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NETWORK-BASED MECHANICAL VIBRATION FAULT DIAGNOSIS SYSTEM

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Abstract. Nowadays researchers are investing in electrical machines fault diagnosis area. The users and manufacturers are strong for containing diagnostic features for reliability and scalability improvement. The regular monitoring enables machine faults early detection and hence helpful for automation by providing process control. The fault detection performance and machine-learning algorithms classification are highly dependent on features involved. The aim of this paper is to solve the network mechanical vibration problem and for that a research on mechanical vibration fault diagnosis is proposed. The first is to use the vibration signal receiving device to record the vibration signal of the target device. In the process of receiving the signal, the measurement point is related to the accuracy of the received signal, so it is necessary to prepare the measurement point. Secondly, the principle of fault detection based on vibration detection is introduced. The main purpose of this method is to identify the fault characteristics, simulate the fault with MATLAB, and obtain the error time-frequency diagram behavior. The feature vector dimension obtained by the idling confirmation example is the same as that of the rotor, which is 14, including 8 relative wavelet packet intensity entropy feature indexes and higher values, minimum value, peak-to-peak value, mean value, mean square error and variance. Finally, the deficiencies of the detected vibration faults are identified and similar improvements are proposed. Improvements only reduce signal vibration, disrupting feature isolation and identifying patterns.The observed percentage accuracy for classification of faults through proposed approach is 98.2%.

Key words: computer network; teaching management; JSP technology; system design

1. Introduction. The equipment in the network operation is accompanied by vibration, and the potentially defective parts will also vibrate when moving, especially the defects of many mechanical parts; Equipment fault diagnosis mainly includes oil analysis, vibration signal analysis, infrared thermal imaging and other methods, at present, vibration signal analysis is the most widely used method, vibration signal analysis is to use sensors to detect mechanical vibration in the form of electricity, after amplifying and filtering the input to the analysis processor, and then analyzing it, a series of processes of artificially extracting the fault characteristic signal, therefore, through vibration signal analysis, we can find out the problems that are occurring in the equipment, at the same time, the comparison of the vibration data and signal energy of the periodic test and the measuring point is used to find the deterioration trend of the equipment, and to provide a basis for the annual maintenance of the equipment [1]. In order to obtain a good frequency response range, the sensor and the measuring point of the device are installed by magnetic suction (rubidium magnet). The test frequency range can reach 10000 Hz, the equipment is tested in this way, indicating the effectiveness of the vibration analysis method for fault diagnosis, as shown in Figure 1.1.

The acquisition of fault information is the first step to realize fault diagnosis of mechanical equipment, and it is an important basis for fault diagnosis work. The acquisition of fault information is a technology of signal detection and quantification of the working parameters, performance indicators, related physical quantities and other information of the mechanical equipment itself, the sensor is a device that obtains various information and converts it into an electrical signal, and is the key and main means of obtaining fault information. The fault characteristics of machinery are often reflected in the vibration condition, the use of vibration signals to diagnose equipment is the most effective and commonly used method in fault diagnosis. The fault diagnosis and its protection background are as earliest as the machineries themselves. Initially, the machineries manufacturers and their users relied on modest safety such as protection from over voltage. The reliability and safety operation are ensured by this precaution. However, the machinery becomes more complex with increase in number of tasks. Therefore, the diagnosing faults improvement is the requirement and the fault diagnosis becomes very

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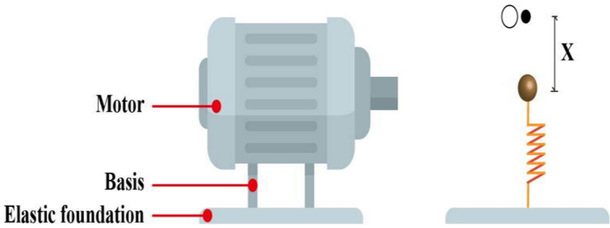

Fig. 1.1: Fault diagnosis of network mechanical vibration [2]

important because the machine unwanted downtime can cause loses.

