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مجلة علمية محكمة تصدر عن كلية التربية

بجامعة المرقب

العدد السادس والعشرين
يناير 2025م

هيئـــة التحريـر

- المجلة ترحب بما يرد عليها من أبحاث وعلى استعداد لنشرها بعد التحكيم .
- المجلة تحترم كل الاحترام آراء المحكمين وتعمل بمقتضاها .
- كافة الآراء والأفكار المنشورة تعبر عن آراء أصحابها ولا تتحمل المجلة تبعاتها .
- يتحمل الباحث مسؤولية الأمانة العلمية وهو المسؤول عما ينشر له .
- البحوث المقدمة للنشر لا ترد لأصحابها نشرت أو لم تنشر .

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يشترط في البحوث العلمية المقدمة للنشر أن يراعى فيها ما يأتي :

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- يرفق بالبحث تزكية لغوية وفق أنموذج معد .
- تعدل البحوث المقبولة وتصحح وفق ما يراه المحكمون .
- التزام الباحث بالضوابط التي وضعتها المجلة من عدد الصفحات ، ونوع الخط ورقمه ، والفترات الزمنية الممنوحة للتعديل ، وما يستجد من ضوابط تضعها المجلة مستقبلا .

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- يخضع البحث في النشر لأولويات المجلة وسياستها .
- البحوث المنشورة تعبر عن وجهة نظر أصحابها ، ولا تعبر عن وجهة نظر المجلة .

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Exploring Vibration-Based Assessment Methods for Wind Turbine Rotor Blades: Simulations with Experimental Validation

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Abstract:

Blades are essential components in the energy conversion process of wind turbines, and faults in these blades may lead to catastrophic failures. Vibration signals can play a crucial role in the early detection of faults in such systems, providing detailed information across a broad spectrum that can be used to prevent injuries, system damage and associated economic losses. But detection and accurate diagnosis of faults in wind turbines using vibration measurements is inherently problematic because of the multiplicity of sources and ways whereby the phenomena are modulated. In this study a custom-designed permanent magnet wind turbine test rig was developed, containing a small horizontal-axis wind turbine featuring a three bladed rotor, each blade with the NACA 2412 airofoil. Baseline vibration data were collected remotely and analysed to compare with signals indicative of blade faults, facilitating an assessment of blade condition. One of the four blades was seeded with a series of similar cracks and data gathered for each crack separately at 150 rpm, while maintaining a constant load of 100 Ohms. Shaft vibration frequencies served as sensitive indicators of changes in blade conditions. A comprehensive dynamic analysis was conducted using a full 3D finite element method (ANSYS) to simulate fundamental vibration characteristics. Simulated and real-time vibration levels were measured and compared. This method proposed here utilizes a development of the Continuous Wavelet Transform (CWT), termed the Wavelet Transform Feature Intensity Level (CWTFIL), to compute the FIL, enabling a fast and accurate comparison of shaft signatures for healthy and damaged blades.

Keywords: Continuous Wavelet Transform (CWT), crack, finite element method, wind turbine blades, total energy.

1. Introduction

The minimization of operational and maintenance expense, alongside the enhancement of the reliability of wind turbine systems (WTSs), to ensure early fault detection and avoidance of any resulting damage, possibly catastrophic failure is a main concern of the renewable energy sector, particularly important given the substantial increase in demand for wind energy and size and mass of, e.g., the turbine blades. In this context, condition monitoring systems (CMSs) are essential for optimizing the efficiency of wind energy in electricity generation and avoiding interruption of supply. Recent advancements in CMSs, facilitating early detection of component failures, have significantly enhanced WT technology. This paper inventories and classifies wind turbine CM technologies, demonstrating that combining reactive with preventative strategies for machine maintenance improves availability and reliability whilst lowering costs. It also demonstrates how integrating intelligent CMSs can support larger WTSs in remote locations, focusing on advanced failure prediction, assessing remaining useful life, and identifying key research areas for future exploration [1].

