault diagnosis, especially for VME parameter optimization involving repeated signal decomposition and feature-index calculation.

Assume that the population size is N , the dimension of the search space is J , and the position of the i -th black-winged kite in the j -th dimension is denoted as x_{ij} . The initial population is randomly generated within the lower and upper bounds of the search space:

$$X = X_{lb} + r \cdot (X_{ub} - X_{lb}), \quad (1)$$

where X_{lb} and X_{ub} are the lower and upper bounds of the search space, respectively, and r is a random number uniformly distributed in $[0, 1]$. After initialization, the individual with the best fitness value is selected as the leader L :

$$f(L) = \min f(X), \quad (2)$$

where $f(X)$ denotes the fitness values of all individuals in the population, and $f(L)$ denotes the fitness value of the current best individual.

In the attacking behavior stage, black-winged kites hover and observe the prey, and then perform a rapid dive attack. This behavior is mathematically modeled as a local exploitation strategy. The position updating equation is expressed as:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t + n_1 \cdot (1 + \sin(r)) \cdot x_{ij}^t, & r > 0.9, \\ x_{ij}^t + n_1 \cdot (2r - 1) \cdot x_{ij}^t, & r \leq 0.9. \end{cases} \quad (3)$$

where x_{ij}^t and x_{ij}^{t+1} are the positions of the i -th individual in the j -th dimension at the t -th and $(t + 1)$ -th iterations, respectively. The variable r is a random number in $[0, 1]$, and n_1 is a nonlinear factor that gradually decreases with the iteration process:

$$n_1 = 0.05 \times e^{-2(\frac{t}{T})^2}, \quad (4)$$

where T is the maximum number of iterations. The decreasing nonlinear factor reduces the disturbance amplitude in the later stage of iteration, which is beneficial for fine local search near the optimal solution.

In the migration behavior stage, the black-winged kite population changes its search region to explore potential global optimal areas. This mechanism is introduced to improve the global search capability and reduce the probability of premature convergence. The migration behavior is described as:

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + C \cdot (x_{i,j}^t - L_j^t), & f_i < f_{ri}, \\ x_{i,j}^t + C \cdot (L_j^t - n_2 \cdot x_{i,j}^t), & f_i \geq f_{ri}. \end{cases} \quad (5)$$

where L_j^t represents the best position in the j -th dimension at the t -th iteration, f_i is the fitness value of the current individual, and f_{ri} is the fitness value of a randomly selected individual. C denotes a standard Cauchy mutation operator, which is used to enhance the search randomness and global exploration ability. The coefficient n_2 controls the guiding effect of the current best position on the individual and is calculated as:

$$n_2 = 2 \sin\left(r + \frac{\pi}{2}\right), \quad (6)$$

where r is a random number in $[0, 1]$. If the current individual has a better fitness value than the randomly selected individual, it performs a Cauchy perturbation along the difference between its current position and the best position, thereby preserving local high-quality solutions while conducting small-scale exploration. Otherwise, the individual is guided by the current best position and performs a wider search to escape from local optima.

After each position update, the fitness values of all individuals are recalculated. If a better individual is found, the leader L is updated. The above attacking and migration operations are repeated until the maximum number of iterations T is reached. Finally, the algorithm outputs the global optimal position and its corresponding fitness value. In this study, BKA is used to optimize the key parameters of the subsequent signal-processing model, thereby reducing the dependence on empirical parameter selection and improving the stability of fault feature extraction.

2.2. Variational Mode Extraction (VME)

Variational Mode Extraction (VME) is an adaptive signal decomposition method developed from the theoretical framework of variational mode decomposition. Different from VMD, which decomposes a signal into several modes and requires the preset mode number, VME aims to extract only one specific desired mode from the analyzed signal. Therefore, VME has better computational efficiency and stronger targeting ability for extracting fault-related components from complex vibration signals.

Assume that the analyzed signal $f(t)$ consists of a desired mode $u_d(t)$ and a residual signal $f_r(t)$, the core principle of VME is that the desired mode $u_d(t)$ should be compactly distributed around its center frequency ω_d , while the spectral overlap between the desired mode and the residual signal should be minimized. Therefore, the constrained variational model of VME can be formulated as:

$$\begin{aligned} \min_{u_d, \omega_d, f_r} & \left\{ \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_d(t) \right] e^{-j\omega_d t} \right\|_2^2 + \|\beta(t) * f_r(t)\|_2^2 \right\} \\ \text{s. t. } & u_d(t) + f_r(t) = f(t) \end{aligned} \quad (7)$$

where α is the penalty factor, t denotes time, $\delta(t)$ is the Dirac distribution, j is the imaginary unit, $*$ denotes convolution, and $\beta(t)$ is the impulse response of the selected filter. The

penalty factor α controls the bandwidth of the extracted mode and has a direct influence on the decomposition performance.

To solve the above constrained optimization problem, a quadratic penalty term and the Lagrange multiplier $\lambda(t)$ are introduced. The augmented Lagrangian function is written as:

$$L(u_d, \omega_d, f_r, \lambda) = \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_d(t) \right] e^{-j\omega_d t} \right\|_2^2 + \|\beta(t) * f_r(t)\|_2^2 + \|f(t) - (u_d(t) + f_r(t))\|_2^2 + \langle \lambda(t), f(t) - (u_d(t) + f_r(t)) \rangle \quad (8)$$

The alternating direction method of multipliers is then used to iteratively update the desired mode and its center frequency. In the frequency domain, the update formula of the desired mode is:

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

The center frequency is updated by:

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

where n is the iteration number, and $\hat{f}(\omega)$, $\hat{u}_d(\omega)$, and $\hat{\lambda}(\omega)$ are the Fourier transforms of $f(t)$, $u_d(t)$, and $\lambda(t)$, respectively.

2.3. Sparse Maximum Harmonics-to-Noise Ratio Deconvolution (SMHD)

Sparse Maximum Harmonics-to-Noise Ratio Deconvolution (SMHD) is an effective signal-processing technique for extracting sparse fault impulses from noisy vibration signals. Its core idea is to combine signal sparsity with harmonic characteristics. Specifically, SMHD takes the harmonics-to-noise ratio (HNR) as the objective function and enhances the periodic impulse components by maximizing the ratio between harmonic components and noise components. Therefore, it can improve the signal-to-noise ratio and make weak bearing fault features more distinguishable. For a signal $x(t)$, the HNR is defined as:

$$\text{HNR} = \frac{\int x(t)x(t+T_0)dt}{\int x^2(t)dt - \int x(t)x(t+T_0)dt}, \quad (11)$$

where T_0 denotes the signal period.

In the SMHD procedure, the input signal $x(t)$ is first filtered to obtain an initial filtered signal:

$$x_1(t) = f_1 \cdot x(t), \quad (12)$$

where f_1 is the initial filter coefficient. Then, sparse processing is performed on the filtered signal to highlight the impulse components. The sparse signal is expressed as:

$$y_1 = x_1(t) \left[1 - \exp(-2\sigma y_1^2) \right], \quad (13)$$

where σ is the sparse threshold. After that, the filter coefficients are updated according to the autocorrelation and cross-correlation information:

$$f_k = \mathbf{A}^{-1} \mathbf{b}, \quad (14)$$

where $\mathbf{A}$ is the autocorrelation matrix of $x(t)$, and $\mathbf{b}$ is the cross-correlation matrix between $x(t)$ and $x_1(t)$.

When the fault period is unknown, the HNR of the sparse signal envelope is used to estimate the period, and the sparse threshold is updated according to the kurtosis variation of the filtered signal. The above process is repeated until the stopping condition is satisfied, and the final deconvoluted signal is obtained.

By enhancing sparse periodic impulses and suppressing noise, SMHD can further improve the quality of the VME-extracted mode, providing a clearer signal for envelope spectrum analysis and fault characteristic frequency extraction.

3. Proposed Method

3.1. Adaptive Hybrid Black-Winged Kite Algorithm (AHBKA)

3.1.1. Motivation for Improvement

Although BKA has a simple structure and strong search ability, the original algorithm still has several limitations when dealing with complex optimization problems. First, the initial population is randomly generated, which may reduce the diversity and quality of candidate solutions. Second, the step size control strategy in the attack phase is relatively fixed, making it difficult to balance global exploration and local exploitation effectively. Third, individuals may gradually gather around the current optimal solution during the migration phase, which increases the risk of falling into local optima.

To overcome these limitations, an adaptive hybrid black-winged kite algorithm, named AHBKA, is proposed in this study. Three improvement strategies are introduced into the original BKA: opposition-based learning initialization, Gompertz-based adaptive step size adjustment, and an NGO-inspired random displacement mechanism. These strategies are designed to improve population diversity, enhance search adaptability, and strengthen the ability to escape from local optima.

3.1.2. Opposition-Based Learning Initialization Strategy

To enhance the initial search quality, an opposition-based learning strategy is used during population initialization [19]. After generating the initial population, the corresponding opposite population is constructed as follows:

$$\bar{X}_i = X_{lb} + X_{ub} - X_i, \quad (15)$$

where $\bar{X}_i$ denotes the opposite solution of X_i .

Then, the original population and the corresponding opposite population are combined to generate a new candidate population. The fitness value of each individual in the new population is calculated and ranked, and the best N individuals are selected as the new initial population.

3.1.3. Gompertz-Based Adaptive Step Size Strategy

In the attack phase of the original BKA, the step size factor directly affects the position update range of individuals. To make the step size change more flexibly during iteration, the Gompertz growth model is introduced to dynamically adjust the step size factor in AHBKA [20]. The improved step size factor is defined as:

$$n = A \cdot \exp \left[- \exp \left(B - Y \cdot \frac{t}{T} \right) \right], \quad (16)$$

where A , B , and Y are the control parameters of the Gompertz model, which determine the variation trend of the adaptive step size. Their specific values are determined through an orthogonal experiment in Section 4.1.2.

Compared with the original fixed exponential decay strategy, the Gompertz-based step size factor changes nonlinearly with the iteration process. This allows the algorithm to adjust the search step more adaptively in different optimization stages, thereby improving the coordination between global exploration and local exploitation.

3.1.4. NGO-Inspired Random Displacement Strategy

To enhance the random displacement ability of the migration phase, the NGO-inspired random adjustment strategy is introduced into AHBKA [21]. By introducing this strategy, the migration behavior model in Equation (5) is updated as follows:

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + C \cdot (x_{i,j}^t - I \cdot L_j^t), & f_i < f_{ri}, \\ x_{i,j}^t + C \cdot (L_j^t - n_2 \cdot x_{i,j}^t), & f_i \geq f_{ri}. \end{cases} \quad (17)$$

where I is a random value of 1 or 2. Compared with the original migration behavior model, the introduced random factor changes the relative displacement between the current individual and the leader. This increases the randomness of the migration process and helps AHBKA reduce the risk of falling into local optima.

3.2. Adaptive Optimization of VME Key Parameters

In VME, the penalty factor α and the center frequency of the desired mode ω_d have significant influences on the extraction quality of fault-related components. Improper parameter settings may lead to mode distortion, insufficient noise suppression, or incomplete extraction of fault information. Therefore, selecting appropriate VME parameters is essential for improving fault feature extraction performance.

To reduce the dependence on empirical parameter selection, the proposed AHBKA is employed to adaptively optimize the key parameters of VME. In the optimization process, each individual in the population represents a candidate parameter combination $\mathbf{X}_i = [\alpha_i, \omega_{d,i}]$. Therefore, the VME parameter optimization problem can be expressed as follows:

$$\mathbf{X}_i = [\alpha_i, \omega_{d,i}], \quad i = 1, 2, \dots, N, \quad (18)$$

$$(\alpha^*, \omega_d^*) = \operatorname{argmin}_{\alpha, \omega_d} F(\alpha, \omega_d), \quad (19)$$

$$\alpha \in [\alpha_{\min}, \alpha_{\max}], \quad \omega_d \in [\omega_{\min}, \omega_{\max}], \quad (20)$$

where $F(\alpha, \omega_d)$ denotes the composite fitness function defined in Section 3.3. The operator argmin is used to obtain the optimal parameter pair (α^*, ω_d^*) that minimizes $F(\alpha, \omega_d)$ within the search ranges of α and ω_d .

