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Application of Robotic Key Technology in Wind Power Bearing Fault Diagnosis and Failure Prediction Technology

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Wind energy occupies a pivotal position in the development of clean energy and has become one of the fastest growing renewable energy sources. This paper analyzes the application of robotic key technology in wind power bearing fault diagnosis and failure prediction technology and studies the current situation and future development of wind power bearing faults. This research uses distributed experimental methods to record data to obtain experimental results. Using the current data statistics of wind capacity across the world, the fault units, forms and causes of wind turbine farms such as Donggang, Saihanba, Yumen are analyzed. To do so, we construct a fault diagnosis technical model and failure prediction model using robotic remote monitoring technology, data analysis and signal acquisition technology. The experiment results show that the total difference between each major wind farm from 2018 is not large and the maximum failure time of each wind turbine subsystem is 33 minutes.

Keywords: robot Key technology, wind power bearing, bearing fault diagnosis, failure prediction technology

1. INTRODUCTION

Wind energy is currently one of the most important renewable energy sources [1]. Due to the low efficiency and randomness of wind power the grid-connected operation of wind turbines has a negative impact on the transmission and stability of the grid. Short-term wind speed and power prediction of wind farms is a prerequisite for large-scale wind power grid integration, which is conducive to the stable operation of the power system and grid dispatching. Wind power suffers from the problem of randomness. Forecasting wind speed is a crucial aspect of research into wind power systems and it is also an important function in the planning and design of wind farms [2]. The prediction accuracy of aircraft wind speed and wind power is directly related to the impact of wind turbines on the power system [3].

With the global energy shortage and environmental pollution intensifying, the use of renewable energy to replace fossil fuels has begun to attract international attention [4]. In the energy industry, wind power is a well-known energy source. The numerous sources of wind energy and the development of energy technology make it suitable for the development of large enterprises. However despite the rapid increase in the power of wind turbine assembly machines, the benefits of wind turbine generators are far lower than expected. The main reason for this is that the frequent failures of wind turbines have reduced wind power consumption and

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increased efficiency and maintenance costs [5]. Therefore, when designing awind turbine, both its performance and reliability must be considered. Improving the reliability of wind turbines means that the quality of wind turbines is improved [6].

A small horizontal axis wind turbine (HAWT) is technology with a non-trivial critical point, and dynamic control optimization, noise reduction and vibration reduction are urgent issues of this type of technology, and the condition monitoring of small HAWT generators is an overlooked topic. Natili performed a damage diagnosis test case study of a HAWT permanent magnet generator with maximum power of 3kW and a 2m rotor diameter and analyzed damaged and undamaged generators at different speed drives via a wind tunnel test and generator test bench [7]. As the operating conditions and loads of the wind turbine main bearings are significantly different from the operating conditions of more conventional power plants and other bearings (i.e. bearings in gearboxes and generators) present in the wind turbine power train, Hart [8] describes the most common main bearing settings and the criteria for bearing selection and ratings. Typical loads generated by the wind turbine rotor and subsequently acting on the main bearing are discussed. Hart aims to thoroughly document current major bearing theory to evaluate existing design and analysis practice, while also seeking to provide asolid foundation for future research in this field [8]. Ali proposed anew vibration-based online diagnosis method for wind turbine high-speed bearing monitoring. Adaptive Resonance Theory 2(ART2) is proposed for the unsupervised classification of extracted features. The Randall model is adjusted to take into account the geometry of the tested bearing to train ART2 in an offline step. To better characterize the bearing failure, the time domain, frequency domain and time-frequency domain are studied, using real measurement data from the wind turbine transmission system to prove that the proposed data-driven method is also suitable for wind power even under real experimental conditions of online condition monitoring of turbine bearings [9]. An analyzed the signals collected from wind turbines and extracted their features through empirical mode decomposition (EMD). In the experiment, the following fault signal is used as an example of EMD learning: a back propagation (BP) neural network algorithm with generator vibration, rotor imbalance and bearing misalignment faults [10]. Turnbull trained the support vector machine algorithm by analyzing high-frequency vibration data and extracting key features. The accuracy rate of successfully predicting a failure 1-2 months before the occurrence can reach 67%. Utilizing all available data reflects the limitations surrounding common training methods, indicating that if too many different examples of different wind turbines and operating conditions are considered, the overall accuracy may be reduced [11]. Ziani's vibration-based method is the most commonly used technique in condition monitoring tasks. In his paper a bearing fault detection scheme based on the support vector machine as the classification method and the binary particle swarm optimization algorithm (BPSO) based on the maximum class separability as the feature selection method is proposed. To maximize the separability of classes, the regularized Fisher criterion is used as the fitness function in the proposed BPSO algorithm. This method uses the vibration data of the bearing under healthy and faulty conditions for evaluation [12]. Hu used multiple examples of bearing failures of the same generator to gain insight into how to use condition monitoring systems to train machine learning algorithms, with the ultimate goal of predicting failures and remaining service life. The results show that by analyzing high-frequency vibration data and extracting key features to train the support vector machine algorithm, successfully predicting a failure 1–2 months before the occurrence can reach an accuracy of 67%. Utilizing all available data reflects the limitations surrounding common training methods, indicating that if too many examples of different wind turbines and operating conditions are considered, the overall accuracy may be reduced [13]. As a key component, the failure of high-speed shaft bearings in wind turbines can cause unscheduled power production stoppages. Relatively few investigations have been conducted on the natural development defects of high-speed shaft bearings in the aforementioned related studies, and there are few online assessments of the severity of damage in the literature.

