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Review

Review of the Typical Damage and Damage-Detection Methods of Large Wind Turbine Blades

Wenjie Wang, Yu Xue *, Chengkuan He and Yongnian Zhao

College of Engineering, Ocean University of China, Qingdao 266100, China
* Correspondence: xueyu7231@ouc.edu.cn

Abstract: With global warming and the depletion of fossil energy sources, renewable energy is gradually replacing non-renewable energy as the main energy in the future. As one of the fastest growing renewable energy sources, the safety and reliability of wind energy have been paid more and more attention. The size of modern wind turbines is becoming larger and larger. As the main component of wind turbines to capture energy, the blade is often damaged by various complex environments and irregular loads. Therefore, the health monitoring and damage identification of wind turbine blades have become a main research focus. At present, in addition to the overview of various detection methods of wind turbine blades, there is a lack of comprehensive classifications and overviews of the main damage types, damage-generation mechanisms, and basic principles of the damage-detection technology of wind turbine blades. In this paper, firstly, the common fault types of wind turbine blades, such as trailing edge cracking, lightning strike, leading edge corrosion pollution, icing, and delamination, as well as their generation mechanism, are comprehensively analyzed. Then, the basic principles and the latest research progress of the current main detection technologies, such as vision, ultrasonic, thermal imaging, vibration, acoustic emission, and so on, are comprehensively reviewed. The advantages and limitations of the various detection technologies for practical application are summarized. Finally, through a comparative analysis of the various damage-detection technologies, we try to find potential future research directions, and draw conclusions. This paper will provide a reference for understanding the mechanism behind the main damage types and the damage-detection methods of wind turbine blades. It has important reference value for further promoting practical research of wind turbine blade damage-detection technology and grasping this research direction.

Keywords: wind energy; wind turbine blade; damage-detection techniques; wind turbine blade damage; online monitoring; sensor

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1. Introduction

Energy plays an important supporting role in global economic development. To realize the green and sustainable development of the global economy, the reform of energy is imperative. At present, non-renewable energy sources, such as fossil energy, is still the main energy in the world. In 2019, non-renewable energy accounted for 84.32% of the total global energy consumption [1]. The high carbon emission of non-renewable energy not only has a significant impact on the global climate deterioration, but also violates the concept of sustainable development of the global economy. On the other hand, with the continuous depletion of fossil energy, human beings have to turn their energy demand to renewable energy. Therefore, renewable energy will replace fossil energy and become the main energy of mankind in the future. In the first quarter of 2020, renewable energy accounted for 28% of global power generation, compared with 26% in 2019. The main sources are hydropower, wind energy, and solar energy [2]. As a clean, renewable energy source with mature technology, wind energy has become one of the fastest growing renewable energy sources. Wind energy accounts for 5.5% of global renewable energy power generation [3].

In ScienceDirect's overall average share of publications on different renewable energy sources between 1996 and 2020, wind accounted for more than half, at 60% [4]. According to the GWEC | 2022 global wind energy report, the global wind energy market is expected to grow at an average annual rate of 6.6% in the next five years [5], as shown in Figure 1. The compound annual growth rate of global onshore wind power is 6.1%. The compound annual growth rate of global offshore wind power in the next five years is 8.3%. In other words, the world is expected to see an increase of 90 GW in offshore power generation capacity from 2022 to 2026 [5]. Compared with onshore wind power, offshore wind power has a higher wind speed, cause less turbulence, occupy fewer land resources, has a relatively small impact on the environment, and the power generation of the same type of offshore wind farms is 50% more than that of onshore wind farms [6]. These are important reasons for the rapid development of offshore wind power in recent years.

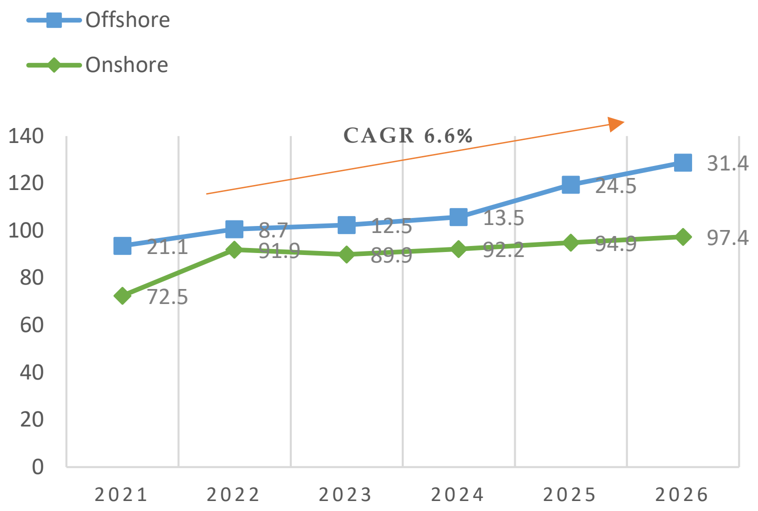

Figure 1. New wind power installations outlook for 2022–2026 (GW).

With the rapid development of wind power generation, the capacity of a single wind turbine unit, which is the equipment necessary to convert wind into energy, has becomes larger. Therefore, the size of the blade, the wind energy-capturing component of the wind turbine, is also increasing; indeed, the length of a single blade has reached more than 100 m. As the main component of the wind turbine, the cost of the blade accounts for 20% of the cost of a single wind turbine [7]. At present, most wind turbine blades are made of glass fiber-reinforced polymer (GFRP), with carbon fiber-reinforced polymer (CFRP) also used in some key parts. Due to environmental constraints, most wind farms are built in remote areas. These areas have a harsh environment, so the blades of wind turbines are facing the test of various harsh environments. As shown in Figure 2, about 19.4% of the failures of wind turbines are blade failures [8]. There are mainly two aspects of blade failure. On the one hand, it is some defects caused by human factors and the limitation of the generation process in the process of blade manufacturing. On the other hand, it is the damage caused by various harsh and complex environments during operation, such as icing, irregular load, moisture absorption, hail, ultraviolet radiation, atmospheric corrosion, fatigue, gust or lightning, and other uncertain factors [9]. When the wind turbine blade fails, if the maintenance is not carried out in time, it will bring higher operation and maintenance costs. In serious cases, it will lead to the complete damage of the wind turbine generator set, resulting in disastrous consequences and huge economic losses [10]. Especially for offshore wind turbines, its operation and maintenance costs are about 15–35% of the total cost [11]. So, real-time monitoring, to understand the health of the turbine blades and facilitate emergency operation and maintenance, would prevent further damage to the blades, and thus is very important.

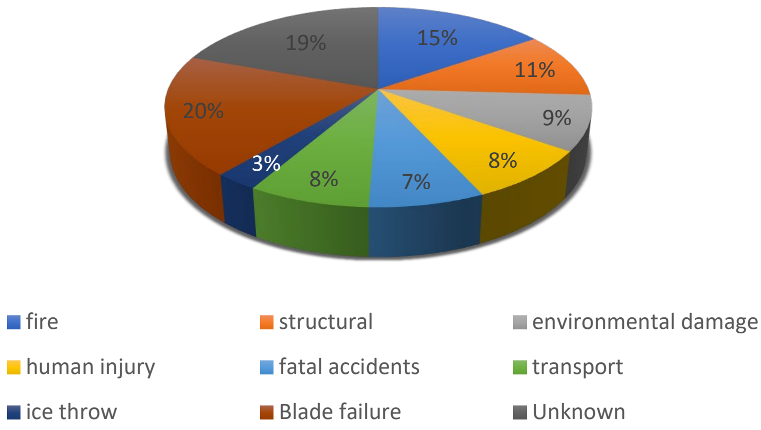

Figure 2. Distribution of wind turbine damage types.

The main sequence of wind turbine blade health monitoring is to monitor whether the blade is damaged the first time, and then find the specific location of the damage, judge the severity of the damage, and find the best solution. It can detect blade damage and give early warning in real time under blade operation conditions, which is very important to avoid the huge economic cost and catastrophic accidents. At present, there are many methods to monitor the health status of wind turbine blades, but the practical applications mainly include vibration monitoring, acoustic emission monitoring, strain monitoring, ultrasonic testing, thermal imaging testing, machine vision testing, and so on. Although there have been many reviews on the detection and monitoring of wind turbine blades, we ask, what are the main faults of wind turbine blades, what is the generation mechanism, what are the basic principles of various detection technologies, and what are the potential research directions and trends in the future. Considering these, there is an urgent need to comprehensively summarize, analyze, and study the main damage types and generation mechanism of wind turbine blades. Furthermore, detailed discussion of and research on the research progress of various wind turbine blade damage-detection technologies, as well as their advantages and limitations in practice, would provide a clearer research direction for researchers of wind turbine blade damage-detection technology in the future, and promote the more practical research of various detection technologies.

The framework of this study is shown in Figure 3, and the highlights of this study are as follows:

- Firstly, the types of common faults and defects of wind turbine blades are comprehensively summarized, and the main generation mechanisms of common faults and defects of the blades are deeply analyzed.
- Then, the principle and the latest research progress of the main damage-detection technologies, such as vision, ultrasound, thermal imaging, vibration, and acoustic emission, are comprehensively and deeply summarized.
- The advantages and limitations of each wind turbine blade damage-detection technology are summarized and analyzed.
- Finally, various blade damage-detection methods are compared, a future potential research direction for wind turbine blade damage-detection technology is put forward, and a conclusion is drawn.

