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“Acoustic Inspection System with Unmanned Aerial Vehicles for Wind Turbines Structure Health Monitoring”

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Acoustic Inspection System with Unmanned Aerial Vehicles for Wind Turbines Structure Health Monitoring

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Abstract

Wind energy is being one of the most important renewable energy in the world, employing larger and more complex wind turbines. They need novel condition monitoring systems to ensure the reliability, availability, safety and maintainability of the main components of the wind turbines. It leads early fault detection, increasing the productivity and minimizing the maintenance costs and downtimes. This paper proposes a novel non-destructive testing system to analyse acoustically rotatory devices of wind turbines. It captures the noise emitted by the devices by an acoustic condition monitoring system embedded in an unmanned aerial vehicle. The signal acquired is sent to ground computer station for recording and analysing the data. It is employed a test rig, previously validated, to carry out a set of experiments to simulate the main faults. A signal processing method is done by wavelet transforms, that filters and analyses the energy patterns of the signals. The results are analysed qualitatively and quantitatively considering different scenarios. A statistical analysis is developed to compare the numerical results provided by different wavelet transform families and convolutional neural network. It is concluded that Symlets and Daubechies families report equivalent results for this case study. The accuracies of the results are more than 75 %, reaching up to 100 %. The approach is validated employing Friedman test.

Key Words: Wind Turbine; Maintenance Management; Acoustic Analysis; Unmanned Aerial Vehicle; Structural Heal Monitoring.

1.Introduction

Wind energy is one of the most important renewable energy due to continuous development and the support of the government policies [1], growing in the last few years, see Figure 1. Wind turbines (WTs) are larger and more complex because of the advances and use of new materials, aerodynamic studies, technologies, information systems and efficient designs [2].

Figure 1. Evolution of global wind energy production capacity [3].

The WT reliability depends on its components, where any failure reduces the productivity and can generate unscheduled downtimes and costs [4]. The most common failures are cracks on the blade, mechanical overheating in the gearbox and electrical issues in the generator, among others [5]. The WT gearbox transmits mechanical energy into the generator with high speeds, suffering heavy weights, transient impulses of brakes and several corrosions. The gearbox faults can be 59% of the total faults in a WT [6]. Li et al. [7] showed that 40% of faults are related to bearings, 38% to the stator, 10% to the rotor and 12% to others. The maintenance of the WT components must ensure the system reliability minimizing resources and costs. The operation and maintenance (O&M) costs have been estimated between 12% and 23% of the total costs, depending of the geographical areas of the WT [8]. The development of an efficient planning and programming of preventive maintenance produces an improvement of the production, minimizing the downtime due to breakdowns for reparations and, therefore, reducing costs [9].

Non-destructive testing (NDT) is employing new technologies and sensors, leading an important advance on it. Structural health monitoring (SHM) uses in most cases NDT together with analytical methods to detect faults [10]. SHM on WT is employed remotely to reduce maintenance costs and increase the productivity [11]. Supervisory Control and Data Acquisition (SCADA) system obtains the operating conditions of the WT, providing signals and alarms with a low sampling rate [12,13]. This system provides the monitorization of several variables of the main WT components [14,15]. There are some studies about WT failure conditions and diagnosis by statistical and mathematical methods applied to the SCADA data [16,17]. It is generating a large number of false alarms [18,19]. Therefore, it is required advanced and novel condition monitoring systems (CMS) to increase the capabilities of current systems and integrate the real-time data acquisition with advanced failure diagnosis method [20,21].