Anew idea is proposed for abnormal identification or early fault prediction based on robotics, namely the wind speed power scatter is matched by least squares to improve the fitting accuracy and the sliding longitudinal comparison scheme for the power curve is proposed to avoid the influence of interference factors. Secondly, for specific fault types, this paper proposes an improved multi-parameter fault prediction method that considers weight, which solves the problem of low single-parameter prediction accuracy and no weight consideration for multiple parameters. Failure prediction technology is the most difficult to achieve but is also the most meaningful.

2. WIND POWER BEARING FAILURE

2.1 Key Robotic Technology and Wind Farm Construction

The artificial intelligence network has become a hot topic in the field of error analysis [14]. With the continuous progress and popularization of technologies such as computers and the Internet, the fault diagnosis process has gradually changed from the original on-site detection to remote online monitoring. The key technologies of robotics include remote monitoring technology, simulation technology, inspection technology, big data and analysis technology, machine autonomous technology, etc. In recent years, the development of diagnostic technology based on acoustic emission signals and the in-depth research into artificial intelligence and mechanical fault diagnosis adds new vitality [15]. Furthermore, the fault diagnosis expert system has not only made great developments in theory, it has also obtained considerable results in practical applications [16].

The wind power industry has the characteristics of large stock, wide distribution, and reliable technology, and has

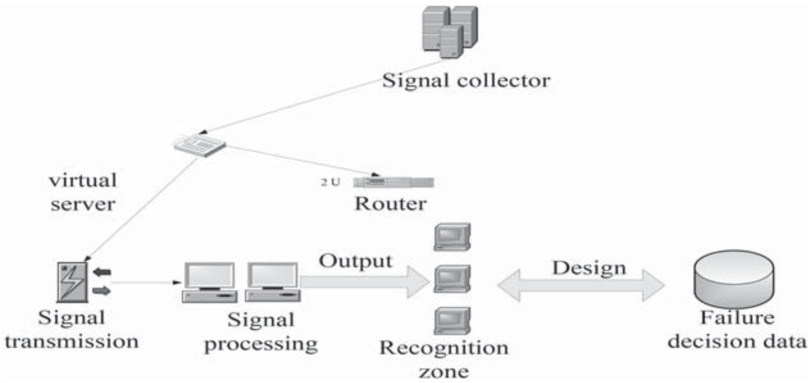

Figure 1 Fault diagnosis structure.

become an important leader in the development of clean energy in our country. However, with the rapid development of wind power construction projects, there are an increasing number of construction projects, and the quality control levels of the departments involved in the construction are uneven. So, to ensure the quality of aviation construction, has become an urgent problem to be solved. Global wind energy technology has become more advanced. The growth trend is mainly reflected in the development of small power to high power, the development of fixed-distance switching speed, conversion speed and frequency, the development of ground wind power to external wind power, and the development of a compact and flexible structure design. At present, the related technologies of wind turbines mainly rely on imports. We can only produce blades and towers, which are the bottleneck of my country's wind power development. Running under other load conditions makes the maintenance and repair of wind turbines more difficult, which greatly increases the operating costs of wind turbines. Bearings, one of the important components of wind turbines, not only connect various rotating parts, they also have to withstand loads from all aspects. These accumulated damages will inevitably cause wear and tear on bearings, which will cause the running state of the bearing to change [17].

2.2 Fault Diagnosis Technology

Airborne fault detection technology can be divided into two parts, physical fault detection technology (the physics of failure) and error analysis technology [18]. To predict the development trend of faults, the control system can act in advance to avoid the occurrence of major faults; for faults that have occurred, fault diagnosis can be used to determine the type of fault so that engineers can repair the fault as soon as possible. With the continuous development of fault diagnosis technology, the scope of the subjects covered has been continuously expanded. Originally applied to mechanical faults, it is now applied in fields such as automation, information, and computer technology, as shown in Figure 1. Hence, fault diagnosis technology is developing rapidly as these disciplines continue to improve Wind speed and a fault signal from the main shaft are the monitoring signals of an online monitoring system. Wind speed has a decisive relationship with the power generation of a wind farm and it also directly affects the dispatching main shaft of the wind farm. A failure of the main shaft will lead to a failure of the mechanical transmission chain as the wind turbine will be shut down immediately. Bearings are high-precision and standardized core components in the motor control system. Their function is to reduce friction loss between the equipment. It can reduce frictional resistance of the rotating components, so the installation operation is more convenient, and the execution performance efficiency is relatively high. Fault diagnosis technology has developed into a discipline that involves a wide range of categories, complex theories, strong dependence on several basic disciplines, and high technology content. With the advancement of science and technology, new technologies are continually being incorporated into fault diagnosis technology [19]. Therefore, fault diagnosis and performance degradation trend prediction can help reasonable judgments to be made on the performance of bearings to control the damage within the operating range, which is important for the maintenance, repair and accident prevention of Wind power equipment [20].

Method based on fuzzy inference. In addition to the two states of "normal" and "faulty", most of the working conditions of the bearing are in an intermediate state between the two. Data mixed programming, data collection, feature extraction, normalization processing, subnet diagnosis and two-level information fusion diagnosis are used to realize the online monitoring of equipment operating status and remote fault diagnosis and analysis. However in this process, the system has fewer measurable parameters, and the model-based hydraulic servo system is faulty, especially for single-output systems. How to use the limited measurement output of the system to design residual vectors with different fault sensitivities to achieve fault isolation and multiple concurrent fault diagnosis is a difficult problem.

