NOVEL APPROACHES FOR MAINTENANCE MANAGEMENT ON WIND TURBINES

by

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Nomenclature: Authors Names, Year. Title, Journal Details. [IF (impact factor), X/Y (Journal Position/Total number of journals into the Subject Category), Subject Category].


Outcomes

Books (chapters)


International conferences (full papers in proceedings)


**Master dissertation**


**Degree projects co-direction**

Outcomes


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<td>A</td>
<td>Approximations.</td>
</tr>
<tr>
<td>AE</td>
<td>Acoustic Emission.</td>
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<td>ARX</td>
<td>Autoregressive exogenous.</td>
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<tr>
<td>CBM</td>
<td>Condition Based Maintenance.</td>
</tr>
<tr>
<td>CM</td>
<td>Condition Monitoring.</td>
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<tr>
<td>CWT</td>
<td>Continuous Wavelet Transform.</td>
</tr>
<tr>
<td>D</td>
<td>Details.</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform.</td>
</tr>
<tr>
<td>FDD</td>
<td>Fault Detection and Diagnosis.</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform.</td>
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<tr>
<td>GPR</td>
<td>Ground Penetrating Radar.</td>
</tr>
<tr>
<td>GWT</td>
<td>Guided Wave Testing.</td>
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<tr>
<td>MFC</td>
<td>Macro Fibre Composites.</td>
</tr>
<tr>
<td>NDT</td>
<td>Non Destructive Test.</td>
</tr>
<tr>
<td>RAMS</td>
<td>Reliability, Availability, Maintainability and Safety.</td>
</tr>
<tr>
<td>RCM</td>
<td>Reliability Centred Maintenance.</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>SHM</td>
<td>Structural Health Monitoring</td>
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<tr>
<td>STFT</td>
<td>Short Time Fourier Transform.</td>
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<td>WT</td>
<td>Wind Turbine.</td>
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Summary

The renewable energy industry is in a constant improvement in order to cover the current demands. Companies are competing to take advantage of any evolving opportunity presented. Nowadays one of those remarkable competitive advantages focuses on maintenance management and some terms such as operating and maintenance costs, availability, reliability, safety, lifetime, etc. emerge.

Wind turbines (WT) are one of the fastest growing sources of renewable energy production [61]. The number of WTs and their complexity has increased in recent years, reducing the reliability of systems and raising the maintenance costs due to the occurrence of non-monitored failures [151] and [128]. There are case studies that present specific faults and consequent maintenance activities on WTs but they depend on the model considered, the geographic and environmental changes that occur in different wind farms, etc.

Techniques such as condition monitoring (CM) are employed to detect and identify these failures/faults at earlier stages, maximising the productivity performance, minimising possible downtimes of the WT, and increasing the reliability, availability, maintainability and safety (RAMS) levels [59].

CM is implemented from basic operations of the equipment to study [61]. The system provides the “condition”, the state of a characteristic parameter that represents the health of the component(s) being monitored. Reliable
data acquisition can be achieved with the optimal type and placement of sensors as well as employing the appropriate number of them. Conditioning also reduces the susceptibility to interferences during the features transport. Data processing, sorting and manipulation according to the objectives pursued, are usually performed by a digital signal processor. Then it can be shown via a screen display, stored or transmitted to another system.

As part of some fault detection and diagnosis (FDD) approaches, features are extracted via CM. FDD is based on different methods employed to obtain the information needed from these features [58]. For example, the most used technique for CM in WTs is vibration, while the most studied components are mechanical components such as gearboxes, blades or bearings.

FDD relies on the number and type of sensors used and the processing and simplification methods employed to extract the information from the signals. Once information is obtained, an electronic measuring system provides the suitable data to an observer or other technical control systems. Therefore the three main block functions in a measurement system are data acquisition, data processing and data distribution. The information about the variables measured is turned into an electrical signal. The main advantages offered by these FDD systems are:

- The prediction, reduction and elimination of downtimes.
- The reduction of energy, maintenance and operating costs.
- The use of monitoring alert notifications.

**Keywords**

- Maintenance management
Summary

- Wind turbine
- Fault detection and diagnosis
- Condition monitoring
- Macro fibre composites
- Pattern recognition
- Wavelet transform
1. Introduction

The objectives of this dissertation will be focused on FDD for the main components of a WT. On the one hand, driving motors placed in the nacelle are examined and, on the other hand, the health of structures is analysed. Both cases are configured in two phases: a first experimental part and a second real part on a WT. When authors discuss about the CM of WTs, they do not usually refer to these locations and maintenance techniques are related to structures such as blades [37] and electrical or electronic components [68]. Thus, this thesis is intended to fill a gap so far unexploited.

The experimental tests of the motors are made from an engine and generator test rig. It represents the mechanisms that are found in cooling devices (for generator, gearbox), electric motors for service crane, yaw motors, pitch motors, pumps (oil, water) depending on the sub system configurations, ventilators, etc. Sound will be the link between the real and the experimental part in this case study. The signal is decomposed into different frequencies by the wavelet transform technique, and a percentage of energy is related to each frequency. The selection of the wavelet transform is based on the fact that unlike vibration, where the study of the sources and consequential analysis can be widespread, the noise analysis is complex from the time and frequency domain point of views. The study of a same engine in similar operating conditions can present different sound signals. This is due to fluctuations in rotational speeds and the non-ideal
1. Introduction

stationary performance of the sound sources [19]. The use of some methods, e.g. power spectrum density, are not advised for these reasons. It is observed that the stability of the signal from the energy is not so noticeable using the wavelet transform, and the results remain almost unaffected.

Vibration patterns are also developed from fast fourier transform (FFT) to support the results. FFT is useful to find potential faults such as misalignment, looseness, unbalances, etc.

Finally, a novel pattern recognition is developed for acoustic signals and vibration analysis. A set of faults are induced in different experiments to obtain it. The pattern recognition determines the location of the failures using a three-dimensional grid.

Furthermore, to complete the analysis in driving mechanisms, measurements are taken in an operating WT through a portable equipment consisting of a set of sensors, a data acquisition board and a laptop. Again the sound is studied by the wavelet transform. Data collection is performed in different periods of time, while the WT is working in fault-free conditions. The objective is to relate these real conditions with the experimental set in order to extend the results from the test bench to the WT.

The structural health monitoring (SHM) study of the structures starts with the collection and analysis of data on a pipe. Non-destructive tests (NDT) for CM are implemented from ultrasound signals to detect structural damage in joints, cracks or corrosion. The wavelet transform is proposed to process the ultrasound signals employing macro fibre composites (MFC). These signals are converted into voltage and their relation with the temperature is analysed through a pattern recognition that is contrasted
1. Introduction

with coefficients of determination. A second experimental set is designed with the aim of forecasting the behaviour of some structures. A pulse-echo is getting via piezoelectric transducers that are also employed as sensors. The signal processing is based on two steps. Firstly, a wavelet transform is applied to the measured signals with filtering purposes, in order to enhance the signal to noise ratio. Secondly, a time series modelling approach is employed for pattern recognition. An experimental platform is proposed to test the procedure, where pulse-echo experiments were employed before and after a fault occurred. The model can anticipate faults and failures, reducing the preventive/corrective tasks and costs, and increasing the availability and the energy production.

Finally, a tower is inspected to conclude with the CM of structures of WT. To expand the study of failures, the wavelet transform is used to analyse directly an ultrasound signal taken from the tower. Detection of imperfections can be developed from the shape and amplitude of signals. The method reports a number of improvements over other alternatives that will be detailed in this thesis.

1.1 Motivation

The reduction of costs without affecting the quality standards is a common strategy developed by companies in order to make WT's competitive with other renewable energy sources. The current trend to achieve this objective is focused on reducing variable costs, especially for operation and maintenance tasks.

The decrease of non-productive hours and the design of new models are some measures that achieve this reduction, especially those costs related to manpower [83]. The introduction of new maintenance programs is also important for this purpose. Nowadays, several options from CM are
1. Introduction

emerging. Some of them achieve a cost reduction to be considered in comparison to investment costs. It has been shown that these types of maintenance are effective in other sectors such as railways, SHM, etc., so that its application into WTs maintenance could be a feasible solution. However it cannot be ensured when maximum reliability is needed due to the novelty character of wind energy.

CMs perform continuous monitoring of WT components to check health conditions. Once data are collected, a FDD can be done to determine specific maintenance tasks before the problem becomes a catastrophic failure. Typically such failures are undesirable because involve major shutdowns to recover the replacement of the overall WT.

This dissertation provides an approach using wavelet technology among other supporting techniques. This approach is made on driving motors and structures whose maintenance is not as widely described in the literature as in the case of other components, e.g. bearings or gearboxes.

Thus, the maintenance schedules are enhanced to:

- Reduce maintenance costs.
- Reduce investment costs.
- Improve safety.
- Improve the replacement of components or structures.

1.2. Research aim and objectives

The main purpose of this dissertation is to improve the maintenance management in those motors or structures of WTs that have not been taken into account so far as it has been justified above. Therefore a brief summary of the objectives will be:
1. Introduction

- To introduce the state of art and current maintenance policies for WTs.
- To introduce the wavelet transform technique and the MFCs sensors in the field of this research.
- To simulate and analyse the performance of driving motors from the sound to create a pattern recognition based on sound instead of vibration, reducing the costs related to the sensors but maintaining the system reliability.
- To analyse the performance of structures from ultrasound using MFCs sensors in order to find potential failures like cracks, corrosion, etc., using a high sensitive technique in the case of temperature and an accurate method to forecast the failures in the WT structure case studies.

1.3. Thesis overview

This document is structured in eight chapters covering the material required to meet the objectives presented in Section 1.1, and it is organized as follows:

- Chapter 1. The introductory chapter presents the background that motivates the development of this thesis and establishes the objectives set.
- Chapter 2. It introduces a review of the state of WTs, types of maintenance and the CM techniques applied to them. Most important sensory signals and signal processing methods are also referenced.
- Chapter 3. Third chapter presents the wavelet transform, stating the most significant families and applications found.
- Chapter 4. Fourth chapter is a brief resume focused on the FFT and its use in different areas.
1. Introduction

- Chapter 5. Likewise previous chapters, the MFCs transducers are introduced and some examples of research areas where the sensors can be found are explained.
- Chapter 6. This section details the CM for driving mechanisms of a WT. The relevance of the sound is explained along with the experimentation and creation of a pattern recognition. The case study of the WT is subsequently shown and to conclude this section, the resemblances between the experimental set and the motors of the WT are highlighted.
- Chapter 7. This chapter praises the importance of the ultrasound analysis in structures. This chapter is divided into three sections. Experiments are done with pipes to develop a new pattern, this time in combination with temperatures in the first one. In the second section, tests are made in plates to predict their performance regarding different types of defects. The wavelet transform acts as a filtering process and forecasting are carried out from an autoregressive model. Finally, a FDD program is established using the wavelet transform in the tower of a WT.
- Chapter 8. The last chapter is devoted to the final conclusions and suggestions for future works are given.
2. Wind Turbines

2.1. Background

The use of renewable energies is in constant increase due to the emergence of the environmental awareness concept. The progress of these energies became clear from the Kyoto Protocol (Japan, 1997) which claimed for a reduction of the noxious gas emissions, although its origin started from the oil crisis registered in 1973. It is expected that in the coming years, renewable energies play an important role, representing a 20% of the total production in the European Union and reaching values close to 50% in 2050 [52]. Today, still far from achieving this limit, the capacity of wind energy produced is about 6.3% in the European Union [64]. However, wind power holds a preferential position within renewable energies and many forecasts show that its capacity is increasing [170]. In 2010, worldwide capacity was around 200 MW, and it is expected to grow to 1200 MW in 2020 (Figure 1).

WTs are one of the most important sources of energy production at present. The life cycle can be up to twenty operational years, but some components have a shorter life. The output power of a WT has gone from 50 kW to 6 MW, although more powerful turbines are under development. This growth has gone hand in hand with sizes and capabilities, which have increased their complexity when WTs are built and inspected. It is estimated that more than half of the costs incurred by a WT correspond to
2. Wind Turbines

maintenance. Figure 2 shows a component cost layout for a WT. Depending on the WT; these costs can have a different distribution.

**Figure 1.** Wind energy capacity: Total installed and forecastings [177].

**Figure 2.** Distribution of the component costs for a WT [129].

Its fast growth makes the reduction of operating costs, availability, reliability, lifetime and maintenance costs a priority in order to create a real competitive against other energy sources. It is in maintenance
purposes where there is a need of improvement and for this reason the term CM appears [86]. Not all the components of a WT have the same level of criticality, or fail after a specific lifetime; therefore unscheduled downtime can be costly and generates uncertainty [10]. The CM will be responsible to improve these two aspects.

Most of the WTs are three-blade units [114]. Once the wind drives the blades, the energy is transmitted via the main shaft through the gearbox to the generator supported by the bearings. At the top of the tower, assembled on a base or foundation, the housing or nacelle is mounted and the alignment with the direction of the wind is controlled by a yaw system. There is also a pitch system in each blade. This mechanism controls the wind power and sometimes is employed as an aerodynamic brake. The WT features a hydraulic brake to stop when it is necessary. Finally, there is a meteorological unit that provides information about the wind (speed and direction) to the control system (Figure 3).

**Figure 3.** Parts of a turbine: (1) blades, (2) rotor, (3) gearbox, (4) generator, (5) bearings, (6) yaw system and (7) tower [74].
2. Wind Turbines

There are problems such as leaking or corrosion that can be detected by visual inspection, e.g. when the surface of a WT changes its colour, i.e. there are significant variations in temperature or assembly deterioration [74][75]. The sound from the bearings is other important factor that indicates problems of physical nature. However, the WT maintenance in others cases requires more sophisticated techniques in other cases.

2.2. Maintenance in Wind Turbines

Maintenance is a key tool to ensure the operation of all components of a set. One of the objectives is to use the available resources efficiently. The classical theory of maintenance is focused on the corrective and preventive maintenance [18]. Corrective maintenance takes place when the detection of the problem comes after the occurrence of the fault and a subsequent breakdown. In these cases, the change of the defective component causes a loss of time and costs. By contrast, preventive maintenance goes a step further and anticipates the failure. To take forward this maintenance is necessary to have a schedule that sometimes leads to unnecessary costs when a replacement is not needed yet.

2.2.1. Reliability Centred Maintenance

Reliability centred maintenance (RCM) determines what must be done to ensure that any physical asset works in its operating context [147]. Nowadays it is the most common type of maintenance for many industrial fields [56] and [57] and it involves maintenance system functions and/or identification of failure modes among others maintenance tasks [108].

2.2.2. Condition Based Maintenance

An effective alternative to corrective and preventive maintenance is Condition Based Maintenance (CBM), which ensures the continuous
monitoring and inspection of the WT, detecting emerging problems and
organising maintenance tasks that anticipate the failure [124]. CBM implies
acquisition, processing, analysis and interpretation of data and the
selection of proper maintenance actions. This is achieved using CM systems
[59] [60]. Thereby, CBM is presented as a useful technique to improve the
maintenance and safety of equipment. Byon and Ding [27] or McMillan and
Ault [105] have demonstrated its successful application in WTs, making the
CBM one of the most employed strategies in the industry.

CBM systems operate from different types of sensors and signal processing
equipment. They monitor components ranging from blades, gearboxes,
generators to bearings or towers. Monitoring can be processed in real time
or in packages of time intervals. The procurement of accurate data will be
critical to determine the occurrence of a problem and determine the
solution to apply. In conclusion, the success of a CBM system will be
supported by the number and type of sensors used and the signal collection
and processing.

Techniques available for Condition Monitoring

Among the techniques applied to CM in WT, those listed below are
highlighted.

Vibration analysis

Any element that performs a rotation is susceptible of being analysed by
vibration. In the case of the WT, vibration analysis is mainly specialized in
the study of gearboxes [103][104] and bearings [161][167]. Different types
of sensors will be required depending on the operating frequency: position
transducers, velocity sensors, accelerometers or spectral energy emitted
sensors.
2. Wind Turbines

Acoustic emission

Techniques based on NDTs are beginning to gain importance. Acoustic Emissions (AE) describe the sound waves produced when a material undergoes stress as a result of an external force [73]. They can detect the occurrence of cracks in bearings [165] and blades [174] in earlier stages.

