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Airborne Acoustic and Empirical Mode Decomposition Techniques for Wind Turbine Condition Monitoring

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Abstract:
Air-borne acoustic signals offer a number of advantages over other monitoring techniques, primarily because they can be measured at a distance away from that machine and contain very helpful information of that machine condition. However, they are prone to background noise, which makes extracting information more difficult.

Microphones offer inexpensive and remote media for measuring wind turbine air-borne acoustic signals. Therefore, the proposed condition monitoring technique is based on airborne-acoustic signals to monitor wind turbine blades condition and introduces a non-contact method for assessing the health of wind turbine blades. The approach involves analyzing remotely captured airborne acoustic signals by decomposing them into their intrinsic components using the empirical mode decomposition (EMD) technique. The presence of wind turbine rotor imbalance is evaluated by monitoring the amplitude of a frequency component corresponding to rotating speed.

A condenser microphone located 50 cm away from the test rig was used to record the emitted acoustic signals. The mechanical faults were simulated for a rotor imbalance on the test rig and the tests were carried out at various rotation speeds. Fundamental characteristics of the measured signals were extracted for the healthy rotor and the condition where two of the three blades were healthy and one blade was replaced with a blade that was 10 %, 20 % and 30% heavier than the healthy one. The results show that the EMD/airborne acoustic signal technique is very sensitive to blade unbalance faults and found to increase in a linear fashion with the severity of the fault.

Keywords: Empirical Mode Decomposition, Condenser Microphones, Wind Turbine Air-borne Acoustic Signals, Rotor imbalance.

مراقبة حالة توربينات الرياح من خلال الإشارات الصوتية وتحليل الأنماط التجريبية

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الملخص:
توفر الإشارات الصوتية العديد من المزايا مقارنة بغيرها من تقنيات المراقبة وذلك نظراً لإمكانية قياسها عن بُعد، فضلاً عن احتوائها على معلومات قيّمة حول الآلة. ومع ذلك، فإن هذه الإشارات محملة بالعديد من الإشارات الصوتية المعقدة والمتولدة من العديد من مكونات الآلة والتي تشكل ضوضاء تجعل عملية استخراج المعلومات منها أكثر تعقيدًا.
ومع ذلك تُعد الميكروفونات وسيلة فعالة ومنخفضة التكلفة لقياس تلك الإشارات وتعتمد تقنية المراقبة المقترحة على قياس وتحليل هذه الإشارات عن بعد لتشخيص وتقييم حالة عدم توازن د وّار توربينات الرياح بحيث تساهم في تحليل الإشارات الصوتية المنبعثة في الهواء والمُلتقطة عن بُعد عبر تفكيكها إلى مكوناتها الاساسية (مصدر كل إشارة) باستخدام تقنية تحليل النمط التجريبي (EMD) حيث يتم تقييم اختلال التوازن في دوار التوربين من خلال مراقبة سعة المكون الترددي المرتبط بسرعة الدوران.
في هذه الدراسة العملية، , وُضع ميكروفون على بُعد 50 سم من التورباين لتسجيل تلك الإشارات. وتمت محاكاة الأعطال الميكانيكية من خلال إحداث اختلال في توازن الدوار على منصة الاختبار وعند سرعات دوران مختلفة.
الخصائص الأساسية للإشارات المقاسة تم تحليلها في حالتين: الأولى عندما كانت شريحتان من الشفرات الثلاثة سليمتين، والثانية عندما تم استبدال شفرة واحدة بأخرى تفوقها وزنًا بنسبة 10%، 20%، و30% على التوالي.
أظهرت النتائج أن تقنية التحليل الصوتي المنبعث من توربين الرياح في الهواء باستخدام تقنية التحليل النمطي التجريبي (EMD) حساسة للغاية لاختلالات التوازن في الشفرات، حيث سجلت زيادة خطية في شدة الإشارة مع زيادة درجة الخلل، مما يثبت فعاليتها في رصد وتشخيص الأعطال في توربينات الرياح.

