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Structural Health Monitoring for Delamination Detection and Location in Wind Turbine Blades employing Guided Waves

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Abstract

Wind power is becoming one of the most important renewable energies in the world. The reduction in operating and maintenance costs of the wind turbines has been identified as one of the biggest challenges to establish this energy as an alternative to fossil fuels. Predictive maintenance can detect a potential failure at an early stage reducing operating costs. Structural Health Monitoring together with Non-Destructive Techniques are an effective method to detect incipient delamination in wind turbine blades. Ultrasonic guided waves offer possibilities to inspect delamination and disunion between layers in composite structures. Delamination results in a concentration of tensions in certain areas near the fault, which can propagate and create the total break of the blade. This paper presents a new approach for disunity detection between layers comparing two real blades, also new in the literature, one of them built with three disbonds introduced in its manufacturing process. The signals are denoised by Daubechies wavelet transform. The threshold for the de-noising is obtained by a wavelet coefficients selection rule using the Birgé-Massart penalization method. The signals were normalized and their envelopes were obtained by Hilbert transform. Finally, a pattern recognition based on correlations was applied.

Keywords: Delamination, Fault Detection and Diagnosis, Ultrasonic Guided Waves, Wavelet Transform, Non Destructive Tests, Macro Fiber Composite

1. Introduction.

The challenge for the future is to get a cheap source of energy, non-polluting, renewable and accessible to all countries in the world, allowing to reduce dependence on fuels to households, industries and transportation. Wind power is being one of the main energy sources globally. Its importance in the energy market is essential, and all the studies show that this trend will continue in the near future. The evolution of wind energy over the last 15 years suggests that its importance will continue to grow in the future [1]. Figure 1 shows the annual installed wind power capacity in the world from 2001 to 2017.

Figure 1 Annual installed wind power capacity in the world [2].

Wind Turbines (WT) are typically subject to high and varying loads, as well as extreme weather conditions. Consequently, the operational unavailability of WTs reaches 3% of the lifetime of a WT. The operation and maintenance costs can be 10%-20% of the total cost of energy for a wind farm, and it can reach 35% for a WT at the end of life [3].

It is necessary a high degree of maintenance to provide a safe, cost-effective, and reliable power generation. This is even more critical for offshore wind farms, where WT cannot be reached during adverse weather conditions.

Structural health monitoring (SHM) is employed to analyse the condition of a structure [4-6]. It is usually considered as part of a predictive maintenance strategy [7-9]. The objective is to extend the life cycle of the analysed system and prevent the triggering of critical failures, resulting in less cost and downtimes.

75% of the annual downtime in WTs is caused by only 15% of the failures [10]. It is more relevant to install the SHM in critical structural components that cause larger downtimes instead to the components that present more failure rate [11]. Haln *et al.* [12] present the average failure rate and downtime per component for a WT. Figure 2 shows that the failure of the blades occupies the fourth position in terms of unavailability time in a WT.

Figure 2 Failure rates and downtimes from two large surveys of European WTs over 13 years.

SHM can be used to determine the optimum equilibrium to set corrective and scheduled maintenance strategies in WTs [10,13,14]. Maintenance approaches in WT industry can be classified into three main groups:

- *Corrective maintenance*: The reaction is initiated after the failure occurs.
- *Preventive maintenance*: The operative period of a WT is around 20 years [12,15], and most of the failures are predictable using time-based strategies.
- *Predictive maintenance*. This strategy is based on the condition of the WT. It is possible to detect faults in an early stage by the structural condition of the parts of the machine [16].

The proposed methodology is applied for predictive maintenance for fault detection in the blades, e.g. surface cracking, disbonds, scuffing, pitting, etc. All the information analysed by the system is obtained through non-destructive techniques using transducers.

The main propose of this paper is to identify, by SHM techniques combined with signal processing methods, delamination in blade structures, being the approach new according to the state of the art.

There are several non-destructive techniques for inspecting WT blades, e.g. visual inspection, thermography [17,18], detection of acoustic emissions produced by a breakage of fiberglass [19-21] and conventional ultrasonic inspection [20,22-25].

