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RESEARCH ARTICLE

Damage Identification of Wind Turbine Blades – A Brief Review

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Abstract: The increasing size of these blades of wind turbines emphasizes the need for reliable monitoring and maintenance. This brief review explores the detection and analysis of damage in wind turbine blades. The study highlights various techniques, including acoustic emission analysis, strain signal monitoring, and vibration analysis, as effective approaches for damage detection. Vibration analysis, in particular, shows promise for fault identification by analyzing changes in dynamic characteristics. Damage indices based on modal properties, such as natural frequencies, mode shapes, and curvature, are discussed.

Keywords: damage modeling; digital twin; vibration-based indices; wind turbine blade

I. INTRODUCTION

The wind is a prominent renewable energy source, and there has been a significant increase in wind turbine efficiency through the use of larger rotors and economies of scale [1–3]. Among the components of a wind turbine, the blade plays a crucial role in transferring mechanical energy into electrical energy, which becomes even more important as blade size increases [4–6]. However, offshore wind turbine blades have distinct characteristics compared to onshore ones. They are typically larger in size, operate in more challenging weather conditions, face higher safety risks and maintenance costs, and require enhanced protection against failure and breakdown.

If all suitable land areas were utilized, approximately a million Gigawatts of economically viable energy could be generated from wind sources [7]. Contrary to a common misconception [8], the power output of wind energy does not increase with the cube of the wind speed due to the fixed area of the wind turbine actuator disk. Real wind turbines' efficiency in converting the kinetic energy in the wind into power is estimated to be around 60%. Wind turbines typically begin generating power at wind speeds of 3–5 m/s and shut down at high speeds of 20–25 m/s. Various factors, including available wind resources, site potential, technical potential, and economic potential, can be used to assess the viability of wind energy compared to other energy resources [9].

The share of renewable energy in the power sector is projected to reach 85% by 2050, as depicted in Fig. 1 [10]. Wind capacity has experienced faster growth than any other technology, as illustrated in Figs. 2 and 3. According to statistics from the World Wind Energy Association, global installations of wind turbines reached a total of 93 GW in 2020, a significant increase of approximately 50% compared to 2019 [11]. The combined electrical power capacity of all wind farms worldwide now accounts for 7% of the global capacity [10]. However, the wind energy industry has not yet reached full commercial maturity, and there is a need to reduce maintenance costs and the overall cost of energy production, particularly in the offshore wind sector.

Despite advancements in wind power generation, challenges persist in optimizing its efficiency, reliability, and cost-effectiveness, especially in offshore installations. To ensure the structural integrity of wind turbine blades and maximize energy production, continuous monitoring, and analysis, including modal-based damage identification, are crucial. Structural damage in blades can compromise system integrity and load-bearing capacity. Monitoring the blades' modal characteristics and comparing them to a standard or healthy condition provide valuable insights into their physical properties and aids in damage identification [12,13]. Analyzing the modal features allows for extracting relevant data to assess the severity and extent of the damage, enabling effective maintenance and repair strategies.

The damage detection based on vibration approach is particularly considered as a promising technique where damage identification and classification can be accomplished through changing in the dynamic characteristics of wind turbine blade. This paper gives a brief review of damage detection approaches for wind turbine blades according to the recent technologies. These are included acoustic emission, strain deformation measurement, and vibration. The vibration technique approach is comprehensively studied as an accurate method based on monitoring the change in the dynamic characteristics of blade.

II. DAMAGE SCENARIOS AND STRUCTURAL HEALTH MONITORING OF WIND TURBINE BLADES

Wind turbine blades are complex structures made of composite materials with different aerofoil cross sections [1,14]. During their continuous operation, various factors can cause damage to these blades. The primary cause is variable loading, driven by the external aerodynamic force of the wind. Wind speeds ranging from 3–5 m/s to 20–25 m/s can lead to severe blade damage [12,13]. Heavy rainfall, especially with strong winds, can cause significant harm [15]. Extreme weather conditions, such as thunderstorms,

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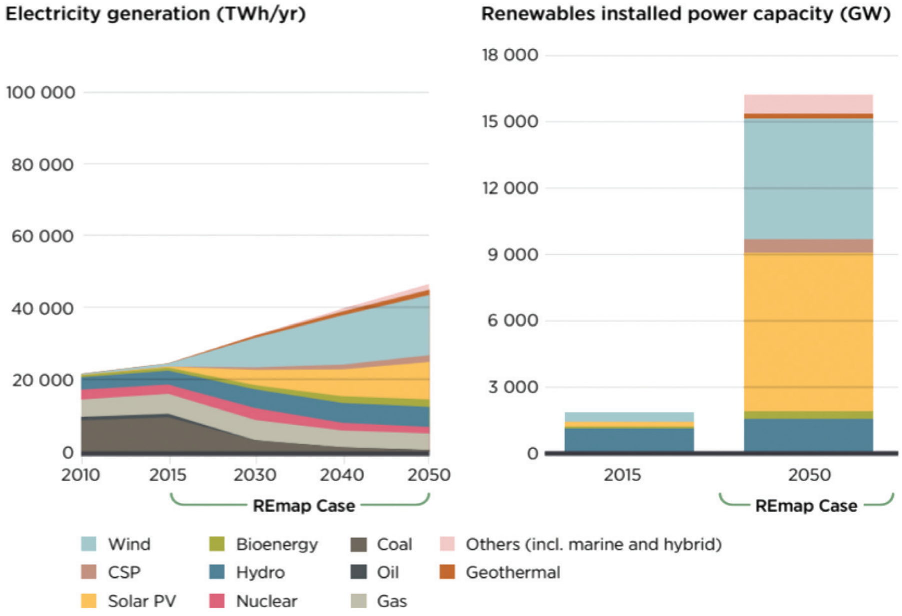

Fig. 1. The rising importance of electricity derived from renewable energy [10].