الكلمات المفتاحية :تحليل النمط التجريبي *(EMD)*، ميكروفون تكثيفي، الإشارات الصوتية المنبعثة في الهواء، اختلال توازن الدوّار.

1. Introduction

Wind energy is one of largest attractive sources for green energy. The economics of wind to energy converters is much influenced by the health of the wind turbine and in particular the turbine's blades. Thus, understanding wind turbine behaviour and, particularly, failure modes helps in the development of effective tool or condition monitoring system (CMS) and the efficient scheduling of maintenance windows. Vibration and air-borne acoustic based monitoring techniques are among the most attractive with the wind turbine rotor being a common source of vibration and airborne sound. A cracked blade will cause rotor imbalance and the centre of mass of the rotating assembly, such as the blades, no longer coincides with the centre of rotation. Rotor imbalance generated a centrifugal force, its magnitude depends on the degree of imbalance [1].

In the context of drivetrain vibration sources and transmission in wind turbines, it is essential to acknowledge that, despite the increasing sophistication of drivetrain systems, the primary objective of vibration analysis remains the determination of their origins and propagation pathways[2]. As turbine blades continue to grow in size, weight, and cost, ongoing research into advanced condition monitoring (CM) technologies becomes increasingly vital. The ability to detect faults at an early stage, thereby preventing secondary damage and averting catastrophic failures, is of paramount importance [3]. CM and anomaly detection methodologies are indispensable for evaluating wind turbine health, as they play a crucial role in enhancing system reliability while simultaneously minimizing operational and maintenance expenditures.

To enable the automated detection of deterioration and the timely issuance of fault alerts, Yan et al. have introduced a CM system that integrates the sparrow search algorithm with self-attenuating bi-directional memory and binary segmented change-point detection [4]. Furthermore, Ogaili et al. have demonstrated the effectiveness of employing the Discrete Wavelet Transform (DWT) alongside the Fast Fourier Transform (FFT) for fault diagnosis in wind turbine blades. The superior sensitivity of DWT arises from its capability to analyze nonstationary signals, whereas FFT excels in providing high-resolution spectral analysis for stationary signals. A comparative analysis of performance metrics has substantiated the dominance of DWT over conventional FFT and statistical techniques [5].

By leveraging the complementary advantages of both methods, this approach enhances the precision of fault detection, facilitating the identification of minor defects that might otherwise remain undetected.

Many studies have focused on applying vibration technology to the monitoring of wind turbines. Among these Zhiqiang et. al.[6] proposed an alternative method for detecting damage in wind turbine blades by measuring the vibration response at a single point on the turbine. They suggest that blade faults can be identified by analyzing the degree of frequency shifts in the signal and assert that their approach is applicable both in general engineering practices and for developing structural health monitoring processes for wind turbine blades. Similarly, Abouhnik et al.[7] employed accelerometers to gather overall vibration signals, exploring the potential of using empirical mode decomposition (EMD) to extract condition indicators associated with the health of wind turbine blades.

However, Both analytical and experimental studies have long established that certain machine faults are directly associated with specific acoustic and vibration harmonics [8]. Compared with transducers used for vibration measurements microphones are less effected by location, offer greater mounting flexibility and are less sensitive to temperature variations. More important, a number of research works claim that they are richer in condition related information. Acoustic signals induced from wind turbines contain useful information but also include considerable noise that can hide a fault and is difficult to remove by using conventional filters with fixed cut-off frequencies. Some techniques commonly used to extract information for CM purposes and to remove the noise include the discrete wavelet transforms (DWT), which has been applied for noise cancellation, after which the continuous wavelet transforms (CWT) is used for feature extraction. Lang *et. al.*,[9] introduced de-noising algorithms employing discrete wavelet transforms (DWTs), where they applied thresholding within the wavelet transform domain. Unlike the conventional orthogonal wavelet transform, they utilized an undecimated, shift-invariant, non-orthogonal wavelet transform. Through simulations and experiments, they demonstrated that the proposed algorithm significantly improved noise reduction compared to traditional wavelet-based methods.