When a wind power bearing is in failure, it is assumed that the wind speed and power of the blade during operation are recorded as:

$$S_i = \frac{1}{W_i} \sum_{i=1}^{n(n+1)} \lambda_{n,i} \tag{1}$$

$$S = \frac{W}{\|w\|} \pm (n_1 - n_2) \sum_{i=1}^{1} (w_{i+1} \bullet w) \tag{2}$$

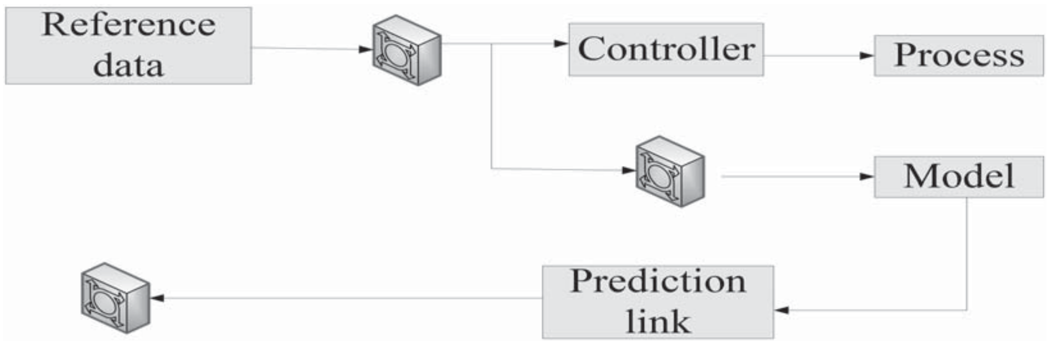

Figure 2 Wind turbine bearing failure prediction structure.

where w_i represents a single power value in the i-th interval and $\lambda_{n,i}$ represents the average value of the corresponding power of a single blade. For any bearing point (a, b) connected by the blade, its running curve trajectory is recorded as:

$$\begin{cases} W \bullet a_i + x \leq -1, \; b_i = -1 \\ W_{i-1} \bullet a_i + b \geq 1, \; b_i = 1 \end{cases} \tag{3}$$

$$S \bullet \; a_i + n + S \; \bullet \; a_{i+1} \frac{\|w\|^2}{2} = 0 \tag{4}$$

We maximize the interval of the optimal position on the optimal plane by W_{i-1}, and perform the quadratic planning as:

$$\min_s \frac{\|w\|}{2}(w \bullet a^i_{i+1} + x) \geq \forall i \tag{5}$$

$$\min \left\{ \frac{1}{2}\|W + S\|^2 + x \sum_1^{n+1} b_i^2 \right\} = 1 \tag{6}$$

Assuming that the bearing point surface after failure has changed due to random factors, the distribution density function of the diagnostic factor is:

$$f(r) = \frac{1}{\nu\sqrt{2\pi}} \mu^{-(a-\nu)/2\nu^2} \tag{7}$$

$$\int (r + 1) = A(\mu - 2v \leq i \leq \mu + 3v)\sqrt{\mu + v_{i+1}} \tag{8}$$

The relationship between $\mu - 2_v$ and $\mu + 3_v$ in the above formula is the relative distribution range of *the controlled diagnostic factor*.

2.3 Failure Prediction Technology

As the world's leading manufacturing country, China's large-scale rotating machinery plays a vital role in the national economy [21]. Shafts and bearings are important components of many large machines and rotating machines with complex structures and require long-term continuous operation. Due to the structural characteristics and operation mode of rotating machinery, this type of equipment often fails in operation. The motor rolling bearing fault data proved that the method showed good separability and characterized the fault characteristics. The laboratory direct-drive wind unit is used to collect the vibration signal of online wind motor bearing and analyze the bearing signal and bearing load from the axial and radial aspects. To effectively predict the output of a wind farm, the two parameters of wind speed and wind direction are critical. The main factor affecting the power generation of wind turbines is wind speed [22]. A wind speed time series is a series of numerical measurements arranged in chronological order Wind speed is random, which makes wind speed time series exhibit variability and nonlinearity [23]. The structure diagram in Figure 2 shows the simulation technology for predicting the failure of wind turbine bearings.

An improved genetic algorithm based on the gradient method is proposed. The improved genetic algorithm hidden Markov model is used to analyze fault features, extract faults, remove redundant characteristic parameters, and effectively classify and calculate faults. Using MATLAB, the genetic algorithm is used to obtain the optimal solution. Using agenetic algorithm with excellent spatial search performance, the initial values of two important kernel parameters in the classification process are optimized to improve the classification recognition rate.

