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Review

Review on the Damage and Fault Diagnosis of Wind Turbine Blades in the Germination Stage

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Abstract: In recent years, 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. This paper reviews the commonly observed types of damage and damage detection methods of wind turbine blades. First of all, a comprehensive summary of the common embryonic damage, leading edge erosion, micro-cracking, fiber defects, and coating defects damage. Secondly, three fault diagnosis methods of wind turbine blades, including nondestructive testing (NDT), supervisory control and data acquisition (SCADA), and vibration signal-based fault diagnosis, are introduced. The working principles, advantages, disadvantages, and development status of nondestructive testing methods are analyzed and summarized. Finally, the future development trend of wind turbine blade detection and diagnosis technology is discussed. This paper can guide the use of technical means in the actual detection of wind turbine blades. In addition, the research prospect of fault diagnosis technology can be understood.

Keywords: wind turbine blades; the germination stage of damage; fault diagnosis; non-destructive inspection

Citation: Song, X.; Xing, Z.; Jia, Y.; Song, X.; Cai, C.; Zhang, Y.; Wang, Z.; Guo, J.; Li, Q. Review on the Damage and Fault Diagnosis of Wind Turbine Blades in the Germination Stage. *Energies* **2022**, *15*, 7492. https://doi.org/10.3390/en15207492

Academic Editor: Davide Astolfi

Received: 6 September 2022
Accepted: 5 October 2022
Published: 12 October 2022

1. Introduction

At present, as primary energy such as oil, coal, and natural gas are gradually consumed, the energy crisis and environmental problems are becoming increasingly serious [1]. To balance and eliminate carbon dioxide emissions, many economies have set targets for carbon peaking and carbon neutrality, including 124 countries committing to achieving carbon neutrality by 2050 or 2060 as of February 2021 [2]. As one of the most commonly used renewable and clean energies, the development and utilization of wind energy play a key role in carbon neutralization [3–5]. By 2021, the world's newly installed capacity of wind energy reached 88 GW, and by 2050, wind and solar power are expected to account for about 70 percent of the global power supply [6,7]. As the installed capacity of wind power increases, the number of wind turbine failures also shows an increasing trend. As shown in Figure 1, by September 2021, there had been a total of 3093 accidents reported [8]. As one of the key components of the wind turbine, the wind turbine blade (WTB) has growing requirements for a safe, stable and sustainable operation environment with its size increasing [9,10]. Onshore wind turbine operational and maintenance costs account for 5–10% of power generation costs, even 25–30% at sea [11]. Therefore, reducing operation and maintenance costs are very important for the healthy development of wind turbines.

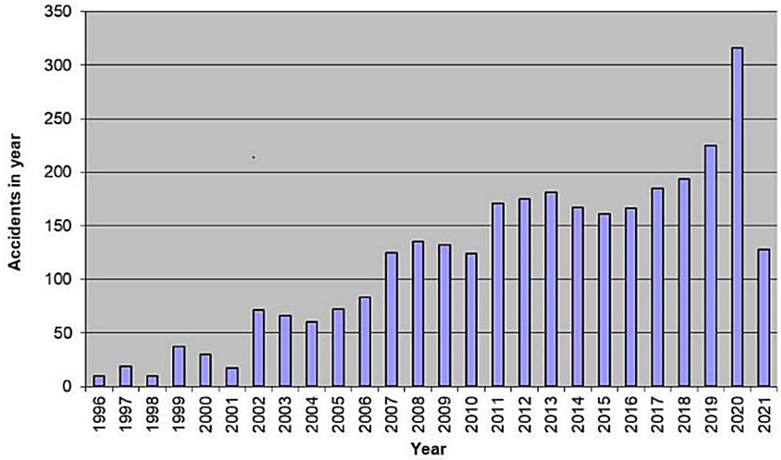

Figure 1. Statistics of wind turbine accidents recorded since 1996 [8].

The main reasons for the damage failure of wind turbines come from two aspects. On the one hand, it is a poor natural environmental factor, and on the other hand, it is a human factor. For example, improper operation in the manufacture, transportation, process, and maintenance of wind turbines causes damage to them. Identically, wind turbine blades are usually located in areas with a relatively poor natural environment, which is prone to damage and failure. The germination stage of damage needs to be paid enough attention to. The slow accumulation of micro-damage may cause serious damage, which directly affects the efficiency of wind turbine power generation. More seriously, it will lead to wind turbine shutdown or even collapse, resulting in catastrophic consequences [12]. The detection and diagnosis of wind turbine blades conducted in time at the germination stage of microscopic damage can lower the probability of failure and prolong the service life of wind turbines. Therefore, in order to ensure the normal operation of wind turbine blades, it is of great significance to realize the structural health monitoring (SHM) of the wind turbine blade monitoring system. The most successful application of SHM technology is condition monitoring (CM) for rotating machinery [13]. CM has become an important part of the wind turbine system. However, SHM technology for blade health monitoring is still in the development stage.

There are three types of diagnosis methods of wind turbine blade damage: the non-destructive testing (NDT) technology of blades, the supervisory control and data acquisition (SCADA)-based method, and the vibration signal-based method. In recent years, NDT has been widely used in wind turbine blade fault diagnosis [14,15]. Li et al. [16] reviewed the latest research progress on wind turbine blade damage detection, mainly including four detection methods, transmittance function, wave propagation, impedance, and vibration method. In further research, Yang et al. [17] comprehensively analyzed the advantages and limitations of common damage types and the NDT of wind turbine blades and predicted the development trend of WTB detection. Furthermore, Fausto et al. [18] summarized the application of nondestructive testing methods and monitoring technology in SHM. In order to avoid the failure of wind turbine blades, in addition to the application of NDT, the condition monitoring system (CMS) is also installed on the wind turbine blades. The real-time signal collected by sensors and electronic equipment can be combined with the SCADA parameters to accurately monitor the operation state of the wind turbine blade and realize the intelligent and digital monitoring of the wind turbine blade [19]. Igba et al. [20] proposed a common approach to CMS for wind turbines (WTs) to meet the requirements of lifetime engineering services (TES). While the intelligent monitoring of CMS is realized, accurate fault identification becomes the research focus. Koitz et al. [21] developed an efficient and accurate fault identification program for improving WTs fault detection, location, and maintenance to solve the problems of monitoring error and false alarms in CMS. The fault diagnosis of wind turbine blades based on vibration signals can not only be applied to wind turbine blades but also the entire wind turbine. Studying noise removal is also the focus of scholars' research. Aiming at the problem of noise interference in vibration signal acquisition, Liu et al. [22] reviewed methods of noise removal by wind turbine health condition monitoring (HCM). Based on the vibration signal analysis method, the wind turbine was monitored, and the noise interference was eliminated to protect the safe operation of the wind turbine. With the continuous development of science and technology, new fault diagnosis technology is continuously applied to the damage detection of wind turbine blades, which is of great significance to the development trend and prospect of WTB fault diagnosis technology.

