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Review Article

A Critical Review of Detecting Faults and Damages in Wind Turbine Blades

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Abstract

Recent years have seen enormous growth in the wind power industry, which serves the growing market and has led to more powerful wind turbines. Blades of the Wind Turbine are susceptible to failure since they are unprotecting them, suffer continually changing loads by cyclic fatigue and wind loads caused by their weight, and experience extreme humidity and temperature fluctuations, corrosion, and erosion. Consequently, blades experience a very high failure rate and suffer considerable downtime, highlighting the importance and necessity of developing and applying blade damage and fault detection techniques. In the past years, it has taken much effort to achieve reliable fault detection methods for wind turbine blades in the literature. However, implementing a reliable blade fault detection methodology has remained an open challenge. In previous reviews, various non-destructive testing techniques have been described, which may be helpful to detect blade damage. However, they fail to mention which approach may be most effective and suitable in detecting blade faults. This review article focuses on examining the pros and cons of the existing blade fault detection techniques. It concludes that image processing methodology effectively detects and locates faults in wind turbine blades.

Keyword: Wind Turbine Blades; Digital Image Analysis; Damage Detection Algorithm; Deep learning Algorithm; Acoustic Sensors, Sensors Applications

Introduction

A wind turbine blade is a crucial component for energy conversion in a wind energy generation system. The blades are made up of laminated glass fibre and carbon fibre reinforced plastics to meet their various requirements, such as increased flexural strength. As a result, wind power is a rapidly growing global market, although currently, there are many reliability issues with wind turbine (WT) systems, particularly in harsh offshore environments. Design faults of the blade include flaking, delamination, inclusions, cracks, or cavities. As a result of working under poor conditions, fatigue and long operation times may cause cracks on the blade surface, which would accumulate until the blade finally breaks, causing damages or losses that can be incalculable and long downtime. WT blade surfaces, in general, are primarily affected by cracks and erosion surfaces. Surface cracks in WT blades were mainly classified into four major categories: composite cracks, transverse cracks, network cracks, and longitudinal cracks. Automatically manoeuvres along the blades of wind turbines using a robotic system. An operator or researcher may augment the traditional approach, in which visual inspection is conducted by a technician, by a variety of support systems, for instance, rope systems, cranes, or man-carrying platforms.

A longstanding goal is to automate the inspection process. Various non-destructive inspection methods have already been investigated or employed, such as infrared thermography, X-ray imaging, terahertz inverse synthetic aperture radar, or camera systems. Continual condition monitoring and fault prediction have been achieved using SCADA models and analyses. Monitors and rope-falling people inspections are the two traditional methods of identifying WT blade surface defects and identifying blades that need resurfacing.

WT blade defect has been monitored and identified using a variety of sensors. It is possible to determine how defects are positioned using acquired signals. Acoustic Emission (AE) signals are used widely in diagnosing WT blade faults. Wavelet analysis methods use adaptive thresholds to analyze AE signals to evaluate WT blade conditions. Consequently, these methods are expensive to test, have low detection efficiencies, have long downtimes, and have high-risk factors. With support vector machine (SVM) classifier and principal component analysis, the blades are analyzed and extracted from background noise from crack acoustics' characteristics. Optimization of the wavelet redistribution scale spectrum can identify high-amplitude energy distributions of various crack types. The pattern identifies tools constructed when AE signals usage provide prompt, sensitive, and reliable fault detection for blade integrity. It is also widely used to replace AE sensors with vibration sensors designed to detect WT blade damage.

Based on the vibration signal gathered by fibre Bragg lattices, an enhanced energy modulation interrogating approach was used to estimate the approximate area of an impact source. WT vibration fault signals can be extracted, identified, and judged using wavelet analysis and SVM. Various other detection methods are employed in practice-ultrasonic guided-wave techniques to examine WT blades' failures. One can combine contact pulse coupling and immersion techniques to determine the shape and size of blade failures. The WT crack classification method utilizes logit boost, decision trees, and SVM to identify cracks acquired from unmanned aerial vehicles (UAV). Sensors that use scanning laser Doppler, macro fibre composites and other advanced technology have also been used to detect blade damage. The diagnosis of blade cracks has also been advanced through machine learning or deep learning techniques [1]. The paper consists of the following sections. In section 2, the motivation behind the structural health monitoring blade techniques is furnished in detail. Section 3 focused on examining the site practicability of existing image processing-based blade fault detection techniques. In section 4, acoustic sensor-based WT blade health monitoring techniques are related to research works. Section 5 provides the sensor-based blade detection approaches. Finally, section 6 discussed the insights and recommendations for the forthcoming wind turbine's blade faults detection research.

Motivation

A wind turbine blade diameter in 2017 was 119 meters, and 37 meters as hub height. Operators of wind farm plants must regularly inspect, maintain, and repair wind power plants due to environmental stress. Due to the related elongated downtimes, this requires considerable effort and costs. Cutting edges of wind turbines need to be monitored for structural health because they are critical parts of the wind turbines, cost about 20% of the total turbine's cost, and were subject to various unpredicted events, including lightning and hailstorms, strong winds, and tempests. A second challenge is that many wind turbines are located in areas where the wind resource is inexhaustible. Support teams often have difficulty reaching these areas. Mountains and seawards have been considered excellent locations to build wind turbines. However, these areas have higher costs because it is more problematic for maintenance and development teams to contact the turbines. To solve these problems, we need to develop an effective maintenance system, and wherever possible, we shall automate the process.

It is essential to accurately monitor the blade surface condition before cracks grow and properly design wind power systems. India has almost all commercial wind turbines within harsh environments and remote areas. They are subjected to extreme variation pressures and corrosion out of various dangerous substances, resulting in various faults, mainly on the surface of WT blades, resulting in a variety of significant mishaps. The WT blades health detection is a significant and worthwhile research issue [2]. Many works of literature have recently been published on the health detection of WT blades. The methodologies of these investigations could be organized into three categories: Image processing, Acoustic Sensors, and Sensors based blade detection techniques. Sensor or acoustic sensor blade detection techniques can be performed on two approaches: an active approach while the other is a passive approach. Active sensors techniques have limitations to retrofit some devices in the wind turbine, but it would accurately detect the fault. The major drawback of this active approach is that it could be done in the lab environment and cannot be deployed in all the Wind turbines since it leads to additional cost. Passive-based techniques would be preferred, as these methods are not disturbing the WT operation. However, various pre-processing techniques are to be deployed and may not be as accurate as possible in detecting blade defects. However, it's necessary to integrate multiple algorithms to categorize damage and healthy WT blades.