Different wind turbine CM techniques have been in use for well over a decade to detect faults at the earliest possible stage, forecasting the remaining working life of components and avoiding catastrophic failure. Such techniques have been widely studied and it is now commonly agreed in the wind turbine industry that they are an excellent means of reducing the costs of power generation through guidance of operational maintenance procedures and processes [2]. Regarding generation and transmittance of vibrations from the rotor blades and drivetrain, it is important to note that while drivetrains are becoming increasingly intricate, the primary aim of vibration and noise analysis remains the identification of their origins and transmission routes [3],[4].

Key to reducing operational and maintenance costs and enhancement of wind turbine dependability are accurate and sensitive methods for CM via anomaly detection. A wind turbine CMS using the swarm based sparrow search algorithm (SSA) with self-attenuating bi-directional memory (SABiLSTM) and binary segmented change-point detection (BinSegCPD) was proposed by Yan et al., to detect and classify deteriorations in systems and give early warning of a possible fault [5].

Ogaili et al., have emphasized the effectiveness of employing the Discrete Wavelet and Fast Fourier Transforms (DWT and FFT respectively) for detection of faults in the rotor blades of wind turbines. The enhanced sensitivity of the DWT is largely attributed to its capacity for filtering non-stationary signals, while the FFT provides high spectral resolution. The superiority of the DWT relative to the FFT was confirmed by a comparative analysis. An approach which combines the strengths of both techniques, successfully enabled the detection of small defects that might otherwise have gone unnoticed [6].

Tang et al., [7] highlight that wind turbines are susceptible to damage from moisture absorption, fatigue, wind gusts, and lightning strikes, underscoring the increasing need for the monitoring of their health. Generally recognised as the most effective method for the CM of wind turbines, the time-frequency analysis of the vibration measurements can be further enhanced by the use of such techniques as the Wigner-Ville distribution (WVD). Theoretically, in terms of time-frequency the WVD offers infinite resolution, but challenges such as strong background noise and cross terms in the analysis persist.

Abouhnik et al., [8] introduced a sensitive method for detecting faults in rotating machinery using vibration signals captured by accelerometers. This method employs Principal Component Analysis combined with Residual Matrix Analysis (PCRMA) which was shown to effectively distinguish between healthy and faulty operational conditions across various types of rotating machinery. The authors have previously filtered noise from vibration signals utilizing PCA, enabling a detailed examination of damage effects in rotor blades [9]. Our analysis focused specifically on a three-bladed rotor, facilitating the extraction of critical information pertinent to the health of the blades.

Today, the popularity of wavelet transform (WT) means it is now as commonly used as the FFT for analysis of time varying signals. Whereas the FFT uses exponential scaling the WT uses a “mother wavelet” that usually includes several wavelet kernels [10] with translation replacing a shift in the zero frequency component. The one dimension of the FFT is replaced by a *two*-dimensional wavelet, meaning that the WT is not limited to one-dimension but can provide analytic data in terms of both frequency and time.

The FFT uses cosine and sine functions, which repeat to infinity, to convert data from the time to the frequency domain. FFTs represent an average of the frequency content for the complete duration during which the signal was acquired. Thus, strictly, FFTs should be used for stationary signal analysis or where only the average energy of each frequency is required. In contrast, a WT transitions the measured time signal into the time-frequency domain using a family of functions derived from the mother wavelet, preserving local features within the original data. This differentiates wavelets because they can perform not only accurate frequency analysis but they can also compress or expand the time-scale over which the frequency analysis takes place. Such a process enables the scale to match the desired resolution, and means WTs can be used for the analysis of non-stationary signals. This advantage has meant WTs are used increasingly for machinery CM, to detect and identify defects including, for example, fractures in rotors. Today, WTs are being used to determine both propagating and stable fractures [11].

