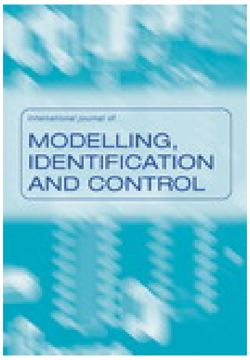

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Detection method of abnormal vibration state of electrical equipment based on random forest

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Abstract: To overcome the problems of low signal-to-noise ratio, low accuracy, and long task completion time in traditional electrical equipment abnormal vibration state detection methods, a new detection method based on random forest is proposed. A signal acquisition architecture is built using fibre Bragg grating sensors to obtain vibration signals of electrical equipment. The joint approximation diagonalisation algorithm performs blind separation on the collected signals, with the high-quality signals obtained through blind separation being input into a random forest to obtain detection results of abnormal vibration states. Experimental results indicate the maximum signal-to-noise ratio of electrical equipment vibration signals reaches 43.67 dB under this method, with abnormal vibration state identification accuracy consistently exceeding 95.6%, and the minimum task completion time being 3.58 s, demonstrating high accuracy and efficiency characteristics.

Keywords: random forest; electrical equipment; abnormal vibration state; state detection; fibre Bragg grating sensors; blind separation.

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1 Introduction

Electrical equipment plays a crucial role in modern industry and social life, and its operational status directly affects the stability and safety of the power system (Zhou et al., 2023; Geng et al., 2024). The technology of electrical equipment is constantly developing and advancing, and its application scope is expanding day by day. Shortcomings in the design phase of the equipment, aging of materials over time, improper operation during installation, or prolonged operation under load can all potentially cause abnormal vibration of the equipment. Once the equipment experiences abnormal vibration, the impact should not be underestimated (Wu et al., 2024; Yushuai et al., 2024). Failure to detect abnormal vibrations in electrical equipment in a timely manner can lead to a series of serious potential consequences. From the perspective of equipment, abnormal vibration may be an external manifestation of problems such as loose, worn, and unbalanced internal components of the equipment. If not dealt with in a timely manner, these problems will gradually worsen and ultimately lead to equipment failure. From a safety perspective, abnormal vibrations of electrical equipment may pose significant safety hazards. Abnormal vibrations of some equipment may cause secondary disasters such as fires and explosions, posing a serious threat to personnel safety and equipment facilities. From an economic perspective, equipment failures and safety hazards caused by undetected abnormal vibrations will result in significant economic losses. On one hand, equipment maintenance and replacement require a significant investment of funds; on the other hand, power outages can cause interruptions in industrial production and damage to commercial activities, resulting in incalculable indirect losses to socio-economic development. In addition, the stable operation of the electricity market depends on the reliable operation of various electrical equipment. Equipment failures and power outages can affect the supply-demand balance and price stability of the electricity market, causing economic losses to market participants. Accurately identifying abnormal vibration states of electrical equipment is of great significance for ensuring the stable operation of the electricity market.

In the operation and maintenance of electrical equipment, vibration monitoring and fault diagnosis are key links to ensure safe and stable equipment operation. Although numerous domestic and foreign experts and scholars have conducted extensive research in this field and proposed various effective diagnostic methods and models, some urgent problems still exist in the current technology, limiting its practical application effectiveness under complex working conditions. Zhang et al. (2024a) proposed a method for identifying abnormal vibration states of electrical equipment in cold environments, which combines empirical mode decomposition and Stan unbiased estimation for signal denoising, and uses long short-term memory networks to classify spectrogram voiceprint samples. However, this method has shown a problem of low signal-to-noise ratio (SNR) in actual testing of vibration signals, which has affected the subsequent detection quality. Similarly, the abnormal vibration detection method for electrical equipment based on fieldbus communication proposed by Zhang et al. (2024b) although using wavelet transform and ultra-high frequency methods to denoise and monitor signal changes through fieldbus technology, did not achieve the expected detection accuracy. In addition, Jin (2024) used an isolated forest based method for identifying abnormal vibrations in equipment. Although they improved the smoothness and feature expression ability of the data through moving average filtering and feature fusion techniques, they found that the task completion time was long and the feasibility was poor during the testing process.

