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Research article

Automatic detection method of abnormal vibration of engineering electric drive construction machinery

Jian Yuan[1], Hao Liu[3] and Yang Zhang[2,3,*]

[1] China Road & Bridge Corporation, Beijing 100011, China
[2] Key Laboratory for Special Area Highway Engineering of Ministry of Education, Xi'an 710018, China
[3] School of Transportation, Southeast University, Nanjing 211189, China

* **Correspondence:** E-mail: yang-zhang@seu.edu.cn; Tel: +8618913344511.

Abstract: Aiming at the problem that the extraction effect of abnormal vibration characteristics of current engineering electric drive construction machinery is poor, an automatic detection method of abnormal vibration of engineering electric drive construction machinery is proposed. Firstly, the abnormal data of mechanical abnormal vibration are collected and identified, and based on the identification results, the dynamic characteristic model of engineering electric drive construction machinery is constructed. The empirical mode decomposition and Hilbert spectrum are used to decompose the abnormal vibration of machinery, calculate the response amplitude and time lag value generated by the operation of the engineering electric drive construction machinery to simplify the diagnosis steps of the abnormal vibration of the engineering electric drive construction machinery and realize the positioning and detection of the transverse and torsional vibration characteristics. Finally, through experiments, it was confirmed that the automatic detection method of the abnormal vibration of the engineering electric drive construction machinery has high accuracy, which can better ensure the healthy operation of mechanical equipment. This endeavor aims to establish scientific methodologies and standards for fault detection techniques in construction machinery, ultimately forging a versatile solution better suited for detecting and resolving issues across various categories of construction equipment.

Keywords: electric drive construction; mechanical equipment; vibration signal

1. Introduction

There are many parts and components in engineering electric drive construction machinery, and the layout of structural parts is complex. The cooperation of various parts is the basis for effectively ensuring the stable and reliable operation of engineering electric drive construction machinery. Engineering electric-drive construction machinery is the mechanical equipment that converts other forms of energy into electric energy [1]. The common engineering electric drive construction machinery mainly includes hydraulic turbines, steam turbines, diesel engines, etc. All forms of engineering electric-drive construction machinery transmit mechanical energy to engineering electric drive construction machinery through transmission engineering electric drive construction machinery, build the magnetic circuit and circuit of transmission engineering electric drive construction machinery through appropriate magnetic and conductive materials and push the piston downward to do work under the extrusion of the piston to realize energy conversion. Engineering electric drive construction machinery is widely used in industrial and agricultural production, national defense, science and technology, life and other fields that have important basic significance. In industrial production, a large number of fluid machinery, such as compressors, pumps, etc., often have abnormal vibration, which has a great impact on normal production [2]. The fault diagnosis technology widely used in the vibration diagnosis of rotating machinery is mostly based on signal analysis. When facing the abnormal vibration of on-site machines, it depends on the experience of on-site technicians to a great extent. Because there is no obvious and quantitative law between vibration causes and characteristic signals, and due to the limitations of production conditions, many fault sites cannot obtain complete detection data. Therefore, on-site diagnosis is a very difficult problem. The abnormal vibration of engineering electric drive construction machinery is divided into bending vibration, torsional vibration and axial vibration. Through the nonlinear dynamic analysis and abnormal feature extraction of engineering electric drive construction machinery, the state test and detection of engineering electric drive construction machinery are realized [3]. Furthermore, existing research struggles to effectively depict the dynamic evolution of the health status of the target object across various time scales [4,5]. Consequently, the concept of digital twins has been introduced as a promising approach for predicting and managing the health of construction machinery [6,7]. However, a fundamental challenge lies in modeling complex systems, which is also an inherent obstacle within the realm of digital twins. Traditional mechanistic models demand an extensive amount of specialized knowledge, making it arduous to encompass all the behaviors and rules of the system, especially for intricate systems featuring global or local unknowns [8,9]. Additionally, these mechanistic models face difficulties keeping up with changing system states or incurring prohibitively high update costs. Consequently, methods grounded in mechanistic models exhibit poor scalability and pose challenges in terms of verification [10–12]. Ke et al.'s groundbreaking proposal of a novel gear wear prediction scheme, designed for forecasting the remaining service life of gear transmission systems, serves as a strong research foundation for advancing detection methods in the field of engineering machinery [13]. Simultaneously, Ma et al. pioneered the development of a digital twin model for a bearing test bench, leveraging multidisciplinary simulation. They adeptly identified closely spaced modal parameters through the application of a modal decomposition algorithm, enabling comprehensive bearing fault analysis across diverse domains [14]. Through the preceding research and analysis, it can be inferred that, among the currently available methods, the power spectral density feature extraction method is commonly employed for capturing abnormal vibration characteristics in electrical transmission engineering machinery. Nonetheless, owing to the non-Gaussian nature of power spectral density, its effectiveness in tracking abnormal vibrations in electrical transmission machinery under varying temperatures is limited. In this paper, an automatic detection method for the abnormal vibration of engineering electrical transmission construction machinery is proposed. Furthermore, the engineering inspection method devised in this study holds the potential for broader applications. It can be utilized for the selection of highly sensitive wireless power transfer (WPT) bands to determine entropy measures for identifying faulty components in axial piston pumps. Additionally, it can enhance laboratory transfer learning techniques for detecting defects in hydraulic machinery and facilitate the development of an innovative convolutional neural network (CNN) tailored for diagnosing bearing defects in rotating machinery.

2. Automatic detection of abnormal mechanical vibration

2.1. Identification of abnormal mechanical vibration data

In the process of abnormal vibration of engineering electrical transmission construction machinery and equipment, the famous bathtub curve law is basically followed and the whole process includes a running-in period, a normal probation period and a wear and tear period. Through the necessary measurement and fault diagnosis of mechanical equipment, we can find the stage of the equipment at a certain point in time to avoid the equipment entering the loss fault in advance [15]. Mechanical abnormal vibration diagnosis technology for mechanical equipment refers to the use of detection devices to detect the state information of mechanical equipment in operation or under relatively static conditions under a certain working environment, judge whether the mechanical equipment is in a normal operation state by analyzing the operation state information of mechanical equipment, and qualitatively and quantitatively judge the real-time operation state of mechanical equipment and its parts in combination with the fault mechanism and historical operation state of the diagnostic object [16]. According to the corresponding fault characteristics, the possible faults and fault locations of mechanical equipment are identified and the operation trend and remaining life of relevant faults are predicted to determine targeted equipment management, maintenance and repair countermeasures. The purpose of fault diagnosis is to find faults in time and minimize losses. Based on this, the steps of the abnormal vibration diagnosis of mechanical equipment are optimized, as shown in Figure 1 below:

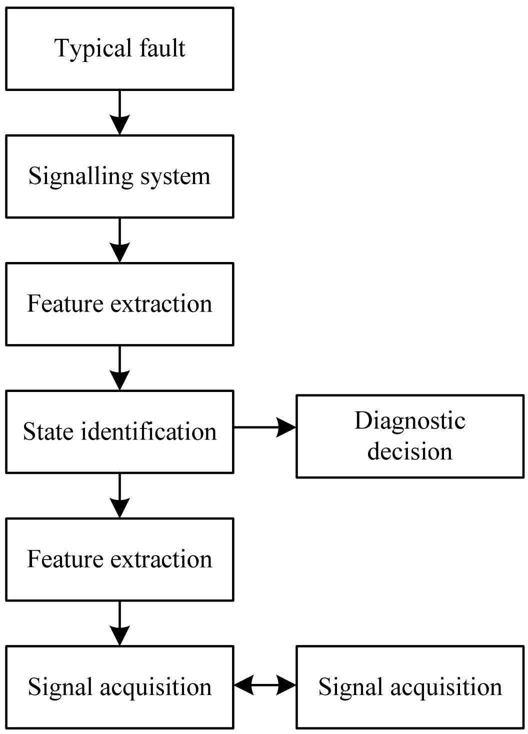

Figure 1. Basic process diagram of abnormal vibration diagnosis.

When a mechanical fault occurs, the intrinsic mode function (IMF) component obtained from the decomposition of the fault signal must be consistent with the normal vibration signal $A(f)$, whose IMF components are different, that is, the vibration characteristics contain df atypism. In order to quantify the characteristics of each IMF vibration signal and form a mechanical fault criterion, this paper uses the power spectral density function to calculate the power of the IMF signal component decomposed by empirical mode decomposition (EMD) P feature extraction [17,18]. Taking intrinsic mode function 1 (imf_1) as an example, the maximum amplitude of the imf_1 component power spectrum is taken according to the experimental data μ_X, Calculate the integral sum of all IMF power spectra $\sum_{i=1}^{n} X_i$. The ratio of this value to the power spectral density integral of IMF in this interval is taken as the characteristic value, which is defined as the local maximum power characteristic, that is:

$$G = \sum_{i=1}^{n} X_i \sigma_X \sum \mathrm{d}f - \mu_X \int_{f-a_0}^{f+a_1} EA(f)\text{-}Pfm \tag{1}$$

where, fm is the frequency corresponding to the maximum amplitude of the power spectrum, and if $R(x)$ is the power spectral density function. In the modeling process of mechanical fault diagnosis, we must first extract the features that can describe the fault category from the original signal [19]. In this paper, local mean decomposition (LMD) is used to extract the mechanical fault characteristics of the original signal v. Set the signal collected by the sensor as $s(a)$, and then the steps of mechanical fault feature extraction are as follows: estimation $s(a)$ is all local extreme points, including local mean function $s_i(t)$ and local envelope function $a_i(t)$, and separates out $s(a)$ from $s_i(t)$ thus:

$$h(t) = \sum R(x) - Gv / a_i(t)[s(a) - s_i(t)] \tag{2}$$

Use $s_i(t)$ divide $a_i(t)$ realize demodulation so that:

$$K = s_i(t) / a_i(t) \tag{3}$$

In an ideal environment, K is a pure frequency modulation (FM) signal. However, in practice, K is difficult to meet this condition, so this condition is met through continuous iteration: $-1 \le K \le 1$; get iteration function $a_{i(\mathrm{n}+1)}(t)$ Satisfy the equation: $Ka_{i(\mathrm{n}+1)}(t) \ge 1$. All local envelope functions are multiplied to obtain the characteristic signal, namely:

$$a_{1q}(t) = a_1(t)a_2(t)\cdots a_n(t) = \prod_{q=1}^{n} Ka_{i(\mathrm{n}+1)}(t) - 1 \tag{4}$$

Separate the characteristic data $s_i(t)$ to generate a new signal:

$$\gamma(t) = \sum s_i(t)h(t) - Ka_{1q}(t) \tag{5}$$

Let $\gamma(t)$ as raw data, repeat the above process until $\gamma_i(t)$ is a monotone function. Then, $X(t)$ can be expressed as n sum of PF component and $u_k(t)$ to obtain:

$$X(t) = PF \sum 1 + \gamma(t) + nu_k(t) \tag{6}$$

Find the extreme point (a_j, b_j). Then, calculate the mean value between the two extreme points, and the local mean function of segment I is:

$$m_j = \left(a_j + b_j\right) / \prod 2i + X(t) \tag{7}$$

Based on the above algorithm, the vibration signal is collected and the specific steps are shown in Figure 2. The acquisition device includes GIS equipment, acceleration sensor, charge amplifier, data acquisition instrument and computer.

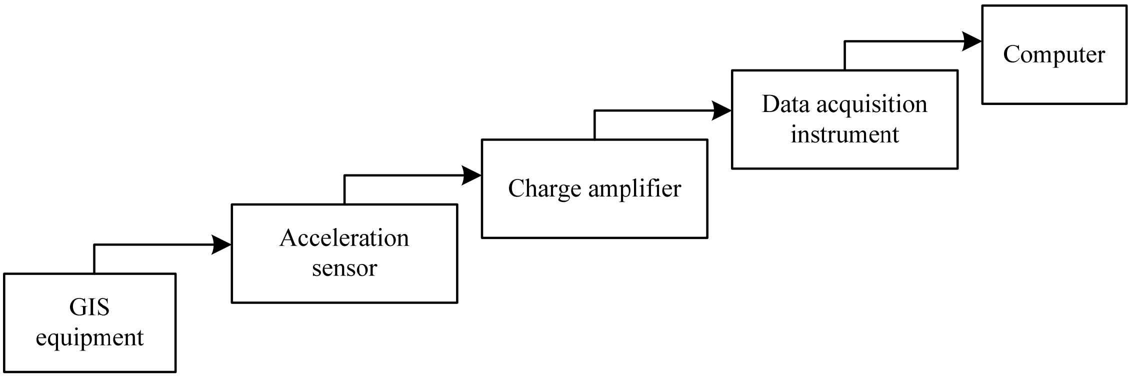

Figure 2. Vibration signal acquisition system.