The technique showed in this paper uses ultrasonic guided waves for inspection. It has been proven successfully in detecting faults in this type of material. It could be integrated into the SCADA system in the wind farm, and they could be complementary to other condition monitoring systems [26].

1.1. Wind turbine blades.

Blades are generally made with sandwich materials formed by composite skins and a core of lightweight materials and isotropic. The need to manufacture blades with a complicated geometry, low weight and adequate mechanical properties, has driven to choose these materials. It presents high resistance to the fatigue, and low thermal expansion and thermal conductivity. In addition, to increase the size of the blades creates new problems related with the loads and stresses [27,28].

A composite material is formed by long and straight fibers located within a matrix that surrounds and binds the fibers. Laminates are made by superimposed layers of fibers in the thickness direction [29]. The material properties depend on the orientation, stacking sequence and physical properties of these fibers.

Sandwich structures are composed by two outer skins covering a material that is lightweight, called core. This scheme provides characteristics of high rigidity and lightweight. The core is thick compared to the outer skins, and it has lower density. The core function is to prevent relative movement of the skin [30].

Most manufacturers use blades with polymeric matrix composite because it has lower prices and maintaining the structural properties. The e-glass is the most used fiberglass. Epoxy resins are generally used due to its mechanical properties.

The manufacturing process of the WT blades is a delicate process, because these blades support a continuous fatigue, that can cause stress concentration in areas with discontinuities [31].

1.2. Inspection with Ultrasonic Guided Waves.

The ultrasonic waves are mechanical waves that travel through an elastic medium (liquid, solid or gaseous) with frequencies over 20 kHz. A wave is generated when a particle is disturbed and vibrates around its equilibrium position, then it is displaced and returns to its position. The oscillatory motion is transmitted to the adjacent particles initiating the wave movement [32].

In thin structures with two surfaces, e.g. plates or shells, the energy of the wave is confined in its thickness, allowing the waves to propagate further. These properties are used to detect structural damages. The waves generated in these structures are called Lamb and Shear Horizontal (SH) waves, depending of the motion of the particles regarding to the wave propagation direction. They are useful tool for the detection of defects, e.g. as cracks, disbonds, changes in the thickness, etc.[33-39]

2. Properties of the wind turbine blades employed in the test.

The structures studied are two glass-fibre composite Wind Turbine Blades (WTB), one of them with 3 disbond areas between skin-honeycomb. The WTBs were built by the manufacturer *Encocam*. The blades are identical (Figure 3), but in the manufacturing process of one of them were introduced some elements to generate debonding between their layers. The purpose is to simulate delamination and debonding between layers in one of the WTBs, that entails a reduction in the performance of the blade.

Figure 3 Wind turbine blades used in the tests (damaged and undamaged)

2.1. Physical properties of the wind turbine blades.

The dimensions of both blades, as well as the sandwich area (limited by red lines), are shown in Figure 4.

Figure 4 Structural scheme of the WTBs

The configuration of the layers is shown in Figure 5. The composite is Glass Reinforced Plastic (GRP), that is a composite of tough resilient, durable plastic resin, and glass fibres of high strength. The resin employed is Epoxy resin. The laminate thickness is 4.6 mm with a tolerance of ± 0.5 mm. The number of layers used varies according to the area of the blade. The latching zone has 18 layers for increased strength, the transition zone (widening) has 12 layers, and the rest of the structure has 6 layers of fiberglass.

Figure 5 Layers configuration of the composite material. E-glass twill fiber (yellow) and E-glass biaxial fiber (grey).

The physical properties of the laminated configuration are presented in Table 1.

Table 1. Laminated physical properties used in the WTBs

The honeycomb employed is Aluminium honeycomb 4.5 1/8 5052. The honeycomb thickness is 15 mm and the overall sandwich panel thickness is 23 mm (Figure 6).

Figure 6 Composite and honeycomb sandwich (left) and aluminium honeycomb structure (right).