The rest of this paper is as follows. The second part mainly analyzes the fault types and generation mechanism of wind turbine blades. The third part summarizes the main monitoring methods, mechanisms, and research progress of the typical fault types of wind turbine blades, and analyzes the advantages and disadvantages of each detection technology. In the fourth part, various detection methods are compared and analyzed through tables, and those research directions with more development potential are discussed. In the fifth part, a summary is made.

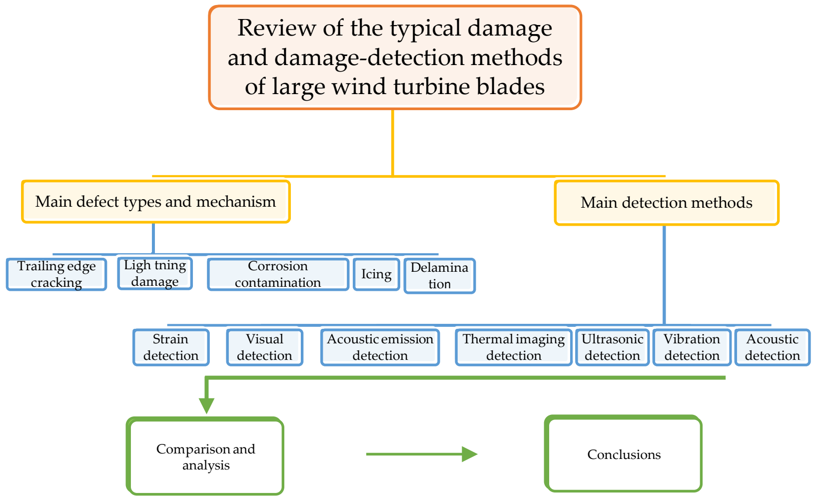

Figure 3. Framework of the present study.

2. Main Defect Types and Mechanism

There are two main reasons for the damage to wind turbine blades. On the one hand, the wind turbine is in a harsh external environment, and the damage faults are directly caused by external factors, such as strong wind, rain or snow, salt fog, lightning strike, freezing, sandstorm, insects, etc. The other is the invisible defects caused by process problems in the technology of man-made manufacturing. These invisible defects are subject to repeated high loads and harsh external environments during the installation and operation of the wind turbine. The gradual expansion of invisible defects can lead to damage. Due to the complexity of the blade material and structure, each damage type may be caused by a combination of causes. Different defects in the production process and different operating conditions will cause different damage types. Therefore, the typical damage types and main damage mechanisms will be reviewed below.

2.1. Trailing Edge Cracking

The main manufacturing materials of wind turbine blades are glass fiber-reinforced polymer (GFRP) and carbon fiber-reinforced polymer (CFRP). The two half shells of the blade, which are made of these two materials, are bonded to form a complete blade. The trailing edge of the wind turbine blade is the area where the two half shells are bonded. There are many damage modes in this area, and cracking is the main damage mode, which is mainly divided into a longitudinal crack and transverse crack. The longitudinal crack at the trailing edge refers to the crack consistent with the length direction of the blade [12], as shown in Figure 4. Such cracks mainly occur at the root and tip of the blade. The longitudinal crack at the trailing edge of the tip is mainly due to a reduction in the thickness of the shell, resulting in a reduction in the stiffness of the blade. This low stiffness leads to increased blade loading, resulting in higher shear stress on the shell and bonding material at the tip. This may be a major cause of the cracking at the tip of the trailing edge, while the longitudinal crack at the root trailing edge may be mainly due to the high stress caused by the geometric changes and fatigue load in these areas [13,14].

The transverse crack at the trailing edge is a crack perpendicular to the length of the blade, as shown in Figure 5. Some of these simple transverse cracks are only on one side of the blade. It may be due to the fact that one side of the blade needs to be polished in order to eliminate the asymmetry between the two shells of the blade during the manufacturing process, which leads to a reduction in glass fiber on one side, and this kind of crack occurs under the high load or stall of the blade. There is also a transverse crack that runs through the shell of the trailing edge of the blade in two measurements. This crack may have slowly penetrated the other side of the blade from the initial side. It is also due to the high load in this area. Such a crack is relatively dangerous because it completely cuts off the high load area of the trailing edge [15].

Figure 4. Longitudinal cracks found on the trailing edge of a wind turbine blade.

Figure 5. Transverse cracks found on the trailing edge of a wind turbine blade.

2.2. Lightning Damage

Although there is already an IEC61400-24 lightning protection standard for wind turbine systems, wind turbines with lightning protection systems are still subject to lightning strikes. The damage caused by lightning to the blades depends to a great extent on the material of the blades. Studies have shown that the use of carbon fiber-reinforced polymer (CFRP) for wind turbine blades makes them highly sensitive to lightning [16–18]. Most onshore wind farms are built on relatively remote, high ridges, which are rich in wind resources but also increase the risk of lightning strikes on wind turbines; this is because higher ridges are mostly made up of rocks or soils with high electrical resistance [19]. The current lightning protection system for wind turbines uses top metal receptors to momentarily introduce strong currents underground. Soils with high resistance on ridges, on the other hand, can make it impossible for large impulse voltages to rush into the ground, which will cause blade damage. More than 88% of the lightning attachments occur within 1 m of the outermost tip, as shown in Figure 6.

Figure 6. Holes in wind turbine blades caused by lightning strikes.

The essence of lightning is caused by the breakdown of a medium of air between a cloud and the ground or between a cloud and a cloud. The negative charge accumulated at the bottom of a thunderstorm cloud forms a strong electric field with the positive charge generated by the ground. As the charge of a thunderstorm cloud accumulates, it discharges to the ground and travels along the air [20,21]. When the tip of the discharge reaches a certain distance from the wind turbine blade, a strong electric field is induced with the metal acceptor of the lightning protection system installed in the blade, as shown in Point P in Figure 7. When the air at this distance reaches the breakdown threshold, the blades will also emit leads in an attempt to capture the tip of the discharge. Charge neutralization occurs in a short time and forms a circuit that forms lightning. Great thermal shock from lightning-induced arcs will cause blade damage [22,23]. Contaminated areas on the surface of blades made of GFRP composite materials (e.g., humidity, dirt, salt, insects, etc.) can also become receptors under a sufficient electric field [19,23].

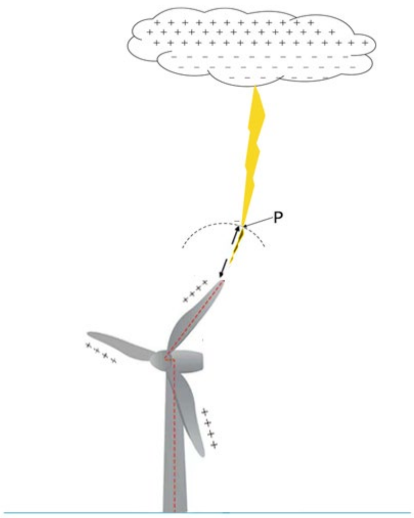

Figure 7. Lead development process diagram for when lightning strikes wind turbine blades.

2.3. Corrosion Contamination at Leading Edge

Corrosion and contamination at the leading edge of wind turbine blades is one of the key problems in wind power production, as shown in Figure 8. Erosion and contamination at the leading edge of the blade results in an increase in the resistance coefficient and a corresponding decrease in lift coefficient, which reduce the generation of electricity. Studies have shown that corrosion contamination on the leading edge of blades can reduce the annual energy production (AEP) by 2% to 3.7% [24]. Severely eroded blades result in AEP up to 25% [25]. The AEP of heavily contaminated blades is reduced by 10–13% [26]. Noise is also generated. The degree of corrosion and contamination of wind turbine blades depends on environmental conditions such as temperature, humidity, pollutants in the atmosphere, and wind speed. Studies have shown that blade erosion and contamination results in the most significant losses at lower wind speeds, while little or no power loss is achieved at higher wind speeds than the rated ones [27].

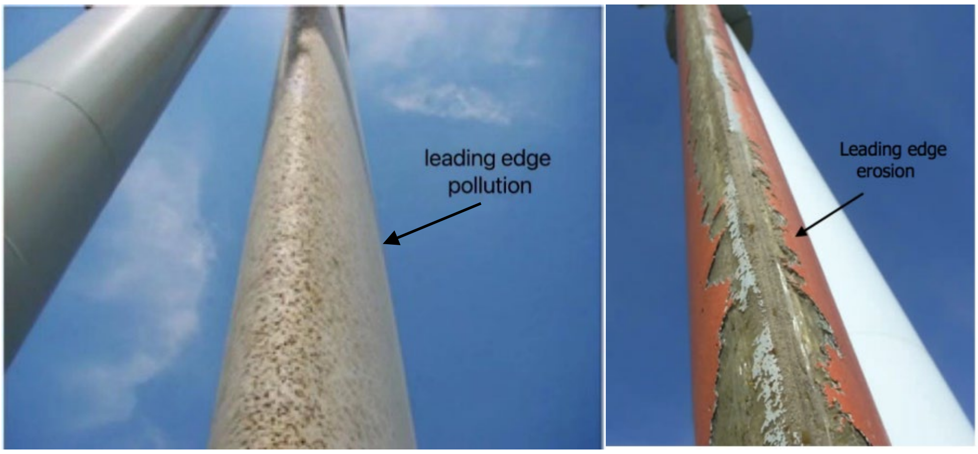

Figure 8. Corrosion pollution of a wind turbine blade's leading edge.