Image Processing Detection Techniques

Image Pre-processing/Enhancement Techniques

Peng and Liu [3] positioned a miniature camera beneath the quadrotor UAV, an image of the fractures in the blade's surface that would be sent to a computer at the actual time. A 486*486 resolution camera with a 30 pfs frame rate is available. Various aspects would influence the quality of the photographs captured by a UAV during the actual investigation, such as motion blur and noise interference, due to relative motion in between the camera and the drone blades. This paper uses the Wiener filter to remove motion blur due to the above problems. The noise generated by eclectic sounds such as a Gaussian and the salt and pepper noise is filtered using an adaptive median-based filtering approach on the crack surface picture. The weakened edges and details of the image are repaired, and the noise in the image is eliminated, highlighting the cracked area using the mathematical morphology-based image enhancement algorithm. Display an image analysis interface with the imtool of command, select the starting point to analyze, and generate the grey value block by block. We can observe from a grey value that was formed such grey value does not change much in the background without cracks, but as cracks begin to expand and deepen, the grey value decreases [3].

Salman et al. [4] analyzed the frequency characteristics of a signal is most commonly done by Fourier transformation. Gabor is credited with proposing the Gabor filter, a joint domain function. The Gabor function achieves an optimal analytical resolution, the lowest bound in a joint domain, convolved with pre-processed input images of a given orientation. It generates a filter bank with multi-orientation filters. Convolution is completed by generating a binary output image by thresholding the kernel's fundamental component of the response. The output image, which comprises spotted crack sections considered as segments, is generated from the binary images resulting from the different orientations of the filters, combined using logical OR operations. According to experiments, authors achieved up to 95% precision on pavement images by applying the proposed Gabor filter bank [4].

Yang and Cheng [5] employed two neural network algorithms in the proposed method, namely, CNNs and ANNs. CNNs identify surface damage images as positive or negative, while ANNs highlight surface damage in the images. In the training process of models, CNN is well trained their data with images-based, while the ANN is well trained their data with feature-based. Gamma correction, equalization, unsharp masking, and de-noising enhance the raw image. The Canny-Edge-Detection technology is subjected to the improved image to detect the edges within the image by generating a sequence of points. The detected edges are used to extract features. CNN model has better accurateness than the ANN model. A CNN model has an accuracy of 89.4%, whereas an ANN model has an accuracy of 70.7%. The ANN process is applied only to positive images. Accordingly, the CNN presents a greater false positive detection rate than the ANN as it cannot detect the image's damage. As a result, surface damage can be more accurately detected. To separate the images of positive surface damage from negative surface damage, CNN is assigned. The CNN is 80.7 % accurate in this two-step approach, whereas the ANN is 98.1 % accurate [5].

Deng et al. [6] used this study to detect the wind turbine blades and their faults using digital image processing to build a safe, convenient, and accurate defect detection approach. The first step was to use the Lévy-Flight algorithm to develop LPSO by improving the PSO. An adaptive filter was generated using the log-Gabor filter and LPSO to compute the optimum outcomes in images with several feature extractions. A log-Gabor filter needs multiple template filters to extract features, so the number of output images was high. The (Histogram of Gradient) HOG + SVM classifier identified and categorized defect types in the final stage. More than 92% of scratch types, crack types, sand holes, and spot types were extracted and identified using the proposed method [6].

Image Augmentation/Annotation Techniques:

Reddy et al. [7] annotated the UAV WT Blade images manually; later, the augmented images were used to divide the binary damage classification data into classes using the CNN technology. We use a method provided by Keras to augment the images of WT blades since they are not readily available. As augmentation methods, many types are available. This article relies on shearing, zooming, and horizontal flipping for generating more data. The original image was sliced using an Image slicer of 16 images having 544*408 pixels. Drones capture images with pixels size of 3264*2448, which cannot directly be used in training CNN models. A more accurate model is trained by manually cropping images of the damage classes, annotating (classification) them based on their damage classes and training them with that information. They were making the Confusion matrix by drawing the curves of accuracy and loss. Change the parameters of CNN and retrain it when necessary, depending on accuracy. As a result, the trained model(s) were saved and utilized as a sliding window to detect damage [7].

Shihavuddin et al. [8] conducted wind turbines' field inspections and annotated the bounding boxes for damaged parts. Augmentations are also applied to annotated images (such as patching, pyramiding, or regular augmentations) to increase the number of training samples. A Faster R-CNN was used in this study to detect and classify surface damage using drone inspection images. Specifically, Faster R-CNN utilizes a Region Proposal Network (RPN) to predict the bounding boxes of objects of interest based on CNN-extracted feature descriptors. InceptionV2 and ResNet50 have experimented in this work with as well as heavier CNN architectures like ResNet101 and Inception-ResNet-V2. The backbone architecture named Inception-ResNet-V2 outperformed the other three for the faster R-CNN framework [8]. The reported mean average precision (MAP) results refer to detecting, classifying, and predicting the detected objects based on the trained model applied to the test images.

Yu, Y et al. [9] presented a CNN-based damage detection of wind turbine's blade surface damages. Deployed the most accurate trained model and validated without parent systems presence. Reduced time and risk are taken for the structural health monitoring of WTB, classified and detected almost all classes of damage commonly occurring in WTB. Patel J et al. [10] implemented AlexNet and VGG16-RCNN in addition to CNN to compare these three models. A model has trained more accurately by cropping and annotating (classifying) images with damage classes, augmenting those images, and training the model. In this case, the augmentation properties used are width-wise shifting, rotation, height-wise shifting, vertical and horizontal flipping, and zoom. This article considered three models: VGG16-RCNN, CNN, and AlexNet, whose accuracy values are 93.8%, 90.7%, and 74.1%. Image processing can be done most efficiently using VGG16-RCNN, followed by AlexNet [10].