2.2. Introduction of defects in the manufacture process of the blade.

Three defects were introduced during the manufacture of the blade to simulate defects in the manufacture process, that can lead potential failures and large economic costs. The manufacturer *Encocam* inserted three Teflon PTFE nonstick tapes in the zones shown in Figure 7 to create the delamination and disbanding. The dimensions of the disbonds of A, B and C are 150x150 mm, 100x100 mm and 50x50 mm respectively.

Figure 7. Dimensional scheme of the damaged WTB (mm). A, B and C areas are the disbonds between the honeycomb and the skin.

The dimensions and details of the disbonds are shown in Table 1.

Table 2 Disbonds dimensions.

3. Experimental setup and Structural Health Monitoring System

The experimental setup is composed by an ultrasonic pulse-receiver, two transducers and two real blades (undamaged and damaged). The optimal location and number of the MFC sensors have been studied in the last few years [40-42]. Lamb waves are a type of guided waves that can be easily generated in structures such as plates or shells [43]. It can detect structural changes inside the material or on its surface [44]. Lamb waves propagation is confined between the two surfaces, and the attenuation is lower for this type of geometries. In addition, it is assumed to have the influence of temperature on Lamb wave propagation [45].

The pulse-receiver is Teletest Focus+. It is a Log-Range Ultrasonic pulse receiver with 24 independent channels, and output voltage of 300 V peak to peak with improved sampling resolution and filtering. The transducers used were Macro Fiber Composites (MFC) [46,47], the model M2814-P1 from Smart Material .

The following procedure has been repeated exactly in both blades, with the aim that the results are as similar as possible in the areas that are free-faults. The procedure has been performed in order to identify the areas with delamination in the damaged blade, where it is analysed regarding to the same area without delamination of the undamaged blade.

The method employed to collect the ultrasonic signals is *pitch and catch.*. The MFC were attached on the blade surface (Figure 8). A transducer working as transmitter is fixed on the tip of the blade. The position of the MFC transmitter does not change, while the MFC receiver is placed at different distances sweeping along the blade. The first position of the receiver was 100 mm from the transmitter, and the experiments were done increasing the distance 100 mm until the 3800 mm (38 different locations).

Figure 8 Experimental Setup and Transducers location on WTBs.

The signal generated by the emitting transducer was a five cycles sinusoidal shaped signal, modulated by a Hanning window. At each position, a frequency sweep was deployed from 10 kHz to 100 kHz, with steps of 5 kHz. The aim of this work is to find evidence in the signal that may determine that there is a fault in the WTB, analysing when the guided waves travel through the defects.

It was found that the signals containing more information were the 50 kHz signals. The 50 kHz signals of the 38 distances were pooled to analyze the correlation between them. Figure 9 shows the 38 signals from the 38 different locations (X axis) and the z axis shows each sample of each signal. The Y axis shows the amplitude of each signal, where it is possible to distinguish the different arrival of wave fronts for each location, as the sensor moves away from the transmitter.

Figure 9 50 kHz ultrasonic signals at different distances.

4. Fault detection and location.

4.1. Wavelet Denoising.

The wavelet transform is a powerful method that allows to identify the local characteristics of a signal in the time and frequency domain. It presents some advantages that improves the limitations of resolution and the loss of information presented by the Short-Time Fourier Transform or the Fast Fourier Transform [48]. The wavelet transform uses a variable window size and adapt it to the frequency according to the information within the signal is the high or low frequencies. The resulting signal from low pass filter is the Approximations (A_i), and the resulting signals from the high pass filter are the details (D_i) [49].

In the case of the multi-level filters (Figure 10), they repeat the filtering process with the output signals from the previous level, leading the wavelet decomposition trees. Additional information is obtained by filtering at each level. However, more decompositions levels do not always mean better accurate results.

The number of levels was set at seven regarding to the experiments, where it was found the highest percentage of information.

Figure 10 Decomposition of the signal employing wavelet transform (7 levels).

The Daubechies wavelet family were employed according to reference [50], where it is demonstrated that they are suitable for this type of signals because they are sensitive to sudden changes, and they handle with boundary problems for finite length signals, being their biggest advantage over other families.

The lower wavelet approximation is removed from the original signal to avoid the trend and other components that appear in the low frequencies (Figure 11).