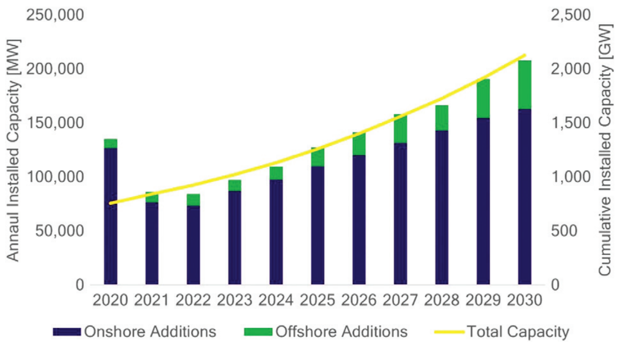

Fig. 2. Wind to account for two-thirds of global power production by 2030 https://www.enlit.world/renewable-energy/wind/wind-to-account-for-two-thirds-of-global-power-production-by-2030/ (accessed 7th July 2023).

lightning strikes, and ice accumulation, pose additional risks, including delamination and tip detachment [16]. Ice accumulation can result in rotor imbalance, mainly due to pitch misalignment and unbalanced mass distribution [16]. Icing also leads to irregular vibrations that, if they exceed a certain threshold level, can cause fatigue and breakdown. Wind turbines located in high-altitude areas face even greater challenges, as they experience higher wind speeds and cold air density. The extremely cold weather can induce additional blade fatigue, such as brittle material fracture and nonuniformities on the surfaces [17].

Other damage scenarios include splitting along fibers, leading to a loss of material adhesion, and reduced blade stiffness. Coat cracks can increase skin roughness and cause buckling-induced skin damage [18]. Invisible defects resulting from manufacturing flaws and poor design can also contribute to blade damage. These invisible defects can grow and cause different types of damage due to the harsh operating environment and repeated high loads. Trailing edge cracking is a common form of damage [19–21].

Damage to wind turbine blades increases the level of vibrations and imposes an additional dynamic load, which can result in failure or breakdown. Hidden defects that go undetected during inspections at the manufacturing facility can grow under stress and manifest as damage. Therefore, regular and frequent inspection and monitoring are crucial to prevent such issues.

Structural health monitoring plays a vital role in ensuring the integrity and dynamic behavior of wind turbines [22]. Several previous studies on condition monitoring of wind turbine blades have utilized existing methods applicable to other rotating structures [23]. Machine condition monitoring can be categorized into different techniques, including vibration analysis, strain measurement, acoustic emission monitoring [24], and vision-based. Advances in sensor technology and data-driven analysis have paved the way for efficient wind turbine operation. One of the innovative approaches is the use of sensor networks for structural health monitoring. By adopting these techniques, useful information about wind turbines can be obtained, enabling the early detection of damage, optimization of efficiency, and reduction of maintenance costs [20,25–27].

One approach is to measure strain signals using strain sensors mounted on the blade surface or inside the blade body. However, it is essential to consider the change in operating conditions, such as temperature variation, lightning strikes, and strong wind waves, as these can degrade the performance and susceptibility of strain gauges [25,26] Changes in strain signals can indicate blade icing, mass imbalance, or other abnormalities in the structural health state. Strain sensors can be mounted on the blade surface or embedded within the blade layer. However, traditional strain gauges are susceptible to degradation and are sensitive to factors such as lightning strikes and temperature variations [28,29]. New techniques based on fiber optic sensors are being developed [30,31].

Another method is analyzing the blade's acoustic emission signals, including parameters such as acoustic

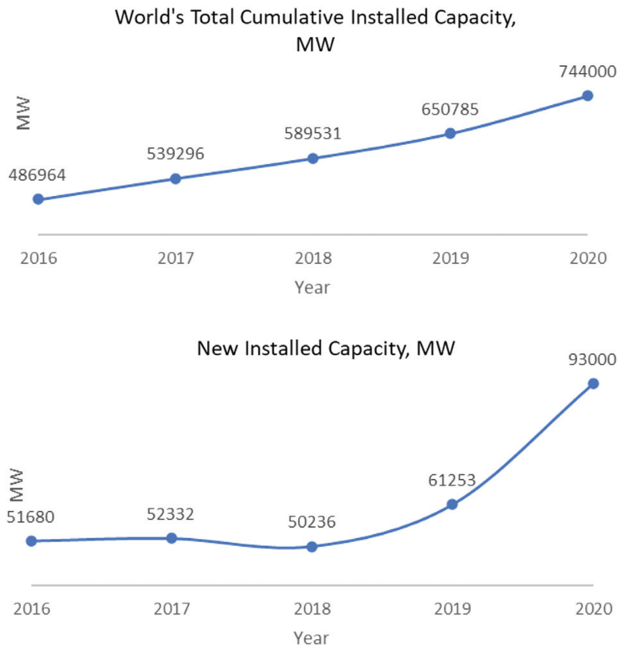

Fig. 3. Total annual installed capacity of wind farms worldwide. The diagram is adopted from [11].

energy, rise time, duration, and kurtosis [20,27]. Acoustic emission sensors are crucial in detecting damage by measuring sound waves emitted by the damaged blades [32]. Monitoring techniques based on airborne sound signals can also provide valuable insights into the presence and severity of damage [30,33,34]. Acoustic emission monitoring is based on detecting strain energy release within the blade material. Strain energy is the mechanical energy stored in a stressed system under various loadings. The strain energy index has been widely employed in the literature to detect and investigate early damage occurrence [30,31]. When wind turbine blades undergo different static loadings, the external work done by the loads as they increase is equal to the strain accumulated by the blade until damage occurs. Acoustic emission signals can be analyzed to extract information about the damage [25,35,36].

The vision-based approach can be used for initial inspections. Advanced techniques are required for precise damage detection. Visual inspections, employing tools like binoculars and drones, can help identify visible defects such as cracks, missing paint, or separation between skin layers. For example, Xu *et al.* [37] proposed a novel blade inspection method using deep learning and unmanned aerial vehicles to overcome the inefficiencies of onsite visual surface inspection, treating the problem as an image recognition task, and evaluating the models based on the F1-score. Moreno *et al.* [38] presented a vision-based deep learning approach that automatically analyzes each part of the blade's face, enabling the detection of specific faults such as ray impacts, wear, and fractures. Wu *et al.* [39] proposed an economical optical technique using digital image correlation (3D-DIC) for monitoring wind turbine blade health, focusing on fault detection through relative deformation analysis.

