Wind Turbine Blade Fault Diagnosis Method

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Wind turbines have shown a maximization trend. However, most of the wind turbine blades operate in areas with a relatively poor natural environment. The stability, safety, and reliability of blade operation are facing many challenges. Therefore, it is of great significance to monitor the structural health of wind turbine blades to avoid the failure of wind turbine outages and reduce maintenance costs.
wind turbine blades Fault Diagnosis Strain

1. Wind Turbine Blade Fault Diagnosis Method

Researchers usually need to spend a lot of time and energy collecting and collating literature in different research fields. With the development of information technology, the application of bibliometric analysis tools dramatically facilitates the work of researchers. The bibliometric analysis supports linking documents by keywords to form visual charts based on specific databases (for example, Web of Science, WoS, CNKI, etc.), articles in specific fields, or a combination of all methods [1][2]. Bibliometric analysis can help researchers understand research hotspots and development trends. The five most commonly used bibliometric analysis tools include VoSviewer, Biblioshiny, Gephi, HistCite, and CiteSpace [3]. This entry mainly selects 53 articles on wind turbine blade fault diagnosis through the Web of Science database and uses VoSviewer software to visualize the literature, and the cluster diagram composed of literature keywords is obtained.

2. Non-Destructive Techniques

NDTs can conduct SHM on wind turbine blades to avoid serious accidents and ensure the safe operation of wind turbines. In addition, NDTs can also determine the cause of the damage. Some detection methods can detect the location and size of the blade damage to use for later maintenance and repair [4]. At present, the non-destructive testing methods of wind turbine blades mainly include strain measurement, acoustic emission, ultrasonic, vibration, thermal imaging, machine vision, etc. Although these detection methods tend to be perfect and mature, few combine multiple detection methods for detection [5]. Muñoz et al. [6] believe that an NDT is applied to SHM systems to detect the internal performance of the material structure, which can reduce maintenance costs and prolong the service life of wind turbines. Gholizadeh et al. [7] classified NDTs into contact and non-contact. This section focuses on the principle, working methods, advantages, and disadvantages of damage detection methods.

2.1. Strain Detection Method

The detection method of strain measurement detects the micro-damage change of wind turbine blade length or deformation by using the strain sensor [8]. The advantage of strain measurement is that it can continuously monitor wind turbine blades for a long time, but the accuracy and sensitivity of strain measurement are dependent on the distance between the sensor and damage [9]. In recent years, strain measurement based on the Fiber Bragg Grating (FBG) sensor has been widely used. The core component of FBG is the grating structure engraved in the fiber core, and it usually changes the refractive index, making the refractive index of the fiber core periodically distribute along the axial direction [10]. The overall performance of FBG can be tested by experimental comparison. Guo et al. [11] used FBG to monitor the internal stress fatigue of composite wind turbine blades. Through experimental comparison, they concluded that the durability of FBG is stronger than other electronic strain sensors. In addition, FBG can effectively monitor the operational status of wind turbines in practical applications. Bang et al. [12] applied FBG to onshore and offshore MW wind turbines for health monitoring. Briefly, 41 FBG on the wind turbine support structure was installed, which had a sampling rate of more than 40 Hz, and it showed good stability and accuracy in dynamic strain monitoring. It is also feasible to apply FBG to wind turbine blade strain monitoring. Schroeder et al. [13] installed the FBG on the wind turbine blade to monitor the blade strain data in real time and used the accumulated data to determine the fatigue load distribution. Compared with the FBG, the strain sensor has no obvious advantages. To improve it, Wu et al. [14] proposed a new strain sensor for surface strain measurement. It was verified that the sensor could be used to generate two-dimensional strain images. In addition, the combination with an intelligent algorithm can improve the measurement accuracy, Lee et al. [15] proposed a new strain estimation method and objective function to obtain the optimal arrangement of strain sensors on the wind turbine blade.

The strain detection method can be applied to the monitoring of both onshore and offshore wind turbine blades. In the future, further exploration is still needed to reduce the development cost and improve detection accuracy.

