Statistical vibration analysis for predictive maintenance of machines working under large variation of speed and load

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ABSTRACT

Prognosis of defects for machines working under large variation of speed and load conditions is a topic still under development. Wind turbines are recent examples of such kind of machines that need reliable diagnosis methods. Vibration analysis can be of very limited use when the speed variation is too high. An effective angular resampling method can be very valuable as the first step of vibration signal processing but it is important to know what are the appropriate variables to be monitored.

The authors present a statistical analysis method consisting of a linear model based on the parameters that characterize the system, in our case the variable speed and load, and the fault condition to which the system is subjected. With this method can be determined if the variable analyzed is significant, that is to say if are sensitive to these parameters and hence can detect the fault faster. The aim of implementing this method is to reduce the number of variables to be monitored, resulting in a savings not only in measuring equipment but also in times of processing and analyzing information.

The results of vibration analysis of a test-bed working under large variation of speed and load are shown. Different tests with increasing level of defects are tried and the corresponding vibration is analyzed and modeled so an effective detection and prognosis can be done. Taking in to account such variation of speed and load for the vibration modeling can lead to a very sensitive detection of incipient defects.*

1. INTRODUCTION

Vibration analysis has been implemented and studied in rotating machinery for many years, and it is widely accepted as one of the main techniques for condition based maintenance (Hameed, 2009). With the advance of technology, more complex machines that operate under more severe conditions have been developed; an example of these conditions are those who operate under varying loads and speeds like wind turbines, excavators and helicopters (Barszcz, 2009; Blunt, 2006; Combet, 2009; Bartelmus, 2009). In these kinds of machines, gear transmissions play a crucial role in terms of their reliability.

The initial research in the area of transmission damage detection was focused on vibration signal analysis (Davies, 1998). At first, as discussed in (Samuel, 2005), the statistical characteristics of the signal in the time domain were the primary focus of study. However, the field quickly expanded to include spectral analysis, time-frequency analysis, wavelet analysis, neural networks and mathematical modeling. This field is continuing to grow. As new signal processing techniques emerge, they are applied to the transmission damage detection problem and must be accommodated to the needs and specificities of each mechanical system.

For systems which work under variable speed and load conditions one of the most appropriate signal processing method is angular resampling, however, using this method is only the fisrt step because it is necessary to analyze the information obtained and it is also important to determine that the variables that are being analyzed are those that provide the best information on fault diagnosis. For the selection of these variables, the authors present in this paper a statistical method based on a linear model to determine the sensitivity of each variable with respect to the failure and system operating conditions.

The main motivation for this work is the diagnosis of wind turbines, so the test bed that will be shown, is used to approach the phenomenon and failures of a real wind turbine.

2. VARIABLE SPEED AND LOAD RESERARCH

For the analysis of systems that operate under variable speed conditions, efforts were made to find techniques that allow for better processing and analysis of the signals captured from these systems. A theory of interpolation applied to time domain averaging was presented in (McFadden, 1989; McFadden, 1991) as an alternative to averaging when there is no rotational reference signal.

Due to the fact that many systems are working under variable speed, the technique known as order tracking is very common in vibration analysis. Each of the steps that comprise the order tracking method are explained in (Fyfe, 1997). In this method the main algorithm is the angular resampling, which repositions the samples of vibration to be equivalents to a signal measured at constant speed. In this article comparisons are made at each step and the best alternatives for each are given. Later, (Bossley, 1999) presented a hybrid, computed order tracking method to perform angular resampling which was compared with two previously proposed methods by comparing the results.

A method to perform angular resampling was presented in (Bonnardot, 2005) using the acceleration signals directly without the need for an encoder signal, but this method has the limitation that it can only be used when speed variations are small and it requires a sufficient number of harmonics.

An extension to the algorithm proposed by Bonnardot was presented by Combet. However, it is not advisable for use in the case of very large speed variations, such as during acceleration (Combet, 2007; Combet, 2009).

Another factor affecting the variability of the speed is the fluctuating load that modulates the amplitude of the vibration signal measurement and causes changes in the rotational speed of the system. Changes in the system speed cause a modulation in the characteristic frequencies of the mechanical elements of the system (Stander, 2005).

The resulting spectra of a signal under fluctuating load conditions presents multiple peaks known as "smearing” in the region around the characteristic frequencies of the system.