Acoustic emission and ultrasonic methods utilize sound waves to detect damage, but they are not without challenges and limitations. One significant challenge is the susceptibility to external noise and interference from other signals, which can distort sound waves and provide misleading information about the state of damage.

Variations in material properties further complicate the use of acoustic emission. Changes in density, elasticity, and geometry can alter sound waves, making them more challenging to detect accurately. Additionally, the complex aerofoil sections of wind turbine blades can cause scattering or refraction of acoustic emissions, adding to the complexity of the method.

Stain gauges, while useful, are also subject to errors and interferences. Factors such as humidity, creep, and fatigue can reduce their accuracy. Furthermore, strain gauges can only measure local strain, requiring calibration and correction under different loading conditions and when working with different composite material properties.

Damage to the structure alters the dynamic characteristics, such as natural frequencies and mode shapes [40–42]. These dynamic characteristics and changes in natural frequencies can also serve as sensitive indicators of damage severity and location [43].

Monitoring the modal features of wind turbine blades and comparing them with a standard or healthy condition is an effective strategy for extracting information about the physical properties of the blade [44]. By utilizing this approach, damage identification becomes more feasible, overcoming many of the challenges associated with damage detection.

Vibration analysis involves capturing vibration signals from the wind turbine blades using various types of sensors. These sensors include displacement sensors for low-frequency range, velocity sensors for middle range, accelerometers for high-frequency range, spectral emitted energy sensors for very high frequency, and ground-based radar as a remote sensor for in-field rotor blades [24]. Changes in the vibration signal's amplitude can be used to detect the severity and location of damage [45]. Signal processing techniques are employed to accurately identify and assess the damage, its location, and its severity [18,44,45]. Vibration analysis techniques may be classified into two main methods, namely model-based and feature-based. More discussions will be given in the next section.

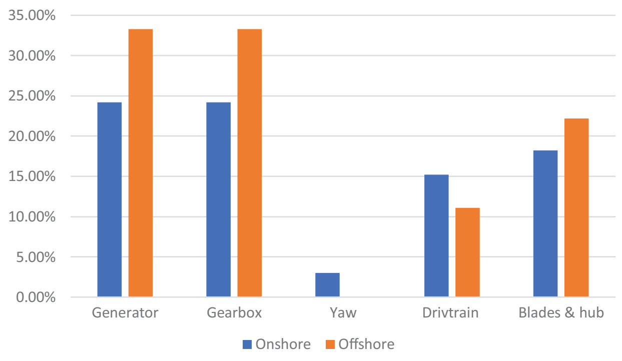

Fig. 4. Critical components in terms of failure and downtime [4].

Structural health monitoring of wind turbines for system integrity and dynamic behavior requires accurate data-driven analysis. One promising technique is the use of digital twin technology [46], which involves creating a numerical model that simulates the performance of an actual wind turbine. This technology, aligned with the principles of Industry 4.0 and smart manufacturing, enables predictive maintenance and optimization of wind turbine operations [7,47–51].

III. BACKGROUND INFORMATION

Horizontal axis wind turbines are commonly utilized in large-scale wind farms for industrial applications, where their electricity generation depends on size and wind speed. These turbines demonstrate a remarkable ability to convert 40 to 50% of the wind power they receive into reliable electricity. However, the challenges arise from their impressive dimensions, with blades extending up to 100 meters long and a typical hub height of 140 meters [4,52]. Operating under high wind speeds exacerbates the complexities associated with inspection and maintenance, which often incur significant costs; see Fig. 4. To address these challenges, integrating structural health monitoring systems with wind turbines has emerged as a viable solution for facilitating continuous monitoring processes [5].

IV. VIBRATION-BASED MONITORING

Vibration analysis plays a crucial role in the condition monitoring of offshore wind turbine blades. Due to the unpredictable external forces and challenging operating conditions, the measurement and analysis of blade vibrations are of immense importance for understanding the dynamic characteristics of wind turbine blades [42,53].

Model-based methods utilize mathematical models and governing equations of motion to extract the blade's mass, stiffness, and damping matrices. These parameters are obtained using finite element techniques, allowing the derivation of the system's equation of motion. By analyzing the dynamic characteristics of the blade, such as natural frequencies, mode shapes, and strain energy, model-based methods can detect and identify damage within the blade [54]. These methods are often referred to as failure detection methods because they correlate observed abnormal features with the model predictions to identify the presence and extent of damage.

On the other hand, feature-based methods focus on extracting relevant features from the measured vibration signals and comparing them to a reference healthy condition. These features include natural frequencies, modal damping, characteristic displacement patterns (mode shapes), and strain energy. Variations in these features indicate the presence of damage or changes in mass, stiffness, and damping due to external factors. Feature-based methods employ statistical analysis and vibration indices to identify and evaluate the likelihood of blade failure at an early stage before reaching unacceptable levels [54–57].

Model-based damage identification techniques utilize the modal parameters to investigate the health condition of wind turbine blades. These methods involve analyzing changes in natural frequencies, mode shapes, curvature of mode shapes, and strain energy caused by damage or defects. Various approaches have been proposed, such as investigating discontinuities in curvature mode shapes, analyzing frequency changes related to bending stiffness, and studying the relationship between strain energy, curvature integrals, and power modes [58–62]. By monitoring these modal parameters, model-based methods can provide valuable insights into the condition and reliability of wind turbine blades.

Advancements in structural health monitoring aim to enhance the reliability and operation of wind turbines. Techniques such as smart rotor blades that estimate aerodynamic loads and deformation caused by wind, static and dynamic loading monitoring, and outlier analysis for damage detection have been employed [63]. The concept of the digital twin, which represents a digital simulation of the real wind turbine system, is also gaining traction. The digital twin integrates real-time data from the physical system into a virtual model, enabling online predictions, decisions, and comparisons between the real and virtual systems to prevent damage problems before failure and downtime [58,64–66].

As Industry 4.0 and smart manufacturing continue to revolutionize industrial practices, the integration of big data, digital twins, and real-time data analysis will play a significant role in enhancing wind turbine condition monitoring. These advancements enable more efficient and accurate analysis of real-time data and facilitate proactive maintenance strategies for offshore wind turbine blades [64].