A flexible system for communication and transmitting the information is provided by the industrial wireless sensor. The wireless sensor networks (WSN) need more attention in service parameters quality such as energy consumption, information and cost reliable transmission for obtaining good performances. The wireless sensor networks and IoT based application is challenging for managing large amount of real time data. The Fault detection and its diagnosis are important for the efficiency of machinery maintenance. The small and large rotating machinery necessity in industrial systems enforces monitoring, maintenance, and reparation. The condition monitoring necessity is rotating machines to provide machines condition knowledge at each moment without production stopping. Common techniques like vibration monitoring is one of the best condition monitoring for detection, location and distinguish faults before they become critical and dangerous. The most essential mechanical of rotating machinery elements is bearing. The rotating shafts are supported by them and on the other side the mechanical faults in rotating machinery are shown by several studies. Therefore, the level of production and equipment is influenced by the bearings fault as well as having an unsafe environment. The condition monitoring, early fault detection and fault diagnosis of these bearings is main fundamental axes of industrial research.

Contribution.

1. In order to solve the problem of network mechanical vibration, a research on mechanical vibration fault diagnosis system is proposed.
2. The first is to use the vibration signal receiving device to record the vibration signal of the target device. In the process of receiving the signal, the preparation of the measurement point is related to the accuracy of the received signal, so it is necessary to prepare the measurement point.
3. Secondly, the principle of fault detection based on vibration detection is introduced. The main purpose of this method is to identify the fault characteristics, simulate the fault with MATLAB, and obtain the error time-frequency diagram behavior.

   The rest of the paper is organized as follows. Section II provides an overview of the exhaustive literature survey followed by a methodology adopted in section III. Proposed method is detailed in section IV and the obtained results are discussed in section V. Finally, concluding remarks are provided in Section VI.

2. Literature Review. The safe and stable operation of machinery and equip- ment is a prerequisite for ensuring normal production. Therefore, it is of great signif- icance for the smooth progress of production to accurately grasp the operating status of machinery and equipment, and to detect and eliminate equipment failures in time. At present, mechanical vibration signal analysis has become one of the main methods for judging the operating status of mechanical equipment [1]. Moreover, with the increasing maturity of network technology, the research on network-based equipment condition monitoring system continues to deepen, it has outstanding advantages in resource sharing and remote monitoring. To this end, the author designs a network-based mechanical vibration signal analysis system for judging the running state of mechanical equipment. In 1984, Gai, J et al. applied the HICLAS fault early diag- nosis device developed by the Japan Construction Machinery Co., Ltd. to carry out early diagnosis of the oil pump, the wear condition inside the oil pump can be directly detected from the oil pump indication in a short period of time, and the device can judge the working life of the oil pump to continue running, make failure prevention possible [2]. In 1992, Glowacz, A used the detection of the vibration velocity of the free end bearing of the centrifuge and the comprehensive trend diagram, and analyzed the spectral characteristics, a centrifuge outer bowl imbalance fault was diagnosed.

Neural network has the ability to deal with complex multi-pattern matching and is an effective fault diagnosis method [3]. In 1996, Kim, H. E., Hwang, S et al. used BP neural network to effectively identify inner ring defective bearings, outer ring defective bearings, roller defective bearings and some comprehensive fault characteristics, which can improve the efficiency of fault diagnosis [4]. In 2004, Shan, P. et al. used the fast ICA algorithm to separate the vibration signal of the bearing, and then compared its power spectrum with the spectrum of the original vibration signal, the results show that ICA is easier to achieve early diagnosis of faults [5]. Same year, Yang, J. et al. proposed a new time-frequency analysis method with adaptive characteristics of local wave time-frequency distribution, the rubbing, misalignment and early fault signals that are common in rotating machinery are analyzed, and the frequency spectrum analysis is compared [6].