For the above reasons, the vibration monitoring systems require signal processing procedures to compensate for the fluctuations in shaft speed and the amplitude modulation caused by the variable load (UpWind, 2006; Stander, 2002; Stander, 2005).

In the fluctuating load research many studies have been developed using various methods of signal analysis, among these studies are those by Stander, Heyns, Zhan and Bartelmus (Stander, 2006; Zhan, 2006; Bartelmus, 2009). However, until now no studies have been developed in an extended work range of speed and load, and that is where our research focuses.

3. ANGULAR RESAMPLING ALGORITHM FOR LARGE SPEED VARIATION

Due to the speed variations caused by the operating conditions itself, and load variations, as is the case of wind turbines, it is necessary to process the vibration so its frequency content can be analyzed. The angular resampling technique can be used to solve this problem.

The works that have been developed previously on the issue of angular resampling are applicable to cases in which the speed fluctuations are small (Bonnardot, 2005; McFadden, 1989; Fyfe, 1997; Bossley, 1999). The application of this kind of signal processing to the vibration analysis of machines like wind turbines is limited, because the angular speed and hence acceleration variations experienced in a wind turbine are high and are not predictable as they depend on the wind.

The method of angular resampling algorithm proposed by (Fyfe, 1997) is valid for linear profile of speed. The authors in (Villa, 2011) presented an evolution of this method, an angular resampling algorithm for a general case of variable speed and a generic number of keyphasors.

The method proposed by (Fyfe, 1997) includes the following steps; first records the data at constant Δt increments, and them resamples this signal to provide the desired data at constant $\Delta\theta$ increments, based on a keyphasor signal. To determine the resample times, it is assumed that the shaft is undergoing constant angular acceleration, the shaft angle; θ is described by the following quadratic equation:

$$\theta(t) = b_0 + b_1\, t + b_2\, t^2 \tag{1}$$

The unknown coefficients b_0, b_1 and b_2 are found by fitting three successive keyphasor arrival times

(t_1, t_2 and t_3), which occur at known shaft angle increments. Once the resample times are calculated, the corresponding amplitudes of the signal are calculated by interpolating between the sampled data. After the amplitudes are determined, the resampled data are transformed from the angle domain to the order domain by means of an FFT.

Due to the fact that the speed varies considerably between consecutive rotations, the decision taken was to use more than one pulse per revolution, and to use the full profile of the speed instead the analysis of three consecutive samples like the algorithm presented in (Fyfe, 1997). The main improvement of the proposed algorithm in (Villa, 2011) is to take full advantage of the whole measured speed to obtain an accurate angular resampled vibration.

Figure 1 shows the results of this algorithm applied to a simulated signal created with parameters that characterize the test bed described in the next section. The simulated signal was created with a wide range of speed variation of and our resampling algorithm can process it without any problem.

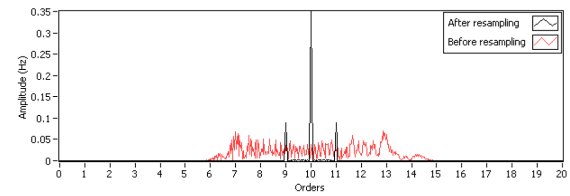

Figure 1. Spectrum before and after angular resampling for a simulated signal

The angular resampling method developed by the authors (Villa, 2011) was also tested with experimental data with satisfactory results. The data shown corresponds to a bearing with damage in the inner ring of the fast Shaft (figure 2).

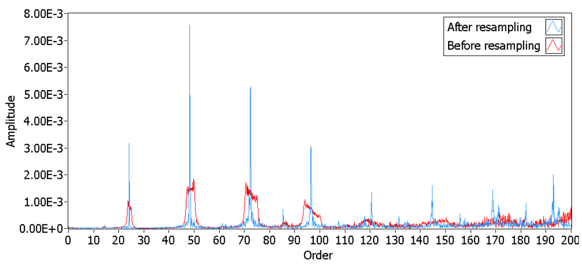

Figure 2. Spectrum before and after angular resampling for an experimental signal

4. TEST-BED TESTS

The experiments presented in the next sections are to simulate in a test bed the behavior that occurs in the wind turbines. This test bed is used to simulate different defects under variable load and speed and it is controlled.