A. MODEL-BASED DAMAGE IDENTIFICATION AND THE EMERGENCE OF DIGITAL TWINS

Identification of damage in dynamic systems can be viewed as an inversion problem, where the data collected by sensors serve as input for the digital twin. The digital twin then processes this input to determine damage localization and severity. The integration of digital twin technology with the physical system enhances system reliability.

Structural vibrations pose significant challenges and design constraints for wind turbine blades. Ensuring the structural integrity of these blades requires a deep understanding of their dynamic characteristics. Many damage identification methods rely on the analysis of modal parameters.

Damage indices techniques can be employed to compare the structural parameters of healthy and damaged wind

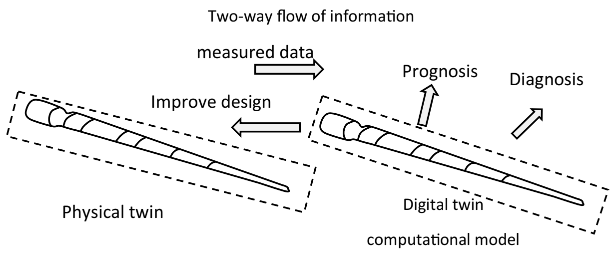

Fig. 5. Digital twin framework.

turbine blades. Digital twins can replicate the actual structure and provide modal parameters like natural frequencies, mode shapes, and curvature mode shapes. These parameters serve as key indicators for assessing the health and reliability of wind turbine blades.

Changes in mass (e.g., due to ice accumulation), stiffness, damping, internal defects, or unexpected excitation forces can lead to variations in modal parameter values. Vibration indices derived from these modal parameters are used to detect potential blade failures at an early stage, preventing them from reaching critical levels.

Figure 5 illustrates a schematic representation of the digital twin framework. Sensor data collected from the physical wind turbine are used to calibrate the digital twin, which usually comprises multiphysics, multiscales, and multi-uncertianty computational model with data connections and information processing mechanisms [67,68]. The primary objective of the digital twin is to monitor, detect, and make informed decisions regarding the blade's health.

For example, Chetan *et al.* [69] outlined the creation of a multi-fidelity digital twin structural model for an as-built wind turbine blade. Their aim was to establish a method for generating a precise and comprehensive model of the actual blade. This model would then be used to validate the performance of a two-bladed, downwind rotor during operation.

Wang *et al.* [70] presents current research progress on reliability analysis and digital twin applications for offshore wind turbine support structure. They also discussed a digital twin framework that combines virtual-real modeling and real-time data updating to address existing reliability analysis limitations, and it emphasises the growing potential of digital twin framework technology, machine learning, internet of things (IoT), big data, and finite element calculations to support offshore wind turbine (OWT) reliability analysis in the future.

Jorgensen *et al.* [71] discussed a strategy for implementing the digital twin paradigm in the context of offshore wind turbine support structures. They explored the use of surrogate models to replicate computationally intensive simulations. Their paper also addressed how to handle sources of uncertainty that can impact predictions made by the Digital Twin and outlined the essential considerations and requirements when developing Digital Twins for offshore wind turbine support structures.

B. DAMAGE IDENTIFICATION BASED ON THE SENSITIVITY ANALYSIS OF MODAL PARAMETERS

Each blade element along the blade span behaves as a separate entity. The generalized eigenvalue problem for each element can be written as:

$$[K - \lambda_i M] z_j^i = 0 \tag{1}$$

where K and M are the local stiffness and mass matrices, respectively, λ_i is the structure eigenvalue at mode i, z_j^i is the eigenvector of the generalized eigenvalue problem at mode i, and j represents the number degree of freedom.

Assuming that the damage determines the reduction of the stiffness matrix, this will lead to a change in the modal frequencies and corresponding mode shapes.

Thus,

$$[(K + \Delta K) - (\lambda_i + \Delta\lambda)M](z^i + \Delta z^i) = 0 \tag{2}$$

and

$$\Delta\lambda_i = z^{(i)T} \Delta K z^{(i)} \tag{3}$$

$$\Delta z^{(i)} = \sum_{j=1}^{N} \frac{z^{(j)T} \Delta K z^{(i)}}{\lambda_i - \lambda_j} \tag{4}$$

which shows that the variation in the displacement of the mode shapes is related to the structural frequencies of the healthy structure. The stiffness matrix, natural frequencies, and mode shapes of the damaged blade can be expressed as:

$$K^d{}_i = K_i + \beta_i K_i \quad and \quad -1 < \beta_i < 0 \tag{5}$$

$$\omega^d{}_i = \omega_i + \Delta\omega_i \tag{6}$$

$$z_i^d = z_i + \Delta z_i \tag{7}$$

V. DAMAGE INDICES

Damage indices play a crucial role in the analysis of wind turbine blade conditions. Several methods are introduced based on the analysis of modal parameters, allowing for a comparison between intact and damaged blades and the evaluation of their health and reliability.

One of the commonly used approaches is the comparison of natural frequencies. The degree of correlation and discrepancies between different modes can be observed by tabulating or plotting the natural frequencies of intact and damaged blades. In undamaged blades, the natural frequencies should lie on or close to a straight line with a 45-degree gradient. Deviations from this line indicate errors in the prediction model, material properties, or the presence of damage. However, this method alone cannot identify the location or features of the damage.

Another important aspect is the comparison and correlation between mode shapes. The baseline modal parameters of a healthy blade are established first. Any changes in these parameters can provide insights into the causes of such variations. The modal scale factor (MSF) is one of the indices used to quantify the correlation between pairs of mode shapes. It measures the similarity in scaling between two mode vectors, allowing for the detection of error vectors superimposed on the modal vectors. The MSF index is calculated based on the modal coefficients of the mode shapes being compared [10].