Vibration monitoring is one of the most employed method for SHM and CMS of components, mainly the gearbox and the bearings [22,23]. The signals are processed in time, frequency or both domains, analysing the main features of the vibration signal to detect patterns associated to failures [24]. However, it is required the installation of several transducers in different parts of the WT [25]. Other types of NDT techniques, e.g., ultrasonic testing techniques and thermography, present reduced reliabilities or high initial investments [26]. Acoustic monitoring is also being employed in CMS and SHM [27-29], leading to monitor mechanical and electrical faults by employing transducers or acoustic acquisition sensors [30,31]. Different algorithms are required to study the main features of the acoustic signal, e.g., Fast Fourier Transform [32], Wavelet Transform [33], statistical methods [34], etc. Acoustic and vibration monitoring present similarities and sometimes are employed for the same objective [35,36]. The frequency ranges in working conditions are different for vibration and acoustic emission [37]. The use of acoustic techniques for failure detection in the industry is a growing topic due to its advantages [38]: Loud et al. [39] showed in their patent a method for acoustic inspection in industrial machinery. They analysed the acoustic signals through a filtering process, detecting and characterizing the different noises produced in these facilities. Poozesh et al. [40] proposed an acoustic monitoring for SHM on a WT blade section with reliable results. These signals on the solid can be also measured in the air, see reference [41]. The combination between unmanned aerial vehicles (UAVs) and acoustic monitoring can allow the improvement of the maintenance management, being a new research topic.

The application of UAVs in maintenance and monitoring tasks is being increased due to easy implementation, cost saving and its capacity to carry CMS [42]. These vehicles can be implemented in several application fields such as construction, mapping, film industry, technical inspections, security and photovoltaic inspection [43,44]. The UAV characteristics may be adjusted to the requirement for ensuring the correct operation [45]. The technical characteristics

of the embedded systems must be reliable, and it may implement different security processes to ensure the reduction of risks [46]. Murphy et al. [47] employed multiple NDT devices in UAVs. This system can evaluate the wind flow and its distribution, analysing, for example, the acoustic impact. Paulson [48] developed a CMS for leaks detection in aerial pipelines. It is used for thermographic inspections and continuous acoustic monitorization. The approach was based on the proposal made by Oerlemans et al. [49], establishing the use of UAVs as a novelty for fault detection [50].

This paper continues the work done by Moraleda et al. [51], where an important review about acoustic noise inspections was done, demonstrating that the noise generated by WT's may provide a useful information for fault detection and diagnosis. Solimine and Niezrecki [52] studied acoustic monitoring for damage detection on WT blades. The acoustic sensor was embedded in UAVs to monitor rotatory components.

The novelties of this paper are summarised as:

- The development of a CMS based on the analysis of sound waves emitted by different devices of a WT. The CMS is formed by an acoustic acquisition system embedded by an UAV. The data acquired is sent by wireless transmitter to the ground station, where the data is storage and analysed.
- The experiments are done in a test rig validated in previous research works for testing the reliability of the proposed system. It has a set of scenarios with the aim of studying different operational conditions and failures.
- Wavelet transform is employed for filtering and signal analysis. This approach leads to classify, identify and study different noises sources simulating the real WT operational conditions, including the UAV and machinery noise. The noise collected in the test rig is analysed by pattern recognition for fault detection and diagnosis.
- The results are qualitative and quantitative analysed, obtaining different patterns for fault detecton and diagnosis with high accuracy. The quantitative study is done employing convolutional neural networks (CNN).

The rest paper of the paper is structured as follows: Section 2 presents the background and the methology employed. The case study and the experiments are detailed in Section 3. Section 4 presents and analyses the results. The accuracy and the validation are discussed in Section 5. Finally, Section 5 shows the main conclusions.

2. Background and methodology

2.1. Background

The noise from WT's can be done by two main sources: aerodynamic noise, mainly by WT blades, and mechanical noise generated by rotating components (gearbox, generator, main axle and auxiliary equipment). Figure 2 shows different noises associated to the WT components. The noises increase with the WT size and rotation speed, varying from 90 to 105 dB [53]. The aerodynamic noise is generated by turbulences in blades [54]. The noise level depends of the size of the blades, the aerodynamic design, the rotational speed, the position of the rotor and the tower, the wind speed, among others [55], see Figure 2.

Figure 2. Noise emissions in the WT components [51].

