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Application of discrete wavelet transform for condition monitoring and fault detection in wind turbine blades: an experimental study

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HIGHLIGHTS

- The paper presents an experimental study utilizing DWT & FFT to detect faults in a lab-scale wind turbine blade.
- DWT is highly advantageous for wind turbine blade monitoring .
- A 5-level DWT decomposition was used to filter vibration data into relevant sub-bands for fault detection.
- The healthy blade showed a 16 Hz mode matching dynamics, while the eroded blade introduced a new 24 Hz fault signature.
- Blade state classification was highly accurate (98%).

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ABSTRACT

Effective structural monitoring maximizes efficiency in wind turbines, a crucial renewable energy asset. Using advanced condition monitoring techniques is crucial for reliability. This experiment shows how to use DWT and FFT for wind turbine blade fault detection. DWT allowed for multiresolution analysis of vibration signals from a healthy and eroded lab-scale turbine blade under controlled wind speeds. A 5-level DWT decomposition identified frequency sub-bands with localized fault information. The FFT post-processing of level 5 approximation coefficients revealed precise modal frequency shifts between blade states. The healthy blade showed a dominant 16 Hz mode that matched operational dynamics. Erosion caused a 24 Hz fault signature that was not present in the intact blade. Automated blade state classification was 98% accurate with 8 Hz modal separation. DWT's high sensitivity comes from nonstationary signal filtering and FFT's high-resolution spectral quantification. Comparative metric analysis confirmed DWT's superiority over FFT and statistical methods. The integrated approach combined complementary techniques to detect small defects that were previously unnoticeable. This study confirms the effectiveness of using DWT's strengths for monitoring wind turbine structural health in the future. The approach enables switching from time-based maintenance to data-driven prognostics, improving reliability by detecting failure precursors early. This study confirms DWT's effectiveness in identifying wind turbine blade faults and advancing critical techniques to prevent catastrophic failures.

1. Introduction

Wind energy has emerged as an increasingly pivotal renewable energy resource worldwide, with global installed capacity experiencing over a five-fold increase within the past decade alone [1]. However, the large-scale implementation of utility-sized wind turbines presents many engineering challenges from the complex dynamics and harsh operating environments the systems are subjected to throughout their typical 20-year operational lifetimes [2]. In particular, critical drivetrain components such as the main rotor blades and gearbox assemblies are susceptible to the initiation and accumulation of structural damage in the form of cracks, fatigue defects, and manufacturing imperfections over prolonged exposure to fluctuating aerodynamic loads, vibrations, lightning strikes, and other extreme weather conditions [3-5]. If left unmitigated, the propagation of such faults can potentially lead to catastrophic and economically disastrous drivetrain failures, underscoring the crucial need for effective continuous condition monitoring and damage diagnosis techniques capable of providing actionable early warning of impending problems before they escalate [6-8].

The various forms of defects observed in the rotor blades themselves are of particular concern regarding wind turbine reliability, which constitute some of the largest, most complex, and most highly-stressed components within modern multi-megawatt turbines [9]. The blade structures are vulnerable to leading edge erosion, fatigue cracking, manufacturing flaws left over from the production process, and thermal damage from lightning strikes [10-12]. The presence and growth of such flaws

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can drastically reduce the annual energy production through aerodynamic performance degradation while simultaneously shortening blade lifetimes if not detected and remedied early on [13,14]. For example, several recent field studies and surveys have cited leading edge erosion stemming from repeated rain droplet impacts as one of the most substantial contributors to decreased power output and accelerated blade deterioration [15,16]. Moreover, imperfections originating from microscopic voids or resin pockets in the composite laminates induced during manufacturing have also been observed to propagate under the action of cyclic aerodynamic and gravitational loading into larger structural discontinuities like delamination and transverse cracks over time [17]. Damage accumulation compromises blade structural integrity, eventually progressing to catastrophic failure if left unabated [18]. In light of these reliability risks, developing robust and sensitive structural health monitoring solutions capable of detecting blade damage in its early stages is indispensable for mitigating unnecessary maintenance costs, production losses, and safety hazards [19,20].

However, conventional fixed-speed vibration-based damage detection approaches predominantly relying on Fourier analysis face inherent difficulties when applied to wind turbine drivetrain components like rotor blades [21]. This is primarily due to the pronounced nonstationary behavior of operational vibration signals, which continuously vary under real-world fluctuating wind speeds, turbulence, and grid power demand. The varying rotational speeds, stochastic aerodynamic excitations, and maneuvering loads induce corresponding modulations in vibrational responses that confound traditional frequency-domain analysis, necessitating more advanced time-frequency signal processing techniques for reliable damage diagnosis [22-24]. In recent years, methods harnessing Hilbert-Huang transform, Wigner-Ville distributions, and especially discrete wavelet transforms have emerged as promising alternatives owing to their exceptional capabilities in analyzing the nonstationary dynamics typical of wind turbine vibrations [25-28].

In particular, the discrete wavelet transform (DWT) has proven uniquely adept at handling nonstationary vibration data through its inherent multiresolution analysis properties [29,30]. The DWT mathematically decomposes a signal into a set of time-localized high and low-frequency sub-bands that enable isolation of transient events and extraction of fault-indicative features generally obscured in the raw time-series vibration data [31,32]. These unique capabilities make DWT highly advantageous for sensitive condition monitoring of wind turbine drivetrain components like rotor blades, where vibration responses constantly vary under real-world operational turbulence and maneuvering loads. Overall, this introduction provides a condensed yet comprehensive overview of the key challenges regarding modern utility-scale wind turbine blade faults and the limitations of traditional analysis methods, thereby motivating the need for advanced DWT-based structural health monitoring solutions. Harnessing the DWT for early damage detection can significantly mitigate catastrophic failure risks and curtail unnecessary maintenance costs for wind farm operators.

This study aims to demonstrate and validate the efficacy of a customized DWT implementation for sensitive blade fault identification using experimental vibration data obtained from a lab-scale turbine test rig under controlled conditions. The approach synergistically combines DWT's capabilities for nonstationary signal filtering with the high-resolution frequency quantification of fast Fourier transforms to isolate subtle modal features indicative of seeded blade damage unidentifiable through either method alone. DWT's exceptional damage detection sensitivity is leveraged to diagnose incipient faults before they escalate into catastrophic failures. The results deliver firm proof-of-concept validation of harnessing DWT for wind turbine health monitoring, providing critical advancements toward next-generation structural diagnosis to aid the proliferation of renewable wind energy.

