# Journal Paper

“Methods and Tools for the Operational Reliability Optimisation of Large-Scale Industrial Wind Turbines”

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# Methods and Tools for the Operational Reliability Optimisation of Large-Scale Industrial Wind Turbines

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**Abstract.**

Wind turbines (WT) maintenance management is in continuous development to improve the reliability, availability, maintainability and safety (RAMS) of WTs, and to achieve time and cost reductions. The optimisation of the operation reliability involves the supervisory control and data acquisition to guarantee correct levels of RAMS. A fault detection and diagnosis methodology is proposed for large-scale industrial WTs. The method applies the wavelet and Fourier analysis to vibration signals. A number of turbines (up to 3) of the same type will be instrumented in the same wind farm. The data collected from the individual turbines will be fused and analysed together in order to determine the overall reliability of this particular wind farm and wind turbine type. It is expected that data fusion will allow a significant improvement in overall reliability since the value of the information gained from the various condition monitoring systems will be enhanced. Effort will also focus on the successful application of dependable embedded computer systems for the reliable implementation of wind turbine condition monitoring and control technologies.

**Keywords:** wind turbines, maintenance management, vibration, fast Fourier transform, wavelet.

# 1. Introduction

## 1.1. 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 [1]. 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 [2] and [3]. 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 [4].

CM is implemented from basic operations of the equipment to study [1]. 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



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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 [5]. 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.

### 1.2. Objectives

A number of turbines (up to 3) of the same type will be instrumented in the same wind farm. The data collected from the individual turbines will be fused and analysed together in order to determine the overall reliability of this particular wind farm and wind turbine type. It is expected that data fusion will allow a significant improvement in overall reliability since the value of the information gained from the various condition monitoring systems will be enhanced. Effort will also focus on the successful application of dependable embedded computer systems for the reliable implementation of wind turbine condition monitoring and control technologies.

## 2. Bearing failures

Bearings are mechanical devices that reduce the friction between a shaft and other rolling parts of a set, providing a continuous displacement. They can be found in several rotating machines.

Bearings failures are mostly focused on improper maintenance policies. It is assumed that only 10% of the bearings complete their life cycle. These failures are caused by a deficient lubrication in 30% of the cases, by a poor assembly or installation in 40% of the cases, including misalignments; and focused on overloads, manufacturing defects or other sources in the remaining cases (20%).

If machines are properly aligned and balanced, if they operate at resonant frequencies or if they are properly lubricated, the life cycle of a device can be higher. A defective bearing will vibrate at non-multiple rotational speed frequencies. This will be the first warning of an emerging failure.

## 3. Vibration (Fast Fourier transform)

### 3.1. Introduction

The Fast Fourier transform (FFT) of a function *f(x)* is defined as [6]:

$$\int_{-\infty}^{\infty} f(x)e^{-i2\pi xs}dx \qquad (1)$$

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

$$\int_{-\infty}^{\infty} f(s) e^{-i2\pi\omega s} ds \tag{2}$$

The use of the FFT is extended for analysis in the frequency domain, allowing a spectral representation and a detail analysis [7]. It is helpful when periodic patterns are studied [8]. Vibration analysis also provides information about a particular reason of the fault origin and/or its severity [9].

## 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 [10]. Although this is the main connection, FFT can be used for other types of analysis or failure detection.

### Wind Turbines

The wide variety of existing WTs 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 [11]. 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 [12]. 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 [13].

The study of the storage capacity, the demand response and the ensemble of generators is considered from a power spectrum and FFT [14]. Swartz *et al.* [15] 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 commonly used.

### 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 [16] and [17].

On the other hand, there are other research fields where the FFT still achieves the set objectives despite its less novel character and limitations, e.g. the engines, employed as 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 [18]. The effect of misalignment is studied to determine the nature and extent of this phenomenon by FFT [19]. The analysis of the acoustic radiation emitted from axisymmetric bodies is carried out using FFT [20]. Noise tracking methods for non-invasive study of defective structures from acoustic signals also introduces the technique [21]. 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 [22].