The content of this article is given as follows. Section 2 introduces the material structure of the wind turbine blade and the damage of leading edge erosion, micro-cracking, fiber defects, and coating defects in the germination stage of the blade. In Section 3, three fault diagnosis and detection methods of wind turbine blades are reviewed, among which the nondestructive detection methods include acoustic emission, ultrasonic, strain measurement, thermal imaging, machine vision, and other methods. The basic principles, advantages, and disadvantages of each method are summarized. Sections 4 and 5 discuss and summarize the development trend of future wind turbine blade damage detection methods.

2. Microscopic Damage of Blades

The blade structure is constructed by the composite structure, forming six different carbon fiber laminate regions [23], and modern wind turbine blades are usually composed of fiber-reinforced composites. Most wind turbine blades are composed of glass fiber/epoxy resin, glass fiber/polyester, wood/epoxy resin, or carbon fiber/epoxy resin composites [24]. The material and structural performance of the blade directly affect the stiffness and strength of the blade. With the rapid development of material technology and the optimization of the structure, the probability of blade damage gradually decreases. The risk of wind turbine blade damage largely depends on the surrounding environment and climatic conditions. Lightning stroke, fatigue load, surface ice on the blades, and the exposure of the blades to air particles, may cause the germination stage of damage such as leading edge erosion and micro-cracking of blades [9]. In addition, offshore wind turbines are faced with the influence of wave climate change and marine corrosion on the blade tension distribution range and fatigue damage. The corrosion environment will reduce the performance of the blade composite material, resulting in the fatigue failure of the blade and accelerated damage [25,26]. Therefore, choosing the appropriate installation site and timely detection in the germination stage of damage are the most effective measures to reduce damage. Damage tolerance design is a modern fatigue fracture control method developed and gradually applied in the 1970 s to ensure the safety of essential components with cracks or possible crack damage [27]. The blade design currently considers a certain margin and adopts the damage tolerance design. However, once installed, there will be many uncontrollable factors that will still lead to damage initiation. In addition, there is surface corrosion damage (due to bad weather), which is very difficult to avoid, so regular testing is needed to detect damage in time. The specific causes and hazards of the germination stage of damage are shown in the following sections.

2.1. Leading Edge Erosion

The leading edge erosion (as shown in Figure 2) of wind turbine blades is mainly caused by the impacts of small particles in the air, such as dust, rain, hail, etc. Leading edge erosion occurs mostly at the tip of the blade, and over time, erosion also occurs inside the blade structure [28]. The leading edge erosion will lead to an increase in blade roughness, thereby increasing the resistance of blade rotation. As a result of that, it will reduce the efficiency of wind turbine power generation and affect economic benefits.

Figure 2. Photo of the leading edge erosion [29].

2.2. Micro-Cracking

Under normal working conditions, a long time of wind load will cause fatigue degradation of the wind turbine blade due to cyclic loading, and the blade material will experience micro-damage cracks, as shown in Figure 3. The slow accumulation of micro-cracking will easily cause blade fracture and hit the nearby wind turbine, causing serious accidents. In addition, wind turbine blades operating in extremely cold weather may have brittle fractures inside the materials and the icing of blades and sensors. Under worse conditions, micro-cracking will develop rapidly, leading to blade failure and even the collapse of the entire wind turbine [16].

Figure 3. Photo of the micro-cracking on the blade [30].

2.3. Fiber Defects

The fiber defect damage (see Figure 4) of wind turbine blades may occur in the process of blade manufacturing or may be caused by load [31]. In addition, fiber defects exist in the interior of the composites, which may cause cracks and other damage over time. Some scholars have studied the mechanism of fiber defects. Elhajjar et al. [32] found that tensile load could cause common fiber defects in carbon epoxy laminates through the test of carbon fibers.

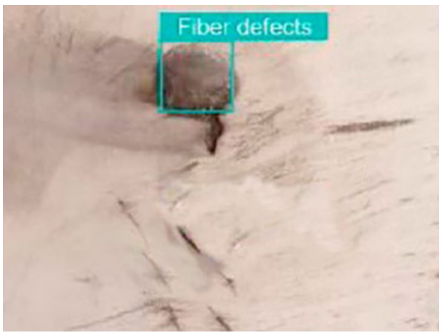

Figure 4. Photo of the blade fiber defects [33].

2.4. Coating Defects

The wind turbine blade coating can protect the composites from environmental factors such as ultraviolet radiation, moisture, and heat [34]. There are mainly two application methods for blade surface coating: the in-mold application and the post-mold application [35]. Because of the long-term and high-speed operation of wind turbine blades, as well as the erosion of solid particles and rainwater in the air, the blade coating will inevitably suffer from damage defects [36], as shown in Figure 5. Any type of defect damage to wind turbine blades will affect its aerodynamic efficiency and reduce power generation.

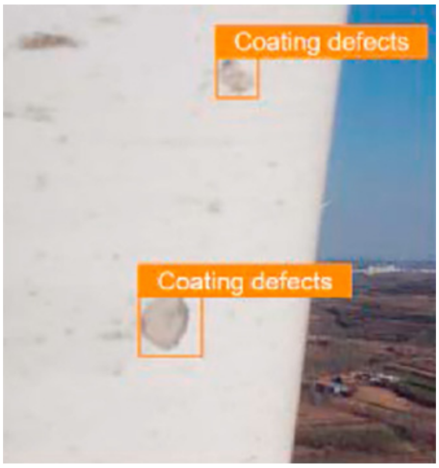

Figure 5. Photo of the blade coating defects [33].

3. 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 [37,38]. 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 [39]. This article 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, as shown in Figure 6. The literature on the fault diagnosis and condition monitoring of wind turbine blades mainly includes three aspects, namely non-destructive testing, fault diagnosis based on operating data, and fault diagnosis based on vibration signals.