This paper has three possible performance measurement methods for defect detection: False Label Rate, Prediction Box Accuracy, and Recognition Rate. Zhang et al. [11] evaluated six deep training algorithms for their ability to detect and classify defects by type, including Mask R-CNN YOLOv3 and YOLOv4. We created three variations of the WTB images dataset provided by the industrial partner using various image augmentation settings. When the algorithm is augmented by Transformation-Based-Augmentations (e.g., flipping and rotation), results show that Mask_R-CNN outperforms all the other algorithms. For example, the Mask R-CNN achieved 86.74%, the YOLOv3 value achieved 70.08%, and the YOLOv4 value achieved 78.28% on the mean Weighted Average (mWA). In addition, a new model, called IE Mask_R-CNN (Image Enhanced Mask_R-CNN), is proposed, which contains pre-processing techniques for improving the images and a Mask_R-CNN model modified to detect WTB defects classification and detection [11].

Image Processing/Classification Techniques

Moreno et al. [12] suggested drones would make the maintenance process of wind turbine blades more effective. The authors first made a mock-up to determine whether the proposal was feasible. A convolutional neural network can detect and classify types of damage in images taken by the drone using a camera installed in the device. The camera was placed at the end effector of our arm robot instead of a drone. The authors utilized the accuracy metric in this study to examine the performance of a system for inspecting blade damage using vision-based images. Overall, the system's accuracy after the experiments 81.25% was achieved [12].

Accuracy = [(No. of images properly classified) / (Total No. of images)] × (100%)

Xu et al. [13] deployed Mavic 2 Pro UAVs to capture their images of the WT blades. These UAVs were controlled from a distance, capturing images communicated using wireless models for instantaneous analysis in real-time. In all, 25,773 images have been collected from UAVs of the WT blade, each with a resolution of 5472*3684. Using a convolutional layer, a pooling layer, and a fully connected layer, CNNs can identify the characteristics of target tasks. TensorFlow is used to test three CNN models for recognizing objects: LeNet-5, VGG-11, and AlexNet. The outcomes of various models are compared; the VGG-11 was chosen as the ultimate model. The F1 score was used for comparison [13]. Zhang et al. [14] used a pavement image to determine whether a particular pixel represents a crack in the crack detection problem. For the classification of patches with and without cracks, the proposed solution takes advantage of a ConvNet trained using square image coverings and the ground truth data. Positive and negative patches are also called cracks and non-cracks to simplify notations. In this article, patches whose centres are crack pixels themselves or close to crack pixels are considered positive patches. The Temple University campus is sampled using a smartphone data sensor to collect 500 pavement images of 3264 x 2448. F1 score metric is used to compare the proposed method with boosting and SVM [14].

Wang and Zhang [15] presented the pioneering study on detecting blade cracks in the WT using their UAV images. Data-driven algorithms are developed to process and identify specifics of blade cracks using images of WT blades. Cracks on WT blades are represented with Haar-like features. Two features' sets are compared: the original Haar-like and the extended form of Haar-like features to detect blade cracks. The next step consists of selecting more effective Haar-like feature sets. The authors proposed a cascading classifier built on the feature set that employs various base classifier techniques, including Support Vector Machines (SVM), Decision Trees (DT), and LogitBoost to develop stage-based classifiers.

Initially, the classifier was trained only according to a local group of Haar-like characteristics to obtain a predetermined rate of false alarms. By considering more features stage-by-stage, the following classifiers are enhanced. Classifiers of subsequent stages are activated only if the classifiers from the previous stage determined that a window contained cracks. Because most windows are negative, a theoretically positive window with cracks is unlikely to get through all categorizations. Cascading classifiers, therefore, quickly identify possible positive windows and filter out potential negative windows, which drastically reduces computation time. Processing time, false alarm, and detection rate were better with the protracted classifier than the LogitBoost classifier [15]. Kim and Cho [16] analyzed images in this process for entire concrete surfaces, cracks, and items not classified as cracks but may easily be misattributed to cracks. AlexNet provides a good transfer learning model to categorize objects in images by recognizing cracks in images. A CNN classifier is developed through transfer learning of the AlexNet neural network model to perceive cracks in entire surfaces and non-crack items. For crack detection, the trained classifier slides a window whose size matches the input into the test structures and analyzes the set of images. As a result of overlapped scanning, the probability map represents the output classification.

A probability threshold determines which groups of pixels to consider as crack parts if they exceed the threshold. Performance measures showed that the proposed method produced higher than 90% accurate results for entire test images, with an 86.73% average accuracy value and a recall value of 88.68% at pixel level [16]. Denhof et al. [17] recommended that transfer learning effectively trains CNN in situations where small amounts of data are available. As per Keras's documentation, the number of parameters and models' depth were compared based on memory use [17]. Akhila et al. [18] described the data is loaded initially, and the image processing process starts. After the image is read, its size is adjusted, the denoise is removed, followed by segmentation and morphology. After all these elements are applied to an image, a crack would be identified, and a filtered image produced. The authors trained the machine to classify images as defective or non-defective. Following the segmentation of the data set, the algorithm is trained on each segment and validated. Finally, the algorithm is passed backwards and forward until the correct prediction results are reached. The class used in this work is the prediction model (CNN). It returns a fault in the particular railway track If the class is less than 0.5. If the class is more significant than 0.5, the fault does not occur in the particular railway track [18].