Mathematically MSF may be expressed as:

$$MSF(A,B) = \frac{\sum_{j=1}^{N} (\Psi_A)_j (\Psi_B)_j}{\sum_{j=1}^{N} (\Psi_A)_j (\Psi_A)_j} \tag{8}$$

where Ψ_A, Ψ_B are the mode shape vectors being compared, N is the number of degrees of freedom for both A and B, and j is the mode number and depends on which mode is taken as reference:

$$MSF(B, A) = \frac{\sum_{j=1}^{N} (\Psi_B)_j (\Psi_A)_j}{\sum_{j=1}^{N} (\Psi_B)_j (\Psi_B)_j} \tag{9}$$

If $\{\Psi_A\} \equiv \{\Psi_B\}$, the two modes are perfectly correlated, and

$$MSF(A, B) = MSF(B, A) = 1$$

In the second case, the two modes differ by a simple scalar multiplier $\{\Psi_A) = \gamma\{\Psi_A\}$ and

$$MSF(B, A) = \gamma \quad \text{while } MSF(A, B) = \frac{1}{\gamma}$$

The modal assurance criterion (MAC) is another statistical indicator used to determine the correlation between mode shapes. It quantifies the consistency between healthy and damaged mode shapes, with values ranging from 0 (poor correlation) to 1 (full correlation) [42]:

$$\mathrm{MAC}(A, B) = \frac{|\{\Psi_A\}_n^T \{\Psi_B\}_m^T|^2}{(\{\Psi_A\}_n^T \{\Psi_A\}_n)(\{\Psi_B\}_m^T \{\Psi_B\}_m)} \tag{10}$$

$$\mathrm{MAC}(A, B) = \frac{|\sum_{i=1}^{N} (\Psi_A)_j (\Psi_B)_j|^2}{(\sum_{i=1}^{N} (\Psi_A)_j (\Psi_A)_j)(\sum_{i=1}^{N} (\Psi_B)_j (\Psi_B)_j)} \tag{11}$$

Additional indices include the auto modal assurance criterion (AutoMAC) and coordinate modal assurance criterion (COMAC). AutoMAC compares the mode shape displacement results with each other, resolving issues related to aliasing and insufficient data points. The diagonal values of the AutoMAC matrix are identically unity, indicating a perfect correlation with itself. COMAC focuses on preserving the characteristics of individual elements and provides information about the location of the damage. It calculates the COMAC parameter for each individual node, considering the mode shapes' values at that position. The COMAC parameter for an individual node, i, is

$$OMAC(X_i) = \frac{\sum_{j=1}^{N} |(\Psi \mathrm{X}_i)_j (\Psi A_i)_j|^2}{(\sum_{j=1}^{N} (\Psi X_i)_j (\Psi X_i)_j)(\sum_{i=1}^{N} (\Psi A_i)_j (\Psi A_i)_j)} \tag{12}$$

here, $(\Psi \mathrm{X})_j$ and $(\Psi A)_j$ represent the values of the jth mode shape vector at position i for the mode pairs being compared.

The frequency-scaled MAC (FMAC) provides a comprehensive interpretation of the correlation between mode shapes. It plots a comparison diagram of natural frequency values and MAC values, allowing for a clear judgment of the correlation level [45].

Furthermore, changes in the mode shape curvature can be utilized to detect the occurrence and changes in the curvature mode shapes are typically localized in the damaged region, allowing for the detection and localization of damage by analyzing the differences between damaged and undamaged blades. The curvature mode shape is directly influenced by the flexural stiffness of the blade element. When damage occurs at any position along the blade span, it causes a reduction in the blade's stiffness within the damaged region. Consequently, the magnitude of the curvature increases at that specific section. The extent of the change in curvature magnitude correlates with the degree of stiffness reduction in the blade. By assessing the decrease in blade stiffness, it becomes possible to estimate the percentage of damage. In a study exploring the presence of discontinuities in the curvature mode shapes of damaged beams, a damage index was proposed [58,66]. This index was developed based on evaluating the Laplacian operator at the element nodes, which helps to identify irregularities or lack of smoothness in the mode shapes.

For example, the Laplacian operator at the element nodes may be written as:

$$\mathcal{L}^{(i)}(x_j) = \varphi^{(i)*}(x_{j+1}) - 2\varphi^{(i)*}(x_j) + \varphi^{(i)*}(x_{j-1}) \tag{13}$$

here, $\varphi^{(i)*}$ denotes the damaged mode shape and i is the mode number.

It was noted in [66] that in case of small damage, the Laplacian operator failed to highlight the damage location. It proposed a damage indicator, $\delta_j^{(i)}$, as a way for amplifying the sensitivity:

$$\delta_j^{(i)} = \mathcal{P}^{(i)}(x_j) - \mathcal{L}^{(i)}(x_j) \qquad j = 3, \ldots N - 1 \tag{14}$$

where $\mathcal{P}^{(i)}(x_j)$ is a third-order polynomial defined using the values of $\mathcal{L}^{(i)}$ over the points x_{j-2}, x_{j-1}, x_{j+1}, and x_{j+2}.

The method described in [29,55] adopted modal curvature as the basis for the detection of damage to the beam structure. The flexural rigidity of the beam cross section is EI, and if the beam is subjected to a bending moment $M(x)$, the curvature mode shape at distance x is

$$\mathcal{K}(x) = \frac{M(x)}{EI} \tag{15}$$

A reduction models the change in the structure stiffness due to damage in the modulus of elasticity of the beam section, where the degree of damage determines the extent of the reduction in the modulus of elasticity. The reduction of stiffness is associated with increasing curvature. The curvature at mode i can be calculated using central differences [45]:

$$\mathcal{K}(x) = \frac{\varphi_{(j+1)i} - 2\varphi_{ji} + \varphi_{(j-1)i}}{l^2} \tag{16}$$

where i is the mode shape number, j the node number, φ_{ji} is the mode shape displacement of node j at mode i, and l is the length of the element.

By extracting the mode shapes from the finite element model for both the intact structure and its damaged counterpart, it becomes possible to calculate the curvature at a specific location, denoted as "x." Equation (16) allows for the identification of damage and its location by determining the difference in curvature between the pre-damage and post-damage mode shapes.

The success of maintenance processes and rehabilitation procedures is closely tied to the accuracy of assessing the severity and location of damage. The curvature method presents itself as an effective tool for this purpose. However, it is important to note that this technique relies on a finite element model that must precisely match the real structure.

These damage indices provide valuable information for identifying and assessing the condition of wind turbine blades. By analyzing modal parameters, such as natural frequencies, mode shapes, and curvatures, the presence, location, and extent of damage can be detected, allowing for timely maintenance and improved reliability of wind turbine systems.