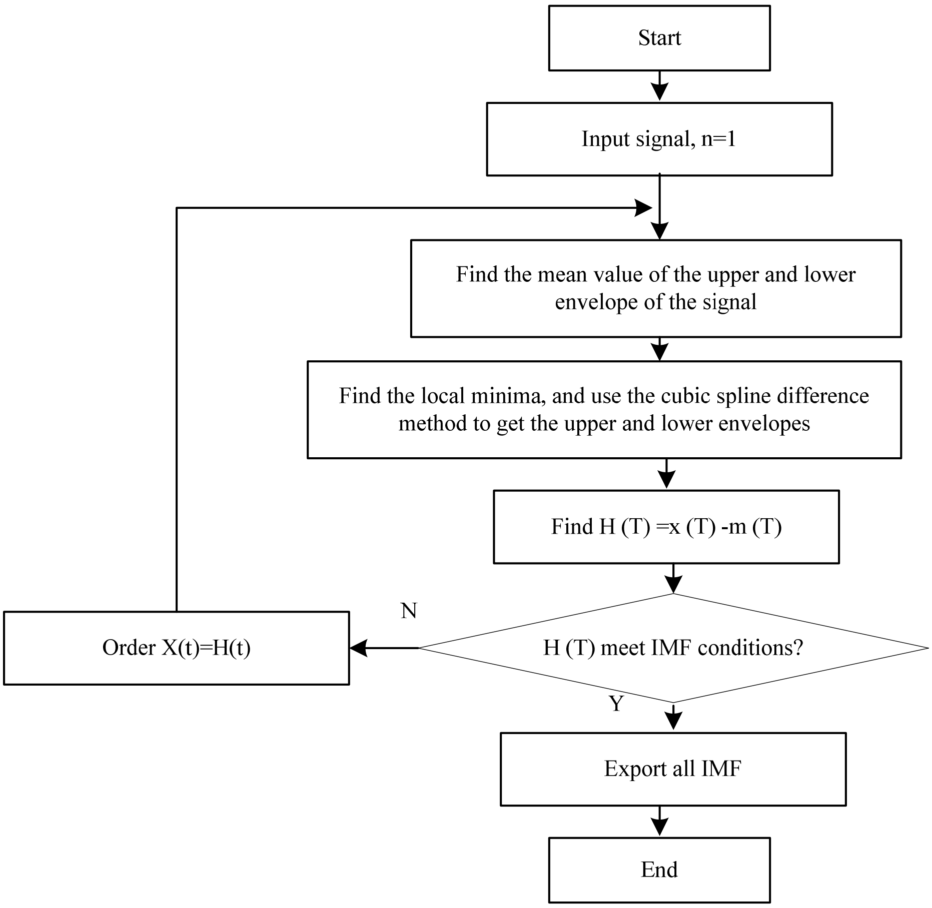

Figure 3. EMD vibration identification processing flow.

The measured mechanical vibration is converted into electrical signals by the piezoelectric acceleration sensor installed on the construction mechanical equipment driven by engineering electrical appliances [20]. The data acquisition instrument is used for data acquisition, and integrates a voltage amplifier, charge amplifier, integral circuit, differential circuit and filter circuit. The selected amplifier and filter circuit can be set through relevant software, signal analysis, display, and recording [21]. Based on this, the EMD vibration identification processing flow is optimized, as shown in Figure 3.

As shown Figure 4, the vibration sensor collects the external vibration acceleration signal of the equipment and transmits it to the computer for data storage, analysis and processing through the data acquisition function of the data acquisition instrument [22]. After any signal completes the EMD process, many IMF components obtained only contain one signal feature. This process not only removes the useless components of the signal (residual function) and realizes signal denoising but also reconstructs the residual signal, which is convenient for the next step of fault diagnosis and analysis [23]. Sample function No T and the resulting function, that is:

$$x_{\mathrm{T}}(t)=\begin{cases} T & \left(-\dfrac{T}{2}<m_j<\dfrac{T}{2}\right) \\ 0 & \left(m_j<-\dfrac{T}{2}, m_j>\dfrac{T}{2}\right) \end{cases} \tag{8}$$

Figure 4. The sensors used in this study.

Abnormal vibration has obvious pulse characteristics. Within a certain sampling time, if the frequency of abnormal vibration is less, the abnormal sound heard is intermittent and the abnormal vibration frequency is higher, then the abnormal sound heard is continuous [24]. According to the different sound qualities, they can be divided into buzzing, rumbling, communication, chirping, popping, clicking, screeching, roaring echo, etc. If the vibration signal of engineering electric drive construction machinery W is the root mean square value, then:

$$x_{RMS}=W\sqrt{\frac{1}{m_j}\sum_{i=1}^{j} W x_{\mathrm{T}}(t)} \tag{9}$$

This value is the average value of time and is not sensitive to the abnormal vibration pulse response of engineering electrical transmission construction machinery. The effective value can only show the overall vibration of the tested engineering electric drive construction machinery but cannot effectively distinguish whether there is an abnormal sound in the engineering electric drive construction machinery.

$$x_{PEAK} = \frac{1}{m_j} \sum_{j=1}^{n} x_{\mathrm{T}}(t) \tag{10}$$

The peak value is very effective for the abnormal vibration pulse caused by various reasons in of the detected engineering electric drive construction machinery. However, due to the different size and structure of the engineering electric drive construction machinery, the size of the peak value is also different, so the maximum peak value alone cannot effectively evaluate the abnormal sound of the engineering electric drive construction machinery [25]. To distinguish the abnormal sound of engineering electric drive construction machinery, it is necessary to compare the maximum peak value of the tested engineering electric drive construction machinery with the effective value, which requires the use of a peak factor to identify whether there is an abnormal sound.

2.2. Optimization of abnormal diagnosis steps of mechanical abnormal vibration

In the process of mechanical fault diagnosis, the working state of mechanical components should be collected first. Currently, the working state information of mechanical components cannot be accurately and comprehensively collected by using a single sensor. Therefore, multiple sensors are used to collect the working state information of mechanical components at the same time and the mechanical fault information features are extracted from the signals. Then, the more important mechanical fault information features are selected by using principal component analysis [26]. Finally, support vector machines are used to learn the feature vector of mechanical fault information and establish a classifier for mechanical fault diagnosis. Therefore, the principle of mechanical fault diagnosis based on sensor signal fusion is shown in Figure 5.

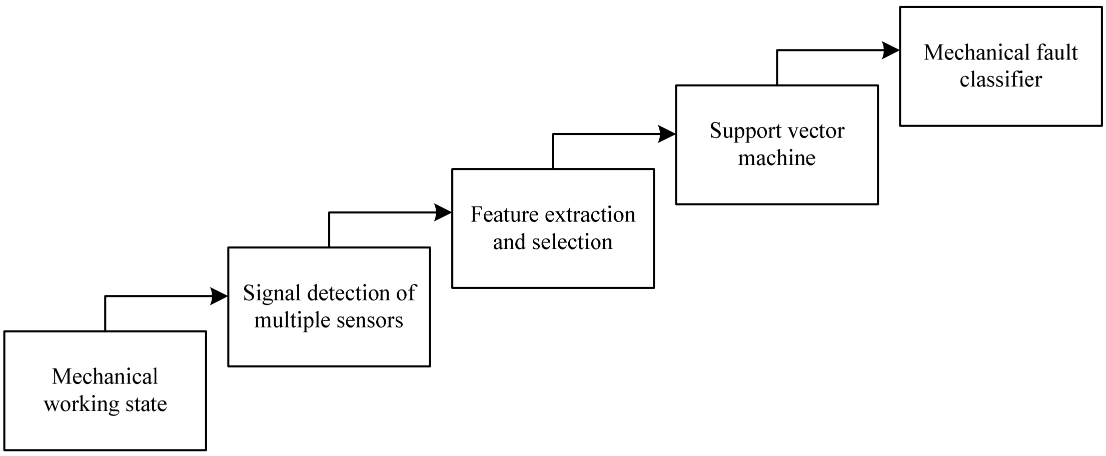

Figure 5. Mechanical fault diagnosis principle of sensor signal fusion.