Driven by different wind speeds, wind turbines establish appropriate models according to time series $|\delta_o|$:

$$Q_i = \sum_{t=0}^{\varepsilon} \delta_o k_{i=t}, \, t \in \phi \tag{9}$$

$$Q_i - \omega_i Q_{i-1} = \phi_k Q_{i-k} \int_{t=1}^{i} k(k-1) \tag{10}$$

Wind speed has a strong randomness [24], but the wind speeds at adjacent moments have a strong correlation. Processing can be simplified using regression models:

$$\phi(k) = 1 - \phi_i r \sum_{r-1}^{r} \omega \tag{11}$$

where ϕ_k represents the time series in a stationary state and ω_i represents the undetermined error value. The maximum order in the designed model is [25]:

$$MAX = (m - a) \log \vartheta^2 + 2(s + t)^2 \tag{12}$$

Making:

$$s = \sum_{i=1}^{\infty} w_i t_{i-1} \kappa \frac{1}{1 - \phi^2} \tag{13}$$

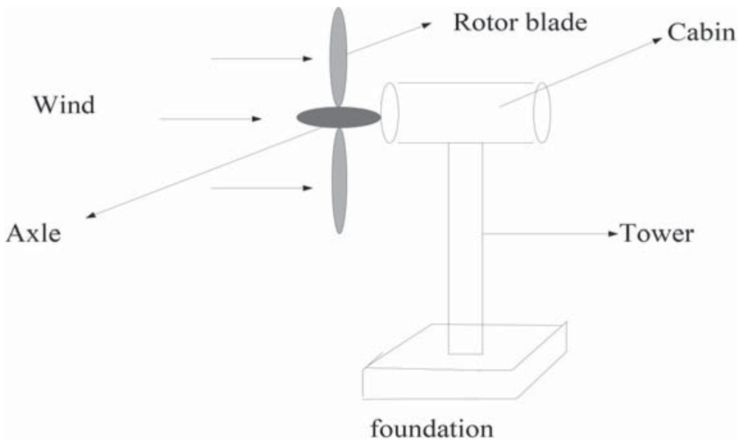

Figure 3 Analysis of wind power generation equipment.

Table 1 The total installed capacity of wind power generation in various countries in the world in the past 5 years.

	2016	2017	2018	2019	2020
China	14800	17234	19017	20201	23673
U.S	7140	7649	8901	8143	9701
France	1035	1280	1432	1789	2749
UK	1379	1942	2730	2947	3742
Sweden	689	987	857	699	837
Germany	652	743	902	970	1127
India	2710	2799	3401	3974	4427

where κ is the deterministic function. The general solution of equation (13) is:

$$W_i = \sum_{i=0} k(k-1) \sum_{s}^{t-1} \vartheta_{st} k^i \omega \tag{14}$$

The ratio of the total amount of wind energy through all the rotating surfaces of the wind wheel and the zero-order difference of the wind speed to the failure prediction [26] is as follows:

$$f[v_0,\ v_1,\ v_2, \ldots, v_x] = \frac{\nabla \int o}{y h_{v-1}} \left(x \left(\sum_{x-1}^{1} f_{k-1} \right) \right) \tag{15}$$

$$\nabla f_k \delta^x = \delta^{x-1} f_{k+1/3} \Delta_{x-1} \tag{16}$$

where ∇f_k represents the ratio between the order difference value and the determined function value. Y is the forward step difference. The recursive algorithm is used to obtain:

$$\delta_{k-1}^2 = \mathring{y} - \sum_{k=0}^{1} \phi_{v,s} y_{v-1} \tag{17}$$

where δ is an independent parameter.

3. EXPERIMENT PREPARATION AND DEVELOPMENT

As China has become the world's largest energy producer and consumer sufficient energy supply is necessary for sustainable development. Wind energy is an inexhaustible renewable clean energy which does not emit radiation or pollution and the prospects for development are very broad. Therefore, wind power generation accounts for an increasing share of the total global power generation, and domestic wind power has also been developed at a rapid rate in recent years. An illustration of wind power generation equipment is shown in Figure 3. The working environment of wind turbines is very harsh, resulting in frequent failures of individual components and long failure times. When an air turbine is running, the first transmission simultaneously verifies the total effect of radial load, external load and rotation time, and under the action of another strong air load, it is prone to failure, which will affect the performance of the entire wind turbine. This experiment first studies the failure situation of the transmission, investigates the faulty machine, and calculates the error frequency of the transmission. Information error signal characteristics and errors are detected. With the rapid development of modern wind power technology, position monitoring and error detection technologies have been widely used in wind turbines. However, the research on fault diagnosis technology for wind turbines is still in the early stage of development.

A wind turbine is composed of four parts, the shaft blade, the unit box, the wind turbine tower and the base. For the purposes of this experiment, the current situation of the world's wind power generation equipment in the past 5 years is shown in Table 1.

The data in Table 1 shows that China's total installed wind power capacity in the past five years has always been the world's largest, and the total installed capacity of wind power each year is greater than the sum of the total installed capacity of other countries. Statistics on the newly added capacity and cumulative total of several major wind farms in China in the past 10 years are shown in Figure 4.