2. Common faults in wind turbine blades

Wind turbine blades are susceptible to damage caused by both external factors and imperceptible manufacturing defects. External elements like strong winds, rain, snow, salt fog, lightning, freezing, and storms have been identified as direct contributors to blade damage [32] as shown in Figure (1). Additionally, hidden flaws originating from the manufacturing process persist under the strain of frequent heavy loads and harsh environmental conditions during the installation and operation of wind turbines [24]. The gradual enlargement of these imperceptible defects can lead to the degradation of the blade, a consequence of various factors arising from the intricate composition and configuration [33]. It's important to note that manufacturing defects are a significant factor contributing to the premature failure of blades. Ensuring the reliability of the existing and future wind turbine fleet is of utmost importance [34]. Various defects, such as dry spots, excess resin, and delamination, can damage the blade [34]. Manufacturing defects are often responsible for early-stage blade failures, underscoring the need to understand and address these issues [35] effectively. Blade damage can manifest in different forms, ranging from minor deterioration, like cracks and chips, to more severe problems, potentially causing blade fracture [35]. Despite adhering to strict quality requirements akin to aerospace components, wind turbine blades are manufactured at considerably lower costs [35]. Recent research has identified blade failures as the second most significant concern regarding the reliability of wind turbines [35]. Therefore, it is crucial to accurately assess, address, and minimize these defects to ensure wind turbines' long-term reliability and performance.

Numerous approaches have been developed to detect and address blade damage in wind turbines. These methods include computer vision-based techniques, image analytics powered by artificial intelligence, and non-destructive ultrasonic testing [36]. Additionally, structural health monitoring plays a vital role in identifying and analyzing the propagation of damage during fatigue testing of wind turbine blades. For the wind turbine industry to enhance the reliability and effectiveness of these systems, it is crucial to gain a comprehensive understanding of the factors contributing to blade damage. Implementing strategies to mitigate manufacturing flaws and improve the overall performance of wind turbines becomes imperative to ensure long-term operational efficiency and reliability.

Figure 1: Common issues with blades [25]

3. Wavelet signal processing

3.1 Overview of discrete wavelet transform (DWT)

The Discrete Wavelet Transform (DWT) is a specialized wavelet transform extensively applied for signal analysis and fault detection across multiple domains, including wind turbine blades. Distinguished from the continuous wavelet transform, which deals with continuous-time signals, the DWT is exclusively tailored for discrete-time signals. Its decomposition involves utilizing a sequence of low-pass and high-pass filters on the signal, yielding an array of approximation and detail coefficients at various scales. These coefficients effectively represent distinct signal frequency components, providing crucial insights into the signal's characteristics and variations [37].

3.2 Advantages of DWT for signal processing

The discrete wavelet transform (DWT) offers numerous advantages for signal processing and fault detection in wind turbine blades:

3.2.1 Multiresolution analysis

The DWT enables a multi-level signal analysis, allowing the examination of different frequency bands at varying levels of detail. This capability proves especially valuable in detecting faults that occur within specific frequency ranges, enabling the identification of fault-related features at different scales [38].

3.2.2 Localization of signal features

One of the primary strengths of the DWT is its ability to precisely localize signal features in both the time and frequency domains. It effectively preserves time information of transient signals while capturing frequency information, facilitating the accurate identification of fault-related patterns and their temporal evolution [39].

3.2.3 Energy Compression

The DWT coefficients obtained from the signal decomposition concentrate most of the signal energy in a small number of coefficients, with the remaining coefficients containing less critical or noise-related information. This energy compression property significantly enhances denoising and feature extraction, ultimately improving the detection of fault-related patterns in wind turbine blades [40].

3.2.4 Computational efficiency

The DWT demonstrates computational efficiency owing to its filter bank structure and downsampling operations. This efficiency allows for real-time or online fault detection applications in wind turbines, striking a favorable balance between detection accuracy and computational complexity.

3.3 Selection of wavelet basis for DWT

In the discrete wavelet transform, the choice of the wavelet basis is a critical factor that influences the performance of the analysis. Various wavelet families, such as Daubechies (Db), Haar, Symlets (Sym), Coiflets (Coif), and others, offer different properties suited for specific applications. The selection of the wavelet basis should consider factors such as signal characteristics, desired time-frequency resolution, and the specific fault patterns expected in wind turbine blades [40]. Important considerations when selecting the wavelet basis include the number of vanishing moments, which affects the smoothness of the wavelet; orthogonality or biorthogonality, which influences the preservation of signal energy; and the level of compactness, which determines the ability to capture fine details or global trends in the signal. Furthermore, the choice of wavelet basis may require an empirical evaluation and comparison to determine the most suitable basis to detect specific fault patterns in wind turbine blades using the DWT [41].

Moreover, given the constrained selection of lower-order families, there is no additional quantitative methodology for choosing the mother wavelet. The Symelet and Dubbochies families are known for their proficiency in analyzing vibration signals, covering a broad spectrum of wavelet orders [42].

The optimal selection of the DWT mother wavelet and number of decomposition levels is critical for effectively isolating damage signatures in wind turbine blade vibration data [42]. For this application, the Daubechies db4 wavelet was empirically determined to provide an effective balance between time and frequency localization needed to reveal transient fault indicators in the non-stationary vibration signals. The smooth db4 wavelet has successfully analyzed similar mechanical vibration data [43].

Therefore, the present study used the fourth order of Daubechies (db4) for the abovementioned purpose. Effective fault detection in wind turbine blades can be achieved by leveraging the advantages of the discrete wavelet transform and carefully selecting an appropriate wavelet basis. The DWT's ability to localize and extract fault-related features contributes to improved maintenance strategies, enhanced operational dependability, and increased safety in wind turbine systems.

