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Remote Fault Diagnosis Method of Wind Power Generation Equipment Based on Internet of Things

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Abstract
According to existing study into the remote fault diagnosis procedure, the current diagnostic approach has an imperfect decision model, which only supports communication in a close distance. An Internet of Things (IoT)-based remote fault diagnostic approach for wind power equipment is created to address this issue and expand the communication distance of fault diagnosis. Specifically, a decision model for active power coordination is built with the mechanical energy storage of power generation equipment with a remote diagnosis mode set by decision tree algorithms. These models help calculate the failure frequency of bearings in power generation equipment, summarize the characteristics of failure types and detect the operation status of wind power equipment through IoT. In addition, they can also generate the point inspection data and evaluate the equipment status. The findings demonstrate that the average communication distances of the designed remote diagnosis method and the other two remote diagnosis methods are 587.46 m, 435.61 m, and 454.32 m, respectively, indicating its application value.

Keywords
Decision Tree Algorithm, Diagnostic Methods, Equipment Failure, Internet of Things, Remote Detection, Wind Power

1. Introduction

The advancement of wind power technology has facilitated the wide application of wind power generator, particularly in terms of intelligent and integrated electromechanical equipment. The post-sale problem diagnosis and maintenance servicing procedure are incredibly challenging due to the ongoing improvements in overall performance and complexity [1,2].

More businesses have realized that the old method of assigning staff to construct a massive after-sales network is not only inefficient and costly, but also time consuming because the mechanical equipment has to be shut down for repair, thus adversely impacting the project's development and quality. Through the remote monitoring platform, technicians oversee the operation of equipment in real time and provide remote assistance to solve fault issues. The cloud repairing not only lowers the high labor costs and save material resources but also reduces the time for mechanical maintenance. The solution enables enterprises to transit from traditional manufacturing to intelligent manufacturing while enhancing their competitiveness in the market. As a result, academics have investigated remote defect diagnostics of power

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generation equipment. In the following sections, this essay will discuss the following aspects: The second section reviews relevant studies. The third part focuses on the fault type feature extraction and operation state, and designs the remote fault diagnosis method of wind power equipment. The fourth section conducts experimental analysis to confirm the method's performance in applications. The conclusion stated in the fifth section summarizes the contribution of this paper and its significance as a reference for future research.

2. Related Work

The authors of [3] propose a remote fault diagnosis and condition evaluation method based on an improved Bayesian network with fuzzy function. Bayesian probability measures the correlation between multi-dimensional feature indices and different faults. A time-varying scoring function integrates the feature information of different timelines to quantify the fault state. In addition, the faults are classified based on their harmfulness, while multiple fuzzy functions are fused in the network to describe the importance of continuously changing fuzzy states of faults in panoramic state evaluation. Additionally, the equipment's condition and likelihood of malfunction are taken into account when determining its total score value.

In [4], the authors propose a cloud-based remote detection system for power equipment. First, it examines the current operation, maintenance and test process of power equipment by explaining the feasibility of the remote control of power equipment test. Additionally, the system examines how cloud computing technology and cloud platform development relate to remote testing, and it builds the remote-control system architecture and system topology for cloud platform testing. Specific equipment has been demonstrated as an example showing the implementation principle of data communication. The function and data storage structure of the system based on the map reduction platform were explained in the final section of [4].

The Internet of Things (IoT) has moved a great step toward easy application, particularly for small and medium-sized equipment manufacturers and companies engaging in the IoT. Existing solutions have saved the time and expenses when building internal IoT server.

3. Remote Fault Diagnosis Method of Wind Power Equipment Based on the Internet of Things

There are four phases in the IoT-based research of a remote defect detection approach for wind power equipment. First, calculate the bearing's fault frequency. Second, specify the fault characteristics and design the key functions of the equipment to dynamically adjust the routine inspection plan (Section 3.1). Third, detect the operation state of wind power equipment with IoT technology to construct the active power coordination decision-making model (Section 3.2). Finally, set the remote diagnosis mode based on the decision tree algorithm for remote operations, solving the dilemma caused by short communication distance of conventional fault diagnosis approaches (Sections 3.3–3.4).