Ultrasonic testing techniques

Ultrasonic tests evaluate structural surfaces in WT [46][50]. Consistent with some other techniques, it is able to locate faults safely.

Oil analysis

Oil analysis, as well as AE, may determine the occurrence of problems in early stages of deterioration. Oil analysis is usually a clear indicator of the wearing of certain components. The technique is widely used in the field of maintenance, being very important for gearboxes in WT [95].

Thermography

Thermographic technique is established for monitoring mainly electrical components [146]; although its use extends to the study of abnormal temperatures on the blade surfaces [135]. Using thermography, hot spots can be found due to bad contacts or a system failure. It is common to find online monitoring systems based on the infrared spectrum.

Other techniques

There are techniques that not being so common, are used in the maintenance of WT. In many cases, their performance is heavily influenced by the costs or excessive specialization, making them not always feasible. Some examples are strain measurements in blades [142]; voltage...
and current analysis in engines, generators and accumulators [141]; shock pulse methods detecting mechanical shocks for bearings [26] or radiographic inspections to observe structural conditions [127].

**Sensory signals and signal processing methods**

Data acquisition is the first step of the CM process. Regardless of the technique, the number and type of sensors, and the extraction and processing of the signals will be significant factors. Data acquisition involves measuring the required variables (e.g. sound, vibration, voltage, temperature, speed) and turning them into electronic signals. The main methods for signal processing are presented.

*Fast Fourier Transform*

The FFT converts a signal from the time domain to the frequency domain. Each frequency range is framed into a particular failure state. There is extensive literature demonstrating the development of the method for rolling elements. Section 4 will explain the technique along with several application examples.

*Wavelet transform*

The wavelet transform is a time-frequency technique similar to Short Time Fourier Transform (STFT) although more effective when the signal is non steady. Wavelet transforms decompose an input signal into a set of levels at different frequencies [157]. Wavelet transforms have been applied to the FDD of various WT parts. Section 3 is related to wavelet transforms, including a wide description and main uses.

*Hidden Markov models*
2. Wind Turbines

A hidden Markov model is a statistical model where the system being modelled is assumed to be a Markov process with hidden states. A hidden Markov model can be considered as the simplest dynamic Bayesian network [15]. Ocak and Loparo presented the application for the bearing fault detection [116].

Statistical methods and trend analysis

In many occasions a statistical study of the data received is enough. In these cases, common statistical, i.e. the root mean square or peak amplitude to diagnose faults are employed. Other parameters can range from maximum or minimum values, means, and standard deviations to energy ratios or kurtosis. Moreover, trend analysis refers to the collection of information in order to find a trend.

Other methods

There are methods that, as it happened with the techniques available for CM, are specific and therefore they are used for selected situations. Filtering methods, for example, are designed to delete any redundant information, removing unnecessary overloads in the process. Analysis in time domain monitors WT faults as inductive imbalances or turn-to-turn faults. Other methodology, the power cepstrum, defined as the inverse Fourier Transform of the logarithmic power spectrum [176], reports the occurrence of deterioration through the study of the sidebands. Time synchronous averaging, amplitude demodulation and order analysis are also signal processing methodologies used in WT.
3. Fast Fourier Transform

3.1. Introduction

The FFT is a well-known mathematical algorithm, so although a chapter is introduced in this thesis, it is presented as a brief summary.

The FFT of a function $f(x)$ is defined as [25]:

\[ \int_{-\infty}^{\infty} f(x)e^{-i2\pi sx} dx \]  \hspace{1cm} (1)

This integral, which is a function of $s$, may be written as $F(s)$. Transforming $F(s)$ by the same formula, equation (2) is obtained, where $F(s)$ is the Fourier transform of $f(x)$:

\[ \int_{-\infty}^{\infty} f(s)e^{-i2\pi xs} ds \]  \hspace{1cm} (2)

The use of the FFT is extended for analysis in the frequency domain, allowing a spectral representation and a deeper insight into potential problems [115]. It is helpful when periodic patterns are searched [8]. Vibration analysis also provides information about a particular reason of the fault origin and/or its severity [88].

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3. Fast Fourier Transform

3.2. Fast Fourier Transform applications

Due to the entailment to vibration, the FFT is introduced into processes where there are rolling elements such as engines or generators [70]. Although this is the main connection, FFT can be used for other types of analysis or failure detection.

3.2.1. Wind Turbines

The wide variety of existing WT's makes also diverse the inclusion of novel techniques that ensure their correct operation. The FFT is one of the most frequent analytical methods used for this purpose.

Within the WT engines, the main efforts are focused on bearings to detect the occurrence of failures in early stages [79]. Diagnoses from generators can find incipient faults on drive trains. The main advantage is that the signal to be analysed is easily detectable. Some authors suggest the use of techniques such as FFT for the analysis [17]. While in contrast, it must be taken into account the considerations of the method since the operation is predominately non steady due the stochastic performance of the wind speed [9].

The study of the storage capacity, the demand response and the ensemble of generators is studied from a power spectrum and FFT [11]. Swartz et al. [163] introduce it on WT structures to check the status of the tower from its vibration. The monitoring is done using wireless communication systems. Therefore although the area of study is ground-breaking, it can be observed that the technique is fairly widespread.
3. Fast Fourier Transform

3.2.2. Other applications

As aforementioned, the analysis of vibration signals is the most exploited technique for CM of rolling machines. However, sometimes the diagnoses are constrained and additional features are needed to obtain accurate results. As a consequence, the FFT is typically supported by other types of signals, e.g. acoustic signals, even when it is well known that sound has inferences to be considered [100][101].

On the other hand, there are other fields of research where the FFT still achieves the set objectives despite its less novel character and limitations. The case studies on engines are a clear example: It is known that the early diagnosis in diesel engines ensures reliable operation over its lifetime. Fault detection in the crankshaft through the FFT has proved to be enough effective for this purpose [32]. Misalignments are other of the most common defects observed in rotors. The effect of misalignment is studied to determine the nature and extent of this phenomenon by FFT [121].

New lines of research dissociate the FFT to vibration and for example, the analysis of the acoustic radiation emitted from axisymmetric bodies is carried out using FFT [180]. Noise tracking methods for non-invasive study of defective structures from acoustic signals also introduces the technique [145]. Depending on the material, there are properties that directly affect the durability and safety of these structures and the consolidation of the FFT for the study of ultrasonic suits with precision [30].
4. Wavelet transform

4.1. Introduction

The wavelet transform is a method of analysis that identifies local characteristics of a signal in the time and frequency domain, e.g. with the use of a series of decomposition coefficients at different frequency bands [51]. Its use is recommended for large time intervals where great accuracy is required at low frequencies and vice versa, e.g. small regions where precision details are required at higher frequencies [48]. The wavelet transform is also a useful method to characterize and identify signals with spectral features, unusual temporary files and other properties related to non-standing waves.

Some authors define it as an improved alternative to the FFT or the Short-Time Fourier Transform since none of them are able to obtain good results in the time domain [81][107]. The signal processing from the time domain to the frequency domain by these methods usually implies the loss of information, making difficult to determine the appearance of specific frequencies [113].

Wavelet transforms are commonly categorized as continuous wavelet transforms (CWT), discrete wavelet transforms (DWT) or wavelet packet transforms (PWT). The difference between them is that the CWT provides more detailed information while the DWT is efficient with fewer
4. Wavelet transform

parameters [33]. The PWT is an extension of the DWT with a larger number of filtering levels.

CWT can be written from the translation and the scale change of the function $\psi_{s,\tau}(t)$, called mother wavelet, which is given by equation (3):

$$
\psi_{s,\tau} = \left(\frac{1}{\sqrt{s}}\right) \psi\left(\frac{t - T}{s}\right) 
$$

(3)

where $s$ is the scale factor, and $\tau$ is the translational factor.

Different functions generated from the same function $\psi(t)$ can have different $s$ and $\tau$, but the same shape. Scale factors are always $s>0$. The wavelets are dilated when $s>1$ and contracted when $s<1$ in order to cover different ranges of frequencies. Large values of $s$ correspond to lower frequency ranges. Small values of $s$ correspond to higher frequency ranges.

The CWT $W_f (s,\tau)$ of a function $f(t)$ will be the decomposition of $f(t)$ in a set of functions forming a base with the conjugate of the mother wavelet ($\psi^*_{s,\tau}(t)$). It is defined in equation (4) [173][140]:

$$
W_f (s,\tau) = \int f(t) \psi^*_{s,\tau}(t) dt 
$$

(4)

DWT introduces a scale discretization given by equation (5) to reduce the redundant information resulting from the continuous changes of the scale and translational parameters:

$$
W_f (i, j) = \frac{1}{\sqrt{2^i}} \int f(t) \psi^*\left(\frac{t - j2^i}{2^i}\right) dt 
$$

(5)

where $s=2^i$ and $\tau=k2^i$ are dyadic scales.
Signals are divided therefore into low frequency *approximations* \((A)\) and high frequency *details* \((D)\), where the sum of \(A\) and \(D\) is always equal to the original signal. The division is done using low pass and high pass filters (Figure 4) \cite{[28]}. In order to reduce the computational and mathematical costs of data duplication, a sub-sampling is usually implemented, containing the half of the collected information from \(A\) and \(D\) without losing information.

The use of DWT is supported by the energy spectrum and multilevel filters when complex calculations are needed \cite{[178]}.

The energy spectrum is based on Parseval’s energy theorem \cite{[54]} and it is presented as in the equation (6):

\[
\sum_{t=0}^{N-1} |x(t)|^2 = \frac{1}{N} \sum_{f=0}^{N-1} |x(f)|^2
\]

(6)

where \(x(t)\) is a signal in the time domain, \(x(f)\) is a discrete signal of the Fourier transform and \(N\) is the sampling period. If \(x(t)\) is defined from \(A\) and \(D\):

\[
x(t) = A_j + \sum_{j=1} D_j
\]

(7)
4. Wavelet transform

The equation can be rewritten as follows:

\[
\sum_{t=0}^{N-1} |x(t)|^2 = \frac{1}{N} \sum_{f=0}^{N-1} |A_j(f)|^2 + \sum_{j<J} \left[ \frac{1}{N} \sum_{f=0}^{N-1} |D_j(f)|^2 \right]
\]

(8)

In the case of the multilevel filters, they repeat the filtering process with the output signals from the previous level. This leads to the so-called wavelet decomposition trees (Figure 5) [5]. Additional information is obtained filtering at each level. However, more decompositions levels do not always mean accurate results.

![Wavelet decompositions tree](image)

**Figure 5.** Wavelet decompositions tree.

4.2. Wavelet families

The concept of wavelet has evolved during the last decades and new families of wavelet transforms are emerging. The most recurrent families of wavelet transforms are Haar, Daubechies or Symlet transforms among others. The selection of a particular family can be set by the application where the wavelet is introduced. Haar wavelets are considered as the Daubechies wavelets in its simplest form [69]. Daubechies wavelets are the most used wavelets, representing the foundations of wavelet signal processing for DWT. They lead more accurate results in comparison to
other families [123]. Symlet wavelet transform is an orthogonal wavelet
defined by a low pass filter [12]. Some other wavelet families, along with
the aforementioned, are described in the following paragraphs.

**Daubechies wavelet transform**

Daubechies wavelets are defined as a family of orthogonal and smooth
basis wavelets characterized by a maximum number of vanishing moments
[62]. Daubechies wavelets handle with boundary problems for finite length
signals, being their biggest advantage over other families [125][179].
Wavelets have not an explicit expression except for order 1, which is the
Haar wavelet. The inability to present a wavelet by a particular equation is
the general trend for almost all the types of wavelet families [156].

**Haar wavelet transform**

Haar wavelets are the simplest orthonormal wavelets. They are one of the
earliest examples of wavelet transforms. These families are represented
from an odd non-continuous rectangular pulse pair [69]; and are defined as
[94] [85] [71] [63]:

\[
H(t)=\begin{cases}
1 & 0 \leq t < \frac{1}{2} \\
-1 & \frac{1}{2} \leq t < 1 \\
0 & \text{elsewhere}
\end{cases}
\]  

(9)

The main advantages of the Haar wavelet are its accuracy and fast
implementation in comparison with the rest of families, its simplicity and
small computational cost, and its capacity for solving boundary problems
[169]. They are widely used in applications as image coding, edge
extraction and binary logic design.
4. Wavelet transform

Symlet wavelet transform

Symlet wavelet transform is an orthogonal wavelet defined by a scaling filter (a low pass finite impulse response filter of length $2N$ and sum 1). Symlet wavelet transform is sometimes called SymletN, where $N$ is the order. Symlet wavelets are near symmetric. Furthermore, they have the highest number of vanishing moments for a given width [12].

Coiflet wavelet transform

Coiflet wavelets share the main characteristics of Symlet wavelets: their high number of vanishing moments and symmetry. Coiflet family is compactly supported, orthogonal and able to give accurate results when the original signal has a distortion. The Coiflet wavelets are defined for 5 orders [36].

Biorthogonal wavelet transform

Biorthogonal wavelets are being introduced in different research areas of study due to their versatility, as they deal with symmetric and antisymmetric signals. They can be used under certain boundary conditions [183]. Moreover the Biorthogonal wavelet transform is an invertible transform. They have two sets of low pass filters for reconstruction, and high pass filters for decomposition [66].

Meyer wavelet transform

Meyer wavelet transform can also be represented by an equation. The Meyer families have multiple applications solving differential equations, signal processing, etc. [82]. Their main drawback is that they do not have compact support. It is defined by equation (10) [90]:

\[ \text{Meyer wavelet transform} \]
4. Wavelet transform

\[
\lambda(\omega) \mid_{\omega \in j} = \begin{cases} 
\frac{\pi}{4} + \theta(\omega - \pi), & \omega \in \left[\frac{2\pi}{3}, \frac{4\pi}{3}\right], \\
\frac{\pi}{4} + \theta\left(\frac{\omega}{2} - \pi\right), & \omega \in \left[\frac{4\pi}{3}, \frac{8\pi}{3}\right], \\
0, & \omega \in \left[0, \frac{2\pi}{3}\right] \cup \left[\frac{8\pi}{3}, +\infty\right],
\end{cases}
\] (10)

where \(\theta(\omega)\) is a continuous and differentiable function equal to \(\frac{\pi}{4}\) for \(\omega \geq \frac{\pi}{3}\).

4.3. Applications of Wavelet transform

The use of the wavelet transform was focused on the process diagnosis and instrumentation over the past two decades. In 1990, Leducq introduced them in the analysis of hydraulic noise for centrifugal pumps [91]. Later other authors demonstrated its usefulness for the detection of mechanical failures and the health monitoring control in gears [24][43][154][160][162][172].

Cracks in rotors [2], structures [20][130][153][171] or composite plates [155] have been another exploitation source for wavelet transforms. In 1994, Newland researched on their properties and applications, discovering the harmonic wavelet and its use for the peak and phase identification in signals [111]. The results showed that the cracks found reduced the rotor speed. The effectiveness of wavelets has also been compared with the envelope detection methodology in the diagnosis of faults for bearings, obtaining results in shorter time analysis [167].

Chancey and Flowers [31] managed to discover a relation between vibration patterns and the coefficients of a wavelet. Kang and Birtwhistle...
4. Wavelet transform

[84] or Subramanian, Badrilal and Henry [158] developed some techniques to find problems in power transformers. Yacamini [182] proposed a method to detect torsional vibrations in engines and generators from the stator currents.

At present, others wavelet transforms purposes are emerging, such as classification of linear frequency modulation signals for radar emitter recognition [164], applications for damages caused by corrosion in chemical process installations [168] and monitoring of pipelines. Some of the most examined cases are presented.

4.3.1. Mechanical, electronic components and structures of WTs

Not many references are found to relate this methodology to WTs. Wavelet transforms are implemented in adaptive controllers for wind energy conversion systems. The drivers are studied under different noise levels to achieve higher performances [143]. The introduction of the wavelet transform in the monitoring and diagnosis of faults for induced generators shows satisfactory results combining DWTs and statistical analysis.

The use of spectral components for decomposed signals is another relevant technique. Its harmonic content has suitable characteristics to be employed in fault diagnosis as an alternative to conventional methods [6].

In the case of the WT tower, the case studies are even less extensive than for electronic and mechanical components. Despite having knowledge of the importance of cracks, gaps, loosen joints or welding damages and their consequences [47], the monitoring of structures is a research field not currently developed.
4. Wavelet transform

### 4.3.2. Other applications

#### Engines

The wavelet transform provides information about frequencies, being an alternative to the FFT for the engines failure detection. There are algorithms that identify the presence of faults in working condition and are ahead of the shutdown, thereby costs and downtimes are reduced \[40][42][140].