2. Simulation work

A three-bladed wind turbine was modelled using ANSYS, see Fig 1. The 3D FE model first simulated three healthy rotor blades and then two healthy blades with the third blade suffering from a crack as shown in Fig 2.

The 3D simulation model was generated via SolidWorks and imported into ANSYS. This approach enabled simulation across a broader range of rotational speeds than was feasible experimentally, with ANSYS facilitating a fast and accurate analysis of the blade’s natural modes of vibration, helping to avoid undesirable resonances.

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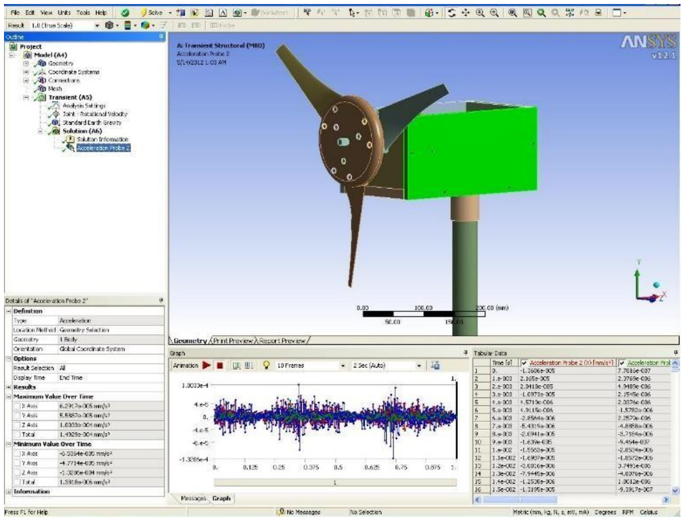

Figure 1: Simulation of wind turbine

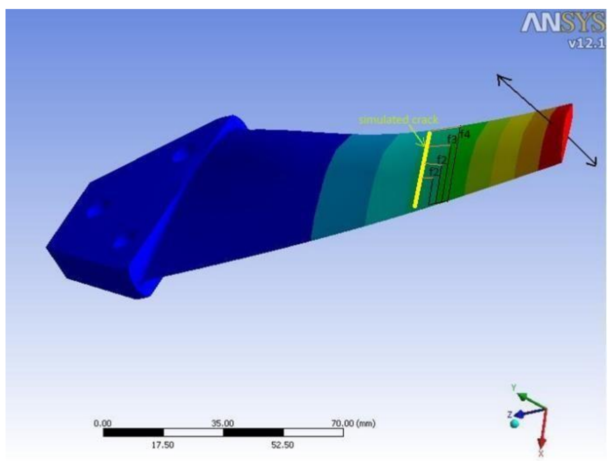

Figure 2: Simulation of a blade suffering from a transverse crack

Three tests were conducted: (a) the original healthy rotor blade, (b) a crack seeded into the healthy blade, and (c) three healthy rotor blades. Extracted simulated vibration signal is shown in Fig 3. ANSYS was then utilized to simulate blade vibrations under the various conditions. These findings confirm that such software can enhance the quality of a product such as a wind turbine by facilitating a more cost-effective design, and has the potential for lowering manufacturing costs through, for example, the rapid exploration of the viability of more affordable materials. Furthermore, these software packages can aid in the understanding of wind turbine operations and in developing strategies to improve efficiency, reliability, and reduce maintenance costs.