For each candidate solution, VME is performed to extract the desired mode, and the corresponding fitness value is calculated according to the fault feature quality of the extracted signal. Then, the population positions are iteratively updated by AHBKA until the stopping criterion is satisfied. Finally, the optimal parameter combination (α^*, ω_d^*) is obtained and used for subsequent signal processing. The overall optimization procedure is illustrated in Figure 1.

3.3. Fitness Function Design

Rolling bearing faults usually generate periodic impulse components in vibration signals. When the extracted mode contains more noise and random interference, the waveform becomes more complex and irregular. The Higuchi fractal dimension (HFD) can effectively reflect the complexity and irregularity of a time series [22]. A larger HFD indicates that the extracted mode contains more noise and random fluctuation components;

conversely, a smaller value indicates that the signal is more regular and the periodic impulse characteristics are more obvious.

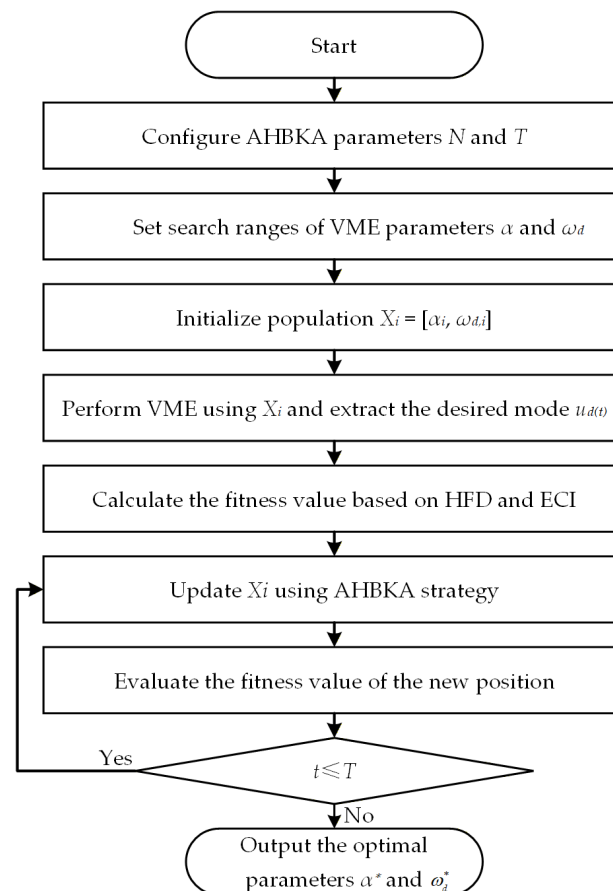


Figure 1. Flowchart of VME key parameters optimization based on AHBKA.

For a time series, the average curve length under scale k is denoted as $L(k)$. According to the Higuchi method, the fractal dimension is estimated from the slope of the logarithmic relationship between $L(k)$ and $1/k$:

$$\text{HFD} = \text{slope} \left(\ln L(k), \ln \frac{1}{k} \right), \quad (21)$$

In addition, the energy concentration index (ECI) of fault-related components is used to evaluate the VME decomposition quality. When fault information is clear, the amplitudes at the fault characteristic frequency and its harmonics become more prominent in the energy spectrum. Therefore, the squared amplitudes of the first four fault-related components are used as the numerator of ECI, while the squared RMS value of the whole energy spectrum is used as the denominator. Thus, ECI measures the relative concentration of fault-related energy, and a larger ECI indicates more prominent fault features. The ECI is defined as:

$$\text{ECI} = \frac{A_1^2 + A_2^2 + A_3^2 + A_4^2}{E_{\text{rms}}^2}, \quad (22)$$

where A_1, A_2, A_3 , and A_4 are the maximum amplitudes near the first-, second-, third-, and fourth-order fault characteristic frequencies, respectively. E_{rms} is the root mean square value of the energy spectrum.

Since the objective of VME parameter optimization is to extract a fault-related mode with low signal complexity and high fault-frequency energy concentration, HFD and ECI

have opposite optimization directions. A smaller HFD indicates lower signal irregularity and weaker noise disturbance, whereas a larger ECI indicates stronger energy concentration around the fault characteristic frequency and its harmonics. Therefore, the two indicators are combined in a ratio form to construct a minimization objective, which is consistent with ratio-based composite fitness functions used in adaptive decomposition-based fault diagnosis [23,24]. Thus, the composite fitness function is defined as:

$$\text{Fitness} = \frac{\text{HFD}}{\text{ECI}}, \quad (23)$$

The optimization objective is to minimize the fitness value. In this way, the optimal VME parameters can be selected when the extracted mode has both strong fault-frequency energy concentration and low signal complexity.

3.4. Overall Procedure of AHBKA-VME-SMHD

The overall procedure of the proposed AHBKA-VME-SMHD method is shown in Figure 2. First, the vibration signal is collected, and the theoretical fault characteristic frequency is calculated. Then, AHBKA is used to optimize the penalty factor and the desired mode center frequency of VME. After the optimal parameters are obtained, VME is performed to extract the fault-related desired mode. Finally, SMHD is applied to further enhance the periodic impulsive components, and envelope spectrum analysis is used to extract the fault characteristic frequency and its harmonics.

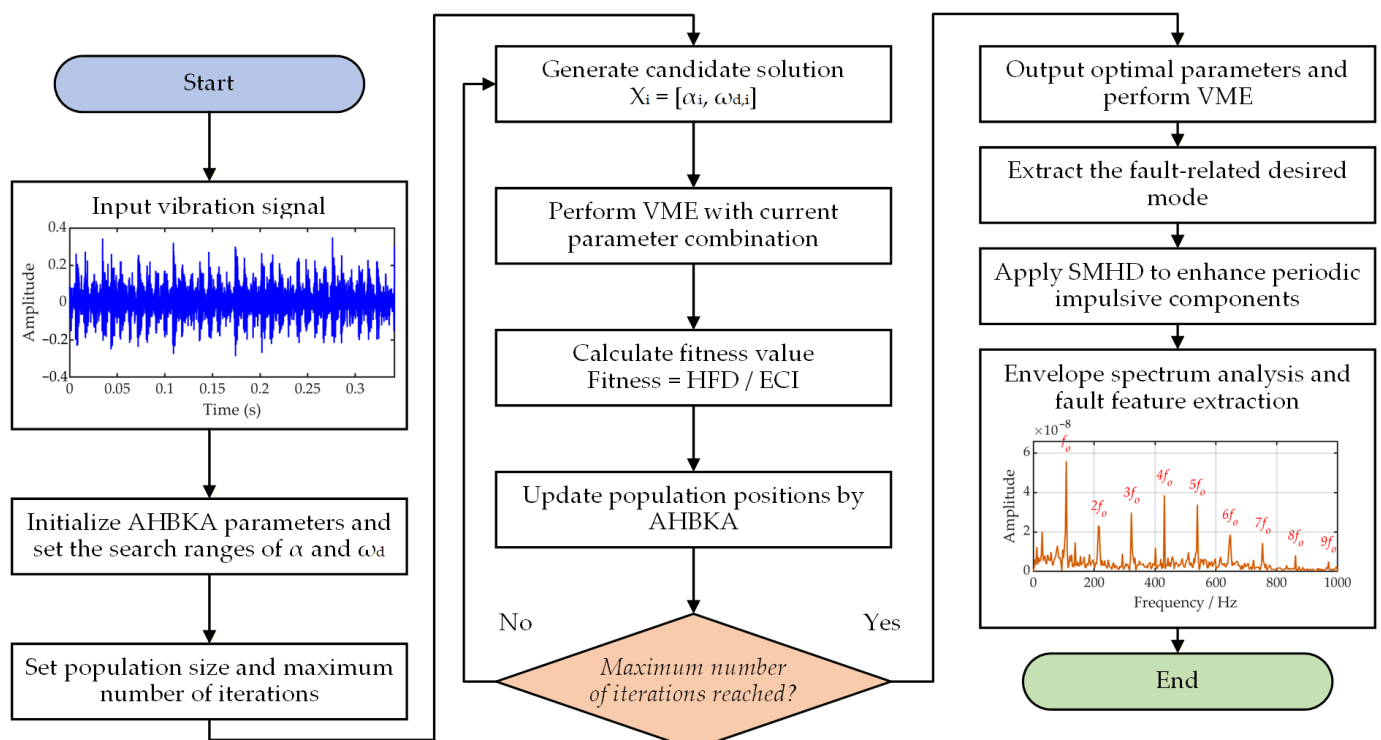


Figure 2. Flowchart of the proposed AHBKA-VME-SMHD fault feature extraction method.

4. AHBKA Performance and Simulation Signal Analysis

4.1. Performance Evaluation of AHBKA

4.1.1. Benchmark Test Functions and Experimental Settings

The effectiveness of the proposed AHBKA algorithm was evaluated using six benchmark test functions. F1–F3 are unimodal functions, mainly used to test local exploitation ability and convergence accuracy. F4–F6 are multimodal functions, mainly used to test

global exploration ability and robustness. The details of these functions are listed in Table 1, where n denotes the search dimension.

Table 1. Benchmark test functions.

Expression	Dimension	Search Space	Optimal Value
$F_1(x) = \sum_{i=1}^n x_i^2$	30	$[-100, 100]$	0
$F_2(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	30	$[-10, 10]$	0
$F_3(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$	30	$[-100, 100]$	0
$F_4(x) = \sum_{i=1}^n [x_i^2 - 10 \cos(2\pi x_i) + 10]$	30	$[-5.12, 5.12]$	0
$F_5(x) = -20 \exp \left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \right) - \exp \left(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i) \right) + 20 + e$	30	$[-32, 32]$	0
$F_6(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos \left(\frac{x_i}{\sqrt{i}} \right) + 1$	30	$[-600, 600]$	0

For fair comparison, AHBKA was compared with BKA, RIME [25] and WOA [26] under the same conditions. The population size was set to 30, and the maximum number of iterations was 1000. Each algorithm was independently run 30 times on each function. The mean value and standard deviation of the final fitness values were used as evaluation indicators. The mean value reflects optimization accuracy, while the standard deviation reflects stability. The calculation formulas are as follows:

$$Mean = \frac{1}{M} \sum_{i=1}^M fitness_i, \quad (24)$$

$$Std = \sqrt{\frac{1}{M} \sum_{i=1}^M (fitness_i - Mean)^2}, \quad (25)$$

where M is the number of independent runs, and $fitness_i$ is the final fitness value obtained in the i -th run. In this study, $M = 30$.

4.1.2. Determination of Gompertz Parameters

To determine the control parameters of the Gompertz adaptive step-size model, an $L_9(3^3)$ orthogonal experiment was conducted on six benchmark functions. The three parameters A , B , and Y were selected as experimental factors, and each factor was assigned three levels. The detailed orthogonal design is listed in Table 2.

In the experiment, the population size, maximum number of iterations, and number of independent runs were set to 30, 1000, and 30, respectively. The optimization performance was evaluated using the mean value and standard deviation of the final optimal fitness values. The results on F1–F3 and F4–F6 are shown in Tables 3 and 4, respectively.

Table 2. Orthogonal design of Gompertz parameters.

Group	A	B	Y
1	0.05	0.1	0.1
2	0.05	0.3	0.5
3	0.05	0.5	1.0
4	0.5	0.1	0.5
5	0.5	0.3	1.0
6	0.5	0.5	0.1
7	1.0	0.1	1.0
8	1.0	0.3	0.1
9	1.0	0.5	0.5

Table 3. Results of Gompertz parameter determination on F1–F3.