2.2. Acoustic Emission Detection Method

The acoustic emission detection method focuses on the detection of electrical signals from transient elastic wave conversion caused by damage initiation, crack propagation, or plastic deformation release energy [16]. the sensor converts the sound signal from damage into an electrical signal. Acoustic emission detection can identify the increase in blade fatigue damage and the location of that. Tang et al. [17] monitored the fatigue damage of 2MW wind turbine blades through acoustic emission technology and verified that acoustic emission technology can effectively detect the occurrence of cracks on blades through experiments. In addition, acoustic emission detection technology can also detect damage generation and processes. Zhou et al. [18] monitored the damage and failure process of wind turbine blades in the tensile test through acoustic emission technology. The test results showed that the damage started from the end of the shear plane, and acoustic emission technology could monitor the occurrence and propagation of damage. The key to improving the accuracy of this technology is to eliminate noise interference to acoustic emission signals. Liu et al. [19] applied acoustic emission technology to the monitoring and fault diagnosis of wind turbine blade bearing. They proposed a new cepstrum editing method to perform the noise reduction processing of the acoustic emission signal source.

The acoustic emission detection method has a good effect on crack damage detection and can also locate internal structural damage. However, there is often noise interference in the process of signal acquisition; eliminating noise interference will also increase the cost of the detection system, and it requires a data acquisition system with a high sampling frequency [12][13].

2.3. Ultrasonic Testing Method

The ultrasonic testing method is where an ultrasonic wave first propagates through the internal material, and then the sensor detects the reflected wave [20]. Ultrasonic sensors are installed on the blades and tower of the wind turbine for signal acquisition. Different reflection, attenuation, resonance, and transmission modes can be distinguished depending on the material or structure [21]. Therefore, this method can be used to detect microdamage and judge the size, location, and other information of damage [22]. The ultrasonic detection method can be used to detect both the internal and surface damages of wind turbine blades. Tiwari et al. [23] used ultrasonic technology to detect the surface debonding damage of wind turbine blades and used discrete wavelet change, variational modal decomposition, and Hilbert transforms to process the signal, to estimate the size and location of blade damage. Lamarre et al. [16] used ultrasonic phased array technology to detect the internal delamination, wrinkles, and adhesive thickness of wind turbine blades. In addition, the ultrasonic detection method can also be applied to the damage detection of offshore wind turbines. Brett et al. [24] used the swept frequency ultrasonic technology below 100 kHz to detect the foundation of offshore wind turbines. This method is also applicable to the fault diagnosis of wind turbine blades.

The ultrasonic detection method can continuously monitor the internal and surface of wind turbine blades. However, ultrasonic testing requires a long time to collect signals, and the signal data processing is also complex, which leads to the delay of damage judgment [25]. Therefore, future research on artificial intelligence algorithms can improve the processing capacity of data.

2.4. Thermal Imaging Detection Method

The thermal imaging detection method is mainly applied to detect the change of thermodynamic properties of wind turbine blades by scanning the surface of that. When the micro-damage fault occurs, the temperature anomaly will occur, which can be utilized to detect and judge the fault [20]. This technology requires accurate image processing. In real applications, it is difficult to eliminate the influence of blade damage on temperature and other factors [20], making ambient temperature interference the key to accurately identifying damage. Doroshtnasir et al. [26] used thermal imaging technology to carry out nondestructive testing on long-distance wind turbine blades and calculated the differential temperature of blades to eliminate signal interference reflection, to ensure the accuracy of thermal imaging technology in blade damage diagnosis. It concluded that the temperature difference near the hub is large, and there is the largest possibility of damage. Thermal imaging detection technology can identify the fault of wind turbine blades and extract the damage characteristics. Hwang et al. [27] proposed thermal imaging technology using the continuous line later to visualize the damage of wind turbine blades under rotating conditions and extract the characteristics of damage. Avdelidis et al. [28] applied infrared thermal imaging technology to wind turbine blade damage detection and summarized the advantages and disadvantages of this technology.