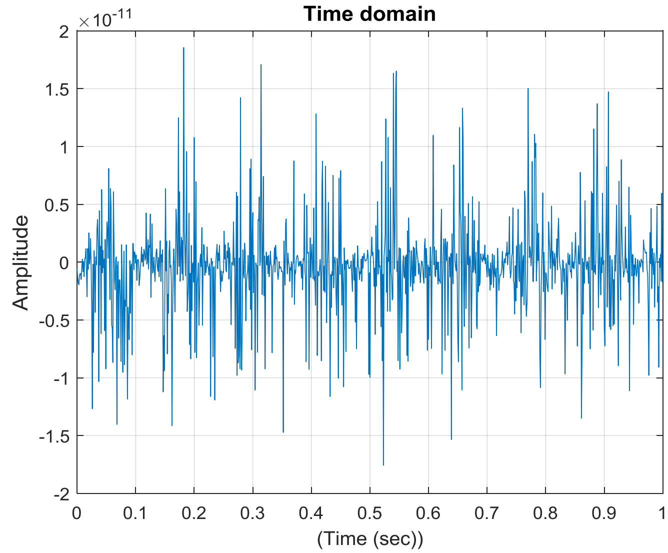

Figure 3: Time-domain signal for simulated vibration with three healthy blades, 150 rpm

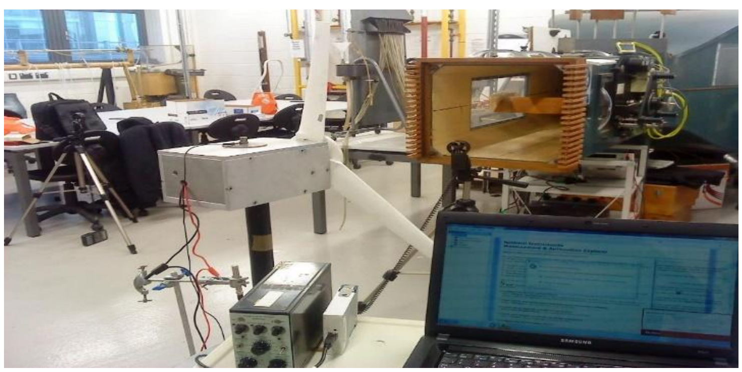

Figure 4: Wind turbine monitoring system

3. Experimental test rig

The laboratory/experimental work was conducted using a rig comprising a three-bladed rotor, with aerofoils shaped according to NACA 2412 and each measuring 32 cm in length. As seen in Fig 4, the wind tunnel was situated approximately 1 meter from the rotor blades. Vibration measurements were made on the nacelle of the turbine using two B&K type 4371 accelerometers. A B&K type 2635 charge amplifier converted the accelerometer output (in pico coulombs) to millivolts. For data collection, a NI USB 9233 data acquisition card interfaced between the PC and charge amplifier.

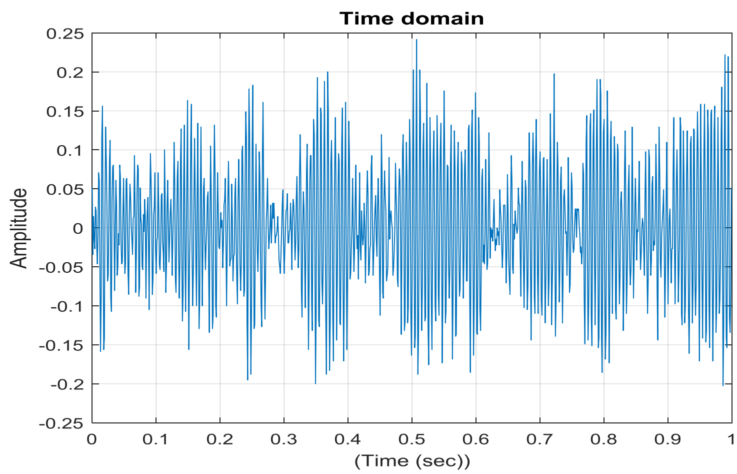

Figure 5: Measured time-domain signal for vibration with three healthy blades 150 rpm**.**

4. Vibration Measurement

Vibration measurement is probably the most common CM method used with rotating machinery, their gears and bearings, providing features that accurately and correctly indicate the condition of the machine. Figs 3 and 5 illustrate the simulated and measured vibration signals, respectively. Conventional time and frequency domain techniques were employed to analyse these vibration signals with the simultaneous use of various statistical quantities which facilitated more reliable decision-making than single parameters alone.