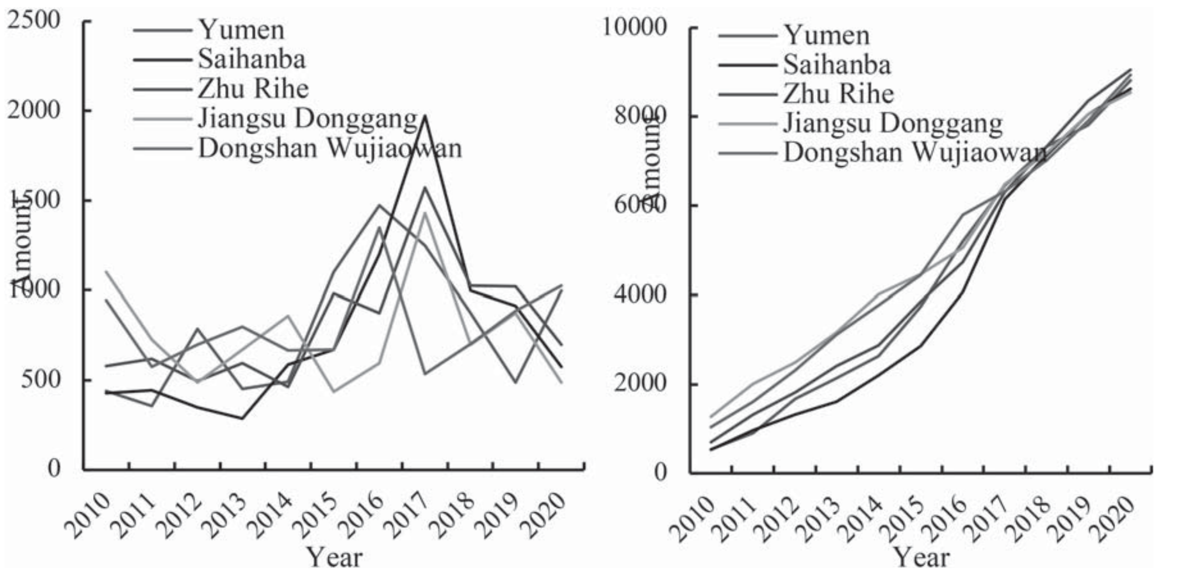

Figure 4 The newly added installed capacity and cumulative total of major domestic wind farms from 2010 to 2020.

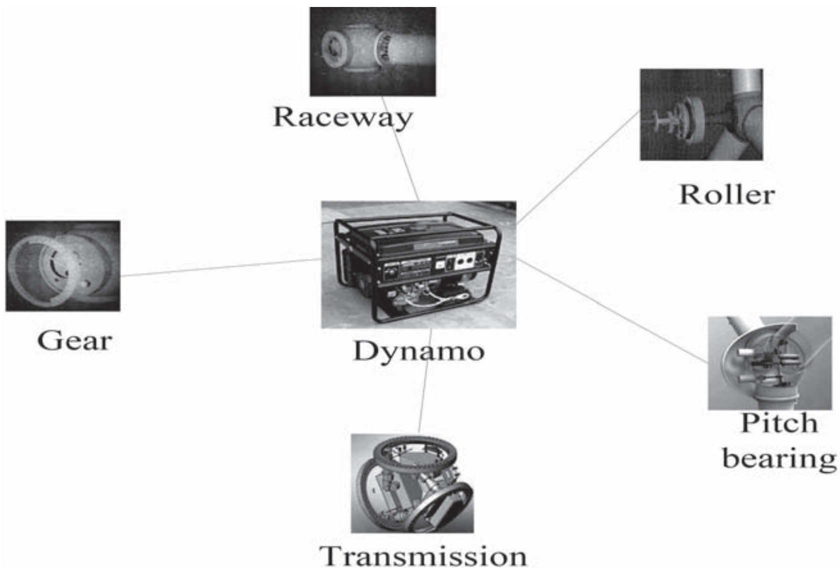

Figure 5 Bearing system.

Table 2 Failure time of each subsystem failure (minutes).

Component	Blade	Pitch system	Dynamo	Electrical System	Inverter	Shaft and bearing
Failure time	27	0.1	10	6	3	3
Component	Sensor	Gearbox	Braking System	Hydraulic system	Yaw system	other
Failure time	2	33	1.5	3	3.5	9

As shown in Figure 4, the capacity of China's wind farms in Yumen, Saihanba, Jiangsu Donggang, and Dongshan Wujiaowan has increased rapidly in the past 10 years, and the total number of wind farms in China has also increased yearly. Saihanba had the largest newly installed capacity in 2017 and Yumen wind farms had the largest newly installed capacity in 2016. From 2018, there was little difference to the total number of wind farms. The wind turbine gearbox connects the blades of the wind turbine to the generator and is usuallya structure of the first-stage world gear and the second-stage parallel gear The blade mother is converted into high speed at the generator end through the speed function of the gearbox, which drives the generator to generate electricity, and is connected to the grid through the substation and transported to all parts of the country. In this process, the bearing plays an important role in supporting and transferring loads. The bearing system is shown in Figure 5.

The transmission system is set to send one-to-one text messages with the type of error and the degree of the defect. These behavioral parameters can be used to describe the type of error or potential error The bearing system of the wind turbine unit structure is composed of the aforementioned 6 parts, and the failure time of each subsystem is counted, as shown in Table 2.

