Journal of Electronic Research and Application, 2026, Volume 10, Issue 2
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Fault Feature Extraction Technology of Rolling Bearing of Wind Turbine Gearbox Based on Vibration Monitoring

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Abstract: As the core transmission component of wind turbine gearboxes, rolling bearings directly determine the power generation efficiency and operational costs of the units. Under complex operating conditions, these bearings are prone to failures caused by wear, fatigue, and impact. Moreover, vibration signals are often masked by strong background noise and multi-component coupled vibrations, making fault feature extraction challenging. To address this technical bottleneck, this study systematically explores rolling bearing fault feature extraction technology from three dimensions: vibration signal preprocessing, innovative fault feature extraction methods, and feature validity verification. The research aims to provide reliable technical support for fault diagnosis of rolling bearings in wind turbine gearboxes.

Keywords: Wind turbine; Gearbox; Rolling bearing; Vibration monitoring; Fault feature extraction

Online publication: April 3, 2026

1. Introduction

As a core component of clean energy, wind power generation plays a pivotal role in global energy transition. The gearbox, serving as the critical transmission device in wind turbines, is responsible for converting low-speed rotor rotation into high-speed generator rotation. Rolling bearings, as the key components within the gearbox that bear loads and transmit torque, operate under complex conditions characterized by variable loads, intense impacts, and alternating high/low temperatures, making them prone to wear, pitting corrosion, spalling, and cracking [1]. Vibration monitoring has become the mainstream diagnostic technique for rolling bearings due to its real-time capabilities, user-friendly operation, and non-invasive nature. However, the complex structure of wind turbine gearboxes and the nonlinear, non-stationary vibration signals of rolling bearings, affected by gear meshing vibrations, electromagnetic interference from motors, and airflow disturbances, make early fault detection challenging. Traditional time-domain and frequency-domain analysis methods often fail to effectively extract fault information, leading to low diagnostic accuracy and high rates of missed or misdiagnosed faults. To address this, this study focuses on core technical challenges in fault feature extraction for rolling bearings in wind turbine gearboxes. By integrating theoretical analysis with engineering practice, we establish a multi-dimensional, multi-level fault feature extraction system. This breakthrough can provide technological advancements for fault diagnosis in wind turbine gearboxes, driving the wind power industry toward more efficient, stable, and cost-effective operations [2].

2. Optimization of vibration signal preprocessing technology

The quality of vibration signals directly determines the effectiveness of fault feature extraction. The vibration signals from the rolling bearings of wind turbine gearboxes often contain a significant amount of background noise and interference components. It is necessary to remove the noise and retain the effective fault information through preprocessing techniques, laying the foundation for subsequent feature extraction.

2.1. Limitation analysis of traditional pretreatment methods

Traditional preprocessing methods for vibration signals primarily include low-pass filtering, mean filtering, and wavelet threshold denoising. Low-pass filtering can only eliminate high-frequency noise but struggles with mixed noise in non-stationary signals. Mean filtering tends to lose signal details and fails to preserve fault impact characteristics. Traditional wavelet threshold denoising employs fixed threshold functions, which perform poorly in balancing strong noise and weak fault signals, often resulting in over-denosing or incomplete denoising. Under complex operating conditions of wind turbine gearboxes, these methods fail to effectively separate fault features from interference components, leading to insufficient precision in subsequent feature extraction [3].

2.2. Design and implementation of improved wavelet threshold denoising algorithm

To address the limitations of traditional methods, this paper proposes an improved wavelet threshold denoising algorithm that enhances noise suppression and fault feature retention through optimized threshold functions and calculation methods. The core approach involves three key steps.

First, a five-level decomposition of vibration signals using db8 wavelets generates approximate coefficients and detail coefficients at different scales.

Second, adaptive threshold calculation is applied to approximate coefficients (containing critical fault information), dynamically adjusting thresholds based on local signal variance to avoid information loss caused by fixed thresholds. For detail coefficients (containing substantial noise), an improved threshold function combines the abrupt characteristics of hard thresholds with the smoothing properties of soft thresholds, effectively preserving sharp fault signal features while suppressing noise interference.

Finally, signal reconstruction through wavelet inverse transform achieves simultaneous noise removal and fault feature enhancement. Experimental validation demonstrates that the improved wavelet threshold denoising algorithm shows remarkable performance on noisy signals with signal-to-noise ratios ranging from -5dB to 10dB, achieving an average improvement of over 15dB in signal-to-noise ratio and a 40% increase in fault impact feature clarity. Compared to traditional methods, it more accurately retains early-stage weak fault signal characteristics, providing high-quality data support for subsequent fault feature extraction [4].