Methods to detect imbalances or monitor fatigue damages in the stator voltage of a three phase induction engine have been studied. The wavelet transform of the stator current is analysed. These methods are less expensive in computational terms and can detect faults in the early stages \[139].

#### Pipelines

Wavelet transform is being implemented on pipes for the filtering and signal processing by the technique of Ground Penetrating Radar (GPR). This technique analyses the state of pipes below the ground \[112]. For offshore pipelines, the monitoring is necessary regardless of the technique employed \[126]. Researches for the detection of leaks in plastic pipes from AE signals \[3], cracks \[184] or evaluation of the corrosion on non-accessible pipes can be found \[1]. Crack initiation studies based on temperatures are expected to be helpful for improvements in material design or maintenance issues \[132]. When temperatures are high or low, the mechanical characteristics of the pipes are modified \[38]. The detection of anomalies is critical to find solutions in earlier stages of deterioration.

The use of sensors for pipeline monitoring linking ultrasound and temperature is not widespread, although it has been shown that certain
4. Wavelet transform

transducers (electromagnetic acoustic transducers) are effective in the detection of corrosion and cracks when the results are discussed with the wavelet transform. These sensors are inexpensive and sensitive to specific temperatures [93].

**Bearing**

Rolling bearings are essential for rotating machinery. Thus the choice of a suitable wavelet family is important in the maintenance and fault diagnosis of these devices [159]. The location of peaks on the vibration spectrum can identify particular faults. Wavelet decomposition trees are a useful tool for this identification [33].

**Images**

The transformation of an image into a wavelet representation by a decomposition method allows the edge feature detection of documents. The images are decomposed into a set of wavelet $A$ coefficients and wavelet $D$ coefficients and after several iterations; the quality of edges is enhanced [53].

With the emergence of communication networks, the alteration of copyrighted images is a common problem. Wavelets generate a digital watermarking algorithm that makes possible the placement of a watermark without degradation of the image and preventing the removal [102].
5. Macro Fibre Composites

5.1. Introduction

Composite materials are a solution for almost all the limitations related to piezoceramic structures [76], e.g. the vulnerability to accidental breakage in handling and bonding procedures, their inability to adapt to curved surfaces or the large add-on mass of the lead-based piezoceramic [152]. There are different types of composites commercially available, such as metal matrix composites [35], ceramic matrix composites [110], active fibre composites [22] or MFCs; and new materials are still under study [23].

MFC is a polymeric matrix made of piezoceramic fibres (see Figure 6) embedded between phases of adhesive film with electrodes that transfer voltage to ribbon-shaped rods and vice versa [41]. The flexible nature of its matrix allows the material to adapt to complex surfaces. MFC is a composite technology originally developed at the NASA Langley Research Center (United States). They offer excellent qualities in performance and repeatability over traditional materials. The MFC does not introduce significant mass or stiffness when they are incorporated in structures.

MFCs present a piezoelectric performance when there is a transformation of electronic impulses into ultrasonic waves. The impulses can turn into a voltage signal by pressure changes. Any device that works as both transmitter and receiver at the same time is called transducer. The MFC actuators can operate as sensors and actuators at the same time [148]. MFC
sensors are capable of recording AEs and detecting damages [49]. A sensor just monitors variables, the transducer converts one form of energy into another and an actuator is a transducer that converts an electric signal into vibrational movement [138].

**Figure 6.** Section of a generic piezoceramic fibre composite.

### 5.2. Macro Fibre Composites applications

The emergence and establishment of MFCs have become essential in different areas of research and development due to its low cost, the flexibility, and the adaptation to the environment. Recent studies analyse MFCs properties using periodic homogenization. The main purpose is to find local details or variations of their poling direction [45]. As follow some applications are discussed.

#### 5.2.1. Monitoring of Wind Turbines

In recent years, a large number of reports of defective blades contributing towards turbine failures have been published. This trend in the analysis of the blades does not extend to the WT towers or driving motors where the
development of maintenance systems associated with the use of MFCs is not yet widespread.

As WTs increase in size, there is a proportional needing to monitor their health [136]. Acquiring an early indication of structural or mechanical problems allows operators to better plan for maintenance. Advances in simulation and optimization have created a unique opportunity to open new lines of research, and some authors start to introduce applications for the analysis of WTs based on composites [16]. The fault detection involves ultrasonic sensors and infrared thermographic imaging. The ultrasonic sensors consist of piezoelectric transducers and MFCs transducers [118]. Experiments prove its accuracy to detect typical failure modes. Other authors focus on the experimental study of wind energy converters situated on the tower using sensors to distinguish incipient faults of the main components [67].

Signal processing techniques provide an indicator for system integrity in WT [175]. For low power consumption, energy harvesting techniques based on MFCs are used to harness the available surrounding environmental energy.

5.2.2. Structural health monitoring

MFC piezoelectric transducers monitor damages or impacts in complex structures. Their main application is the recognition of high frequency directivities and turning conditions and the suppression of vibration. The information obtained can be achieved through a single or several MFC patches [39].

Active controls to remove structural vibration have been developed for smart hull structures using configurations based on actuators. In these cases the right placement of the MFC actuators is essential. Some vibration
5. Macro Fibre Composites

tests under optimal running conditions reveal that the monitoring and control can be done with a limited number of actuators, which reduces costs [149]. For civil structures, a special emphasis on MFCs has been shown, applying them to trusses, steel frames or cable-stayed bridges [150].

5.2.3. Pipelines monitoring

Pipe degradation is induced by corrosion, decreasing the thickness of the pipe wall. Internal (material, shape, age, etc.) and external (temperature, weather or pressure) factors influence the structural deterioration. Pipelines require regular inspections to restore the damage and to replace the structure when it is inappropriate for operation [29]. Fault detection becomes further complicated when pipelines are located in inaccessible places [97].

The health monitoring systems that work with MFC can operate online and access to complicate areas. MFC transducers utilize impedance methods (structural damage in joints) and Lamb wave propagations (cracks and corrosion on the surface) to achieve these objectives. The main advantage is related to the low cost of MFC transducers that improves the implementation of NDT [166].

5.2.4. Other areas of study

Acoustic Emissions

In the field of AE, the use of MFC sensors is highly integrated to detect faults, and new applications are emerging such as monitoring of aerospace structures. In these situations, MFC sensors record AE data and detect damage by analysis of activity [49].
Railroad tracks

Fault detection in railroad tracks incorporates two important factors as SHM using MFC and wireless technology. Through laboratory simulations, monitoring systems detect damage in railroad tracks including head damage, web damage and flange damage [120].

Aeroelastic analysis

The aeroelastic analysis specializes in problems of the helicopter rotor systems. The main source of these problems comes from the aerodynamic environment variability that produces instability, undesirable vibrations and capacity constraints of the rotors during the operation. The establishment of an advanced active twist rotor blade incorporating single MFC actuators, partly solve the initial situation. Researches made by numerical simulation demonstrate that vibration can be relieved [119].

Ambient energy

Another application for MFC is the collection of ambient energy by power sensor networks. If the network is consistent, the maintenance and running costs are reduced. Some experiments have been done even under low speed wind conditions shows the viability for long periods of time [72].

Aerofoil control

Studies of aerofoil shapes can be found in literature. The tests are applied to aircrafts to determine the viability and small strains produced on the surface through the use MFC actuators [21].
5. Macro Fibre Composites

**Inflated torus**

An inflated torus is a structural support used in antennas, landing systems, etc. Inflated materials face problems when vibration needs to be controlled due to their flexibility, light weight and high damping. The study of feasibility on inflated torus is supported by MFC patches (sensors and actuators). The MFC patches are integrated into the inflated torus in order to find a gossamer structure's modal parameters and to reduce interferences [134]. Moreover, these applications can be extended beyond the vibration to the acoustic control for curved and flat panels [13]. They are also essential for space structures as they present a minimum level of vibration under working conditions. [80][117].
6. **Condition Monitoring for driving mechanisms of Wind Turbines**

A novel CM approach based on wavelet transforms is introduced in this chapter. The objective is focused on mechanisms as cooling devices (generators, gearboxes), electric motors for service crane, yaw motors, pitch motors (depending on the configuration) or pumps (oil, water) according to the sub system configurations, ventilators, etc. (Figure 7).

The study is divided into two phases: a phase developed on an experimental set and phase on a WT. The common link between both phases is the sound. The creation of a pattern recognition from a WT is a complex task due to the occurrence of multiple faulty scenarios is virtually impossible. For this reason, different experiments are done on the test bench to reproduce the performance of a real engine located in the nacelle. In both cases, the performance of the engine in operating conditions needs to be considered.

6.1. **Condition Monitoring based on sound. Relevance and benefits**

As noted in the introductory section, the sound is not as predictable as other types of signals as a result of its non-standing character. For this reason, the use of certain techniques that require a stationary performance, i.e. the FFT, is not recommended. However, this difficulty is settled with the selection of the wavelet transform.
Figure 7. Different locations of a WT where the CM can be used: (1) fans, (2) gear oil pump, (3) oil pump for brake and (4) water cooling pump.

The pattern designed from the sound can report any type of problem that appears in the mechanisms, notifying the severity as any change in the device will represent changes in sound (amplitude or shape of the waveform). Thus, the study departs from the standards and does not use the vibration as the main feature. This characteristic is translated in a reduction of costs since the collection and vibration analysis devices, as well as respective sensors, usually involves heavy investments. The sensor used in the case of sound is a standard microphone.

One of the aspects to be considered is the strategic placement of the microphone to avoid the noise from other external sources. The sound produced by rotating machinery can be influenced by contact of surfaces,
6. Condition Monitoring for driving mechanisms of Wind Turbines

bearings, misalignments, geometry of aerodynamic parts, etc. The first step is to determine the origin of the sound. It may come from an electromagnetic, aerodynamic or mechanical source [89]. The electromagnetic original appears when AC voltage is applied to the engine; the aerodynamic noise depends on the geometry and the mechanical noise occurs when there are misaligned elements or an impact between moving parts. The last one is the most common sound source.

Benko and others [19] suggest filtering the sound to focus on mechanical noise. The incidence of mechanical noise is found at low ranges of rotational speeds. Depending on whether the mechanism is fault-free or not, the occurrence of failures can increase significantly. The wavelet transform is able to filter automatically selecting as many decomposition levels as ranges of frequencies are needed.

6.2. Experimental case study

The CM system operates with sound, vibration, current, temperature, and velocity sensors. Current and temperature signals are discarded because do not provide useful information. The speed sensor controls the rotational speed of the assembly. Vibration and sound will be the main features in this case study.

A set of faults is induced in the several experiments: ski-slope faults, misalignment faults, angular misalignment faults, parallel misalignment faults, rotating looseness faults and external noise faults. The FDD method assigns categories from a common characteristic that is distinguishable from the rest. In order to recognize the patterns, three basic steps are followed [78]:

1. The data acquisition on a testing bench (Figure 8).
6. Condition Monitoring for driving mechanisms of Wind Turbines

2. The extraction of the features of the experiment using specific algorithms.
3. A decision-making.

A classification is done to obtain the optimal pattern recognition employing the data from FFT and wavelet transforms applied to the vibration and sound signals respectively.

Figure 8. Experimental set.

The experiments are made on a mechanism consisting of an engine and a generator linked by an elastic coupling joint (Figure 9). A total of 96 points is collected: 8 experiments with 4 measuring points per experiment, and three samples per point. A characteristic sample of each measurement point and for the fault-free experiment is chosen as the reference.
Data obtained by the sensors are stored in an acquisition board, except for the vibration which are collected with a vibrometer (Figure 10). The software employed is LabView (Figures 11 and 12) and specific software provided by the manufacturer Kionix in the case of vibration (Figure 13). The speed of the engine and frequency is set by a frequency variator, and the energy is dispelled using a resistive element (Figure 14).

**Figure 9.** Elastic coupling.

**Figure 10.** Vibrometer Kionix USB KXPA4-2050.
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Figure 11. Block diagram for temperatures, sound and current in LabView.

Figure 12. LabView main window.
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Figure 13. Vibration software.

The allocation of the measurements is two points for the engine and two for the generator. Points of selection are at the end of each machine and as
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close as possible to the axis which is the main rotational element of the mechanism (Figure 15).

![Diagram of a wind turbine mechanism with measuring points labeled 1 to 4.](image)

**Figure 15.** Measuring points.

The experiments are completed in an average time of 10 seconds. In the case of vibration, the vibrometer collects information for the ‘x’, ‘y’ and ‘z’ axis, as well as a mean measurement of the point from the 3 axis (Table 1).

<table>
<thead>
<tr>
<th>Data register</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vibration Matrix (Accx, Accy, Accz, Acctotal)</td>
<td>10</td>
</tr>
<tr>
<td>Sound Matrix (time and value)</td>
<td>10</td>
</tr>
<tr>
<td>Room temperature Matrix (time and value)</td>
<td>10</td>
</tr>
<tr>
<td>Temperature Matrix (time and value)</td>
<td>10</td>
</tr>
<tr>
<td>Current Matrix (time and value)</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.** Data register.

The data gathered by the data acquisition board and the vibrometer are stored in *lvm* and *txt* files respectively. Then, they are renamed following the pattern *number.name.extension*, where numbers are valued from 01 to 96; name may be *sound, current, temperatureroom, temperaturemotor* (the
motor nomenclature refers to the whole mechanism) or vibration; and the extensions are the above mentioned.

When the files are imported into Matlab™, they are saved with the mat extension. The files are again renamed according to the xnumbername model; e.g. file 11.temperatureroom.lvm is recalled x11temperatureroom.mat as Matlab™ does not allow variables initiated by a number.

The engine has 4 rubber clamping (silemblocks), while the generator has 3 rubber clamping. The silemblocks are located at the ends, having two on the right side and two on the left side in the case of the engine. The generator has them placed in a triangle; two in the area closest to the coupling and one at the end. The first experiment records the normal working conditions, while other experiments are performed when the silemblocks are removed from the engine and the generator in order to simulate different degrees of decoupling (Table 2 and Figure 16).

**Figure 16.** Misalignments induced removing silemblocks from the engine and the generator and experimentation with a rigid coupling.
For each measurement, 7 files are saved (temperature of the room, temperature of the point selected, 3 phases of current, vibration and sound), representing a total of 672 files. The samples stored are 110248 for sound, 1250 for vibration and 50000 for current and temperature.

### Table 2. Experiments (1500 rpm).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Type of experiment</th>
<th>Data set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fault-free conditions.</td>
<td>From 1 to 12</td>
</tr>
<tr>
<td>2</td>
<td>Misalignment removing silemblocks from the right side of the engine.</td>
<td>From 13 to 24</td>
</tr>
<tr>
<td>3</td>
<td>Misalignment removing silemblocks from the right side and the front left one of the engine.</td>
<td>From 25 to 36</td>
</tr>
<tr>
<td>4</td>
<td>Induction of resistance in the coupling.</td>
<td>From 37 to 48</td>
</tr>
<tr>
<td>5</td>
<td>Misalignment removing the silemblock from the right side of the generator.</td>
<td>From 49 to 60</td>
</tr>
<tr>
<td>6</td>
<td>Misalignment removing 2 silemblocks near to the coupling in the generator.</td>
<td>From 61 to 72</td>
</tr>
<tr>
<td>7</td>
<td>Misalignment removing the silemblock from the right side of the generator and one from the left side of the engine.</td>
<td>From 73 to 84</td>
</tr>
<tr>
<td>8</td>
<td>Use of a rigid coupling.</td>
<td>From 85 to 96</td>
</tr>
</tbody>
</table>

### 6.2.1. Vibration fault diagnosis

There are a considerable number of publications regarding the diagnosis of faults for rolling machinery that justifies the models and patterns based on the FFT. Misalignment is one of the most common observed faults in rotating machines, being the second principal malfunction after unbalance
6. Condition Monitoring for driving mechanisms of Wind Turbines

[122]. It is present due to improper machine assemblies, thermal distortions and asymmetries in loads. Misalignment produces reaction forces in couplings that are the major cause of machinery vibration. Some authors evaluated the effect of coupling misalignment and suggested the occurrence of strong vibrations at twice the natural frequency [144][181], although rotating machinery can excite vibration harmonics from twice to ten harmonics depending on the signal pickup locations and directions [109].