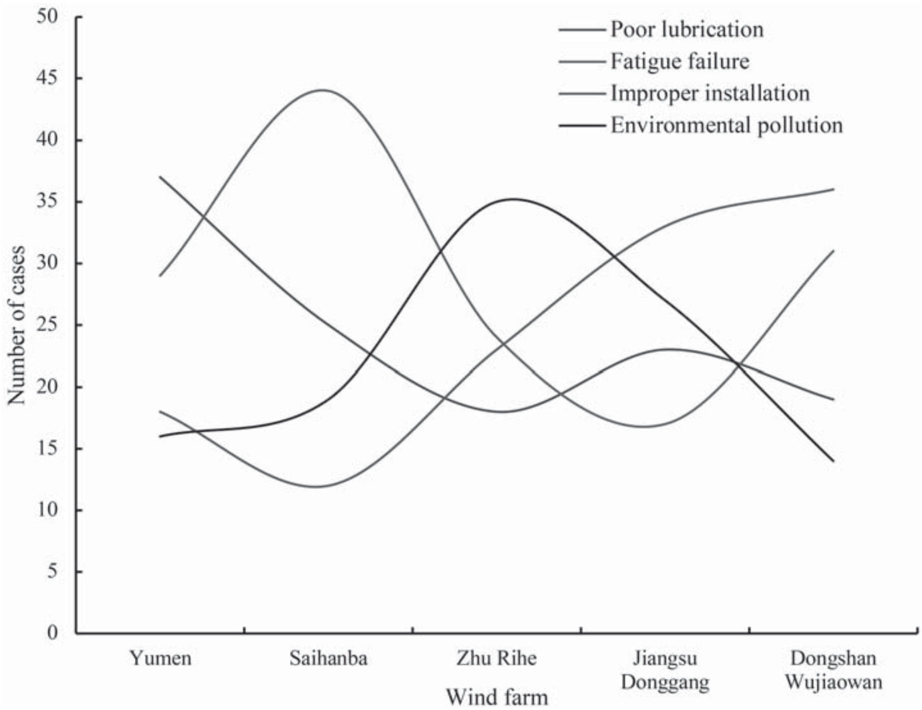

Figure 6 100 wind turbines from each wind farm were randomly selected to investigate the cause of failure.

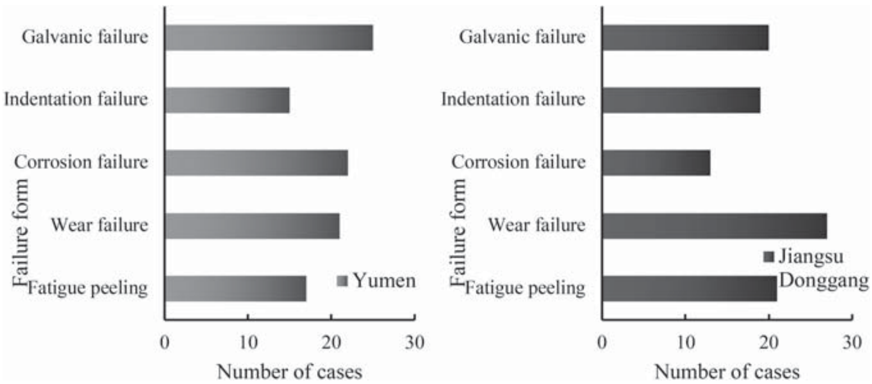

Figure 7 Power plant fan failure condition.

The longest failure time of each subsystem as shown in the statistics is 33 minutes for transmission system failure, and the shortest is the pitch system as the pitch system rarely fails. The fault processing time of the inverter and the sensor is relatively short. 100 wind turbines from each wind farm were randomly selected to investigate the cause of failure, as shown in Figure 6.

If the ball bearing is too large, fatigue and pitting will occur that is, spots on the spherical surface will affect the normal rolling of the ball bearing. When the ball is continuously pressed, pitting corrosion will expand, which will cause a large area of flaking on the surface of the ball. Fatigue spalling is the main failure form of rolling bearings, which will accelerate the aging of and damage to the bearings. The main reason for the failure of wind turbines in Dongshan Wujiaowan Wind Farm is unreasonable installation; the main cause of the failure of Yumen Wind Farm is poor lubrication. Of the 100 wind turbines randomly checked, 37 wind turbines experience such failures. The main reason for the failure of 100 wind turbines in Hanba Wind Farm is fatigue. There are many ways to classify abearing failure. Depending on its life, it is divided into normal failure or premature failure. Because the bearing working environment varies, its failure mode is also different. The fault forms are studied for the Yumen Wind Farm and the Jiangsu Donggang Wind Farm, as shown in Figure 7.

As shown in Figure 7, research on the types of failures focuses on the following: fatigue peeling, wear failure, corrosion failure, indentation failure, and galvanic corrosion failure.

In the vibration signal, some characteristics will change with the type of fault and the scale of the fault. Multi-entropy has the advantage of analyzing multi-dimensional complex data and the overall deviation may reflect the overall trend and the benefit of reliability. It will use key robotics technology for data analysis and display collection. The construction of this model is shown in Figure 8.

Traditional performance indexing methods are delay analysis, area frequency analysis and field frequency analysis.

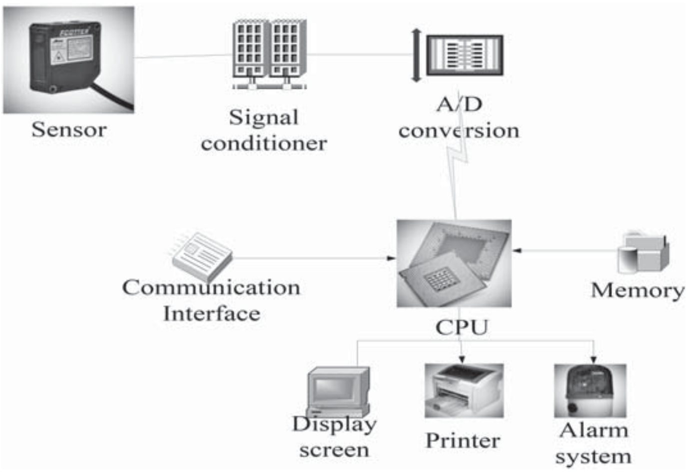

Figure 8 Data analysis and signal acquisition.