Based on the dynamic model of engineering electric drive construction machinery constructed above, the vibration analysis model of engineering electric drive construction machinery is constructed and the energy fuzzy rule equation of engineering electric drive construction machinery is constructed as follows:

$$H_r = \frac{M(x_{RMS} - x_{PEAK})}{16\pi\mu_0 h^3}\left(1 - \frac{1}{2}\sin^2\theta\right) \tag{11}$$

Calculate the response amplitude of the engineering electric drive construction mechanical force generated by contacting machinery μ_0 and time lag value h to effectively compensate the measurement error θ. At present, transverse and torsional positioning and detection of vibration characteristics are carried out. Based on the above system structure analysis and vibration mechanics model construction, the abnormal vibration spectrum characteristics of engineering electrical transmission construction machinery are extracted [27]. At present, the power spectral density feature extraction method is used to extract the characteristics of abnormal vibration in engineering electrical transmission construction machinery. Because the power spectral density feature is non-Gaussian, the tracking performance of abnormal vibrations of engineering electrical transmission construction machinery under alternating temperatures is not good. In order to overcome the disadvantages of traditional methods, a feature extraction algorithm for the abnormal vibration spectrum of engineering electrical transmission construction machinery is proposed [28]. First, the vibration signal acquisition is carried out, and the abnormal vibration signal acquisition and generation model design of engineering electrical transmission construction machinery are analyzed. Suppose T represents the vibration source, S1, S2, S3 and S4 represent four vibration signal sensors respectively and the signal acquisition structure is shown in Figure 6:

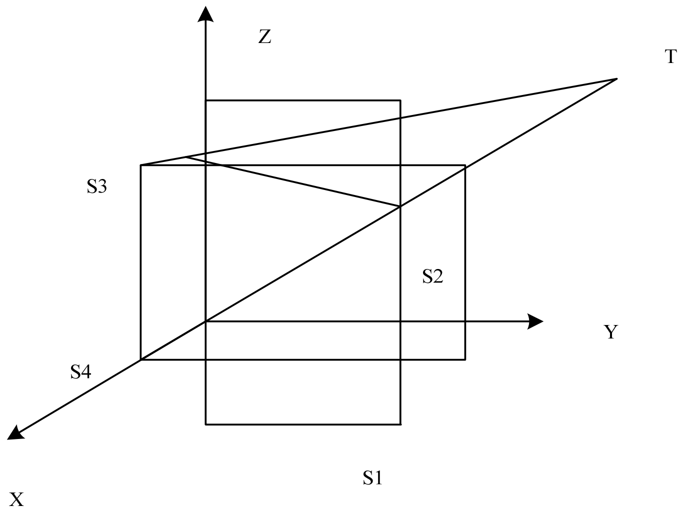

Figure 6. Layout of abnormal vibration signal sensor of engineering electric drive construction machinery.

According to the analysis of the basic structure, structural characteristics, and working principle of engineering electric drive construction machinery, it is found that the mechanical seal structure is complex and there are many parts [29]. However, as typical rotating equipment, the reliability of engineering electric drive construction machinery mainly depends on whether the rotor rotates normally. Therefore, most of the faults in engineering electric drive construction machinery are related to the rotor. No matter which kind of vibration fault is present, it will be reflected in the most sensitive part of engineering electric drive construction machinery, that is, the rotor. In addition to high fault-rate of the rotor itself, engineering electric drive construction machinery and mechanical seals that closely cooperate with the rotor are also the high fault prone parts of engineering electric drive construction machinery [30]. In order to have a more in-depth and comprehensive understanding of various possible failure forms and their causes in oil transfer pumps, this paper summarizes the common failure forms by consulting the literature. See Table 1 for the main fault forms of the electric drive construction machinery of the project.

Table 1. Main failure modes of mechanical equipment.

Parts	Rotor	Rolling bearing	Sliding bearing	Impeller
Main fault types	Out-off-balance	Fatigue spalling	Oil film oscillation	Local damage
	Not right	Damage	Friction induced surge	Mechanical looseness
	Looseness	Rust	Air gap excitation	Axial sliding
	Eccentric	Crack	——	Out-off-balance
	Bend	Gluing	——	Cavitation
	Transverse axis crack	Damaged cage	——	——
	Friction damage	——	——	——

The data acquisition system is composed of sensors for obtaining vibration signals and amplifiers or converters for processing the output electrical signals. The function of a vibration test sensor is to transform the measured vibration physical quantity into a signal in the form of an electric quantity or electrical parameters [31]. The electrical parameters of the signal output by the sensor are output as an analog signal.

Table 2. performance parameters of vibration sensor.

model	application environment	Sensitivity (V/ms^{-2})	frequency range (Hz)	Linearity (m/s^2)	Weight (g)	Install resonance point (Hz)
YD35	General measurement in harsh environment	0.006	0.5–10,000	2000	15	35k
YD38	General measurement in harsh environment	5	0.3–10,000	16,000	15	40k

The data acquisition module is to sort out the signals collected by the data acquisition card. It is the combination of the whole program end, the software system and hardware system and plays an important role in the whole system. The modeling of LabVIEW makes it extremely convenient data acquisition. The data acquisition module converts the collected vibration signals into digital signals and then integrates the digital signals into the computer, which can be transferred to other modules of the software system as the original data. The data analysis module constitutes the core part of the live detection system. This module applies a large number of algorithms and some digital signal processing modules to analyze the transmitted raw data to complete the implementation of the analysis and diagnosis algorithms. The most important part of designing the whole software system is the design of the data analysis module and algorithm programming. Whether the function of the software system can be realized correctly depends on the feasibility of the application algorithm. The algorithm and function tools of LabVIEW greatly facilitate the programming requirements. In addition, Lab View also has interface operations that can be used for the C language and MATLAB. At the same time, it can realize the parallel application of the comprehensive analysis and fault diagnosis algorithms proposed above in MATLAB. The data storage module forms many records of the original signal data (received from the data acquisition module) and the analysis and calculation results (obtained from the data processing and analysis module) and stores them in the database, which is conducive to the management and query of records. LabVIEW has data access technology. We can use this technology to create an automatic test system that is convenient for queries at any time. The data retrieval module can query the existing data in the database in real time according to needs, which is convenient for research work.

2.3. Realization of automatic detection of abnormal vibration

The purpose of signal acquisition is to obtain the state and characteristic information of the target object, but often the useful signal is mixed with complex noise. The target features cannot be obvious or make the target features buried, and the collected signals cannot be directly recognized and applied. Therefore, we often process the collected vibration signals through various methods in order to obtain the required characteristic signal. The processing can be understood as decomposing a complex signal into multiple simple signals. The purpose is to eliminate or weaken the redundant components in the original signal, weaken the noise and interference mixed in the signal or convert the signal into a form convenient for identification and feature extraction. The whole process is shown in Figure 7.