### 3.3. Results employing FFTs

Frequencies appear in the 20 to 60 kHz range in a first damage phase. The higher frequencies correspond to the natural frequencies. When damage becomes bigger, they tend to cause a bearing resonance. This resonance appears as a bell at the natural frequency. In a third stage, failure modes can be seen and harmonic peaks are generated as the result of the bearing impacts. Vibration levels increase and therefore more harmonics and sidebands will appear in a fourth stage. In most severe stages, the amplitude of the natural rotational frequency (1X) and their corresponding harmonics increases. These features can be attributed to the emergence of gaps due to the failure. Finally, the natural frequency tends to be lessened, leading to noise accumulations.

Based on the above, three sources of failure can be considered in this case study. Each type is supported by a graphical representation of the signals taken at different dates and loads (Table 1). Sensors collect axial, radial and non-radial signals. It must be taken into account that the main failure mode does not always have a unique nature, so frequency spectrum can overlap characteristics coming from different sources, e.g., in the case of the gaps, they can be the consequence of failures in the bearings.

| Date | 11/04/2014 | 11/04/2014 | 13/04/2014 | 19/04/2014 | 26/04/2014 | 27/04/2014 |
|---|---|---|---|---|---|---|
| Load | 44% | 100% | 50% | 7% | 51% | 26% |

Tab. 1: measurements.

#### Rolling element bearing wear

The first case is a summary of the aforementioned. Failures associated with rolling element bearings follow a classic pattern, beginning with a high-frequency "ringing" of the bearing. As the failure progresses, the spectrum will change in a characteristic way. There will be peaks at non-synchronous frequencies, typically with harmonics, and often with sidebands around the 1X or the cage frequency (Figure 1).

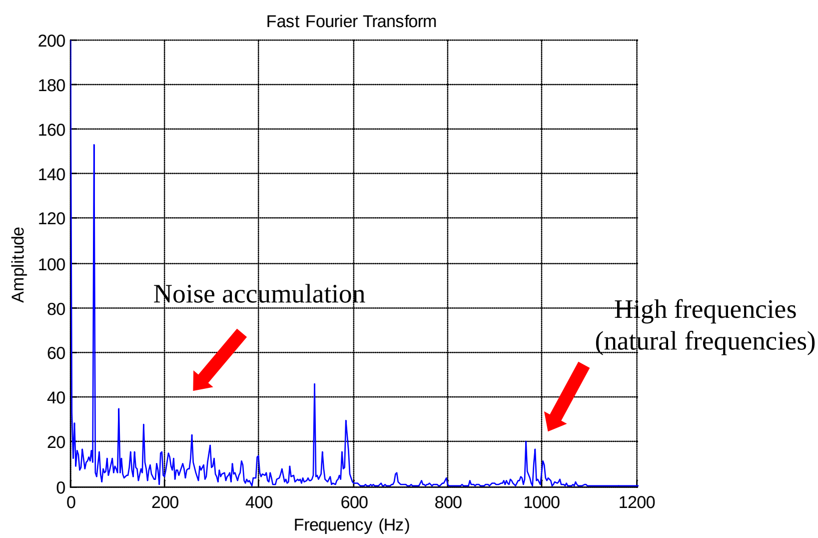


Fig. 1: Fast Fourier transform (100% load).

## Cocked bearing

This misalignment generates a considerable axial vibration. Peaks will often be observed at 1X, 2X as well as 3X (see Figure 2). The presence of peaks at 2X and 3X would indicate a cocked bearing condition. The strong axial vibration is often confused with misalignment, and with imbalance in an overhung pump or fan.

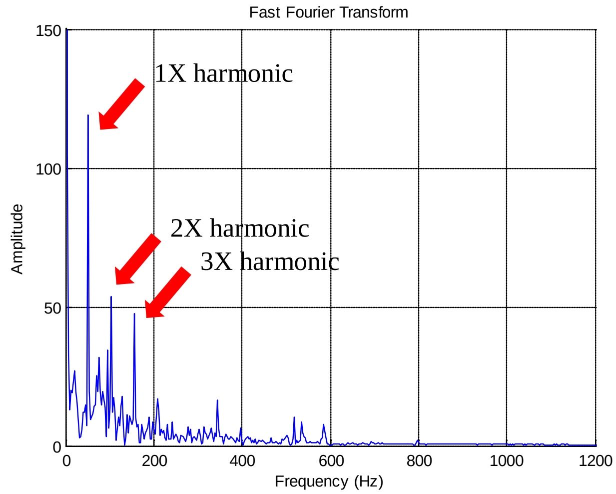


Fig. 2: Fast Fourier transform (100% load).