The thermal imaging detection method can detect the internal structure of the wind turbine blade without contact. However, the temperature change caused by damage is delayed, and it is easy for the environmental temperature to cause interference in the detection process. In future research, the influence of environmental temperature has to be reduced to improve the reliability and accuracy of this method.

2.5. Machine Vision Detection

At present, a large number of innovative sensing and monitoring systems based on machine vision technology have been developed and applied in the field of SHM [29]. The full-scale condition monitoring of wind turbine blade surfaces can be carried out by shooting images. Yang et al. [30] proposed a video measurement technology for monitoring the deformation of large wind turbine blades in full-scale tests and operations. This technology requires two photos from different angles of three-dimensional samples through a parallel network measurement method, which are prepared by applying a grid on the surface to be tested. This method improves the measurement accuracy and reliability, but the measurement accuracy is highly dependent on the measurement position. Poozesh et al. [31] used a relatively new optical sensing technology for the early detection of the design and manufacturing defects of wind turbine blades, and the images taken from a pair of stereo cameras were used to determine the surface strain of the blade surface. This method has high accuracy, but the calculation process is relatively complex and needs to be optimized and improved. Compared with ordinary machine vision technology, vision performed by unmanned aerial vehicles (UAVs) has better detection accuracy. QIU et al. [32] built an image acquisition system; the system uses a latitude and longitude M600 UAV equipped with a Zenmuse Z30 cloud camera. The images obtained by the system were of high resolution, so the microscopic damage to the blade could be detected clearly. Moreover, based on the image data collected by UAVs, Long et al. [33] automatically detect and diagnose the surface cracking of wind turbine blades. By analyzing the image taken by the UAV to quickly detect blade cracking, a data-driven framework is developed to process blade images and obtain blade cracking. However, the time and effectiveness of image processing need to be further optimized. In addition, efficient intelligent algorithms are used to recognize images captured by UAVs. Wang et al. [34] collected a large number of wind turbine blade data through UAVs, and they proposed an unsupervised learning method combined with image data features to distinguish the normal and abnormal parts of the blade.The results show that this method is very useful for detecting anomalies in the blade image. However, this method cannot effectively identify and eliminate the fouling on the blade surface. Traditional wind farms need manual periodic maintenance detection. In order to improve safety and detection efficiency, the robot detection of wind turbine faults has been gradually developed. Kuang et al. [35] proposed that the wind turbine blade could be crawled by magnetic adsorption force and friction force. At the same time, infrared sensors and high-definition cameras were installed on the robot to diagnose the micro-damage on the blade surface. However, it was difficult to maintain the robot, and the equipment for blade detection needed to be further improved. Similarly, Josef Franko et al. [36] proposed a light magnetic crawler with visual and laser radar sensor surface contact to NDT the wind turbine. In addition, Zhang et al. [37] proposed a new method of using climbing robots with ground control stations and high-resolution cameras to scan wind turbine blades.

At present, the research on the SHM of wind turbine blades based on the machine vision detection method is still in its infancy; the machine vision technology will have more extensive applications in the future. Although machine vision detection accuracy highly depends on image processing and data acquisition, its advantages are still obvious. The staff can remotely control the machine equipment to detect the wind turbine blades, which can improve the detection efficiency and protect their safety [38][39]. In the future, the combination of the machine vision detection method and big data can realize earlier detection of the occurrence of damage, making it an important part of SHM.

3. Fault Diagnosis Method Based on Operation Data

In recent years, with the rapid development of artificial intelligence algorithms and big data analysis, artificial intelligence can imitate the learning skills of the human brain. At the same time, it combined with data analysis is widely used. The application of intelligent algorithms such as a neural network in the fault diagnosis of wind turbine blades has been well tested.