Group	F1 Mean	F1 Std	F2 Mean	F2 Std	F3 Mean	F3 Std
1	1.0212×10^{-220}	0	9.6694×10^{-114}	5.1731×10^{-113}	1.1673×10^{-221}	0
2	3.0891×10^{-221}	0	1.6747×10^{-114}	5.2485×10^{-114}	1.8614×10^{-224}	0
3	8.1595×10^{-221}	0	2.7160×10^{-114}	1.3893×10^{-113}	6.0088×10^{-222}	0
4	1.2384×10^{-216}	0	5.9755×10^{-107}	3.2078×10^{-106}	1.4013×10^{-209}	0
5	8.2282×10^{-215}	0	3.6592×10^{-110}	1.8955×10^{-109}	1.6272×10^{-213}	0
6	3.2924×10^{-220}	0	5.8978×10^{-111}	3.0783×10^{-110}	1.0012×10^{-216}	0
7	2.1021×10^{-218}	0	1.6982×10^{-111}	5.5069×10^{-111}	1.2658×10^{-218}	0
8	2.5331×10^{-216}	0	6.6982×10^{-112}	1.6075×10^{-111}	5.5740×10^{-207}	0
9	1.5186×10^{-219}	0	2.7256×10^{-109}	1.4574×10^{-108}	2.3258×10^{-215}	0

Table 4. Results of Gompertz parameter determination on F4–F6.

Group	F4 Mean	F4 Std	F5 Mean	F5 Std	F6 Mean	F6 Std
1	0	0	4.4409×10^{-16}	0	0	0
2	0	0	4.4409×10^{-16}	0	0	0
3	0	0	4.4409×10^{-16}	0	0	0
4	0	0	4.4409×10^{-16}	0	0	0
5	0	0	4.4409×10^{-16}	0	0	0
6	0	0	4.4409×10^{-16}	0	0	0
7	0	0	4.4409×10^{-16}	0	0	0
8	0	0	4.4409×10^{-16}	0	0	0
9	0	0	4.4409×10^{-16}	0	0	0

As shown in Tables 3 and 4, Group 2 obtains the smallest Mean values on F1, F2, and F3, while all parameter combinations achieve the same results on F4, F5, and F6. Therefore, considering the overall optimization performance, the Gompertz parameters are set as $A = 0.05$, $B = 0.3$, and $Y = 0.5$ in the subsequent experiments.

4.1.3. Ablation Study of AHBKA

To verify the effectiveness of different improvement strategies, an ablation study was conducted on the selected benchmark functions. Four algorithms were compared, including BKA, AHBKA-1, AHBKA-2, and the complete AHBKA. AHBKA-1 introduces opposition-based learning initialization, AHBKA-2 further introduces the Gompertz adaptive step size, and AHBKA incorporates all three improvement strategies. The population size, maximum number of iterations, and number of independent runs were kept the same as those in Section 4.1.1. The results are shown in Table 5.

Table 5. Ablation results of AHBKA on benchmark functions.

Function	Indicator	BKA	AHBKA-1	AHBKA-2	AHBKA
F1	Mean	2.9278×10^{-160}	3.5436×10^{-173}	5.0454×10^{-179}	3.0891×10^{-221}
F1	Std	1.5767×10^{-159}	0	0	0
F2	Mean	1.5650×10^{-96}	6.8295×10^{-104}	8.1633×10^{-105}	1.6747×10^{-114}
F2	Std	5.3231×10^{-96}	3.6778×10^{-103}	4.3961×10^{-104}	5.2485×10^{-114}
F3	Mean	1.4003×10^{-172}	9.5352×10^{-179}	1.6960×10^{-181}	1.8614×10^{-224}
F3	Std	0	0	0	0
F4	Mean	0	0	0	0
F4	Std	0	0	0	0
F5	Mean	4.4409×10^{-16}	4.4409×10^{-16}	4.4409×10^{-16}	4.4409×10^{-16}
F5	Std	0	0	0	0
F6	Mean	0	0	0	0
F6	Std	0	0	0	0

As shown in Table 5, AHBKA-1 and AHBKA-2 obtain smaller Mean values than BKA on F1, F2, and F3, indicating that both opposition-based learning initialization and Gompertz adaptive step size contribute to the improvement of optimization accuracy. Moreover, the complete AHBKA achieves the smallest Mean values on these three functions, showing that the further introduction of NGO-inspired random displacement enhances the search capability of BKA. For F4, F5, and F6, all algorithms obtain the same results, so these functions are not further discussed. Overall, the ablation results demonstrate that the three improvement strategies are effective and that their integration further improves the overall optimization performance of AHBKA.

4.1.4. Comparison with Other Optimization Algorithms

Table 6 shows the optimization results of AHBKA, BKA, RIME and WOA on six benchmark functions. For F1–F3, AHBKA obtains the smallest mean values among all algorithms, indicating that it has the highest convergence accuracy on unimodal functions. Especially on F3, AHBKA achieves 1.8614×10^{-224} , while RIME and WOA obtain 367.5769 and 21,311.5685, respectively. This shows that AHBKA has stronger local exploitation ability. For F4–F6, AHBKA also shows excellent performance. On F4 and F6, AHBKA reaches the theoretical optimum value of 0. On F5, AHBKA obtains 4.4409×10^{-16} , which is also very close to the optimum. In contrast, RIME performs worse on these functions, and WOA only achieves comparable results on some functions.

In terms of stability, the standard deviation of AHBKA is 0 on most functions, indicating stable convergence in repeated runs. In addition, the running time of AHBKA is close to that of the comparison algorithms on all six functions. Although AHBKA introduces additional improvement strategies, its time cost does not increase significantly compared with BKA, RIME, and WOA. This indicates that the proposed algorithm improves optimization accuracy while maintaining acceptable computational efficiency.

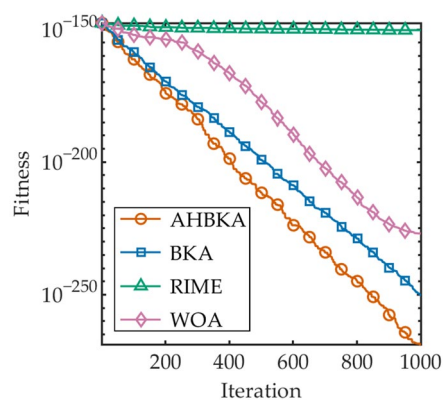
4.1.5. Convergence Curve Analysis

Figure 3 illustrates the convergence curves of AHBKA, BKA, RIME, and WOA on six benchmark functions. It can be observed that AHBKA exhibits the fastest convergence speed and the highest optimization accuracy in most cases. For F1, F2, and F3, AHBKA rapidly reduces the fitness value in the early iteration stage and maintains continuous optimization in the later stage, with final fitness values of 1.25×10^{-238} , 1.08×10^{-117} , and 6.51×10^{-236} , respectively. For F4 and F6, AHBKA converges to 0, while for F5, the final fitness value reaches 4.44×10^{-16} , which can be regarded as the global optimum within

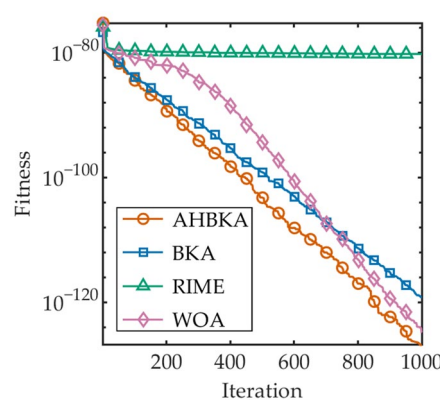
numerical precision. These results indicate that AHBKA has strong global exploration ability and high solution accuracy.

Table 6. Optimization results of different algorithms on benchmark functions.

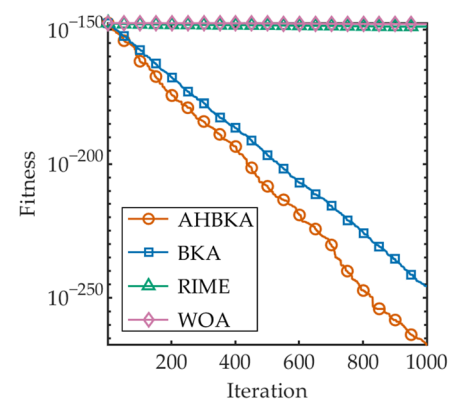
Function	Indicator	AHBKA	BKA	RIME	WOA
F1	Mean	3.0891×10^{-221}	2.9278×10^{-160}	0.3977	8.0910×10^{-150}
	Std	0	1.5767×10^{-159}	0.1594	3.9939×10^{-149}
	Time	1.9100	1.7389	1.7283	1.8103
F2	Mean	1.6747×10^{-114}	1.5650×10^{-96}	0.5910	2.4549×10^{-101}
	Std	5.2485×10^{-114}	5.3231×10^{-96}	0.8216	1.2177×10^{-100}
	Time	2.0368	2.027	2.0063	2.0319
F3	Mean	1.8614×10^{-224}	1.4003×10^{-172}	367.5769	21,311.5685
	Std	0	0	127.5147	10,634.0344
	Time	8.5891	8.4957	8.5421	8.6731
F4	Mean	0	0	46.4325	0
	Std	0	0	12.7469	0
	Time	2.0684	2.0891	2.1037	2.0998
F5	Mean	4.4409×10^{-16}	4.4409×10^{-16}	1.3835	3.6415×10^{-15}
	Std	0	0	0.5104	2.8049×10^{-15}
	Time	2.1645	2.1846	2.0742	2.1630
F6	Mean	0	0	0.5171	0.0035
	Std	0	0	0.1334	0.0138
	Time	2.9100	2.8504	2.9989	2.9434



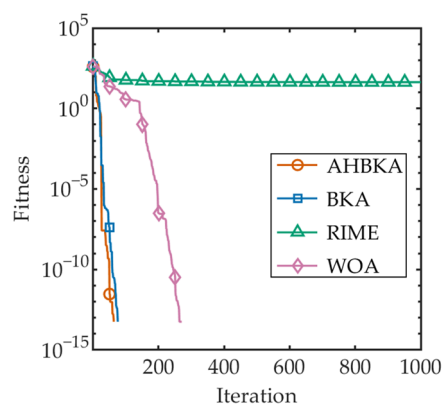
(a) F1



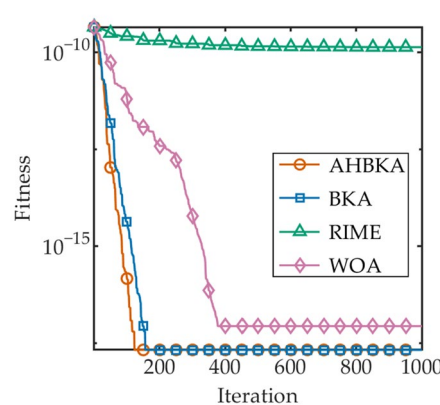
(b) F2



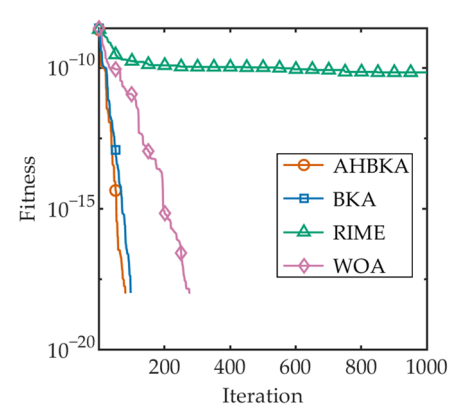
(c) F3



(d) F4



(e) F5



(f) F6

Figure 3. Convergence comparison of AHBKA, BKA, RIME, and WOA on six benchmark functions: (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, and (f) F6.

Compared with the other algorithms, BKA and WOA can obtain competitive results on some functions, but their convergence speeds are generally slower than AHBKA. For example, AHBKA reaches the 10^{-6} accuracy level on F4, F5, and F6 at the 27th, 56th, and 41st iterations, respectively, whereas WOA requires 199, 263, and 155 iterations. RIME shows relatively weak convergence performance, with final fitness values of 0.296, 0.321, 293.274, 42.963, 1.884, and 0.481 on F1–F6, respectively, and fails to reach the 10^{-6} accuracy level on all functions. Overall, AHBKA achieves a better balance between exploration and exploitation, demonstrating superior convergence speed, optimization accuracy, and robustness.