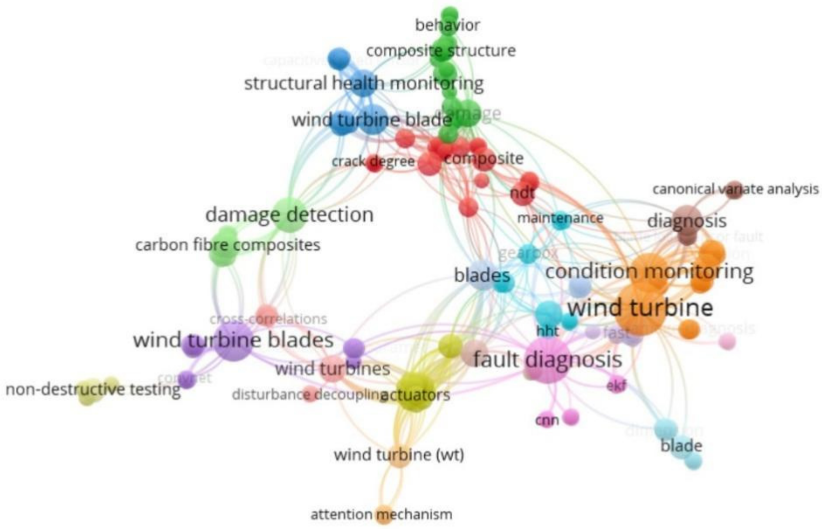

Figure 6. Keywords cluster of wind turbine blade fault diagnosis method.

3.1. 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 [40]. 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 [41]. Muñoz et al. [42] 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. [43] classified NDTs into contact and non-contact. This section focuses on the principle, working methods, advantages, and disadvantages of damage detection methods.

3.1.1. 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 [44]. 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 [45]. 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 [46]. When the surrounding stress changes, the reflection wavelength λ_B will move to realize the strain detection, as shown in Figure 7. The overall performance of FBG can be tested by experimental comparison. Guo et al. [47] 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. [48] 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. [49] 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. [50] 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. [51] proposed a new strain estimation method and objective function to obtain the optimal arrangement of strain sensors on the wind turbine blade.

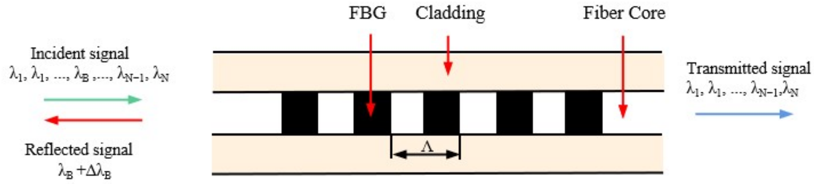

Figure 7. Structure and principle of FBG [52].

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.

3.1.2. 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 [53]. The working principle is shown in Figure 8; 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. [54] 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. [55] 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. [56] 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.

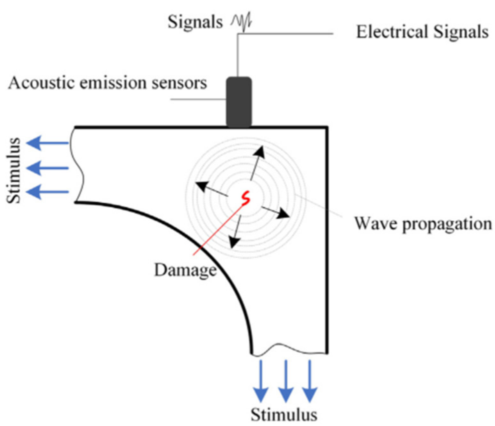

Figure 8. Principle of acoustic emission detection technology [53].

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 [48,49].

3.1.3. 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 [57]. As shown in Figure 9, 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 [58]. Therefore, this method can be used to detect microdamage and judge the size, location, and other information of damage [59]. The ultrasonic detection method can be used to detect both the internal and surface damages of wind turbine blades. Tiwari et al. [60] 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. [53] 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. [61] 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.

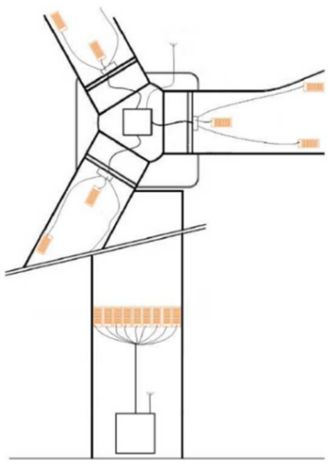

Figure 9. Sketch of the ultrasonic sensors placed on wind turbines [18].

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 [62]. Therefore, future research on artificial intelligence algorithms can improve the processing capacity of data.

3.1.4. 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 [57]. This technology requires accurate image processing. In real applications, it is difficult to eliminate the influence of blade damage on temperature and other factors [57], making ambient temperature interference the key to accurately identifying damage. Doroshtnasir et al. [63] 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. [64] 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. [65] 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.

3.1.5. 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 [66]. The full-scale condition monitoring of wind turbine blade surfaces can be carried out by shooting images. Yang et al. [67] proposed a video measurement technology for monitoring the deformation of large wind turbine blades in full-scale tests and operations. Figure 10a shows the setup of the machine vision system on a wind turbine. 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. [68] 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. [69] 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. [70] 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. [71] 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, as shown in Figure 10b.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. [72] 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. [73] proposed a light magnetic crawler with visual and laser radar sensor surface contact to NDT the wind turbine, as shown in Figure 10c. In addition, Zhang et al. [74] proposed a new method of using climbing robots with ground control stations and high-resolution cameras to scan wind turbine blades.