The identification of abnormal vibration states in electrical equipment represents a key technology for ensuring power system safety. Existing methods face three main technical bottlenecks in practical applications: SNR, a core concept in signal processing and communication, measures the relative strength between useful information and noise interference. During signal acquisition, traditional electrical sensors demonstrate insufficient anti-interference capability in complex electromagnetic environments, resulting in original signal SNR typically below 30 dB. In feature extraction, inadequate separation of mixed vibration sources limits anomaly identification accuracy below 90%. Poor algorithm real-time performance causes existing models to average over 5 s processing time, failing online monitoring requirements. A random forest-based electrical equipment abnormal vibration state detection method is proposed as the target solution, addressing the low SNR in vibration signals, high detection accuracy requirements, and lengthy task completion time present in current approaches. Therefore, this scheme features high SNR in electrical equipment vibration signals, high accuracy in abnormal vibration state detection, and short task completion time. The research on identifying abnormal vibration states of electrical equipment contributes through continuous exploration and innovation, proposing and optimising a series of efficient and accurate identification methods that significantly improve electrical equipment vibration monitoring sensitivity and accuracy. This advancement provides strong technical support for ensuring safe and stable operation of electrical equipment, reducing maintenance costs, extending equipment service life, and promoting technological progress with industrial upgrading in related fields. The technical roadmap is as follows:

1 Build a signal acquisition architecture using fibre Bragg grating sensors to obtain electrical equipment vibration signals. Perform blind separation on the collected signals using the joint approximation diagonalisation algorithm. Fibre Bragg grating sensors provide advantages including high sensitivity, anti-interference capability, and long-distance transmission, enabling high-precision acquisition of electrical equipment vibration signals and supplying high-quality raw data for subsequent signal processing and analysis. The joint approximate diagonalisation algorithm, as a blind signal separation technique, separates source signals from observed signals without requiring prior knowledge of source signal forms or mixing matrices. This technique proves particularly effective for multi-source vibration signal separation, successfully eliminating noise and interference while enhancing signal quality.

2 Input the high-quality signal obtained through blind separation processing into a random forest to obtain the detection results of abnormal vibration states of electrical equipment. The random forest algorithm is an ensemble learning method that classifies and recognises input signals by constructing multiple decision trees and voting on their results. Applying the random forest algorithm to abnormal vibration state detection in electrical equipment can fully utilise its advantages in handling complex data and classification problems, thereby improving detection accuracy and robustness.

3 The effectiveness of this method was validated using the SNR of electrical equipment vibration signals, the accuracy of abnormal vibration state identification, and task completion time as performance indicators.

2 Detection method for abnormal vibration state of electrical equipment

2.1 Vibration signal acquisition of electrical equipment based on fibre Bragg grating sensors

This study employs fibre Bragg grating sensors for electrical equipment vibration signal collection, with necessity demonstrated in three aspects: first, fibre Bragg grating sensors operate on optical sensing principles, exhibiting superior anti-electromagnetic interference capability to reduce noise interference at the source and significantly enhance SNR; second, inherent corrosion resistance and temperature stability of optical fibre materials ensure reliable data acquisition in complex industrial environments; third, theoretical derivation and experimental calibration prove fibre Bragg grating sensors' acceleration sensitivity precisely matches electrical equipment micro-vibration characteristics, effectively preventing signal omission. These characteristics directly address existing methods' insufficient SNR caused by sensor limitations, establishing high-quality data foundations for subsequent blind source separation and random forest modelling. Compared with traditional electrical sensors, fibre Bragg grating sensors' signal acquisition quality superiority ensures this method's high-precision anomaly detection capability. Fibre Bragg grating sensors (Burhanuddin et al., 2025; Sahota et al., 2024) utilise internal grating structures as sensing elements, where applied external physical quantities, (e.g., vibration) alter grating refractive index or period, modifying optical signal transmission characteristics. This optically-based sensing mode demonstrates sensitivity and accuracy advantages over traditional electrical or mechanical sensors (Kuroda, 2023). Figure 1 displays the basic fibre Bragg grating structure.

Fibre Bragg grating sensors exhibit high sensitivity capable of detecting minute vibration signals. As optical fibres constitute non-conductive materials, fibre Bragg grating sensors demonstrate exceptional electromagnetic interference resistance and maintain stable operation in complex electromagnetic environments. Additionally, these sensors possess outstanding corrosion resistance and thermal stability, enabling vibration signal acquisition in harsh conditions, significantly enhancing signal collection efficiency and accuracy (Srivatzen et al., 2024).