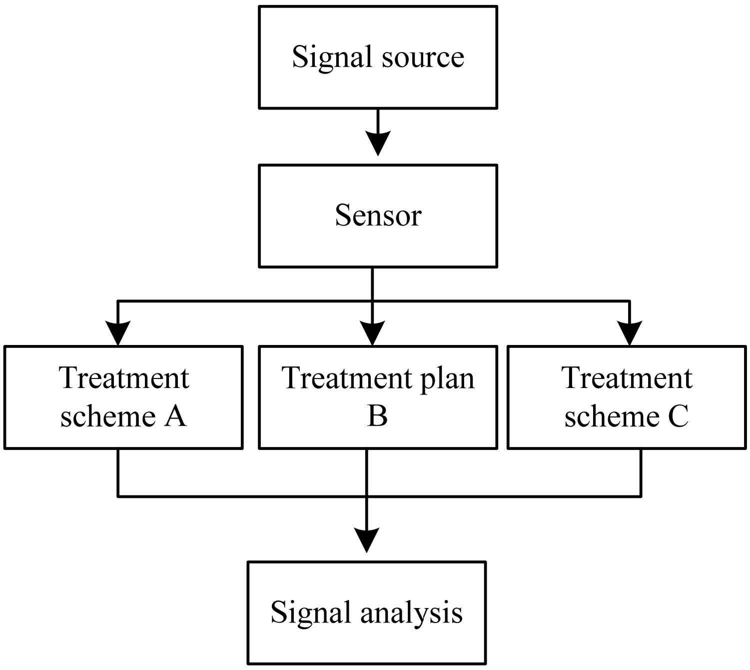

Figure 7. Basic processing process of vibration signal.

Engineering electric-drive construction machinery will produce vibration in the working process, which is composed of normal vibration and abnormal vibration. Affected by the elastic characteristics, the vibration generated by qualified engineering electric drive construction machinery during operation is normal. If the vibration is affected by the surface condition of the engineering electric drive construction machinery, it is abnormal vibration. During operation, the internal components of engineering electric drive construction machinery may impact each other to produce forced vibration. If the frequency is equal to the natural vibration frequency, the vibration will be intensified. The natural frequency is only related to its own nature and has nothing to do with the speed of engineering electrical transmission construction machinery. The natural frequency of rolling elements.

$$f_b = \frac{0.424}{r}\sqrt{\frac{E}{2\rho}} \tag{12}$$

where r is the radius of the rolling element, is the material density and E is the elastic modulus. If the surface of rolling engineering electric drive construction machinery is damaged, it will lead to the failure of engineering electric drive construction machinery. In general, the characteristic frequency of engineering electric drive construction machinery is lower than 1 kHz, which is important information reflecting the failure of engineering electric drive construction machinery. When diagnosing the fault of engineering electric drive construction machinery, it is necessary to separate the low-frequency vibration generated by the fault from the complex high-frequency natural vibration, and calculate the fault characteristic frequency of engineering electric drive construction machinery with low-frequency vibration to judge the fault location of engineering electric drive construction machinery. If the rolling engineering electric drive construction machinery fails during operation, it can be classified according to different vibration characteristics, including scratching, peeling, pitting and other surface damage and wear faults. Generally, the surface wear of engineering electric drive construction machinery, as a gradual failure, takes a long time to go through during normal operation. When the surface wear of engineering electric drive construction machinery occurs, its vibration property is the same as that of normal engineering electric-drive construction machinery, which is an irregular waveform with strong randomness, but compared with normal engineering electric drive construction machinery, the vibration amplitude of fault engineering electric drive construction machinery is significantly higher. Therefore, it is only necessary to monitor the peak value and effective value to diagnose the wear fault of engineering electric drive construction machinery. If it exceeds the normal value by a lot, the wear fault of engineering electric drive construction machinery will occur. Wear will not directly lead to the damage of engineering electric drive construction machinery, and the degree of harm is small. During the vibration detection and fault diagnosis of the rolling engineering electric drive construction machinery, the rolling engineering electric drive construction machinery is running, and the interference of the engineering electric drive construction machinery itself will produce vibration signals. After the vibration signal is generated, it needs to be picked up and converted by the sensor first, and the vibration signal is converted into a weak voltage signal. Then the signal can be amplified by the amplification circuit to diagnose the fault of engineering electrical transmission construction machinery. The amplified signal also contains noise and other interference signals from the non-engineering electric drive construction machinery itself. The interference signals need to be filtered out through the filter. Only the vibration signals of the engineering electric drive construction machinery itself are retained, so that the signal can more accurately reflect the operation state of the engineering electric drive construction machinery. Then, it will collect the filtered signal through the acquisition card, convert the signal into a digital signal, transmit it to the upper computer through the USSB data line and process the signal in the upper computer to diagnose the fault of engineering electrical transmission construction machinery.

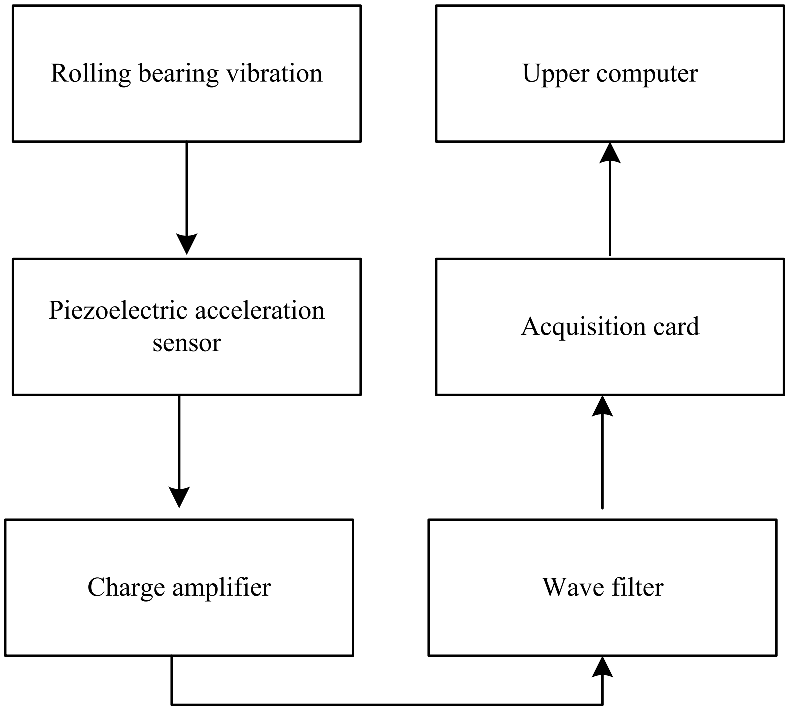

Figure 8. Flow of vibration detection and fault diagnosis system.