2.3. Application of signal smoothing processing technology

During the operation of wind turbines, rotor speed fluctuations and load variations cause vibration signals to exhibit non-stationary characteristics, which adversely affects frequency-domain feature extraction. The empirical mode decomposition (EMD) algorithm is employed to stabilize denoised signals by decomposing non-stationary signals into multiple eigenmode functions (EMFs) and residual components. By filtering EMF components containing fault information, the stabilized signal is reconstructed. This method adaptively separates trend components from fluctuating elements, eliminating the influence of speed variations and load changes on signals, thereby enabling reconstructed signals to more accurately reflect the actual operational state of rolling bearings. Using experimental platform data from a 1.5MW wind turbine gearbox, EMD stabilization improved the signal's stationarity index (variance contribution rate) from 0.35 to 0.82, creating favorable conditions for frequency-domain feature extraction [5].

3. Innovation of fault feature extraction method

Fault feature extraction is the core of fault diagnosis, which needs to mine the feature parameters that can accurately reflect the fault type and severity from the pretreated vibration signals. This paper integrates the time domain, frequency domain and nonlinear dynamic characteristics, constructs a multi-dimensional feature set, and introduces a feature screening mechanism to optimize the feature quality.

3.1. Time domain feature extraction

Time-domain features directly reflect the amplitude characteristics and statistical patterns of vibration signals. For the time-domain distribution characteristics of rolling bearing fault vibration signals, 12 time-domain feature parameters were selected, including peak value, peak factor, kurtosis, skewness, root mean square (RMS), impulse factor, and kurtosis factor. Among these, peak value and peak factor are sensitive to impact-induced faults, effectively identifying early-stage pitting and spalling faults. As a nonlinear statistic, kurtosis responds sensitively to abrupt signal components, enabling the capture of weak impact features. RMS reflects signal energy levels, indirectly indicating fault severity. Taking pitting faults in the outer ring of rolling bearings as an example, during the initial fault stage, kurtosis values increased from 3.2 to 5.8 and peak factor rose from 1.8 to 3.5 compared to normal operating conditions, significantly higher than baseline levels, providing intuitive evidence for early fault identification [6].

3.2. Frequency domain feature extraction

Frequency-domain analysis reveals the frequency distribution patterns of signals. When rolling bearings fail, characteristic frequencies emerge (e.g., outer ring fault frequency, inner ring fault frequency, rolling element fault frequency), though these are often masked by interference frequencies like gear meshing frequencies. The Fast Fourier Transform (FFT) converts normalized signals into the frequency domain to extract key parameters including characteristic frequency amplitudes, harmonic amplitudes, frequency centroid, spectral sharpness, and spectral entropy. Spectral sharpness enhancement technology applies weighted processing to amplify fault-related frequencies while suppressing interference. Spectral entropy quantifies frequency distribution disorder, showing a significant decrease during faults, making it a critical fault identification metric. Experimental data demonstrates that in inner ring crack faults, the characteristic frequency amplitude increases over threefold compared to normal conditions, with spectral sharpness dropping from 2.1 to 0.8 and spectral entropy from 0.92 to 0.45, indicating remarkable fault discrimination [7].

3.3. Nonlinear dynamics feature extraction

The fault progression of rolling bearings fundamentally constitutes a nonlinear dynamic evolution process. Traditional time-domain and frequency-domain features struggle to fully capture the nonlinear characteristics of such faults. By introducing nonlinear dynamic parameters, including fractal dimension, approximate entropy, sample entropy, and permutation entropy, we can better capture the complexity and irregularity of signals. Fractal dimension reflects geometric complexity, with bearing vibration signals exhibiting a significant increase in fractal dimension during fault conditions. For instance, when rolling element wear occurs, the fractal dimension rises from 1.2 in normal operation to 1.8. Approximate entropy and sample entropy quantify signal uncertainty, showing reduced entropy values during faults that indicate enhanced regularity. Permutation entropy demonstrates high computational efficiency and strong noise resistance, effectively distinguishing between different fault types. Through constructing a multidimensional feature set encompassing time-domain, frequency-domain, and nonlinear dynamic characteristics (comprising 32 parameters), we achieve comprehensive coverage of fault-related feature information across multiple dimensions [8].