Statistical measures such as Crest Factor and Root Mean Square derived from the time-domain of vibration signals, are commonly employed to evaluate damage severity. However, previous research has indicated that these measures are inadequate for analyzing non-stationary signals, highlighting the need for more advanced monitoring techniques for wind turbines [12]. Thus, this study focuses on the application of the CWT, and proposes a new means of enhancing the analysis of the CM signal from wind turbines.

5. Continuous Wavelet Transforms (CWT)

Selecting the window function in conventional methods such as the FFT and DFT results in their resolution being fixed in both frequency and time domains. However, the major benefit offered by a WT is the capacity to provide greater resolution of transient phenomena, making the WT particularly appropriate for analysing signals whose frequency content and magnitude vary with time, as is required for detection of faults in their early stages, in for example, gear trains. The WT achieves this by adjusting the length of its time window according to the frequency content of the signal.

Here we introduce the CWT as a method for detecting faults in wind turbine rotor blades. For a continuous signal x(t), the CWT is [13]:

$$CWT_x(a,\tau) = W_\psi(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt \qquad 1$$

Where a factor a (a>0) is introduced with $1/\sqrt{a}$ used for energy normalisation. a is referred to as the scaling parameter, and τ is the shift parameter. Dilation or contraction is determined by the scaling parameter while the shift parameter controls the position of the wavelet in time. The mother wavelet, $\psi(t)$, defines the wavelet family because when scaled by factor a and translated by factor τ, it becomes the daughter wavelet ($\psi_{a\tau}(t)$) as:

$$\psi_{a\tau}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-\tau}{a}\right) \qquad 2$$

As the scaling factor, a, and translation factor τ are varied there will be corresponding variation of the daughter wavelet, $\psi_{a\tau}(t)$. With wavelets which extend over significant time (for use with low frequencies) the scale required is large, and for high frequency analysis the opposite is required. Because the CWT is summed over all time (mathematically from -∞ to +∞) for the signal it is a good transform for singularity detection. Various functions can serve as analyzing wavelets, each possessing distinct properties, see for example the Haar and Morlet wavelets.

5.1 Selection of Analysing Wavelet

When determining local characteristics using the STFT, the duration of the time-frequency window, defined by its duration Δt and the bandwidth Δf (see Eq. 3) is critical. To be effective in extracting and exhibiting local properties, the window function should be of suitably small duration; however, the uncertainty principle imposes an ultimate constraint on resolution [10].

$$\Delta t\,\Delta f \geq \frac{1}{4\pi} \qquad 3$$

Maximum accuracy is obtained when Δt Δf.= 1, attained if the window is Gaussian [11]:

$$g_\alpha(t) = \frac{1}{2\sqrt{\pi\alpha}}e^{\left(\frac{-t^2}{4\alpha}\right)} \qquad 4$$

Where α > 0.The Gabor Transform is such a window:

$$G(f) = \int_{-\infty}^{\infty} x(t)e^{iwt}g_t(t-\tau)dt = \int_{-\infty}^{\infty} x(t)\overline{G(t)}dt \qquad 5$$

Where *G(t)* is the window function, and *x(t)* is the signal to be transformed. Here, we use Eq. 5 as the analysing wavelet and set:

$$G(t) = \psi(t) = ce^{i\alpha t} g_{\infty}(t-\tau) \quad \text{where } c \neq 0, \alpha > 0 \qquad 6$$

Good localisation is obtained when the analysis is performed using wavelets with rapid rates of decay. One major advantage of the Gabor transform is that the rate of decay can be determined by both a and α, which makes it easier to enhance the time-frequency resolution.

5.2 Wavelet Transform Properties

Four properties considered most important for WTs are [13], [14], [15]

Signal Energy Conservation: The signal energy is the total value of the square of the modulus of the CWT over the given time interval [16]:

$$E_x = \int_{-\infty}^{\infty} |x(t)|^2 dt = \iint |CWT_x(a,\tau)|^2 \frac{da d\tau}{a^2} \qquad 7$$

Linearity: when analysing signals with many components, bi-linearity is undesirable because it can cause interference between one component and another. However, because WT is a linear representation of the signal and does not generate interference it is suitable for such analysis.