When detecting minute vibration signals with corresponding acceleration (along the sensor's sensitive axis), the fibre Bragg grating sensor achieves torque balance through inertial force, establishing the following relationship:

$$mad - k\Delta lh - K\theta = 0 \tag{1}$$

In formula (1), m represents the mass of mass block z; d represents the distance between the centre of gravity of z and the centre of gravity of the hinge rotation; k represents the elastic coefficient of optical fibre U; Δl represents the elongation of the optical fibre; K represents the rotational stiffness of the hinge, and θ represents the rotational angle of z; h represents the height of U (Chandana et al., 2024).

According to the definition of Young's modulus, the calculation formula for the elastic coefficient of U is as follows:

$$k = \frac{A_f E_f}{l} \tag{2}$$

In formula (2), A_f represents the cross-sectional area of U; E_f represents the Young's modulus of U.

The hinge rotational stiffness is calculated using the following formula:

$$K = \frac{EwR^2}{12} \Bigg/ \left[\frac{2s^3\left(6s^3 + 4s^3 + 1\right)}{(2s+1)(4s+1)^2} + \frac{12s^4(2s+1)}{(4s+1)^{5/2}} \operatorname{acrtg}\sqrt{4s+1} \right] \tag{3}$$

In formula (3), w represents the width of the hinge; s represents its hinge quality.

In general, the calculation formula for the acceleration sensitivity of a sensor is as follows:

$$S = \frac{\Delta\lambda}{a} \tag{4}$$

In formula (4), $\Delta\lambda$ represents the change in the centre wavelength of the grating.

The strain relationship between the $\Delta\lambda$ and U axes can be described using the following formula:

$$\Delta\lambda = \left(1 - p_e\right)\lambda_B \varepsilon_f \tag{5}$$

In formula (5), p_e represents the elastic optical coefficient; λ_B represents the centre wavelength of the grating.

The strain of U can be calculated using the following formula:

$$\varepsilon_f = \frac{\Delta L}{l} \tag{6}$$

Substitute the obtained ε_f into formula (4) to obtain the acceleration sensitivity of the fibre Bragg grating sensor. The specific calculation formula is as follows:

$$S = \frac{(1 - pe)\lambda_B}{l} \frac{md}{kh + \dfrac{K}{h}} \tag{7}$$

Based on actual electrical equipment operation conditions, the fibre Bragg grating sensors' acceleration sensitivity undergoes adjustment. The calibrated fibre Bragg grating sensors subsequently acquire electrical equipment vibration signals, with the specific signal acquisition architecture illustrated in Figure 2.

Figure 1 Basic structure of fibre Bragg grating (see online version for colours)

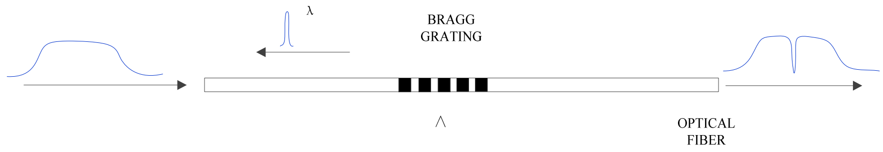
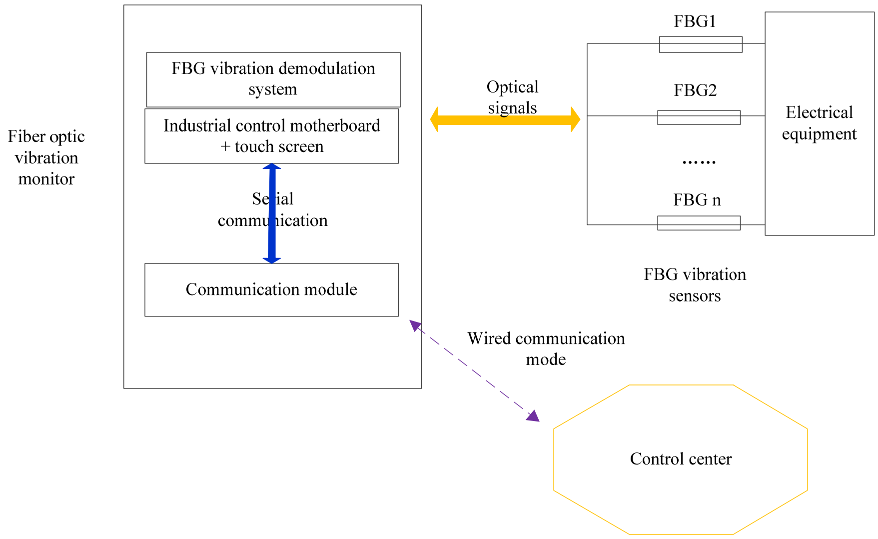