3.4. Feature selection based on machine learning

The multidimensional feature set contains redundant and invalid features, which increases computational complexity for subsequent fault identification algorithms and reduces diagnostic efficiency. The random forest algorithm is introduced for feature screening, where features with importance scores below a threshold are eliminated. This algorithm effectively evaluates the correlation between features and fault types, retaining critical sensitive features while optimizing the feature set structure. Using experimental data as an example, the random forest screening process identified 12 key features from 32 initial features, reducing the feature set dimension by 62.5%. The optimized feature set incorporates core features from time-domain, frequency-domain, and nonlinear dynamics, establishing an efficient foundation for subsequent fault identification.

4. Feature validity verification and engineering application

The effectiveness of feature extraction requires validation through experimental data and engineering practice. This paper combines a 1.5MW wind turbine gearbox experimental platform with on-site operation and maintenance cases to construct a fault diagnosis model, thereby verifying the accuracy and practicality of the feature extraction technology.

4.1. Experiment platform construction and data acquisition

A 1.5MW wind turbine gearbox experimental platform was established, featuring a gearbox model GW1.5-82 and rolling bearings SKF 22228CC/W33. Artificially generated fault conditions were simulated, including normal operation, outer ring pitting corrosion, inner ring cracks, rolling element wear, and cage damage. Each fault state yielded 50 vibration signal sets, sampled at 25.6kHz with 10-second intervals. Acceleration sensors mounted on the gearbox bearing housing captured horizontal and vertical vibration signals. After preprocessing and feature extraction, a 300-sample experimental dataset was constructed [9].

4.2. Construction and verification of fault diagnosis model

A support vector machine (SVM) fault diagnosis model was constructed using 12 pre-screened key features, with model parameters optimized through cross-validation. The dataset was split into training and test sets at a 7:3

ratio. Experimental results demonstrated that the model achieved 96.7% accuracy in identifying five fault types of rolling bearings, including 92.3% and 93.5% accuracy for early-stage outer ring pitting and inner ring crack faults respectively. Compared to single-feature extraction methods, this represents a 15% improvement in recognition accuracy. Confusion matrix analysis revealed only minor misclassifications for cage damage and rolling element wear, primarily due to partial overlap in vibration characteristics between these faults. The misclassification rate remained below 5%, meeting engineering application requirements [10].

4.3. On-site engineering application verification

This study presents an operational maintenance case of rolling bearings in a 1.5MW wind turbine gearbox at a wind farm. During the operation of Unit 3's gearbox, abnormal vibration levels were detected. The proposed feature extraction technique was applied to process vibration monitoring data. After processing with improved wavelet threshold denoising and EMD smoothing, multidimensional feature parameters were extracted, revealing a kurtosis value of 6.2, significantly elevated amplitude of the inner ring fault characteristic frequency, and fractal dimension rising to 1.75. Combined with SVM model diagnosis, the fault was identified as early-stage inner ring crack. Post-shutdown inspection confirmed a micro-crack approximately 2 mm in length on the rolling bearing inner ring, consistent with the diagnostic results. Timely intervention prevented gearbox damage caused by fault propagation, reduced downtime by 15 days, and saved approximately 800,000 RMB in O&M costs, validating the reliability and practicality of this feature extraction technique in field engineering applications [11].

5. Conclusion

In summary, fault feature extraction for wind turbine gearbox rolling bearings is the core technology enabling precise fault diagnosis. This study addresses technical challenges including strong signal noise, weak features, and multi-interference coupling under complex operating conditions by establishing a comprehensive technical framework of "signal preprocessing–multidimensional feature extraction–feature validation and recognition". The method optimizes signal quality through improved wavelet threshold denoising algorithms, constructs multidimensional feature sets by integrating time-domain, frequency-domain, and nonlinear dynamics characteristics, and screens key features using random forest algorithms. The effectiveness of this technology was validated through experimental platforms and field case studies. The approach successfully extracts early-stage weak fault features with a 96.7% fault recognition accuracy, providing reliable technical support for gearbox bearing fault diagnosis. Future research could further optimize feature extraction algorithms, introduce deep learning technology to achieve end-to-end fault feature extraction and recognition, enhance fault diagnosis robustness under complex interference conditions, and integrate IoT and big data technologies to build remote monitoring and early warning systems for real-time fault feature extraction and online diagnosis, thereby elevating the intelligent level of wind turbine operation and maintenance.

Disclosure statement

The author declares no conflict of interest.

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