Faults do not have a unique nature, and in most cases problems on a smaller scale are linked, e.g. in the case of misalignment, when an angular misalignment is studied, parallel misalignment (minor fault) needs to be taken into account [7].

Some companies and researchers tabulate the most common failures from the frequency domain, so that the analysis can be carried out easier. Thus, the appearance of different frequency peaks determines the existence of incipient problems such as gaps, unbalances or misalignments among other circumstances [65]. The main advantage of these tables is that can be adapted to any situation where the natural frequency (or the rotational speed) is known.

In this case study, the rotational speed of the engine is 1500 rpm, i.e. 25 Hz (natural frequency) for the experimental set. In order to analyse a fuller vibration spectrum, the number of samples goes from 25 Hz to 125 Hz. Therefore, the range of frequencies discussed includes 25 Hz (1X), 50 Hz (2X), 75 Hz (3X) and 100 Hz (4X). Frequencies exceeding 4X have been discarded as they are not relevant for the pattern recognition.

A FFT algorithm is done using Matlab™. This program compares two signals for a given frequency in order to make a diagnosis from the peaks.
Another advantage of the program is that it is possible to obtain the amplitude values for a given frequency range (Figure 17). With a click on a particular peak, the program provides the data automatically.

![FFT of a vibration signal](image)

**Figure 17.** FFT of a vibration signal.

**Machine faults diagnosing**

The most common spectrums for engine-generator mechanisms are detailed with examples from the experimental set.

**Ski-slope fault**

A ski-slope fault appears when there is a big peak around 0 Hz (Figure 18). A ski-slope is linked to problems with the quality of the sensor. It usually happens because the sensor has experienced a transient during the measurement process. The transient may be mechanical, thermal or electrical.

**Misalignment faults**

Misalignment faults take place when the centrelines of coupled shafts do not coincide. If the misaligned shaft centrelines are parallel but not
coincident, then the misalignment is a parallel misalignment. If the misaligned shafts meet at a point but they are not parallel, the misalignment is angular. Most of the cases are a combination of them. The diagnosis is based on dominant vibration from the natural frequency (1X) at twice the rotational rate (2X), with increasing rotational rate levels (3X, 4X, etc.) acting in the axial, vertical or horizontal directions.

![FFT](image)

**Figure 18.** Ski-slope fault.

Angular misalignment fault produces a bending moment on both shafts and this generates a strong vibration at 1X, and some others at 2X and 3X for the axial direction. There will also be strong radial components for vertical and horizontal directions (Figure 19).

Parallel misalignment fault makes a shear force and a bending moment on the coupled end of each shaft. High vibration levels at 1X as well as 2X emerge over the radial direction. 2X component is higher than 1X most of the time. Depending on the coupling, there can be 3X or 4X frequencies, even reaching 8X when the misalignment is severe (Figure 20).
Rotating looseness fault

Rotating looseness fault will create harmonics or sub-harmonics every 0.5X. Even 1/3 order harmonics are possible (Figure 21).

**Figure 19.** Angular misalignment.

**Figure 20.** Parallel misalignment.
External noise fault

It is very common to find peaks in a spectrum that are difficult to analyse. This happens because of the vibration from another machine or process. The peak will typically be in a non-synchronous frequency (Figure 21). External noise can be verified stopping the machine (or varying the speed) and seeing if the vibration is still present or checking local machines for the same frequency source.

![FFT](image)

**Figure 21.** Rotating looseness and external noise.

Vibration results

Vibration patterns are different according to the points studied. Factors such as proximity to the coupling, the existence of nearby rolling elements, housings, fans, etc., make harmonics differ. It has been detected that the natural frequency tends to predominate in the experiments done at point 1, 3 and 4. On the other hand, point 2 has most predominant peaks from the frequency at 50 Hz.
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To make the vibration analysis more accurate, it must be taken into account not only the appearance of peaks, but also the amplitude as it gives information about the severity of the fault. The main symptoms show up when peaks at 0.5X, 1X, 2X and 3X, sidebands and noise appear. When a failure is studied in an advanced stage, the appearance of the peaks at 4X is also noticeable e.g. in the case of the rigid coupling. The prominent symptoms for each point are summarized below.

The diagnosis of the experiments reveals that the mechanism has a minor looseness which causes the appearance of a high peak at the natural frequency in some cases, even under fault-free conditions. This looseness appears because the engine and the generator are not directly anchored to the test bench. The assembly was done on a surface that makes easier the removal of the silemblocks when the experiments requires it, e.g. to create different degrees of misalignment. This action expands the vibration intentionally approaching the actual performance of the nacelle.

The results of experiment 8 are remarkable. The rigid coupling causes a severe looseness and vibration. The growth of a frequency at 4X and a constant noise over the spectrum is observed. Although it is usual to find sidebands, peaks below 1X and high frequency peaks, this feature is unique to this last experiment. A similar diagnosis for cases 1, 4 and 8 was expected, but the performance is slightly different for this reason.
6. Condition Monitoring for driving mechanisms of Wind Turbines

**Table 3. Symptoms for point 1.**

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>Peaks at 1X and 2X. Sidebands around 1X and 2X. Peaks decrease from 3X.</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>Peaks at 2X and 3X. Sidebands around 2X and 3X. Minor peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Peak at 2X. Minor peaks at 1X and 3X. Sidebands around 1X, 2X and 3X. Big peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>Peak at 1X and decreasing at 2X and 3X. Peak between 0 and 1X (amplitude ~ 1X).</td>
</tr>
<tr>
<td>Experiment 5</td>
<td>Peaks at 1X and 2X. Sidebands around 1X and 2X. Peaks decrease from 3X. Peak between 0 and 1X (amplitude ~ 1X).</td>
</tr>
<tr>
<td>Experiment 6</td>
<td>Peak at 1X and decreasing at 2X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X (amplitude ~ 1X).</td>
</tr>
<tr>
<td>Experiment 7</td>
<td>Peak at 1X and decreasing at 2X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X (amplitude ~ 1X).</td>
</tr>
<tr>
<td>Experiment 8</td>
<td>Peak at 1X and decreasing at 2X and 3X. Noise between peaks.</td>
</tr>
</tbody>
</table>

**Table 4. Symptoms for point 2.**

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>Peaks at 2X and 3X.</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>Peak at 1X and decreasing at 2X and 3X.</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Peak at 2X. Minor peaks at 1X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>Peaks at 2X and 3X. Minor peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 5</td>
<td>Peaks at 2X and 3X. Minor peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 6</td>
<td>Peaks at 2X and 3X. Minor peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 7</td>
<td>Peak at 2X. Minor peaks at 1X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 8</td>
<td>Big peak at 1X. Noise around 3X. Peak between 0 and 1X.</td>
</tr>
</tbody>
</table>
Table 5. Symptoms for point 3.

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>Peak at 2X. Minor peaks at 1X and 3X. Sidebands around 1X, 2X and 3X. Minor peak between 0 and 1X.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 2</td>
<td>Peaks at 2X and 3X. Sidebands at 1X and 2X.</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Peak at 1X and decreasing at 2X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X (amplitude ~ 1X).</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>Big peak at 1X and decreasing at 2X and 3X. Sidebands around 1X.</td>
</tr>
<tr>
<td>Experiment 5</td>
<td>Peak at 2X. Minor peaks at 1X and 3X. Sidebands around 1X, 2X and 3X.</td>
</tr>
<tr>
<td>Experiment 6</td>
<td>Big peak at 1X and decreasing at 2X and 3X. Minor peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 7</td>
<td>Peak at 2X. Minor peaks at 1X and 3X. Noise from 0 to 3X.</td>
</tr>
<tr>
<td>Experiment 8</td>
<td>Big peak at 1X and 4X and decreasing at 2X and 3X. Sidebands around 1X, 2X, 3X and 4X. Noise. Peak between 0 and 1X.</td>
</tr>
</tbody>
</table>

Table 6. Symptoms for point 4.

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>Peaks at 2X and 3X. Sidebands around 1X, 2X and 3X. Minor peak between 0 and 1X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 2</td>
<td>Peaks at 2X and 3X. Sidebands around 2X and 3X. Peak between 0 and 1X</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Similar peaks at 1X, 2X and 3X. Sidebands around 2X and 3X. Big peak between 0 and 1X.</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>Minor peak at 1X.</td>
</tr>
<tr>
<td>Experiment 5</td>
<td>Peak at 1X and decreasing at 2X and 3X. Sidebands around 1X, 2X and 3X. Peak between 0 and 1X (amplitude ~ 1X)</td>
</tr>
<tr>
<td>Experiment 6</td>
<td>Peak at 2X and decreasing at 2X and specially 1X. Noise between 1X and 2X. Peak between 0 and 1X (amplitude &gt; 1X)</td>
</tr>
<tr>
<td>Experiment 7</td>
<td>Peak at 2X. Noise between 0 and 1X and 2X and 3X. Sidebands at 1X, 2X and 3X</td>
</tr>
<tr>
<td>Experiment 8</td>
<td>Big peak between 0 and 1X. Noise and sidebands.</td>
</tr>
</tbody>
</table>
### Table 7. Diagnosis for point 1.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Looseness.</td>
</tr>
<tr>
<td>2</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>3</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>4</td>
<td>Looseness. Severe vibration.</td>
</tr>
<tr>
<td>5</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>6</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>7</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>8</td>
<td>Severe looseness.</td>
</tr>
</tbody>
</table>

### Table 8. Diagnosis for point 2.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Looseness.</td>
</tr>
<tr>
<td>2</td>
<td>Looseness. Misalignment.</td>
</tr>
<tr>
<td>3</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>4</td>
<td>Looseness. Severe vibration.</td>
</tr>
<tr>
<td>5</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>6</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>7</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>8</td>
<td>Severe vibration. Severe looseness.</td>
</tr>
</tbody>
</table>

### Table 9. Diagnosis for point 3.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Looseness. Severe vibration.</td>
</tr>
<tr>
<td>2</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>3</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>4</td>
<td>Looseness. Severe vibration.</td>
</tr>
<tr>
<td>5</td>
<td>Looseness. Misalignment.</td>
</tr>
<tr>
<td>6</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>7</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>8</td>
<td>Severe looseness. Severe vibration.</td>
</tr>
</tbody>
</table>
6. Condition Monitoring for driving mechanisms of Wind Turbines

Table 10. Diagnosis for point 4.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>Looseness. Severe vibration.</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>Minor looseness</td>
</tr>
<tr>
<td>Experiment 5</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>Experiment 6</td>
<td>Looseness. Misalignment. Severe vibration.</td>
</tr>
<tr>
<td>Experiment 7</td>
<td>Looseness. Misalignment.</td>
</tr>
<tr>
<td>Experiment 8</td>
<td>Severe looseness. Severe vibration.</td>
</tr>
</tbody>
</table>

6.2.2. Wavelet transform processing approach

Wavelet transforms are employed to analyse the sound signals and their energies. Another algorithm is done using Matlab\textsuperscript{TM}. This program plots and compares two signals.

The family of wavelets selected for the case study is Daubechies in a symmetric mode [44]. Nevertheless, different families were tested and results did not differ significantly. Data is divided in 5 decompositions named $a_4$, $d_4$, $d_3$, $d_2$ and $d_1$, where each of them has an energy rate over the total and is located at a specific range of frequency (Figure 22). The values of energy along with the decomposition levels are examined in this section. This choice is determined from several experiments confirming that more than five levels do not provide more accurate information, and computational complications linked to the large amount of data can appear.

The approximated decomposition is noted as $a_4$. It has a similar pattern to the original signal. Level $a_4$ is the low frequency component of the original signal while $d_1$ is the high frequency component.
As experiments are performed at 1500 rpm, it is necessary to verify if pattern recognition can be extrapolated to other rotational speeds before starting any analysis. In the case of WT, most of the engines rotate at speeds close to 3000 rpm.

A certain number of tests are done varying the speed from 500 to 3000 rpm (at intervals of 500 rpm) in order to ensure the existence of a proportional pattern. Experiments are repeated under normal working conditions and causing misalignments. The collected signals belong to the 4 points previously studied. Results assure that regardless of speeds or
points of study, patterns are proportional to the rotational speed. Figure 23 is an example of measurements applied to point 1.

![Figure 23. Energies at different rotational speeds.](image)

**Sound results**

After the previous demonstration, the study of energies is carried out. It can be said that the energy distribution of point 1 is ruled by a similar pattern where experiments have maximums for the *approximated* signal and minimums for levels $d_1$ or $d_2$. This means that the *approximated* signal is alike the original one. When experiments are closer to the generator (points 2, 3 and 4), the energy is distributed among the 5 decompositions and not concentrated on the *approximated wavelet* as it is for point 1. An example for two experiments is shown in Table 11.

**Table 11. Energy distribution for two experiments.**

<table>
<thead>
<tr>
<th>Experiment</th>
<th>approximated</th>
<th>$d_4$</th>
<th>$d_3$</th>
<th>$d_2$</th>
<th>$d_1$</th>
<th>energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>95.22%</td>
<td>2.27%</td>
<td>1.24%</td>
<td>0.87%</td>
<td>0.39%</td>
<td>1389</td>
</tr>
<tr>
<td>2</td>
<td>5.16%</td>
<td>11.57%</td>
<td>50.35%</td>
<td>25.47%</td>
<td>7.44%</td>
<td>311.4</td>
</tr>
</tbody>
</table>
Experiment 1 corresponds to point 1, and experiment 2 is related to point 2. Experiment 1 has the maximum percentage of energy in the approximated decomposition and the minimum in $d_1$ level; while point 2 has its maximum in $d_2$ and the minimum located in the approximated level. It must be taken into account that the value of energy also varies according to the experiment and the measured point.

### 6.3. Case study on motors of a Wind Turbine

This phase of the research is focused on the fault-free conditions of the WT. Data collection is performed in drive motors and cooling systems of a WT (Figure 24). Both of them are in the nacelle of the WT. The drive motor rotates the nacelle before the blades start to spin for the wind energy production. The cooling systems are responsible for maintaining the temperature of the facilities.

The signals collected are sound, current, rotor speed, and wind speed; being sound the main feature to be analysed. Sensors are placed using the same criteria than in the experimental set, but only measure at one point as once they are fixed, cannot be relocated (the facilities must be evacuated when the WT is working for security reasons). The microphone is attached in the same place as it was for point 2 in the experimental set.

Signals are recorded using the `signal_year-month-day_time_numberoffile` format and saved every 60 seconds. The software increases the variable `numberoffile` when a new file needs to be stored. Since none of the files kept a valid reading format for Matlab™, a program that changes this format to a readable new one is done. In some cases, there is an additional problem with the size of the files as Labview is not always able to save the partitions every minute and some signals are recorded in a single file that surpasses 700 MB. This process involves an extra complication as they must be
divided containing the same amount of data, otherwise, any comparative analysis could not run from Matlab™.

**Figure 24.** From left to right: (1) sensors, data acquisition board and laptop, (2) yaw motor and (3) cooling device.

### 6.3.1. Sound analysis

Regarding the experimental set, a number of preliminary considerations must be considered:

- Due to the conditions of the nacelle, the audio signal will contain noise at high frequencies that must be removed (Figure 25). The filtering process must be thorough because useful information may be removed. The engine-generator mechanism was adequately isolated to not collect unwanted noise.
- As previously commented, the origin of the noise (electromagnetic, aerodynamic or mechanical) is an important factor to obtain accurate results.
- A possible influence of the rotor could also be considered.
With a frequency range between 0 and 11025 Hz, the collection of the audible sound is assured as it is usually situated in the band from 20 to 20000 Hz.

Previous to any analysis, the usefulness of the signals needs to be checked due to the motors are not always in operation. The determination of the working conditions is a simple task as the signals show a completely different performance when the motors are stopped. Figure 26 represents a sound data capture when the device is not working. The opposite situation is shown in Figure 27.

An example of the start of a particular motor is presented for a better understanding. A first stage where the rotor and the motor are not working is collected, then the start-up of the motor is followed by the start-up of the rotor, and finally all the data is recorded when both mechanisms are running in fault-free conditions.