## Journal bearing clearance

The spectrum shows very similar characteristics to rotating loosenesss. There are strong harmonics. In most cases, the vertical axis of vibration will have higher levels than the horizontal. In more severe cases, half-order and even one-third order harmonics will be present in the spectrum (Figure 3).

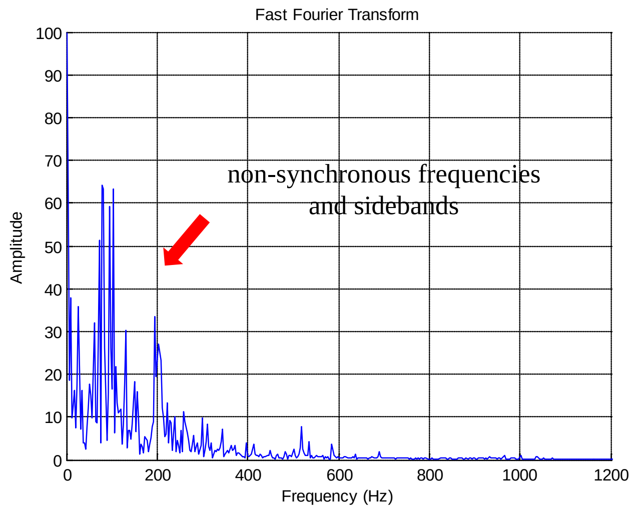


Fig. 3: Fast Fourier transform (51% load).

# 4. Vibration (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 [23]. 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 [24]. 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 [25] and [26]. The signal processing from the time domain to the frequency domain by these methods usually implies loss of information, making difficult to determine the appearance of specific frequencies [27].

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 parameters [28]. The PWT is an extension of the DWT with a larger number of filtering levels.

The wavelet transform is an alternative representation of a signal. It usually represents the characteristics of the original signal in the time or space domain. It decomposes the original signal into several components at different frequency bands. These levels are a linear combination of all the frequency components of the original signal and their sum results in the original signal. In addition, one of the features of the signal is the energy. In the time domain, the energy is defined as the integral of its square over time.

$$E_f = \int_{-\infty}^{\infty} |f(t)|^2 dt \tag{3}$$

For a Fourier signal representation, the energy can be characterized from the Parseval's theorem, providing an energy relationship. This energy distribution across the frequency domain is the so called spectrogram and is used to estimate the power spectrum of a signal. When this differential is integrated over all frequencies, the energy of the signal is (4):

$$E_f = \frac{1}{2\pi} \int_{-\infty}^{\infty} |F(\omega)|^2 d\omega \tag{4}$$

The concept of energy can also be defined for the wavelet transform. The main difference is that a scale-translation differential element will be required to obtain the energy in both domains. The energy is:

$$E_f = \frac{1}{C_g} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |W_g f(a,b)|^2 \frac{da db}{a^2} \tag{5}$$

where $C_g$ is an admissibility constant used to normalize the energy when required. The mother wavelet-energy dependence will be always relevant: there will not be a unique energy distribution for a particular signal.

Before continuing, it must be noted that the case study base their results in the energy. The first phase of this research focuses on the selection of accurate frequencies. It is important to choose a significant frequency range to use the wavelet transform as in the case of the Fourier transform. The right selection of the levels of decomposition will provide better findings in the signal processing and analysis. Signals are decomposed in different levels employing the Daubechies wavelet family. The approximated decomposition is called $a_n$, where $n$ is the highest level of decomposition. It is considered the low frequency component while $d_1$ is the high frequency component.

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) [29]. In order to reduce the computational and mathematical costs due to the data duplication, a sub-sampling is usually implemented, containing the half of the collected information from $A$ and $D$ without losing information.

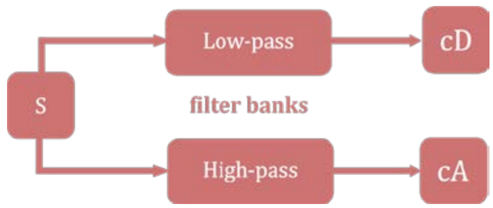


Fig. 4: decomposition diagram.