Figure 2 Vibration signal acquisition architecture for electrical equipment (see online version for colours)



Fibre Bragg grating sensors have advantages such as high sensitivity, anti-interference, and long-distance transmission, which can achieve high-precision acquisition of vibration signals from electrical equipment. Compared to traditional sensors, fibre Bragg grating sensors are not affected by electromagnetic interference and can work stably in harsh environments, providing high-quality raw data for subsequent signal processing and analysis. They can comprehensively capture equipment vibration information, improve monitoring accuracy and reliability. The main features of this architecture are as follows:

1 High precision measurement: utilising the fibre Bragg grating principle, fibre Bragg grating sensors enable high-precision vibration signal measurement with significantly greater accuracy than conventional sensors, capable of detecting minute vibration variations to facilitate precise identification of electrical equipment abnormal vibration states.

2 High sensitivity: exhibiting exceptional vibration signal sensitivity, fibre Bragg grating sensors rapidly respond to vibration variations while generating corresponding electrical signals, permitting real-time monitoring of electrical equipment vibration status for timely potential issue detection.

3 Electromagnetic immunity: employing optical fibres as transmission media, fibre Bragg grating sensors exhibit inherent electromagnetic immunity characteristics. Within power environments where electromagnetic interference constitutes a common noise source, these sensors maintain unaffected signal transmission and stable vibration data acquisition.

4 Corrosion resistance and high temperature resistance: fibre Bragg grating sensors demonstrate corrosion resistance and high temperature tolerance, enabling long-term stable operation in harsh industrial environments, thereby ensuring wide applicability in power equipment vibration monitoring.

5 Real-time monitoring: fibre Bragg grating sensors perform real-time vibration signal acquisition and transmission to fulfil electricity market monitoring requirements, allowing timely detection of electrical equipment abnormal vibration states and prompt implementation of corresponding measures.

6 Large dynamic range: fibre Bragg grating sensors possess an extensive dynamic range capable of measuring signals ranging from subtle vibrations to intense vibrations, enabling adaptation to diverse vibration intensity monitoring requirements.

7 High integration capability: fibre Bragg grating sensors readily integrate with existing monitoring systems and equipment to facilitate data sharing and interaction, allowing seamless incorporation into current power monitoring systems.

2.2 Blind separation of vibration signals from electrical equipment

The signal acquisition architecture utilising fibre Bragg grating sensors obtains electrical equipment vibration signals, while the joint approximate diagonalisation algorithm performs blind separation and processing of collected signals, establishing a critical foundation for subsequent electrical equipment abnormal vibration state detection.

Blind vibration signal separation technology enables extraction of independent vibration source signals from complex mixed signals. During electrical equipment operation, multiple vibration sources typically coexist with overlapping signal patterns, forming complex mixed signals. The blind separation technique effectively isolates individual vibration source components from these mixed signals, allowing precise analysis of each vibration source's characteristics (Dhoulath et al., 2024; Esmaeiloghli et al., 2024) while generating data support for subsequent research.

This section presents an improved joint approximation diagonalisation (JADE) algorithm to resolve the separation challenge of multi-source mixed vibration signals in electrical equipment, with the method comprising the following key steps:

Assuming the mixed vibration signal collected by the fibre Bragg grating sensor is $x(t) = [x_1(t), x_1(t), \ldots, x_m(t)]^T$, it is linearly mixed from n independent source signals $s(t) = [s_1(t), s_1(t), \ldots, s_m(t)]^T$:

$$x(t) = As(t) + \eta(t) \tag{8}$$

In formula (8), $A \in R^{m\times n}$ represents the unknown mixing matrix, and $\eta(t)$ represents additive noise.

Step 1 Centralisation and decorrelation

- Calculate the covariance matrix of the sample:

$$R_x = E\left[x(t)x(t)^T\right] \tag{9}$$

- By performing eigenvalue decomposition $R_x = U \wedge U^T$, the whitening matrix is obtained:

$$B = \wedge^{-1/2} U^T \tag{10}$$

In formula (10), $\wedge = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_m)$ represents the eigenvalue matrix and U represents the eigenvector matrix.