Sound will be assessed from its energy again. Figure 28 shows the start-up of the motor. The overall energy of the sound is plotted. The first part
6. Condition Monitoring for driving mechanisms of Wind Turbines

corresponds to the moment prior to the start-up. Then the motor starts to run. The third part corresponds to working conditions. In the first phase, the energy is close to zero. Then, the performance is randomness during the start-up and finally, the energy remains almost constant. The relation between the energy and the performance of the original data can be seen in Figure 29.

![Sound Signal in Non-Working Conditions](image1.png)

**Figure 26.** Sound signal in non-working conditions.

![Sound Signal in Working Conditions](image2.png)

**Figure 27.** Sound signal in working conditions.
The energies values and percentages that fall on each decomposition are shown below (Table 12). In the first phase, the energy remains around zero. The biggest weight is on the *approximated* decomposition, dividing a residual amount among the other levels. Then, the motor starts to spin and a random phase is introduced where energy is in constant increasing. The
distribution of energies is similar to the previous phase. Finally, when the motor sets its rotational speed, the percentages of energy move from the approximated wavelet to \( d_4 \), \( d_3 \) and \( d_2 \) levels. Values are almost constant in this stabilization phase. This last phase must have a similar performance to the fault-free conditions in the test bench. If similar values and distributions of energy are not found, the case study would not have sufficient reliability.

**Table 12.** Energy decomposition and values.

<table>
<thead>
<tr>
<th></th>
<th>approximated</th>
<th>( d_4 )</th>
<th>( d_3 )</th>
<th>( d_2 )</th>
<th>( d_1 )</th>
<th>energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(^{st}) phase</td>
<td>5.90%</td>
<td>66.20%</td>
<td>24.33%</td>
<td>3.22%</td>
<td>0.34%</td>
<td>2.04</td>
</tr>
<tr>
<td></td>
<td>7.31%</td>
<td>66.81%</td>
<td>22.38%</td>
<td>2.91%</td>
<td>0.59%</td>
<td>5.93</td>
</tr>
<tr>
<td></td>
<td>6.40%</td>
<td>65.35%</td>
<td>24.06%</td>
<td>3.36%</td>
<td>0.83%</td>
<td>4.49</td>
</tr>
<tr>
<td></td>
<td>5.91%</td>
<td>55.32%</td>
<td>26.69%</td>
<td>7.67%</td>
<td>4.41%</td>
<td>1.20</td>
</tr>
<tr>
<td></td>
<td>8.85%</td>
<td>62.75%</td>
<td>24.96%</td>
<td>3.09%</td>
<td>0.36%</td>
<td>2.25</td>
</tr>
<tr>
<td>2(^{nd}) phase</td>
<td>7.16%</td>
<td>65.55%</td>
<td>21.60%</td>
<td>3.97%</td>
<td>1.72%</td>
<td>3.91</td>
</tr>
<tr>
<td></td>
<td>5.06%</td>
<td>60.34%</td>
<td>26.51%</td>
<td>5.46%</td>
<td>2.63%</td>
<td>26.75</td>
</tr>
<tr>
<td></td>
<td>6.56%</td>
<td>67.06%</td>
<td>21.41%</td>
<td>3.64%</td>
<td>1.32%</td>
<td>223.5</td>
</tr>
<tr>
<td></td>
<td>3.57%</td>
<td>37.07%</td>
<td>14.00%</td>
<td>18.71%</td>
<td>26.65%</td>
<td>1096</td>
</tr>
<tr>
<td></td>
<td>5.55%</td>
<td>64.34%</td>
<td>19.09%</td>
<td>4.84%</td>
<td>6.18%</td>
<td>2682</td>
</tr>
<tr>
<td>3(^{rd}) phase</td>
<td>3.19%</td>
<td>40.12%</td>
<td>22.97%</td>
<td>20.11%</td>
<td>13.61%</td>
<td>616.1</td>
</tr>
<tr>
<td></td>
<td>0.94%</td>
<td>19.34%</td>
<td>41.74%</td>
<td>29.72%</td>
<td>8.26%</td>
<td>342.3</td>
</tr>
<tr>
<td></td>
<td>0.86%</td>
<td>9.96%</td>
<td>26.17%</td>
<td>39.23%</td>
<td>23.78%</td>
<td>315.8</td>
</tr>
<tr>
<td></td>
<td>1.26%</td>
<td>9.70%</td>
<td>47.99%</td>
<td>33.11%</td>
<td>7.94%</td>
<td>436.6</td>
</tr>
<tr>
<td></td>
<td>1.36%</td>
<td>12.24%</td>
<td>42.33%</td>
<td>32.34%</td>
<td>11.73%</td>
<td>370.7</td>
</tr>
<tr>
<td></td>
<td>1.93%</td>
<td>19.82%</td>
<td>42.91%</td>
<td>27.92%</td>
<td>7.42%</td>
<td>374</td>
</tr>
<tr>
<td></td>
<td>1.12%</td>
<td>21.26%</td>
<td>41.20%</td>
<td>27.53%</td>
<td>8.90%</td>
<td>420.2</td>
</tr>
<tr>
<td></td>
<td>1.51%</td>
<td>19.99%</td>
<td>43.57%</td>
<td>28.55%</td>
<td>6.38%</td>
<td>542.1</td>
</tr>
<tr>
<td></td>
<td>1.37%</td>
<td>13.05%</td>
<td>48.65%</td>
<td>29.74%</td>
<td>7.18%</td>
<td>362.9</td>
</tr>
</tbody>
</table>
6.3.2. Resemblances to case study

Results will be presented connecting the experimental set and the WT signals. As mentioned, due to the conditions of the WT, this connection can be only done from the fault-free conditions and using the sound. Although temperature and current was collected in both cases, these features are not helpful for any analysis due to its stability even under changing conditions.

Table 13 shows a comparison between decompositions and values of the energy in several situations. The objective is to demonstrate the existence of a relation between the normal working conditions of the WT with the experiments carried out throughout the engine in the experimental set. Thereby a pattern recognition based on the sound can be used to find potential failures from the testing bench.

**Table 13.** Comparison of energy and decomposition values.

<table>
<thead>
<tr>
<th></th>
<th>approximated</th>
<th>d₁</th>
<th>d₂</th>
<th>d₃</th>
<th>d₄</th>
<th>energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Turbine</td>
<td>1,26%</td>
<td>9,70%</td>
<td>47,99%</td>
<td>33,11%</td>
<td>7,94%</td>
<td>436,6</td>
</tr>
<tr>
<td></td>
<td>1,51%</td>
<td>19,99%</td>
<td>43,57%</td>
<td>28,55%</td>
<td>6,38%</td>
<td>542,1</td>
</tr>
<tr>
<td></td>
<td>1,37%</td>
<td>13,05%</td>
<td>48,65%</td>
<td>29,74%</td>
<td>7,18%</td>
<td>362,9</td>
</tr>
<tr>
<td>Experimental set</td>
<td>5,16%</td>
<td>11,57%</td>
<td>50,35%</td>
<td>25,47%</td>
<td>7,44%</td>
<td>311,4</td>
</tr>
<tr>
<td>(1)</td>
<td>4,60%</td>
<td>13,87%</td>
<td>52,43%</td>
<td>22,51%</td>
<td>6,58%</td>
<td>487,6</td>
</tr>
<tr>
<td></td>
<td>5,23%</td>
<td>13,34%</td>
<td>50,69%</td>
<td>23,99%</td>
<td>6,76%</td>
<td>308,4</td>
</tr>
<tr>
<td>Experimental set</td>
<td>95,22%</td>
<td>2,27%</td>
<td>1,24%</td>
<td>0,87%</td>
<td>0,39%</td>
<td>1389</td>
</tr>
<tr>
<td>(2)</td>
<td>95,54%</td>
<td>2,25%</td>
<td>1,10%</td>
<td>0,77%</td>
<td>0,35%</td>
<td>1557</td>
</tr>
<tr>
<td></td>
<td>95,13%</td>
<td>2,19%</td>
<td>1,31%</td>
<td>0,96%</td>
<td>0,42%</td>
<td>1607</td>
</tr>
</tbody>
</table>

The first set of data is linked to three different moments where the sound energy is collected in the WT. The second section is for the experimental set, representing the energy of point 2. Finally, the third set belongs to the study of a misalignment for point 1. All selections are made randomly and taking into account that the energies from the set engine-generator
mechanisms are at different rotational speed so they have been multiplied by a coefficient that makes the tests comparable.

Contrasting the results, the energy values and the percentages remain within the same ranges for real and tested data. It is observed that decompositions $d_3$ and $d_2$ have a greater weight over the total, sharing out a residual component among the rest. Furthermore, by comparing the first and third block, the importance of selecting an appropriate measurement point is reinforced. The variation of the energy according to the experiments is also noted. Almost all the energy falls on the approximated wavelet (low frequencies) and the energy value varies between 5 and 6 times over the total for point 1 in comparison with point 2. Hence it can be concluded that the development of a pattern recognition based on the faults generated on the test bench will give accurate results.

6.4. Pattern recognition and results

The pattern recognition links the sound energy extracted from the wavelet transform with the FFT applied to the vibration. The vibration analysis was initially extended until the fourth harmonic; but the most prominent information is presented in the first two harmonics so that pattern is reduced to 1X and 2X. In the case of the sound signal, the overall energy is selected. Since the study of vibration is highly extended and the relation between the FFT and faults is easily detectable, an accurate pattern is assured when it is supported by the technique.

Algorithms based on grids are created and each experiment will be located from a set of coordinates. The $x$ axis represents the first harmonic of the vibration, the $y$ axis represents the second harmonic of the vibration, and the $z$ axis represents the sound energy for three-dimensional graphics. The
two-dimensional graphic are combinations of 1X vs. 2X and 1X vs. energy values.

**Results**

It is observed that the energy of commissioned conditions and the fourth experiment are alike at point 1. It can be also seen that applying a resistance (experiment 4) does not report any energy variance in comparison with experiment 1. The misalignment experiments are enclosed in a second group as it can be seen in Figures 30, 31 and 32. There is a third group where the change of the rigid coupling for the flexible coupling is highlighted. The first harmonic rises mainly due to the misalignments, being the second harmonic almost constant. Table 14 introduces the three-dimensional blocks, according to the parameters x, y and z, where the above mentioned groups can be found.

![Figure 30](image-url). Vibration and sound at point 1.
6. Condition Monitoring for driving mechanisms of Wind Turbines

**Figure 31.** 1X vs. 2X at point 1.

**Figure 32.** 1X vs. energy at point 1.
Table 14. Range of values for point 1.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>1X-2X-energy ranges</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>X axis</td>
<td>Y axis</td>
<td>Z axis</td>
</tr>
<tr>
<td>1, 4</td>
<td>[0, 60]</td>
<td>[0, 50]</td>
</tr>
<tr>
<td>2, 3, 5, 6, 7</td>
<td>[25, 150]</td>
<td>[75, 200]</td>
</tr>
<tr>
<td>8</td>
<td>[175, 200]</td>
<td>[50, 100]</td>
</tr>
</tbody>
</table>

Point 2 presents less particularities and the performance of the fault-free conditions is not as distinctive as in the previous case; possibly because although it is closer to the coupling, point 2 moves away from the fan (point 1) and housing vibration is not so strong. The energy is stabilized with the exception of the last experiment, where the values significantly grow. Vibrations and looseness are bigger and for this reason, the second harmonics have more weight than before. This conclusion can be appreciated in Figure 33.

![Figure 33. Vibration and sound at point 2.](image-url)
6. Condition Monitoring for driving mechanisms of Wind Turbines

Figure 34. 1X vs. 2X at point 2.

Figure 35. 1X vs. energy at point 2.
Table 15. Range of values for point 2.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>X axis</th>
<th>Y axis</th>
<th>Z axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[20, 30]</td>
<td>[150, 180]</td>
<td>[130, 150]</td>
</tr>
<tr>
<td>2, 3, 4, 5, 6, 7</td>
<td>[25, 100]</td>
<td>[50, 150]</td>
<td>[25, 350]</td>
</tr>
<tr>
<td>8</td>
<td>[240, 260]</td>
<td>[40, 80]</td>
<td>[500, 600]</td>
</tr>
</tbody>
</table>

The conclusions obtained from point 2 can be extended to point 3. The energy for the fifth misalignment increases because the silentblock close to this point is removed, creating high levels of vibration. Once again, the second harmonics gains importance (Figure 36). Table 16 shows the ranges for 1X, 2X and the energy.

Figure 36. Vibration and sound at point 3.
6. Condition Monitoring for driving mechanisms of Wind Turbines

**Figure 37.** 1X vs. 2X at point 3.

**Figure 38.** 1X vs. energy at point 3.
At point 4, the commissioned experiment and the one with a resistance in the coupling have higher energy levels than the rest of the experiments with the exception of number 8. The misalignment 5 presents the same performance explained in point 3. This is observed graphically in Figure 39, where it approaches to experiment 8 which has the highest energy results. In Table 17 this case is separated from the rest paying special attention.

**Table 16.** Range of values for point 3.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>1X-2X-energy ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X axis</td>
</tr>
<tr>
<td>1</td>
<td>[20, 50]</td>
</tr>
<tr>
<td>2, 3, 4, 5, 6, 7</td>
<td>[20, 200]</td>
</tr>
<tr>
<td>8</td>
<td>[250, 350]</td>
</tr>
</tbody>
</table>

**Figure 39.** Vibration and sound at point 4.
6. Condition Monitoring for driving mechanisms of Wind Turbines

Figure 40. 1X vs. 2X at point 4.

Figure 41. 1X vs. energy at point 4.
Table 17. Range of values for point 4.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>X axis</th>
<th>Y axis</th>
<th>Z axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1, 4</td>
<td>[20, 30]</td>
<td>[80, 120]</td>
<td>[100, 300]</td>
</tr>
<tr>
<td>2, 3, 5, 6</td>
<td>[20, 70]</td>
<td>[10, 80]</td>
<td>[75, 250]</td>
</tr>
<tr>
<td>7</td>
<td>[55, 70]</td>
<td>[70, 80]</td>
<td>[475, 525]</td>
</tr>
<tr>
<td>8</td>
<td>[60, 80]</td>
<td>[30, 50]</td>
<td>[320, 500]</td>
</tr>
</tbody>
</table>
7. Condition Monitoring on structures of Wind Turbines

Despite the relevance of the WT tower, current CM systems do not usually focus on these structures, giving them less importance than required (Figure 42). There are many factors that can deteriorate a tower from the wind, fire or ice to impacts, fatigue or age [35]. As a consequence, cracks, gaps, loosen joints and welding damages can appear. This study takes advantage of this circumstance, to introduce a robust monitoring based on the wavelet transform with the use of MFC transducers.

Figure 42. Details of a WT tower.
7. Condition Monitoring on structures of Wind Turbines

The use of MFCs transducers is also implemented on pipes and plates to detect faults from ultrasound. These pipelines and plates are intended to represent some other structures of a WT.

7.1. Condition Monitoring based on ultrasound and the use of Macro Fibre Composites transducers. Relevance and benefits

It is known that temperature is a factor that affects to corrosion and erosion. Serious mechanical stress may appear as a result of temperature changes [106]. These temperature changes are responsible for the detachment of material [137]. One of the motivations for the experimentation in pipes is precisely to obtain results from the monitoring of this feature analysing ultrasound signals.

Since many problems can be only detectable in the ultrasonic range, the use of the technique is recommended when noise must to be ignored. This characteristic is important in environments where great amount of noise is concentrated and must be considered in areas closest to the nacelle [77].

Other basic advantages of ultrasound are the early warning when a mechanical or electrical failure is coming and the possibility of testing while equipment are operating [14]. Therefore ultrasound can be performed with other techniques during maintenance inspections. Its use is spread to complement the vibration based maintenance as it is able to detect defects at low frequencies, collecting information in a cheaper and faster way [133].

The location of the inspected mechanism or structure, e.g. the CM of a tower with a failure at a certain height, must be taken into consideration. The selection of a reliable sensor that is able to be placed anywhere is a guarantee of success.
As it was explained in Section 5, MFCs transducers offer excellent qualities in performance and repeatability over traditional materials and does not introduce mass or stiffness when they monitor structures. Moreover, they have a low cost and excellent qualities related to flexibility and adaptation to the environment.

7.2. Experimental case study on a pipe

As previously stated, the objective of this experimentation on pipes will be to extract conclusions related to the temperature using sensors based on MFC transducers and to develop a FDD method based on wavelet transforms.