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) [30]. Additional information is obtained filtering at each level. However more decompositions levels do not always mean accurate results.

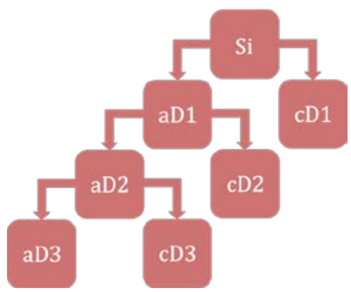


Fig. 5: Wavelet decompositions tree.

## 4.2. Results employing Wavelet transform

Tables 2-4 demonstrate the effectiveness of decomposing the signal at adequate levels (it will be divided into 12 levels in this case study). When 4 levels were initially chosen (Table 2), the most representative information was linked to the natural frequency, giving less importance to any contribution of mechanical nature. The later choice of 12 levels indicated that there were low frequencies peaks associated to the bearings and significant percentages appeared. Any “low frequency” citation is related to the rotational frequency of the generator and must be the starting point of the study.

Discussed frequencies are around the rotational speed (1X) and its multiples. Therefore, a prefiltering is necessary. However, to select appropriate decomposition levels is relevant again, since more decompositions means more accurate information for a specific frequency (Tables 3 and 4).

Vibration is collected by sensors placed in three different points of the generator: drive end axial, drive end radial and non-drive end radial. Knowing the location of the defective bearings in the generator, it can be considered that the non-drive end radial signal is closer to the fault free operation since it is the farthest point from the bearing. Failures will modify the original vibration signal.

| Device | Load | Date | a | d4 | d3 | d2 | d1 | energy |
|---|---|---|---|---|---|---|---|---|
| Generator drive end axial | 44% | 11-abr | 19,55% | 65,30% | 13,80% | 1,26% | 0,09% | 111800 |
| | 100% | 11-abr | 19,67% | 65,01% | 14,01% | 1,23% | 0,09% | 50860 |
| | 50% | 13-abr | 17,84% | 64,93% | 15,58% | 1,54% | 0,11% | 17900 |
| | 7% | 19-abr | 14,65% | 64,85% | 18,37% | 1,98% | 0,15% | 7170 |
| | 51% | 26-abr | 17,68% | 66,67% | 14,35% | 1,22% | 0,08% | 44470 |
| | 26% | 27-abr | 17,85% | 66,16% | 14,62% | 1,28% | 0,09% | 39230 |
| Generator drive end radial | 44% | 11-abr | 1,82% | 7,10% | 66,03% | 22,84% | 2,21% | 49500 |
| | 100% | 11-abr | 2,47% | 5,30% | 66,04% | 23,87% | 2,31% | 40350 |
| | 50% | 13-abr | 1,66% | 6,00% | 65,40% | 24,61% | 2,34% | 28520 |
| | 7% | 19-abr | 1,99% | 6,54% | 66,79% | 22,54% | 2,14% | 18830 |
| | 51% | 26-abr | 1,42% | 2,45% | 65,58% | 27,81% | 2,74% | 41320 |
| | 26% | 27-abr | 1,21% | 2,91% | 66,08% | 27,11% | 2,68% | 53100 |
| Generator non drive end radial | 44% | 11-abr | 2,14% | 5,64% | 60,79% | 28,57% | 2,87% | 4151 |
| | 100% | 11-abr | 6,78% | 11,83% | 55,54% | 23,45% | 2,41% | 1580 |
| | 50% | 13-abr | 6,30% | 11,40% | 54,89% | 24,81% | 2,59% | 1395 |
| | 7% | 19-abr | 3,78% | 23,53% | 55,06% | 16,05% | 1,58% | 1837 |
| | 51% | 26-abr | 2,02% | 7,41% | 58,86% | 28,80% | 2,91% | 5449 |
| | 26% | 27-abr | 1,99% | 4,83% | 60,53% | 29,63% | 3,03% | 6911 |