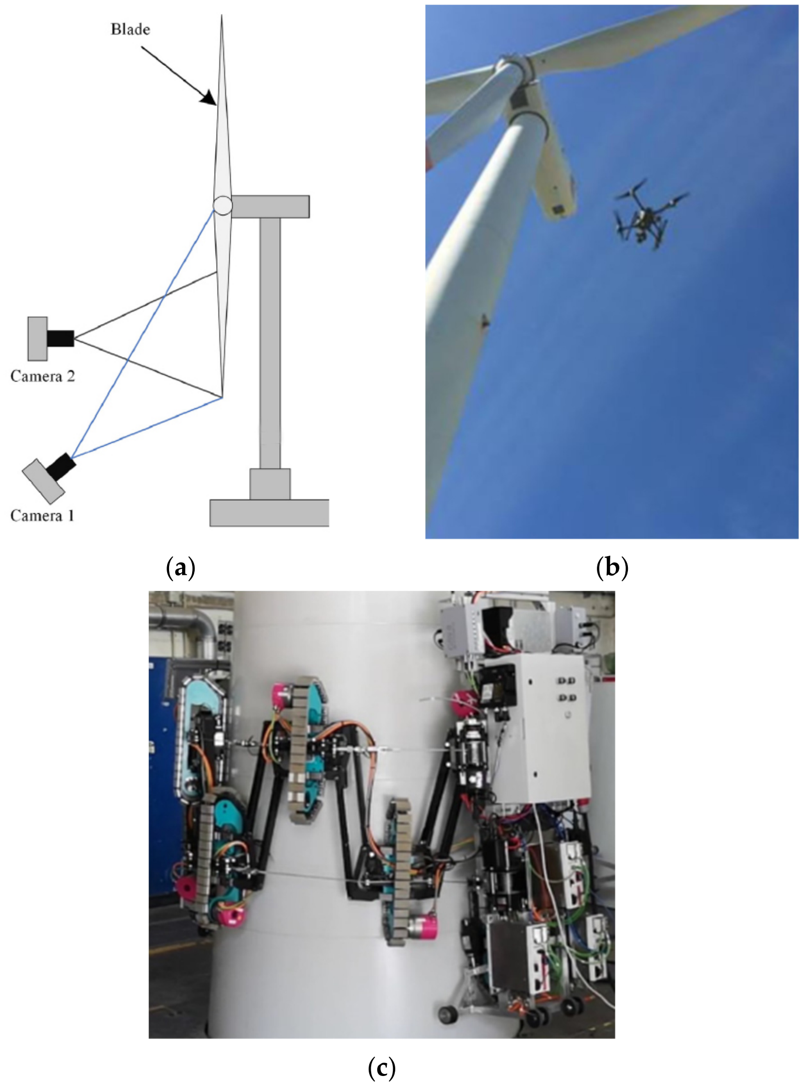

Figure 10. (**a**) Machine vision [67]. (**b**) Data collecting using the UAV [71]. (**c**) Crawling robot [73].

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 [75,76]. 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.

Although the aforementioned technologies have been widely developed and utilized, there are certain deficiencies in each of them. A better choice for NDT is to combine various technologies into the SHM system. As shown in Table 1, the advantages and disadvantages of each detection method are summarized. In addition, new NDT techniques have been developed and applied. For instance, shear imaging can visualize the change of blade surface deformation by interfering laser points and can effectively detect joint failure caused by adhesive expansion [77,78]. X-ray technology can effectively detect the internal structure of the blade. Evenly, X-ray tomography can present three-dimensional information inside the blade of a wind turbine [18]. In summary, NDT is applied to the fault diagnosis of wind turbine blades, which can examine the surface and internals of blades. However, due to the limitation of technical means, cost, and complex signal processing, new technologies are still needed to be developed and utilized to make up for defects in the future.

Table 1. List of the advantages and disadvantages of different detection methods [45,59,75,76,79–81].

Test Methods	Advantages	Shortcomings
Acoustic emission	The increase in blade fatigue damage degree and the determination of location were detected	Affected by the noise environment, this makes the data processing task complex and the cost higher
Ultrasonic	The size, location, and other information on damage degree can be judged	Signal acquisition for a long time is also complex for signal processing, and there is a delay in judging the signal
Strain measurement	Continuous monitoring of wind turbine blades for a long time	The sensitivity depends on the distance between the sensor location and the damage
Thermal imaging	The detection of all blades is more intuitive and effective	The influence of the environment on temperature leads to deviation in the results
Machine vision	Low Cost, High Safety, and Real-time Online Detection of Personnel Wind Farm	Accuracy depends on image accuracy and cannot explain the physical mechanism of damage

3.2. 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. [82] 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. [83] 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. [84] 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%. As shown in Figure 11, 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. [85] 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. [70] 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. [86] 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. [87] 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.

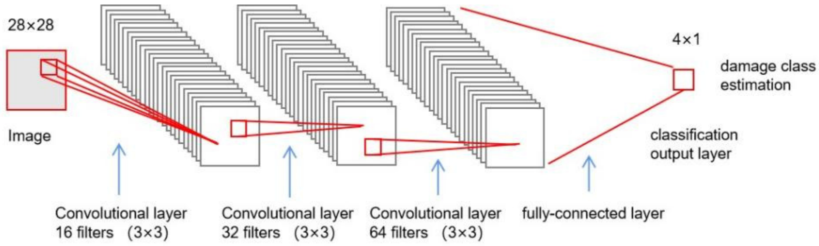

Figure 11. CNN structural model.

The combination of artificial intelligence algorithms and operation data can improve the reliability and accuracy of the monitoring system. However, this method is still in the exploratory stage for various types of damage identification and the real-time online monitoring test of large-scale wind turbine blades, and it cannot be widely promoted at present.

3.3. 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. [88] 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. [89] 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. [90] 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. [91] 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. [92] 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.

The fault diagnosis method based on vibration signals can identify damage by comparing modal parameters such as natural frequency, vibration mode, and damping. However, it remains a huge challenge to distinguish between signals collected by damaged blades and environmental and operational conditions.

4. Prospect of Wind Turbine Blade Damage Detection Method

The future development trend of wind turbine blade damage detection methods is discussed as follows:

1. Intelligent detection methods and deep learning methods require high accuracy of image processing. How to improve the accuracy and algorithm of collected data is the focus of future research. In addition, the use of new sensors on CMS, with SCADA-generated data analysis;
2. In the future, the combination of 5G technology, big data, artificial intelligence, and detection technology has achieved real-time, accurate, and timely results. The operation of smart wind farms and the self-maintenance of some fault damage can reduce the operation and maintenance costs and improve the detection efficiency;
3. With the development of NDT technology, new technologies continue to emerge, such as electromagnetic detection, shear imaging, photogrammetry, spectroscopy, radar imaging system, etc. Most NDT technologies need to stop wind turbines for detection. The new development direction is towards real-time online detection without shutdown, and different technologies are combined to improve the accuracy of detection. The combination of UAVs and the nondestructive testing system can achieve this purpose, such as UAVs equipped with image, thermal imaging, photogrammetry, and other equipment.