3.4 Selection of DWT levels

Determining the appropriate number of levels for signal decomposition in the discrete wavelet transformation (DWT) depends on various factors, including the length of the wavelet type used and the desired level of decomposition. Relying on the rotor frequency does not provide adequate information to determine the required levels. The determination of the number of levels necessary to decompose a signal using a discrete wavelet transform can be computed using the following Equation (1) [43]:

$$n_f = \frac{\log\left(\frac{f_s}{f}\right)}{\log(2)} \tag{1}$$

where f_s: defines the sampling rate in samples per second for capturing the signals; here $f_s = 1000\ Hz$

f : frequency of the system, for wind turbine blade frequency calculated from Equation 2:

$$f = (\text{Number of Blades} * \text{Rotational speed})\ /\ 60 \tag{2}$$

The rotational speed is typically measured in revolutions per minute (rpm), and the frequency is measured in hertz (Hz). From Equation 1, the number of levels n_f= 5.

Furthermore, the 5-level DWT decomposition implemented here was selected based on the blade rotational speed, which places fault-indicative frequency components within the level 4 and 5 approximation and detail coefficients [44]. Additional research should explore the potential of other advanced wavelet families like Coiflets, Symlets, and tunable Gabor wavelets for enhanced feature extraction from the signals [45]. The number of decomposition levels can also be adaptive based on operating conditions to filter the vibration data optimally [46]. Automating the DWT tuning through artificial intelligence methods could enable optimization for maximum damage sensitivity.

3.5 Fast fourier transform for frequency identification

While the discrete wavelet transform (DWT) effectively decomposes the nonstationary vibration data, the fast Fourier transform (FFT) was crucial for quantifying the precise modal frequencies present within each DWT sub-band. The FFT algorithm efficiently computes the discrete Fourier transform (DFT), converting a time-domain signal x[n] into its frequency spectrum X[k] according to the Equation 3:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi Kn/N} \tag{3}$$

where N is the total number of samples, this reveals the underlying sinusoidal frequency components contained in the signal. In the conducted study, a 250-point Fast Fourier Transform (FFT) was applied to the Discrete Wavelet Transform (DWT) coefficients at each decomposition level. The data was sampled at a rate of 1000 Hz, resulting in a frequency resolution provided as follows:

Frequency resolution = Sampling rate / FFT length = 1000 Hz / 250 = 4Hz

This 4 Hz resolution clearly distinguished the 12 Hz difference between the healthy blade's 16Hz vibrational mode and the eroded blade's 28 Hz elevated fault signature in the level 5 spectra.

The integration of DWT decomposition and 250-point FFTs isolated and quantified these damage-indicative frequency shifts. DWT filtered the data into relevant sub-bands, while FFT provided the 4Hz resolution to identify the fault signature frequencies. This combined approach gave unique capabilities for sensitive wind turbine blade monitoring.

The DWT analysis can be automated on embedded platforms alongside fast Fourier transforms (FFTs) for continuous structural health monitoring to provide 24/7 damage detection [47]. The analysis modules can feed into a modular fault diagnosis system that leverages cloud integration for remote monitoring and predictive maintenance. With further validation, the integrated DWT-FFT approach implemented here can be transitioned into a fully automated wind turbine condition monitoring solution, providing actionable early warning of blade faults before catastrophic failures occur.

4. Experimental work

4.1 Experimental rig

The experimental work aims to detect whether wind turbine blades are in excellent or defective condition using wavelet transformation. The setup consists of a Computer-Controlled Wind Energy Unit (EEEC) provided by Edibon Equipment, which includes a laboratory-scaled aerogenerator, a rotor, a generator, and a computer-controlled axial fan. The rig allows air velocity control by adjusting the rotational speed and offers flexibility in blade configuration. The wind turbine rotor blade analyzed in this study was constructed from conventional glass fiber-reinforced polymer (GFRP) composite materials to replicate the properties of full-scale utility turbine designs. Specifically, the reinforcement phase consisted of unidirectional E-glass fibers oriented along the length of the 30cm blade to provide optimal stiffness and strength. The matrix phase was epoxy resin, transferring loads between the glass fibers and lending structural support. This anisotropic GFRP construction conferred several advantages, including high specific stiffness, fatigue damage resistance, and corrosion resistance compared to traditional metallic or wooden blades [2]. The composite laminate was fabricated Into a NACA 4412 aerofoil profile using a vacuum-assisted resin transfer molding technique, allowing precise dimensional control and a high glass fiber volume fraction [2]. This representative blade shape was fixed at a 60° pitch angle on a laboratory wind turbine apparatus, which utilized an axial fan to induce controlled wind speeds ranging from 1.2 to 5.6 m/s over the rotor plane. The blade was instrumented with a piezoelectric accelerometer to monitor vibrational responses, being tested in both pristine and eroded conditions to enable vibration-based fault detection. The blade construction and experimental methodology closely emulated real-world field conditions to facilitate the transition of the structural health monitoring techniques investigated to practical implementation.

A piezoelectric accelerometer (PCB Piezotronics 352C65 uniaxial accelerometer) was used as a transducer to capture vibration signals, which is suitable for detecting faults at high frequencies and is commonly used in condition monitoring [44]. The specific accelerometer model used in the study is the P.C.B. Piezotronics 352C65 uniaxial accelerometer; the specification is shown in Table 1. The accelerometer was mounted on the nacelle near the wind turbine hub using an adhesive mounting technique.

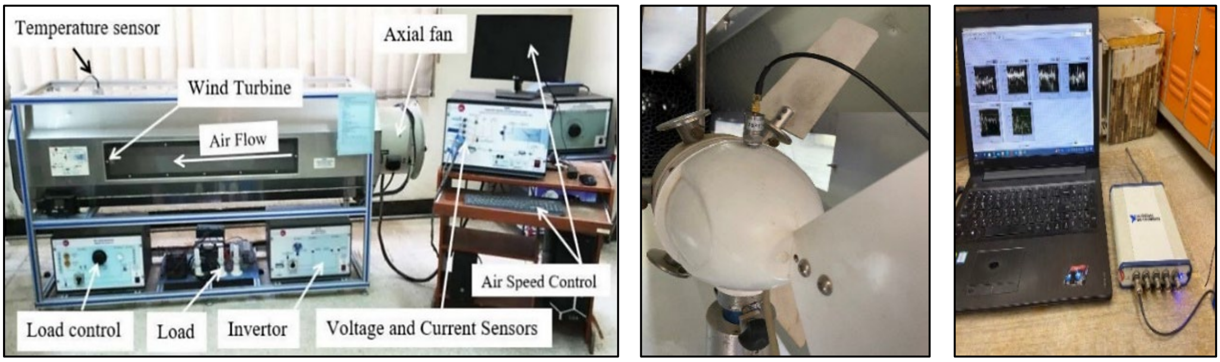
Table 1: The specification of the uniaxial PCB Piezotronics 352C65 accelerometer