Front edge corrosion contamination is a complex process. The main reason is that raindrops, hail, sand particles, etc., repeatedly hit the leading edge of blades, together with environmental conditions such as insects, dust, salt (corrosion of salt mist of offshore blower), and so on. Large droplets of rain hit the leading edge of the blade and generate pressure waves on the surface. These pressure waves propagate in the material of the blade and begin to cause fatigue, cracking, and surface roughening of the blade surface. As the density of the pit increases, a groove will eventually form [28,29]. Other large and hard particulates, such as hail and gravel, have high kinetic energy when impacting the leading edge of the blade. Especially in areas close to the tip of the blade where the speed is very fast, the erosion of the blade surface is a direct result. In severe cases, delamination and cracking will occur, which will reduce the structural stability of the blades. Blade contamination caused by insects occurs mainly in areas with low humidity and wind speed and temperatures of 10 degrees Celsius or higher because these are favorable conditions for insect survival [27]. Additionally, chemicals such as salts and acids in rain or sea air will accelerate the corrosion of the blades, because they can interact chemically with the coating material [28,30].

2.4. Icing

The icing of wind turbine blades is also an issue of great concern. Because wind turbine blades are very precise aerodynamic components, even slight icing can cause slight changes in blade shape, which increases the friction coefficient and creates turbulence; ultimately, the aerodynamic performance of the blades is affected, resulting in an impact on power generation, A research project analyzed 517 wind turbines that produced 682 MW and discovered that in 29 months there was a loss of 18,966 MWh of the total produced power because of turbine blades icing [31,32]. Because ice can increase the drag coefficient of the blades, the noise generated by the blades is also higher than normal operating levels. Icing causes an imbalance in the mass of each blade and leads to irregular vibration. When this irregular vibration exceeds a certain threshold value, the blades will fatigue and break. Because the blades themselves become brittle in cold weather, this irregular vibration increases the risk of blade breakage. In addition, if the frozen blades are still running, the broken blades will be thrown out at a high speed, which brings great safety hazards to nearby residents and facilities. So, it is very important to detect ice and start de-icing on time.

The icing on wind turbine blades depends on temperature, humidity, air density, wind speed, and other variables. Ice characteristics are influenced by different parameters in ISO 12494, 2001 [33]. Different environments produce different ice types. The most common type of icing on wind turbine blades is frost, which is dense and very brittle. Because of the velocity of the incident. This ice first appears at the leading edge of the blade and then gradually covers the rest of the blade, as shown in Figure 9. Twenty percent of wind farms are located at high altitudes, where populations are scarce but there are abundant wind resources [34]; however, these areas have very strong wind and high cold air density, which poses a great challenge to the anti-icing and de-icing of wind turbine blades [35].

Figure 9. Ice on wind turbine blades.

2.5. Delamination

The manufacturing materials of wind turbine blades are composite materials. In the composite material, the bonding may not be good or there could be areas without bonding, which are prone to delamination defects. Under these operating conditions, the wind turbine blade will bear a high aerodynamic load, which will make the blade bend. Delamination may reduce the critical buckling load of the blade and reduce the overall stiffness and strength of the blade [36]. Delamination triggers different buckling modes. If the delamination is near the outer or inner surface of the blade, it may cause local buckling; if the delamination is near the center of the blade laminate, it will cause overall buckling, as shown in Figure 10. Buckling will reduce the strength of the blade, which poses varying degrees of danger to the structure. However, when the combined effect of local buckling and delamination reaches a certain degree, the blade will suddenly break [37,38].

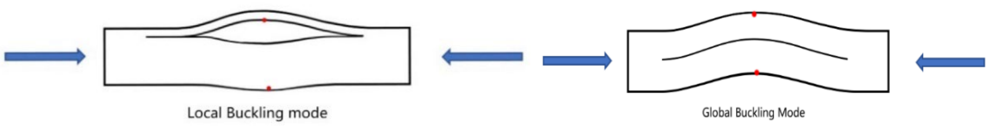

Figure 10. Local and global buckling modes for layering.

The delamination defect of the blade is usually caused by limitations during the manufacturing process, areas with a high stress concentration (such as hole and notch) around the discontinuous part of the structure, and/or impact damage during the process of production, transportation, and maintenance, etc. In order to avoid large delamination defects of wind turbine blades, the quality control of the blades is usually carried out through visual inspection or ultrasonic scanning after production.

2.6. Other Defects

With the increasing service time of wind turbines, the surface of wind turbine blades will gradually show slight cracks. These cracks usually expand with the service time of the wind turbine and the load of the wind turbine. If it is serious, it will lead to the fracture of the blade. Generally, a strong wind will make the blade bear complex and changeable high-strength loads, resulting in cracks and damage from the root, surface, and trailing edge of the blade, as shown in Figure 11. Therefore, the complex and changeable load is a direct factor affecting the service life of wind turbines.

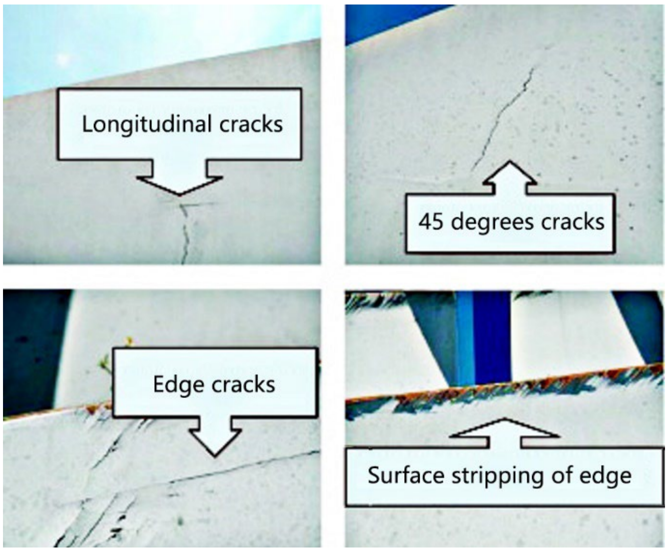

Figure 11. Different types of cracks.

3. Main Detection Methods

The health monitoring of wind turbine blades is mainly to find the damage to blades and thus potential safety hazards in time, avoid serious catastrophic accidents, and ensure the safe and healthy operation of wind turbines. Timely maintenance for faults and potential safety hazards can greatly reduce the cost of operation and maintenance, reduce downtime, improve power-generation efficiency, and reduce economic losses. At present, the methods of detecting damage to wind turbine blade's structure and material mainly include strain monitoring, acoustic emission monitoring, ultrasonic monitoring, vibration monitoring, thermal imaging monitoring, machine vision monitoring, and so on. This section will comprehensively review the monitoring principles and research progress of each monitoring technology, and will discuss the advantages and disadvantages of each monitoring technology in detail.

3.1. Strain Monitoring

3.1.1. General

Blade strain monitoring is a relatively mature and economical monitoring technology. When the wind turbine blade is running, it will deform to a certain extent under the action of external force. When the deformation of a local position of the blade exceeds the historical threshold of deformation, we can judge that there may be damage there. The strain sensor can monitor the micro changes of blade deformation. There are two kinds of strain monitoring sensors for wind turbine blades. One is the resistance strain gauge. The strain gauge is composed of a plastic film (15–16 μm) as the base and a sensitive grid (3–6 μm) made of thin metal foil on it. When this kind of strain gauge is attached to the surface of the blade shell, when the position of the strain gauge is deformed, the metal foil sensitive grid of the strain gauge will be deformed, and its electric resistance will change. The change in resistivity will produce voltage fluctuation. This fluctuation is measured by a special instrument and converted into the strain value of the measuring point. Thus, the monitoring of blade fatigue, stress concentration, and damage can be realized by monitoring the strain value [39,40]. Another strain gauge is based on the fiber

Bragg grating (FBG). FBG sensors are generally composed of Bragg grating glass fibers with a diameter of no more than 4–9 microns. When light propagates through a grating, there is little signal attenuation or signal change. When FBG is embedded into the structure of the blade, the optical characteristics of the optical fiber sensor will change when the blade is subjected to strain change or stress concentration. This change is very sensitive, thereby monitoring the damage to blades [41–43]. The principle is shown in Figure 12.

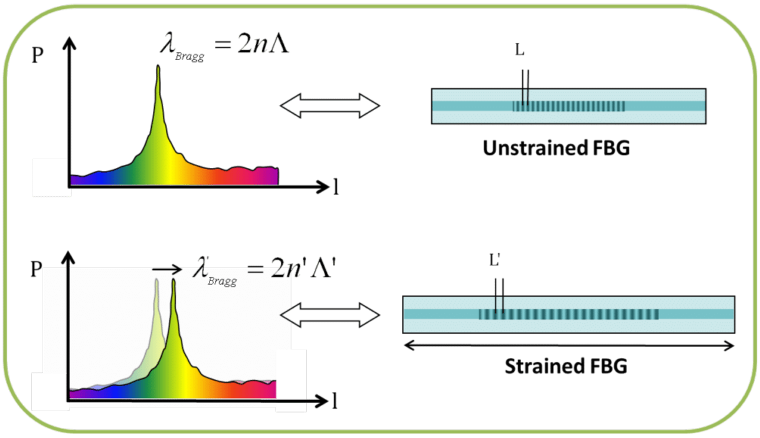

Figure 12. Schematic diagram of fiber Bragg grating (FBG).