The case study attempts to verify that the ultrasonic signal provides information about the behaviour of the pipe from the temperature and the relation to structural changes. This issue may not be noticeable when the temperature is not subject to sudden changes, but it can cause structural problems in the medium and long-term.

22 experiments were recorded at random dates by the NDT Technology Group during 6 months in order to observe the behaviour of the pipe in an extended period of time (Table 18). The measured temperatures are under environmental conditions to ensure a resemblance to the working performance of this type of structures in operating facilities. 17 of the 22 signals were finally selected by the NDT Technology Group for the study. Temperature data were not successfully stored in the rest of cases so that the temperature-behaviour relation was not possible to be determined.

The data captured by the transducers was an ultrasound signal. Then, they were saved by the monitoring system employing an excitation AC voltage (V) signal at high frequency (30 kHz). The frequency has been set according to the information that is needed, and therefore the samples are
obtained. Every signal had 11321 samples with a sampling frequency of $10^6$ samples/s. The proposed sample selection includes all the important information that is obtained up to 8000 samples for the case study. The signal contains a series of reflections and echoes from that point. A larger signal just adds the attenuation of the ultrasonic pulse, which does not involve the collection of relevant data. This is a standard information that depends on the system monitored (dimensions, material, etc.).

**Table 18.** Temperatures.

<table>
<thead>
<tr>
<th>Date (DD/MM)</th>
<th>Temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20/06</td>
<td>22.96</td>
</tr>
<tr>
<td>22/06</td>
<td>20.10</td>
</tr>
<tr>
<td>24/06</td>
<td>25.00</td>
</tr>
<tr>
<td>27/06</td>
<td>31.63</td>
</tr>
<tr>
<td>29/06</td>
<td>20.96</td>
</tr>
<tr>
<td>04/07</td>
<td>25.00</td>
</tr>
<tr>
<td>06/07</td>
<td>20.26</td>
</tr>
<tr>
<td>15/07</td>
<td>24.36</td>
</tr>
<tr>
<td>18/07</td>
<td>20.33</td>
</tr>
<tr>
<td>08/08</td>
<td>21.96</td>
</tr>
<tr>
<td>10/08</td>
<td>24.06</td>
</tr>
<tr>
<td>16/08</td>
<td>20.50</td>
</tr>
<tr>
<td>15/09</td>
<td>22.10</td>
</tr>
<tr>
<td>27/09</td>
<td>13.66</td>
</tr>
<tr>
<td>14/10</td>
<td>17.73</td>
</tr>
<tr>
<td>13/12</td>
<td>7.16</td>
</tr>
<tr>
<td>18/01</td>
<td>10.43</td>
</tr>
</tbody>
</table>
The sensors (R1A, R1B, R1C and R1D) were located as is shown in Figure 43 and separated 90 degrees. The objective is to analyse the overall performance of the pipeline. The pipe had a diameter of 20.32 cm and a length of 9 m.

![Diagram of sensors on a pipe](image)

**Figure 43.** MFC transducers set on a pipe.

Figure 44 represents an example of the sum for the signals stored by the four sensors. A study of correlations shows that the signals collected by the four transducers are highly correlated between them with only uncorrelated noise effect (see an example in Table 19). A matrix of p-values for testing the hypothesis of no correlation is also included. Each p-value is the probability of getting a correlation as large as the observed value by random chance, when the true correlation is zero. It was assumed that if p-value is smaller than 0.05, then the correlation is significant.

Ultrasound detects any discontinuity or deformation produced on the surface and shape changes will be associated with structural changes of the pipe. The pulses were basically longitudinal wave modes with a speed of
5400 m/s. The pulse-echo along the surface of the pipe is also shown in Figure 44.

Table 19. Correlation of sensors at 25°C.

```
<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1</td>
<td>0.6974</td>
<td>0.8686</td>
<td>0.6761</td>
</tr>
<tr>
<td>S2</td>
<td>0.6974</td>
<td>1</td>
<td>0.7948</td>
<td>0.8484</td>
</tr>
<tr>
<td>S3</td>
<td>0.8686</td>
<td>0.7948</td>
<td>1</td>
<td>0.6792</td>
</tr>
<tr>
<td>S4</td>
<td>0.6761</td>
<td>0.8484</td>
<td>0.6792</td>
<td>1</td>
</tr>
</tbody>
</table>
```

A pattern recognition is established from a MATLAB™ code where signals are compared in pairs to take into account the full range of temperatures of the case study. This model works by finding differences in the signal amplitudes for each pair. When these differences in amplitude are constant, then a pattern recognition can be found. This must be understood as a surface modification at a particular temperature [92].
7.2.1. Pattern recognition based on temperature

Signals are again decomposed in five levels employing the Daubechies wavelet family (Figure 45).

The same algorithm based on the wavelet transform is used to establish this new pattern recognition. All the signals are compared to take into account the full range of dates and temperatures. Several performances are expected since they are collected at different temperatures.

Table 20 identifies the occurrence of a pattern, where $Y$ means that the pair of signals is similar in shape but not in amplitude; $N$ is for the cases where pattern recognition does not exist (signals are completely different) and; $E$ states that signals are similar in shape and amplitude with a high degree of accuracy. Table 21 complements the $Y$ option, providing the information of the signal with the biggest amplitude. Finally, Table 22 describes if the pattern recognition is found for the complete signal or just in certain
sections. Data are divided into three parts to obtain detailed results: the start-up, a stabilised second phase and an irregular third phase. These three parts can be distinguished visually in Figure 46.

Figure 45. Wavelet decompositions.

Figures 47a, 47b and 47c correspond to three zoomed comparisons of ultrasound. Each graphic compares the contour of two signals. It is observed that the shape is similar, but the amplitude differs in 47a (Y,<, P or Y,>,P). Second graphic is for an E,C or E,P case because the amplitude and the shape resembles, while there is no similarity in 47c. Figure 47d plots
the amplitude differences of signals represented in 47a, 47b and 47c. Amplitude differences are close to zero and constant for 47a and 47b, but noticeable where it is not possible to find a pattern recognition (Figure 47d).

**Table 20.** Pattern recognition.

<table>
<thead>
<tr>
<th>Pattern recognition</th>
<th>Y</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>Signals are (nearly) equal</td>
</tr>
</tbody>
</table>

**Table 21.** Amplitude.

<table>
<thead>
<tr>
<th>Signal amplitude</th>
<th>&gt;</th>
<th>Amplitude $i$ &gt; Amplitude $j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;</td>
<td>Amplitude $i$ &lt; Amplitude $j$</td>
<td></td>
</tr>
</tbody>
</table>

**Table 22.** Degree of similitude.

<table>
<thead>
<tr>
<th>Signal</th>
<th>C</th>
<th>Complete pattern similitude for pair $i$,$j$ in the section</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>Partial pattern similitude for pair $i$,$j$ in the section</td>
</tr>
</tbody>
</table>

**Table 23.** Pattern recognition.

<table>
<thead>
<tr>
<th>Heading</th>
<th>Pattern recognition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>No pattern recognition</td>
</tr>
<tr>
<td>$Y_{&lt;,P}$</td>
<td>Partial pattern recognition where signal $i$ is smaller than $j$</td>
</tr>
<tr>
<td>$Y_{&gt;,P}$</td>
<td>Partial pattern recognition where signal $i$ is bigger than $j$</td>
</tr>
<tr>
<td>$Y_{&lt;,C}$</td>
<td>Complete pattern recognition where signal $i$ is smaller than $j$</td>
</tr>
<tr>
<td>$Y_{&gt;,C}$</td>
<td>Complete pattern recognition where signal $i$ is bigger than $j$</td>
</tr>
<tr>
<td>$E,P$</td>
<td>Signals are almost identical but with minor differences in amplitude</td>
</tr>
<tr>
<td>$E,C$</td>
<td>Signals are almost identical in shape and amplitude</td>
</tr>
</tbody>
</table>
7. Condition Monitoring on structures of Wind Turbines

Figure 46. Voltage vs. samples.

Figure 47. Pattern recognition.
7. Condition Monitoring on structures of Wind Turbines

7.2.2. Results

The results of the pattern recognition are shown in Table 24 considering all possible combinations. In summary, the possibility of finding shape changes cannot be determined correctly with the original signals.

Table 24. Results of the initial graphical pattern recognition.

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Amount</th>
<th>% per specific case</th>
<th>% pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>E,C</td>
<td>219</td>
<td>31.60</td>
<td>89.47</td>
</tr>
<tr>
<td>E,P</td>
<td>401</td>
<td>57.87</td>
<td></td>
</tr>
<tr>
<td>Y,&lt;,C / Y,&gt;,C</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Y,&lt;,P / Y,&gt;,P</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>73</td>
<td>10.53</td>
<td>10.53</td>
</tr>
<tr>
<td><strong>Total of comparisons</strong></td>
<td><strong>693</strong></td>
<td><strong>100</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

Once the similarity has been verified, the next step is to demonstrate that choosing the appropriate frequency range it is possible to draw conclusions from the changes in amplitude and, therefore, there is a relationship with temperature changes.

Signals are decomposed in five levels employing as outlined in Section 6.2.2. This first approach discloses how the energy is split among the divisions (Table 25).

The second section will be the segment of interest. It corresponds to operating conditions. The first section is irregular and involves a lot of randomness due e.g. to start-ups, stray signals from adjacent MFCs or coupling. Such phenomena are often found in the first samples; and do not provide valuable information on the overall behaviour of the pipe. Something similar is found in the third segment with the appearance of the echoes and reflections.
Table 25. Energy rates per signal.

<table>
<thead>
<tr>
<th></th>
<th>(a_4)</th>
<th>(d_4)</th>
<th>(d_3)</th>
<th>(d_2)</th>
<th>(d_1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28,38</td>
<td>33,19</td>
<td>21,64</td>
<td>9,94</td>
<td>6,85</td>
</tr>
<tr>
<td>2</td>
<td>29,81</td>
<td>30,43</td>
<td>23,62</td>
<td>8,19</td>
<td>7,95</td>
</tr>
<tr>
<td>3</td>
<td>25,9</td>
<td>35,38</td>
<td>22,65</td>
<td>7,59</td>
<td>8,48</td>
</tr>
<tr>
<td>4</td>
<td>29,28</td>
<td>31,76</td>
<td>20,14</td>
<td>10,02</td>
<td>8,8</td>
</tr>
<tr>
<td>5</td>
<td>26,12</td>
<td>31,79</td>
<td>26,7</td>
<td>9,25</td>
<td>6,14</td>
</tr>
<tr>
<td>6</td>
<td>24,91</td>
<td>32,18</td>
<td>25,03</td>
<td>12,46</td>
<td>5,42</td>
</tr>
<tr>
<td>7</td>
<td>25,38</td>
<td>33,49</td>
<td>24,27</td>
<td>9,95</td>
<td>6,91</td>
</tr>
<tr>
<td>8</td>
<td>24,29</td>
<td>29,78</td>
<td>24,04</td>
<td>14,1</td>
<td>7,79</td>
</tr>
<tr>
<td>9</td>
<td>27,63</td>
<td>27,95</td>
<td>23,09</td>
<td>15,38</td>
<td>5,95</td>
</tr>
<tr>
<td>10</td>
<td>25,2</td>
<td>31,06</td>
<td>17,97</td>
<td>19,12</td>
<td>6,65</td>
</tr>
<tr>
<td>11</td>
<td>26,09</td>
<td>30,73</td>
<td>23,82</td>
<td>12,33</td>
<td>7,03</td>
</tr>
<tr>
<td>12</td>
<td>28,98</td>
<td>29,2</td>
<td>16,01</td>
<td>18,97</td>
<td>6,84</td>
</tr>
<tr>
<td>13</td>
<td>31,27</td>
<td>30,44</td>
<td>19,69</td>
<td>11,67</td>
<td>6,93</td>
</tr>
<tr>
<td>14</td>
<td>23,95</td>
<td>29,65</td>
<td>21,31</td>
<td>17,42</td>
<td>7,67</td>
</tr>
<tr>
<td>15</td>
<td>29,96</td>
<td>30,27</td>
<td>22,95</td>
<td>11,07</td>
<td>5,75</td>
</tr>
<tr>
<td>16</td>
<td>23,15</td>
<td>33,67</td>
<td>21,03</td>
<td>14,41</td>
<td>7,74</td>
</tr>
<tr>
<td>17</td>
<td>22,97</td>
<td>33,12</td>
<td>23,46</td>
<td>14,06</td>
<td>6,39</td>
</tr>
</tbody>
</table>

The graphical pattern recognition is repeated. It is observed that the variation of the temperature and its relation with the behaviour of the pipe can be determined from amplitude changes in \(d_1\) and \(d_2\). The possible results can be considered acceptable as they are comprised between the 15\% and the 25\% of the total energy depending on the case, taking into account the weight of these decompositions based on the energy ratios described in Table 25. These decompositions provide better results and even patterns \(Y,<,P; Y,>,P; Y,<,C\) or \(Y,>,C\) will be found (Tables 26, 27 and 28). The \(Y,>,P\) and \(Y,<,P\) cases are the 8.65\% of the total cases for \(d_1\) decomposition, while \(Y,>,P\) cases are the 1.3\% of the total cases for \(d_2\). From \(a_4\) to \(d_3\) the patterns are similar to the original, being \(N\) patterns undesirable because of the randomness.
Table 26. Results of the graphical pattern recognition for the first part.

<table>
<thead>
<tr>
<th></th>
<th>a₄</th>
<th>d₄</th>
<th>d₃</th>
<th>d₂</th>
<th>d₁</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
</tr>
<tr>
<td>N</td>
<td>17</td>
<td>7.36</td>
<td>20</td>
<td>8.66</td>
<td>20</td>
</tr>
<tr>
<td>Y₁,&lt;P / Y₁&gt;,P</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Y₁,&lt;C / Y₁&gt;,C</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>E, P</td>
<td>161</td>
<td>69.70</td>
<td>45</td>
<td>19.48</td>
<td>27</td>
</tr>
<tr>
<td>E, C</td>
<td>53</td>
<td>22.94</td>
<td>166</td>
<td>71.86</td>
<td>184</td>
</tr>
<tr>
<td>Total</td>
<td>231</td>
<td>100</td>
<td>231</td>
<td>100</td>
<td>231</td>
</tr>
</tbody>
</table>

Table 27. Results of the graphical pattern recognition for the second part.

<table>
<thead>
<tr>
<th></th>
<th>a₄</th>
<th>d₄</th>
<th>d₃</th>
<th>d₂</th>
<th>d₁</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
</tr>
<tr>
<td>N</td>
<td>33</td>
<td>14.29</td>
<td>28</td>
<td>12.12</td>
<td>16</td>
</tr>
<tr>
<td>Y₁,&lt;P / Y₁&gt;,P</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Y₁,&lt;C / Y₁&gt;,C</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>E, P</td>
<td>106</td>
<td>45.89</td>
<td>123</td>
<td>53.25</td>
<td>67</td>
</tr>
<tr>
<td>E, C</td>
<td>92</td>
<td>39.83</td>
<td>80</td>
<td>34.63</td>
<td>148</td>
</tr>
<tr>
<td>Total</td>
<td>231</td>
<td>100</td>
<td>231</td>
<td>100</td>
<td>231</td>
</tr>
</tbody>
</table>

Table 28. Results of the graphical pattern recognition for the third part.

<table>
<thead>
<tr>
<th></th>
<th>a₄</th>
<th>d₄</th>
<th>d₃</th>
<th>d₂</th>
<th>d₁</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
<td>%</td>
<td>Am.</td>
</tr>
<tr>
<td>N</td>
<td>23</td>
<td>9.96</td>
<td>22</td>
<td>9.52</td>
<td>21</td>
</tr>
<tr>
<td>Y₁,&lt;P / Y₁&gt;,P</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Y₁,&lt;C / Y₁&gt;,C</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>E, P</td>
<td>134</td>
<td>58.01</td>
<td>153</td>
<td>66.23</td>
<td>20</td>
</tr>
<tr>
<td>E, C</td>
<td>74</td>
<td>32.03</td>
<td>56</td>
<td>24.24</td>
<td>190</td>
</tr>
<tr>
<td>Total</td>
<td>231</td>
<td>100</td>
<td>231</td>
<td>100</td>
<td>231</td>
</tr>
</tbody>
</table>

A statistical study provides more findings on the performance of ultrasound. This study complements the results from the pattern...
recognition. The lowest temperature will be taken as the reference signal for this part of the case study. This reference will be related to the remaining signals, so that conclusions can be extracted from the increases in temperature. A linear regression is performed to evaluate the reference and each ultrasound data. The outputs of the algorithm used are the fitted values, the output forecast, the standard deviation, the estimated recursive coefficients, and the coefficient of determination \( R^2 \) adjusted for degrees of freedom. The main purpose of \( R^2 \) is to predict future results or to test a hypothesis. The coefficient determines the quality of a model to replicate the results, such that the proportion of variation in results can be explained by the model. Therefore, this factor will be selected for the analytical measurement.