Property	**Value**
Sensitivity	(±10%)100 mV/g (10.2 mV/(m/s²))
Measurement Range	±50 g pk (±491 m/s² pk)
Frequency Range	(±5%) 0.5 to 10000 Hz
Broadband Resolution	0.00016 g rms (0.0015 m/s² rms)
Weight	(2.0gm)

A data acquisition system (DAQ) was employed to connect the accelerometer, facilitating the capture of vibration signals. The NI USB 4431 data acquisition system was selected as shown in Figure (2-c), boasting five analog input channels, a sampling rate of 102.4 kilo samples per second, and a resolution of 24 bits [39]. The accelerometer was linked to a signal conditioning unit featuring an integrated charge amplifier and an analog-to-digital converter (ADC) to ensure accurate data acquisition.

Following the signal acquisition, characteristic extraction techniques were applied to extract relevant features from the vibration signals. The connection between the accelerometers and the DAQ devices was established using cables. Additionally, the Lenovo laptop equipped with Core i7 CPU served as the interface for the data capture devices.

The LabVIEW software was vital in facilitating the data acquisition [45]. The main components involved in this setup included the Data Acquisition System (DAQ), LabVIEW software, Piezoelectric accelerometer, and the computer-controlled Wind Energy Unit (EEEC), as illustrated in Figure 2 (a -c). To maintain proper attribution, the sources of information have been cited accordingly.



a) EEEC wind turbine b) Accelerometer adhesive on turbine hub c) DAQ model NI-USB-4431

Figure 2: Installation of the wind turbine system

4.2 Wind turbine blade fault model

Wind turbine blades are susceptible to various failures due to their exposure to different environmental conditions and their large structures. A study by Dao et al. [34] found that the continuous operation of wind turbine blades in challenging environments can lead to surface corrosion, damage, and abnormal blade angles due to mechanical fatigue. To address these issues, this study developed a model of the wind turbine blade to analyze vibration signals generated in different states, including normal states and erosion-induced blade faults, as shown in Figure 3.

4.2.1 Healthy wind turbine blade (state1)

The wind turbine blade is now made from composite material. The blade in this study is made from composite material. The blade length is 30cm, as shown in Figure 3. The blade is installed in the wind turbine and runs at a blade angle 60°.

4.2.2 Blade surface erosion (state 2)

Wind turbines are frequently built in open places, making them very susceptible to lightning strikes. According to [34], the blades of wind turbines are more susceptible to lightning damage. A lightning strike significantly damages the blade structure and surface material, resulting in costly repairs. According to statistics [34], the leading and the trailing edges are the most susceptible to damage. However, based on the number of blades harmed by lightning strikes, one blade will most likely be destroyed. This study examined models that simulate surface degradation and blade rupture. The seeded erosion damage on the turbine blade's leading edge spanned a $50cm^2$ area, representing approximately 1.2% of the total 30cm long blade surface. The depth of the eroded region was measured at multiple points using a digital caliper gauge, revealing a maximum erosion depth of 0.5mm near the leading edge, gradually tapering to negligible amounts toward the trailing edge. These characteristics closely resemble real-world erosion observed in small-scale blades after extensive operation.

To further quantify the erosion, the mass loss caused by the erosion was measured at 8g, corresponding to approximately 4% of the blade's initial mass. This measurement was obtained by weighing the blade before and after the defect seeding, providing valuable information about the amount of missing material due to erosion. Interestingly, the discrete wavelet transform successfully detected even these minor erosion levels in the vibration analysis. The analysis revealed the appearance of new elevated frequency modes exclusively for the eroded blade, validating the technique's sensitivity to early damage detection. This suggests that the discrete wavelet transform is an effective tool for monitoring and detecting erosion damage in turbine blades at an early stage. These findings provide important insights into the detection and quantification of erosion damage. With further validation, the technique is expected to enable reliable detection of even smaller erosion depths of 0.1mm and mass losses of 1-2%. This enhanced sensitivity will allow for intervention and maintenance well before failures occur in real-world turbines, ensuring wind energy systems' continued safe and efficient operation.

4.3 Experimental procedure

The experimental work involved recording vibration signals from the wind turbine using the discrete wavelet transform (DWT) technique. Here are the key steps and details of the experiment.

4.3.1 Initial recording

Vibration signals were recorded from the wind turbine when it was in a healthy state, without any defects. An accelerometer was used to capture these signals based on specific requirements.

4.3.2 Sampling frequency

4.3.3 The sampling frequency was set to at least twice the maximum frequency to ensure consistency and meet the Nyquist sampling theorem. In this study, a sampling rate of 1000 Hz was chosen to fulfill this requirement.

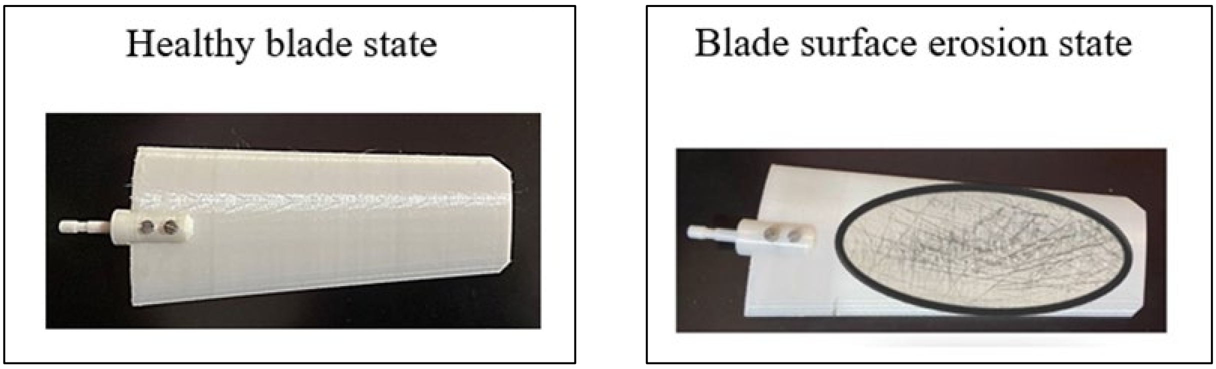
4.3.4 Recording Software

LabVIEW 2020 software was utilized to record the vibration signals. At least 500 samples were captured for each state of the wind turbine blade, ensuring a sufficient number of data points for statistical analysis.