3.1.2. Research Progress

Jorgenson et al. Installed more than 30 resistance strain gauges on wind turbine blades to measure the static strain distribution. The results show that there are high strain values and nonlinear characteristics at the position of blade damage [44]. Based on the strain field pattern recognition and nonlinear detection methods, Sierra-Peréz et al. embedded an optical fiber sensor into the blade structure. The measured values obtained from the different sensors were used to infer the strain field, and the defects and nonlinear characteristics of the blade were detected [39]. Nobuotakeda embedded plastic optical fiber (POF) and fiber Bragg grating (FBG) sensors into the composite laminates to detect and monitor the transverse crack evolution of composite laminates. The results show that the changes in optical power loss and reflected optical power spectrum are important indicators of crack density [45]. Jingzhe Wu et al. proposed the deployment of a large flexible strain gauge network and proposed a strain derivation algorithm. The algorithm has good performance in reconstructing the surface strain map and can be applied to the state evaluation of wind turbine blades in real time [46]. Shaohuatian et al. proposed a new non-baseline blade damage-detection method using the fiber Bragg grating (FBG) and proposed feature information fusion (FIF) methods to obtain the globally optimal decision of damage detection. The damage can be accurately detected by global optimal decisions [47]. Simon Laflamme proposed a method to convert the strain on the blade surface into measurable capacitance change using a low-cost, soft, elastic capacitor. Numerical simulation shows that the data-driven algorithm based on the distributed strain data can prove the existence and location of damage and rank its severity [48]. Kyunghyun Lee et al. proposed a deflection monitoring system installed on wind turbine blades. The system is based on the strain estimation algorithm and objective function to realize the optimal arrangement of sensors and monitor the vibration of wind turbine blades [49]. Aihara et al. designed a blade-vibration monitoring system. The system uses a strain gauge installed at the root of the blade to calculate and measure the deflection of the blade in real time according to the monitored stress [50]. Binrongwen et al. developed a floating wind turbine blade load online monitoring system based on a fiber Bragg grating (FBG) sensor and fiber optic rotary joint (forj) and verified its feasibility and reliability [51]. Ginu Rajan proposed to use different types of optical fiber optical sensors (FOS) to monitor the strain and temperature changes of wind turbine blades [52]. Ting-Yu Hsu et al. proposed a local flexibility method for locating blade damage [53]. Researchers also developed an algorithm for detecting blade damage using an FBG-based strain gauge [54], and several other studies have successfully used strain monitoring for wind turbine blade condition monitoring [55–58].

3.1.3. Analysis of Advantages and Disadvantages

The resistance strain gauge is widely used because it can easily monitor the small strain changes at each position of the blade and has a low cost. However, the resistance strain gauge needs to select the point to be detected in advance, and then arrange the strain gauge to detect the strain change at this point. It is difficult to directly realize the global damage detection of the blade. At least two wires are required to arrange a strain gauge. The arrangement of a large number of strain gauges will be a very large project and not realistic [39]. The resistance strain sensor attached to the blade surface has difficulty in detecting the damage inside the blade [59]. Furthermore, for long-term monitoring, the resistance strain gauge fails due to creep, temperature, and other reasons [60]. On the other hand, the detection accuracy of the strain gauge is easily affected by electromagnetic interference. Compared with a resistance strain gauge, FBG is favored by more and more people, having fewer connecting wires, anti-electromagnetic interference, anti-fatigue, high sensitivity, and less prone to failure [42]. The FBG-based strain gauge can be embedded into the material structure of the blade and can monitor the strain changes inside and outside the blade material under working conditions [61,62]. Although optical fiber strain detection can measure the many dynamic parameters of blades, it is not easy to directly identify the damage to blades [51,63–65]. On the other hand, the optical fiber strain gauge is embedded in the material of the blade, which puts forward higher requirements for the manufacturing process of the blade and affects the structure of the blade. Especially for wind turbine blades with a larger size, this impact cannot be ignored. Studies have shown that the characteristics and geometric parameters of materials will affect the measurement accuracy of FBG [42]; thus, there remains many challenges in practical application.

3.2. Visual Inspection

3.2.1. General

Visual inspection is a detection technology used in various fields. Similar to human eyes, the state information of the blade cracks, scratches, holes, ice, and so on, can be obtained by taking two-dimensional or three-dimensional images, as shown in Figure 13. At present, UAVs are mostly used to carry high-definition shooting equipment to detect the blades [66–71]. With the development of optics and computer technology, visual monitoring technology has achieved a leap from static detection to dynamic monitoring [31,72]. Image recognition technology has become an important technology [73], and many algorithms have been proposed to extract deformation, cracking, and other features from two-dimensional or three-dimensional images of blades [66,68,74]. With the development of deep learning, such as SVM and convolutional neural networks (CNN), the technology of automatically extracting the depth features of the blade damage is becoming more and more popular [75]. Visual measurement technology includes digital image correlation (DIC) and three-dimensional point tracking (3dpt).

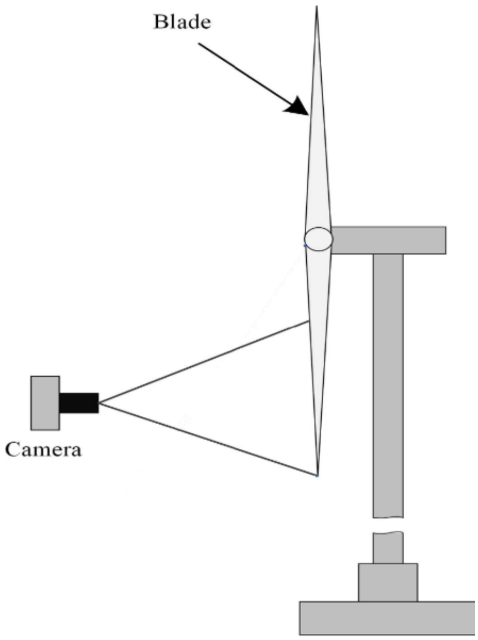

Figure 13. Machine vision-based detection.

3.2.2. Research Progress

Jay T. Johnson et al. developed a three-dimensional image-measurement system to measure the shape change of the wind wing and blade surface displacement change in static and fatigue tests [76]. Jinshui Yang et al. developed video measurement technology for the structural deformation of wind turbine blades during full-scale tests and operation. Based on the principle of convergent photogrammetry, the video measurement technology restores the three-dimensional blade from the photo, marks the blade with specific points, collects the images of these points, and measures the positions of these points at different angles. Finally, the three-dimensional coordinates of these points are determined by triangulation [77]. Dayi Zhang et al. used UAV to conduct remote photographic detection on a retired blade indoors; subsequently, a 3D reconstruction of the blade was carried out through the adaptive path of the UAV, and the damage to the wind turbine blade was clearly observed in the texture 3D reconstruction section of the blade [78]. M. Akhloufi et al. proposed a method to remotely detect and measure the icing of wind turbine blades by using a digital camera in a cold climate. Through algorithm development and experiments on the collected digital images, good results were obtained; but, the thickness of icing could not be obtained [79]. Peymanpoozesh used three-dimensional (3D) digital image correlation (DIC) technology to measure quasi-static and cyclic loads on a 50 m blade. The results show that DIC can accurately provide information on strain distribution and deformation changes during static loading and fatigue loading, which can better understand the state of the blade [80]. They also proposed a multi camera measurement system for dynamic spatial data stitching using three-dimensional digital image correlation (3D DIC) and three-dimensional point tracking (3dpt) to measure the large-area strain and displacement of the blade [81]. Martin Stokkeland et al. proposed a vision module, which enables the UAV to independently calculate the distance from the wind turbine blade and determine the blade position, and detected the blade through the Hough transform algorithm and Kalman filter algorithm [82]. Long Wang, et al. proposed a data-driven framework, which was verified by unmanned active blade images and artificially generated images. The results show that the proposed framework can realize the identification and location of blade cracks [73]. Sahir Moreno et al. proposed a method based on deep learning vision to automatically analyze and detect blade surface faults (wear and fracture) [83]. J. Carr et al. used digital image correlation (DIC) technology combined with a finite element model to measure the displacement of an optical target placed at the specified position through a three-dimensional point tracking method. The two methods are applied to predict the dynamic strain of the blade under dynamic load. The results show that the static and dynamic strains measured by DIC are consistent with those measured by conventional strain gauges [84]. Rong Wu et al. proposed the optical technology based on three-dimensional digital image correlation (3D-DIC), obtained the full field dynamic parameters of blade displacement and strain during operation, and detected the relative deformation and fault during blade operation in a time domain and frequency domain [85]. Abhishek Reddy et al. used the method of deep learning to write the kkeras framework in Python. The neural network model is trained through the images captured by UAV to realize the classification and detection of different types of blade damage [69].