- Whitening signal

The JADE algorithm performs whitening operation on the vibration signal $x(t)$ of electrical equipment to remove the correlation of the signal, resulting in:

$$z(t) = Bx(t) \tag{11}$$

In formula (11), B represents the whitening matrix; $z(t)$ represents the vibration signal of electrical equipment after whitening, satisfying $z(t) = E[Z(t)Z(t)^T] = I_n$.

Step 2 Calculate the fourth-order cumulative quantity

For whitening signal $z(t)$, its fourth-order cumulant tensor $Q \in R^{n\times n \times n\times n}$ is defined, and the definition of the fourth-order cumulant is:

$$\begin{aligned} Q_{ijkl} &= cum\left(z_i, z_j, z_k, z_l\right) = E\left[z_i z_j z_k z_l\right] \\ &\quad -E\left[z_i z_j\right]E\left[z_k z_l\right] - E\left[z_i z_k\right]E\left[z_j z_l\right] \\ &\quad -E\left[z_i z_l\right]E\left[z_j z_k\right] \end{aligned} \tag{12}$$

Step 3 Build a cumulative matrix set

Select a set of basis matrices $\{M_r\}_{r=1}^{n^2}$ (usually the standard basis matrix E_{ij}) and calculate the corresponding fourth-order cumulative matrix:

$$Q_z\left(M_r\right) = \sum\nolimits_{k,l=1}^{n} Q_{ijkl}\left(M_r\right)_{kl}, i, j = 1, 2, \ldots, n \tag{13}$$

Step 4 Joint approximation diagonalisation

Find orthogonal matrix V so that all $Q_z(M_r)$ are approximately diagonalised simultaneously:

$$\mathrm{V}^{\mathrm{T}} Q_z\left(M_r\right)V \approx \wedge_r \tag{14}$$

In formula (14), $\wedge_r$ represents the diagonal matrix.

By minimising the energy of non-diagonal elements:

$$J(V) = \sum\nolimits_{r=1}^{n^2} \left\| off\left(\mathrm{V}^{\mathrm{T}} Q_z\left(M_r\right)V\right)\right\|_F^2 \tag{15}$$

In formula (15), off(.) represents preserving the non-diagonal elements of the matrix.

Step 5 Source signal recovery

The final separation matrix is $W = V^T B$ and the calculation formula for blind separation of electrical equipment vibration signals is as follows:

$$X(t) = Wx(t) \tag{16}$$

2.3 *Abnormal vibration state detection of electrical equipment based on random forest*

Through the above process, the joint approximation diagonalisation algorithm efficiently separates vibration signals of different types of electrical equipment, improving the generality and practicality of the method. Applying the random forest algorithm to detect abnormal vibration states in electrical equipment can utilise its advantages in handling complex data and classification problems, improving the accuracy and robustness of detection. Traditional vibration signal detection methods rely on a single vibration feature, which is easily affected by noise and interference, resulting in biased detection results. The random forest algorithm can comprehensively consider multiple features and reduce errors caused by single feature detection by integrating the judgement results of multiple decision trees, thereby improving detection accuracy. Random forest, as an ensemble learning algorithm, demonstrates significant innovation in identifying abnormal vibration states of electrical equipment.