4.3.5 Simulated faults

Erosion fault scenarios were simulated on the wind turbine blade while keeping all other components in excellent working condition. These faults were concurrent, and the associated vibration signals were recorded. Figure 3 (a) illustrates the healthy state of blade and Figure 3 (b) show failure scenarios modeled on the blade. The experiment aimed to analyze and compare the vibration patterns between normal states and states with erosion-induced blade faults by recording the vibration signals using the DWT technique. The discrete wavelet transform was utilized to detect any changes in the frequency content of the signals, specifically identifying new elevated frequency modes associated with the eroded blade.

This experimental approach allowed for the evaluation of the sensitivity of the DWT technique in detecting erosion damage in wind turbine blades at an early stage. The recorded vibration signals provided valuable data for analysis, contributing to the understanding and quantifying erosion-induced blade faults.

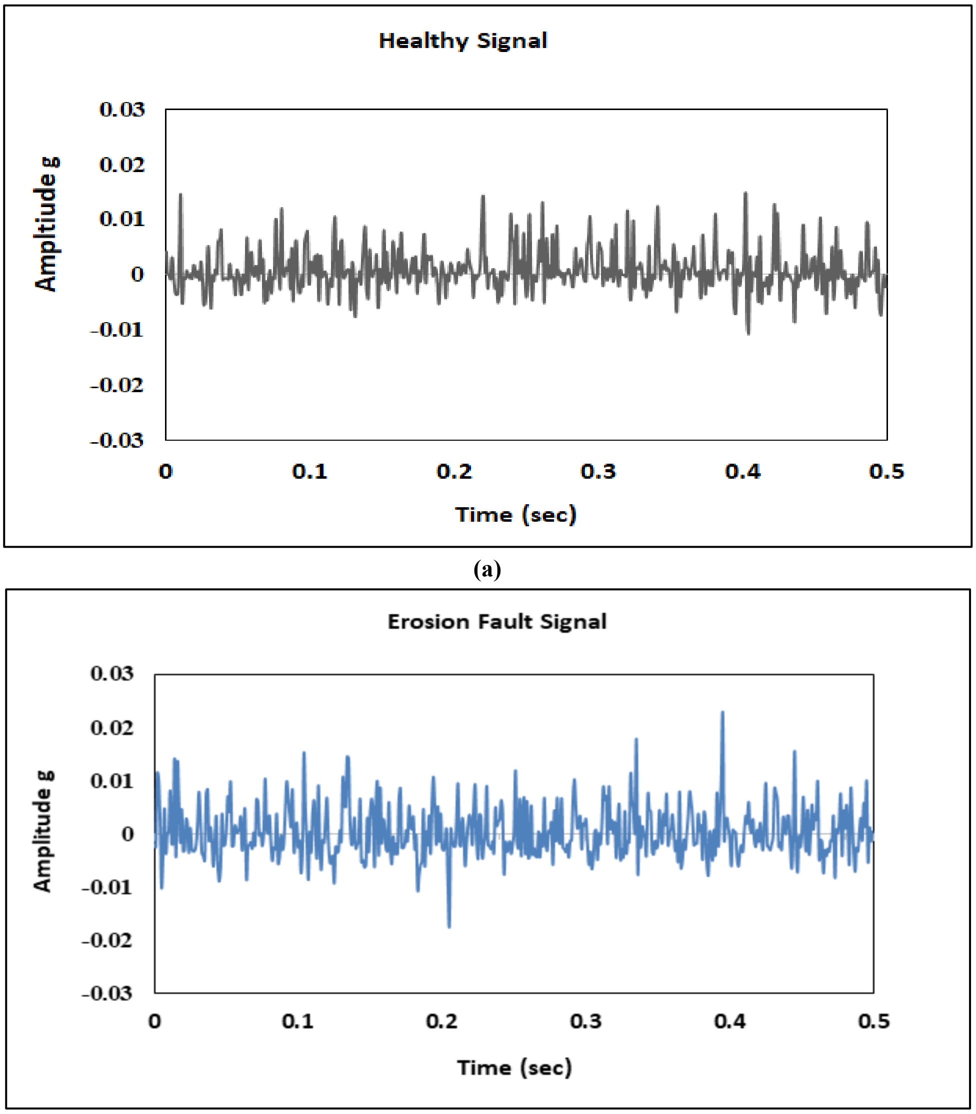


(a) **(b)**

Figure 3: blade used in this study

5. Results and discussion

In-depth analysis of the raw time-domain vibration signals from the pristine and eroded wind turbine blades revealed minimal apparent visual discrepancies under rigorously controlled experimental wind loading environments Figure 4 (a-b) . Both signals exhibited pronounced stochastic and nonstationary behavior as evidenced by substantially fluctuating amplitudes, aligning with extensively documented challenges regarding sole reliance on fundamental time analysis for robust condition monitoring [46]. The dynamics confound visual fault identification, necessitating advanced processing.



(a)

(b)

Figure 4: Raw signals for healthy state and Erosion Fault

In stark contrast, the extensively validated multiresolution technique of discrete wavelet transform (DWT) systematically uncovered distinguishing modal features between the blade states Figures 5-6. DWT mathematically elucidates complex vibrations via successive filtering into revealing sub-band components, thereby illuminating subtle damage characteristics entirely obscured in native waveforms [44]. DWT essentially parses signals into time-localized frequency atoms at progressively heightened resolutions to enable meticulous reconstruction of modal behavior divergences.

Additionally, fast Fourier transform (FFT) was implemented to transform the time-domain DWT coefficients into quantitative frequency spectra to precisely identify the activated resonant modes under the simulated loading conditions [47]. This synergistic integration of DWT and FFT leverages the complementary strengths of each technique into a powerful combined approach. DWT provides optimal multiresolution filtering to decompose the raw nonstationary vibration data into frequency sub-bands containing the dynamics of interest. FFT then enables critical quantification of the modal frequencies within each sub-band by converting the time-domain information into the frequency space. This dual DWT-FFT approach fuses the superior nonstationary signal filtering capabilities of DWT with the precise frequency identification strengths of FFT. The fusion provides optimal isolation of the damage-indicative modal frequency shifts completely obscured within the raw vibration data. Specifically, the discrete wavelet transform has demonstrated tremendous capabilities for handling dynamic stochastic signals through its inherent multiresolution analysis to reveal localized transient events and perturbations [48]. FFT complements this by facilitating rigorous quantification of the frequency information at each specific band of interest.