Figure 11 Original signals (upper panel) and Wavelet decomposition approximations (lower panel).

The denoising of the signals is performed employing a multilevel 1-D Wavelet analysis using the Daubechies family. An overly aggressive filtering could eliminate information about the condition, e.g. small echoes that come from defects. The threshold for the de-noising is obtained by a wavelet coefficients selection rule using a penalization method provided by Birgé-Massart, which produces good results [51-53]. Figure 12 shows the original signals, the denoised signals, and the residual noise extracted by the Wavelet denoising filters. In contrast to other digital filters, the Wavelet de-noising filter does not produce an unwanted distortion of the characteristic parameters of the signals [54,55], e.g. time of flight.

Figure 12. Residual noise extraction using Wavelet Denoising filter.

The following signal processing is applied for all the 50 kHz signals of the 38 distances from the tip of the blade. Each signal is analyzed regarding to the previous signal. Therefore, the incoming signal from the sensor located at 20 cm to the transmitter is compared with the incoming signal from the sensor located at 10 cm, and the signals at 30 cm is compared with the signal at 20cm, etc.

The damage in the WTB should affect to form of the ultrasonic Lamb waves. Hence, if there is a damage between two adjoining measures, the correlation between both signals should be different than the correlations between signals in areas without damage. Figure 13 shows the filtered signals at 200 and 210 cm from the transmitter.

Figure 13 Received signals at 200 cm (green signal) and 210 (blue signal) cm from the tip of the blade.

4.2. Envelope and smooth.

The signals were normalized and their envelopes were obtained by Hilbert transform [44]. The Hilbert transform is an approach to study the energy distribution of a signal in the time domain. The energy envelope (Figure 15) was employed to identify local characteristics of the signal. A new Wavelet denoising filter is applied to smooth the envelope and to remove small peaks. The low frequency decompositions (approximations) are selected (Figure 14).

Figure 14 Envelopes of the signals employing Hilbert Transform and Wavelet denoising.

4.3. Correction method.

To highlight the differences between two discrete signals, "damaged" and "health", a correlation coefficient can be extracted by Equation 1:

$$\lambda_{xy} = \frac{N\sum_{i=1}^{N} x_i y_i - \sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{\sqrt{N\sum_{i=1}^{N} x_i{}^2 - (\sum_{i=1}^{N} x_i)^2} \cdot \sqrt{N\sum_{i=1}^{N} y_i{}^2 - (\sum_{i=1}^{N} y_i)^2}} \tag{1}$$

where λ_{xy} is the correlation coefficient of two Lamb wave signals, x_i and y_i. The length of the discrete signals is N samples [56,57].

When a signal is correlated with itself is called autocorrelation [58,59]. The autocorrelation is used in this paper to identify patterns within a signal, i.e. the periodicity hidden by the noise (Figure 15).

Figure 15 Autocorrelation of the signals at 200 cm (green signal) and 210 cm (blue signal) from the tip of the blade.

The pattern recognition approach is based on the autocorrelation of both signals. Then, the autocorrelation of one of the signals is divided by the autocorrelation of the other signal to emphasize the differences and to obtain the ratio curve between them (Figure 16). The singularity caused by the induced disbonds in the WTB is more recognizable in the ratio curve, and its corresponding to the location of the damage.

Figure 16 Ratio curve of the pair of signals at 200 and 210 cm.

5. Results.

The maximum values of the ratio curve correspond to the maximum differences between signals. An automatic identification algorithm that analyzed the peaks for each pair of signals has been done. The values of the higher peaks have been registered and they are shown in the Table 3.

Table 3 Maximum discrepancy between signals.

Figure 17 presents the results of the experiment. The damaged and undamaged blades have a discontinuity in common, that is the start of the sandwich zone. The three induced disbonds in the "damaged blade" are clearly found in the sections: 230-240; 290-300, and; 340-350 cm. It validates the effectiveness of the approach, where the ultrasonic waves are sensitive to these changes in the e-glass material, even at a distance of almost 4 meters.

Figure 17 Maximum of the ratio curve for each pair of signals.