Figure 3 CART decision tree construction process

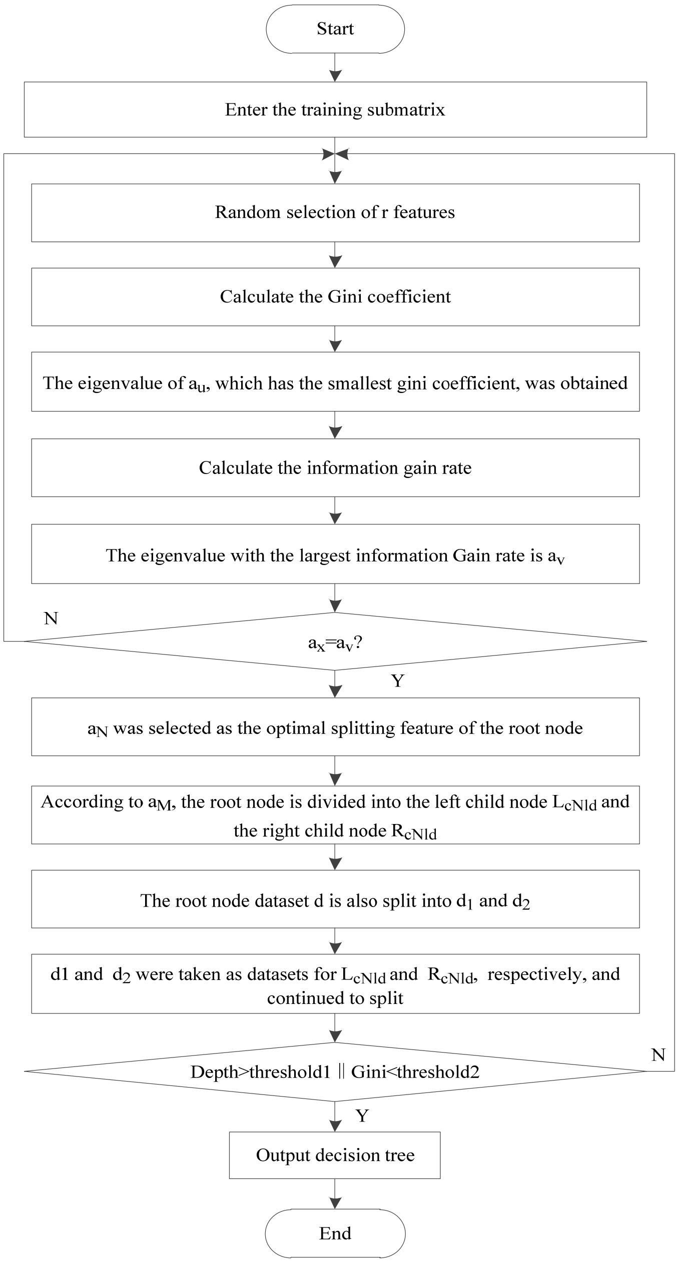
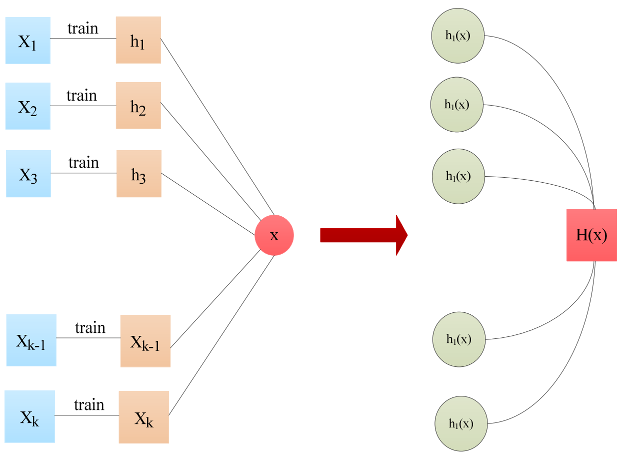


Figure 4 Classification voting process (see online version for colours)



1 Advantages of ensemble learning: random forest significantly improves model accuracy and stability by constructing multiple decision trees and combining their outputs. This integrated learning approach proves particularly important in detecting abnormal vibration states of electrical equipment; as vibration signals are often complex and variable, making it difficult for a single model to fully capture their characteristics.

2 Randomness and diversity: in random forest, each decision tree is constructed based on different random samples and feature subsets, increasing model diversity. This diversity enables random forest to handle various complex vibration signals and improves abnormal vibration state identification capability.

3 Automatic feature selection: random forest automatically evaluates feature importance during training and selects the most critical features for abnormal vibration state identification. This automatic feature selection mechanism reduces manual intervention while improving feature extraction efficiency and accuracy.

4 Nonlinear feature capture: abnormal vibration signals of electrical equipment often contain nonlinear features, which traditional methods are difficult to effectively capture. Random forest can process nonlinear data and better capture complex patterns in vibration signals by constructing multiple decision trees.

5 Robustness and generalisation ability: random forest demonstrates strong robustness against noise and outliers while maintaining stable performance in complex environments. This method exhibits excellent generalisation capability for identifying abnormal vibration states across various electrical equipment types and scales.

The original training sample dataset construction utilises blind-separated electrical equipment vibration signals as the foundation, with abnormal vibration labels incorporated to complete the training sample dataset.