Table 3 Key technology test results of different bearing states.

Bearing status	Key technology test results			
Normal status	0.9989	0	0	0
Inner ring failure	0	0.9999	0	0.001
Outer ring failure	0	0.0023	0.9891	0.0001
Rolling element failure	0	0	0	0.9987

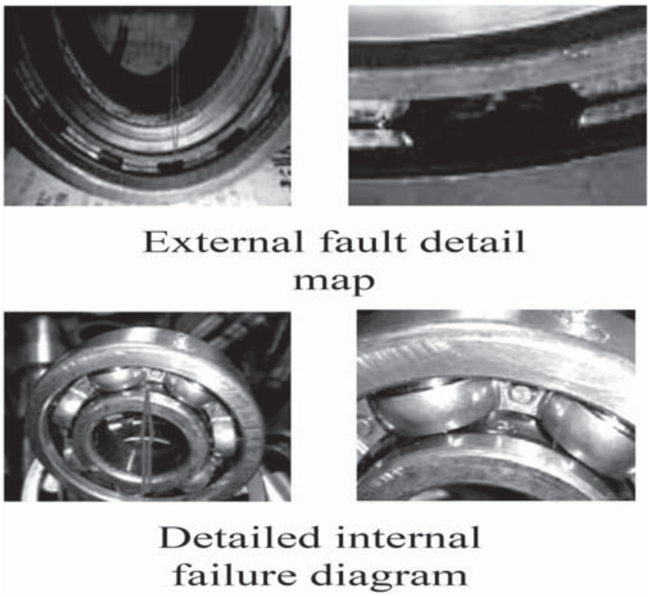

Figure 9 Details of internal faults and external faults.

As time goes by, the workload gradually decreases from the normal working mode to the perfect failure mode during use, and the degradation process is irreversible. Among them, the data processing results under different bearing states are shown in Table 3.

Under normal circumstances, the outer ring does not rotate and serves as a fixed transmission. The ball is the first part of the rolling transmission. It rotates in the seat ring made between the outer ring and the outer ring of the inner ring, so that the motion form of the transmission becomes a rotating fist, which greatly reduces friction. When the bearing shaft is normal, the test result of the key mechanism is 0.9989. When the inner ring fails, the test result is 1.0009; when the outer ring fails, the test result is 0.9915; when the rotating object fails, the test result is 0.9987. Figure 9 shows the details of internal faults and external faults.

Remote monitoring technology is a key robotics technology. Figure 10 illustrates a flowchart of wind power remote monitoring mode.

While the transmission is used as a connection between rotating parts, it is also used as a supporting part to carry the load. Therefore, during the transfer process, a series of physical effects such as mechanical wear need to be suppressed. In this regard, based on the failure prediction

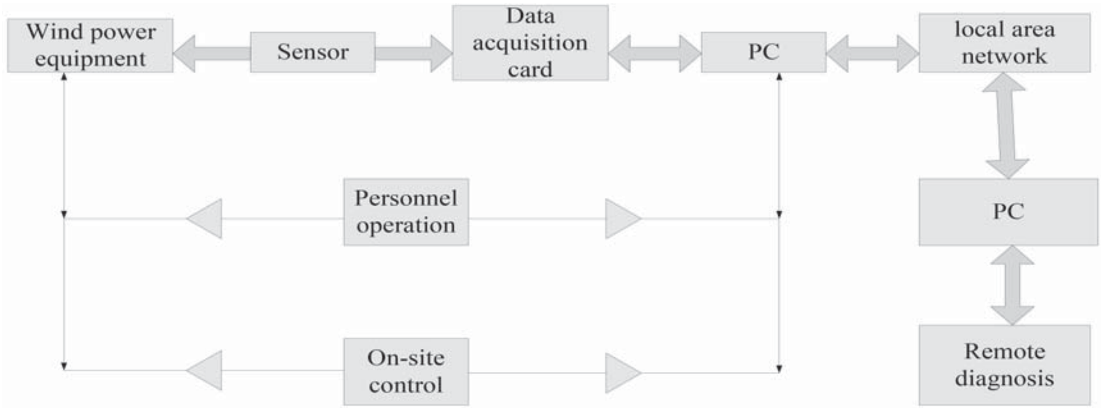

Figure 10 Wind power remote monitoring mode.

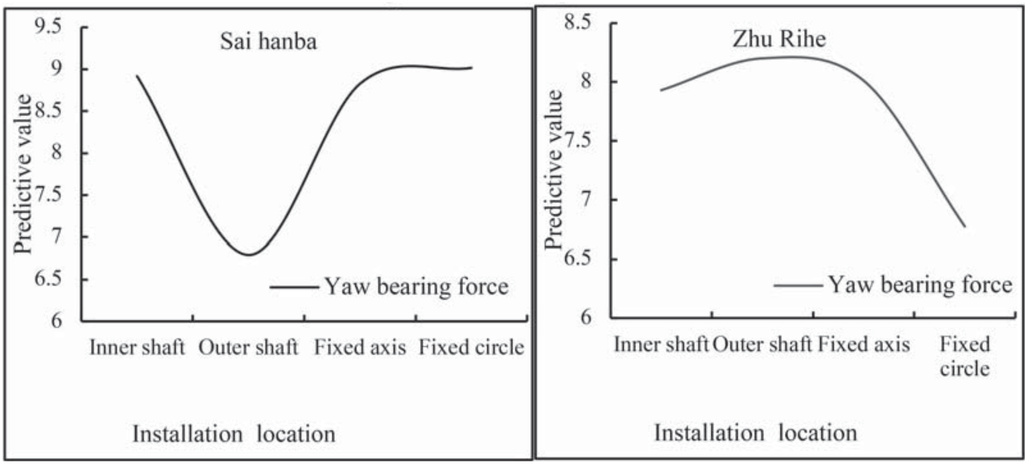

Figure 11 Bearing monitoring installation position.