4.2. Simulation Signal Analysis

4.2.1. Construction of Simulation Signals Under Different Noise Conditions

To evaluate the parameter optimization performance and noise robustness of the proposed AHBKA algorithm for VME under different noise conditions, a simulated bearing inner race fault signal was constructed. The simulated signal consists of four components: an inner race periodic impulse component, a random impulse component, a discrete harmonic interference component, and Gaussian white noise. According to the simulation model, the mixed signal can be expressed as:

$$x(t) = b(t) + r(t) + h(t) + n(t), \quad (26)$$

where $x(t)$ is the mixed signal, $b(t)$ is the inner race periodic impulse component, $r(t)$ is the random impulse component, $h(t)$ is the discrete harmonic interference component, and $n(t)$ is Gaussian white noise.

The inner race periodic impulse component is modeled as:

$$b(t) = \sum_s a(t) e^{-\alpha_1(t-s/f_m-\tau)} \sin[2\pi f_1(t-s/f_m-\tau)], \quad (27)$$

where s is the impulse index, $a(t)$ is the amplitude modulation term caused by shaft rotation, f_m is the inner race fault characteristic frequency, f_1 is the resonance frequency of the fault impulse, α_1 is the attenuation coefficient, and τ is a small random disturbance used to simulate the slip effect, and it is uniformly distributed as $\tau \sim U(-\eta/f_m, \eta/f_m)$. Here, η denotes the slip factor.

For the inner race fault, the amplitude modulation term is given by

$$a(t) = 0.5[1 - \cos(2\pi f_0 t)], \quad (28)$$

where f_0 is the rotating frequency. The random impulse component is expressed as:

$$r(t) = \sum_{i=1}^{M_2} A_i e^{-\alpha_3(t-t_i)} \sin[2\pi f_3(t-t_i)], \quad (29)$$

where I is the random impulse index, M_2 is the number of random impulses, A_i is the impulse amplitude, t_i is the occurrence time of the i -th random impulse, f_3 is the resonance frequency of the random impulse, and α_3 is the attenuation coefficient.

The discrete harmonic interference is given by:

$$h(t) = P_1 \sin(2\pi f_{s1} t + \beta_1) + P_2 \sin(2\pi f_{s2} t + \beta_2) + P_3 [0.5 + 0.3 \sin(2\pi f_{s3} t + \beta_3)], \quad (30)$$

where P_1 , P_2 , and P_3 are the amplitudes of the harmonic components; f_{s1} , f_{s2} , and f_{s3} are the corresponding harmonic frequencies; and β_1 , β_2 , and β_3 are the initial phases.

The Gaussian white noise $n(t)$ is added to simulate background noise interference. The main parameters used in the simulation are listed in Table 7.

Table 7. Main parameters of the simulated inner race fault signal.

Parameter Type	Values
Sampling setting	$F_s = 4096$ Hz
Inner race fault impulse	$f_o = 26$ Hz, $f_m = 142$ Hz, $f_1 = 900$ Hz, $\alpha_1 = 950$, $\eta = 0.01$
Random impulse	$M_2 = 2$, $A_i = 1.5$, $f_3 = 1500$ Hz, $\alpha_3 = 700$
Harmonic interference	$P_1 = 0.2$, $P_2 = 0.2$, $P_3 = 0.4$, $f_{s1} = 73$ Hz, $f_{s2} = 170$ Hz, $f_{s3} = 7.5$ Hz, $\beta_1 = \pi/6$, $\beta_2 = -\pi/3$, $\beta_3 = 0$

Figures 4–6 show the simulated inner race fault signals and their envelope spectra under different noise conditions, corresponding to SNR levels of 3 dB, 0 dB, and -3 dB, respectively. In each figure, the first five subfigures present the time-domain waveforms of the inner race periodic impulse signal, random impulse signal, discrete harmonic interference, Gaussian white noise, and mixed signal, while the last subfigure shows the envelope spectrum of the mixed signal. It can be observed that, as the noise level increases, the periodic fault impulses in the mixed signal become increasingly difficult to identify. Meanwhile, the random impulses and harmonic interference introduce obvious disturbance components, causing the fault characteristic frequency and its harmonics to be insufficiently prominent in the envelope spectrum. Therefore, the inner race fault feature cannot be reliably identified directly from the mixed signal, indicating that further fault feature extraction is necessary.

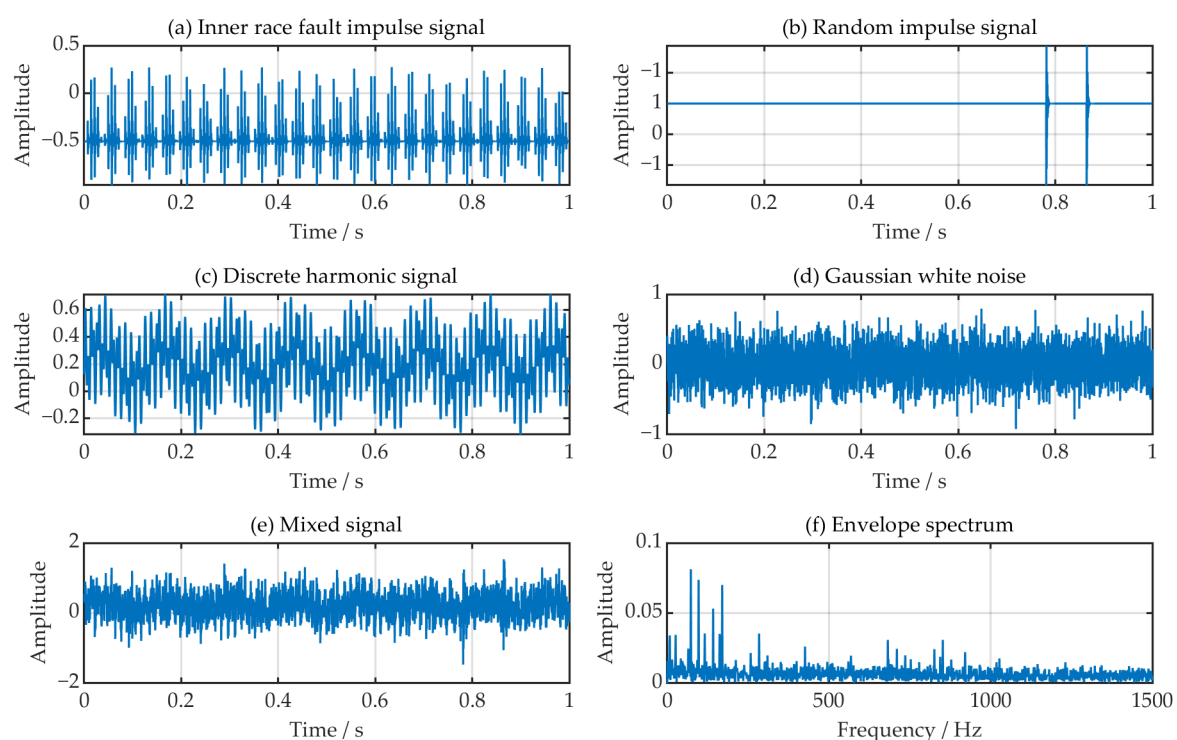


Figure 4. Simulated inner race fault signal under the 3 dB noise condition and its envelope spectrum: (a) inner race periodic impulse signal; (b) random impulse signal; (c) discrete harmonic interference; (d) Gaussian white noise; (e) mixed signal; (f) envelope spectrum of the mixed signal.

4.2.2. Comparative Analysis Under Simulated Signal

To verify the effectiveness of the proposed AHBKA-VME method, the simulated signals under different noise levels were processed using unoptimized VME, PSO-VME [10], AOA-VME [11], BKA-VME, and AHBKA-VME, respectively, where AOA denotes the Arithmetic Optimization Algorithm. For the unoptimized VME, the penalty factor and initial

center frequency were set to $\alpha = 2000$ and $\omega_d = 5147$, respectively. For the optimization-based VME methods, the maximum number of iterations and population size were set to 30 and 50, respectively.

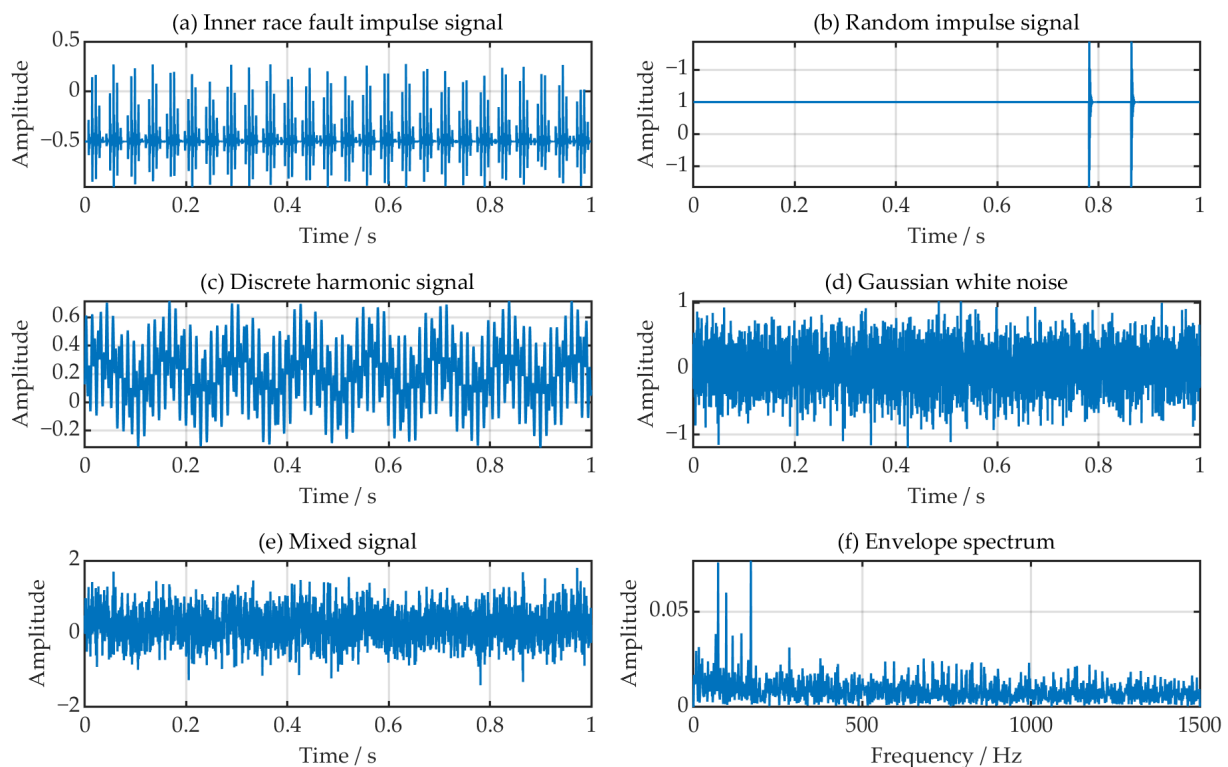


Figure 5. Simulated inner race fault signal under the 0 dB noise condition and its envelope spectrum: (a) inner race periodic impulse signal; (b) random impulse signal; (c) discrete harmonic interference; (d) Gaussian white noise; (e) mixed signal; (f) envelope spectrum of the mixed signal.

Figure 7 shows the time-domain comparison between the original signal and the reconstructed signals under SNR levels of 3 dB, 0 dB, and -3 dB. The reconstructed signals obtained by VME, PSO-VME, and AOA-VME appear almost as straight lines under the same coordinate scale, indicating that the extracted components have much lower energy than the original mixed signal. By contrast, BKA-VME and AHBKA-VME produce more obvious periodic impulses at 3 dB, while the impulse characteristics become weaker as the noise level increases.