Abouhnik et al [10] employed Principal Components Analysis (PCA) to minimize unwanted noise in vibration signals during wind turbine blade damage investigations.. Fazenda[11] explored the potential of acoustic condition monitoring (CM) for detecting structural faults in turbine blades by collecting data using microphones positioned near the blades of a small three-bladed wind turbine in a laboratory and a five-bladed turbine in outdoor conditions with variable wind speeds. Faults, such as added masses and delaminations near blade tips, were deliberately introduced into a single blade for each test. The findings revealed that the faults caused shifts in the energy distribution of Intrinsic Mode Functions (IMFs), particularly around harmonic frequencies, indicating that faults could be identified by observing increased harmonic energy in the magnitude spectra derived from valid IMFs. Albarbar *et. al.*[12] used adaptive filtering techniques to extract information about diesel fuel injector needle impacts, enhancing air-borne acoustic signals remotely captured by a condenser microphone 25 cm from the injector head. Signals were processed and band-pass filtered using MATLAB. Traditionally, wind turbine monitoring has relied on vibration analysis using accelerometers, which are costly due to the number of sensors required and their environmental sensitivity.

This study by Abouhnik et al.[13] investigated air-borne acoustic signals as an alternative, demonstrating that condenser microphones provide coherent results with vibration measurements across critical frequency bands, including rotational speeds, gear meshing, and blade-passing frequencies. This acoustic approach offers broader spectral information and a cost-effective, non-contact solution for wind turbine condition monitoring, validated by coherence analysis and experimental data. The study highlights the feasibility of using microphones for reliable wind turbine diagnostics, advancing cost-effective and practical remote sensing technologies for the wind energy sector.

2. Wind turbine vibration and air-borne acoustic sources

A thorough understanding of wind turbine design and operational principles is critical for the development and implementation of effective condition monitoring (CM) systems and maintenance strategies. The noise generated by wind turbines during operation can be categorized into two primary types: mechanical and aerodynamic. Mechanical noise primarily originates from components such as the gearbox and generator, traveling through the turbine's structure and radiating from its surfaces. On the other hand, aerodynamic noise is produced by the interaction of airflow with the turbine blades. Various components of the turbine generate both vibration and airborne acoustic signals, as depicted in Figure (1). A detailed explanation of these noise generation mechanisms is provided below.

2.1 Mechanical sources

The dynamic interactions resulting from the relative motion of mechanical components can produce mechanically induced acoustic signals. Noise sources include the gearbox, generator, yaw drives, cooling fans, rotor blades, and auxiliary equipment. This noise is often tonal, corresponding to the rotational frequencies of shafts and generators or the meshing frequencies of gears, though it may also exhibit broadband characteristics. For example, distinct tones may emerge at specific frequencies due to these rotational and interactional dynamics. Moreover, structural components such as the rotor, hub, and tower can amplify and radiate mechanical noise, acting as loudspeakers. Noise propagates through two primary pathways: airborne, where it is emitted directly into the air from interior components or surfaces, and structure-borne, where it travels along structural components before radiating into the surrounding air [14].

2.2 Aerodynamic sources

Aerodynamic noise results from the interaction of airflow with turbine blades, involving complex flow phenomena that contribute to noise generation. Typically, the intensity of aerodynamic noise increases with rotor speed, with broadband noise being the dominant type. Aerodynamic noise mechanisms can be categorized into three groups[15]. They are divided into three groups:

1- **Low-Frequency Noise**: This type of noise is generated when blades encounter localized flow disturbances, such as those resulting from tower wakes, variations in wind speed, or wakes created by other blades.

2- **Inflow Turbulence Noise**: Caused by atmospheric turbulence, this noise arises from local force or pressure fluctuations around the blades.