Through the aforementioned analysis, it can be seen that it is of great significance to timely diagnose the damage of wind turbine blades, and more and more experts have paid attention to the fault diagnosis of wind turbine blades by using different methods. Although many practical problems have not been solved, there is no doubt that the development potential of future fault diagnosis technology is huge.

5. Summary

With the global installed capacity increasing, the risk of wind turbine blade damage enlarges with the length of wind turbine blades. It is of great significance to make the early warning and identification of wind turbine blade failure in advance through different fault diagnosis methods to avoid serious damage. The development of wind turbines needs to meet the requirements of SHM, ND, and CM. Therefore, damage detection technology will develop towards real-time online, remote, global detection, and non-destructive non-contact. This paper summarizes three common diagnostic methods, including nondestructive testing technology, data acquisition, monitoring-based detection technology, and vibration signal detection technology. At present, most nondestructive testing technology depends on the performance of the testing instrument, and the detection accuracy is greatly affected by the environment. The research of intelligent detection methods for wind turbine blade diagnosis is a new trend, and intelligent detection technology to some extent makes up for the lack of the accuracy of nondestructive testing. In the future, in the era of the rapid development of computers, artificial intelligence, and big data, the damage detection method based on data fusion will continue to optimize and improve the diagnosis and treatment of wind turbine blades with great potential.

Author Contributions: Conceptualization, X.S. (Xiaowen Song) and Q.L.; writing of the manuscript, Z.X. and Y.J.; updating of the text, X.S. (Xiaowen Song) and Y.Z.; literature searches, X.S. (Xiaojuan Song), Z.W. and J.G.; critical reviewing of the manuscript, Z.X., X.S. (Xiaojuan Song) and C.C.; organization and editing of the manuscript, Z.X., X.S. (Xiaowen Song) and Y.Z.; Project administration: C.C.; Supervision: Q.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 52176212 and Grant No. 11962020) and the National Engineering Research Center for Offshore Windpower (Grant No. HSFD22001). We are also very grateful to the Program for Innovative Research Team in Universities of Inner Mongolia Autonomous Region (NMGIRT2213) and Inner Mongolia Science and Technology Program under Grant (2021GG0336).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Mooney, H.; Larigauderie, A.; Cesario, M.; Elmquist, T.; Hoegh-Guldberg, O.; Lavorel, S.; Mace, G.M.; Palmer, M.; Scholes, R.; Yahara, T. Biodiversity, climate change, and ecosystem services. *Curr. Opin. Environ. Sustain.* **2009**, *1*, 46–54. [CrossRef]
2. Chen, J.M.J.T.I. Carbon neutrality: Toward a sustainable future. *Innovation* **2021**, *2*, 100127. [CrossRef]
3. Zhang, M.; Zhang, J.; Li, Y.; Yu, J.; Qin, J.; Wei, K.; Song, L. Multi-site measurement for energy application of small distributed wind farm in complex mountainous areas. *Energy Rep.* **2020**, *6*, 1043–1056. [CrossRef]
4. Arutyunov, V.S.; Lisichkin, G.V. Energy resources of the 21st century: Problems and forecasts. Can renewable energy sources replace fossil fuels? *Russ. Chem. Rev.* **2017**, *86*, 777–804. [CrossRef]
5. Wang, F.; Harindintwali, J.D.; Yuan, Z.; Wang, M.; Wang, F.; Li, S.; Yin, Z.; Huang, L.; Fu, Y.; Li, L.; et al. Technologies and perspectives for achieving carbon neutrality. *Innovation* **2021**, *2*, 100180. [CrossRef]
6. Council, G.W.E. Floating Offshore Wind—A Global Opportunity. The Global Wind Energy Council. 2022. Available online: https://www.abeeolica.org.br/wp-content/uploads/2019/07/GWEC2018-compactado.pdf (accessed on 3 October 2022).
7. GWEC. Global Wind Report 2021. Global Wind Energy Council: Brussels, Belgium, 2021. Available online: https://gwec.net/global-wind-report-2021/ (accessed on 3 October 2022).
8. Caithness Windfarm Information Forum. Available online: http://www.caithnesswindfarms.co.uk (accessed on 3 October 2022).
9. Katsaprakakis, D.A.; Papadakis, N.; Ntintakis, I.J.E. A Comprehensive Analysis of Wind Turbine Blade Damage. *Energies* **2021**, *14*, 5974. [CrossRef]
10. Song, Y.-D.; Li, P.; Liu, W.; Qin, M.J.M. Control, An overview of renewable wind energy conversion system modeling and control. *Meas. Control.* **2010**, *43*, 203–208. [CrossRef]
11. Karyotakis, A.; Bucknall, R.J.J. Planned intervention as a maintenance and repair strategy for offshore wind turbines. *J. Mar. Eng. Technol.* **2010**, *9*, 27–35. [CrossRef]
12. Chou, J.-S.; Ou, Y.-C.; Lin, K.-Y. Collapse mechanism and risk management of wind turbine tower in strong wind. *J. Wind. Eng. Ind. Aerodyn.* **2019**, *193*, 103962. [CrossRef]
13. Farrar, C.R.; Worden, K. An introduction to structural health monitoring. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2007**, *365*, 303–315. [CrossRef]
14. de la Hermosa González, R.R.; Márquez, F.P.G.; Dimlaye, V.; Ruiz-Hernández, D.J.M.S. Pattern recognition by wavelet transforms using macro fibre composites transducers. *Mech. Syst. Signal Process.* **2014**, *48*, 339–350. [CrossRef]
15. Jiménez, A.A.; Zhang, L.; Muñoz, C.Q.G.; Márquez, F.P.G. Maintenance management based on machine learning and nonlinear features in wind turbines. *Renew. Energy* **2020**, *146*, 316–328. [CrossRef]
16. Li, D.; Ho, S.-C.M.; Song, G.; Ren, L.; Li, H. Structures, A review of damage detection methods for wind turbine blades. *Smart Mater. Struct.* **2015**, *24*, 033001. [CrossRef]
17. Yang, R.; He, Y.; Zhang, H. Progress and trends in nondestructive testing and evaluation for wind turbine composite blade. *Renew. Sustain. Energy Rev.* **2016**, *60*, 1225–1250. [CrossRef]
18. Márquez, F.P.G.; Chacón, A.M.P. A review of non-destructive testing on wind turbines blades. *Renew. Energy* **2020**, *161*, 998–1010. [CrossRef]
19. Asensio, S.E.; Pérez, J.; Márquez, F. *Economic Viability Study for Offshore Wind Turbines Maintenance Management*; Springer: Berlin/Heidelberg, Germany, 2015.
20. Igba, J.; Alemzadeh, K.; Durugbo, C.; Eiriksson, E.T. Technology, Through-life engineering services of wind turbines. *CIRP J. Manuf. Sci. Technol.* **2017**, *17*, 60–70. [CrossRef]
21. Koitz, R.; Wotawa, F.; Lüftenegger, J.; Gray, C.S.; Langmayr, F. Wind Turbine Fault Localization: A Practical Application of Model-Based Diagnosis. In *Diagnosability, Security and Safety of Hybrid Dynamic and Cyber-Physical Systems*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 17–43.
22. Liu, W.Y. A review on wind turbine noise mechanism and de-noising techniques. *Renew. Energy* **2017**, *108*, 311–320. [CrossRef]
23. Herrera, C.; Correa, M.; Villada, V.; Vanegas, J.D.; Garcia, J.G.; Nieto-Londono, C.; Sierra-Perez, J. Structural design and manufacturing process of a low scale bio-inspired wind turbine blades. *Compos. Struct.* **2019**, *208*, 1–12. [CrossRef]
24. Jureczko, M.P.M. Optimisation of wind turbine blades. *J. Mater. Process. Technol* **2005**, *167*, 463–471. [CrossRef]
25. Du, J.; Wang, H.; Wang, S.; Song, X.; Wang, J.; Chang, A.J.O.E. Fatigue damage assessment of mooring lines under the effect of wave climate change and marine corrosion. *Ocean. Eng.* **2020**, *206*, 107303. [CrossRef]
26. Jimenez-Martinez, M.J.H. Harbor and coastal structures: A review of mechanical fatigue under random wave loading. *Heliyon* **2021**, *7*, e08241. [CrossRef] [PubMed]
27. Chang, J.B.; Rudd, J.L. *Damage Tolerance of Metallic Structures: Analysis Methods and Applications*; ASTM International: West Conshohocken, PA, USA, 1984; Volume 842.
28. Slot, H.; Gelinck, E.; Rentrop, C.; Van Der Heide, E.J.R.E. Leading edge erosion of coated wind turbine blades: Review of coating life models. *Renew. Energy* **2015**, *80*, 837–848. [CrossRef]
29. Gaudern, N. A Practical Study of the Aerodynamic Impact of Wind Turbine Blade Leading Edge Erosion. *J. Phys. Conf. Ser.* **2014**, *524*, 012031. [CrossRef]