Resolution: the *uncertainty principle* imposes an unavoidable limit on the resolution between time and frequency. However, WT can offer local resolution in frequency and time as [17][18]:

$$\Delta t = a \Delta t_g \qquad 8$$

$$\Delta f = \frac{\Delta f_g}{a} \qquad 9$$

Where Δt_g and Δf_g are, respectively, duration and bandwidth of the wavelet being used for the analysis, Eqs 8 and 9, show that time resolution improves at higher frequencies, and frequency resolution increases at low frequencies. These resolution characteristics mean the WT is well-suited to detect transients.

Localisation in time and frequency domains: as seen in in Eq. 2, the CWT value at given values of (a, τ) will always depend on the analysed signal and will be *non-local*.

5.3 CWT Detection of Crack in Wind Turbine Rotor Blade

The frequency of sampling used by the wavelet function is an important parameter that has major consequences for how well the WT analysis determines the frequency bandwidth of the analysis. The frequency with which the signal is sampled will determine the time resolution.
Here CWT was used to detect the presence of seeded faults and so distinguish healthy and faulty conditions of the rotor blade. Figs 6 and 7, respectively, show CWT contours for faulty and

healthy rotor blades, for simulated and experimental results. The displays are in the form of time-frequency plots with signal magnitude represented by different colours.

From Figs 6 and 7, it can be seen that both measured and simulated energies in the vibration signal are concentrated in the region close to the fundamental shaft frequency of 2.50 Hz (150 rpm). However, as cracks are introduced into the rotor blade, a greater proportion of the vibration energy becomes even more concentrated in the region around the fundamental shaft frequency.

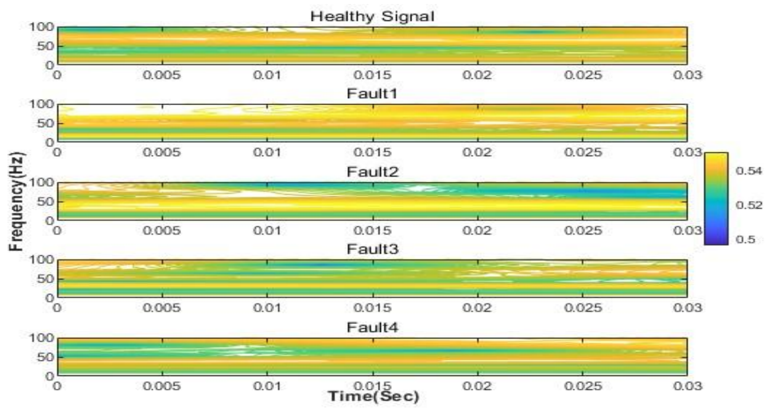

Figure 6: Simulated CWT contours for rotor blade healthy and seeded with four faults

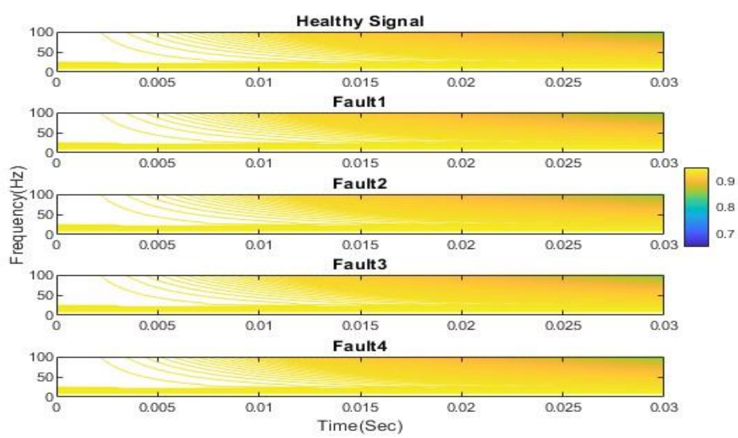

Figure 7: Experimental CWT contours for rotor blade healthy and seeded with four faults