Galleguillos et al. [19] used active infrared thermography (IRT) as a means of defect detection in composite materials has proven effective for detecting cracks, delamination, water intrusion, and impact damage. This study used rotor platforms of unmanned aerial systems (UASs) to inspect wind blades using thermographic analysis. An assessment of the capability of the UAS-System in the self-governing flight mode has been performed, and a campaign to test the capability of identifying typical blade faults. First, the detectability limits for passive IRT have been established by introducing artificial defects to the rotor blade. Many inspections have taken place throughout the day (early in the morning, midday, and end) [19]. Li et al. [20] proposed network structure has several components in the network: four modules such as convolution, conversion, supervisory, dense connection, and also deconvolution layers. A deep supervision module is linked after a convolution module and a dense connection module. The convolution and dense connection modules first extract the multiscale feature maps when an image is loaded into the network. In the dense connection and convolution modules, feature maps are extracted for deep supervision, while prediction maps with loss functions are generated in the deep supervision modules. During training, deconvolution layers or deep supervision modules generate feature maps and calculate the loss function. The final crack prediction map is generated by merging the deconvoluted feature map with the fusion module. In this study, the proposed algorithm is related to four existing approaches as comparative methods such as RCF, CrackForest, FCN, and FC-DenseNet [20]. AEL, cracktree200, and crack500 are three public datasets that authors have evaluated with the proposed technique.

In this paper, Yang and Ji [21] proposed a deep transfer learning method to detect cracks at the pixel level for engineering applications. In the proposed detection method, crack semantic segmentation and crack recognition are combined in two stages, making it easy for extensive collections of images to be detected reliably and efficiently. In the first stage, fine-tuned Vgg16 can correctly identify crack images so that no further processing costs are incurred on non-crack images. A pixel-level semantic segmentation of crack images was performed using the Unet++ model at the second stage. To advance the generalization and performance of these models, we propose a weighted loss function and multi-fold knowledge-based transfer learning as well. A mIoU of 84.62% was achieved for the proposed method on five publicly available datasets. A mean detection speed of 8.1ms per image was achieved by the proposed technique using 8064 images with a resolution of 224*224. In experiments, the projected method effectively-identified pixel-level cracks [21].

Zhang et al. [22] used a wind farm in Shandong province to conduct blade defect detection tests with a technique for detecting defects in wind turbine blades. First, images of two blades with comparatively more significant surface defects were obtained using the camera array. The HD01 image recognition software was used to help discover faults in the gathered photos. Those outcomes were analyzed statistically and contrasted to the conventional examination method of WT blades to recognize and categorize the images. This experiment examines the applicability and feasibility of using the defect detection system to test the wind turbine blades non-destructive way. A high detection accuracy indicates a high detection effect, attesting to the high precision and efficiency of the detection method [22]. Ramesh kumpati1and Anna bzymek [23] analyzed the images of actual wind turbine blades to detect surface defects to find wind turbine cracks. An unmanned vehicle with a high-definition camera captured a real-time image of the cracks on the wind turbine blade. For this purpose, the wind turbine's blade surface cracks were detected via image processing analytical tools. The field images were processed using algorithms. The cracks on wind turbine blades were identified and characterized by grey colour using Python Open CV2 software. An analysis of the surface images of the edge revealed that the damage inside the surface dots caused deep surface cracks. A contrasted image and gradient image analysis of the algorithm thresholds and histograms revealed the blade cracks. The digital image processing and algorithms effectively reduce costs inestimably by detecting these cracks early by detecting them at an earlier stage [23]. Juan and Kim [24] characterized solar cells using electroluminescence imaging (EL). This technique can characterize solar panel modules in various ways, such as the characteristics of the solar cells, the type of material, and the defect status. A significant source of photovoltaic information comes from the derived features in solar panel images, namely fault detection assessment. Through applying Support Vector Machine (SVM) and Digital Image Processing techniques algorithms, the researchers developed a method for categorizing normal and faulty solar cells. The proposed algorithm has been implemented using MATLAB R2019b. It was observed that the system delivered an accuracy of 95% when using feature extraction procedures on the EL images. [24].

Zhang and Jackman [25] observed on-tower wind turbine blades (WTB) to determine if a novel image processing technique can detect surface flaws. Variations of parameters of the flaws and parameters of the technique were used to test the method. Cracks as thin as hair could be detected and quantified using computer-based optical inspection. An examination camera could not have to be positioned at a precise angle to spot cracks because the positioning of the crack doesn't matter to its image processing. Optimizing the threshold value with the Canny method also significantly reduced uneven background illumination. A crack was also quantified with greater accuracy by reducing noise and combining from Canny and Sobel methods as 2 processed images [25].

Zhang et al. [26] proposed a deeper Neural Network named Mask-MRNet is to spot the blade faults in wind turbines (WT) by using images taken by unmanned aerial vehicles. Two datasets are constructed to train and optimize the blade image. A CNN-512 mask is stacked with MRNet for network detection. A Mask R-CNN modified to reduce inference time, Mask R-CNN-512, can be used when detecting large objects, as with WT blade faults. MRNet is proposed to identify fault types from low noise fault images by correcting the mask angle for cropping. Compared to more than 20 classification models, DenseNet-121 was selected as one of the best sorting models for Mask-MRNet based on testing and training accuracy, detection efficiency, and f1 score. The computational study also demonstrated that Mask-MRNet could detect blade faults in the WT and provide dynamic monitoring while the WT is running [26]. Duan et al. [27] proposed that crack detection on pavement surfaces is of great importance in road maintenance. However, it is difficult to detect cracks accurately due to the complex nature of the irregularity of cracks and road surfaces. This article suggested a crack detection method that combines the patches in the multi-staged approach to attack the patch-wise crack detection problem. These features are then learned by deep supervision for each stage, based on the fusion features that model the structural relevance between cracks. The proposed model achieved 86.97% accuracy in experimental data to get the present state-of-the-art models by various comparisons [27]. In experiments performed on industrial environments, the proposed method was effective.

Acoustic Sensor Detection Techniques

Blanch and Dutton [28] tested an in-service WT blade using the Acoustic Emission (AE) testing trials established in a blade testing laboratory. This study collected operating modes such as parking, started, synchronized, and shutdown. Data was collected for 135 minutes while the turbine was synchronized and operating at more than 9 m/s winds. A remarkable consistency of low amplitude data can be observed in sensors 1 to 3. Sensor 4 looks to pick up a few high-amplitude hits despite the periods of abruptly decreased signal levels. The artefacts may be related to tape fretting or aerodynamic noise. The Acoustic Emission Examination Load (AEL) test on wind turbine blades mounted on wind turbines has been demonstrated in principle by using a pulley mechanism to give load on the blades. The rotating frame uses a high-speed radio transmission method to transmit AE data to the ground without signal degradation. Some minor issues with temporary signal loss and sensor attachments need to be resolved. For a demonstration of this sort, a low-cost sensor network would need to be developed for deployment on a blade set, with inexpensive onboard processing capabilities [28].