VI. CONCLUSION

Wind energy has emerged as a prominent renewable energy source, and wind turbine blades play a crucial role in converting mechanical energy into electrical energy. As the size of wind turbine blades increases, their reliability becomes increasingly important. This review has highlighted various approaches for detecting damage in wind turbine blades, including acoustic emission analysis, strain signal monitoring, and vibration analysis. Damage detection based on vibration analysis shows promise as it allows for the identification and classification of faults by analyzing changes in the dynamic characteristics of the blades.

Several damage indices have been reviewed, focusing on modal properties such as natural frequencies, mode shapes, MAC, COMAC, and mode shape curvature. Ensuring the structural integrity of blades requires a comprehensive understanding of their dynamic characteristics. By analyzing modal parameters, various damage identification methods can be employed. Establishing a numerical simulation model that represents a healthy, intact blade is essential, serving as a baseline for effective comparison with a damaged blade. This comprehensive model facilitates damage detection and enables prediction and risk reduction.

Continuous monitoring and analysis of wind turbine blades are essential for ensuring reliability, minimizing downtime, and optimizing maintenance efforts. Damage indices and modal analysis techniques enable early detection, identification, and quantification of damage, leading to effective blade health management and enhanced performance of wind energy systems. The emerging concept of digital twin holds promise for optimizing wind turbine operation and maintenance through data fusion, computational modeling, and decision-making modeling. Further research is needed to fully realize these approaches' potential in practical applications. The approach described may be developed in different ways with the following recommendations suggested as possible directions:

- Developing an accurate and computationally efficient structural dynamics model is crucial for creating wind turbine digital twins. These models enable real-time predictions and decisions using live data from the physical structure. By comparing real and virtual data, potential damage can be identified and prevented, minimizing downtime. The integration of physical and virtual systems into digital twins streamlines these tasks. However, there is a need for further development in analyzing real-time data using nontraditional methods.
- Calculating costs and addressing challenges in offshore wind farm manufacturing is complicated due to the absence of a globally agreed infrastructure. Practical concerns, such as training programs tailored to offshore projects, remain in the planning stages. Research into these aspects can provide valuable insights and aid in the development of more effective methods for assessing wind turbine performance.

CONFLICT OF INTEREST STATEMENT

Alhussein Albarbar is a guest editor for the special issue on Monitoring and Diagnostics of Renewable Energy System for the *Journal of Dynamics, Monitoring and Diagnostics*, and he was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflict of interest.

REFERENCES

[1] A. Tummala, R. K. Velamati, D. K. Sinha, V. Indraja, and V. H. Krishna, "A review on small scale wind turbines," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1351–1371, Apr. 2016.

[2] H. D. de Azevedo, A. M. Araújo, and N. Bouchonneau, "A review of wind turbine bearing condition monitoring: State of the art and challenges," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 368–379, Apr. 2016.

[3] X. Chen, R. Yan, and Y. Liu, "Wind turbine condition monitoring and fault diagnosis in China," *IEEE Instrum. Meas. Mag.*, vol. 19, pp. 22–28, May 2016.

[4] C. Dao, B. Kazemtabrizi, and C. Crabtree, "Wind turbine reliability data review and impacts on levelised cost of energy," *Wind Energy*, vol. 22, pp. 1848–1871, Dec. 2019.

[5] T. Burton, N. Jenkins, D. Sharpe, and E. Bossanyi, *Wind Energy Handbook* New Delhi, India: John Wiley & Sons, 2011.

[6] J. Moccia, J. Wilkes, I. Pineda, and G. Corbetta, "Wind energy scenarios for 2020," in *Eur. Wind Energy Assoc. Rep., EWEA*, 3 p, July 2014. https://www.ewea.org/fileadmin/files/library/publications/scenarios/EWEA-Wind-energy-scenarios-2020.pdf.

[7] World Energy Council, World Energy Resources, 2013. https://www.worldenergy.org/assets/images/imported/2013/10/WEC_Resources_summary-final_180314_TT.pdf

[8] J. F. Manwell, J. G. McGowan, and A. L. Rogers, *Wind Energy Explained: Theory, Design and Application*, Chichester, UK: John Wiley & Sons, 2010.

[9] Office of Energy Efficiency and Renewable Energy, *Advantages and Challenges of Wind Energy*. https://www.energy.gov/eere/wind/advantages-and-challenges-wind-energy

[10] D. Gielen et al., "Global energy transformation: a roadmap to 2050," *[online]*.

[11] World Wind Energy Association, "Worldwide wind capacity reaches 744 Gigawatts–an unprecedented 93 Gigawatts added in 2020," *Press Release, Statistics*, 2021.

[12] H. Crespo, W. Ostachowicz, M. McGugan, J.-U. Schröder-Hinrichs, and M. Luczak, "Damage sensing in blades," in *MARE-WINT: New Materials and Reliability in Offshore Wind Turbine Technology*, W. Ostachowicz, M. McGugan, J. Schröder-Hinrichs, and M. Luczak, Eds. Springer Nature, 2016, pp. 25–52.

[13] D. Li, S. C. M. Ho, G. Song, L. Ren, and H. Li, "A review of damage detection methods for wind turbine blades," *Smart Mater. Struct.*, vol. 24, p. 033001, Feb. 2015.

[14] S. Sun, T. Wang, and F. Chu, "In-situ condition monitoring of wind turbine blades: a critical and systematic review of techniques, challenges, and futures," *Renew. Sustain. Energy Rev.*, vol. 160, p. 112326, 2022.

[15] J.-S. Chou, C.-K. Chiu, I.-K. Huang, and K.-L. Chi, "Failure analysis of wind turbine blade under critical wind loads," *Eng. Failure Anal.*, vol. 27, pp. 99–118, Jan. 2013.

[16] S. Cacciola, C. E. Riboldi, and A. Croce, "Monitoring rotor aerodynamic and mass imbalances through a self-balancing

control," *J. Phys.: Conf. Ser.*, vol. 1037, no. 3, p. 032041, 2018.

[17] T. Ackermann and L. Söder, "Wind energy technology and current status: a review," *Renew. Sustain. Energy Rev.*, vol. 4, pp. 315–374, Dec. 2000.

[18] W. Qiao and D. Lu, "A survey on wind turbine condition monitoring and fault diagnosis—Part I: components and subsystems," *IEEE Trans. Ind. Electron.*, vol. 62, pp. 6536–6545, Apr. 2015.