Tab. 2: 4 levels energy decomposition (red: high level of energy; green: medium level of energy)

| Device | Load | Date | a | d12 | d11 | d10 | d9 | d8 | d7 |
|---|---|---|---|---|---|---|---|---|---|
| Generator drive end axial | 44% | 11-abr | 13,21% | 0,99% | 0,50% | 0,60% | 0,89% | 1,01% | 1,53% |
| | 100% | 11-abr | 13,29% | 0,99% | 0,82% | 0,40% | 1,26% | 2,16% | 1,37% |
| | 50% | 13-abr | 27,93% | 0,47% | 0,19% | 0,11% | 1,30% | 2,29% | 1,06% |
| | 7% | 19-abr | 32,93% | 1,16% | 0,67% | 0,82% | 1,27% | 1,78% | 1,24% |
| | 51% | 26-abr | 14,66% | 0,84% | 0,34% | 0,72% | 0,93% | 1,47% | 2,05% |
| | 26% | 27-abr | 21,00% | 1,25% | 0,67% | 0,94% | 1,95% | 3,17% | 1,78% |
| Generator drive end radial | 44% | 11-abr | 28,50% | 5,29% | 2,35% | 1,85% | 2,88% | 10,39% | 14,51% |
| | 100% | 11-abr | 70,27% | 0,84% | 0,51% | 1,24% | 0,65% | 3,98% | 3,91% |
| | 50% | 13-abr | 77,17% | 1,75% | 1,54% | 0,85% | 0,70% | 4,40% | 5,43% |
| | 7% | 19-abr | 59,49% | 5,70% | 1,90% | 0,86% | 0,64% | 5,76% | 6,70% |
| | 51% | 26-abr | 52,32% | 2,36% | 1,86% | 1,20% | 1,55% | 11,47% | 9,96% |
| | 26% | 27-abr | 72,08% | 1,40% | 0,41% | 1,02% | 0,95% | 6,81% | 6,15% |
| Generator non drive end radial | 44% | 11-abr | 31,04% | 6,17% | 0,71% | 1,07% | 5,55% | 14,27% | 7,04% |
| | 100% | 11-abr | 71,94% | 0,51% | 0,86% | 0,62% | 3,16% | 4,47% | 2,70% |
| | 50% | 13-abr | 74,23% | 1,61% | 0,82% | 0,51% | 0,98% | 8,27% | 3,72% |
| | 7% | 19-abr | 63,53% | 5,27% | 1,52% | 1,48% | 2,41% | 13,06% | 6,74% |
| | 51% | 26-abr | 52,72% | 3,60% | 0,86% | 1,21% | 2,76% | 6,23% | 5,29% |
| | 26% | 27-abr | 72,51% | 0,94% | 0,84% | 0,47% | 1,83% | 7,38% | 4,36% |

Tab. 3: 12 levels energy decomposition (red: high level of energy; green: medium level of energy).

| Device | Load | Date | d6 | d5 | d4 | d3 | d2 | d1 | energy |
|---|---|---|---|---|---|---|---|---|---|
| Generator drive end axial | 44% | 11-abr | 9,27% | 35,52% | 31,09% | 4,98% | 0,39% | 0,03% | 372,20 |
| | 100% | 11-abr | 5,86% | 40,47% | 29,24% | 3,83% | 0,30% | 0,02% | 233,70 |
| | 50% | 13-abr | 9,68% | 37,00% | 17,26% | 2,50% | 0,19% | 0,01% | 120,90 |
| | 7% | 19-abr | 12,80% | 37,05% | 9,02% | 1,17% | 0,09% | 0,01% | 116,20 |
| | 51% | 26-abr | 6,98% | 41,43% | 26,35% | 3,89% | 0,30% | 0,02% | 190,90 |
| | 26% | 27-abr | 7,62% | 27,73% | 28,68% | 4,80% | 0,38% | 0,03% | 118,40 |
| Generator drive end radial | 44% | 11-abr | 7,37% | 19,85% | 6,11% | 0,82% | 0,07% | 0,00% | 16,62 |
| | 100% | 11-abr | 4,16% | 11,11% | 3,00% | 0,31% | 0,02% | 0,00% | 46,64 |
| | 50% | 13-abr | 2,75% | 3,24% | 1,84% | 0,30% | 0,02% | 0,00% | 38,82 |
| | 7% | 19-abr | 6,84% | 9,48% | 2,35% | 0,26% | 0,02% | 0,00% | 33,18 |
| | 51% | 26-abr | 6,62% | 9,33% | 2,96% | 0,33% | 0,03% | 0,00% | 30,32 |
| | 26% | 27-abr | 4,84% | 4,60% | 1,51% | 0,21% | 0,02% | 0,00% | 37,33 |
| Generator non drive end radial | 44% | 11-abr | 5,64% | 22,83% | 5,17% | 0,47% | 0,03% | 0,00% | 31,80 |
| | 100% | 11-abr | 2,58% | 10,28% | 2,62% | 0,24% | 0,02% | 0,00% | 67,24 |
| | 50% | 13-abr | 1,81% | 6,35% | 1,54% | 0,14% | 0,01% | 0,00% | 65,37 |
| | 7% | 19-abr | 2,42% | 2,93% | 0,58% | 0,06% | 0,00% | 0,00% | 48,61 |
| | 51% | 26-abr | 3,90% | 18,49% | 4,53% | 0,40% | 0,03% | 0,00% | 46,56 |
| | 26% | 27-abr | 2,05% | 7,60% | 1,84% | 0,17% | 0,01% | 0,00% | 63,88 |