30. Yu, Y.; Cao, H.; Yan, X.; Wang, T.; Ge, S.S.J.N. Defect Identification of Wind Turbine Blades based on Defect Semantic Features with Transfer Feature Extractor. *Neurocomputing* **2019**, *376*, 1–9. [CrossRef]
31. Talreja, R. Fatigue damage mechanisms. *Model. Damage Fatigue Fail. Compos. Mater.* **2016**, *4*, 25–40.
32. Elhajjar, R.F.; Shams, S.S.J.C.S. Technology, A new method for limit point determination in composite materials containing defects using image correlation. *Compos. Sci. Technol.* **2016**, *122*, 140–148. [CrossRef]
33. Guo, J.; Liu, C.; Cao, J.; Jiang, D.J.R.E. Damage identification of wind turbine blades with deep convolutional neural networks. *Renew. Energy* **2021**, *174*, 122–133. [CrossRef]
34. Zhang, S.; Kiil, S.; Dam-Johansen, K.; Bernad, P.J., Jr. *Accelerated Rain Erosion of Wind Turbine Blade Coatings*; Danmarks Tekniske Universitet (DTU): Copenhagen, Denmark, 2014.
35. Keegan, M.H.; Nash, D.H.; Stack, M.M. On erosion issues associated with the leading edge of wind turbine blades. *J. Phys. D: Appl. Phys.* **2013**, *46*. [CrossRef]
36. Cripps, D. The future of blade repair. *Reinf. Plast.* **2011**, *55*, 28–32. [CrossRef]
37. Qiao, Q.; Yunusa-Kaltungo, A.; Edwards, R.E. Towards developing a systematic knowledge trend for building energy consumption prediction. *J. Build. Eng.* **2021**, *35*, 101967. [CrossRef]
38. Van Raan, A. The use of bibliometric analysis in research performance assessment and monitoring of interdisciplinary scientific developments. *TATuP* **2003**, *12*, 20–29. [CrossRef]
39. Rabbani, M.R.A.; Bashar, A.; Atif, M.; Jreisat, A.; Zulfikar, Z.; Naseem, Y. Text Mining and Visual Analytics in Research: Exploring the Innovative Tools. In Proceedings of the 2021 International Conference on Decision Aid Sciences and Application (Dasa), Online, 7–8 December 2021.
40. Kusiak, A.; Zhang, Z.; Verma, A. Prediction, operations, and condition monitoring in wind energy. *Energy* **2013**, *60*, 1–12. [CrossRef]
41. Raišutis, R.; Jasiūnienė, E.; Šliteris, R.; Vladišauskas, A.J.U.U. The review of non-destructive testing techniques suitable for inspection of the wind turbine blades. *Ultrasound* **2008**, *63*, 26–30.
42. Muñoz, C.Q.G.; Márquez, F.P.G. Future Maintenance Management in Renewable Energies. In *Renewable Energies*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 149–159.
43. Gholizadeh, S. A review of non-destructive testing methods of composite materials. *Procedia Struct. Integr.* **2016**, *1*, 50–57. [CrossRef]
44. Schubel, P.J.; Crossley, R.J.; Boateng, E.K.B.; Hutchinson, J.R. Review of structural health and cure monitoring techniques for large wind turbine blades. *Renew. Energy* **2013**, *51*, 113–123. [CrossRef]
45. Ozbek, M.; Rixen, D.J. Operational modal analysis of a 2.5 MW wind turbine using optical measurement techniques and strain gauges. *Wind Energy* **2013**, *16*, 367–381. [CrossRef]
46. Hill, K.; Meltz, G. Fiber Bragg grating technology fundamentals and overview. *J. Light. Technol.* **1997**, *15*, 1263–1276. [CrossRef]
47. Guo, Z.-S.; Zhang, J.; Hu, H.; Guo, X. Structural health monitoring of composite wind blades by fiber bragg grating. In Proceedings of the International Conference on Smart Materials and Nanotechnology in Engineering, International Society for Optics and Photonics, Harbin, China, 1–4 July 2007; p. 64230I. [CrossRef]
48. Bang, H.-J.; Jang, M.; Shin, H. Structural health monitoring of wind turbines using fiber Bragg grating based sensing system. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*; SPIE: Bellingham, DC, USA, 2011; Volume 7981, pp. 716–723. [CrossRef]
49. Schroeder, K.; Ecke, W.; Apitz, J.; Lembke, E.; Lenschow, G. A fibre Bragg grating sensor system monitors operational load in a wind turbine rotor blade. *Meas. Sci. Technol.* **2005**, *17*, 1167–1172. [CrossRef]
50. Wu, J.; Song, C.; Saleem, H.S.; Downey, A.; Laflamme, S. Network of flexible capacitive strain gauges for the reconstruction of surface strain. *Meas. Sci. Technol.* **2015**, *26*, 055103. [CrossRef]
51. Lee, K.; Aihara, A.; Puntsagdash, G.; Kawaguchi, T.; Sakamoto, H.; Okuma, M. Feasibility study on a strain based deflection monitoring system for wind turbine blades. *Mech. Syst. Signal Process.* **2017**, *82*, 117–129. [CrossRef]
52. Wen, B.; Tian, X.; Jiang, Z.; Li, Z.; Dong, X.; Peng, Z. Monitoring blade loads for a floating wind turbine in wave basin model tests using Fiber Bragg Grating sensors: A feasibility study. *Mar. Struct.* **2020**, *71*, 102729. [CrossRef]
53. Nair, A.; Cai, C.S. Acoustic emission monitoring of bridges: Review and case studies. *Eng. Struct.* **2010**, *32*, 1704–1714. [CrossRef]
54. Tang, J.; Soua, S.; Mares, C.; Gan, T.-H. An experimental study of acoustic emission methodology for in service condition monitoring of wind turbine blades. *Renew. Energy* **2016**, *99*, 170–179. [CrossRef]
55. Zhou, W.; Li, Y.; Li, Z.; Liang, X.; Pang, Y.; Wang, F. Interlaminar Shear Properties and Acoustic Emission Monitoring of the Delaminated Composites for Wind Turbine Blades. In *Advances in Acoustic Emission Technology*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 557–566. [CrossRef]
56. Liu, Z.; Wang, X.; Zhang, L. Fault Diagnosis of Industrial Wind Turbine Blade Bearing Using Acoustic Emission Analysis. *IEEE Trans. Instrum. Meas.* **2020**, *69*, 6630–6639. [CrossRef]
57. Tchakoua, P.; Wamkeue, R.; Ouhrouche, M.; Slaoui-Hasnaoui, F.; Tameghe, T.A.; Ekemb, G. Wind Turbine Condition Moni-toring: State-of-the-Art Review, New Trends, and Future Challenges. *Energies* **2014**, *7*, 2595–2630. [CrossRef]
58. Amenabar, I.; Mendikute, A.; López-Arraiza, A.; Lizaranzu, M.; Aurrekoetxea, J. Comparison and analysis of non-destructive testing techniques suitable for delamination inspection in wind turbine blades. *Compos. Part B: Eng.* **2011**, *42*, 1298–1305. [CrossRef]