[19] W. Wang, Y. Xue, C. He, and Y. Zhao, "Review of the typical damage and damage-detection methods of large wind turbine blades," *Energies*, vol. 15, p. 5672, Aug. 2022.

[20] N. Beganovic and D. Söffker, "Structural health management utilisation 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.*, vol. 64, pp. 68–83, Oct. 2016.

[21] A. C. Garolera, S. F. Madsen, M. Nissim, J. D. Myers, and J. Holboell, "Lightning damage to wind turbine blades from wind farms in the US," *IEEE Trans. Power Deliv.*, vol. 31, pp. 1043–1049, Nov. 2014.

[22] A. Algolfat, A. Albarbar, and W. Wang, "Dynamic modelling of wind turbine structure for health monitoring," in *Int. Virtual Conf. Ind.*, Singapore: Springer Nature Singapore, 2021.

[23] C. Crabtree, D. Zappalá, and P. Tavner, "Survey of commercially available condition monitoring systems for wind turbines," UK EPSRC SUPERGEN Wind Energy Technologies programme, 2013.

[24] J.-S. Hwang, D. J. Platenkamp, and R. P. Beukema, "A literature survey on remote inspection of offshore wind turbine blades: automated inspection and repair of turbine blades (AIRTuB)-WP1," 2017. https://reports.nlr.nl/items/ed256eb0-d76f-4fce-8e15-001cc20c3f78.

[25] Y. Du, S. Zhou, X. Jing, Y. Peng, H. Wu, and N. Kwok, "Damage detection techniques for wind turbine blades: a review," *Mech. Syst. Signal Process.*, vol. 141, p. 106445, July 2020.

[26] M. Ramakrishnan, G. Rajan, Y. Semenova, and G. Farrell, "Overview of fiber optic sensor technologies for strain/temperature sensing applications in composite materials," *Sensors*, vol. 16, p. 99, Jan. 2016.

[27] S. Gholizadeh, "A review of non-destructive testing methods of composite materials," *Proc. Struct. Integr.*, vol. 1, pp. 50–57, Jan. 2016.

[28] F. X. Ochieng, C. M. Hancock, G. W. Roberts, and J. Le Kernec, "A review of ground-based radar as a noncontact sensor for structural health monitoring of in-field wind turbines blades," *Wind Energy*, vol. 21, pp. 1435–1449, Dec. 2018.

[29] W. Yang, P. J. Tavner, C. J. Crabtree, Y. Feng, and Y. Qiu, "Wind turbine condition monitoring: technical and commercial challenges," *Wind Energy*, vol. 17, pp. 673–693, May 2014.

[30] C. U. Grosse, M. Ohtsu, D. G. Aggelis, and T. Shiotani, Eds., *Acoustic Emission Testing: Basics for Research–Applications in Engineering*, Switzerland: Springer Nature, 2021.

[31] J.-T. Kim and N. Stubbs, "Improved damage identification method based on modal information," *J. Sound Vib.*, vol. 252, pp. 223–238, Apr. 2002.

[32] J. White, D. Adams, M. Rumsey, and J. Paquette, "Estimation of wind turbine blade operational loading and deflection with inertial measurements," in *47th AIAA Aerosp. Sci. Meeting Incl. New Horizons Forum Aerosp. Exp.*, IAAA, p. 1407, 2009.

[33] T. Krause and J. Ostermann, "Damage detection for wind turbine rotor blades using airborne sound," *Struct. Control Health Monit.*, vol. 27, p. e2520, May 2020.

[34] T. Krause, S. T. Preihs, and J. Ostermann, "Acoustic emission damage detection for wind turbine rotor blades using airborne sound," *Struct. Health Monit.*, pp. 340–347, Sept. 2015.

[35] T. Krause, S. Preihs, and J. Ostermann, "Detection of impulse-like airborne sound for damage identification in rotor blades of wind turbines," in *EWSHM-7th Eur. Workshop Struct. Health Monit.*, 2014.

[36] W. Li, S. Zhang, and S. Rakheja, "Feature denoising and nearest–farthest distance preserving projection for machine fault diagnosis," *IEEE Trans. Ind. Inf.*, vol. 20, no. 2, p. 393–404, Aug. 2015.

[37] D. Xu, C. Wen, and J. Liu, "Wind turbine blade surface inspection based on deep learning and UAV-taken images," *J. Renew. Sustain. Energy*, vol. 11, 2019.

[38] S. Moreno, M. Peña, A. Toledo, R. Treviño, and H. Ponce, "A new vision-based method using deep learning for damage inspection in wind turbine blades," in *2018 15th Int. Conf. Electr. Eng., Comput. Sci. Automat. Control (CCE)*, 2018, pp. 1–5.

[39] R. Wu, D. Zhang, Q. Yu, Y. Jiang, and D. Arola, "Health monitoring of wind turbine blades in operation using three-dimensional digital image correlation," *Mech. Syst. Signal Process.*, vol. 130, pp. 470–483, 2019.

[40] G. R. Gillich, H. Furdui, M. A. Wahab, and Z. I. Korka, "A robust damage detection method based on multi-modal analysis in variable temperature conditions," *Mech. Syst. Signal Process.*, vol. 115, pp. 361–379, Jan. 2019.

[41] A. Algolfat, W. Wang, and A. Albarbar, "Comparison of beam theories for characterisation of a NREL wind turbine blade flap-wise vibration," *Proc. Inst. Mech. Eng., Part A: J. Power Energy*, vol. 236, pp. 1350–1369, Nov. 2022.

[42] A. Algolfat, W. Wang, and A. Albarbar, "Dynamic responses analysis of a 5MW NREL wind turbine blade under flap-wise and edge-wise vibrations," *J. Dyn. Monit. Diagnost.*, pp. 208–222, Sept. 2022.

[43] Y. Yang, Y. Zhang, and X. Tan, "Review on vibration-based structural health monitoring techniques and technical codes," *Symmetry*, vol. 13, no. 11, p. 1998, Oct. 2021.

[44] A. Algolfat, W. Wang, and A. Albarbar, "Study of centrifugal stiffening on the free vibrations and dynamic response of offshore wind turbine blades," *Energies*, vol. 15, p. 6120, Aug. 2022.