3- **Airfoil Self-Noise**: Produced by airflow moving along and over the blade surface, this noise is typically broadband but can include tonal components due to blunt trailing edges or airflow over slits and holes.

The drive train within the wind turbine, consisting of the drive, gears, bearings, and shafts, serves as a major source of vibration, with the most notable excitations occurring at the gear mesh frequency, f_{gm}:

$$f_{gm} = Z.\, N_{gear} \qquad (1)$$

Here, is Z the represent the number of teeth on the gear while Ngear is its rotational speed (in Hz).

Bearing frequencies, each originates from a specific type of bearing vibration, are commonly utilized for the condition monitoring (CM) of bearings [16].

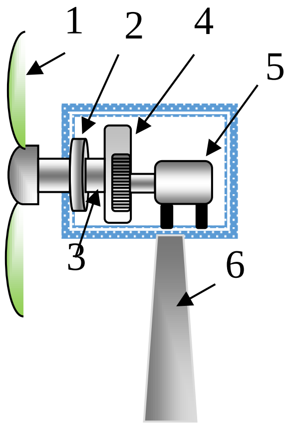

Fig. 1. A schematic representation of a wind turbine, illustrating its key components: 1. Blade, 2. Bearing, 3. Shaft, 4. Gearbox, 5. Generator, and 6. Tower.

The generator can serve as a source of excitation for the drivetrain at higher frequencies due to two primary factors. The first factor is the stator's notch passing frequency, typically determined by the product of the rotor's rotational speed and the number of poles. The second factor is the generator's frequency control when indirectly connected to the grid, which can introduce higher harmonic components in the electric voltage. Vibrations and airborne acoustic signals generated by the rotating blades can reach significant magnitudes and are recognized as a major contributor to wind turbine failures. As a result, considerable research has been directed towards devising effective methods for measuring and analyzing these vibrations [17]. A critical parameter in this context is the blade passing frequency (BPF), defined as the product of the number of blades and the rotor speed. This parameter indicates the frequency at which the blades pass a fixed point:

$$BPF = n.x/60 \qquad (2)$$

Where n represents the rotational speed of the turbine blades in rpm and x is the number of blades. The vibration signal measured at any point on a wind turbine, along with the airborne acoustic signal captured using non-contact microphones, comprises a complex mix of components with varying frequencies, amplitudes, and phases. As a result, specialized techniques are required to effectively analyze the obtained signals. Additionally, since the vibration signal changes over time, it must be treated as a non-stationary signal for accurate analysis.

3. Proposed blade’s condition monitoring algorithm

Figure 2 illustrates the proposed methodology for monitoring wind turbine blades and detecting associated faults. The monitoring process begins with the measurement of airborne acoustic signals emitted by the wind turbine. Baseline data is collected during turbine operation under various speed and load conditions and stored for future reference. The captured signal is then decomposed into its fundamental frequency components using Empirical Mode Decomposition (EMD). Subsequently, the feature intensity level of the shaft frequency is calculated and recorded as baseline data. The algorithm continuously monitors the intensity level of the shaft frequency and compares it against the stored baseline levels. Based on this comparison, the system evaluates the condition of the blades and provides a diagnostic report on their health.