This paper presents a novel approach for fault detection and diagnosis of the main rotatory devices located in the nacelle employing acoustic sensor embedded in UAVs. The noise generated by a WT is collected by the CMS and sent to a remote-control centre to be stored and analysed, see Figure 3.

Figure 3. Condition Monitoring System.

The environmental temperature has a relevant influence in the measurement process, reducing the frequency band and incrementing the sensitivity. Saeedivahdat et al. [56] developed a mathematical modelling that analyses the influence of the temperature in the acoustic acquisition system. For WT inspection, the temperature range of these types of operations does not cause any relevant influence in the operation in several conditions. The efficiency of the techniques to filter the undesirable noise have been demonstrated in literature [46,47]. This paper does not consider the environment conditions. According to the literature, the system proposed in this work would be suitable for outdoor conditions despite the temperature and noise influence.

Figure 4 shows the signal in the time domain obtained by the CMS. It does not report any information about the system condition. Noise wave is a non-periodic deterministic signal that can be given by different sinusoidal signals, and set by the frequency, wavelength, amplitude and compression [57,58]. The frequency analysis of the noise signals is usually done in time-frequency domain [59,60]. This paper employs wavelet transforms together with CNN for fault detection and diagnosis. The wavelet transform allows the analysis of non-stationary signals to be performed efficiently [61]. The signal is divided into a series of sinusoidal components to facilitate its analysis, assuming the seasonality of the signal [62,63].

Each signal is filtered eliminating the initial and final period of the signals, i.e., removing the periods that present wrong measurements. Several researchers have employed a time period

between 15 and 30 seconds to ensure a proper analysis [64]. For this case study, the time period analysed is set to 15 seconds. The sample frequency studied is 44100 Hz. Then, a pre-processing methodology employing wavelet transforms is applied to extract the main characteristics of the dataset (Section 2.2). Finally, CNN is used for fault detection and diagnosis employing as inputs the energies of the signals.

Figure 4.Noise signal in time domain.

It is demonstrated that the spectra analysis provides limited accuracy in this case due to the undesirable noise influence and the wide range of frequencies related with the noise sources from a WT [65]. Spectra analysis is mainly applicated in WT for analysing the fundamental wind conditions and blade noise [66]. Therefore, spectra analysis is not considered in this paper, being energy analysis employed in this study.

2.2. Wavelet Transforms

The wavelet transform filters the signal successively in the time domain by low-pass and high-pass filters, allowing the signal to be separated into low-frequency and high-frequency ranges. Therefore, it is possible to performance a deeper analysis employing this decomposition [67,68]. The wavelet transform is given by equation (1),

$$S(\tau, a) = \int_{-\infty}^{+\infty} s(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t - \tau}{a} \right) dt \quad (1)$$

where ψ^* is the conjugate of the mother wavelet, scaled and moved point to point to determine the levels of comparison of the signal $s(t)$. $a=f/f_0$ ($a \neq 0$) is the scale factor or dilation of the wavelet, with f_0 as central frequency and τ the translation in time [62].

The function scaling and shifting are related to the manipulation of the signal in order to launch the wavelet transformation. The wavelet transform can be analysed by Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). CWT could fall into redundant data generation since scale parameter s and translation parameter τ are changed constantly. Some of the common families of CWT are the Morse, Morlet and the Bump families [69]. Peter et al. [70] developed an approximation using the autocorrelation function of the CWT coefficients for a gearbox vibration signals analysis to detect fault pattern of the components. The increment of the CWT computational cost may discard this method to ensure the analysis efficiency.

DWT is an application of the wavelet transforms by a discrete set of wavelet translations and scales following some rules [71]. For example, Kim et al. [72] developed a DWT comparative study about the shaft-crack condition in acceleration deceleration process. The main difference with CWT is that DWT decomposes the signal into an orthogonal set of wavelets. There are different studies using DWT for fault diagnosis through nonstationary signal analysis in rotatory elements, using piezoelectric sensors to monitoring mechanical or electrical faults [73]. CWT and DWT allow the signal analysis in a similar way to the FT, but they can provide valuable information in the time and frequency domains [35]. The choice of the type of wavelet depends on several variables. This paper considers the DWT according to the properties of the signals.