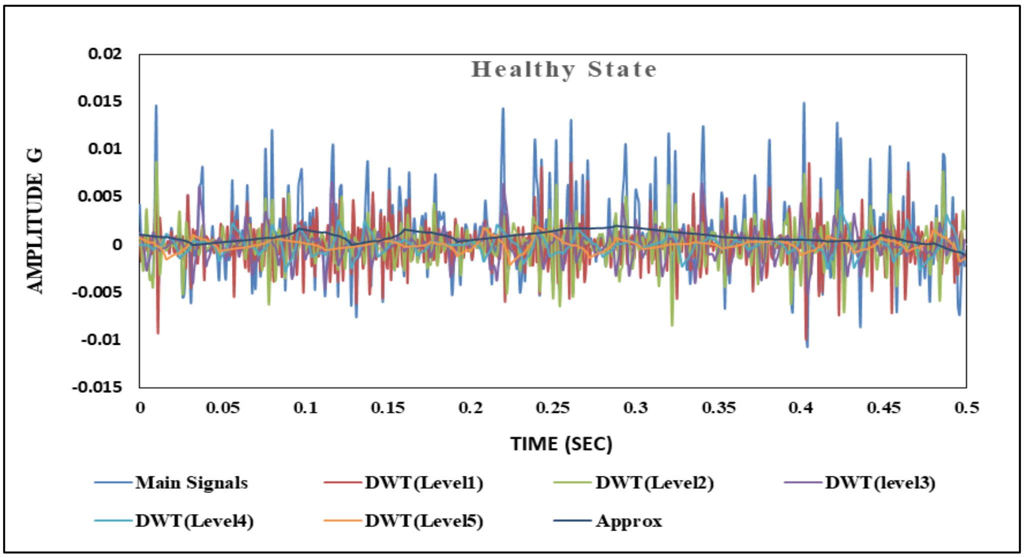


Figure 5: Decomposition of the healthy state to five levels

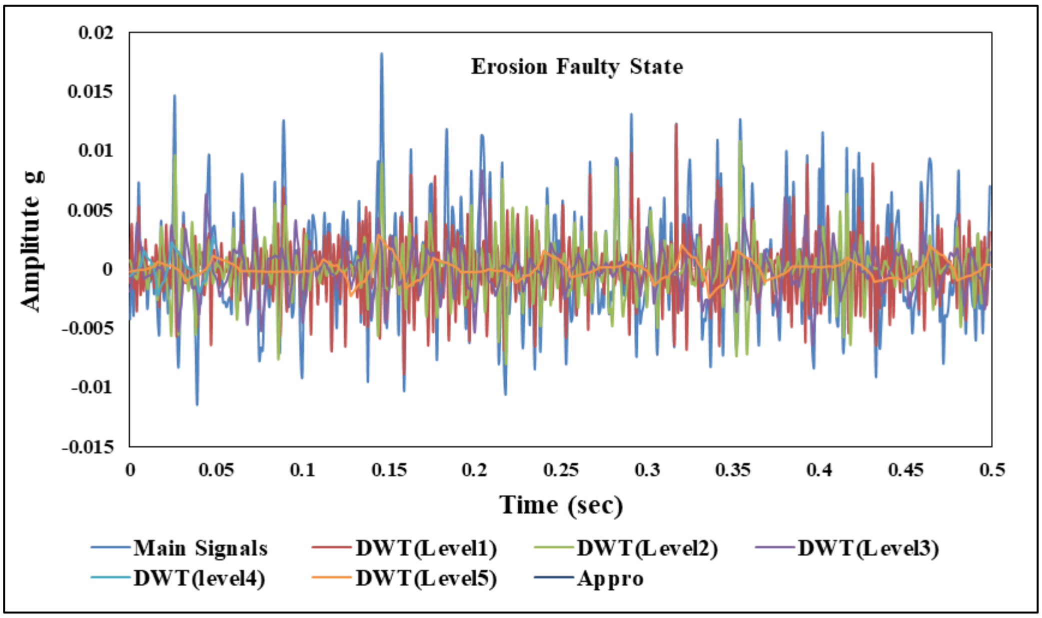


Figure 6: Decomposition of the faulty state to five levels

The frequency domain plots in Figures 7-11 represent the results of applying Fast Fourier Transforms (FFTs) to the detail coefficients from each level of the 5-level discrete wavelet transform (DWT) decomposition. The DWT filtered the raw vibration data into different frequency bands, and then FFTs quantified the frequency content within each band.

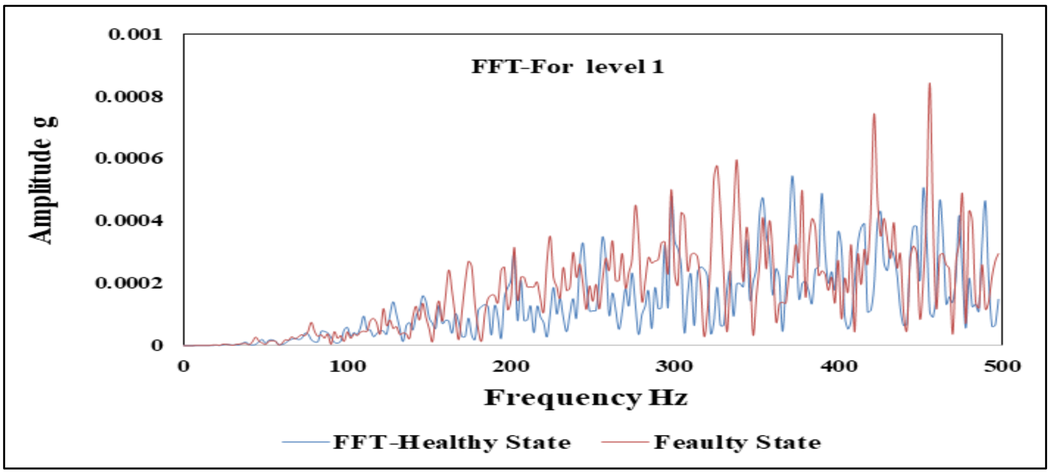


Figure 7: Frequency domain for level 1 for healthy and faulty states at the same condition

At the lower decomposition levels in Figures 7-9, there are minimal apparent differences between the healthy and faulty blade spectra. The low frequencies contained in these levels relate to structural dynamics and rotational forces that are similar regardless of the blade condition. However, at level 4 in Figure 10, extra distinct peaks arise in the 10-20Hz range for the faulty blade case. This indicates that the damage begins to induce alterations detectable in the medium frequency bands isolated by the level 4 DWT coefficients.