The CWT method has demonstrated considerable success in various fields, but its effectiveness in detecting minor faults or structural changes in wind turbine blades has been limited, as evidenced by both simulation and experimental results. This limitation may arise from several factors, including the complexity of the signals generated by the blades or inherent noise in the data. Additionally, the sensitivity of the CWT can be influenced by the choice of the analyzing wavelet, which may not be optimal for capturing subtle variations in blade integrity. Therefore,

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further refinement of the CWT parameters, along with the exploration of complementary diagnostic techniques and the development of innovative approaches is essential to improve the capacity to detect faults in, e.g., the rotor blades of wind driven turbines.

Analysis techniques using Wavelets offer distinct benefits over FFTs in identifying non-stationary and/or random elements within signals. Such analysis is particularly effective for signals that include short duration high-frequency components, though lower-frequency components may have longer durations, a common occurrence in practical scenarios. Furthermore, the CWT serves as an excellent tool for denoising frequency and time domain signals.

Developing the CWT technique and a MATLAB code for analysis of turbine vibrations, a new technique (CWTFIL) is introduced which combines the CWT with the Feature Intensity Level (FIL). This approach has been tested and proven to be reliable, robust, and sensitive to different fault severities. Consequently, it is well-suited as a detection tool for integrating into wind turbine CM systems.

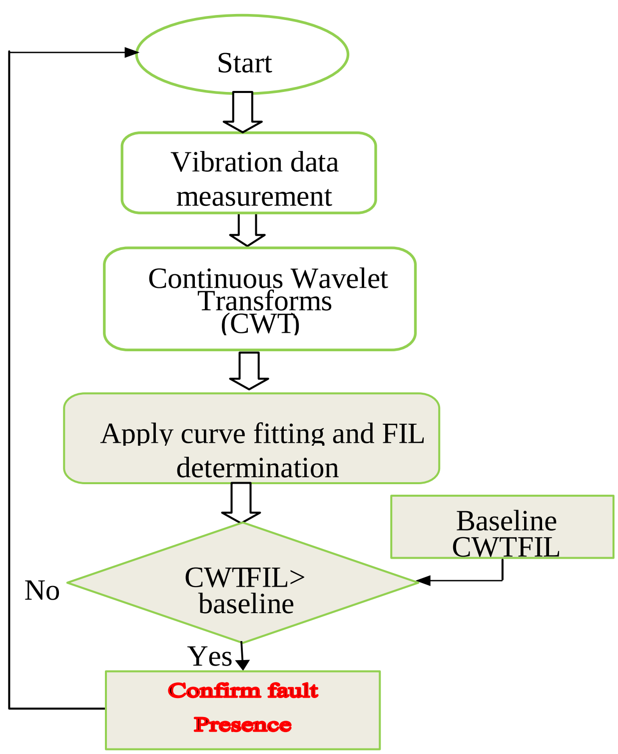

Figure 8: Flowchart of the proposed CWTFIL method

The suggested method begins by measuring vibrations of the turbine nacelle. Given p(*f*) is the curve fitted to the measured signal over the frequency band f_1 to f_2, the corresponding FIL may be expressed as:

$$FIL = \int_{f_1}^{f_2} p(f)df$$
10

Figure 9: Simulated results for normalized FIL: h - healthy rotor blade, f1, f2, f3 and f4 are, in order, rotor blade with 10, 20, 30, and 40mm long seeded crack. All cracks were 2mm deep and 3mm wide. All measurements made at rotational speed 150 rpm