[45] A. Algolfat, W. Wang, and A. Albarbar, "The sensitivity of 5MW wind turbine blade sections to the existence of damage," *Energies*, vol. 16, p. 1367, Jan. 2023.

[46] D. J. Wagg, K. Worden, R. J. Barthorpe, and P. Gardner, "Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications," *ASME J. Risk Uncert Eng. Syst. Part B.*, vol. 6, no. 3, p. 030901, Sep. 2020.

[47] S. Mittal, M. A. Khan, D. Romero, and T. Wuest, "Smart manufacturing: characteristics, technologies and enabling factors," *Proc. Inst. Mech. Eng., Part B: J. Eng. Manuf.*, vol. 233, pp. 1342–1361, Apr. 2019.

[48] A. M. Madni*, "Expanding stakeholder participation in upfront system engineering through storytelling in virtual worlds," *Syst. Eng.*, vol. 18, pp. 16–27, Jan. 2015.

[49] J. Hochhalter, W. P. Leser, J. A. Newman, E. H. Glaessgen, S. R. Cornell, S. A. Willard, and G. Heber, "Coupling damage-sensing particles to the digitial twin concept, 2014," 2014.

[50] M. Grieves, "Digital twin: manufacturing excellence through virtual factory replication," White paper, 1, pp. 1–7, 2014.
[51] T. Fei, C. Jiangfeng, Q. Qinglin, M. Zhang, H. Zhang, and S. Fangyuan, "Digital twin-driven product design, manufacturing and service with big data," *Int. J. Adv. Manuf. Technol.*, vol. 94, pp. 3563–3576, Feb. 2018.
[52] D. T. Griffith and T. D. Ashwill, "The Sandia 100-meter all-glass baseline wind turbine blade: SNL100-00," *Infor. Técnico, Sandia Nat. Lab.*, 2011.
[53] D. Goyal and B. S. Pabla, "The vibration monitoring methods and signal processing techniques for structural health monitoring: a review," *Arch. Comput. Methods Eng.*, vol. 23, pp. 585–594, Dec. 2016.
[54] J. P. Amezquita-Sanchez and H. Adeli, "Signal processing techniques for vibration-based health monitoring of smart structures," *Arch. Comput. Methods Eng.*, vol. 23, pp. 1–5, Mar. 2016.
[55] T. D. Popescu and D. Aiordachioaie, "Fault detection of rolling element bearings using optimal segmentation of vibrating signals," *Mech. Syst. Signal Process.*, vol. 116, pp. 370–391, Feb. 2019.
[56] H. Wang and X. Jing, "Vibration signal–based fault diagnosis in complex structures: a beam-like structure approach," *Struct. Health Monit.*, vol. 17, p. 472–493, May 2018.
[57] Y. Wang, M. Liang, and J. Xiang, "Damage detection method for wind turbine blades based on dynamics analysis and mode shape difference curvature information," *Mech. Syst. Signal Process.*, vol. 48, p. 351–367, Oct. 2014.
[58] V. B. Dawari and G. R. Vesmawala, "Structural damage identification using modal curvature differences," *IOSR J. Mech. Civil Eng.*, vol. 4, pp. 33–38, 2013.
[59] U. Galvanetto and G. Violaris, "Numerical investigation of a new damage detection method based on proper orthogonal decomposition," *Mech. Syst. Signal Process.*, vol. 21, pp. 1346–1361, Apr. 2007.
[60] P. Cornwell, S. W. Doebling, and C. R. Farrar, "Application of the strain energy damage detection method to plate-like structures," *J. Sound Vib.*, vol. 224, pp. 359–374, July 1999.
[61] S.-E. Fang and R. Perera, "Power mode shapes for early damage detection in linear structures," *J. Sound Vib.*, vol. 324, pp. 40–56, July 2009.
[62] M. M. Rezaei, M. Behzad, H. Moradi, and H. Haddadpour, "Modal-based damage identification for the nonlinear model of modern wind turbine blade," *Renew. Energy*, vol. 94, pp. 391–409, Aug. 2016.
[63] J. Dai, W. Hu, and X. Shen, "Load and dynamic characteristic analysis of wind turbine flexible blades," *J. Mech. Sci. Technol.*, vol. 31, pp. 1569–1580, Apr. 2017.
[64] Z. Li, B. Wen, X. Dong, Z. Peng, Y. Qu, and W. Zhang, "Aerodynamic and aeroelastic characteristics of flexible wind turbine blades under periodic unsteady inflows," *J. Wind Eng. Ind. Aerodyn.*, vol. 197, p. 104057, Feb. 2020.
[65] D. J. Ewins, *Modal Testing: Theory, Practice and Application*, Philadelphia, USA: John Wiley & Sons, 2009.
[66] C. P. Ratcliffe, "Damage detection using a modified Laplacian operator on mode shape data," *J. Sound Vib.*, vol. 204, pp. 505–517, July 1997.
[67] C. Snider, A. Nassehi, J. Yon, B. Hicks, and D. Jones, "Characterising the digital twin: a systematic literature review," *CIRP J Manuf. Sci. Technol.*, vol. 29, pp. 36–52, 2020.
[68] G. von Wichert, G. Lo, K. D. Bettenhausen, and R. Rosen, "About the importance of autonomy and digital twins for the future of manufacturing," *IFAC-papersonline*, vol. 48, no. 3, pp. 567–572, 2015.
[69] S. Yao, D. T. Griffith, and M. Chetan, "Multi-fidelity digital twin structural model for a sub-scale downwind wind turbine rotor blade," *Wind Energy*, vol. 12, pp. 1368–1387, 2021.
[70] C. Wang, A. Hnydiuk.-Stephan, S. Feng, I. Atilla, Z. Li, and M. Wang, "Recent progress on reliability analysis of offshore wind turbine support structures considering digital twin solutions," *Ocean Eng.*, vol. 232, p. 109168, 2021.
[71] J. Jorgensen, M. Hodkiewicz, E. Cripps, and G. M. Hassan, "Requirements for the application of the digital twin paradigm to offshore wind turbine structures for uncertain fatigue analysis," *Comput. Ind.*, vol. 145, p. 103806, 2023.