The original condition and the detailed decompositions are chosen in order to demonstrate the improvement of the method in Figure 48, where the coefficients of determination for two original ultrasounds and their decomposition \( d_1 \) (above) and \( d_2 \) (below) are shown. It is observed that \( R^2 \) has a rising trend when appropriate levels are chosen and contrasted with the random behaviour of the original ultrasound, although this slight increasing trend was noticed in all cases. Furthermore, it is noteworthy that the \( R^2 \) values increase when frequencies decrease.

Figure 49 plots the coefficient of determination of previous cases \( d_1 \) and \( d_2 \) along with their trends in the form of a quadratic equation. A big adjustment is appreciated in cases where data are between 20°C and 25°C.

This ensures the monitoring of pipelines in operating conditions for the range of temperatures considered (from 7.16°C to 31.63°C) with a high frequency filter. The wavelet transform can be proposed to find a pattern recognition in cases where the original signals are quite similar regardless of the temperature. On the other hand, being able to adjust the
performance of the pipe to an equation, an alarm system that links amplitude changes with superficial changes from R2 can be generated.

Figure 48. Original vs. $d_1$ and $d_2$ coefficients of determination.
7. Condition Monitoring on structures of Wind Turbines

7.3. Case study on a plate

The purpose of this section is to design a FDD model using ultrasound inputs in conjunction with advanced signal processing methods to monitor the structural assessment of wind turbines. This system will be able to detect faults or structural modifications e.g. scratches, cuts, changes in thickness or edges by identifying pattern changes in the pulse-echo signals. Note that pattern changes are associated with the aforementioned potential faults. The signal processing is based on the wavelet transform as

\[ y = 8.5e^{-0.05\times^2} - 0.0017\times + 0.0078 \]

\[ y = 0.0015\times^2 + 0.0047\times - 0.13 \]

**Figure 49.** Trends for \( d_1 \) (above) and \( d_2 \) (below) coefficients of determination.
7. Condition Monitoring on structures of Wind Turbines

a filtering technique and an autoregressive exogenous (ARX) model to estimate potential faults, where the exogenous variable is the input signal. An experimental platform is designed in order to illustrate the results. A steel plate is used as a test bed. The plate features may simulate the behaviour of certain parts of wind turbines as the tower.

7.3.1. Laboratory platform

Different experiments were carried out in an experimental platform to obtain the proposed FDD. The platform (see Figure 50) consists of a device that is able to read and generate signals at 4 MS/s. The device is connected to a PC for condition monitoring. The output signal from the device goes through an amplifier to drive the piezoelectric transducers. The high frequency amplifier is used to enhance the signal to noise ratio. In this particular case, the Hanning window is employed for the pulse inputs. The main advantage of the Hanning window is its low aliasing and loss of resolution. Furthermore, it reduces the generation of side lobes in its frequency spectrum. The piezoelectric transducers used are MFCs working as actuators and sensors.

![Figure 50. Laboratory NDT.](image)

Novel Approaches for Maintenance Management on Wind Turbines
The methodology to identify defects can be divided in two steps. Firstly, in order to enhance the signal to noise ratio and to avoid noise at different frequencies, a pre-filtering step based on a wavelet transform is proposed. Secondly, an ARX is estimated to predict the output response for the baseline condition. This predicted output response can then be compared to the actual response measured during other experiments to determine whether a significant variation between both signals is present. In case that difference is important, the system is assumed to have changed in such a way that faults may be present [96]. The rest of the section is devoted to introducing the wavelet and ARX methods, respectively.

### 7.3.2. Autoregressive exogenous model

Time series methods have been previously employed for failure prediction and detection. For instance, [59][124] utilize a vector auto-regressive moving-average and harmonic regressions, respectively, for failure prediction in railway elements. Here, an ARX is proposed to identify faults in WT elements. Basically, an ARX can be expressed by a linear difference equation, such as (11):

\[
y_t + a_1y_{t-1} + \cdots + a_{na}y_{t-na} = b_1u_{t-nk} + \cdots + b_{nb}u_{t-nk-nb+1} + \epsilon_t
\]  

(11)

where autoregressive refers to the autoregressive part and exogenous to the extra input. The parameters \( n_a \) and \( n_b \) are the orders of the model, and \( n_k \) is the number of input samples that occur before the input affects the output, also called the delay in the system [98]. The variables \( y_t \) and \( u_t \) stand for the output and input responses, respectively. Model orders \( n_a, n_b \) and \( n_k \) have been chosen by minimising the Akaike's Information Criterion [4]. Model selection and the estimation of the unknown parameters \( a_i, i=1,\ldots,n_a \) and \( b_j, j=1,\ldots,n_b \) have been done by means of the routines implemented in the MATLAB™ System Identification toolbox [99].
7.3.3. Experimental results

To achieve the objectives of the case study, several experiments on a free fault plate are carried out. They are then repeated after making a cut over the entire thickness of the plate. Distances and measurement conditions remain unchanged in order to analyse the behaviour of the material in both circumstances.

The square steel plate has a length of 106 cm² and a thickness of 1.2 mm. Three MFC transducers are located as shown in Figure 52. The first sensor located at 14 cm from the left extreme acts as actuator; and the remaining as sensors. The emitted signal will be a Hanning pulse at 25 kHz, 2 cycles and a sampling time of 40000 samples per second (see Figure 51). The input frequency is set to 25 kHz to achieve a compromise between good response and MFC limitations when they work as actuators. Additionally, the pulse is composed of 2 cycles, in order to create a narrow pulse and to avoid undesired overlaps between the emitted pulse and the first received echoes.

The received signals are recorded and the pattern between both sensors is analysed. Next, the different cuts between the second and the third sensor are made as is depicted in the right panel of Figure 52. Then, the same input signal is applied to determine how the pattern has changed with regards to the initial fault-free experiment.

It should be pointed out that the model uses as input $u$ in (11) the observations measured with the sensor 1 (25 cm to the right of the actuator) and as output the sensor 2 closer to the right extreme.

A MATLAB™ code is implemented to pre-filter the signals. The inputs are the two original signals received by the sensors and the outputs are the filtered signals. The process is carried out by the DWT.
The chosen family is again the Daubechies wavelet transform. An example of the signals without and with filtering is depicted in Figure 53. The technique also prevents border limitations, scaling errors or fidelity with a proper accuracy in the results. The approach is intended to avoid any type of noise complexity associated to the signal to be analysed.
To identify the ARX orders and to estimate their respective parameters, two experiments were carried out for the free-fault plate. The data of the first experiment were employed to identify and estimate an ARX with $n_a=17$; $n_b=13$ and $n_k=20$, by minimising the criterion. The second experiment was used to validate the previous estimation.

Figure 54 shows the measured observations of that experimental validation, where the sensor 2 measurements are in solid line and the 20 step model predicted output in dashed line. The Root Mean Squared Error (RMSE) associated to this predicted output is $2.27 \times 10^{-4}$.

![Figure 53. Unfiltered (left) vs. filtered signal (right).](image)

As previously mentioned, the same input was applied after a cut was made into the plate. Figure 55 shows again the measured and 20 step predicted output in solid and dashed line, respectively.

In this case the model previously estimated is not adequate to reproduce the measured observations as a consequence of the fault. In fact, the RMSE is $4.45 \times 10^{-4}$ which is significantly higher than the RMSE computed when no fault was present on the plate.
Figure 54. Measured (solid line) and 20 step predicted output (dashed line) for the free-fault case.

Figure 55. Measured (solid line) and 20 step predicted output (dashed line) when a fault has occurred.
7.3.4. Fault diagnosis

It is more appealing from a practical point of view to be capable of detecting the potential fault before the complete system failure. In that sense, a third experiment is designed, where the plate was partially cut (8.5 cm long x 0.6 mm deep). Unlike the previous experiment, the plate was not cut over the entire thickness.

Figure 56 displays the RMSE found for each sensor. Upper and lower plot refer to the RMSE calculated from the sensor 1 and 2, respectively. Note that the RMSE was computed with respect to the free-fault experiment. Each bar in the figure corresponds to the average of the three experiments carried out under each condition. In other words, the fault-free experiment was repeated three times and the average RMSE was computed. Likewise, the early stage experiment (partial cut) was repeated three times. The average RMSE was calculated and the same procedure was applied to the crack case (entire thickness cut). The lower plot shows that the second and third bar provides a higher RMSE than the free-fault case. Therefore, the model is capable of detecting a fault or potential fault. Nevertheless, in order to distinguish whether the fault is at an early stage or it corresponds to a complete failure; the RMSE provided by the sensor 1 needs to be analysed. Recall that the RMSE of the sensor 1 is the average of the RMSE computed with respect to the fault-free measured output of the same sensor 1. Here, it should be pointed out that the sensor 1 RMSE is similar to the fault-free RMSE when a fault is at an early stage, whereas the RMSE is higher than the other two cases when a complete fault is present.

In summary, the results of sensor 2 inform about the presence of a fault in the structure, however, in order to distinguish whether that fault is at an early stage or a complete failure, information from sensor 1 should be analyzed. If RMSE in sensor 1 is higher than the fault-free RMSE a complete
fault is found. Otherwise an early stage fault is emerging and maintenance activities should be carried out.

**Figure 56.** RMSE found for sensor 2 (upper plot) and sensor 1 (lower plot) between the measured sensor output and the free-fault baseline.

In order to interpret these results, it is interesting to plot the measured output of sensor 2 (Figure 57) and sensor 1 (Figure 58) for each type of fault. When the plate starts to crack, Figure 57 shows how a delay in the sensor 2 early stage fault signal appears with respect to the free-fault case. However, when the plate suffers a complete crack, the sensor 2 does not receive the input signal and it mainly measures noise.

In addition to the information provided by sensor 2, it is important to analyse the sensor 1 output. Figure 58 shows when an early stage fault is present, how the signal goes through the material, and that the difference with respect to the fault-free test is negligible. On the other hand when the plate is completely cracked, the input signal does not go through the material and it is echoed back, yielding a totally different signal regarding the fault-free case.
Figure 57. Sensor 2 measured signal for the free-fault (solid line), early stage (dashed line) and crack (dotted line) cases.

Figure 58. Sensor 1 measured signal for the free-fault (solid line), early stage (dashed line) and crack (dotted line) cases.
7. Case study on the tower of a Wind Turbine

Experiments take place on a tower of 27 meters of length and 3.5 meters of diameter. The tower has ten welds uniformly distributed and a gateway to access the nacelle (Figure 59). 24 MFC transducers are placed around the diameter of the tower at 6 meters above the ground (Figure 60).

Data collection is done by the technique of Guided Wave Testing (GWT). Gan and others [55] introduces this technique for the detection of metal loss from corrosion and fatigue cracking in tubular steel towers supporting WT generators. The GWT system consists of a pulser-receiver unit, a laptop, a multiband directional antenna, and an array of MFC transducers (Figure 61). GWT employs mechanical stress to allow the ultrasound signal going along a distance with little loss of energy. The ultrasound signal is sent by the transducers and returns to the sensor. Then it is saved employing an excitation AC voltage. The transducers are individually connected to an MCX male connector. The cables are in turn connected to an MCX female to DLM connector that is plugged into the pulse-receiver. The captured data have a frequency of 30 kHz and a speed of 3076 m/s.

The pulser-receiver is a system with multiple channels that allows up to 24 transducers to be connected. The system is built to be operational at low-frequencies, which is suitable for the tower monitoring. Additionally, the system can be controlled manually and automatically through the laptop. The remote access for the tower monitoring is set up by the use of a multiband directional antenna. The directional antenna is mounted around 5 meters from the tower, and the cable is extended through a hole below the ground flange. Finally, the remote access to the system is achieved through software and data are collected and downloaded (Figure 62).
The analysis of the signal will enable the detection of joints, defects, cracks, etc., from changes in shape and amplitude. The study is based on the pulse-echo technique, which means that the sensors transmit the signal and when an imperfection is detected, part of the signal returns to the sensor while the other part goes forward until it reaches the top flange. The case study must consider that the tower is made up from different joints that should be taken into account in order to not be confused with any other types of defects or cracks.

Figure 59. Distances.
7. Condition Monitoring on structures of Wind Turbines

**Figure 60.** Array of transducers.

**Figure 61.** Taxonomy of the GWT system.
7.4.1. Fault Detection and Diagnosis on the tower and results

Before starting the analysis, an accurate working frequency range must be selected as the high frequency noises generated from the high voltage transformer need to be removed with the wavelet transform. This will be possible with the decomposition $a_4$. Figure 63 shows a comparison between the decomposition $d_1$ (blue) and selected decomposition ($a_d$), stating that the information provided by $d_1$ is irrelevant since there are no changes in shape and amplitude to base the case study.

For the determination of the surface irregularities, some initial features are calculated, e.g. the time of propagation, using the equation (12) and the distances shown in Figure 59. The speed is always constant (3076 m/s). The total length $2e$ is the sum of the distance between the transducer and the surface defect considering that the information goes back to transducer before being saved (Figure 64).

$$t = \frac{2e}{v}$$ (12)
7. Condition Monitoring on structures of Wind Turbines

Figure 63. Decompositions $d_1$ vs. $a_4$.

Figure 64. Distance measurement.
Once the propagation time \( t \) is obtained, it is possible to identify the location of a joint, crack or defect. This identification can be expressed in time or samples. Additionally it is possible to convert the samples into time by considering that \( 10^6 \) samples were recorded per second. It must be remembered that there exists a small displacement of 186 samples, as the main pulse excitation is not exactly located at \( t=0 \) s. This corresponds to the ski-slope effect that occurs when the sensor experiences a mechanical, thermal or electrical transient during the measurement process. This value must be added to the results in order to identify each particular imperfection or joint.

Two examples are presented in order to introduce the FDD where the objective is to find the different welds and surface variations of a tower. A signal from one of the arrays located above the gateway is selected. Figure 65 is from a section of \( a_4 \), where different amplitude increases are observed. The first one will be studied to determine, in this case, the third weld (the weld closest to the array).

The distance from weld_3 to the array is 0.776 m. With the use of the equation that relates the space over time, the calculation of the time invested to detect the third weld is as shown in (13):

\[
 t_{\text{weld}} = \frac{2e}{v} = \frac{2 \times 0.776}{3076} = 504.5 \mu s
\]  

The sample where there is a joint can be studied by the cross relation (14):

\[
 1 \text{ s} \quad \rightarrow \quad 10^6 \text{ samples} \\
504.5 \times 10^{-6} \text{ s} \quad \rightarrow \quad x=504.5 \text{ samples}
\]

Adding the displacement of the start-up:
7. Condition Monitoring on structures of Wind Turbines

\[ t_{\text{weld}3} = 504.5 \text{ samples} + 186 \text{ samples} = 690.5 \text{ samples} \]  

(15)

The calculated value coincides with the amplitude variation rounded in red for Figure 65.

![Figure 65. Third weld.](image)

Repeating the calculations in decreasing order, Table 29 is obtained. The second column indicates the distance between the array and the different welds, the ends of the tower or the gateway (Figure 59). The third column comes from the equation (12) and finally, the samples are calculated as in the example (15).

Table 29 can be more detailed and complex taking into account that the ultrasound, in its return to the array, detects again the same joints or imperfections that had already found before reaching the top flange. As a consequence, there may be overlaps between signals intersecting at a particular point. The FDD considers these situations and overlaps can be seen from increases of the amplitude. Figure 66 is another example.
Table 29. Distance, time and samples calculations.