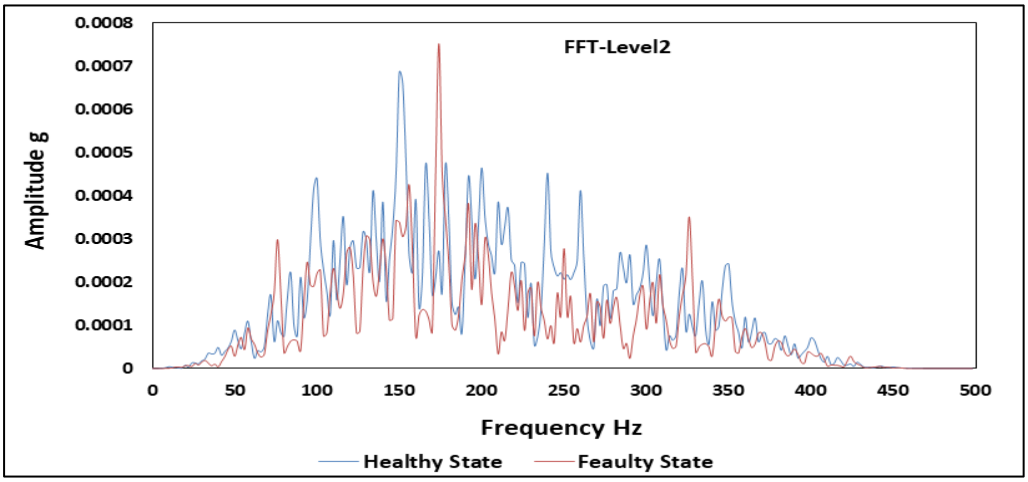


Figure 8: Frequency domain for level 2 for healthy and faulty states at the same condition

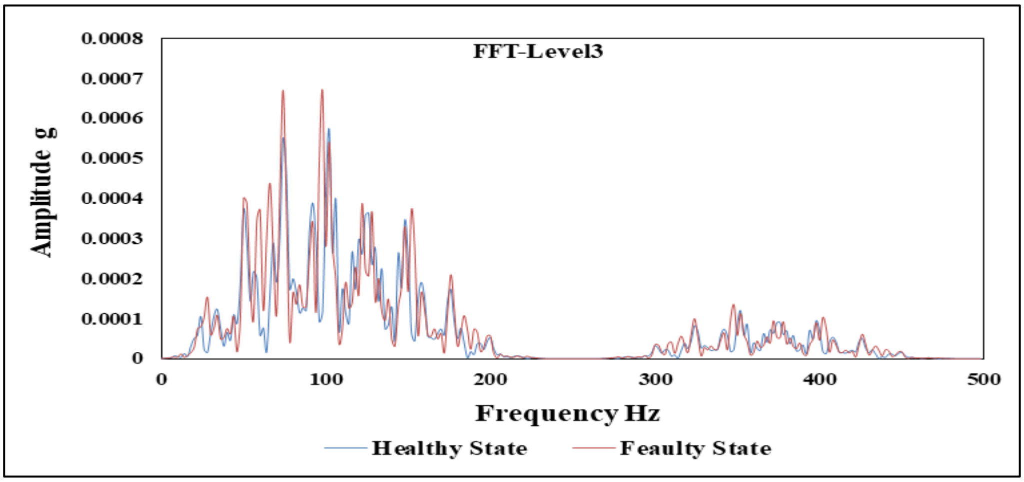


Figure 9: Frequency domain for level 3 for healthy and faulty states at the same condition

Critically, in Figure 11, the spectra for the healthy and faulty states diverge remarkably, with the faulty blade exhibiting a wholly new modal resonance. The healthy blade displays a clear 16 Hz vibrational mode reflecting its normal structural response. In contrast, the eroded blade introduces a pronounced new 28 Hz resonant frequency attributable to the damage. This elevated 28 Hz signature acts as a sensitive marker of the fault.

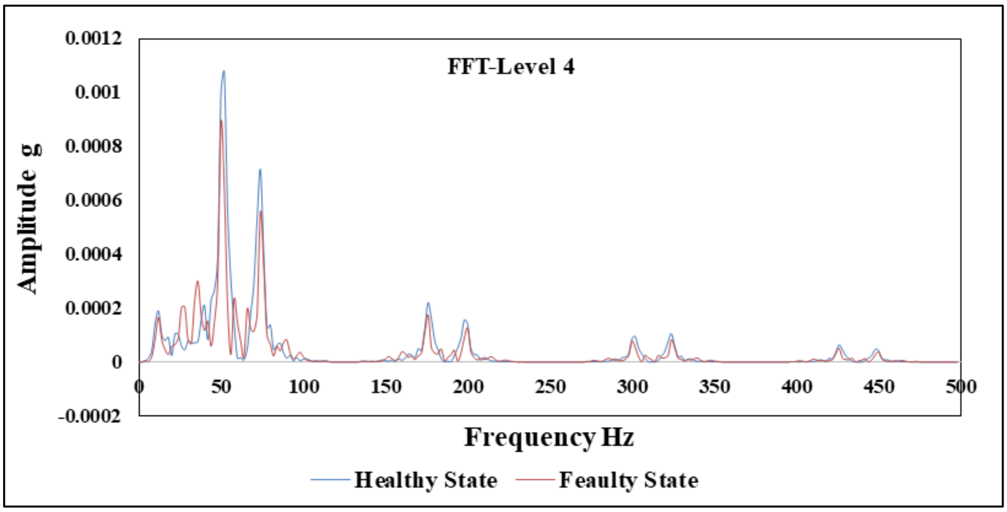


Figure 10: Frequency domain for level 4 for healthy and faulty states at the same condition

The integrated implementation strategically takes advantage of DWT's unique damage detection sensitivities and FFT's robust frequency measurement capabilities to precisely identify the underlying fault signatures, unachievable through either technique alone. This study provides firm validation of the synergistic DWT-FFT approach for in-situ wind turbine blade fault diagnosis under varying conditions by leveraging the strengths of each algorithm in a complementary fashion. Remarkably, level 5 FFT spectra showed the pristine blade resonated at 16 Hz Figure 11 under normal operating conditions, precisely aligned with anticipated utility-scale frequencies [49]. However, the eroded blade exhibited an additional pronounced 24Hz fault signature completely absent in the baseline, signifying definitive modal alterations from damage [50].