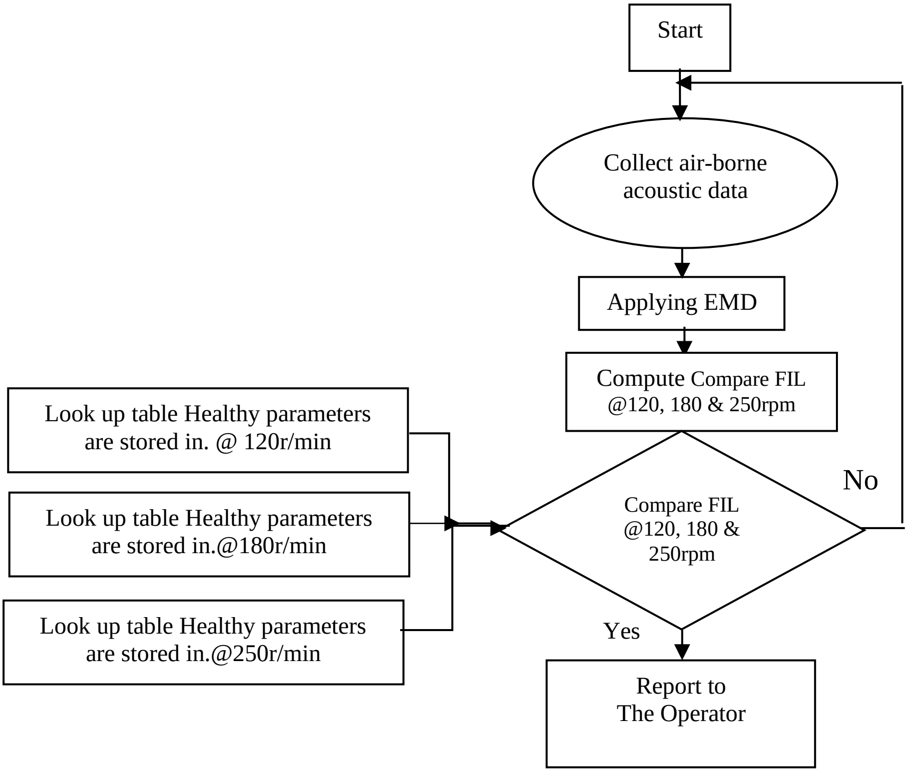

Fig.2. Flowchart of monitoring algorithm

3.1 Empirical Mode Decomposition

EMD can decompose the vibration or acoustic signal X(t) into a finite set of signals known as IMFs, to give K modes:

$$X(t) = \sum_{k=1}^{K} d_k(t) + r(t), \tag{3}$$

Where $d_k(t)$ is the kth mode, $r(t)$ is the residual term and $k=1,2,\ldots\ldots\ldots\ldots.K$

The EMD process has been summarized by Huang *et. al*. [18] as:

1. it starts with the k=1 and signal $d_1(t)$,

2. Sifting process begins with $j=0$, $h_j(t)=d_k(t)$.

3. The local extrema of $h_j(t)$.are identified.

4. Using the cubic spine interpolation the lower and upper envelopes (EnvMin and EnvMax respectively) are calculated.

5. The maximum and mean values of both upper and lower envelopes are fund, and m(t) determined where:

$$m(t) = 1/2[EnvMin(t) + EnvMax(t)] \quad (4)$$

6. Determine $h_{j+1} = h_i(t) - m9t)$

7. If $h_{j+1}(t)$ is an IMF, GOTO to step 8, otherwise repeat steps 2 to 6 with $h_{j+1}(t)$ and $j = j + 1$

8. Extract the mode $d_k(t)=h_{j+1}(t)$.

9. Calculate the residual. $r_k(t) = X(t) - d_k(t)$ (5)

10. If $r_k(t)$ has less than 2 minima or 2 extrema, the process is finished and $r(t)= r_k(t)$, otherwise repeat the iteration from step 1 on the residual $r_k(t)$, $k = k+1$.

3.2 Calculation of Feature Intensity Level

The curve fitted to the signal is p(f) and the feature intensity level (FIL) of the signal in the frequency band from upper frequency f1 to lower frequency f2, is:

$$FIL = \int_{f_1}^{f_2} p(f)df \quad (6)$$

Using the DFT, the FIL can be written as:

$$FIL = \sum_{f_2}^{f_1} 1/2\,[p(f_i) + p(f_{i+1})]d_f \quad (7)$$

Where $df = f_{(j+1)} - f_i$ and p(fi) = amplitude of signal. The whole range of frequencies obtained using the DFT.