The most used wavelet is the Haar, Daubechies and Symlet wavelets [74]. Due to its characteristics of orthogonality and biorthogonality, the transformed Symlet wavelet is used in its continuous or discrete form [27]. The Symlet family is used in vibration and acoustic analysis. The Symlet family was implemented by Kumar and Singh [75] in a condition monitoring bearing fault measurement. This family is given by equation (2).

$$\Psi(t) = \sum_{k=0}^{N-1} (-1)^k c_k \varphi(2t + k - N + 1) \quad (2)$$

The wavelet decomposition of a function $f(t)$ is given by equation (3):

$$f(t) = f^{(\varphi)}(t) + f^{(0)}(t) + f^{(1)}(t) \dots + f^{(i)}(t) + \dots \quad (3)$$

being:

$$f^{(\varphi)}(t) = a_0 \varphi(t) \quad (4)$$

$$f^{(0)}(t) = a_1 \Psi(t) \quad (5)$$

$$f^{(1)}(t) = [a_2 \ a_3] \begin{bmatrix} \Psi(2t) \\ \Psi(2t - 1) \end{bmatrix} \quad (6)$$

where $f^{(\varphi)}(t)$ is the -1st order wavelet component, $f^{(0)}(t)$ is the 0st order wavelet component, $f^{(1)}(t)$ is the 1st order wavelet component, ..., $f^{(i)}(t)$ are the levels of the decomposed signal $f(t)$ is the i^{th} order wavelet component, and $f(t)$ the digitized signal in the time domain with length N, where the value of N must be a power of two. The decomposition of the signal is done by equation (3) [76].

This paper has considered Symlet and Daubechies families, but Symlet provided better results. Due to the complexity of some acoustic signals, the use of various levels of decomposition and ramifications is required to determine the band of frequencies distributed by level, given by the wavelet decomposition tree. This iteration diagram had been also used in some vibrations studies as [31]. This representation of a sinusoidal wave signal (s) is decomposed in low frequency approximation coefficient (ca_i) and in high frequency detail coefficients (cd_i), being (i) the ordinal coefficient that provides the different decomposition levels [74]. However, this analysis does not provide the pattern classification in this acoustic engine inspection, and it a further analysis is necessary.

The acoustic noise produced from rotatory components, e.g., engine, gearbox, etc., or the propellers of the UAV, have different frequency ranges in comparison with other environmental sources such as the air or blades. Dividing this range into a set of consecutive frequency bands, it is possible to associate different AE signals to working and failure conditions, e.g., gearbox plates, rare friction or hubs misalignment, and, therefore, to filter or eliminate other undesirable signals. The definition of representative frequency bands is necessary to identify each failure mode [77].

The energy decompositions $E^{(\varphi)}(t)$, $E^{(0)}(t)$, $E^{(1)}(t)$, ..., $E^{(j)}(t)$ are given by equations (4-7) [78], i.e., the decomposed accumulative energy of different levels at any time t during the tests.

$$E^{(\varphi)}(t) = \sum_{\tau=1}^t (f^{(\varphi)}(\tau))^2 \quad (4)$$

$$E^{(0)}(t) = \sum_{\tau=1}^t (f^{(0)}(\tau))^2 \quad (5)$$

$$E^{(1)}(t) = \sum_{\tau=1}^t (f^{(1)}(\tau))^2 \quad (6)$$

$$E^{(j)}(t) = \sum_{\tau=1}^t (f^{(j)}(\tau))^2 \quad (7)$$

The total energy is given by equation (8):

$$E^{(T)}(t) = \sum_j (E^{(j)}) \quad (8)$$

3. Case Study and Experiments

The approach defined in this work is based on fault detection and diagnosis by analysing acoustic data of the motors located in the nacelle of the WT. Figure 5 shows the main motors employed for: fans (Figure 5.1); Gear oil pump (Figure 5.2); Oil pump for brakes (Figure 5.3), and; Water cooling pump (Figure 5.4).