3.2.3. Analysis of Advantages and Disadvantages

The machine vision inspection method can adequately replace the manual visual inspection, especially for the manual inspection of offshore wind farms, which has great risks and high costs. This technology is a non-contact detection method. Three-dimensional digital image correlation (DIC) can quickly realize the large-area damage detection of the entire blade structure, and can also capture the dynamic strain of the blade surface when the blade is running [31,72]. This technology has great advantages over strain gauge detection; the combination of visual inspection and UAV also makes this technology more practical. However, optical measurement is easily affected by light and weather conditions, and the use of UAVs also needs to meet certain environmental conditions [68]. A large number of image processing and analysis need more data and computing resources, and the complex calibration program also limits the further popularization of this technology [76,86,87]. It is difficult to detect the damage inside the blade by visual inspection, which is also a disadvantage of this technology [86]. In the future, the keys to this technology is to realize image acquisition at a higher resolution, have fast and high-precision full-field damage detection, image processing technology, and related algorithms, as well as synchronous positioning. Better adaptation to the use environment is also an important research direction in the future.

3.3. Acoustic Emission

3.3.1. General

Acoustic emission is a passive online detection method. In short, the sensor installed on the blade is used to collect the transient elastic waves emitted from the blade structure and materials. These transient elastic waves may be emitted due to common blade damage such as crack propagation and delamination [88]. Usually, multiple AE sensors are combined to build a sensor network. Using these sensors, damage detection and location can be easily realized. This technology is very sensitive; it can detect transient elastic waves much smaller than normal sound and record this elastic wave for signal feature extraction. For example, blind deconvolution separation and ML algorithms are used to extract damage-related data. Figure 14 is the schematic diagram of the acoustic emission detection. The important characteristics of a typical AE waveform include rise time, duration, counting, energy, peak amplitude, and peak frequency [89,90]. By extracting these parameters, the monitoring of blade damage events such as fatigue, stiffness, and cracks of turbine blades can be realized.

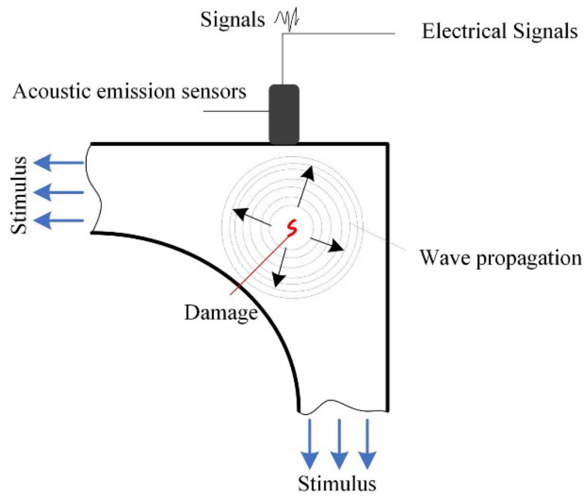

Figure 14. Schematic diagram of acoustic emission detection.

3.3.2. Research Progress

Jialin Tang and others monitored a wind turbine blade using acoustic emission technology simulation of defect growth over a 1-m rectangular area. The result of the experiment showed the successful detection of the growth of the source of the defects caused by fatigue damage, using the method of the triangle to analyze the sensor relative time of arrival, and successfully determined the location of damage growth. In addition, an unsupervised pattern recognition method was proposed to characterize the different acoustic emission behaviors corresponding to different fracture mechanisms [91,92]. D. Xu et al. proposed a clustering method for fast searching and discovering density peaks (cfsfdp), which realizes the identification of different damage modes through the similarity of AE signals. Secondly, a waveform feature extraction method based on wavelet packet decomposition (WPD) was developed to capture the information contained in the original AE signals [93,94]. B. Han et al. used acoustic emission technology to evaluate the damage in the static load test of wind turbine blades, tried to use a new algorithm with the concept of energy contour mapping, and analyzed the correlation between stress conditions and damage identification. The results showed that the acoustic emission was in good agreement with the stress distribution and damage location of the blades [95]. Dimitrios Zarouchas analyzed acoustic emission data based on the frequency method to identify the different damage mechanisms of blades during loading and measured the displacement and deformation of blades in combination with digital image technology [96]. O. Bouzid, et al. proposed an in situ wireless structure state-detection system based on acoustic emission (AE) technology. The system used the developed constraint positioning model to extract the features of the blade damage from the aliased AE signals, which was a new signal processing method. The application of this method in continuous in situ monitoring systems of blade status of large offshore wind turbines is of great significance [97]. Carlos Quiterio Gómez Muñoz et al. studied a blade-condition-detection system and a new signal-processing method, which successfully detected and located fiber breakage in wind turbine blades by collecting and analyzing acoustic emission data from wind turbine blades with three low-cost (MFC) sensors [98]. Wei Zhou et al. studied the damage and failure process of blades by using acoustic emission (AE) technology. They found that the relative energy, amplitude distribution, and duration of acoustic emission were related to the damage process of the sample. The occurrence and propagation of damage was proved by locating the linear acoustic emission source [99]. Z Bo et al. proposed a new method for wind turbine blade fatigue crack identification. The method extracts and analyzes weak crack characteristics based on the BDS algorithm. The results show that the AE signal analysis based on BDS is an appropriate method for distinguishing and interpreting different fatigue damage states of wind turbine blades [100].

3.3.3. Advantages and Disadvantages Analysis

Compared with other non-destructive detection technologies, acoustic emission technology can realize the dynamic monitoring of blades. Compared with visual monitoring, acoustic emission can monitor the occurrence of damage in real time and can detect damage to blades earlier and give an early warning [101,102]. Acoustic emission monitoring requires fewer sensors than surface or local strain monitoring of blades to monitor the health of the entire blade interior and surface and to accurately locate damage [95].

As the blade size becomes larger and larger, the acoustic emission signal tends to fade during the propagation process. Various noise sources reduce the signal-to-noise ratio of the acoustic emission signal [87]. Acoustic emission sensor location, number of sensors, and sampling rate directly affect the accuracy of the technology to a certain extent. A high sampling rate and more sensor arrangement will increase the calculation cost and economic cost [38,101]. Therefore, removing noise pollution, accurately extracting the acoustic emission signal generated by damage, accurately evaluating the critical area of the blades, reasonably arranging the position of the acoustic emission sensor, and realizing reliable acoustic emission data collection and robust data processing under operation are important research directions of this technology.

3.4. Thermal Imaging Monitoring

3.4.1. General

Thermal imaging monitoring technology is also a non-contact monitoring technology, which mainly detects the thermodynamic changes on the blade surface. When the blade is damaged and defective after repeated cyclic loading (such as delamination, cracking, holes, etc.), the structure of the blade is discontinuous. The heat is locally retained at the discontinuous position with low thermal conductivity, resulting in the temperature at the discontinuous position being higher than that at other positions of the blade [103]. When there is a temperature difference on the surface of the blade, this temperature difference can be captured and visualized by a highly sensitive infrared camera in a relatively suitable environment, to realize the rapid detection of blade-damage defects [104–108]. In addition, with the increase in the number of cyclic loads, the high strain area inside the blade will generate heat energy by friction, which allows the engineer to determine the high strain area of the blade [109]. Figure 15 shows the detection and thermal imaging results of the wind turbine blades using infrared thermal imaging technology.

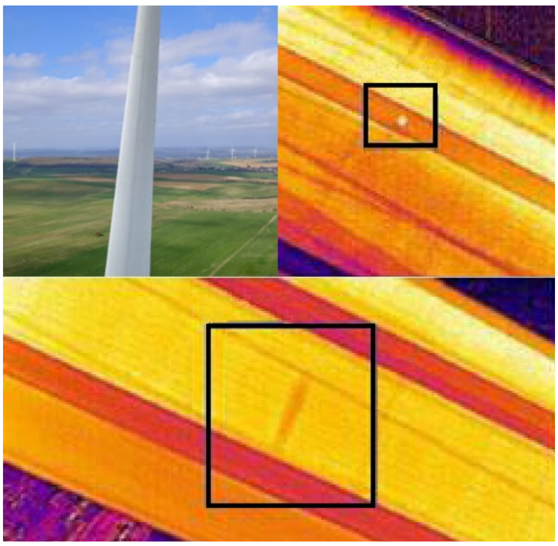

Figure 15. Detection of wind turbine blades by infrared thermal imaging technology and thermal imaging results.

3.4.2. Research Progress

Xiaoli Li et al. used transmission thermal imaging technology to detect the adhesive samples of wind turbine blades. The results show that this technology can effectively detect the adhesion quality of wind turbine blades [110]. Tamara Worzewski et al. took the sun as the excitation heat source, used thermal imaging technology to detect blade damage and defects, and verified the similarity between outdoor experiments and numerical simulation [104]. Miguel Lizaranzu et al. used transient active thermal imaging technology to detect and analyze the defects found in the blades of the wind turbine. The results show that the experimental results of this technology mainly depend on the resolution of the thermal imaging camera, heat source, and the required minimum defect size/accuracy ratio [111]. Soonkyu Hwang proposed a continuous line laser thermal imaging technology and developed a new pixel-tracking and statistical pattern-recognition algorithm, which can detect the damage to the blade without stopping the wind turbine. Using this technology, the internal delamination at 1 mm below the blade surface is successfully detected at the position ten meters away from the wind turbine blade [112,113]. Christoph Dollinger uses thermal imaging flow visualization to non-invasively measure the boundary layer flow disturbance caused by pollution and erosion of wind turbine blades in operation. The measurement results can be used to evaluate the annual energy loss caused by leading edge conditions [114]. C. Galleguillos et al. proposed the feasibility study of using UAV system (UAS) thermal imaging technology in wind turbine blade damage and defect detection, and developed flight software to process the images online [115]. Carlos Quiterio Gómez Muñoz et al. proposed a method of detecting the icing of wind turbine blades with a broadband thermal radiometer using remote sensing technology. This method is based on the drastic emissivity change on the surface when blade icing occurs, and collects the measured value of radiation temperature to detect the icing of wind turbine blades [116]. Hadi Sanati et al. proposed a method called "step phase and amplitude thermal imaging" to process the thermal image obtained by active thermal imaging. This method applies a transformation-based algorithm to the step heating and cooling data, which can greatly improve the image quality and the visibility of internal defects [117]. F. Hahn et al. studied the static and fatigue integrity of cross-section blades under DLR for up to 5 million load cycles. During the fatigue test, the blade stress distribution was observed by a thermoelastic stress analysis camera (TSA), and the measured values located the stress concentration that could not be predicted by finite element analysis [118]. Dutton Ag et al. developed a new thermoelastic stress analysis technology, which can identify all damage areas in the test blade, and the signal size is directly proportional to the damage severity. The technology can also be used to verify the overall stress distribution on the blade surface and detect developing damage [119].