3.3 Experimental setup and Blade's fault simulation

A custom-designed test rig featuring a three-blade horizontal-axis wind turbine positioned in front of a wind tunnel, as illustrated in Figure 3, was employed to capture airborne acoustic signals. The measurements were conducted using a YG-201 condenser microphone with a frequency response of up to 20 kHz, paired with a 2635 B&K charge amplifier. A National Instruments data acquisition card interfaced between a Laptop and the charge amplifier facilitated the collection of experimental data, which was subsequently analyzed using MATLAB. The signals were sampled at a rate of 1 kHz, with 3000 samples acquired for each dataset. Airborne acoustic data were recorded at rotational speeds of 120, 180, and 250 rpm to ensure comprehensive analysis under varying operational conditions.

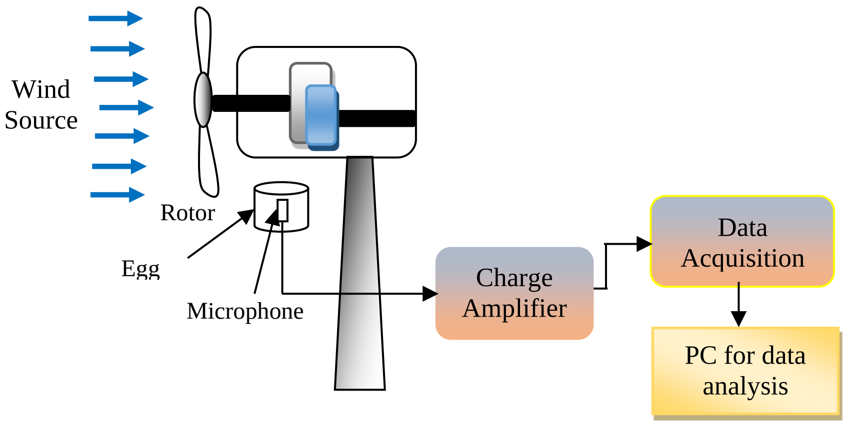

Fig. 3. Wind turbine test rig

To ensure accurate measurements in a controlled environment, the experiment was conducted in a closed field, and an egg box was placed around the microphone to minimize unwanted reverberation noise. Mechanical faults were simulated on the test rig by inducing rotor imbalance, achieved by replacing one blade with another that was 10%, 20%, and 30% heavier than the original healthy blade. This setup allowed for the systematic investigation of the acoustic and vibrational responses associated with varying levels of rotor imbalance.

4. Experimental results

The airborne acoustic signal obtained from the experimental setup with healthy blades is presented in Figure 4. In general, the time-series signals exhibit non-stationary behavior and are inherently contaminated by noise originating from various sources, which complicates the analysis and necessitates advanced signal processing techniques for accurate interpretation.

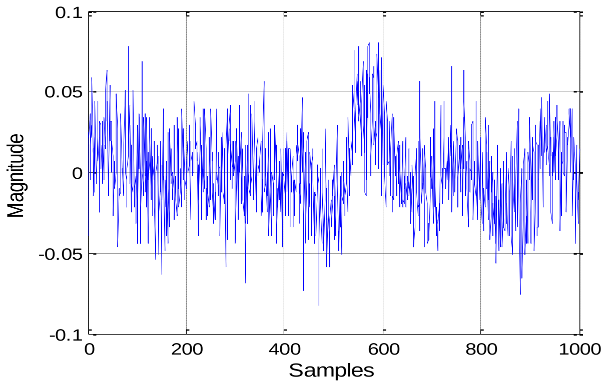

Fig. 4. Time domain airborne acoustic signal for healthy blade condition

4.1. Empirical mode decomposition technique

Empirical Mode Decomposition (EMD) was employed to extract diagnostic information for condition monitoring (CM) under both healthy conditions and simulated fault scenarios. Figure 5 presents the Intrinsic Mode Functions (IMFs) derived from the airborne acoustic signal at a rotational speed of 120 rpm, with each IMF representing a distinct frequency component. Fast Fourier Transform (FFT) was subsequently applied to each IMF to generate the corresponding frequency spectrum, enabling detailed analysis of the signal's frequency characteristics.