Figure 5: WT devices studied: (1) Fans; (2) gear oil pump; (3) oil pump for brake; (4) water cooling pump.

The WT aerial inspection will be simulated in a test rig in order to validate this approach. The test rig has been validated previously by different research papers: the vibration signals from the test rig were employed to analyse the mechanical devices related to the gearbox-generator set of a WT. Wavelet transforms and Fast Fourier transform analysis were employed for signal analysis. The data were validated by a set of real motors in WT [32]. A similar approach was presented in reference [34], considering statistical methods. Reference [35] analysed the noise and vibration signals measured in the test rig, and a pattern recognition method was employed for fault detection and diagnosis. The noise signal was measured by acoustic sensors located fixed in the test rig, and they were analysed together with acoustic signals given by real devices of WTs. García et al. [79] employed the test rig with the signals mentioned, and also the temperatures given in the devices and the room temperature, voltage, rotation velocity and current.

The test rig is employed to study different WT conditions by the acoustic sensor embedded in the UAV. The acoustic signals are from the UAV and the test rig. Figure 6 shows the scheme and the test rig. The gearbox-generator set is given in Figure 6 (a) by (1, 7, 2). Figure 6 (a) (5) shows the UAV together with the acoustic sensor in Figure 6 (a) (6). The frequency variator is given by Figure 6 (a) (3), that is employed to set the rotation velocity. Finally, the computer and data acquisition equipment are shown in Figure 6 (a) (4).

(a)

(b)

Figure 6: (a) Diagram of the experimental set. (b) Real experimental set

The specifications of the acoustic sensor have a relevant influence on the sensibility of the CMS and quality of the data. The acoustic sensor is connected wirelessly with a receptor, with a power that can reach 50 mW, being possible to operate at 300 m of distance. The most relevant specifications of the sensor are detailed in Table 1.

Table 1 Acoustic Sensor Specifications.

Type	Electret Condenser
Polar Pattern	Cardioid
Frequency Response Range	20 to 20000 Hz
Output Impedance	150 Ω
Sensitivity	-41 dBV/Pa
Maximum SPL (1 kHz at 1% THD)	1000 Ω load: 139 dB
Dynamic Range (at 1 kHz)	1000 Ω load: 122 dB
Maximum operating distance	300 m without interferences

The UAV employed in the experiments was the XFOLD SPY with 6 rotors and DJI A2 navigation system, see Table 2. This model is employed for industrial applications due to reduced weight and great performance.

Table 2: XFOLD Spy specifications

Dimensions	25cmx25cmx10cm
Batteries	5200 mAh
Weight	3810 gr
Default propeller size	12"
Navigation system	DJI A2 with GPS system

The measurement conditions, e.g., room temperature and humidity, are constant during the experiments, and the influence of the environment conditions in the experimental process is not considered. The engine room is soundproof. The distance between the sensor and the test rig is constant for all experiments, except the scenario in experiment 0.3, where the distance between the test rig and the UAV is 5 m.

The measurement process in outdoor scenario requires a reliable wireless transmission between acoustic sensor and the ground station. The technical specifications of the system presented in this paper ensure that the CMS can work in outdoor conditions with an efficient data transmission. The environmental noises produced by the wind or other external sources increase the complexity of the signal processing, and novel techniques are required to remove noise from the useful signals. There are several types of research focused on the outdoor noise cancellation employing adaptative filtering, software algorithms and neural networks [80].

The rubber clamping of the engine is showed in Figure 7 (a). It has 4 silemblocks, while the generator has 3 rubber clamping. The silemblocks are located two on the right side and two on the left side in the engine. The generator has them placed in a tripod distribution: two in the area closest to the coupling and one at the end. It has been designed an elastic coupling between generator and engine axis, see Figure 7 (b), simulating the mechanical joints.