3.4.3. Analysis of Advantages and Disadvantages

Thermal imaging technology can detect the damage and defects of wind turbine blades over a large range in a short time [111], especially the delamination fault under the blade surface. Its efficiency and accuracy can be comparable to other detection technologies [120]. Using this technology avoids the installation of more sensors. Only a high-resolution thermal imaging camera is needed to complete the detection, which reduces the operation and maintenance cost. However, generally, the temperature change of the damaged position of the blade is very slow. Thermal imaging technology requires enough heat at the damaged defect position to be perceived by the thermal imaging camera. Due to the slow development of temperature, it is not suitable for early-stage fault detection [121]. Thermal imaging technology has certain requirements for ambient temperature; in other words, the detection results of the infrared camera are easily affected by the ambient temperature [105,106,122]. In addition, the reflection and pollution on the blade surface will also interfere with thermal imaging detection [109]. At present, most thermal imaging technologies need to shut down the wind turbine for detection, which increases the shutdown time and causes certain economic losses. Therefore, how to reduce external interference and how to carry out thermal imaging detection of wind turbine blades under operating conditions remains a challenge.

3.5. Ultrasonic Testing

3.5.1. General

Ultrasonic testing technology is a relatively mature technology to detect the defects of composite and other materials [123]. Ultrasonic testing technology is widely used to detect the internal debonding, delamination, and other defects of wind turbine blade materials. An elastic wave of more than 20 kHz is introduced into the mechanism of the blade through a transmitter. The wave propagates along the structure of the blade and passes through or interacts with the defects (such as delamination, debonding, and crack) to make the wave change in the propagation process. The second sensor measures the mode changes, such as propagation, amplitude, phase, time, reflection, and attenuation of the elastic wave, to accurately judge the location and size of the damage [90,124]. Figure 16 shows the basic detection mechanism of ultrasonic detection.

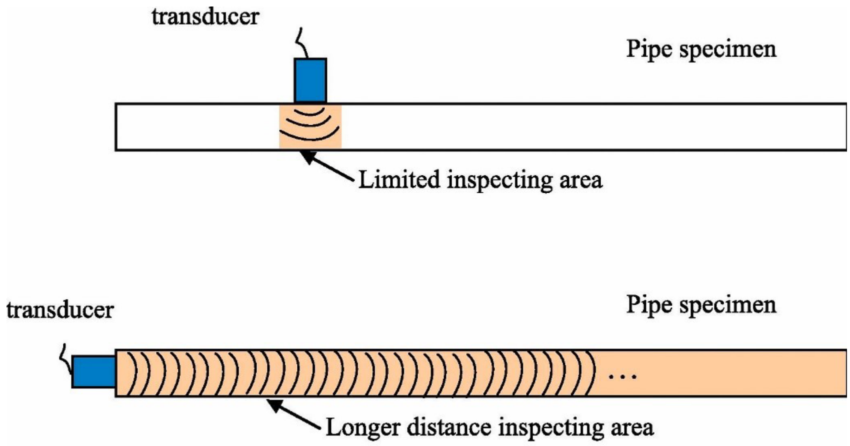

Figure 16. Basic detection mechanism of ultrasonic detection.

3.5.2. Research Progress

Kumar Anubhav Tiwari et al. used ultrasonic nondestructive testing on wind turbine blades made of composite glass fiber-reinforced materials. The acoustic signal is refined to characterize the types of defects, such as debonding at different positions of the blade [125]. The team proposed a hybrid signal-processing technology, which combines discrete wavelet transform with an amplitude detection method to estimate the size and location of defects in wind turbine blades. The variational modal decomposition is combined with the Hilbert transform to compare the instantaneous frequency and amplitude of defective and non-defective signals, and for measuring the time delay between defective and non-defective signals [126,127]. Q. Liu et al. designed an automatic positioning system for ultrasonic detection of wind turbine blade defects, which can automatically send and obtain ultrasonic waves. Thus, the damage detection of the blade can be realized efficiently [128]. Byeongjin Park et al. proposed a non-contact laser ultrasonic measurement system. Firstly, the system uses adaptive rough scanning of the wind turbine blades to identify layered areas and locate them quickly. Then the layered area is scanned in high resolution and high density, and finally, the rapid visualization of the layered part of the blade is realized. The system shortens the detection time and improves the detection efficiency [129]. Based on ultrasonic nondestructive testing, Alfredo Arcos Jiménez et al. used advanced signal-processing methods and machine learning to detect the dirt and corrosion of blades. This method first carries out wavelet transform on the signal and reduces the dimension of the signal through feature extraction and feature selection. The experimental results show that this method provides good results for the detection and diagnosis of blade mud [130]. André Lamarre et al. proposed advanced ultrasonic phased-array technology to detect the bonding integrity between the structural beam and the shell in the manufacturing process of composite wind turbine blades. This technology can realize the rapid detection of 100% coverage [131]. Li Ting et al. studied the quantitative relationship between ultrasonic parameters and millimeter debonding defects using time domain analysis and short-time Fourier transform (STFT) time-frequency analysis through simulation. An STFT time–frequency diagram is helpful to visually distinguish different degrees of defects [132]. Guoliang Ye et al. used pulse echo ultrasound to detect the internal damage of wind turbine blades and developed a software system to control automatic scanning and display the internal damage area in 2D/3D maps of different colors [123]. Haozuo proposed a two-dimensional multiple signal classification (Music) damage-identification algorithm based on a guided wave propagation model. Using the orthogonality of signal subspace and noise subspace to search for the peak point of the spatial spectrum in the monitoring area, the damage can be successfully identified [133]. S. Shoja et al. developed a calculation model to simulate the propagation of guided waves in frozen blade materials, and introduced a post-processing algorithm and icing index. The results show that this method can be used to detect the icing of wind turbine blades [134]. T. Michaels proposed a non-contact ultrasonic testing method without a coupling agent, which is realized by connecting sparse ultrasonic transducers to the back of the assembly or embedding them in the assembly. These transducers are excited to generate ultrasonic waves propagating through the structure, and the generated acoustic field is imaged by using non-contact air-coupled transducers, This ultrasonic wave field imaging method is called acoustic field imaging (AWI). The results show that the recorded wavefield image clearly shows the bonding defects at the internal interface [135]. Byeongjinpark proposed a complete non-contact laser ultrasonic field imaging technology. The scanning laser beam is used as the transmitter and the laser Doppler vibrometer as the receiver. The receiver is used to automatically detect and visualize hidden delamination and debonding in composite structures [136]. Moisés A. Oliveira et al. proposed using bubble pulse echo ultrasonic technology to obtain data from the wind turbine blade samples. Wavelet denoising and principal component analysis are used to preprocess the ultrasonic signal. Finally, the relevant defect features are extracted from ultrasonic signals [137].

3.5.3. Analysis of Advantages and Disadvantages

Ultrasonic detection technology can detect the millimeter level damage inside the blade [138], which has great advantages for the defect and delamination detection of the blade sub surface. which provides strong support for the early detection and early warning of blade internal damage [132]. Ultrasonic testing technology is not affected by the external environment (such as temperature, humidity, noise, etc.). The attenuation of ultrasonic signals in long-distance transmission is small [125].

Ultrasonic testing needs the help of a liquid couplant, and if the damage is not on the propagation path of ultrasonic waves, the damage will be difficult to detect, or the sensitivity will be reduced. This technology is difficult to use to detect wind turbine blades that have been in service [139]. The multilayer composite structure is prone to noise pollution and complex signal processing [9]. It is an important research direction of this technology to study the efficient algorithm of ultrasonic detection based on artificial intelligence.

3.6. Vibration Monitoring

3.6.1. General

Vibration monitoring is a widely used monitoring technology, which mainly monitors the health state of the blade based on the dynamic response of the blade structure under external force excitation [140,141]. Since the dynamic response of the blade depends on the characteristics of the blade material and structure (such as mass, stiffness, and damping), the reduction in blade stiffness caused by the blade damage leads to the change in modal characteristics, Therefore, damage changes in the blade structure can be characterized and detected from the characteristics of the dynamic response and modal parameters [124].

However, only those sensors located near the defect location can respond sensitively to the crack propagation in the blade.