In 2006, Sun, Y. et al. combined wavelet filtering and cy- clostationarity analysis method, and first carried out Morlet wavelet defect bearing failure on the original vibration signal, moreover, the severity of the fault can be identified within a certain error range [7]. On the basis of the current research, a research on mechanical vibration fault diagnosis system is proposed. Through actual data acquisition, the accuracy of the system acquisition module is verified. Through the analysis of unbalance fault signal, oil film whirl fault signal, vibration signal of rotor speed up and down process and rolling bearing fault signal, the correctness of the vibration signal analysis module is verified. The unbalanced rotor is dynami- cally balanced by the system dynamic balance module, and a good balance effect is obtained. The system has good expansibility, and can form a vibration signal acquisi- tion network through combination. The author's research has good application value in remote acquisition and analysis of vibration signals of mechanical equipment and rotor dynamic balance. Author presented the scattering transform utilizing machine learning for translational, rotational and deformation extraction for the first time from vibration signals found from rolling element bearings (REBs). The scattering transform core idea lies in scattering network construction which is formed from a signal processing layers. The association of a linear filter bank associate each layer and utilizes wavelet filter bank, modulus rectifiers and averaging operators cascading for deep convolution network and multi-scale co-occurrence coefficients are computing. Features are extracted as scattering transform coefficients from vibration signal prognosis data repository then input to a support vector machine (SVM) classifier. To obtain distinguishing features, test results analysis and solutions are utilized [8]. Author discussed that due to the potential advantages machine fault diagnostic and prognostic techniques have been the considerable for condition-based maintenance system from reducing downtime and increasing machine availability. Research on ma- chine fault diagnosis and prognosis for the past few years has been developing quickly.

Author summarizes and recent published techniques classification of rotating machinery in diagnosis and prognosis. Furthermore, opportunities as well as the challenges are also discussed for conducting the research machine prognosis field [9]. Author in this paper presents the relevant features extraction based on oriented sport vector machine (FO-SVM) and it is capable for extracting the most relevant feature set. The most relevant features extraction before classification process in higher classification accuracy. As observed the presented technique consumes less time for cloud. The presented approach provides prediction of fault accurately based on cloud platform by utilizing the industrial wireless sensor networks. In this paper, author discussed the bearing vibration frequency features for motor fault diagnosis. This paper presents an approach using NN and time/frequency-domain for vibration analysis. The Vibration simulation is utilized in the design of various motor rolling bearing fault diagnoses. The result obtained from the presented technique indicates that NNs can be efficient agents in the various motor bearing faults diagnosis through the measurement of motor bearing vibration [10]. Author presented and implements the identification, diagnosis and common fault remedy techniques utilizing vibration analysis and summaries important techniques utilizing for rotating systems condition monitoring such as fast Fourier transform, frequency domain decomposition method and deep learning [11]. Author in this paper presented a convolutional neural network (CNN) to learn features directly from frequency data of vibration and testing the feature learning performance from raw data, frequency spectrum and combined time-frequency data [12]. The time domain, frequency domain and wavelet domain are used for comparison purpose. The presented method is validated by using gearbox challenge data and a planetary gearbox test rig. This presented method is able to learn features from frequency data adaptively and achieve higher diagnosis accuracy. This paper presents a deep CNN-based transfer learning approach and it consists of two parts; the first part is constructed with a pretrained DNN that extract the features automatically from the input, and the second part is connected stage for the feature extraction that needs to be trained by using gear fault data [13]. Case analyses by utilizing the experimental data from a gear system indicate that the presented approach not only entertains preprocessing adaptive feature extractions, but also requires training data. Author in this paper proposed a selective kernel convolution deep residual network based on the channel-spatial attention mechanism and feature fusion for mechanical fault diagnosis. The model effectively extracts fault features from the vibration signal as compared to conventional deep learning methods, and the fault recognition effectiveness is improved [14]. As compared to other algorithms, the presented method has higher fault identification ability, therefore demonstrating the channel-spatial attention mechanism network advantages and accuracy and the robustness of the model were verified.