Figure 7: (a) Silemblocks in engine-generator. (b) Elastic coupling between the engine and the generator

The faults considered in the experiments has been done according to Gao et al. [81], shown in Table 3. The vibrations are generated by different conditions of silemblocks and varying the coupling between the engine and the generator. The experiments are divided in two scenarios: The first group analyses the normal working conditions of the UAV, the test rig without faults and the combination of both experiments at different rotation velocities (experiments 0, 0.1, 0.2 and 0.3). This scenario pretends to obtain the fundamental acoustic information about the components of the test rig and the rotation velocity conditions.

The second phase is given by experiments 1-5 to study misalignments. Misalignment is one of the most relevant fault in rotatory components, causing undesirable vibrations: Sekhar and Prabhu [82] modelled the misalignment with finite element method to analyse the influence of the vibrations. The temperature monitoring was employed by Tonks and Wang [72] to detect different modes of misalignment in WTs, measuring operating temperatures. The misalignment can be determined by SCADA data analysis [73]. To simulate the faults in this paper, silemblocks are removed from the engine and the generator to study the decoupling. The mechanic transmission is studied by using two types of coupling: elastic and rigid.

Table 3 Experiments.

Experiment	Type of experiment	Samples	Total
▼ First phase ▼			
0	UAV	15	15
0.1	Fault-free condition and different velocities without UAV (500, 750, 1000, 1250 rpm.)	15 at each velocity	90
0.2	0.1 with UAV	15 at each velocity	90
0.3	0.2 with velocities 750 and 1500 rpm. UAV at 5m to the test rig	15 at each velocity	60
▼ Second phase ▼			
1	Fault Free	15	15
2	Misalignment removing silemblocks from the right side of the engine.	15	15
3	Resistance in the coupling.	15	15
4	Misalignment removing 2 silemblocks close to the coupling in the generator.	15	15
5	Use of a rigid coupling.	15	15

4. Results

The results are analysed by patterns recognition. The algorithm developed is based on the 1-D discrete wavelet decomposition, and the output in the energy domain is studied. Experiments 0, 0.1, 0.2 and 0.3 are shown in Figures 8, 9, 10 and 11 respectively, where the wavelet decomposition is of 12 levels. The wavelet family used for this comparison has been the order 4 of the Symlet wavelet.

Figure 8. Energy percentage of each degree of decomposition box-plot graph for experiment 0.0 (UAV alone).

Figure 9. Energy percentage of each degree of decomposition box-plot graph for experiment 0.1 with the engine rotating at 750 rpm (test rig alone).

Figure 10. Energy percentage of each degree of decomposition box-plot graph for experiment 0.2 with the engine rotating at 750 rpm (UAV and test rig).

Figure 11. Energy percentage of each degree of decomposition box-plot graph for experiment 0.3 with the engine rotating at 750 rpm (engine with UAV 5 m to the test rig).

The main results obtained from Figures 9-12 are:

- It is observed that the decomposition levels 9, 10, 11 and 12 do not provide any clear pattern of the cases considered. The energy percentage at these degrees of decomposition is zero, or close to it, for each experiment. The wavelet decompositions will be done until level 8 in further analysis.

- Figures 9-11 present the same energy decomposition level distribution pattern. The maximum energy percentage is reached at level 3 of decomposition in experiments 0.0, 0.2 and 0.3. In experiment 0.5 (test rig alone), the energy percentage is low at level 3, and the maximum value is at level 4. Level 2 of decomposition seems very stable in all cases. Therefore, it will be the degree of decomposition chosen in this paper.