Hongwu et al. [29] analyzed the WT vibration monitoring system and fault analyzing system in this paper and the complete program design, sensor acquisition system, and fault analyzing system. This article discusses the advantages of using visual programming for software control development. Authors can determine the state of the object control by analyzing the amplitude and frequency of AE signals. MATLAB SIMULINK developed a virtual device based on secondary methods of the operator of 1st, 2nd, and 3rd order, which simulates three circuits of self-adapting systems. It is possible to operate the Graphical User Interface (GUI) without intervening in the program coding to implement the desired display elements to communicate through the simulation model. This study examined how LabView and MATLAB work together to determine the effects of data treatment time and data processing points. As a scientific approach, it identifies the signals and their causes. It also predicts the future development of the proposed system. Defects and potential failures must be detected early to avoid more damage [29]. Schubert et al. [30] presented a conceptual approach to structural health monitoring using acoustic Lamb waves for structural health monitoring. In the observation structure, it is possible to localize and detect defects with the help of a suitable damage indicator, like the correlation coefficient. There are two approaches to SHM: Passive and Actuators / Sensors. A portion of a rotor blade was used to perform a static load test. A piece about 21m long was used, a portion that was the smallest and rearmost. The surface of the blade was fitted with 32 fibre transducers. The correlation coefficient detected cracks during the statistical load test on this rotor blade by measuring the correlation coefficient. Now dynamical loads are being applied to the whole blade. Increasing the space among two transducers and developing consistent sensor networks are required for appropriate health monitoring of blades with large structures [30].

Dutton et al. [31] developed a method for detecting damage processes in wind turbine blades structures has been by using acoustic emissions (AE) detection as part of the AEGIS consortium. An AE system in the modern era consists of AE sensors mounted on structures, preamplifiers to boost the signal and noise protection, cables to send signals to an analysis of the data acquisition system, and the existing AE system. Sensors used were usually piezoelectric crystals defined by their usual frequency, which governs the sensor's response. The AEGIS experiment was the first to use radio-transmitted AE signals data collecting and acquired data on a single turbine running at modest wind speeds. The results show that receiving AE signals from such a revolving frame is possible and that there is an acceptable amount of noise at Wind speeds from low to moderate. Aegis PR, a robust damage classification system, has been designed to categorize AE data since a wind turbine blade fatigue test, static test, or other heavy loading events. A crucial damage cluster was discovered in various blade tests, but it only appeared in blades acquiring damage. Subsequent blade tests must use the software to confirm further the outcomes on different geometries and types of blades. Aegis PR technology might be the foundation for a wind turbine AE monitoring system to discover different damage cluster patterns [31].

Fazenda and Comboni Bustos [32] described a non-contact defect detection approach depending on the noise generated by the turbine while operating. Under experimental conditions, an examination of a micro wind turbine was conducted. A solitary microphone is put in front of every rotor to collect acoustic data. The data is available for about 10 seconds per observation, and a wave file is generated for subsequent Matlab processing. Two prediction algorithms were implemented and tested on actual data: one relying on a unique feature – rotational frequency spectrum magnitude – and another proposed a fuzzy logic interference using two inputs

– rotational peak and spectral peak change with time. According to the findings, the solitary spectral peak characteristic could evaluate defect severity in ranges. A fault was planted just on the apex of one blade in a higher proportion to replicate fault intensity at various degrees. Weighted (to an accuracy of 0.01g) chunks of 5gram blue-tac are used to introduce the flaw. The aerodynamic interaction between the blades and the tower changes as the physical property of a blade changes, leading to changes in the spectral response of the rotational frequency. The magnitude of this peak should change according to the severity of the fault. An increase in the severity of a fault leads to an increase in rotational frequency [32].

Poozesh et al. [33] proposed a non-contact measurement method that observes sound radioactivity by a beamforming array or single microphone to detect cracks and damage in a structure without contacting it. An acoustic speaker emitting random noise was placed within a chamber simulating a blade in a wind turbine model. The sound radiated from the structure was measured using an acoustical microphone array comprising 62 microphones. We employed CLEAN-based reduction using point spread functions from reference and phased array beamforming to locate the various damage kinds on the test materials. The same experiment was performed using an available commercially 48-channel acoustic circle array to evaluate the testing results. It was demonstrated that both CLEAN-based subtraction and acoustic beamforming of transfer function on reference approaches could accurately identify damage in experimental constructions. The findings show that the three holes as tiny as 1 mm diameter on the blade surface could be detected accurately. The separation of densely packed damage may be a realistic restriction for this strategy due to conventional beamforming techniques' restricted spatial and temporal resolution; yet beamforming demonstrates that damage localized is attainable [33].

Joosse et al. [34] have worked with AE, damage processes in blades can be located and characterized, starting with relatively low loading processes that cause non-audible signals. An analysis of the test methodology for blade certification is presented, along with a collection of fatigue and static component assessments in the research laboratory. The self-test facility on the sensors can be used to accomplish this, or an additional pulsar can be used. A strain gauge was attached to each blade at different radial positions to measure the surface strain. A surface-mounted sensor was used to monitor acoustic emissions. Lead break tests were done at the beginning of every test (at various intervals throughout the fatigue examinations) to ensure that the sensors were adequately mounted. The blades remained loaded in a flap-wise direction, uni-axially. Most of the blades were put through their paces in the load control method. The load was applied with the wooden saddle with a radius of 3.0 m. Integrated optical AE sensors and strain gauges were also used to control the very last two blades. Critical locations can be recognized, and damage evaluated using a pattern recognition system at load grasps near ultimate lateral levels. Damage location is possible, which may be valuable in enabling other procedures in the questionable area [34].