2.1. Research Gap. After exhaustive literature survey it is found that there is a problem of network mechanical vibration and existing techniques are unable for early detection of machine faults providing process control. The feature extraction techniques are also not effective and the fault detection performance is highly depend on features involved.

3. Methodology.

3.1. Research trends at home and abroad. The state analysis and fault diagnosis technology of mechanical equipment is a new discipline developed in the middle and late 1960s. In the theoretical and applied research of state analysis and fault diagnosis, some developed countries in the United States, Japan and Europe are at the forefront of the world. Condition analysis and fault diagnosis originated in the United States, and have been widely used in aviation, military, energy, machinery and other departments, and are in a leading position in the world. In the 1970s, the U.S. Department of Defense began research on reliability-centered condition analysis techniques and applied them to aircraft, ships, and vehicles. At present, in terms of rotating machinery state analysis system, the M800A system of SKF Bearing Com- pany in the United States, the Tranmaster2000 system of Bently Nevada Company in the United States, etc., are all representative rotating machinery state analysis systems". Japanese state analysis and fault diagnosis technology began in the 1970s. In 1971, Japan began to develop its own total production maintenance (TPM), and learned about the research work of diagnostic technology from Europe and the United States, which basically reached the practical stage in 1976 [15]. Among the national research institutions, the Institute of Mechanical Technology and the Institute of Ship Technology focus on the diagnostic technology of mechanical basic parts.

Research status of fault diagnosis methods for mechanical equipment The beginning of fault diagnosis technology is the analytical redundancy method proposed by Beard of the Massachusetts Institute of Technology. [16]. After more than 20 years of research and development, although there are many research achievements in mechanical fault diagnosis in my country, fault diagnosis technology is a comprehensive discipline, with the development of fuzzy set theory, genetic algorithm, support vector machine, expert system, neural network technology and wavelet analysis theory. Due to the differences in the feature description and decision-making methods adopted by the system, the current fault diagnosis technology, different diagnoses have been formed [17].

3.1.1. The basic process, principle and method of fault diagnosis of mechanical equipment. During the degradation process of mechanical vibration, it basically follows the well-known "bathtub curve" law, the whole process includes: The running-in period, normal trial period, and wear-out period are shown in Figure 3.1.

Through the necessary measurement and fault diagnosis of mechanical vibration, it is possible to find out which phase the equipment is in at a certain stage in time, so as to prevent the equipment from entering the wear and tear period in advance. Mechanical fault diagnosis technology (Mechanical Fault Diagnosis) refers to in a certain working environment, use the detection device to detect the state information of the mechanical equipment in operation or under relatively static conditions, by analyzing the operating status information of the mechanical equipment to determine whether the mechanical equipment is in a normal operating state, combined with the failure mechanism and historical operating status of the diagnostic object, in order to qualitatively and quantitatively determine the real-time operating status of mechanical equipment and its components, and according to the corresponding fault characteristics to determine the possible faults and fault locations of the

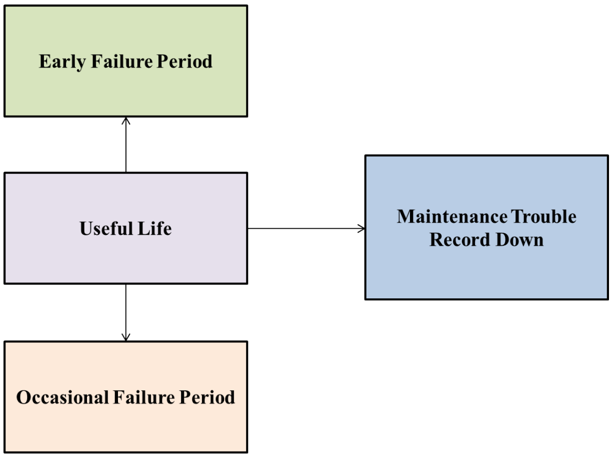

Fig. 3.1: Bathtub Curve

mechanical equipment, predict the operating trend and remaining life of related failures to determine targeted equipment management, maintenance and repair countermeasures.