The dataset is mainly represented by $X = (x_i, y_i)_{nm}$, where n represents the number of electrical equipment vibration signals, m represents the number of electrical equipment vibration signal properties, that is, the number of sample feature quantities, x_i is the i^{th} of m^{th} training sample vector, represented as $x_i = [x_{i1}, xi_2, \ldots, x_{im}]$, and y_i is the label corresponding to x_i, including normal and abnormal. Using bootstrap resampling method, n samples were randomly placed back from $X = (x_i, y_i)_{nm}$ to form a new training sample subset $X_1 = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_n, y_n)\}$. A total of k such training subsets were constructed, forming a training sample set of $D = \{X_1, X_2, X_3, \ldots, X_k\}$.

Assuming that the vibration signal dataset d of electrical equipment is split into d_1 and d_2 based on the value a_u of feature A_k, the calculation formula for Gini coefficient and information gain rate of dataset d is as follows:

$$\text{Gini}(d, a_u) = \frac{|d_1|}{|d|}\text{Gini}(d_1) + \frac{|d_2|}{|d|}\text{Gini}(d_2) \tag{17}$$

$$\text{InfGaiRat}(d) = \frac{\text{Gain}(d)}{\text{SplInf}(d)} \tag{18}$$

In the formula, Gini represents the Gini coefficient; InfGaiRa represents the information gain ratio; Gain represents the information gain value, and InfGaiRat represents the node splitting information. The construction process of CART decision tree is shown in Figure 3.

Merge the trained k decision trees into the required random forest classifier, which is $\{h_1(x), h_2(x), h_3(\text{x}), \ldots, h_k(x)\}$. The random forest model serves as a powerful classifier without requiring high performance from individual decision trees. Each decision tree generates randomly and operates independently, with final results determined through collective voting by all decision trees. The specific classification voting process appears in Figure 4.

The decision-making formula for electrical equipment abnormal vibration state identification using random forest appears as follows:

$$H(x) = arg\max_{Y} \sum_{i=1}^{k} I\left(h_i(x) = Y\right) \tag{19}$$

In formula (17), x represents the input variable, which is the vibration signal of the electrical equipment; $h_i(x)$ represents the i^{th} decision tree; Y represents the target classification label; $I(\cdot)$ represents a demonstrative function, which is 1 when the expression is satisfied and 0 otherwise.

3 Experimental design

3.1 Experimental scheme

To validate the practical application effectiveness of the random forest-based electrical equipment abnormal vibration state detection method, experimental testing was implemented according to the following specific experimental plan:

1 Experimental data

Electrical equipment abnormal vibration state identification experiments utilise sensors to collect relevant experimental data ensuring result authenticity and reliability. The main experimental data types include:

- Vibration signal data: fundamental data for identifying abnormal vibration states, collected via vibration sensors to reflect equipment operational vibration conditions.
- Sound signal data: captured through sound sensors and converted into digital signals for analysis, revealing equipment acoustic characteristics including frequency and loudness to assist abnormal vibration identification.

- Temperature/pressure data: operational equipment may exhibit physical quantity variations including temperature and pressure changes potentially related to abnormal vibration states.
- Operating history data: records of equipment operational status and fault conditions during specific historical periods.

2 Evaluation indicators

Selected experimental comparison methods include the Zhang et al. (2024a, 2024b) method, and the proposed method. Method effectiveness verification involves comparing electrical equipment vibration signal SNRs, abnormal vibration state detection accuracy, and detection task completion times.

- In electrical equipment abnormal vibration state identification experiments, signals represent useful vibration state information while noise denotes interference components during signal acquisition, transmission and processing. The SNR indicates the power ratio between signal and noise, where higher ratios correspond to better method-collected signal quality.
- The accuracy of electrical equipment abnormal vibration state identification measures the proportion of correctly identified states among all detected vibration states, serving as a key indicator for evaluating detection method effectiveness.
- The task completion time for electrical equipment abnormal vibration state identification represents the total duration from vibration-related data collection (including signals and operating parameters) to final diagnosis confirmation. Shorter durations indicate higher method efficiency.

3.2 *Experimental result*

3.2.1 *Signal to noise ratio of vibration signals in electrical equipment*

Table 1 presents the SNR test results of electrical equipment vibration signals obtained by three methods.

Analysis of Table 1 data indicates the electrical equipment vibration signal achieves maximum SNRs of 29.75 dB with Zhang et al. (2024a) method and 17.41 dB with Zhang et al. (2024b) method, while reaching 43.67 dB with the proposed method – representing 13.72 dB and 26.26 dB improvements respectively. Minimum SNRs measure 20.39 dB for Zhang et al. (2024a) method and 12.36 dB for Zhang et al. (2024b) method, compared to 36.78 dB for the proposed method, demonstrating 16.39 dB and 24.42 dB enhancements. Comparative results confirm the proposed method's superior vibration signal collection quality, enabling more accurate motor vibration state representation and ensuring reliable abnormal vibration state identification.