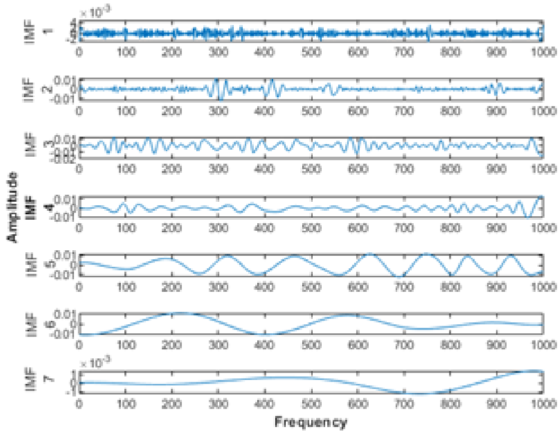

Fig. 5. Intrinsic mode functions (IMFs) of airborne acoustic health signal at 120 rpm

Figure 6 shows the FFTs of the IMFs of the airborne sound from the healthy mind turbine at a 120 rpm. It is shown that each spectrum represents the frequency of a different source (this includes the spectra corresponding to high frequencies related to wind tunnel noise, see Figure 6a). Other IMFs are related to different components such as bearings and gears. This study is focused on the shaft frequency - mode IMF7, its spectra is shown in Figure 6g.

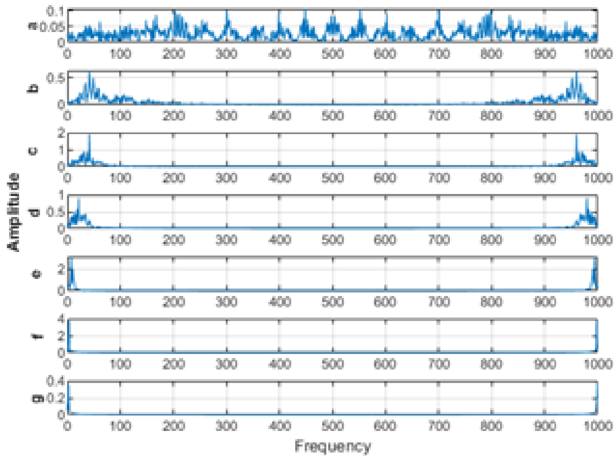

Fig.6. FFT for health signal generated at 120 rpm.

Figure 7 illustrates the Fast Fourier Transforms (FFTs) of the Intrinsic Mode Functions (IMFs) derived from the airborne acoustic signals of a healthy wind turbine operating at a rotational speed of 180 rpm. Here, as well we focus on the shaft frequency, represented by mode IMF7, with its corresponding spectrum shown in Figure 7g.

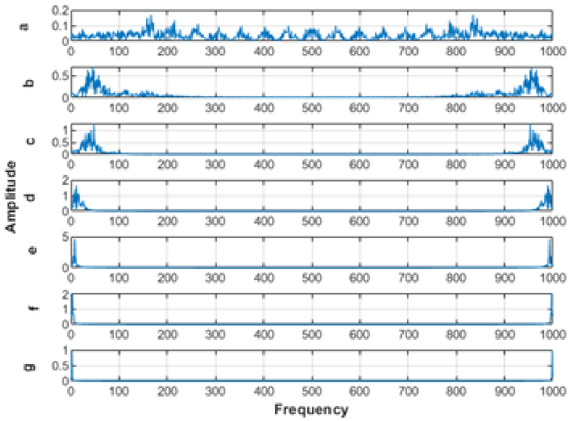

FIG. 7. FFT for health signal generated at 180 r/min.

While Figure 8 illustrates the Fast Fourier Transforms (FFTs) of the Intrinsic Mode Functions (IMFs) derived from the airborne acoustic signals of a healthy wind turbine operating at a 250 rpm and 8g shows the shaft frequency, represented by mode IMF7.