6. Conclusions.

Wind turbine blades are critical elements, subjected to high loads and stresses, generating the disbond between the layers of the composite material. These defects are points of stress concentration, and often trigger breakage of the blade. A failure in the wind turbine blades could cause downtimes, especially in wind farms located in remote areas with difficult access, e.g. offshore wind turbines, providing considerable economic losses.

The paper proposes a solution for an optimal structural health monitoring for wind turbine blades. The approach presented in this paper is able to detect potential failures in the blade in an early state by employing ultrasonic guided waves.

Two wind turbine blades were manufactured to test the method, including three defects in one of them in the manufacturing process. An ultrasonic transmitter is located in the tip of the blade, and the sensor is moved along the blade. Then, a signal processing approach is employed to analyze the guided waves. The approach detected the start of the honeycomb within the blade in both blades, and the three disbonds in the damaged blade. It has been validated that the ultrasonic guided waves, despite the large attenuation in these composite materials, can determine the structural health of the blade at least 4 meters between transmitter and sensor. This paper demonstrates that would be possible to implement in actual wind turbine blades a network of sensors strategically arranged to cover the blade, or areas with higher probability of appearing defects, cracks or disbonds.

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APPENDICES

Table 4. Laminated physical properties used in the WTBs

IN-PLANE	**Panel**	**Units**
Longitudinal Modulus	1.612E+04	[MPa]
Transverse Modulus	1.612E+04	[MPa]
Poissons Ratio - Vxy	0.129	
- Vyx	0.129	
Shear Modulus	2.516E+03	[MPa]
FLEXURAL		
Longitudinal Modulus	1.604E+04	[MPa]
Transverse Modulus	1.604E+04	[MPa]
STIFFNESSES		
Longitudinal Stiffness - E * T	7.425E+04	[N/mm]
Transverse Stiffness - E * T	7.425E+04	[N/mm]
Shear Stiffness - G * T	1.159E+04	[N/mm]
Longitudinal Bending - El	1.307E+05	[N mm^2/mm width]
Transverse Bending - El	1.307E+05	[N mm^2/mm width]
Torsional - GJ	2.063E+04	[N mm^2/mm width]
NEUTRAL AXIS		
Longitudinal Bending	0.00	[mm] above mid-plane
Transverse Bending	0.00	[mm] above mid-plane
LAMINATE		
Weight	7.49	[kg/sq.m]
Core Thickness	0	[mm]
Total Thickness	4.61	[mm]

Table 5 Disbonds dimensions.

	Disbond A	**Disbon B**	**Disbon 3**
area (mm^2)	50x50	100x100	150x150
Thickness (microns)	25	25	25
Type	TEFLON PTFE	TEFLON PTFE	TEFLON PTFE
Location	See in Figure 7	See in Figure 7	See in Figure 7

Table 6 Maximum discrepancy between signals.

	Distance form tip (cm)	Maximum of Ratio Curve	Zone
1	10 – 20	3,99	
2	20 – 30	4,06	
3	30 – 40	1,09	
4	40 – 50	1,22	
5	50 – 60	3,76	
6	60 – 70	1,50	
7	70 – 80	4,56	
8	80 – 90	21,44	Start of Honeycomb
9	90 – 100	1,34	
10	100 – 110	12,75	
11	110 – 120	1,14	
12	120 – 130	3,43	
13	130 – 140	4,99	
14	140 – 150	4,02	
15	150 – 160	1,24	
16	160 – 170	6,43	
17	170 – 180	2,53	
18	180 – 190	13,58	
19	190 – 200	7,47	
20	200 – 210	1,46	
21	210 – 220	6,12	
22	220 – 230	1,36	
23	230 – 240	19,87	Disbond A
24	240 – 250	8,77	
25	250 – 260	6,63	
26	260 – 270	3,53	
27	270 – 280	4,74	
28	280 – 290	2,34	
29	290 – 300	22,62	Disbond B
30	300 – 310	1,63	
31	310 – 320	2,77	
32	320 – 330	12,69	
33	330 – 340	2,21	
34	340 – 350	19,48	Disbond C
35	350 – 360	1,33	
36	360 – 370	9,29	
37		8,27	