59. Márquez, F.P.G.; Tobias, A.M.; Pérez, J.M.P.; Papaelias, M. Condition monitoring of wind turbines: Techniques and methods. *Renew. Energy* **2012**, *46*, 169–178. [CrossRef]
60. Tiwari, K.A.; Raisutis, R. Post-processing of ultrasonic signals for the analysis of defects in wind turbine blade using guided waves. *J. Strain Anal. Eng. Des.* **2018**, *53*, 546–555. [CrossRef]
61. Brett, C.R.; A Gunn, D.; Dashwood, B.A.J.; Holyoake, S.J.; Wilkinson, P.B. Development of a technique for inspecting the foundations of offshore wind turbines. *Insight Non-Destructive Test. Cond. Monit.* **2018**, *60*, 19–27. [CrossRef]
62. Sarrafi, A.; Mao, Z.; Niezrecki, C.; Poozesh, P. Vibration-based damage detection in wind turbine blades using Phase-based Motion Estimation and motion magnification. *J. Sound Vib.* **2018**, *421*, 300–318. [CrossRef]
63. Doroshtnasir, M.; Worzewski, T.; Krankenhagen, R.; Röllig, M. On-site inspection of potential defects in wind turbine rotor blades with thermography. *Wind Energy* **2016**, *19*, 1407–1422. [CrossRef]
64. Hwang, S.; An, Y.-K.; Sohn, H. Continuous Line Laser Thermography for Damage Imaging of Rotating Wind Turbine Blades. *Procedia Eng.* **2017**, *188*, 225–232. [CrossRef]
65. Avdelidis, N.P.; Gan, T.-H. Non-destructive evaluation (NDE) of Composites: Infrared (IR) thermography of wind turbine blades. In *Non-Destructive Evaluation (NDE) of Polymer Matrix Composites*; Karbhari, V.M., Ed.; Woodhead Publishing: Sawston, UK, 2013; pp. 634–650. [CrossRef]
66. Ye, X.W.; Dong, C.Z.; Liu, T. A Review of Machine Vision-Based Structural Health Monitoring: Methodologies and Applications. *J. Sens.* **2016**, *2016*, 7103039. [CrossRef]
67. Yang, J.; Peng, C.; Xiao, J.; Zeng, J.; Yuan, Y. Application of videometric technique to deformation measurement for large-scale composite wind turbine blade. *Appl. Energy* **2012**, *98*, 292–300. [CrossRef]
68. Baqersad, J.; Poozesh, P.; Niezrecki, C.; Harvey, E.; Yarala, R. Full Field Inspection of a Utility Scale Wind Turbine Blade Using Digital Image Correlation. *CAMX* **2014**, *10*, 2891–2960. [CrossRef]
69. Qiu, Z.; Wang, S.; Li, M. Defect Detection of Wind Turbine Blade Based on Unmanned Aerial Vehicle-taken Images. *Power Gener. Technol.* **2018**, *39*, 277–285.
70. Wang, L.; Zhang, Z. Automatic Detection of Wind Turbine Blade Surface Cracks Based on UAV-Taken Images. *IEEE Trans. Ind. Electron.* **2017**, *64*, 7293–7303. [CrossRef]
71. Wang, Y.; Yoshihashi, R.; Kawakami, R.; You, S.; Harano, T.; Ito, M.; Komagome, K.; Iida, M.; Naemura, T. Unsupervised anomaly detection with compact deep features for wind turbine blade images taken by a drone. *IPSJ Trans. Comput. Vis. Appl.* **2019**, *11*, 3. [CrossRef]
72. Kuang, N. Blade Detection Robot. In Proceedings of the 7th International Conference on Mechatronics, Computer and Education Informationization (MCEI 2017), Shenyang, China, 3–5 November 2017; Atlantis Press: Amsterdam, The Netherlands, 2017; pp. 317–321.
73. Franko, J.; Du, S.; Kallweit, S.; Duelberg, E.; Engemann, H. Design of a Multi-Robot System for Wind Turbine Maintenance. *Energies* **2020**, *13*, 2552. [CrossRef]
74. Huiyi, Z.; Jackman, J. A Feasibility Study of Wind Turbine Blade Surface Crack Detection Using an Optical Inspection Method. In Proceedings of the 2013 International Conference on Renewable Energy Research and Applications (ICRERA), Madrid, Spain, 20–23 October 2013; pp. 847–852.
75. Beganovic, N.; Söffker, D. Structural health management utilization for lifetime prognosis and advanced control strategy deployment of wind turbines: An overview and outlook concerning actual methods, tools, and obtained results. *Renew. Sustain. Energy Rev.* **2016**, *64*, 68–83. [CrossRef]
76. Kim, D.Y.; Kim, H.-B.; Jung, W.S.; Lim, S.; Hwang, J.-H.; Park, C.-W. Visual testing system for the damaged area detection of wind power plant blade. In Proceedings of the ISR 2013, Seoul, Korea, 24–26 October 2013; pp. 1–5. [CrossRef]
77. Francis, D. Non-Destructive Evaluation (NDE) of Composites: Introduction to Shearography. In *Non-Destructive Evaluation (NDE) of Polymer Matrix Composites*; Elsevier: Amsterdam, The Netherlands, 2013; pp. 56–83. [CrossRef]
78. Macedo, F.J.; Benedet, M.E.; Fantin, A.V.; Willemann, D.P.; da Silva, F.A.A.; Albertazzi, A. Inspection of defects of composite materials in inner cylindrical surfaces using endoscopic shearography. *Opt. Lasers Eng.* **2018**, *104*, 100–108. [CrossRef]
79. Qiao, W.; Lu, D. A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis—Part II: Signals and Signal Processing Methods. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6546–6557. [CrossRef]
80. Amezquita-Sanchez, J.P.; Adeli, H. Signal Processing Techniques for Vibration-Based Health Monitoring of Smart Structures. *Arch. Comput. Methods Eng.* **2016**, *23*, 1–15. [CrossRef]
81. Sanati, H.; Wood, D.; Sun, Q. Condition Monitoring of Wind Turbine Blades Using Active and Passive Thermography. *Appl. Sci.* **2018**, *8*, 2004. [CrossRef]
82. Xin, Z. *Simulation Research on Deep Learning in Structural Damage Identification of Fan Blades*; Lanzhou Jiaotong University: Lanzhou, China, 2016.
83. Wang, L.; Zhang, Z.; Xu, J.; Liu, R. Wind Turbine Blade Breakage Monitoring with Deep Autoencoders. *IEEE Trans. Smart Grid* **2016**, *9*, 2824–2833. [CrossRef]
84. Moreno, S.; Pena, M.; Toledo, A.; Trevino, R.; Ponce, H. A New Vision-Based Method Using Deep Learning for Damage Inspection in Wind Turbine Blades. In Proceedings of the 15th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE), Mexico City, Mexico, 5–7 September 2018.
85. Yanxia, L. Wind turbine blade crack identification based on migration learning. *Sens. Microsyst.* **2019**, *38*, 107–110.