Kim et al. [35] described the new method for detecting cracks in the blades of wind turbines subjected to vibroacoustic modulation to control the operating loads' approach. The vibrational acoustic modulation identifies cracks by mixing low-frequency pumping stimulation with high-frequency probing stimulation. Pumping occurs at a low frequency known as pumping frequency (FPU), whereas probing occurs at such a high frequency known as the probing frequency (FPR). Southwest Wind Power's Whisper 100 wind turbines were used for these experiments. The Whisper 100 turbines generate 900 W at an approaching wind speed of 12.5 m/s. Whisper 100 blades are made from fibreglass of carbon reinforced. The healthy and damaged blade models have different frequency response functions between MFC actuators and MFC sensors. Because the minimal frequency variance among natural frequencies remained 2 Hz, a frequency resolution of df with 0:1Hz was adopted. The test outcomes demonstrated that the suggested methodology could assess nonlinearity in the reaction of the blades in operation utilizing structure vibration employing pumping signal as efficiently as other traditional Vibro-Acoustic techniques that use different kinds of pumping signals. As a result, the technology can detect microscopic cracks in blades far earlier than conventional methods. [35].

Inalpolat and Niezrecki [36] offered a general overview of a novel mechanism developed for structural health monitoring of wind turbine blades. Acoustic transmission loss is measured by detecting changes resulting from structural deformations and damage incurred. The active and passive acoustic damage detection techniques comprise this acoustics-based damage detection technique. The test structures comprise i) blade sections, ii) turbine blade in the field, box iii) turbine blade under fatigue test at the WTTC (Wind Technology Testing Center), and iv) a composite. Acoustic transmission loss is investigated in these tests and can detect turbine blade damage. In summary, both active and passive damage detection approaches have been successfully detected blade damage on full-sized blades of the wind turbine in this study. The methods established would allow for new monitoring systems, which would aid in improving turbine reliability and, as a result, lowering the Levelized cost of wind energy [36].

Traylor et al. [37] employed an active and passive approach to detecting damage using acoustics-based methods. Sound pressure levels (SPLs) between normal and damaged states are measured employing microphones inserted within internal cavities of a blade cross-sectional area. The aeroacoustic analysis is performed on wind turbine blade cases with damaged airfoils to establish a baseline model. Based on these findings, it might be possible to design a system for detecting blade damage based on acoustic pressure changes within the blade's interior cavity. Four damage sizes and five damage locations were chosen in computational case analysis. There was damage on both the pressure (P) and suction (S) sides of the airfoil's front (F), rear (R), and leading-edge (LE) regions midspan. In the healthy baseline case, the internal SPL measurements ranged between approximately 70 and approximately 100 dB based chiefly on one microphone and frequency location. Damage location, size, and frequency were essential factors in determining the success of SPL in identifying damage. Many front cavity instances have seen significant increases in SPL due to cavity damage. In 22 of the 36 cases of front cavity damage caused by 1-kHz signals, the SPL increased by more than 3 dB. SPLs increased by more than three decibels in only six of the twenty-four examples of damage to the rear cavity. These results suggest that the front cavity damage can probably be detected through ΔSPL by one or five kHz on this airfoil. In contrast, rear cavity damage would likely be detected only when more significant. The proposed study uses computational methods to investigate turbine blade aeroacoustics and passive detection further. [37].

Sensor Detection Techniques

Tcherniak and Molgaard [38] presented a system for monitoring the structural health of wind turbine blades, which can detect cracks, leading-edge openings, and delamination. In the present system, structural health is monitored through vibrations, artificially introduced through an electromechanical actuator's plunger that regularly contacts the blade. The vibrations spread out through the blade were detected by accelerometers. The vibrations within the mid-range frequency range are used: the range was above those caused by blade-wind interactions, which ensures good signal-to-noise ratios. The vibrations were measured utilizing 12 piezoelectric accelerometers attached to the blade. Plastic clips were used for mounting the accelerometers on the blade. The accelerometers were wrapped with silicon to protect them, and the "helicopter tape" was placed on the top to smooth out the silicon. The data-gathering equipment and electronics were housed in a watertight box attached to the spinners inside the surface. Bruel & Kjr PULSE LabShop software was used to control the data acquisition equipment. The software was set up to begin data collection, a record for 10 seconds, then initiate an actuator hit and record it for an additional 20 seconds. The system then paused acquisition and waited four and a half minutes before restarting it. Every hour, actuator hits of 12 and accompanying datasets were generated. An automated hammer and an accelerometers array are used in this experiment to demonstrate an active SHM system based on vibration. The covariance matrix among the recorded acceleration values was employed as a damaged feature [38].

Fantidis et al. [39] demonstrated that detection could locate the defect in wind turbine blades while reducing the inspection cost using a transportable radiographic unit. Notably, in stormy conditions, wind blades would experience enormous stress. A radiograph can reveal corrosion, inclusions, and cracks are examples of internal faults and imperfections and different thicknesses; Therefore, it is an increasingly important technique for industry and science to locate defects in the structure. It is possible to construct the 3D object representation by computing a series of radiography images at different angles of rotation of the sample. The approach is called neutron computed tomography. In the blade, there are two defects, a radius of 0.05 cm and a height of 1.5 cm cylindrical void (1) and a 0.2 cm radius sphere from water (2). Radiography using photons and neutrons can provide a non-destructive method for recovering detailed information about blade interiors, including inaccessible parts not accessible by conventional methods [39]. Computed tomography for turbine blade inspection can be highly effective because of its high contrast and spatial resolution. Failure could result in very high costs and even life and limb. The MCNPX Monte Carlo code has been used to simulate a portable system with an Sb-Be source near to achieve gamma and the neutron radiography of the wind turbine blades. For the two radiography options, suitable collimators were simulated for suitable Sb-Be sources because of their low cost, ease of transport, and ability to be switched on/off.