Figure 8 shows the envelope spectra of the reconstructed signals obtained by different VME-based methods under SNR levels of 3 dB, 0 dB, and -3 dB. For VME, PSO-VME, and AOA-VME, the spectra contain dense interference components, and the energy is not clearly concentrated around the inner race fault characteristic frequency f_m and its harmonics. In comparison, BKA-VME and AHBKA-VME show clearer fault-related frequency components, especially under the 3 dB condition.

As the noise level increases, the characteristic peaks gradually weaken due to stronger interference. Nevertheless, AHBKA-VME still presents relatively clear peaks at f_m , $2f_m$, and $3f_m$, indicating that the proposed AHBKA algorithm can improve the parameter optimization effect of VME and enhance inner race fault feature extraction under different noise conditions. However, although AHBKA-VME achieves acceptable extraction performance, the amplitudes of the fault-related peaks become less prominent as the noise level increases. Therefore, SMHD is further introduced to enhance the periodic impulsive components and improve the visibility of fault features.

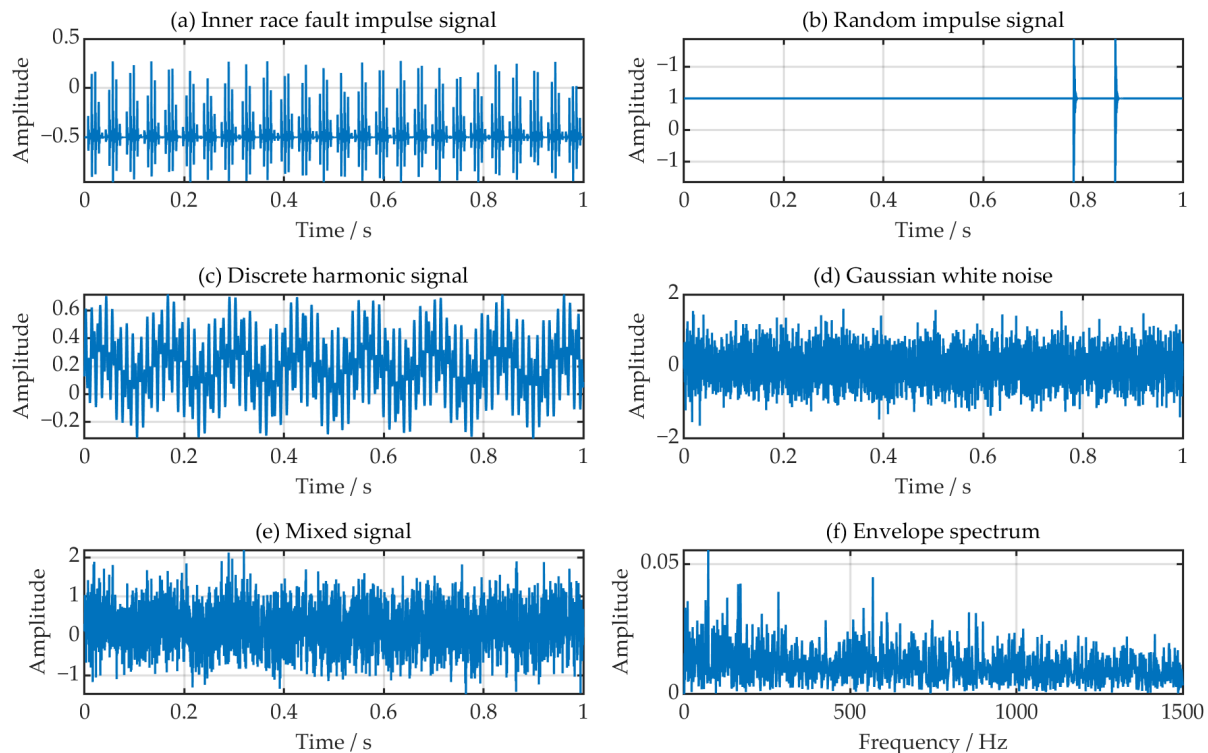


Figure 6. Simulated inner race fault signal under the -3 dB noise condition and its envelope spectrum: (a) inner race periodic impulse signal; (b) random impulse signal; (c) discrete harmonic interference; (d) Gaussian white noise; (e) mixed signal; (f) envelope spectrum of the mixed signal.

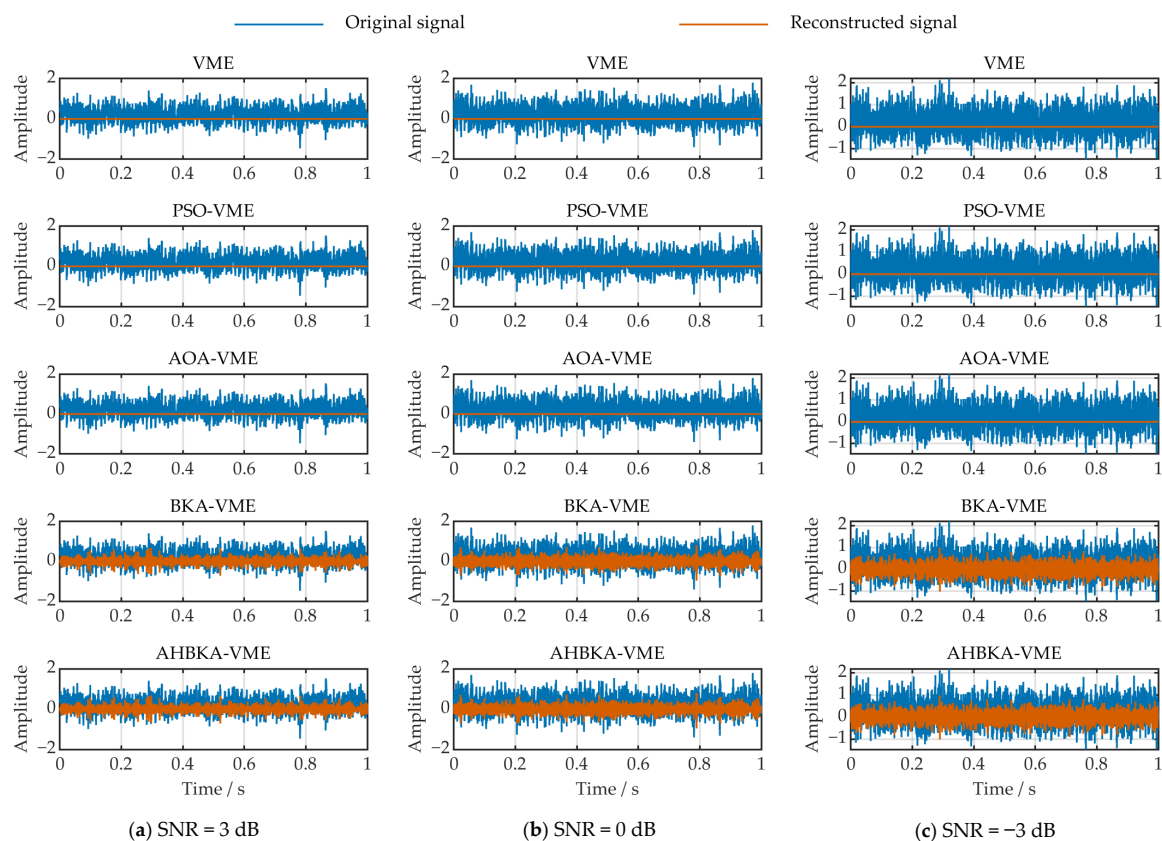
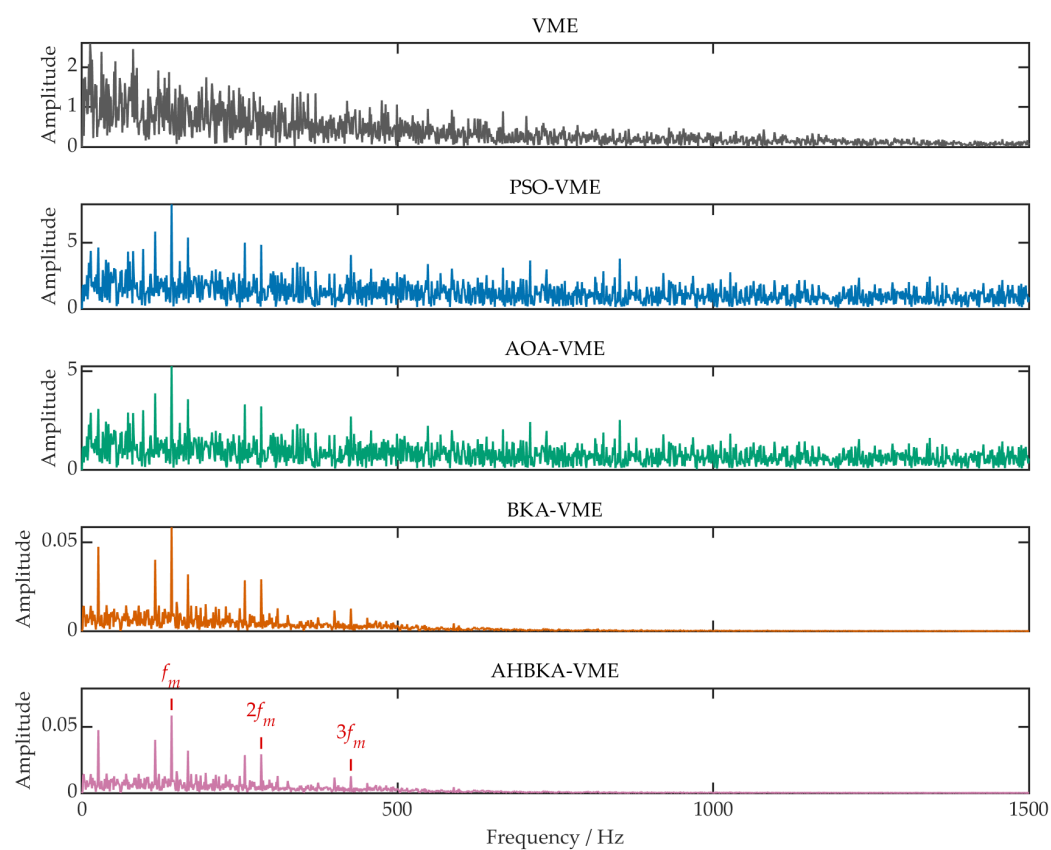
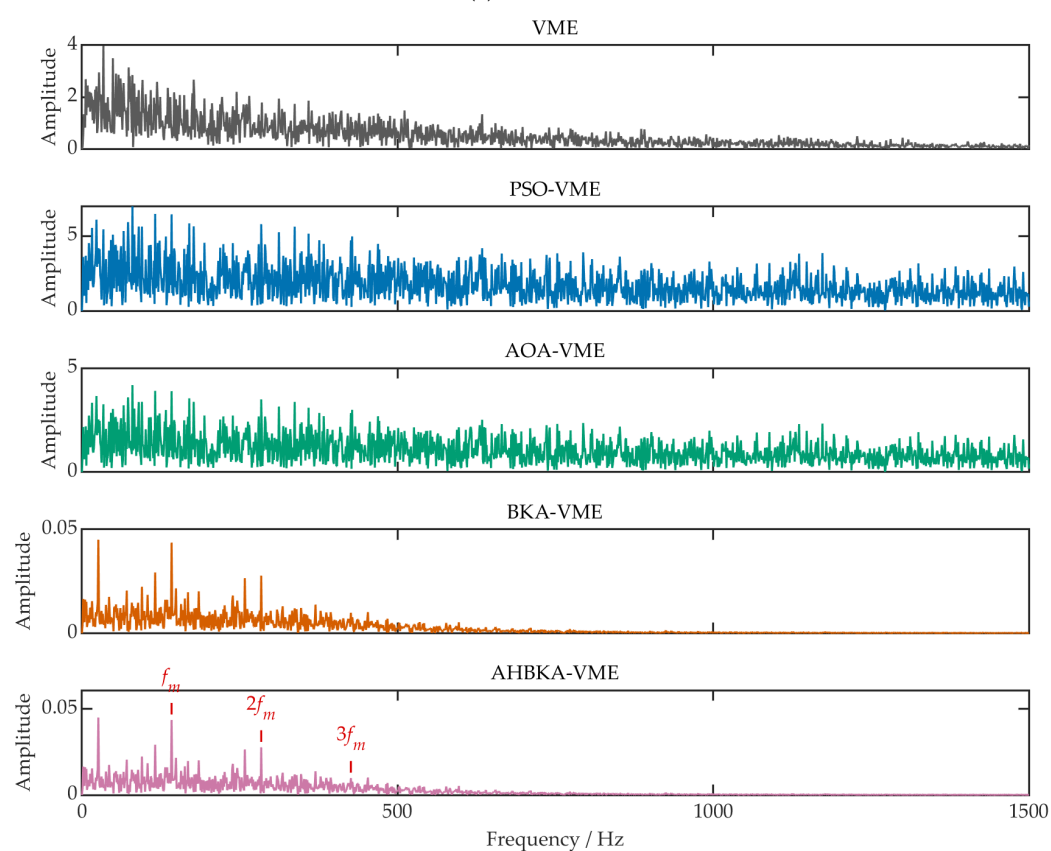


Figure 7. Time-domain comparison of the original signal and the reconstructed signals obtained by different VME-based methods under different noise levels: (a) SNR = 3 dB; (b) SNR = 0 dB; (c) SNR = -3 dB.