The purpose of fault diagnosis is to find faults in time and minimize losses. The basic process of mechanical equipment fault diagnosis is shown in Figure 3.2, there are three main steps in the diagnosis process: The first step is to obtain characteristic signals of mechanical equipment status, such as vibration, noise, temperature, pres- sure and other signals; The second step is to extract fault features from the measured characteristic signals, and the extraction of fault features; The third step is the core of the whole diagnosis process, namely: Judging the specific fault of the equipment and forming a maintenance decision.

4. Proposed method. Fault diagnosis mainly includes the following aspects: Research on fault mechanism and fault symptom; Research on fault information acquisition method; Research on signal processing and fault feature extraction methods; Research on diagnostic reasoning methods; Research on the development of fault diagnosis systems.

(1) The program is not good, and the research is not good. A criminal investi- gation is the basis for a misdiagnosis. Defects or failures of equipment are usually caused by signal events during operation. The failure process has studied the causes of failures and the relationship between failures and symptoms, and found general laws through theoretical calculations or experimental studies. As the basis of fault diagnosis technology, only by studying the faults of the detected products can the primary and secondary causes of the faults be distinguished, and a reliable basis for judging and diagnosing faults can be provided. Many experts and scholars at home and abroad have done a lot of theoretical and experimental research on ma- chine tool failures, and made many important decisions, which are conducive to the inspection and testing of defective products. In 1968, American scientist John Sohre gave a general description of the symptoms and causes of machine dysfunction in the form of a table, and clearly and concisely divided criminal behaviors into 9 categories and 37 categories, research results. It is widely used in practice.

(2) Research on the method of fault information acquisition. The acquisition of fault information is the first step to realize fault diagnosis of mechanical equipment, and it is an important basis for fault diagnosis work. The acquisition of fault information is a technology of signal detection and quantification of the working parameters, performance indicators, related physical quantities and other information of the mechanical equipment itself, the sensor is a device that obtains various information and converts it into an electrical signal, and is the key and main means of obtaining fault information. The main physical quantities involved in the detection of mechanical equipment information include vibration, force, sound, rotational speed, temperature, and flow rate. Since the fault characteristics of machinery are often reflected in the vibration condition, the use of vibration signals to diagnose equipment is the

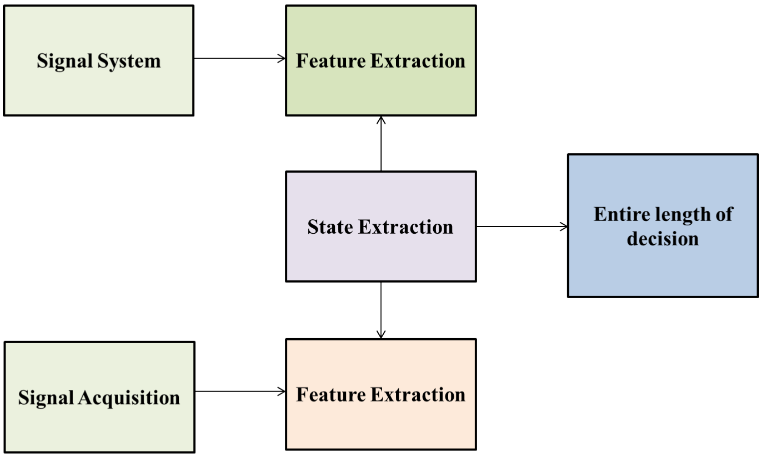

Fig. 4.1: Fault diagram for fault diagnosis

most effective and commonly used method in fault diagnosis.

(3) Research on signal processing and fault isolation. In the development of investigative technology, the most important and most important problem is the elimi- nation of illegal features, which directly affects the accuracy of the investigation, the guilt and the reliability of predicting the crime. To solve the key problem of data leak- age, people can only rely on signal processing, especially the theoretical and technical means of processing signal processing.