Xin et al. [40] extracted the feature vector of modal parameters by using a deep belief network. Aiming at the problem of inaccurate modal parameters caused by environmental noise, measurement error, and other factors during the operation of wind turbine blade damage, the feature vector was used as the input signal of the error backpropagation training (BP) neural network to reduce the influence of noise and improve the accuracy of the microdamage diagnosis of wind turbine blades. However, this method only diagnoses single microscopic damage and cannot be applied to other types of damage. Wang et al. [41] introduced the depth automatic encoder (DAE) model. They combined the neural network with SCADA data to monitor the damage to wind turbine blades and verified the effectiveness of this method in the fault diagnosis of wind turbine blades in practice. Sahir et al. [42] built a Convolutional Neural Networks (CNN) model to diagnose the micro-damage of wind turbine blades. The model can diagnose a variety of damage types, including radiation effects, wear, and fracture. The diagnostic accuracy could be as high as 81.25%. The CNN structure consists of three types: the convolution layer, the pool layer, and the full connection layer. Different damage categories are classified by full connection layer calculation. In addition, migration learning can also improve the network training results. Liu et al. [43] used the transfer learning method of the Inception v3 model to diagnose the damage to wind turbine blades. The experimental results show that the calculation speed and accuracy of the model algorithm are better than R-CNN. However, a more accurate diagnosis of micro-damage images of wind turbine blades has always been the difficulty of deep learning optimization. Long Wang et al. [33] proposed an extended Haar-like feature set classifier based on the optimization and improvement of the original Haar cascade classifier for the crack damage of the wind turbine blade, which was verified by being proved superior to the LogitBoost classifier. Xiao-Yi et al. [44] proposed a deep learning framework, the Alexnet model, to solve the problem of the low accuracy of the identification and detection of micro-damage on the surface of wind turbine blades. The accuracy of the model for damage diagnosis reached 99.001%, which was 19.424% higher than that of the traditional BP neural network model. In order to improve the diagnostic performance of the deep learning model for micro-damage of wind turbine blades, Yang et al. [45] added transfer learning and ensemble learning classifiers based on convolutional neural network, which enhanced the ability of abstract feature extraction for the micro damage faults of wind turbine blades. Most of these studies focus on single blade microscopic damage diagnosis. Whether it is feasible to apply a deep learning model to other wind turbine blades for image diagnosis accuracy still needs to be discussed.

4. Fault Diagnosis Based on Vibration Signal

The fault diagnosis of wind turbine blades based on vibration signal is mainly through the selection of damage index and modal parameters. In the process of signal acquisition, it is necessary to eliminate the interference of environmental noise on the signal. The interference of the signal will reduce the accuracy of the vibration signal and the error of the modal parameters. Therefore, it is necessary to reduce the influence of the environment in the study of vibration signal damage identification.

The damage can be effectively identified by comparing the modal parameters before and after it occurs. Emilio Di Lorenzo et al. [46] installed accelerometers on wind turbine blades to collect vibration data. By comparing the modal parameters before and after the buckling test, the occurrence of damage can be successfully predicted. In addition, the establishment of the finite element model can also be used to analyze the structural damage of the blade. Moradi et al. [47] firstly installed intelligent sensors on wind turbine blades for experiments to obtain strain and vibration data and then simulated the structural state, and after the blade damage by finite element simulation, which can comprehensively detect the blade damage, this method can achieve a reliable SHM system. To exclude the influence of environmental noise, Abouhnik et al. [48] used the empirical mode decomposition method to divide the vibration signal into basic components and built a model in the finite element software ANSYS to simulate the vibration of the wind turbine with three blades. At the same time, the crack damage was set on the wind turbine blade, and the vibration characteristics of the blade at different speeds were tested. By comparing the simulation and experimental results, the method can identify the location and extent of the blade damage. Gómez et al. [49] proposed a supervised statistical method to solve the interference of uncertainty in the vibration signal detection of wind turbine blade damage under different environments, and they developed three specific methods to improve the accuracy of damage detection. Furthermore, Wang et al. [50] proposed a finite element method combined with dynamic analysis (modal analysis and response analysis) to obtain modal shape difference curvature. The numerical results show that the method can detect the blade damage location and improve detection accuracy.

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