(a) SNR = 3 dB



(b) SNR = 0 dB

Figure 8. Cont.

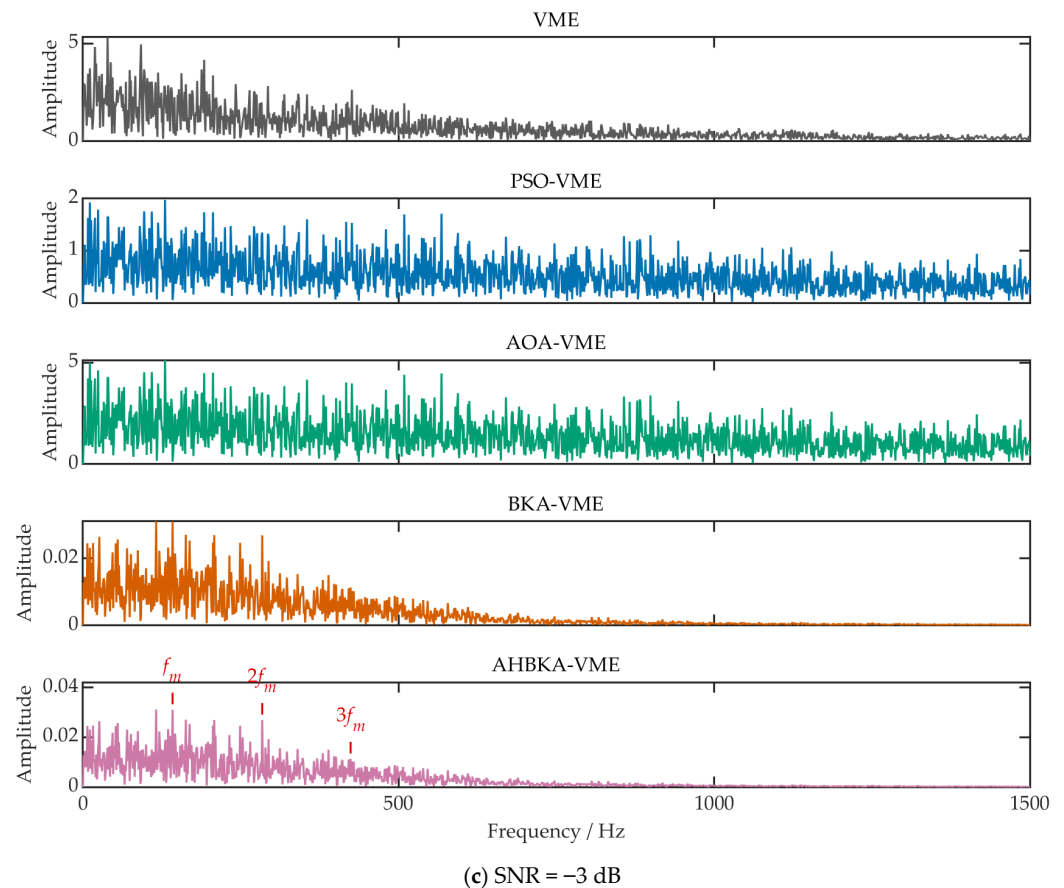


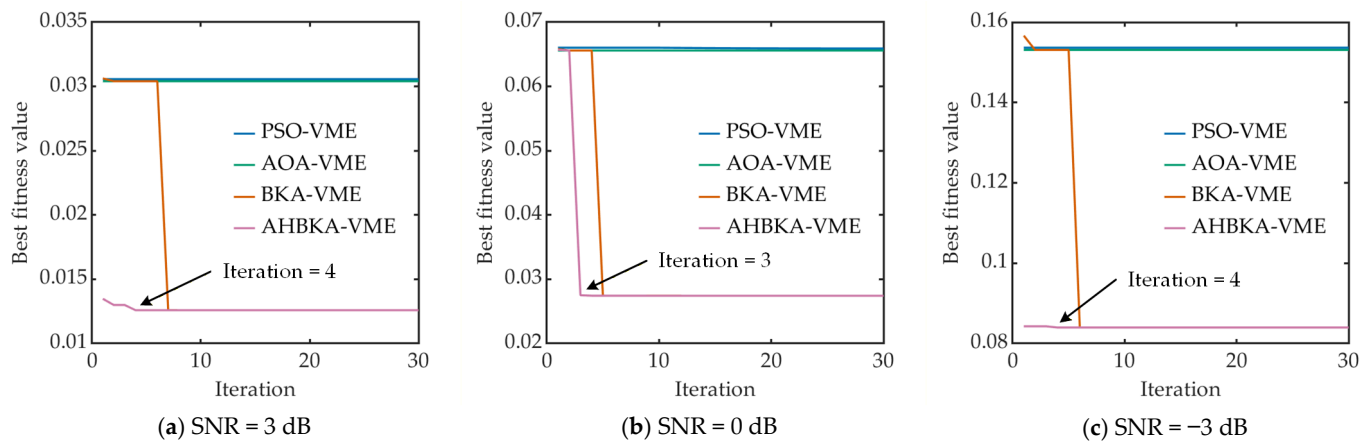
Figure 8. Envelope spectra of the reconstructed signals obtained by different VME-based methods under different noise conditions: (a) SNR = 3 dB; (b) SNR = 0 dB; (c) SNR = −3 dB.

Figure 9 shows the convergence curves of PSO, AOA, BKA, and AHBKA under SNR levels of 3 dB, 0 dB, and −3 dB. It can be observed that PSO and AOA quickly reach a stable state, but their final fitness values remain relatively high, indicating that premature convergence limits their VME parameter optimization performance. In contrast, BKA and AHBKA obtain much lower final fitness values under all three noise conditions. Although the final fitness values of BKA and AHBKA are almost the same, AHBKA requires fewer iterations to reach convergence. As marked in the figure, AHBKA converges after only 3, 4, and 3 iterations under SNR levels of 3 dB, 0 dB, and −3 dB, respectively.

To further evaluate the computational cost of different optimization-based VME methods, the running time is compared in Table 8. Compared with PSO-VME and AOA-VME, AHBKA-VME requires more running time; however, PSO and AOA tend to converge prematurely, resulting in higher final fitness values and poorer fault feature extraction performance. Compared with BKA-VME, AHBKA-VME only introduces a small increase in running time due to the additional improvement strategies. Considering that AHBKA-VME achieves fewer convergence iterations and clearer fault characteristic frequencies under different noise levels, the additional time cost is acceptable. Therefore, AHBKA-VME provides a better balance between fault feature extraction performance and computational cost.

Table 8. Running time comparison of different optimization-based VME methods under different noise levels.

Noise Level	PSO-VME	AOA-VME	BKA-VME	AHBKA-VME
3 dB	27.851 s	38.840 s	40.903 s	44.834 s
0 dB	29.825 s	40.764 s	63.152 s	66.198 s
−3 dB	37.242 s	49.726 s	58.501 s	66.431 s

**Figure 9.** Convergence curves of different optimization algorithms under different noise conditions: (a) SNR = 3 dB; (b) SNR = 0 dB; (c) SNR = −3 dB.

5. Experimental Signal Analysis

5.1. Comparison Methods and Evaluation Metrics

To verify the effectiveness of the proposed method, four methods are compared in this section, including VME, AHBKA-VME, WOA-VMD [27], and AHBKA-VME-SMHD. VME is used as the baseline method with preset parameters. AHBKA-VME is used to verify the effect of adaptive optimization on the VME key parameters, namely the penalty factor α and the initial center frequency ω_d . WOA-VMD is selected as an optimized VMD-based comparison method, in which WOA is used to optimize the mode number K and the penalty factor α . The proposed AHBKA-VME-SMHD method further introduces SMHD after AHBKA-VME to enhance periodic impulses and suppress interference components.

For fair comparison, the main parameter settings of different methods are summarized in Table 9. The dataset-related parameters are set according to the corresponding experimental data. For AHBKA-VME, the penalty factor α and the initial center frequency ω_d were selected as the optimization variables because they directly affect the bandwidth and initial frequency region of the desired mode extracted by VME. According to related VME-based rolling bearing fault diagnosis studies and preliminary tests, the search range of α was set to [100, 4000] [28]. The search range of ω_d was determined according to the sampling frequencies and effective frequency bands of the two datasets. The sampling frequencies of the CWRU and XJTU-SY datasets are 12 kHz and 25.6 kHz, respectively, corresponding to Nyquist frequencies of 6 kHz and 12.8 kHz. Therefore, the upper bound of ω_d was set to 6000 Hz, which covers the effective frequency range of the CWRU dataset and the main low- and medium-frequency resonance components of the XJTU-SY dataset. The lower bound was set to 120 Hz to avoid very-low-frequency trend components and rotational-frequency interference.

Table 9. Parameter settings of different comparison methods.

Method	Parameter Setting
VME	$\alpha = 2000, \omega_d = 3600$ Hz
AHBKA-VME	$\alpha \in [100, 4000], \omega_d \in [120, 6000]$; population size: 50; maximum iteration number: 30
WOA-VMD [27]	$K \in [2, 7], \alpha \in [10, 3000]$; population size: 5; maximum iteration number: 20
AHBKA-VME-SMHD	filter length: 100; deconvolution iterations: 30

In this study, kurtosis, Gini index, and envelope spectrum entropy (ESE) are used to quantitatively evaluate the fault feature extraction performance of different methods [29,30]. Kurtosis and Gini index are used to evaluate the impulsiveness and sparsity of the extracted signal, respectively, while envelope spectrum entropy is used to measure the degree of energy concentration in the envelope spectrum. The expressions of these three indicators are given as follows:

$$K = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \mu}{\sigma} \right)^4, \quad (31)$$

$$G = \frac{2 \sum_{i=1}^N i |x_{(i)}|}{N \sum_{i=1}^N |x_{(i)}|} - \frac{N+1}{N}, \quad (32)$$

$$\text{ESE} = -\frac{1}{\ln M} \sum_{i=1}^M \frac{A^2(v_i)}{\sum_{j=1}^M A^2(v_j)} \ln \left(\frac{A^2(v_i)}{\sum_{j=1}^M A^2(v_j)} \right), \quad (33)$$

where K , G , and ESE denote kurtosis, Gini index, and envelope spectrum entropy, respectively. x_i is the i -th sample, N is the signal length, and μ and σ are the mean value and standard deviation of the signal, respectively. In the calculation of the Gini index, the absolute amplitudes of the signal are sorted in ascending order as $|x_{(1)}| \leq |x_{(2)}| \leq \dots \leq |x_{(N)}|$. $A(v_i)$ is the envelope spectrum amplitude at the i -th frequency point v_i , and M is the number of frequency points in the envelope spectrum.