3.1 Fault Characteristics Identification

Discharge frequently occurs along with these failures. Flashover, arc or short circuit, ground, and other severe faults may occur in severe instances [5,6], which may damage wind power equipment and result in generator disconnection, leakage, power wind power equipment off, and other productive mishaps [7-9]. The shaft is at the same frequency position despite the rotation speed. In light of this, the expression formula for the frequency of bearing failure in machinery used in power generating is:

$$Q = \frac{d}{2}\left(1 - \frac{p}{W}\right) \times U \tag{1}$$

In formula (1), d represents the diameter of parts, p is the number of shaft rolling elements of power generation equipment, W refers to the rotation frequency of rolling shaft, and U is the contact angle of bearing. Partial discharge (PD) means that the field strength generated by the applied high voltage is enough to break through the insulation area of the wind power equipment and produce discharge, but there is no fixed channel in the discharge area. PD will neither produce a penetrating channel to the ground inside the equipment insulation, nor will it cause instantaneous and complete damage. However, long-term PD may cause gradual erosion and damage, which eventually leads to insulation, flashover, arc or short circuit, ground and other severe faults [10,11]. Motor consists of different components in a complex structure. Despite the elaborate structure built by high requirements, it is possible for each component to fail when operating due to its own electrical parameters and the feedback of the driven machinery. Given the modulation effect of rotating frequency, the fault frequency of bearing inner ring is often accompanied by 1×. Meanwhile, the sum of the fault frequencies of the bearing inner and outer rings in the equipment is equal to the product of rolling element number and the speed frequency. Accordingly, the calculation formula is:

$$I_0 + I_1 = l \times T \tag{2}$$

In formula (2), I_0, I_1 are two arbitrary speed bands, l represents the speed frequency, and T is phase characteristic. As the motor may have both rotating machine fault and electrical fault when operating, the vibration and temperature change reflect the abnormality. Therefore, the fault diagnosis should incorporate different detection techniques. According to the above description, the fault character identification step is completed.

3.2 IoT Spot Check Operation Status

The three influencing factors in risk assessment are of different importance, so the risk weighting coefficient is introduced. A higher risk weighting coefficient means a greater influence that a factor may have in risk assessment. The expression formula of risk weighting coefficient matrix is as follows:

$$S = \begin{bmatrix} e_1 & 0 & 0 \\ 0 & e_2 & 0 \\ 0 & 0 & e_3 \end{bmatrix} \tag{3}$$

In formula (3), e_1 is the probability of failure, e_2 is the severity of failure, e_3 is the level of failure monitoring. The operation of remote diagnosis function depends on a physical device. As the checking results shows, dynamic adjustment means that the spot check data are regularly analyzed and the status of the equipment is evaluated when operating. The operation risk of the equipment is evaluated according to the analysis of the equipment status and the prediction results, and the equipment involved in the key functions is further divided into high-risk equipment and low-risk equipment. Point inspection and precision inspection are adjusted flexibly according to the risk degree, so equipment with higher risks will be strengthened while those with lower risks are maintained or weakened. As a result, the efficiency of point inspection is improved and the wind power equipment operation is secured and economic. It is required to extract the state parameters that reflect the characteristic function of the equipment according to the possible important failure modes, and set the monitoring items under completed supervision. Given the abovementioned cases, the process of spot checking the operation status of wind power equipment is completed.

3.3 Construction of Active Power Coordination Decision Model

Under traditional power control strategy, the wind power equipment based on VSC-HVDC transmission facilities may pose a potential threat to the fault ride through of DC lines. In the multi terminal DC equipment with wind power access, there is also an aggravating DC network fault due to continuous wind power injection. Accordingly, the generator meets the power demand of the converter station on the transmission grid side through power regulation, while the DC voltage is secured to be stable by the change of grid frequency. In addition, the unbalanced power of the DC network will gradually reduce in the process of structural frequency recovery. As the frequency of the wind power side is stable or the fault is removed, the converter station will switch back to the constant voltage and frequency control. Since the grid side converter station has restored the power regulation function to provide constant voltage for the DC network, the transmission structure will return to the initial operation state. The virtual inertial control method provides effective inertial support for wind power equipment with optimized power tracking characteristics by switching the power tracking curve. The expression formula of power tracking curve scale coefficient is as follows:

$$H = \frac{1}{2}\rho\pi r^2\left(\frac{r}{\delta}\right) \tag{4}$$

In formula (4), ρ is the power regulation value of wind power equipment, δ is the maximum power point, and r is the compensation DC. In order to improve the stability of wind power equipment, wind turbines should be incorporated into power coordination. It can not only mitigate the fault severity due to the wind power, but also improve the fault ride capability of equipment, which further enhance the safety and stability of DC equipment. According to the frequency deviation signal of AC power grid generated by the power regulation of wind farm converter station, the variable speed wind power equipment uses the proposed frequency integrated control to change the proportion coefficient of the unit power tracking curve and switch the curve through the virtual inertia control and primary frequency modulation control. It also uses the variable pitch link to adjust the angle. Then the electromagnetic power of wind power equipment could be adjusted quickly, and the mechanical power of the unit is changed continuously.

3.4 Remote Diagnosis Mode Set by Decision Tree Algorithm

As a classification method of machine learning, decision tree reflects a kind of mapping relation. The resource communication interface shields the heterogeneity of fault diagnosis resources. The fault diagnosis mode of maintenance platform can easily access to different remote diagnosis resources to provide diagnosis services for power generators. The remote diagnosis structure of wind power generation is shown in Fig. 1.

As shown in Fig. 1, the reconfiguration of fault diagnosis system at the maintenance platform can be understood from two aspects: the reconfiguration of function modules and the reconstruction of fault diagnosis system structure. It is necessary to have these two reconfiguration modes simultaneously, so that functional modules with similar types but different specific functions can be replaced when fault diagnosis is different.

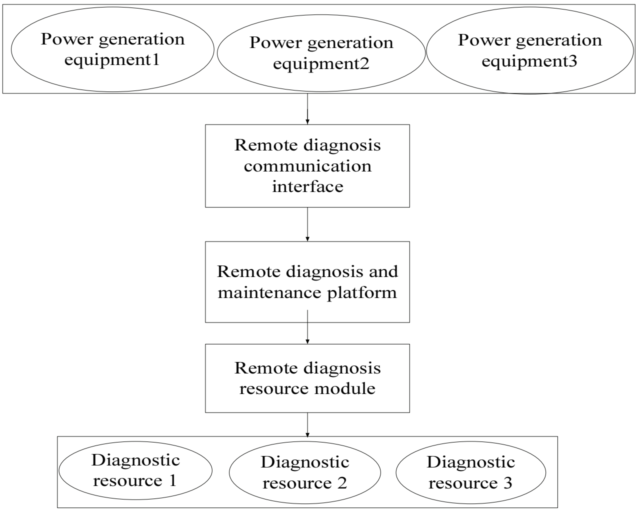

Fig. 1. Structure of remote diagnosis.

4. Experimental Analysis

4.1 Experiment Content

The controller reads the data from the view layer. The experiment is mainly performed in three stages. The first stage is user self-diagnosis. To be specific, when the power generation equipment fails, the on-site maintenance personnel can log in to the system through the browser and conduct self-diagnosis by querying the relevant equipment technical parameters and typical fault database. The second stage conducts intelligent fault diagnosis. If the equipment fault cannot be solved at the first stage, the user can use the remote diagnosis module to check and diagnose. In this process, the user logs in on the Internet, inputs the fault parameters in the intelligent diagnosis interface, and calls the corresponding diagnosis module of the diagnosis center. After the diagnosis, the results are sent back to the user interface to guide the user through the maintenance process. The third stage is alliance consultation. This paper selects an open dataset of a power company as the experimental dataset. The sample size and experimental environment configuration are shown in Table 1.

Table 1. Experimental environment configuration

Item	Parameter
Network environment	100 M switch
Network	DDR 20 GB Infiniband
HD	6 TB
Operating system	Centors 7.0
CPU	Intel Xeon 64 2.33 GHz
RAM	16 G
Dataset sample size	450 GB
GPU	GeForce RTX 2080 Ti (0.789)
Development environment machine vision software	HALCON 21.11
Visual window	Diagnostic console

4.2 Analysis of Experimental Results

In order to verify the effectiveness of remote diagnosis, the data-mining-based method and the fuzzy clustering-based method are selected for comparative testing. The communication distances of the three diagnosis methods under different grid load conditions are tested respectively. Longer distance demonstrates better performance. The experimental results are shown in Figs. 2–4.