In order to further understand the equipment status, frequency domain information is often required. Because the amount of information provided by time-domain analysis is very limited, the time-domain eigenvalues can only roughly judge whether the equipment has a fault or the severity of the fault, but cannot judge the equipment or its location. The most common method of fault location is to analyze the signal in the frequency domain. Through the Fourier transform, the relationship between time domain and frequency domain is established, and the time domain signal is changed into a frequency domain signal. Then, through the analysis of each frequency domain signal, the characteristic frequencies of equipment parts are compared, so as to find the fault source. Amplitude spectrum: Fourier transform the sampled time-domain signal directly, and the obtained model is the amplitude spectrum of the signal. The mathematical expression is:

$$X_n(f)=\int_{-\infty}^{\infty} X(t)H_r e^{-2\pi}-1 \tag{13}$$

Power spectrum refers to the signal energy in the frequency domain n or power v. Self-power spectrum is often used to describe the distribution v'. Although it provides the same amount of information as the amplitude spectrum, it is clearer than the amplitude spectrum. There are two calculation methods, which are essentially the same. The self-power spectrum expression of the amplitude spectrum based on discrete sampling is

$$S_n(f)=\frac{1}{n}\left|X_n(f)-(v-v')\right|^2 \tag{14}$$

The formula for calculating the power spectrum based on the correlation function is:

$$S_x(f)=S_n(f)\int_{-\infty}^{+\infty} R_x(\tau)\cdot e^{-2\pi i}d\tau \tag{15}$$

where τ represents the effective value of the harmonic frequency time domain signal, R_x is the linear distribution of the amplitude of each harmonic of the time domain signal with frequency. $d\tau$ is the self-multiplication of harmonic frequency time domain signal amplitude, highlighting the main frequency components. The logarithmic spectrum is analysed for response analysis and averaging is achieved using frequency components with small amplitude, which can be used to observe all frequency components of the signal. Based on the above algorithm, abnormal data can be retrieved quickly to improve the accuracy of diagnosis and detection.

3. Analysis of experiment results

In order to test the performance of this algorithm in realizing the abnormal vibration spectrum feature extraction of engineering electric drive construction machinery and improving the accuracy of mechanical condition monitoring, a simulation experiment is carried out. The experiment is established on a large engineering electric drive construction machinery platform, and the TED2014 engineering electric drive construction machinery vibration signal acquisition system developed by our laboratory is used to collect the original information of mechanical vibration data. The vibration performance of electric drive construction machinery in transmission engineering is tested under five working modes of electric drive construction machinery. Set up sensor components inside the construction machinery for data collection, as shown in Figure 9.

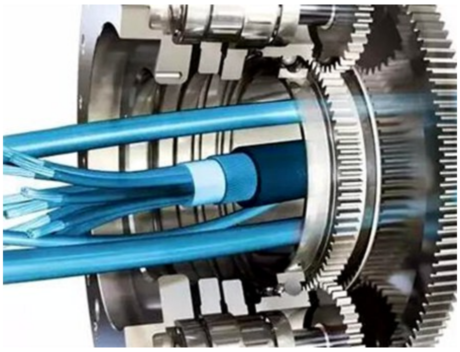

Figure 9. Schematic diagram of mechanical state detection.

The signal sampling frequency is 60 kHz, the parameter setting is v = 8, w = 2, the number of subcarriers of abnormal vibration signal to a single engineering electric drive construction machinery is 32 and 256, the delay is 5 sampling points, the signal-to-noise ratio is -10 dB and the number of weights selected is m = 20, step = 0.005. According to the above simulation environment and parameter settings, the vibration signal collection of the original engineering electric drive construction machinery is obtained. The abnormal vibration problems of the engineering electric drive construction machinery can be specifically divided into rotating body failure, inner ring failure and outer ring failure. Therefore, in this study, the setting state of the engineering electric drive construction machinery is divided into normal state, rotating body failure state, inner ring failure state, and outer ring failure state, and then wavelet packet analysis is used. The vibration signals of engineering electric drive construction machinery in different setting states are decomposed and reconstructed, and the energy entropy characteristics of the signals processed by wavelet packets are extracted. Finally, the frequency band energy entropy and relative energy entropy data groups of engineering electric drive construction machinery vibration signals in different setting states are obtained as follows:

Table 3. Energy entropy data of vibration signal frequency band of engineering electric drive construction machinery.

Bearing setting state	Band energy entropy after wavelet packet decomposition and reconstruction E30	E31	E32	E33	E34	E35	E36	E37
Normal state of bearing	9.8158	6.7278	1.5026	4.2036	0.0879	0.3075	0.3869	0.8563
Rotating body failure state	29.5359	14.5315	46.7812	21.4458	2.1178	2.6212	35.3036	15.2661
Inner ring failure status	6.3847	6.0751	14.9889	3.9798	0.8262	1.7497	17.0583	2.6867
Outer ring failure status	60.9998	39.4902	41.7067	16.7605	1.4975	1.74325	31.3845	6.7973

Take two data points as training samples for the rotor misalignment state and the rotor imbalance state, respectively. The eigenvector is shown in the table. Train the samples, set the global error to 0.07 and set the maximum training time as 1000. After training, the test results of the training samples are shown in Tables 4 and 5:

Table 4. Identification results of rotor misalignment.

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7
Output vector	0.062312	-0.00953	-0.02926	0.022017	0.044389	0.011575	-0.01336
	0.941718	1.005568	1.097797	0.857989	0.655599	0.86522	0.948149
	0.000469	0.004695	-0.0589	0.100118	0.302843	0.123948	0.071576

Table 5. Identification results of rotor unbalance state.

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7
Output vector	-0.0445	-0.0137	-0.02952	0.005159	0.036477	-0.02095	0.051465
	0.051817	0.090086	-0.09217	0.182567	0.287448	0.198947	0.055799
	0.981582	0.916898	1.106422	0.798733	0.678728	0.830456	0.908983

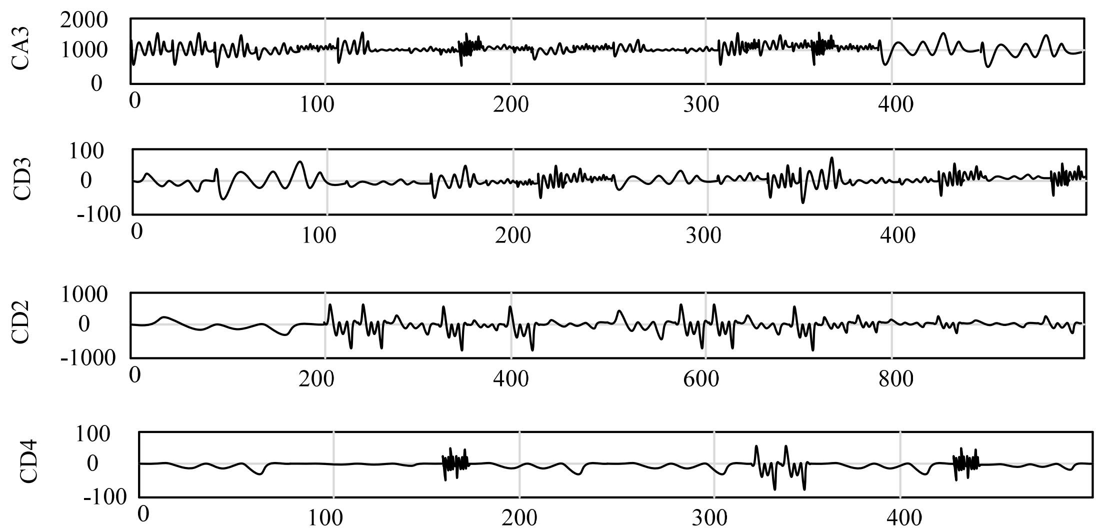

Figure 10. Characteristics of abnormal vibration of electric drive construction machinery.