(4) Development and research of misdiagnosis. Regardless of craftsmanship and technological output, they will eventually become practical. Fault diagnosis technology is a practical technology. Therefore, while paying attention to theoretical innovation, attention should be paid to the development of a fault detection system with certain practical value. At present, the improvement of the criminal justice system mainly includes the following two aspects: physical examination and online monitoring of criminal investigation.

4.1. Principle of fault diagnosis based on vibration detection. In the fault detection based on vibration detection, the first vibration signal collection device is used to collect the vibration signal of the target device. In the process of receiving the signal, the preparation of the measurement point is related to the accuracy of the received signal, so it is necessary to study the preparation of the measurement point. Different functions of the device will cause changes in the vibration signal, that is, when the device has some abnormality or failure, the vibration signal will change accordingly, and the change in guilt is the sin. It is based on this principle that vibration detection and vibration signal analysis can be used to diagnose the rotor and bearing faults of centrifugal fuel pumps. It can be seen from its principle that the most important part of error detection as vibration detection is to identify fault features, and through different features, detect irregularities. The author will focus on the simple vibration signal receiving system, the time-frequency characteristics of the fuel pump failure theory, and the characteristics of the fuel pump summarized in the gas station.

5. Experiments and Research.

5.1. System Composition. The network-based mechanical vibration signal analysis system relies on the network to realize the acquisition, analysis and rotor dynamic balance of mechanical vibration signals. The system is mainly composed of sensors, data acquisition cards, and vibration signal analysis systems. Among them, the vibration signal analysis system is a software system rooted in the computer, including a vibration signal acquisition module, a vibration signal analysis module, and a rotor dynamic balance module. The block diagram of the network-based me- chanical vibration signal analysis system is shown in Figure 5.1.

In Figure 5.1, the sensor first converts the measured physical quantity into an output analog signal. Subsequently, the data acquisition card preprocesses the analog signal output by the sensor, and performs AID

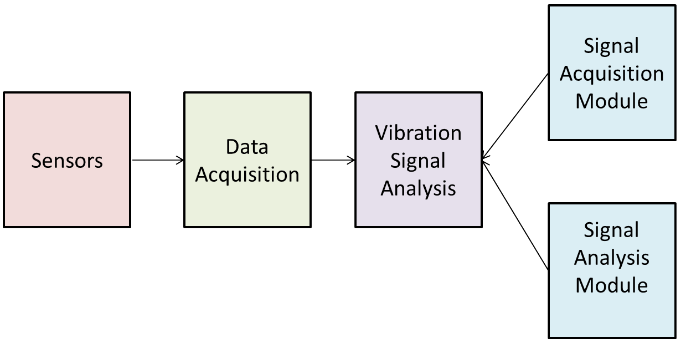

Fig. 5.1: Block diagram of network-based mechanical vibration signal analysis system

conversion on the preprocessed analog signal to convert it into a digital signal. The vibration signal analysis system completes the analysis and processing of digital signals. Among them, the signal acquisition module mainly realizes the acquisition of vibration signals; The signal analysis module can complete the offline analysis of the collected vibration signals; The rotor dynamic balancing module can dynamically balance the unbalanced rotor.