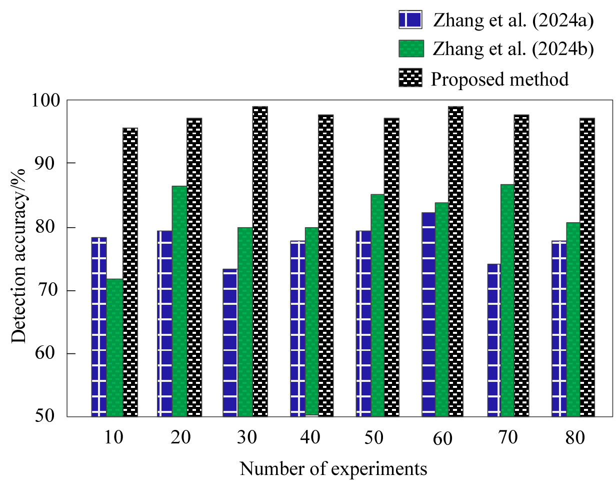
Table 1 Signal to noise ratio of three methods

Number of experiments	*Signal to noise ratio/dB*		
	Zhang et al. (2024a) method	*Zhang et al. (2024b) method*	*Proposed method*
10	20.39	15.23	36.78
20	21.46	17.41	38.99
30	23.51	14.32	37.41
40	21.49	16.33	36.97
50	22.37	12.45	39.42
60	24.58	12.36	40.12
70	26.31	15.48	43.67
80	29.75	16.31	38.76

3.2.2 *Detection accuracy*

Figure 5 displays the accuracy test results for identifying abnormal vibration states in electrical equipment using three methods.

Figure 5 Detection accuracy of three methods (see online version for colours)



Analysis of Figure 5 data reveals the Zhang et al. (2024a) method achieves 73.6%–82.4% accuracy in identifying electrical equipment abnormal vibration states, compared to 72.3%–86.3% for Zhang et al. (2024b) method. The proposed method maintains consistent accuracy above 95.6%, demonstrating high reliability for practical electrical equipment monitoring applications and suitability for equipment status monitoring and fault warning systems.

3.2.3 *Identify task completion time*

The completion time test results of the three methods for identifying abnormal vibration states of electrical equipment are shown in Table 2.

Table 2 data analysis shows maximum task completion times of 9.67 s for Zhang et al. (2024a) method and 8.63 s for Zhang et al. (2024b) method, while the proposed method achieves 2.98 s – representing 6.69 s and 5.65 s reductions respectively. Minimum task completion times measure

5.89 s for Zhang et al. (2024a) method and 5.62 s for Zhang et al. (2024b) method, with the proposed method reaching 3.58 s (2.31 s and 2.04 s reductions). These results confirm shorter task completion times, demonstrating the method's advanced random forest algorithm effectively processes electrical equipment vibration data for rapid abnormal state identification.

Table 2 Task completion time for three methods

Number of experiments	*Task completion time/s*		
	Zhang et al. (2024a) method	*Zhang et al. (2024b) method*	*Proposed method*
10	8.96	5.62	2.36
20	7.41	5.74	2.47
30	5.89	8.63	2.58
40	7.45	6.74	2.46
50	7.63	6.55	2.33
60	6.38	7.18	2.98
70	6.87	7.26	2.75
80	9.67	7.39	2.31

4 Conclusions

Electrical equipment inevitably encounters various operational fault risks, with abnormal vibration representing a common and critical fault manifestation. This study proposes a novel random forest-based detection method for electrical equipment abnormal vibration states. Experimental results demonstrate 43.67 dB maximum vibration SNR, consistent abnormal state identification accuracy exceeding 95.6%, and 3.58 s minimum task completion time, confirming high accuracy and efficiency characteristics. Equipment vibration state identification enables timely detection of potential faults and hazards, allowing the implementation of preventive measures that reduce maintenance costs and production loss while enhancing equipment reliability and safety. Future research should prioritise exploring new signal processing technologies and algorithms, emphasising multi-source information integration and utilisation to advance electrical equipment fault diagnosis technology innovation.

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Declarations

All authors declare that they have no conflicts of interest.

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