Empirical mode decomposition and the method in this paper are used to decompose the abnormal vibration of engineering electric drive construction machinery into multiple components and extract the spectral characteristics of the abnormal vibration of engineering electric drive construction machinery. The spectral feature extraction results are shown in Figure 10.

It can be seen from the figure that the method in this paper can effectively reflect the variation characteristics of abnormal vibration harmonic components of engineering electric drive construction machinery, carry out pre-distortion chemotactic correlation analysis of vibration signals, optimize the structure and dynamic parameters of the transmission system on this basis, carry out abnormal correction, obtain the correction results, carry out pre-distortion chemotactic correlation analysis of vibration signals and optimize the structure and dynamic parameters of the transmission system on this basis. The abnormal correction of the gear is carried out and the correction results are shown in Figure 10.

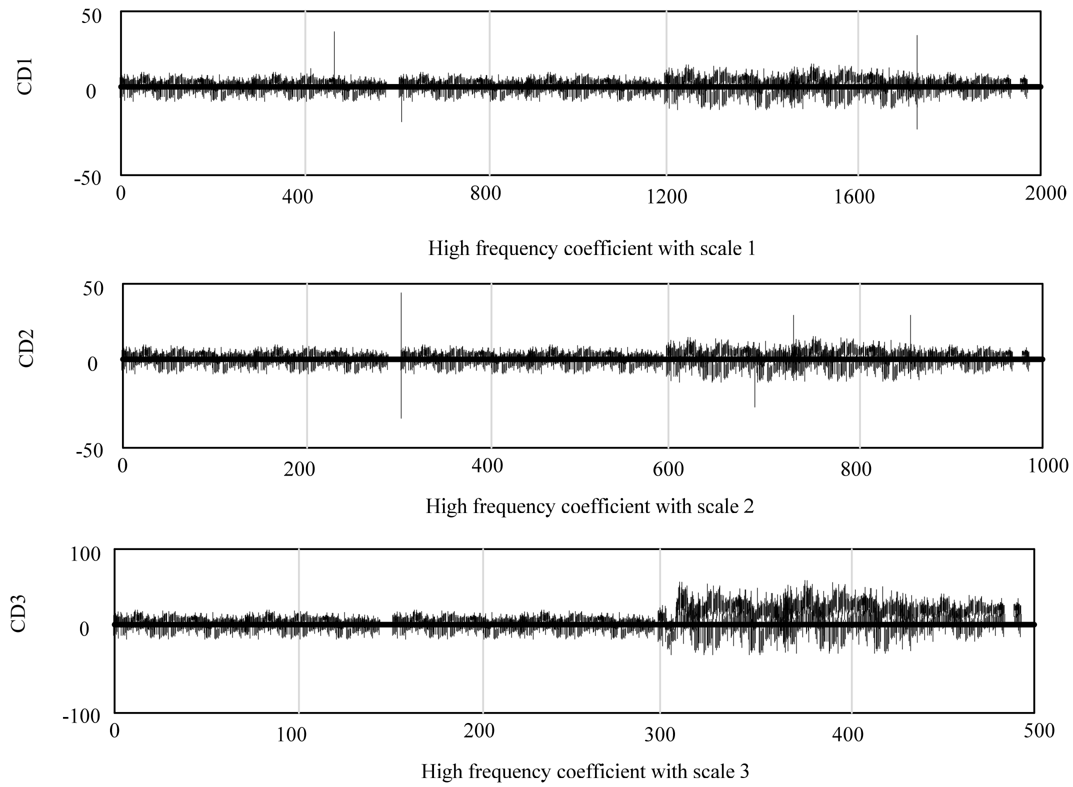

Figure 11. Correction results of abnormal meshing of engineering electric drive construction machinery.

Figure 11 shows the correction results of abnormal meshing of engineering electric drive construction machinery. It can be seen from the figure that this method is used to correct the abnormal meshing of engineering electric drive construction machinery. Through this method, the influence of alternating temperature and clearance on engineering electric drive construction machinery can be effectively avoided. With the increase in eccentricity, the lateral and axial vibrations are corrected, which improves the stability and reliability of the operation of engineering electric drive construction machinery. In order to test the abnormal diagnosis effect of mechanical vibration, a machine is used as the research object and the MATLAB 2020 toolbox is used for programming and simulation experiments. The equipment and testing machines used in the experiment are shown in Figure 12(a),(b). Mechanical faults include initial imbalance, oil film oscillation, coupling fault, misalignment, eccentricity, etc. The number of training samples and test samples for generating a mechanical working state is shown in Table 6. Support vector machine (SVM) without principal component analysis is selected to test the superiority of this method in mechanical fault diagnosis.

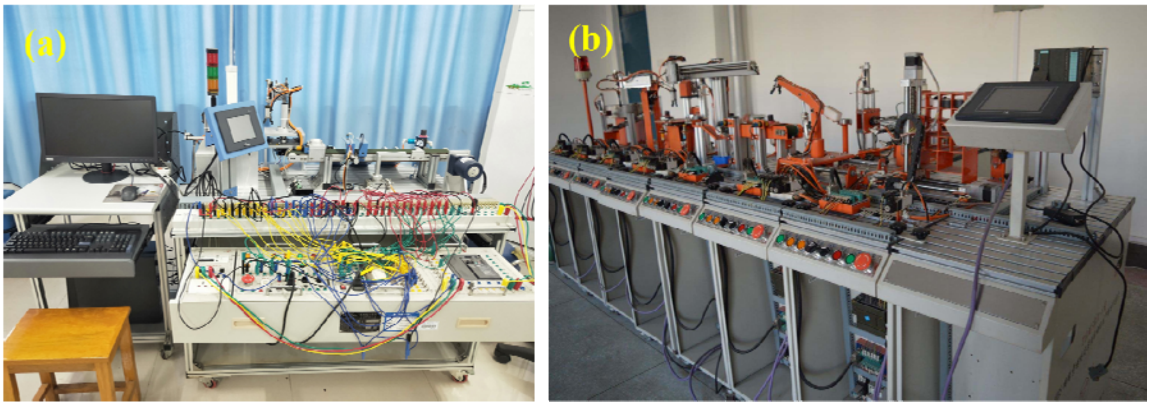

Figure 12. Equipment and testing machines used in the experiment.