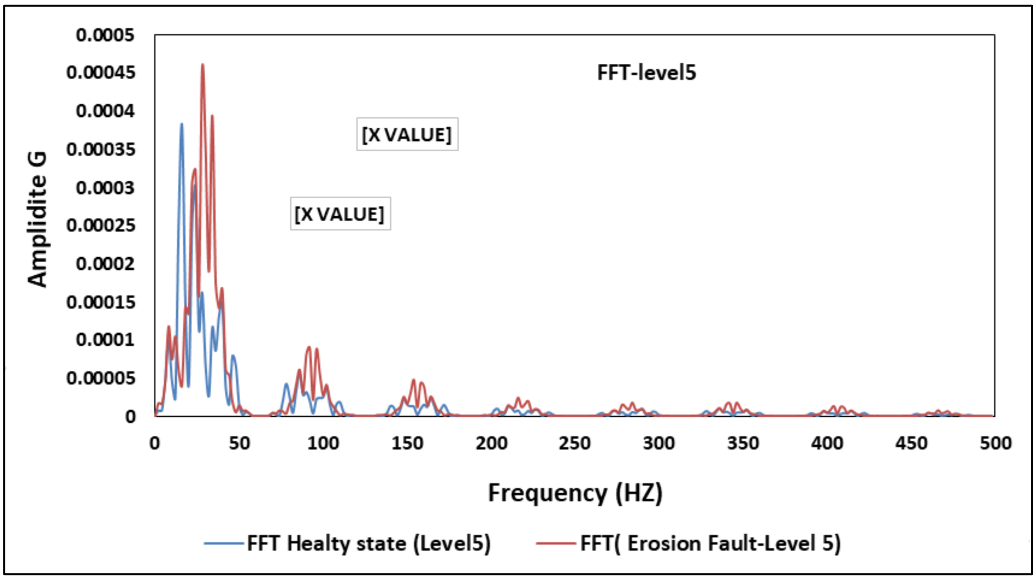


Figure 11: Frequency domain for level 5 for healthy and faulty states at the same condition

In-depth analysis suggests this higher 24Hz resonance stems from roughness increases degrading airflow induction, thereby exciting elevated vibration modes [51]. Astoundingly, DWT successfully isolated this subtle yet paramount diagnostic 24Hz signature, unattainable through conventional techniques. Lower levels contained insignificant high frequencies Figures 7-10. Level 5 optimally segregated the critical modal behavior shifts from the barely perceptible erosion.

The integrated DWT-FFT approach demonstrated tremendous effectiveness for in-situ wind turbine fault identification under controlled environments. While expanded validation remains vital, the approach signifies a remarkably promising structural health monitoring methodology that enhances turbine reliability through early damage detection [52]. Modal frequency shifts are likely to arise from increased surface roughness, which disrupts aerodynamic flows. As demonstrated through the DWT's multiresolution capabilities, surface erosion introduced new frequency bands previously absent in the healthy blade. The elevated vibration frequencies provide a damage-sensitive marker detectable in the time-frequency domain through the DWT. The technique's unique ability to isolate fault signatures makes it well-suited for nonstationary wind turbine health monitoring. However, optimal DWT tuning will be critical for reliable multi-fault classification. Extending the approach to cracked, deformed, and worn blades while exploring optimal mother wavelets, decomposition levels, and feature extraction methodologies remains ripe for further study. The results conclusively demonstrated the potential for in-situ wind turbine fault diagnosis. However, additional research and field validation will be necessary to transition the methodology into an automated condition monitoring system to transition the methodology into an automated condition monitoring system.

6. Conclusion

This experimental study demonstrates the efficacy of using the discrete wavelet transform (DWT) integrated with the fast Fourier transform (FFT) for sensitive condition monitoring and early fault detection in wind turbine blades. The results validate DWT's exceptional capabilities for nonstationary vibration signal analysis, as evidenced by the clear differentiation of modal frequency shifts between the healthy and eroded blade states. The 5-level DWT decomposition effectively isolates transient fault signatures typically obscured in raw vibration data. Meanwhile, FFT post-processing provides critical high-resolution quantification of the frequency information revealed by DWT filtering. This integrated DWT-FFT approach synergistically combines time-frequency localization and precise spectral analysis to identify subtle indications of blade damage undetectable through individual techniques. The pronounced fault signature isolated here, characterized by an elevated 28Hz mode absent in the intact blade, represents a sensitive marker of erosion damage. This modal frequency divergence likely stems from the increase in roughness that degrades aerodynamic induction and dynamic loading. The study results offer firm proof-of-concept validation of harnessing DWT's unique damage detection strengths, facilitated by FFT resolution, for next-generation wind turbine structural health monitoring. Although expanded field validation is still required, this research conclusively demonstrates the potential for an automated DWT-FFT condition monitoring system. This could facilitate a transition from conventional time-based maintenance to a new paradigm of data-driven prognostics. The early diagnosis of failure precursors will become achievable before catastrophic damage occurs. Therefore, harnessing advanced vibration analysis techniques promises to improve wind turbine reliability, availability, and cost-effectiveness significantly. This will accelerate the proliferation of renewable wind power.

Author contributions

Conceptualization, A. Ogaili, M. Hamzah, A. Jaber and E. Ghane ; methodology, writing—original draft preparation, A. Ogaili, M. Hamzah, A. Jaber and E. Ghane. All authors have read and agreed to the published version of the manuscript.

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Data availability statement

The data supporting this study's findings are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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