Design of vibration signal analysis module Vibration occurs natu- rally when equipment is in operation, the severity of the vibration is often a precursor to a crash, and the characteristics are usually obvious. Therefore, from the perspec- tive of vibration signal analysis and diagnosis, it is also the main means of maintaining and controlling equipment at present. Time domain analysis and frequency domain analysis are the types of vibration signal analysis, especially frequency domain anal- ysis. is one of the best ways to detect vibration faults. The vibration signal analysis module developed by the author only recognizes offline analysis of stored data, includ- ing: time domain analysis, frequency measurement instrument. Frequency anal- ysis includes: amplitude spectrum, starting power spectrum, cross power spectrum, ZOOM-FFT, envelope spectrum, cepstrum, order spectrum, waterfall plot, Bode plot. 1Time domain analysis The time domain analysis functions of vibration signals in this system mainly include: Waveform display, filtering, probability density analysis, au- tocorrelation analysis, cross-correlation analysis, bar graph analysis, recursive graph analysis, time domain indicator analysis, data playback. 1. Waveform display The waveform display can reproduce the waveform of the collected data of each channel. By observing the time-domain waveform of the vibration signal, the operating state of the mechanical equipment can be estimated. 2. Filtering The actual collected vibration signal usually contains a lot of noise, the superposition of the noise and the useful signal will distort the waveform of the useful signal, it is not conducive to the analysis of useful signals. Filtering the vibration signal can remove the noise in the signal and make the characteristics of the useful signal more obvious, which is beneficial to the waveform analysis of the useful signal.

5.2. Examples of Failure Mode Recognition. Similar to the example of fault pattern recognition of centrifugal oil pump rotor based on BP neural network, when identifying the bearing structure of oil centrifugal pump, the neural network structure of bearing fault structure should be designed first. Similarly, suppose the number of nodes in the input process is n, the number of nodes in the output process is m, and the number of nodes in the input process is o, then designing a neural network includes the following steps: 1. Determine the number n of the input process: the number of input nodes is the size of the eigenvector, the length of the eigenvector used in the fault type identification system is the same as the rotor example, a total of 14, including 8 relative wavelet packet power characteristics features and 6-time fill features such as max, min, high out, mean, squared error, and variance. 2.Determine the number of output layer nodes m: The purpose of determining the output vector is to make for each input sample, there are different output vectors corresponding to the pattern recognition. In this example, the determination principle of the output vector is as follows: When the bearing is set to the normal state, let the network output be y1=[1 000]T; When the bearing is set to the failure state of the rotating body, let the network output be y2=[0 1 00]T; When the bearing is set to the failure state of

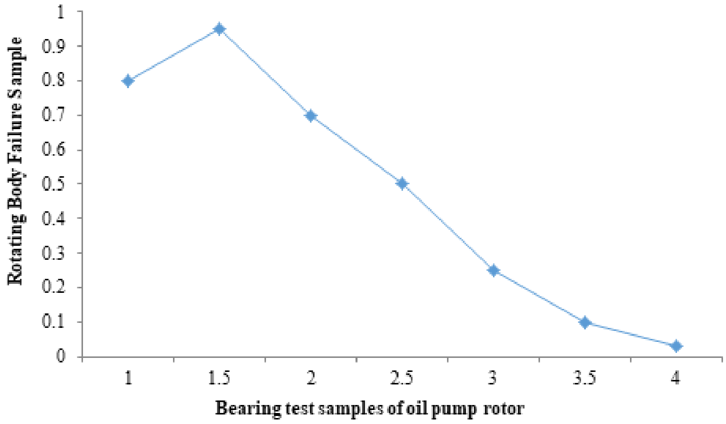

Fig. 5.2: State identification diagram of bearing test samples

the inner ring, let the network output be y3=[00 1 0]T; When the bearing is set to the failure state of the outer ring, let the network output be y4=[0 001]T. Since the fault may be one type of fault or multiple faults occur at the same time, with the deepening of research, it is necessary to continuously adjust the output layer nodes. 3. Set the number of hidden layers o: Since the three-layer BP neural network can identify the mapping from 1 n-wide to 1 m-dimensional space, the author chooses the three-layer BP neural network for fault identification. Types of centrifugal oil pump rotors. The number of latches is 2n + 1, or 29, as shown in Figure 5.2.