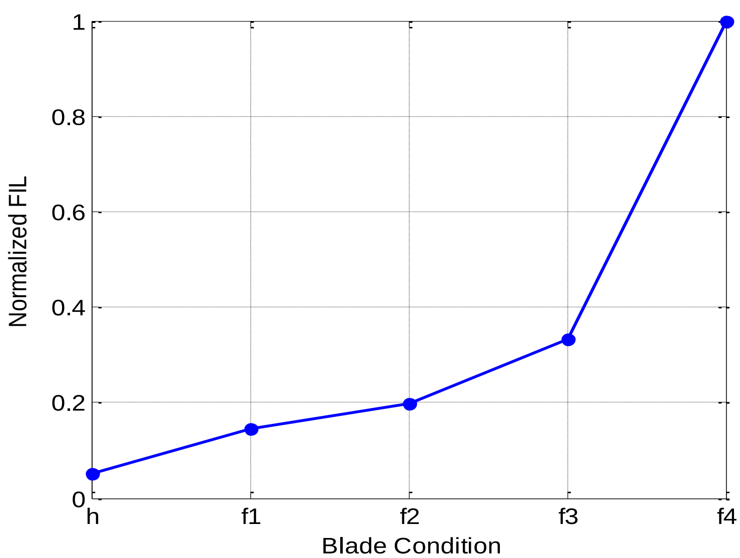

Figure10: Experimental results for normalized FI: h - healthy rotor blade, f1, f2, f3 and f4 are, in order, rotor blade with 10, 20, 30, and 40mm long seeded crack. All cracks were 2mm deep and 3mm wide. All measurements made at rotational speed 150 rpm

For the frequency band, f_1 to f_2, the FIL obtained using the Discrete FFT, can be written:

$$FIL = \sum_{f_1}^{f_2} \frac{1}{2}\left[p(f_i) + p\left(f_{(i+1)}\right)\right]df \qquad 11$$

Where $df = f_{(i+1)} - f_i$, $p(f_i)$ = amplitude of signal at f_i , and $p(f_{(i+1)})$ = amplitude of signal at $f_{(i+1)}$.

The summation can be carried out over the entire frequency range as determined via a FFT. Here, the trapezoidal rule, in MatLab, was used to determine the area under the envelope between the required frequencies, f_1 and f_2. Fig 8 shows the CWTFIL algorithm's flowchart.

The results presented in Figs 9 and 10 represent the normalised FIL for the healthy condition (h– no seeded cracks), then with one rotor blade seeded with cracks of different lengths: f1, f2, f3 and f4 were, in order, 10, 20, 30, and 40mm long, all were 2mm deep and 3mm wide. The rotational speed was maintained constant at 150 rpm.

6. Conclusions

This research utilized finite element analysis to produce a 3D simulation of a three-bladed rotor which generated simulated vibration signals, first with all three blades healthy and then with a single blade seeded with a distinct crack of four different lengths. Vibration signals on the turbine nacelle for both healthy and faulty blades were collected in real time using accelerometers. Both measured and simulated sets of vibration signals were analyzed using MATLAB, employing CWTFIL, a combination1 of FIL and CWT. This approach was proved valuable for CM for fault detection and prognostic maintenance of rotor blades compared with, for example, WVD and DWT. The CWTFIL method successfully detected the existence of the seeded cracks and their increased severity, demonstrating its ability to prevent a disastrous failure. The results indicate that CWTFIL is an excellent indicator of changes in operational conditions of wind turbine rotor blades, enabling online detection of the initiation of cracks and thus allowing optimisation of the company's maintenance policy. This approach could help facilitate a transition from a time-based reactive approach to a pro-active data-driven approach regarding future performance, thereby enhancing dependability through the early detection of wind turbines blades failure precursors.

This study highlights the potential of utilizing information derived from wind turbine vibration signals, paving the way for further exploration of this method's capabilities as a diagnostic tool. Future work will focus on applying this technique at varying operational speeds and extracting information from different components and other rotating machinery, potentially leading to its broader adoption by industry.

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