Tab. 4: 4 levels energy decomposition (red: high level of energy; green: medium level of energy) (cont.).

Another particular feature of this study is that each signal has been picked at different load and in several dates. The performance of the wind turbine depends on the wind conditions so different behaviors for different workloads should be expected. This information is presented with an example in Figure 6, which shows that despite the above-described; load changes do not modify significantly the behavior of the signals, but they will depend on their location as expected. In general terms, a pattern where the approximate signal and intermediate decompositions from $d_5$ to $d_8$ are highlighted, is repeated.

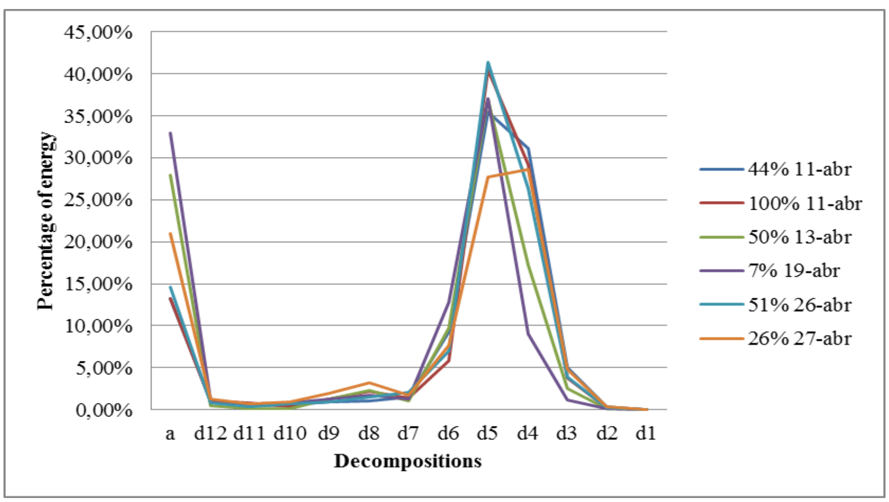


Fig. 6. generator drive end axial (performance per decomposition in time).

If the study is further specific on the differences for the three signals taken at the same time interval, then Figures 7-9 must be referenced. Their graphics provide information on possible operation anomalies for the generator in relation to the bearings.

Sensors that collect information next to the bearings have a different performance between them (drive end radial and axial). The radial components (drive end radial and non-drive end radial) have a similar behaviour, even with differences, despite their different location regarding to the bearing. If this last comment is considered for possible failures, one of the aforementioned features needs to be reviewed: the load.

Figures from 7-9 are examples that evidence the influence of the load, especially when the set loads are below the 50% of the total. For these cases, the percentage of energy is distributed along different frequencies (from $d_8$ to $d_4$) when the sensor is close to the bearing, while specific peaks are observed at the so-called free fault conditions.