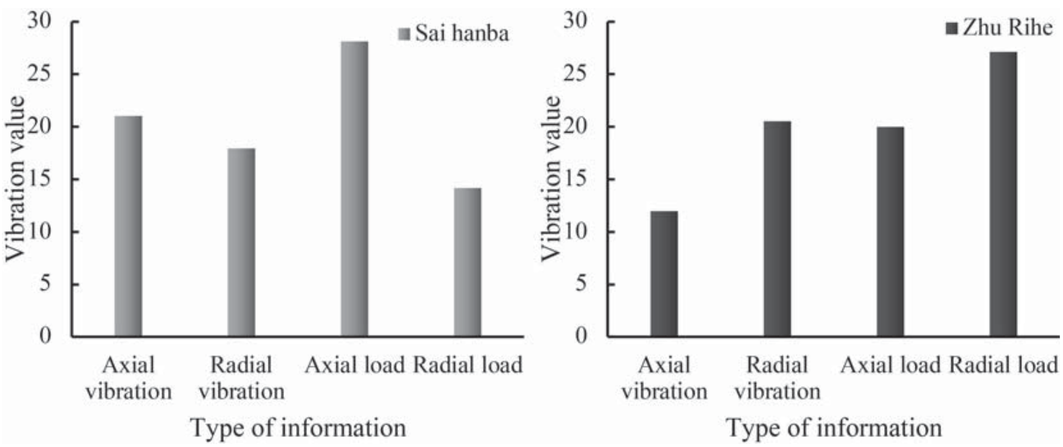

Figure 12 Bearing monitoring vibration signal.

results of the machine self-service technology, taking the Saihanba and Zhulihe wind farms as examples, data analysis was carried out on the relationship between the measurement direction of the yaw bearing mechanics and the installation position, and the vibration signal. The four elements of inner shaft, outer shaft, centering shaft and fixed circle are used for data recording, as shown in Figure 11.

The vibration signal can best reflect the characteristics of the equipment. Through the analysis of the time-domain signal, the amplitude of the signal can be extracted, the change law of the signal can be obtained, and the operating condition of the equipment can be preliminarily judged. The vibration signal is the provider of the error characteristics of the transmission chain. How to extract the power level signal that can indicate the running state of the turbine transmission chain from the vibration data is very important for the research on the bearing shaft of the wind farm. The four factors of the vibration signal are calculated: axial vibration, radial vibration, axial load, and radial load, as shown in Figure 12.

The accuracy of the diagnosis when the load is unknown is not much different from the accuracy of the fault diagnosis when the load is known. This shows that the same fault type has inherent characteristics that characterize the fault category and does not change with the load change or the depth of the fault. When the load is known, further fault diameter diagnosis is performed on the known fault type and the result obtained is not much different in accuracy compared with the case where the load is unknown.

4. DISCUSSION

The decrease in traditional energy consumption and global attentions to environmental issues has led countries to pay more attention to the development and utilization of renewable energy. Of all the forms of renewable energy, wind power is being increasingly used globally. With the development of online monitoring technology for power applications, many online monitoring devices have been widely used in power systems, effectively improving the reliability of power grid equipment operation. The software system of the existing robotic system adopts the client/server model, which defines the environmental protection, pollution-free, and low-cost advantages of the software system and behavior mode of the robot port and the background monitoring system, which have attracted wide attention from various countries. The wind power remote monitoring mode predicts the failure of wind power bearing vibration signals and installation location. Fault monitoring of various parts of the bearing can promote the development of wind farm construction and maintenance in China. This is of great importance to understand the status of China's wind power capacity and to apply and discuss key robotics technologies.

5. CONCLUSION

Wind power technology is high-tech with broad development prospects. The research on fault diagnosis and failure prediction technology for wind power bearings has just started, and the use of key robotic technologies for research and application practice has significant practical value. With the large-scale commissioning of wind turbines for power generation, fault diagnosis of key components and maintenance of the normal operation of the generators has become an increasingly important task. Bearing fault diagnosis technology has undergone the development process of amplitude, time domain, and time-frequency analysis. However, with the development of society, the requirements for mechanical equipment are becoming higher and the safe operation of bearings used for support has been proposed. Higher requirements require methods that can automatically and intelligently identify bearing faults. In addition, wind turbines are easily damaged and difficult to maintain when operating under variable load conditions. This puts higher requirements on the reliability and performance of the wind turbine system. The most easily damaged part of the transmission system is the transmission. Therefore, it is urgent to study new signal processing and pattern recognition technologies to realize automatic and intelligent recognition of bearing faults and improve the efficiency and accuracy of diagnosis.

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DATA AVAILABILITY STATEMENT

No data were used to support this study.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

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