Park et al. [40] described a laser ultrasonic imaging and damage detection technology that produces images of acoustic energy propagating on such a spinning structure while also detecting damage. Images of the transmission of ultrasonic waves were taken using a pulse laser instead of a revolving blade light for ultrasonic emission, a galvanometer enabling laser scanning, and an integrated piezoelectric sensor in ultrasonic measurements. A steel fan is used to test the performance of the suggested laser ultrasonic imaging method. The fan has four steel blades, one used to capture ultrasonic pictures. Each blade measures a length of 24.5 cm, a width of 21.5 cm, and 1 mm in thickness. The geometry of each blade is complicated, and some designs are pressed into the blade surface. A pulse laser is synchronized with only a galvanometer, consisting of two revolving mirrors, to scan the laser beam in two dimensions (2D). Visualizing the propagation of ultrasonic waves on a revolving steel blade is used to test the efficiency of the suggested imaging technology. Despite the quick spinning speed and intricate blade structure, it was proved that ultrasonic pictures might be successfully produced. The damage that was not evident on the scanned surfaces was also recognized, as well as its visibility was improved using the standing wave filter [40].

McGugan and Mishnaevsky [41] proposed a damage apparatus-based solution to monitor wind turbine blades. The structural health monitoring system includes sensors mounted to the structure and accompanying software and hardware for data analysis. The method depends on identifying the blades' eigenfrequencies and measuring the blades' vibration spectra. Piezoelectric sensors that sense high-frequency flexible waves induced by crack or debond in the AE-based technologies. The acoustic emission sensors track sound waves that spread over the blade surface due to structural degradation. Damage condition at various sites is assessed at various locations. The sensor data were analyzed to determine the condition of the blade's damage. A damage scale and matrix and the history of sensor damage index matrix by various sites were constructed based on the wavelet packet outcomes obtained to analyze the damage condition. Temperature trends can be caused by faults or local degrading of materials, which can be identified utilizing infra-red thermography and evaluated to detect the faults. The damage is visualized using damage imaging methodology. The examples proved the feasibility of monitoring exact damage devices and wind turbine blades localizations [41].

Jasinien et al. [42] compared the results of radiographic and ultrasonic methods used to inspect wind turbine blades and to adapt them for that purpose. Several structural defects within a blade were detectable using radiographic techniques. In radiography, ionizing radiation is transmitted through the material, and its attenuation is measured. Therefore, differences in density within the blade structure were identified. Material density and thickness determine the amount of attenuation. Immersion testing using a new combination of pulse-echo and contact was used with a stirring water container to examine wind turbine blades using two ultrasonic methods explicitly altered for this purpose: pulse-echo immersion examination with something like a floating container employing a planar transducer at f = 400 kHz and a focused transducer with f = 2.2 MHz and air-coupled testing with guided Lamb waves at f = 290 kHz. A pulse-echo immersion test utilizing a focused transducer makes it possible to detect the approximate size and position of the defect and locate defects at the surface that would otherwise be hidden, for example, the absence of glue right beneath the surface of the skin. Pulse-echo immersion testing with a focused transducer, on the other hand, can more precisely determine the position and approximate size, along with detecting faults closer to the surface, like glue insufficiency just beneath the skin layer [42]. Arnold et al. [43] suggested that efficient and dependable maintenance methods for wind turbine blades were required to reduce operation and maintenance costs. It necessitates the development of novel non-destructive testing (NDT) procedures for characterization and damage detection of composite materials, preferably while wind turbines are in operation. The same differential signal processing method is used in this article aimed at radar-based SHM structures, where variations in divergence signals are linked to damage, environmental, or influences water accumulation such as ice or rain on the blades. Even though the radar methodology is promising for inspecting various dielectric materials, the electrical conductivity of carbon fibre composites limits its application. The frequency-modulated consistent wave–radar sensor is bistatic is mounted 1.5 meters in wind turbine front end and maybe adjusted vertically using a linear stage [43]. The electromagnetic radiation has a limited absorption in this material system and depends on the fibres' arrangement. As a result, material flaws in carbon fibre composites are typically undetectable. But, when the damage progresses and the surface of the blade changes, these variations can also be measured.

Zhang et al. [44] have recommended that the surveillance system of crack is vital for offshore wind farms and land wind farms. Distributed fibre sensors built on the Brillouin scattering have mainly two schemes at present: Brillouin optical time-domain reflectometer (BOTDR) sensing approach and Brillouin optical time-domain analysis (BOTDA) sensing approach. Measurement of the fibre attenuation is done by measuring the power received from the backscattered signal after the incident pulse is detected; the location of scattering points can be determined by measuring between the incident pulse and the backscattered signal's time delay. The spontaneously Brillouin reflecting light is used in the BOTDR test. Because the intensity and frequency shift of Brillouin is proportional towards temperature and fibre strain, the signal is generated by spontaneous Brillouin scattering. BOTDA has many advantages, including simple construction and accurate cracks measurement, temperature, strain, and lightning, based on the analysis of hidden faults induced in WTs blades and contrasts with existing Brillouin scattering-based distributed fibre sensing methods [44].

Zhao et al. [45] have applied the signal decomposition into subbands by applying wavelet packets. The extraction of the effective signal in the frequency range was completed by reconstructing the wavelet packet decomposition coefficient. Each frequency band was analyzed to extract the signal energy. A feature vector of fault diagnosis was generated, with energy taken into account as the feature element. A wavelet packet was used to extract 10 feature vectors. By re-processing the feature vector normalized, the sample's mean can be summarized, and the convergence of the training is accelerated. Five data sets were utilized for the training model and five sets for testing. Optimizing the parameters of the penalty factor and kernel function produced the obtained accuracy value is 90% [45]. Arsenault et al. [46] described a strain sensor distributed system using fibre Bragg gratings (FBG) to detect structural health changes in a wind turbine rotor in real-time and its validation on a laboratory test set up. An instrumented wind turbine with three blades measuring 1.6 m diameter and 1 kW and the horizontal axis is used for this study. Strain sensors are surface mounted on the blade and are positioned at various locations. The sensors are calibrated under static loading conditions to test the mounting of the FBG and the planned data collection methodologies. The sensor system's capacity to collect natural frequencies and their accompanying mode shapes is assessed under various dynamic non-rotating loading scenarios via operational modal analysis (OMA). A rotating wind tunnel is next used to test the sensor system under rotating conditions, including both a standard wind turbine and one with blades that have been structurally changed. A lump of mass was attached to the blade's tip to simulate ice accretion or structural damage. The baseline (healthy) blade compared to the modified (altered) blade to verify the system's sensor functionality and determine rotor structural health in real-time. [46].