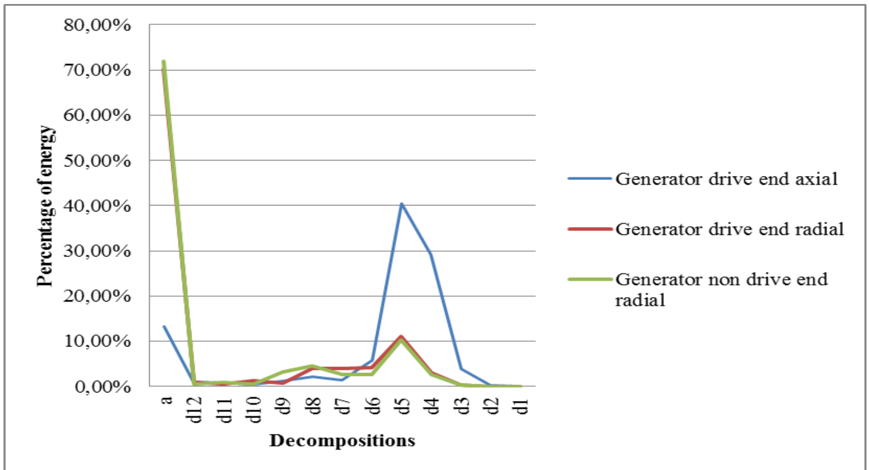


Fig. 7. 100% load (11th April).

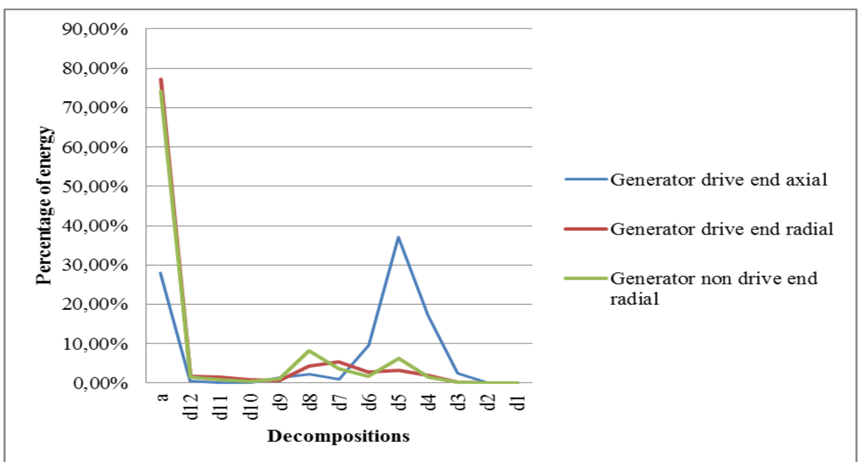


Fig. 8. 50% load (13th April).

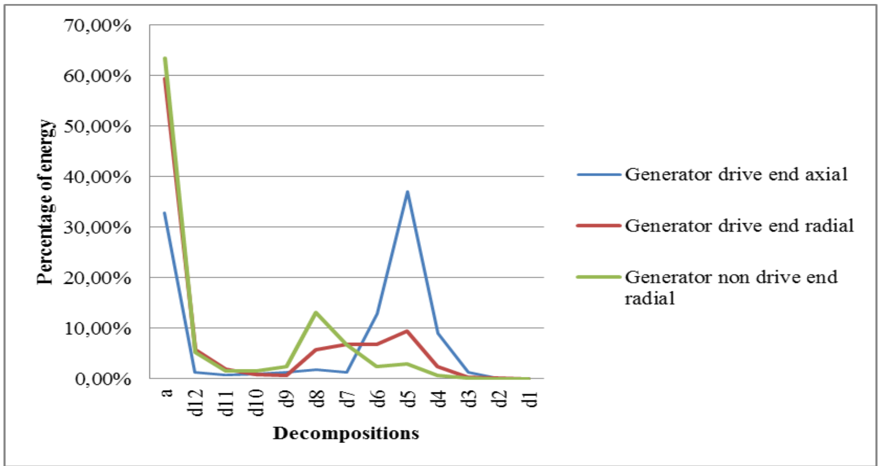

Fig. 9. 7% load (19th April).

This could be an expected situation since in the case of damaged bearings, it was earlier said that noise is produced throughout the whole spectrum as the result of gaps for advanced stages of deterioration, emphasizing that these gaps become evident when the system load is lower. This may be due to high load attenuating this effect.

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