86. Zhao, X.-Y.; Dong, C.-Y.; Zhou, P.; Zhu, M.-J.; Ren, J.-W.; Chen, X.-Y. Detecting Surface Defects of Wind Turbine Blades Using an Alexnet Deep Learning Algorithm. *Trans. Fundam. Electron. Commun. Comput. Sci.* **2019**, *102*, 1817–1824.
87. Yang, X.; Zhang, Y.; Lv, W.; Wang, D. Image recognition of wind turbine blade damage based on a deep learning model with transfer learning and an ensemble learning classifier. *Renew. Energy* **2020**, *163*, 386–397. [CrossRef]
88. Di Lorenzo, E.; Petrone, G.; Manzato, S.; Peeters, B.; Desmet, W.; Marulo, F. Damage detection in wind turbine blades by using operational modal analysis. *Struct. Health Monit.* **2016**, *15*, 289–301. [CrossRef]
89. Moradi, M.; Sivoththaman, S. MEMS Multisensor Intelligent Damage Detection for Wind Turbines. *IEEE Sensors J.* **2014**, *15*, 1437–1444. [CrossRef]
90. Abouhnik, A.; Albarbar, A. Wind turbine blades condition assessment based on vibration measurements and the level of an empirically decomposed feature. *Energy Convers. Manag.* **2012**, *64*, 606–613. [CrossRef]
91. González, A.G.; Fassois, S. A supervised vibration-based statistical methodology for damage detection under varying environmental conditions & its laboratory assessment with a scale wind turbine blade. *J. Sound Vib.* **2016**, *366*, 484–500. [CrossRef]
92. Wang, Y.; Liang, M.; Xiang, J. Damage detection method for wind turbine blades based on dynamics analysis and mode shape difference curvature information. *Mech. Syst. Signal Process.* **2014**, *48*, 351–367. [CrossRef]