5.3. Key Technologies of Fault Diagnosis. Globus is a research and development project of Argonne National Laboratory in the United States, and 12 universities across the United States participated in the project. Globus researches key communication concepts such as resource management, security, data services and data management, develops network tools (Toolkit) that can run on multiple platforms, helps plan and build large-scale projects, develops large-scale network operations at the scale required application. Toolkit is the most important feature of Globus, its first version was launched in 1999. Toolkit is open source, and anyone can download the code from its website. Currently, Globus technology is used in eight applications, including the National Aeronautics and Space Administration Grid (NASA IPG), the European Data Grid (Data Grid) and the US National Technology Grid (NTG). Generally speaking, network computing focuses on large-scale projects, which, according to Globus, require collaboration between multiple organizations, who create ”virtual entities” and are done by Chinese equipment that all organizations participate in virtual organization cooperative.

5.4. Comparative analysis on the basis of performance metrics. The performance of the proposed technique is compared with the existing technique as shown in Figure 5.3 and Figure 5.4 . The observed percentage accuracy for classification of faults through proposed approach is 98.2%. The sensitivity and specificity of the existing SVM technique and the proposed technique are compared and it is obtained that the higher values of specificity and sensitivity are obtained by the proposed technique as compared to the existing technique. The precision, recall and accuracy values are also compared and the improvement is shown by the proposed technique.

6. Conclusion. Through the research on the principle of vibration detection fault diagnosis method, the author finds that its core lies in the identification of fault features. Through theoretical research and the help of MATLAB simulation, the time-frequency characteristics of common faults of centrifugal oil pump are summarized and studied. In addition, due to the gap between the theory and the present, it is theoretically possible to diagnose the corresponding fault according to the time frequency characteristics, however, in the actual operation of the oil station, other characteristics must be integrated in order to have a better identification of the fault. Even so, there are still some deficiencies in the commonly used vibration detection and fault

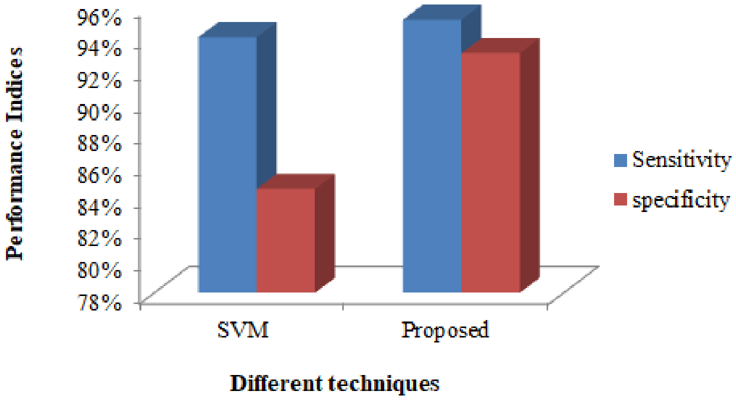

Fig. 5.3: Performance indices: Sensitivity and specificity

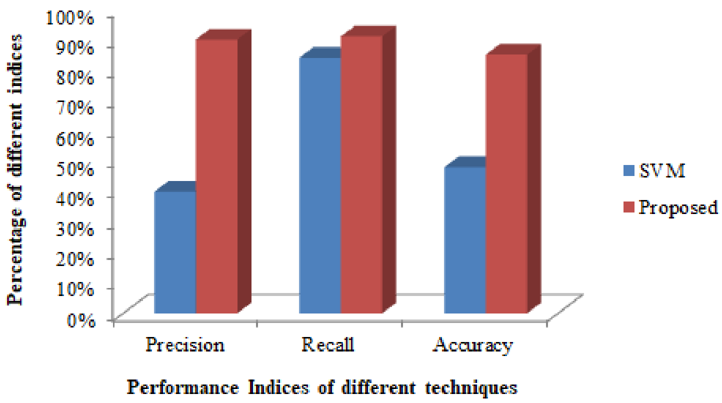

Fig. 5.4: Performance indices: Precision, recall and accuracy

diagnosis methods, therefore, it is proposed that the next step will be to focus on the noise reduction of vibration signals, the feature extraction of wavelet packet energy entropy and the use of BP neural network to identify faults.

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