Table 6. Sample distribution of mechanical working state.

State	Code	Number of training samples	Number of test samples
Initial unbalance	1	12	7
Oil film oscillation	2	12	7
Coupling failure	3	16	7
Not right	4	12	7
eccentric	5	16	7
normal	6	20	7

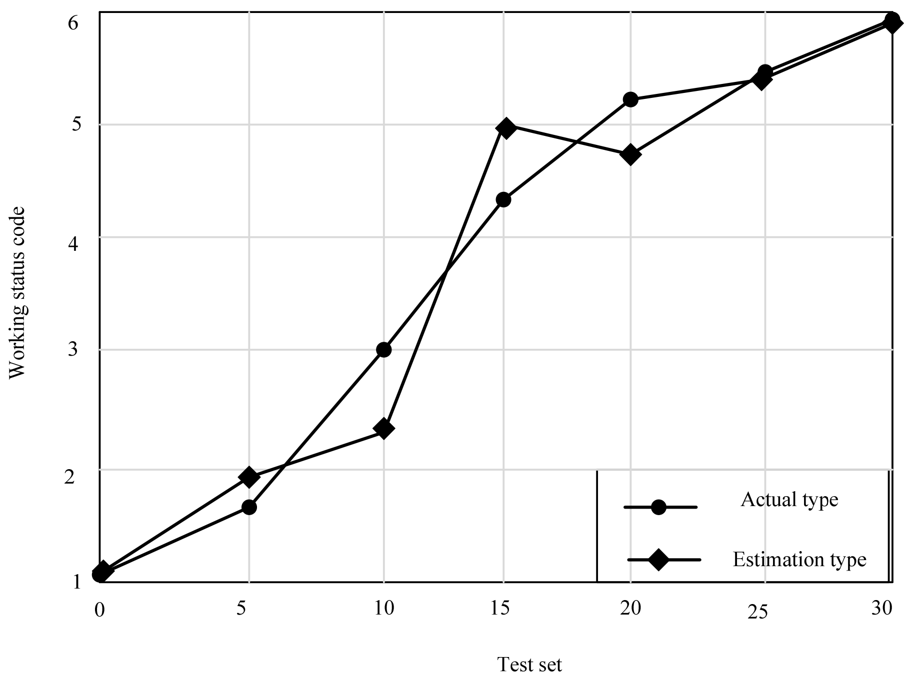

Figure 13. Mechanical fault results of SVM.

The vibration detection effect of the traditional SVM detection method and this method in a noise interference environment is compared and recorded, as shown in Figures 13 and 14.

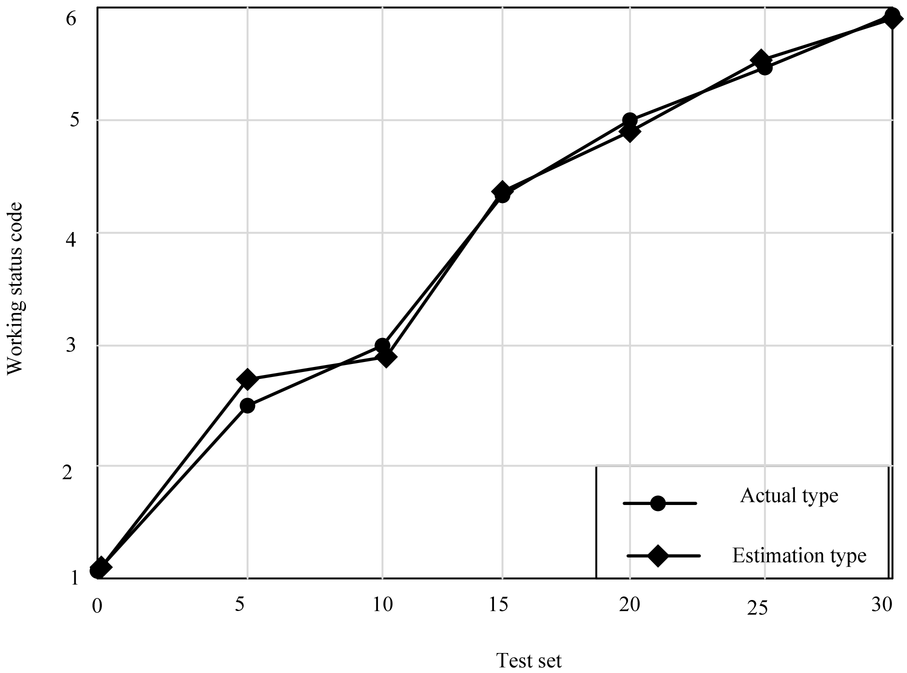

Figure 14. Mechanical failure results of this method.

Based on the above comparison, the detection results are true. Compared with the traditional SVM detection method, this method fits the standard curve better, which shows that this method can diagnose mechanical vibration more accurately. The overall running time and diagnostic accuracy of the two methods are compared. And the results are shown in Table 7:

Table 7. Comparison of fault diagnosis results of different methods.

Method	Fault diagnosis time /s	Correct rate of fault identification /%
SVM	5.25	85.25
Method in this paper	1.25	96.29

According to the above results, this method can better detect and control the vibration wave frequency and the wave fluctuation is relatively small under the influence of the noise environment, which proves that this method can better identify, diagnose and warn about vibration and noise quickly. However, there are still some deficiencies in this method, which cannot completely eliminate the vibration and noise, and it still needs to be improved.

4. Conclusions

The failure of abnormal mechanical vibration is not inevitable but cannot be fundamentally eliminated. For relevant staff, we should adhere to the concept of prevention first and do a good job of prevention. It is particularly important for the maintenance of steam turbine units to be loyal to the mechanical equipment and the responsible personnel of the unit. The inspection records must be kept completely and properly. If the parts at the fault point of mechanical equipment have just been repaired or replaced, it is necessary to confirm the fault point. For abnormal vibration of mechanical equipment, first find out the cause of the fault. Then, "Suit the remedy to the case" is the most important. Utilizing the identification results, we have developed a dynamic characteristic model for engineering electrically driven construction machinery, aimed at streamlining the diagnostic procedures for detecting abnormal vibrations in such machinery. Subsequently, we conducted specific experiments to validate the accuracy of this method in detecting abnormal vibrations in construction machinery, ensuring the safety and stability of engineering electric transmission construction machinery during operation. Notably, our research in this article highlights the absence of comparative analysis concerning alternative detection methods. Considering that the primary objective of this study is to introduce a novel approach to engineering diagnostics, it becomes imperative to undertake more comprehensive analysis and research on various detection methods in future investigations.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there is no conflict of interest.

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