Figure 12 shows the linear increasing trend of the energy percentage according to the rotatory speed of the engine. Some outliers and irregular energy values are found at 500 rpm. Relatively wide distribution is given at 1000 rpm due to the large range of energy values obtained. The experiment at 1250 rpm presents outlier points, and the minimum of the boxplot are the same to the maximum boxplot at 1000 rpm. The energies found at 750 rpm do not present outliers and shows better patterns of the signals.

Figure 12. Energies at engine speeds of [500-750-1000-1250].

Figure 13 shows the energies obtained in the experiments of the first phase at 750 rpm: the first experiment considers only the UAV; The second considers test rig alone, and; The third and fourth experiments show the UAV and the test rig engine, being the UAV close to the test rig and then at 5 m. It is observed that the scenario with only the test rig provides lower energy, around 10% compared to other cases. The other experiments present similar energies, where the scenario with

the UAV shows more energy. All the energies are between the maximum and minimum values and, therefore, there are no outliers in UAV and test rig when they are studied alone. The cases of UAV+Test Rig in close distance and at 5 m present similar energies percentages, i.e., the distance between the test rig and the CMS has low influence in the energies of the signals. The specifications of the acoustic sensor allow measurements to more distance, but it has not been considered in this research work. The variance in the energies given by the wavelets is reduced when the distance between UAV and the test rig increase. In both cases, close distance and at 5 m, several outliers are observed, where the UAV+Test Rig at 5 m presents lower and upper outliers.

Figure 13. Energies in cases of the first phase at 750 rpm

The energies for 1 to 5 at 750 rpm are shown in Figure 14. The analysis has been done by pairs to obtain a better classification between different fault cases, analysed together with the fault free. Figure 14 (a) shows that the energy rises when a resistance is inducted. This is the same conclusion when any other fault is studied. The case of inducted resistance presents low accuracy for fault detection and diagnosis, and it will depend on the resistance severity. In this case, this approach should not be recommended. Figure 14 (b) presents a clear pattern for fault detection and diagnosis when there is a fault in the coupling. The cases where the silemblocks are removed from the engine present also a clear pattern according to the fault free case, see Figure 14 (c). Finally, the same conclusions from Figure 14 (c) are obtained in Figure 14 (d), where the silemblock are removed from the generator.

Figure 14. Second Phase. **(a)** Fault free and inducted resistance; **(b)** Elastic coupling and rigid coupling; **(c)** Engine with silemblocks and silemblocks removed; **(d)** Engine silemblocks removed and generator silemblocks removed

5. Accuracy and Validation

It has been done a statistical analysis of the wavelet families employed. The Daubechies wavelet transform family has been employed to validate the results given by the Symlet family applied in this paper. Tables 4 and 5 show the main statistical parameters given by the energies of the signals calculates by wavelets analysis employing both families, Daubechies and Symlet, considering the mean and standard deviation of the energies by each set of experiments.

Table 4. Statistical analysis of the results obtained in experiments 1 to 5 using different orders of Symlet wavelets for the signal decomposition performed.

SYMLETS														
	sym2		sym3		sym4		sym5		sym6		sym7		sym8	
Exp	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2
1	17,16	1,12	16,40	0,99	15,95	0,87	15,65	0,82	15,48	0,84	15,36	0,80	15,24	0,75
2	17,69	0,45	16,88	0,50	16,45	0,53	16,16	0,53	15,92	0,53	15,77	0,56	15,69	0,58
3	17,94	0,39	17,15	0,45	16,70	0,50	16,39	0,55	16,19	0,55	16,09	0,59	15,97	0,62
4	16,55	0,02	15,67	0,03	15,22	0,02	14,94	0,02	14,72	0,02	14,58	0,03	14,49	0,03
5	17,78	0,25	17,17	0,27	16,88	0,26	16,71	0,26	16,61	0,26	16,54	0,28	16,48	0,27

Table 5. Statistical analysis of the results obtained in experiments 1 to 5 using different orders of Daubechies wavelets for the signal decomposition performed.