A larger kurtosis value indicates stronger impulsive components, while a larger Gini index indicates stronger sparsity and higher energy concentration. A smaller envelope spectrum entropy value indicates that the envelope spectrum energy is more concentrated and that interference components are more effectively suppressed. Therefore, these three indicators are used to evaluate the impulsive enhancement, sparse feature extraction, and envelope-spectrum energy concentration ability of different methods.

5.2. Case 1: CWRU Dataset

The first experimental case uses the bearing fault data from the Case Western Reserve University (CWRU) bearing dataset [31]. Figure 10 shows the CWRU bearing test platform, which mainly consists of a motor, a torque transducer, a dynamometer, and a bearing test unit. The test bearing is installed at the motor drive end, and the vibration signal is collected by an accelerometer mounted on the bearing housing. The test bearing is a 6205-2RS JEM SKF (AB SKF, Gothenburg, Sweden) deep groove ball bearing, and its structural parameters are listed in Table 10.

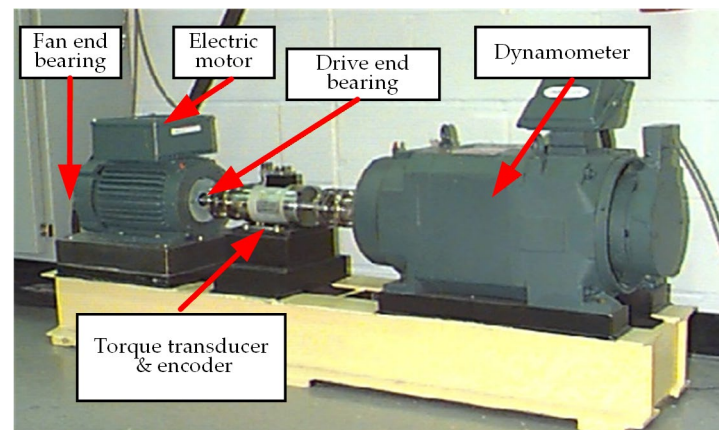


Figure 10. CWRU bearing test platform.

Table 10. Structural parameters of the 6205-2RS JEM SKF bearing.

Parameter	Symbol	Value
Rolling element diameter	d	7.94 mm
Pitch diameter	D	39.04 mm
Number of rolling elements	Z	9
Contact angle	α_1	0°

In this case, an outer race fault signal is selected for experimental analysis. The fault diameter is 0.007 inches, and the motor load is 0 hp. The sampling frequency is 12 kHz, and the rotating speed is 1797 r/min. The theoretical outer race fault characteristic frequency is calculated as:

$$f_o = \frac{Zn}{120} \left(1 - \frac{d}{D} \cos \alpha_1 \right), \quad (34)$$

where f_o is the outer race fault characteristic frequency, Z is the number of rolling elements, n is the rotating speed in r/min, d is the rolling element diameter, D is the pitch diameter, and α_1 is the contact angle. By substituting the bearing parameters into the equation, f_o is calculated as 107.4 Hz.

Therefore, the theoretical outer race fault characteristic frequency is approximately 107.4 Hz. The selected signal is processed by VME, AHBKA-VME, WOA-VMD, and the proposed AHBKA-VME-SMHD method to verify the fault feature extraction performance under real bearing fault conditions. For the CWRU dataset, the optimized VME parameters obtained by AHBKA were $\alpha = 249$ and $\omega_d = 2311$ Hz, both of which are within the predefined search ranges.

Figure 11 shows the envelope spectra of the reconstructed signals obtained by different methods on the CWRU dataset. The VME method identifies the fundamental fault characteristic frequency, but the harmonic components are relatively weak and incomplete. AHBKA-VME enhances the fault-related components, and more low-order harmonics can be observed, indicating that adaptive optimization of the VME parameters improves fault feature extraction. WOA-VMD also extracts several fault-related harmonics, but their continuity and clarity are still limited. In addition, AHBKA-VME-SMHD presents the most complete and continuous harmonic structure, with both low-order and high-order fault-related harmonics clearly identified. This result demonstrates that SMHD further enhances the periodic impulsive components after AHBKA-VME decomposition and improves the visibility of fault-related harmonics.

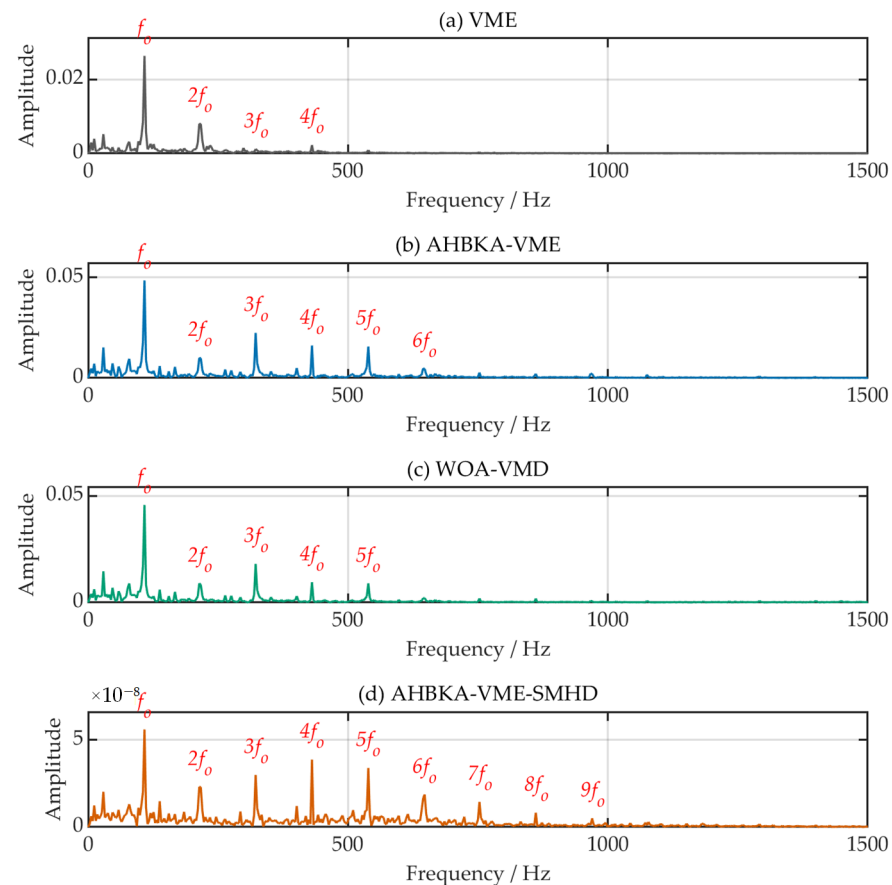


Figure 11. Envelope spectra of the reconstructed signals obtained by different methods for the CWRU outer race fault signal: (a) VME; (b) AHBKA-VME; (c) WOA-VMD; (d) AHBKA-VME-SMHD.

Table 11 lists the original kurtosis, Gini index, and envelope spectrum entropy values obtained by different methods on the CWRU dataset, and Figure 12 further visualizes the normalized quantitative comparison for a clearer display of indicators with different numerical scales. Compared with VME, AHBKA-VME obtains higher kurtosis and Gini index values and a lower envelope spectrum entropy value, indicating that the adaptive optimization of VME parameters improves the extraction of impulsive fault features and enhances the energy concentration of the envelope spectrum. Although WOA-VMD achieves a slightly higher Gini index and a lower envelope spectrum entropy than AHBKA-VME, its kurtosis is lower, suggesting that its ability to enhance fault-related impulses is still limited.

Table 11. Kurtosis, Gini index, and envelope spectrum entropy values of different methods on the CWRU dataset.

Method	Kurtosis Value	Gini Index	Envelope Spectrum Entropy
VME	3.9249	0.4865	0.4226
AHBKA-VME	4.4033	0.5151	0.3641
WOA-VMD	4.0346	0.5228	0.3306
AHBKA-VME-SMHD	53.9169	0.8722	0.2660

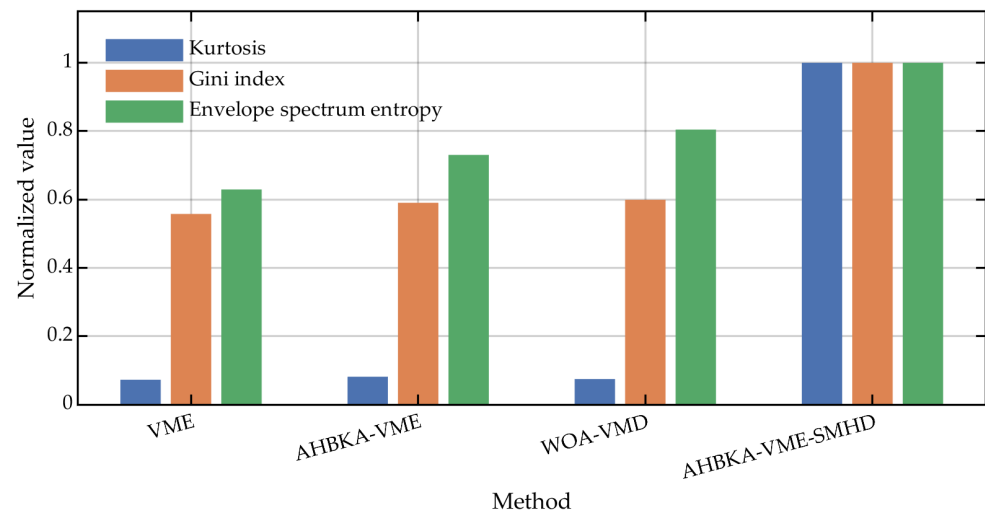


Figure 12. Normalized quantitative comparison of different methods on the CWRU dataset.

In contrast, AHBKA-VME-SMHD achieves the best overall quantitative performance, with a kurtosis of 53.9169, a Gini index of 0.8722, and an envelope spectrum entropy of 0.2660. Compared with VME, AHBKA-VME, and WOA-VMD, the proposed method obtains a substantially higher kurtosis value, indicating that the periodic impulsive components are significantly enhanced. In addition, the Gini index is increased by approximately 79.3%, 69.3%, and 66.8%, respectively, while the envelope spectrum entropy is reduced by approximately 37.1%, 26.9%, and 19.5%, respectively. These results indicate that the proposed method not only enhances periodic impulsive components and improves the sparsity of fault-related features, but also makes the fault-related energy more concentrated in the envelope spectrum.

5.3. Case 2: XJTU-SY Dataset

The second experimental case uses the XJTU-SY bearing dataset to further verify the effectiveness of the proposed method [32]. Figure 13 shows the XJTU-SY bearing test platform. The platform mainly consists of a motor, a support shaft, support bearings, a hydraulic loading system, and a tested bearing.

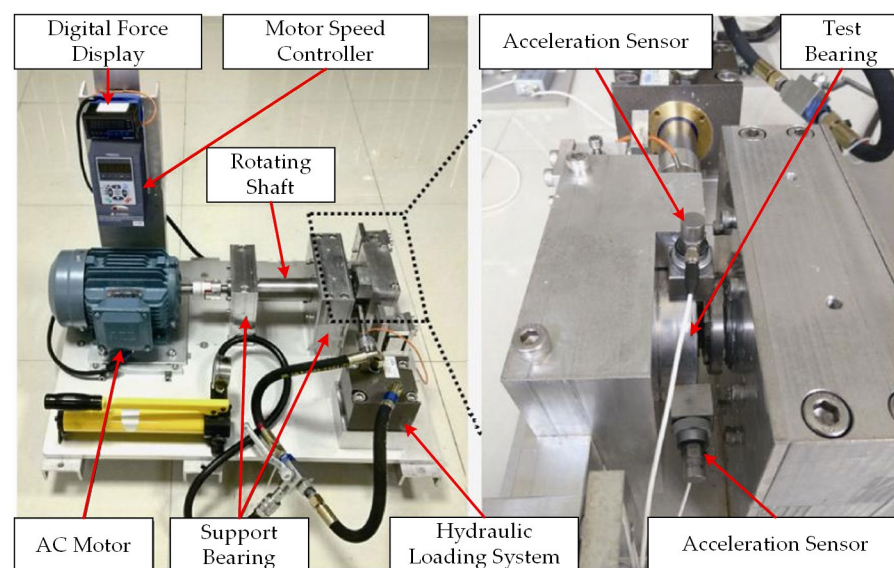


Figure 13. XJTU-SY bearing test platform.