<table>
<thead>
<tr>
<th>Location</th>
<th>Distance (m)</th>
<th>Time (µs)</th>
<th>Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>weld10</td>
<td>17,18</td>
<td>11176,20</td>
<td>11362</td>
</tr>
<tr>
<td>weld9</td>
<td>14,83</td>
<td>9643,04</td>
<td>9829</td>
</tr>
<tr>
<td>weld8</td>
<td>12,47</td>
<td>8113,13</td>
<td>8299</td>
</tr>
<tr>
<td>weld7</td>
<td>10,12</td>
<td>6585,82</td>
<td>6771</td>
</tr>
<tr>
<td>weld6</td>
<td>7,78</td>
<td>5061,11</td>
<td>5247</td>
</tr>
<tr>
<td>weld5</td>
<td>5,44</td>
<td>3539,66</td>
<td>3725</td>
</tr>
<tr>
<td>weld4</td>
<td>3,10</td>
<td>2020,80</td>
<td>2206</td>
</tr>
<tr>
<td>weld3</td>
<td>0,77</td>
<td>504,55</td>
<td>690</td>
</tr>
<tr>
<td>weld2</td>
<td>1,55</td>
<td>1009,10</td>
<td>1195</td>
</tr>
<tr>
<td>weld1</td>
<td>3,87</td>
<td>2519,50</td>
<td>2705</td>
</tr>
<tr>
<td>top flange</td>
<td>18,23</td>
<td>11857,60</td>
<td>12043</td>
</tr>
<tr>
<td>bottom flange</td>
<td>6,19</td>
<td>4027,30</td>
<td>4213</td>
</tr>
<tr>
<td>top of door</td>
<td>2,99</td>
<td>1946,68</td>
<td>2132</td>
</tr>
<tr>
<td>bottom of door</td>
<td>5,61</td>
<td>3650,19</td>
<td>3836</td>
</tr>
<tr>
<td>array</td>
<td>0</td>
<td>0</td>
<td>186</td>
</tr>
</tbody>
</table>

Figure 66. Joints detected in [2,500, 4,500] interval.

Circles 2 and 6 correspond to the first and fifth weld respectively, while points 7 and 8 are the bottom of the door to access to the WT and the
7. Condition Monitoring on structures of Wind Turbines

bottom of the tower (ground). Points 3, 5 and 9 are the result from the overlapping of different signals: the third weld with the top of the door (3), the second weld with the fourth weld (5) and the fourth weld with the top of the door again (9). It is noted that overlaps usually have bigger amplitudes since several signals are superposed. Finally, points 1 and 4 are detected when the signal returns to the array after having completed its displacement through the tower. Point 1 is for the third weld and 4 for the second weld.

7.4.2. Benefits over other techniques

Some other techniques are used to determine fatigue cracks or corrosion with the same data. A tower feature identification using the Hilbert transform is performed (Figure 67). The amplitude of the features is measured from the rectified summed of the pulse-echo data and plotted several times to collect a pattern following the same trend. It is supposed that any deviation from the trend indicates a change in the structure. The main drawback of this method is that signals must be filtered to suppress the high frequency noise from the raw signal

An image processing method based on a delay and sum technique is also developed. The noise at high frequencies needs to be removed again so that a band pass filter is used (Figure 68). The data are analysed with a cross-correlation between the received and the drive signals (Figure 69). The width of the peaks is determined by the frequency, but the high periodicity of the waves limits the results. This is improved using coded waveforms, although this represents a problem at highly dispersive frequency range. Among the alternative coded waveforms to be considered, the complimentary Golay coded waveform is suggested due to its reduction of the signal processing complexity [131]. On the other hand this requires doubling the waveforms collected.
7. Condition Monitoring on structures of Wind Turbines

**Figure 67.** Tower feature identification.

**Figure 68.** Enlarged section of raw received waveform (up) and after filtering (down).
Comparing with the case study, the wavelet transform has a major advantage: the filter process is immediate and it is not necessary to introduce a prior step to the fault detection. All methods have low complexity once their respective algorithms have been completed, though the accuracy of the results is not similar. In the case of the image processing, the efficiency is not as good as for the other methods. Additionally to these limitations, some issues related to the distortion of the acoustic signals or scaling errors are presented which means the reduction of the imaging fidelity.

The wavelet transform approach will be intended to avoid this type of complexity associated with noise, distortion or resolution of the signal to be analysed.
8. Conclusions and future work

Conclusions

The growth of the renewable energy industry forces companies to emphasize key factors such as maintenance. The complexity of WTs is increasing and maintenance costs represent a significant cost over the total. As a consequence, new techniques are emerging to obtain high levels of RAMS.

Although maintenance in WTs is a widespread practice, not much attention has been paid to certain structures in comparison to other mechanical and electrical devices located on the nacelle or the blades, even when it is known that a proper monitoring of the tower can help to anticipate catastrophic failures related to corrosion, leaks or cracks. This dissertation is also focused on to guarantee correct levels of RAMS in mechanisms used in cooling devices for generators and gearboxes, electric motors for service crane, yaw motors, pitch motors, pumps, ventilators, etc., for similar reasons.

Different case studies are described based on experimental sets and researches on elements of a real WT. First, a mechanical brake has been simulated linking a generator and an engine by a coupling joint. Sound and vibration are the main features to be analysed from experiments that have been done in as commissioned conditions and considering misalignments, resistances and the use of a rigid coupling. A second stage is performed in
8. Conclusions and future work

the nacelle of a WT. The objective is to extend the results from the test bench.

A novel FDD that relies on the use of the wavelet transform and the FFT to demonstrate the feasibility of the obtained conclusions is created. An algorithm that locates faults in a three-dimensional grid has been designed. Each coordinate represents the position of a feature: first harmonic of vibration \(x\), second harmonic of vibration \(y\) and sound energy \(z\). This pattern recognition will get a significant reduction of costs as the audio sensor entails a remarkable lowering in comparison with the current vibration sensors. It can be an alternative to standard maintenance methods in any driving motor. In addition, the tests can be extended and made up for other failures that may occur, for example, in bearings or unbalances.

Summarized results from the pattern recognition are (per point):

- **Point 1:** Experiments in fault-free conditions and applying a resistance are in nearby areas. When the different degrees of misalignment are studied, the results are in the same region. A third group, related to the change of the rigid coupling for the flexible coupling is highlighted. The first harmonic grows when misalignments are noticeable while the second harmonic remains stable.

- **Point 2:** Fault-free conditions appear mixed with the misalignments. The energy levels are stabilized with the exception of the last experiment. Vibrations and looseness increases and the second harmonics are not steady.

- **Point 3:** There are some resemblances with the previous point. The energy for the fifth misalignment gains importance as well as the second harmonic for all the experiments.
• Point 4: As stated for point 1, the fault-free conditions and experiment number 4 are closer in the three-dimensional graphic. They also have higher energy levels along with the seventh and last tests. 1X and 2X grow when the degree of misalignment increases.

Continuing with the research work, the thesis introduces another NDT approach as part of a SHM in WTs. The temperature is now a relevant factor to solve problems related to cracks, leaks or corrosion as it is well known that high or low temperatures can modify the characteristics of pipelines.

The experiments are done with pipes that have been analysed using 4 MFC transducers. The strategic placement of the sensors assures the quality of the monitoring system. An algorithm based on the wavelet transform is designed for a new FDD. The signals are converted into voltage and compared to observe the relation with their temperature.

Data are analysed in different sections, where the second section is chosen for the pattern recognition. It has been shown that the wavelet transform is enough sensitive to small changes in shape and amplitude, finding a relation between the temperature and the performance of the pipe. A study based on the coefficient of determination is applied to the pattern recognition.

The original condition and the $d_1$ level are chosen in order to demonstrate the improvement of the method. It is observed that $R^2$ has a rising trend when appropriate levels are chosen and contrasted with the random behaviour of the original ultrasound. Thus, the wavelet transform is able to study the performance of signals from their temperatures, even when they are quite similar, searching differences in their amplitudes.
8. Conclusions and future work

A third subsection also focused on structures is presented in this thesis. Guided ultrasonic waves as a NDT technique are introduced because of their ability to monitor different geometries of limited access.

The section reports the design of a FDD model using ultrasound along with advanced signal processing tools: wavelet transform to filter the measured data and an ARX model to estimate potential faults. The system detects structural changes by identifying pattern modifications in pulse-echo experiments. To achieve the intended objectives, several experiments are carried out on both a defect-free surface and on a damaged plate, with different extents of severity ranging from superficial cuts to a complete crack over the plate. The experimental results corroborate the adequacy of the proposed methodology to identify potential faults.

To finish, the design of a GWT method to collect the ultrasound signal in a tower of a WT from the 24 MFC transducers is described. The selection of a low-frequency decomposition for the analysis of the voltage signals permits to avoid the noise at high frequencies. Joints, welds and other modifications on the surface of the structure are detected even in overlaps situations, proving the robustness of the wavelet transform once again.

Thus, the determination of any imperfection is ensured from changes of shape or amplitude, providing the exact position where it appears, regardless of the complexity of the structure and/or the number of defects.

**Future work**

The wavelet transform and the use of MFC transducers start to expand in the field of the FDD aimed to WTs. For this reason there are many future works proposed, e.g.:
8. Conclusions and future work

- Planning scheduled maintenance programs that include the techniques listed in this dissertation.
- Extension of the pattern recognition based on the sound and vibration using non-linear methods to other typical failures.
- Study of failure modes focused on other types of motors located on a real WT.
- Analysis of features, e.g. vibration for technical support in WTs.
- Expansion the range of temperatures so that conclusions can be drawn to extreme situations, for example frosts.
- Inclusion of the proposed advanced signal processing tools to identify other surface defects, e.g. corrosion in plates or blades, taking into account material and superficial differences.
9. References


9. References


9. References


9. References


9. References


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9. References


9. References


9. References


9. References


9. References


References


9. References


9. References


9. References


About the author / supervisor

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More information: http://www.uclm.es/profesorado/fausto/
Appendix A. Elements of the experimental mechanism

The main experimental set components are described in this appendix. The first part focuses on the five principal components: engine, generator, load, frequency converter and data acquisition board. Then the sensors and their corresponding modules are described. Appendix concludes with the introduction of the clamping elements of the set.

Engine

It is a three-phase asynchronous induction engine (Ingersoll-Rand) with the following characteristics:

<table>
<thead>
<tr>
<th>Table A1. Characteristics of the engine.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
</tr>
<tr>
<td>Current</td>
</tr>
<tr>
<td>Voltage</td>
</tr>
<tr>
<td>Spins</td>
</tr>
<tr>
<td>Frequency</td>
</tr>
<tr>
<td>Phases</td>
</tr>
</tbody>
</table>

Generator

The electric generator (Mecc-Alte model T16F) has 2-pole brushes with the following characteristics:
Appendix A. Elements of the experimental mechanism

Table A2. Characteristics of the generator.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>6KVA</td>
</tr>
<tr>
<td>Current</td>
<td>230 / 400 V</td>
</tr>
<tr>
<td>Voltage</td>
<td>15,1 / 8,7 A</td>
</tr>
<tr>
<td>Spins</td>
<td>3000 rpm</td>
</tr>
<tr>
<td>Frequency</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Phases</td>
<td>3</td>
</tr>
<tr>
<td>Cos φ</td>
<td>0.8</td>
</tr>
<tr>
<td>Protection</td>
<td>IP23</td>
</tr>
<tr>
<td>Weight</td>
<td>30,5 Kg.</td>
</tr>
</tbody>
</table>

Load

The generator is connected to an electric motor as a load. This motor (CIMA) is an asynchronous three-phase with the following characteristics:

Table A3. Characteristics of the electric motor for the load.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>1,5 Kw.</td>
</tr>
<tr>
<td>Current Δ /Υ</td>
<td>6,1 / 3,5 A</td>
</tr>
<tr>
<td>Voltage Δ /Υ</td>
<td>230 / 400 V</td>
</tr>
<tr>
<td>Spins</td>
<td>2820 rpm</td>
</tr>
<tr>
<td>Frequency</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Phases</td>
<td>3</td>
</tr>
</tbody>
</table>

Frequency converter

The frequency converter used (ABB series ACS350 and model 03E-12A5-4) is a 380V three-phase converter with an output power of 5.5 KW and 12.5 Amps (Figure A1).
Appendix A. Elements of the experimental mechanism

**Figure A1.** Frequency converter.

To operate with the converter is necessary to introduce the motor parameters. The rotating speed motor and the frequency can be seen on the display that the converter has in its frontal panel.

**Data acquisition board**

A modular system from National Instruments has been chosen for the data acquisition. It consists of a chassis and conditioning modules for the different signals that will be measured. This system connects to the computer via a USB cable. This system is robust and reliable and can purchase or send multiple digital and analogic signals through various modules offered by National Instruments (Figure A2).

**Figure A2.** Data acquisition board.
Appendix A. Elements of the experimental mechanism

**Chassis**

The cDAQ-9172 (National Instruments) is a NI CompactDAQ chassis 8-slot that can support up to eight input / output (I/O). The frame operates from 11 to 30 VDC, and includes a power adapter AC/DC. The NI cDAQ-9172 is a USB 2.0 compatible device. It has two 32-bit integrated chip counter/timers into the chassis. With a I/O digital module correlated and installed in slot 5 or 6 of the chassis, the user can access all the functionalities of the counter/timer chip, including event counting, generation or pulse width measurement and quadrature encoders (Figure A3).

![Figure A3. CompactDAQ-9172 chassis.](image)

**Acquisition modules**

**NI 9211**

4-channel thermocouple input module. 15 S/s, 24. Bit, ± 80 mV. The thermocouple input module includes a delta-sigma ADC of 24-bit, anti-aliasing filters, detection of open thermocouple and cold junction compensation for thermocouple measurements of high precision. This module contains traceable calibration, certificates issued by NIST and dual
Appendix A. Elements of the experimental mechanism

channel isolation barrier to ground for safety, noise immunity and high range of common mode voltage.

**NI 9203**

8-channel analog current input module. 16-Bit, ± 20 mA, 200 kS/s. The NI 9203 includes eight channels of analog input current for high-performance control and monitoring. It has programmable input ranges of ± 20 mA or 0 to 20 mA, 16-bit resolution and a maximum sampling rate of 200 kS/s. It also provides open-loop detection, which is programmed using the LabView software. To protect against signal transients, the NI 9203 includes two isolation barrier channels to ground for safety and noise immunity (250 Vrms).

**NI 9421**

8-channel sinking digital input module. 24 V logic and 100 μs. Each channel is compatible with signals from 12 to 24 V and offers transient overvoltage protection of 2,300 Vrms between input channels and earth. Each channel also has an LED that indicates the status of the channel. It works with industrial logic levels and signals for direct connection to a wide variety of switches, transducers and industrial devices.

**Sensors**

The sensors used in the system are sensors for temperature, current and generator shaft rotation.

**Temperature**

There are two J-type thermocouples to acquire temperature data from the engine and the generator and temperature of the room. The thermocouple
Appendix A. Elements of the experimental mechanism

temperature sensor is constituted by two different metals whose main characteristic is that produces a voltage proportional to the temperature difference between the binding sites of both metals (Figure A4).

![Figure A4. J thermocouple.](image)

In general, the electrons in the outermost level are attached weakly to the nucleus. When a conductor is heated at one end, these electrons increase their energy and reach to the other end by diffusion mechanisms. This causes an electric field that opposes the diffusion so that an equilibrium state is reached.

Therefore, the thermo-electric effect is not due to the existence of two different metals, but to the temperature difference between two points of a same metal. However, the generated electromotive force could not be measured if it had a single metal. Thus, if the metal is heated in a single point, the voltage between the terminals B and C is zero, since the voltage between A and B is equal to the voltage drop between A and C.

The measurement must be performed on asymmetric circuits, i.e. consisting of two or more different metals to force the appearance of a nonzero force. The voltage drop depends on the material and the temperature difference.
Current

A Hall effect sensor to acquire current data is used. A current sensor with analogical output can be accomplished by a ferrite core and a linear Hall sensor mounted in a plastic case. The current flowing through a conductor creates a magnetic field. This magnetic field is carried by the ferrite core to a Hall sensor, which converts the field to an output voltage proportional to the current in the conductor.

These devices allow monitoring both continuous and alternating signals providing isolation between the measuring circuit and power. The output can be either current or voltage. The current output of the sensor is 4-20mA (Figure A5).

Experimenting bench assembly

The generator and electric motor are assembled on a base that has a buffer to the vibrations of rotating electrical machines. This buffer system is performed by silemblocks or rubber blocks (Figure A6).

Figure A5. LEM current sensor.
Appendix A. Elements of the experimental mechanism

Figure A6. Silemblock.