DAUBECHIES																		
	db2		db3		db4		db5		db6		db7		db8		db9		db10	
Exp	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2	$\bar{X}$	σ^2
1	17,16	1,12	16,40	0,99	15,93	0,88	15,66	0,85	15,51	0,83	15,35	0,78	15,22	0,76	15,17	0,75	15,09	0,72
2	17,69	0,45	16,88	0,50	16,45	0,51	16,13	0,51	15,94	0,55	15,81	0,57	15,66	0,54	15,57	0,57	15,51	0,59
3	17,94	0,39	17,15	0,45	16,68	0,52	16,37	0,55	16,23	0,57	16,09	0,61	15,94	0,63	15,89	0,64	15,84	0,68
4	16,55	0,02	15,67	0,03	15,24	0,02	14,93	0,02	14,72	0,03	14,60	0,03	14,49	0,02	14,39	0,03	14,33	0,03
5	17,78	0,25	17,17	0,27	16,87	0,25	16,71	0,25	16,62	0,27	16,54	0,27	16,48	0,26	16,45	0,28	16,41	0,27

The accuracy of the approach has been set analysing the fault detection and diagnosis by CNN. The dataset of the experiments is divided into training phase, using 80% of the data, and the rest of the dataset is 10% for both validation and test phases. CNN requires an initial phase of feature extraction to define the first layer. The different layers of the network have several capabilities, e.g., a layer employed to reduce the spatial size, a layer connected with the activation functions of previous layers, etc. The accuracy of the training is around 81.25%. Figure 15 shows the confusion matrix of the process, reaching the 88,3% of total accuracy.

Output Class	1	25 20.8%	0 0.0%	1 0.8%	0 0%	96.2% 3.8%
	2	4 3.3%	30 25%	5 4.2%	1 0.8%	75% 25%
	3	1 0.8%	0 0.0%	24 20%	2 1.7%	88.9% 11.1%
	4	0 0%	0 0%	0 0%	27 22.5%	100% 0%
		85.3% 16.7%	100% 0%	80% 20%	90% 10%	88.3% 11.7%
		1	2	3	4	
Target Class						

Figure 15. Neural network confusion matrix.

Friedman tests has been employed to validate the results. Friedman test is a non-parametric statistical technique similar to ANOVA [83]. Let H_0 be the hypothesis that assumes that there is not difference between the nine scenarios, and H_1 be the hypothesis in the other cases, with a significance level $\alpha = 0.05$. This value is defined following the most widely value used in the state of the art. The p-value $< 0,05$ is required for contradicts de null hypothesis. It is obtained a p-value= $1,968e-23 < 0.05$, therefore, the null hypothesis H_0 is rejected.

6. Conclusions

This paper presents a novel non-destructive approach for fault detection and diagnosis in wind turbines. It is based on acoustic signals acquisition by a condition monitoring system embedded in an unmanned aerial vehicle. It has been employed a test rig to do the experiments. The acoustic data have been analysed by wavelet transforms, where the acoustic energy level decomposition has been optimized and validated by different wavelet transform families. A set of scenarios has been designed to consider the main faults in a wind turbine. The data has been analysed quantitative and qualitative analysis of the installation, establishing an accuracy percentage for the methodology. The quantitative is done by convolutional neural network. The main conclusions are summarised as:

- This study purposes a complementary methodology in the field of acoustic condition monitoring systems.
- The variations in the rotating velocity of the engine show a proportional increasing tendency of the signal energy. The data analysis using wavelet transforms allows the detection of the regimens of working conditions patterns for each experiment, considering frequencies and energy intervals.
- The fault-free condition produces energy ranges that vary significantly from the energy ranges obtained from the experiments with some misalignments in the engine. The energy values given by the rigid coupling or induced resistance are bigger than the fault-free conditions. It is probed the possibility of detecting noise patterns associated to these faults.
- The wavelet transforms by using the Daubechies and Symlets families provides similar results.
- The accuracy of the approach has been determined with the energy analysis of the signals. The accuracies found are between 75-100% according to the scenario.

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