The tested bearing is an LDK UER204 bearing, and its structural parameters are listed in Table 12. In this case, the inner race fault signal under working condition 2 is selected, where the rotating speed is 2250 r/min and the radial load is 11 kN. The sampling frequency is 25.6 kHz.

Table 12. Structural parameters of the LDK UER204 bearing.

Parameter	Symbol	Value
Rolling element diameter	d	7.92 mm
Pitch diameter	D	34.55 mm
Number of rolling elements	Z	8
Contact angle	α_1	0°

The theoretical inner race fault characteristic frequency is calculated as:

$$f_i = \frac{Zn}{120} \left(1 + \frac{d}{D} \cos \alpha_1 \right), \quad (35)$$

where f_i denotes the inner race fault characteristic frequency. By substituting the bearing parameters into the equation, f_i is approximately 184.38 Hz. The selected signal is processed by VME, AHBKA-VME, WOA-VMD, and AHBKA-VME-SMHD for comparative analysis. For the XJTU-SY dataset, the optimized VME parameters obtained by AHBKA were $\alpha = 3856$ and $\omega_d = 1337$ Hz, which are located within the predefined search ranges rather than exactly at the boundaries. This indicates that the selected parameter ranges are effective for the XJTU-SY dataset.

Figure 14 shows the envelope spectra of the reconstructed signals obtained by different methods on the XJTU-SY dataset. For VME, only the second harmonic of the inner race fault characteristic frequency has a relatively large amplitude, while the fundamental component and other harmonics are not clearly extracted. For AHBKA-VME and WOA-VMD, the fundamental fault characteristic frequency can be observed, but the harmonic components are weak. Compared with WOA-VMD, AHBKA-VME produces a slightly larger amplitude at the fundamental fault characteristic frequency, indicating that adaptive optimization improves the extraction effect of VME to some extent.

In addition, AHBKA-VME-SMHD provides a clearer envelope spectrum. The fundamental fault characteristic frequency and its second and third harmonics can be clearly observed, and the interference caused by the rotational frequency is reduced. Overall, compared with the outer race fault signal, the envelope spectrum of the inner race fault signal is more strongly affected by interference components. This is because the inner race fault rotates with the shaft and periodically enters the load zone. This process causes amplitude modulation of the fault impulses and introduces rotational-frequency-related components and sidebands. Therefore, inner race fault features are usually more difficult to identify in the envelope spectrum. Nevertheless, AHBKA-VME-SMHD still extracts clearer fault-related components than the other comparison methods, demonstrating its effectiveness in inner race fault feature enhancement.

Table 13 lists the original kurtosis, Gini index, and envelope spectrum entropy values obtained by different methods on the XJTU-SY dataset, and Figure 15 further visualizes the normalized quantitative comparison for a clearer display of indicators with different numerical scales. Compared with VME, AHBKA-VME increases the kurtosis from 2.8377 to 4.1934 and the Gini index from 0.4091 to 0.4666, while reducing the envelope spectrum entropy from 0.4803 to 0.4118. This indicates that adaptive parameter optimization improves the impulsiveness and sparsity of the extracted signal and makes the envelope spectrum energy

more concentrated. WOA-VMD obtains similar quantitative results to AHBKA-VME, but its kurtosis and Gini index are slightly lower than those of AHBKA-VME.

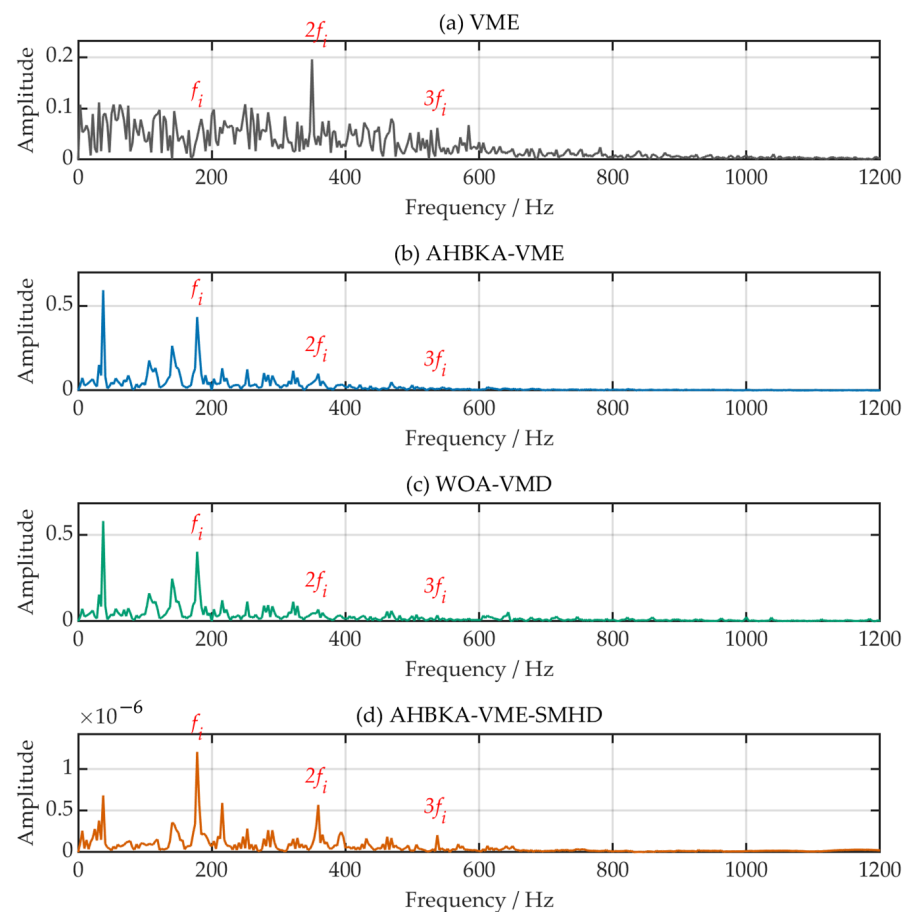


Figure 14. Envelope spectra of the reconstructed signals obtained by different methods for the XJTU-SY inner race fault signal: (a) VME; (b) AHBKA-VME; (c) WOA-VMD; (d) AHBKA-VME-SMHD.

Table 13. Kurtosis, Gini index, and envelope spectrum entropy values of different methods on the XJTU-SY dataset.

Method	Kurtosis Value	Gini Index	Envelope Spectrum Entropy
VME	2.8377	0.4091	0.4803
AHBKA-VME	4.1934	0.4666	0.4118
WOA-VMD	4.0890	0.4637	0.3946
AHBKA-VME-SMHD	39.8991	0.8201	0.3803

In contrast, AHBKA-VME-SMHD achieves the best overall quantitative performance, with a kurtosis of 39.8991, a Gini index of 0.8201, and an envelope spectrum entropy of 0.3803. Compared with VME, AHBKA-VME, and WOA-VMD, the proposed method obtains a substantially higher kurtosis value, showing that SMHD further enhances the periodic impulsive components after AHBKA-VME decomposition. Moreover, the Gini index is increased by approximately 100.5%, 75.8%, and 76.9%, respectively, while the envelope spectrum entropy is reduced by approximately 20.8%, 7.6%, and 3.6%, respectively. These results further confirm the effectiveness of the proposed method under inner race fault conditions. The proposed method improves the sparsity of fault-related features and enhances energy concentration in the envelope spectrum.

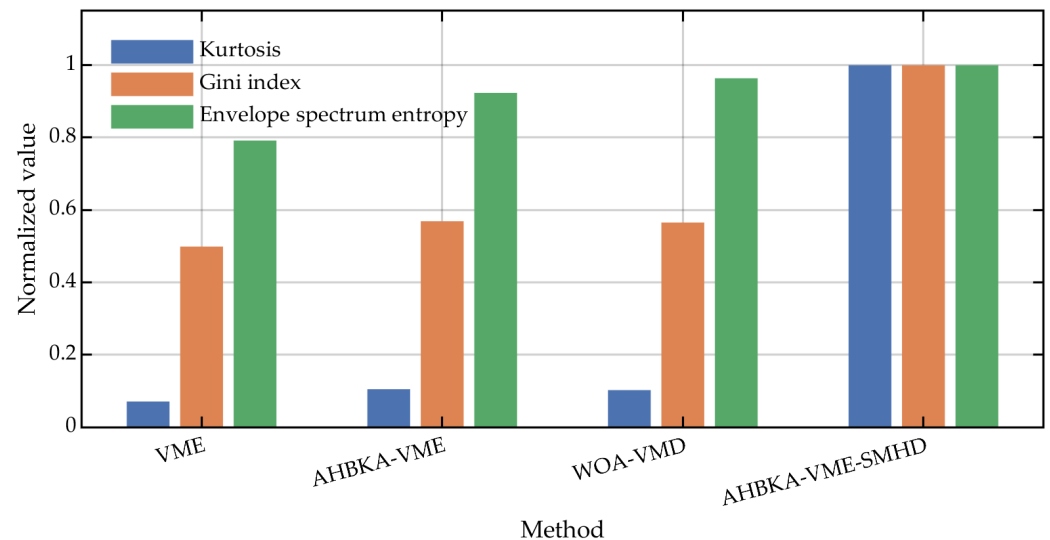


Figure 15. Normalized quantitative comparison of different methods on the XJTU-SY dataset.

6. Conclusions

6.1. Main Conclusions

In this study, a rolling bearing fault feature extraction method based on AHBKA-VME-SMHD is proposed. First, an adaptive hybrid black-winged kite algorithm is developed by introducing opposition-based learning initialization, a Gompertz-based adaptive step size strategy, and an NGO-inspired random displacement strategy. Then, AHBKA is used to adaptively optimize the penalty factor and the desired mode center frequency of VME, reducing the dependence on empirical parameter selection. Finally, SMHD is introduced to further enhance periodic impulsive components and improve the extraction of fault-related features.

The benchmark function results show that AHBKA has better optimization accuracy, convergence speed, and stability than the other algorithms. The simulation results under different noise conditions indicate that AHBKA-VME can extract clearer fault-related components than VME, PSO-VME, and AOA-VME. Furthermore, the experimental results on the CWRU and XJTU-SY datasets demonstrate that AHBKA-VME-SMHD obtains clearer envelope spectra and more complete harmonic structures than VME, AHBKA-VME, and WOA-VMD. The higher kurtosis and Gini index values, together with the lower envelope spectrum entropy values, further verify its stronger impulsive enhancement, sparse feature extraction, and envelope-spectrum energy concentration ability.

6.2. Future Work

Although the proposed method achieves good results on the two bearing datasets, its generalization ability still needs to be further verified. In future work, the proposed method will be tested under compound fault cases and stronger noise environments. In addition, the fitness function will be further improved by considering more fault-sensitive indicators and different fusion forms. This will help improve its interpretability and adaptability to different fault diagnosis tasks.

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Data Availability Statement: Publicly available datasets were analyzed in this study. The CWRU dataset can be downloaded from its official repository (<https://engineering.case.edu/bearingdatacenter/download-data-file>, accessed on 30 May 2026). The XJTU-SY dataset is publicly available at (<https://github.com/WangBiaoXJTU/xjtu-sy-bearing-datasets>, accessed on 30 May 2026).

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

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