Pitchford et al. [47] demonstrated the structural health monitoring technique based on impedance to analyze the effectiveness on a wide variety of structures. In addition to destroying blades, wind turbines failures can cause severe damage to other wind turbines. This technique uses piezoceramic (PZT) patches to apply high-frequency excitations to a structure and to monitor alterations in the mechanical impedance of the structure. Assessing the mechanical integrity of a structure can be done by monitoring the electrical impedance of its PZT. In this paper, the feasibility of installing an onboard system in turbine blades as a means for detecting damage on the ground is examined. Sandia National Laboratories performed a series of tests on an actual section of a wind turbine blade fabricated from an experimental carbon/glass/balsa composite blade to determine the capability of onboard detection. [47]. Song et al. [48] developed a wireless sensor network (WSN) based on piezoceramic, which can monitor wind turbine blade health with an active sensing approach. WSNs use access points to coordinate the network. They connect to a PC that controls the wireless nodes. An embedded piezoceramic patch is excited by one wireless node through guided waves. A diverse network of wireless sensors detects and transmits the wave responses at the rest of the nodes. Wavelet packet investigation was used to assess the damage status inside the blade. Damage indices and damage matrix results were developed based on the wavelet results for each location of the blade. An experimental wind tunnel test and static loading test were performed at Harbin Institute of Technology (HIT), China, to assess the proposed strategy's validity. The proposed method can detect and evaluate damage in wind turbine blades based on experimental results [48].

Matsuzaki and Todoroki [49] have analyzed a wired system, making delamination in rotational composite components harder to identify, such as blades on helicopters or wind turbines. The current study investigated the wireless system based on a micro-oscillation circuit to detect carbon/epoxy delamination during the separation of the composite component, a small oscillation circuit associated with it. The change in electrical resistance causes the component to oscillate at a different frequency due to delamination. In addition to applying to rotating components due to composite construction as a detector, the oscillating circuit is also tiny. Carbon/epoxy specimens are used to measure the change in electrical resistance due to delamination. Using a temperature compensation circuit minimizes the effect of temperature change [49]. Embedded delamination can be detected, and its size estimated using the wireless method. Moradi et al. [50] presented a real-time, non-destructive SHM technique that depends on multisensory data fusion to identify and locate blade damages. The aim is to critically examine the technique's feasibility to detect and locate wind turbine blade damage in real-time. Finite element simulations of the turbine blade were utilized to study the structural properties before and after damage. According to the obtained results, intelligent sensors that measure vibrations and strains dispersed over the turbine blades could detect damage and preserve them. Data fusion integrates the two diagnostic techniques to create a more accurate detection system of fewer false alarms [50].

Hwang et al. [51] proposed an approach for detecting damage using laser thermography in a continuous line for wind turbine blades under rotating conditions. The thermal response of the rotating wind turbine blade is directly measured by an infrared camera while the thermal waves remain produced with a laser beam in a continuous line. In addition to the proposed noncontracting mechanism, no coolant is required. There is no intuitive interpretation mechanism and spatial data scanning required for continuous line laser thermography. Furthermore, statistical pattern recognition and pixel tracking techniques are developed and applied to thermal images in the temporal domain, allowing only damage features to be recovered, even when the images are in operating conditions. Experiments with a scaled wind turbine system at various speeds confirm the accuracy of the suggested laser thermography in a continuous line approach [51].

Discussion and Prospects

Image Annotation was also performed on WT blade images. Using Image Pre-processing techniques, research works as discussed above the Wiener Filter, Adaptive Median Filter, Morphological image enhancement, Zooming, Gabor Filter, log-Gabor filter is used in most of the works for image pre-processing. In addition to that, image Augmentation techniques such as Pyramid, Patching algorithm, Image data generator, Geometry Transformation, Blurring, and colour conversion are applied to enhance the blade images. The image processing techniques mainly applied to WT blade images are, identifying suitable greyscale value for cracks, sliding window technique, Edge detection technique using Gabor filter, and using the histogram-based empirical model the healthy and damaged blades are classified effectively.

In Acoustic Emission Sensors based research studies, keeping the speaker inside the blade and capturing Sound radiation will get more radiation if the blade gets damaged. The damage point causes a non-audible acoustic signal when applying a small load fraction—using Pattern recognition technique, sending Lamb waves using correlation coefficient possible to detect the fault in WT blades. An array of microphones is also used. Fibre Bragg sensor and modal analysis technique, piezoelectric crystal capture the non-audible acoustic signal, and clustering algorithm were used to localize the fault location. They placed the microphone in front of the rotor and subtracted the standard signal. The rotational frequency with time, applying transmission of the pulses inside the blade, a low frequency pumping excitation signal is utilized in conjunction with a high frequency probing excitation signal in vibroacoustic modulation were also applied to find fault WT blades. The significant limitations with acoustic emission are not possible to carry out in real-life conditions, and it has to be carried out in a laboratory. Using Radiography with Ultrasonic techniques such as Sb-BE Gamma-ray radiography is used to detect the internal flaws in WT blades. Applying Laser Ultrasonic Piezoelectric sensor would sense the ultrasonic signal and capture pattern. The Laser and Blade vibration spectra and detecting the eigenfrequencies of the blade would detect cracks based on high-frequency elastic waves.

Conclusion and Future Work

Wind power has proliferated in recent decades due to its low energy costs compared to other renewable energy sources, like solar power. As wind turbines are erected and managed, data shows that wind farm owners/operators must bear a large share of the total energy expenses due to maintenance expenditures. This paper describes three kinds of methodology for detecting turbine blades. Three different types of approaches are discussed in this article. It is studied how to detect faults in wind turbine blades using different sensor technologies. Among them are various image processing techniques, acoustic sensors, and other sensors designed to aid in the early detection of wind turbine blades. It can be concluded that the passive technique would be better; hence more research shall be carried out using the Image processing technique integrating image pre-processing and classification techniques depending on deep learning or machine learning algorithms. In addition, the limitations of acoustics or sensors cannot be used in all environments and have many challenges. As future work, a novel method can be proposed for detecting wind turbine blade failures by considering the benefits of both technologies mentioned in this article.

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