A vibration sensor will be used for vibration monitoring. The use of a vibration sensor depends on the range of frequency. Generally, a displacement sensor measurement is used for low frequencies, speed sensor measurement is used for medium frequencies, and acceleration sensor measurement is used for high frequencies [90]. Among them, the acceleration sensor is widely used for WTB detection [142]. Figure 17 shows the dynamic experiment of using an acceleration sensor to monitor wind turbine blades. Signal processing is a key component of any vibration-based structural health monitoring (SHM). The purpose of signal processing is to extract the subtle changes in the vibration signals in order to detect, locate, and quantify the damage, and its severity, to the structure [143]. For example, empirical mode decomposition (EMD), Markov model (HMM), deep neural network (DNN), and other methods are regarded as signal-processing tools for blade fault detection [9,101].

Figure 17. The dynamic experiment of monitoring wind turbine blades with acceleration sensors.

3.6.2. Research Progress

Yanfeng Wang et al. combined the finite element method (FEM) with the modal difference curvature (MSDC) information method for damage detection/diagnosis and proposed a dynamic analysis method (modal analysis and response analysis) to realize blade-damage detection and diagnosis. The results show that this method can detect the spatial location of wind turbine blade damage [144]. N. Dervilis et al. used probabilistic principal component analysis (PPCA) and other methods to convert the original measured value into a low-dimensional representation. This novel detection technology provides a machine learning method for the structural health monitoring of wind turbine blades [145]. Alexandros Skrimpas used a cabin vibration acceleration sensor and power performance curve analysis to detect the icing of the wind turbine blades. In the process of detecting and verifying the wind turbine with frozen blades, similar patterns on the vibration and power curve data verified the effectiveness of this method in detecting ice formation [146]. M. D. Ulriksen proposed a method based on modal and wavelet analysis, which was applied to the damage identification of wind turbine blades. Firstly, the modal shapes of undamaged and damaged blades were obtained. The modal shape was analyzed by a one-dimensional continuous wavelet transform for damage identification [147]. Łukasz Doliński et al. used the finite element method (FEM) and laser-scanning vibration method (LSV) to obtain numerical results. One-dimensional, continuous wavelet transforms based on the vibration parameters of the wind turbine blades were used to determine the delamination position and nondestructive diagnosis in wind turbine blades [148]. Lijun Zhang et al. used SCADA data to detect the ice of wind turbine blades, and proposed a model based on a random forest classifier. Compared with other classification models, the model based on a random forest classifier is more accurate and efficient in computing power and is more suitable for the practical application of blade icing detection [149]. L. Colone proposed a method to detect the quality of wind turbine blades by using natural frequencies, which is based on statistical pattern recognition of structural natural frequency changes [105]. Andrew Summers et al. combined coherent lidar technology with B-spline point generation and alignment to establish accurate measurement technology for wind turbine blade detection [106]. Philip Arnold proposed a radar-based method for structural health monitoring of wind turbine blades. This method proposed a differential damage location framework, which uses the signal difference between the measured values of intact and damaged blades to image the defects in 3D [122]. S. Ganeriwala used modal analysis to detect cracks in wind turbine blades. The acceleration was measured at 13 locations on the blade surface. The modal frequency, shape, and damping of the first eight modes were extracted and compared in different health states. The results show that the natural frequency and damping of the specific modes are sensitive to surface cracks [150]. Tcherniak et al. developed a vibration-based SHM system. The system uses the impact generated by the electromechanical actuator installed inside the blade, and the accelerometer array measures the vibration response generated by the blade to detect the damage. The detected damage is described based on the covariance matrix calculated from several measured acceleration responses [151].

3.6.3. Analysis of Advantages and Disadvantages

Vibration monitoring is a widely used and easy-to-understand technology, which is mainly based on the modal changes between the intact state and the damaged state of the structure. The vibration-based method is an easy-to-implement, mature, and highly reliable blade fault identification method. It is also a non-destructive testing technology. It has been proved that the external damage and edge damage of blades are identifiable in the laboratory [152–154]. The main disadvantage of this method is that many sensors are needed to detect the location and severity of the damage, and wind speed, rotation speed, temperature, environmental operating conditions, etc., will significantly affect the dynamic characteristics of the blades [124,155]; this will cause the detection of damage to go wrong. In addition, the vibration-based method has difficulty in detecting early damage because the vibration signal has a low signal-to-noise ratio. The difficulty and research hotspot of this technology is to distinguish the vibration caused by the environment and operating conditions from the vibration caused by blade damage [9,156].

3.7. Acoustic Monitoring

3.7.1. General

Acoustic monitoring technology is mainly used to monitor the sound pressure change of the air medium to realize the detection of blade structure health. The sensor of the sound pressure change measurement is a microphone. The wind turbine will produce a lot of noise during operation, and some of them are directly related to the health state of the blades [157]. The sound collected by the microphone can be used to extract the information related to blade damage by using a variety of signal-processing strategies, which can realize the monitoring of blade health [158,159]. In addition to single microphone measurements, multiple microphones can also be assembled into a microphone array to realize the directional measurement of the sound source [160].

Acoustic monitoring technology is divided into active acoustic detection and passive acoustic detection. As shown in Figure 18, active acoustic monitoring is used to detect the damage to blades by using the sound generated by generators such as speakers. Passive acoustic detection is mainly based on the sound generated by the natural operation of the blade structure, such as the sound naturally generated by structural changes such as blade cracking and corrosion.

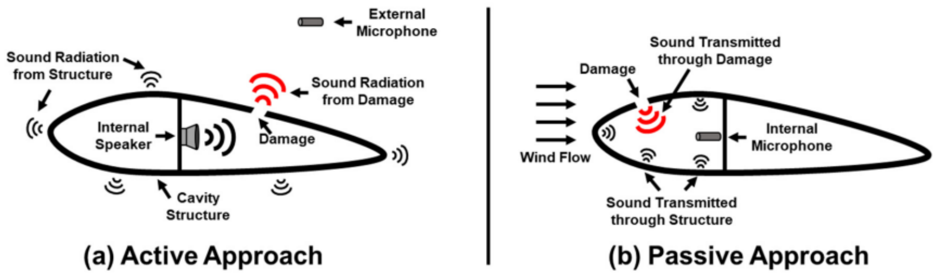

Figure 18. Active acoustic detection and passive acoustic detection.

3.7.2. Research Progress

Bruno M. Fazenda et al. used a microphone to collect the sound generated by the stratification near the tip of a small wind turbine blade during operation and proposed a feature extraction as well as fault diagnosis method through time synchronization analysis (TSA), overall empirical mode decomposition (EEMD), and a single eigenmode function spectrum. The results showed that obvious harmonic changes were observed [161]. The team also used this method to simulate the acoustic characteristics of blade icing. Two detection methods were developed to detect the degree of blade icing and improve the detection accuracy [162]. Thomas C. Krause et al. developed a detection algorithm based on signal analysis. The algorithm considers the power spectral density, tone, spectral slope, spectral similarity, and pulse attenuation characteristics to detect the crack sound from the sound pressure measurement inside the wind turbine blade, but the accuracy is relatively low. Later, the algorithm considers pulse detection in a single frequency band. Compared with the previous version, the number of correctly identified crack events is three times [163,164]. V. Aroraa et al. proposed a damage-detection method based on active acoustics. By comparing the changes in the vibration acoustic flexibility matrix between damaged and undamaged blades, the location and degree of damage were obtained. The results show that the proposed method can be used to accurately detect the location and extension of damage [165]. Peyman Poozesh et al. proposed to use a single microphone or beamforming array to observe the sound radiation of the blade to detect the damage in the blade. First, install the audio speaker in the wind turbine blade, and then observe the sound radiated by the blade to identify the damage. The results show that both acoustic beamforming and CLEAN-based point spread function subtraction can identify the damage in the blade with high enough fidelity [166]. Regan et al. measured the sound signal generated by the Bluetooth speaker in the wind turbine blade through the microphone installed outside the tower. The combination of calculated statistical and spectral features was used as the input of the machine learning model to classify the health state of the wind turbine blades. The results show that 98% of the data can be correctly classified, including several individual edge cracks and hole damage [167]. Some computational acoustic methods have been used for damage identification of wind turbine blades [168,169]. Shilin sun et al. proposed an adaptive identification method of blade damage based on microphone array and compressed beamforming to realize the overall and remote health assessment of blades [160]. Christopher Beale proposed an adaptive wavelet packet denoising algorithm to enhance the denoising performance of real-time active acoustic monitoring [170].

3.7.3. Analysis of Advantages and Disadvantages

Based on acoustic blade-monitoring technology, passive acoustic monitoring can capture blade sound information in real time and online. Only one microphone device is needed to evaluate the health status of the blade under operating conditions. This technology has great potential for timely detection of blade faults. However, this requires continuous and intermittent sampling, storage, and calculation, and the collected sound is vulnerable to other noise interference. Active acoustic monitoring is more flexible and can control when to carry out acoustic detection of blades. However, this technology requires additional power and acoustic excitation equipment (such as speakers) in addition to microphone equipment. Both technologies need a high sampling rate to capture the sound signal of blade damage more accurately. In future research, how to accurately identify and extract the sound of various damaged types of blades and how to realize robust signal processing in a noise environment are important research directions.