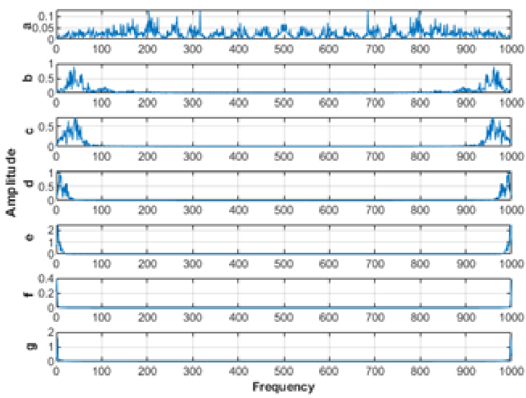

Fig. 8. FFT for health signal generated at 250 r/min.

The method was applied to the selected IMF7 mode for the experimental signals, and the normalized FIL was calculated for each signal. Figure 9 illustrates the FIL values for healthy blades (denoted as h) and blade with incremental mass increases of 10%, 20%, and 30%, corresponding to faults f1, f2, and f3, respectively, across rotational speeds of 120, 180, and 250 rpm.

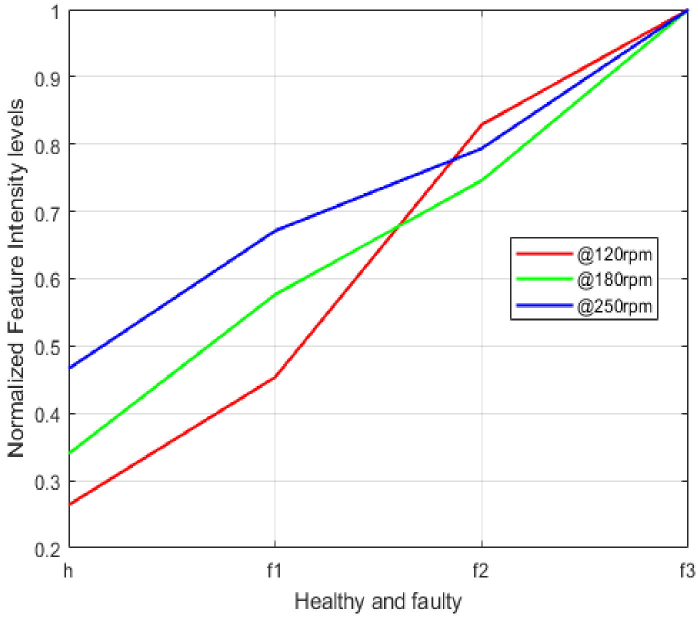

Fig. 9. Normalized Feature Intensity levels of healthy and faulty signals for imbalanced rotor

It is obvious from the experimental results that there is a clear increase in feature intensity level (FIL) with increase in fault severity at three different rotational speeds. This is encouraging, as it implies that the rate of growth in feature intensity level (FIL) could be substantial, making it highly relevant for practical applications.. Moreover, the proposed approach with EMD is potentially a power tool for indicating various faults including rotor imbalance.

5. Conclusion

This study introduces the combined technique for the analysis of measured airborne acoustic signals, achieved using the integration of Empirical Mode Decomposition (EMD) and Frequency Indicator Line (FIL) methodologies, collectively termed EDFIL. This approach has been rigorously validated on a specifically designed wind turbine test rig, thereby demonstrating its efficacy in accurately diagnosing wind turbine conditions and detecting fault presence. Additionally, the study reveals that the shift energy encapsulated within the Intrinsic Mode Functions (IMFs) of the airborne acoustic signals furnishes valuable insights into the condition of WT blades.

Although the findings underscore the feasibility of using microphones a cost-effective technology as an alternative to accelerometers in condition monitoring (CM) applications, there is still room for further exploration.

The future work endeavors will focus on applying the proposed method to acoustic signals generated by simulate cracks on one blade, with the objective of extending its applicability in addition to the detection of faults in other critical components; gearboxes and generators.

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