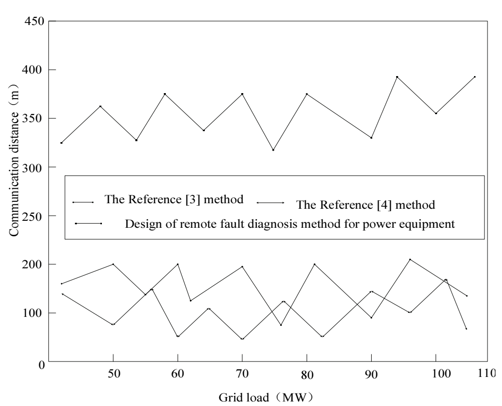

Fig. 2. Grid load, 100 MW.

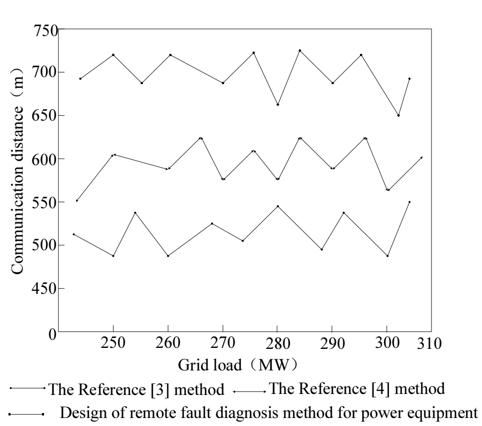

Fig. 3. Grid load, 300 MW.

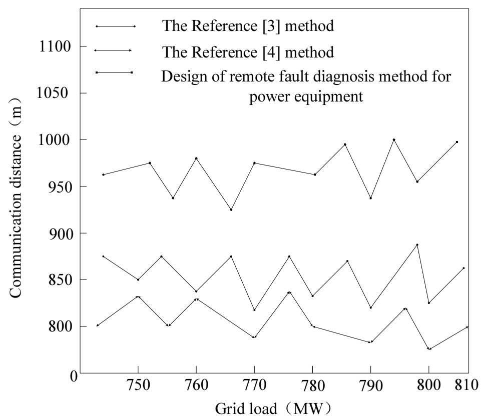

Fig. 4. Grid load, 800 MW.

Figs. 2–4 shows the average communication distance of the three remote diagnosis methods under different grid load conditions, as shown in Table 2.

Table 2. Average communication distance of the three diagnostic methods (unit: m)

Grid load (MW)	Remote fault diagnosis method of power equipment based on data mining	Remote fault diagnosis method of power equipment based on fuzzy clustering	Remote diagnosis method of designed
50	140.74	152.89	220.36
100	168.94	186.37	360.47
200	213.37	220.04	462.81
300	543.37	584.68	713.48
500	711.05	706.19	794.36
800	836.22	875.79	973.29
p-value	<0.05	<0.05	<0.05

According to Table 2, the average communication distance data of the designed method and the other two methods is 587.46 m, 435.61 m and 454.32 m respectively, indicating that the performance of the designed remote diagnosis method is better. To be specific, this method first identifies the fault type characteristics to provide data basis for the IoT to detect and evaluate the wind power equipment, and then it extends the average communication distance. In addition, an active power coordination decision model will be built with a remote diagnosis mode based on a decision tree algorithm. The last step is to conduct a remote fault diagnosis.

5. Conclusion

This paper designs a IoT-based remote fault diagnosis method for wind power equipment to address the short communication distance problem in the existing remote fault diagnosis of wind power equipment. According to the designed method, the first step is to specify the fault type characteristics, and then detect and evaluate the operation state of wind power equipment through the IoT. On the basis of this, the active power coordination decision model is built, and the remote diagnosis mode is configured based on the decision tree algorithm to perform remote fault diagnosis.

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