3.8. Other Case Study Methods

There are other blade damage-detection technologies, such as the ray-detection method. There are two different radiation sources in the industry: X-ray and gamma ray. These two methods have been used to identify the density difference detection in the wind turbine blade structure, which can detect the damage and defects inside the blade. Holub W et al. analyzed different types of defects of blades through X-ray image processing, especially defects in fiber materials [171]. J. G. Fantidis et al. used gamma radiography to detect defects such as blade cracks, corrosion, inclusions, and thickness changes [172]. Shear imaging detection technology shows the change in surface deformation by interfering with the laser point mode [173]. Hyperspectral imaging is a nondestructive testing technology, which has high accuracy and precision in blade-defect detection [174]. Some researchers have developed a fault-detection method for helicopter rotor systems based on a neural network. In detail, the two neural networks are composed of an input layer, hidden layer, and output layer, which are used to classify the fault type and characterize the damage degree. Introducing this method to the fault detection of wind turbines is a direction worthy of study [175]. Andrea Skypranou et al. proposed a damage-detection method based on spatiotemporal continuous wavelet transform (spt-cwt) analysis of time response series. The proposed method does not need to understand the actual environmental conditions [176].

4. Comparison and Analysis

4.1. Comparison

In the previous part of this article, the main detection methods of and research progress on blade damage are introduced. The blades of wind turbines are rotating components, and most of the wind turbines are located in remote areas. Offshore wind turbines are also gradually moving towards the deep sea, and their operation and maintenance costs are much higher than that of onshore wind turbines. In this section, various damage-detection technologies are compared and analyzed through tables, comparison for major NDT methods are provided in Table 1 and the possible research directions for the future are analyzed and predicted.

Table 1. Summary and comparison of the major methods for WTB inspection (based on the data from references used in this paper).

Main Detection Methods	Advantage	Disadvantage
Strain detection	➢ It can sensitively detect local small structural changes and realize early fault detection ➢ It can detect continuously during operation and predict the service life ➢ Sensitive to internal defects (optical fiber sensor) ➢ Low cost, small size, low sampling rate, without external active incentives ➢ Free from electromagnetic interference (optical fiber sensor), better frequency response. ➢ No external power supply (optical fiber sensor) is required. ➢ Long-distance signal transmission will not degrade	➢ The sensor needs to contact the blade to get better detection results ➢ It needs the theoretical support of high strain zone, and accurate installation can improve the detection accuracy ➢ Due to the limited monitoring range of sensors, more sensors are needed to realize the whole global detection ➢ The reliability of the sensor is easy to deteriorate due to creep and fatigue ➢ Insensitive to internal defects (resistance strain gauge) ➢ Complex manufacturing process (optical fiber sensor) ➢ Each resistance strain gauge requires at least two wires, which increases the complexity of the system

Table 1. *Cont.*

Main Detection Methods	Advantage	Disadvantage
Visual detection	➢ Low cost, high precision, suitable for surface damage detection ➢ Use UAV to realize flexible detection and avoid the safety risk of manual climbing detection ➢ It can carry out a wide range of global detection in a short time ➢ Abundant image processing algorithms can realize online	➢ A lot of calculation is needed, the accuracy of detection depends on the high-precision calculation and processing of image processing software. ➢ Unable to detect internal damage ➢ It needs to cooperate with accurately controlled UAV to realize detection ➢ Easily disturbed by weather and light
Acoustic emission detection	➢ High sensitivity for different types of damage ➢ Continuous on-line detection and early detection of damage ➢ It can realize the location of damage ➢ No need for external incentives	➢ It requires domain contact and can be detected more accurately when it is installed on the blade ➢ Need multiple sensors to improve detection accuracy ➢ It is easy to be disturbed by noise. Only the damage near the sensor is easier to be detected ➢ It is often used in noisy operating environment, and the signal is weak and easy to decay, so it is difficult to identify AE signals
Thermal imaging detection	➢ It can realize the intuitive detection of the whole field ➢ Simple application and relatively short detection time ➢ It is sensitive to fatigue, delamination and other tests ➢ UAV detection can be used ➢ Non-contact installation	➢ It is sensitive to temperature changes and is affected by temperature and air humidity ➢ Cannot be used for early detection of damage ➢ Not applicable to continuous operation detection ➢ Active imaging requires external excitation ➢ Requires high resolution and thermal image processing
Ultrasonic detection	➢ It has high sensitivity and reliability for internal damage detection ➢ The location, depth and severity of damage can be determined ➢ Very small defects can be detected ➢ The size and shape of the damage can be imaged ➢ Long-distance propagation, less attenuation	➢ The sensor needs to be connected to the surface for detection ➢ For such a large structure, the detection time is relatively long ➢ Damage detection cannot be carried out during operation ➢ Need additional incentives ➢ Multilayer composite structure is more susceptible to noise pollution, resulting in complex signal processing
Vibration detection	➢ Nondestructive and highly sensitive detection technology ➢ Abundant signal processing algorithms ➢ Easy to install and implement ➢ The location and severity of the damage can be detected	➢ The environment will affect dynamic properties, resulting in errors in detection ➢ In the limited detection range, it requires multiple sensors to detect the location and severity of damage ➢ It has low sensitivity (low SNR) to minor damage and early damage ➢ Extensive interference makes it difficult to distinguish between vibration characteristics from normal use and changes due to damage
Acoustic detection	➢ Comprehensive detection can be carried out in the operation of wind turbines ➢ Relatively few sensors are required ➢ It is sensitive to weak defects and early defects ➢ The event and severity of damage can be detected ➢ Microphone array can be used for positioning	➢ Damage with constant sound energy cannot be detected ➢ High slave sampling rate makes signal processing difficult ➢ As the distance increases, the sound signal will decay ➢ Active acoustic detection requires external excitation ➢ The correlation between signal and damage is not clear enough and needs further study

4.2. Future Research Directions

Most detection technologies need shutdown detection. A shutdown will cause certain economic losses in the future and will also have a certain impact on the power grid.

How to classify and evaluate blade damage under operating conditions is a research direction worthy of attention. All kinds of blade-damage-detection methods have their own advantages and limitations. The combination of different detection technologies can give full play to their respective advantages and realize the synchronous detection of different types of damage in different areas of blades. With the development of machine vision and image-processing technology, the detection technology based on machine vision has the characteristics of low cost and simple operation. Through the application of special image acquisition equipment and image-processing methods, the detection accuracy can be easily improved. Image processing and related algorithms, and machine learning of visual damage recognition, are promising research directions. Various data will be generated in the operation of current wind turbine equipment. Combining these data with blade detection data can accurately monitor the damage to the whole blade. In addition, the installation, design, and integration of a wind turbine blade-damage-detection device is not only an interesting and challenging problem but also a potential future direction. The operation and maintenance cost of offshore wind power is much higher than that of onshore wind power. According to the characteristics of offshore wind power, new detection methods and equipment are needed. The noise interference of onshore wind turbines has become an important condition to limit the installation. Most noise studies focus on how to reduce noise. However, at sea, the influence of aerodynamic noise generated by wind turbine blades is relatively small. Furthermore, offshore wind farms are being located farther and farther away from the shore, so using acoustic technology as the monitoring method to assess offshore wind turbine blade damage has very high potential.

5. Conclusions

The health monitoring of wind turbine blades is very important for the safe and efficient operation of wind turbines. Detection of blade failure on time can not only reduce downtime, lower operation and maintenance costs, but also avoid greater catastrophic losses. Based on practical problems, this paper comprehensively summarizes the typical damages and their mechanism. The mechanism and research progress of the main detection technology at present were deeply studied and analyzed. Finally, the possible research direction of wind turbine blade damage-detection technology is highlighted. Vibration monitoring, strain monitoring, and acoustic emission (AE) are widely used, economical, and practical methods to detect wind turbines in operation. However, the sensor needs to be in close contact with the blade surface to get a better detection effect. Ultrasonic detection is also a contact detection method. Although this technology has great advantages for detecting the hidden damage of the blade, this technology cannot efficiently realize full-field detection under a running state, and most of the detection requires the use of couplants. Visual inspection and thermal imaging can intuitively detect the surface and internal damage of blades without contact, but most of them need to be detected when the wind turbine is stopped to have more accurate results. The acoustic detection can detect the health state of the blade under the running state without contact. This method only needs to install a microphone, and the installation is relatively simple. It can be directly installed in a suitable position, but the accurate identification of blade noise changes caused by blade damage needs further research. Most wind farms are located in remote areas, and offshore wind power is also gradually moving towards the deep sea. To sum up, non-contact, real-time, online, remote, accurate health detection of blades under operating conditions will be the main trend in wind turbine blade damage detection in the future. This paper will provide a reference for understanding the mechanisms behind the main damage types and collates the main damage-detection methods of wind turbine blades, which has important significance for further promoting practical research in damage-detection technology of wind turbine blades and grasping the research directions.

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Abbreviations

The abbreviations employed in this article are listed below:

WTB	Wind turbine blade
GFRP	Glass fiber-reinforced polymer
CFRP	Carbon fiber-reinforced polymer
AEP	Annual energy production
FBG	Fiber Bragg grating
POF	Plastic optical fiber
FIF	Feature information fusion
FOS	Fiber optical sensors
DIC	Digital image correlation
CNN	Convolutional neural network
3D-DIC	Three-dimensional digital image correlation
AE	Acoustic emission
WPD	Wavelet packet decomposition
TSA	Thermoelastic stress analysis camera
STFT	Short-time Fourier transform
TSA	Time synchronization analysis

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