The right side of the test bed (figure 3) is composed of a motor (instead of the generator of a wind turbine), a parallel gearbox and a planetary gearbox. Both gearboxes resemble the configuration and the gear ratio of a commercial wind turbine of 1:61.

To simulate the load variable that is under the drive train due to the randomness of the wind, an electrical brake has been added to the test bed. For coupling it with the right side of the test bed, it is necessary to add another gearbox to compensate for the torque in the slow axis against the torque of the motor in the fast shaft.

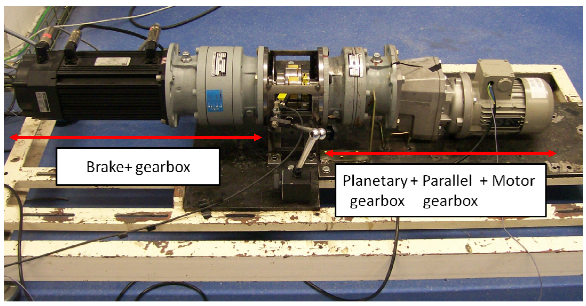

Figure 3. Test-bed

For the acquisition of vibration signals we used four accelerometers distributed in axial and radial position in the gearboxes located on the right side of the test-bed.

5. EXPERIMENTATION

The failures simulated on the test bed were unbalance and misalignment, starting with small values of defects and increasing with each new set of measurements to simulate a progressive failure (table 1). The table shows the value of the weight in grams and the equivalent percentage of the total weight of the rotor test bed, and the thickness of the sheet used to misalign and their respective angle of misalignment.

To guarantee variable speed and load conditions, different profiles were generated to cover a random range of velocity between 1000 and 1800 rpm, and a range between 0 and 100% of load. An example of these profiles are shown in figure 4.

Table 1: Kind of faults

Unbalance			Misalignment		
	gr	%		mm	º
Unbalance A	5.79	0.077	Misalignment A	0.75	1.53
Unbalance B	9.13	0.12	Misalignment B	2	0.78
Unbalance C	19.5	0.26			
Unbalance D	28.8	0.38			

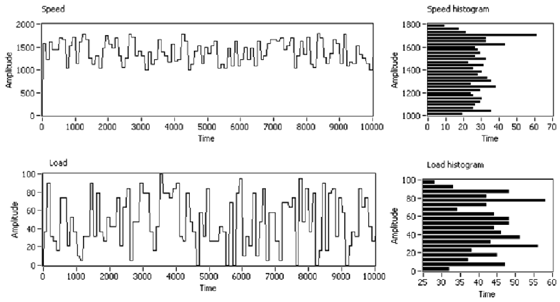

Figure 4. Speed and load profile

These profiles were generated to cover a full day of measurements (24h), with constant intervals of speed and load every 100 sec. Speed measurements were generated starting at 1000 rpm because this is the approximately equivalent speed in the slow axis when a wind turbine begins to generate energy.

Captures were made of 72 seconds with each of the four accelerometers mentioned in section 4 with a sampling frequency of 25600 Hz. The speed signal captured in the slow axis used for angular resampling was sampled at a frequency of 6400 Hz.

The variables monitored from the vibration signals captured are order and natural frequencies of the system determined experimentally, calculated orders for specific elements such as gears and bearings, statistical parameters extracted from the time domain and the harmonics of order 1 to 10 of the rotation speed resulting in a final set of 166 variables (table 2).

Table 2. Variables monitored

Type of variable	Number of variables
Statistical variables	5
Electrical variables	4
Order 1X to 10X	10
Gears	12
Common orders for the 4 accelerometers	58
Common frequency bands for the 4 accelerometers	40
Planetary Axial	15
Planetary Radial	4
Parallel Axial	10
Parallel Radial	8

6. ANALYSIS AND RESULTS

From monitored variables, we selected the classical parameters used for the analysis of the defects that are in analysis; the harmonic 1x in radial direction of the planetary gearbox to analyze the unbalance, and the harmonics 1x and 2x in the radial and axial direction of the planetary gearbox to analyze misalignment.

6.1 Unbalance analysis

First of all an analysis of the radial vibration level (first harmonic) for the different defects was made. It is presented the vibration for the 4 levels of unbalance compared with the vibration without defect, and can be clearly seen that the defects cannot be distinguished directly (figure 5) and are not statistically different (figure 6) due to the fact that the amount of unbalance and the speed shaft are very low.

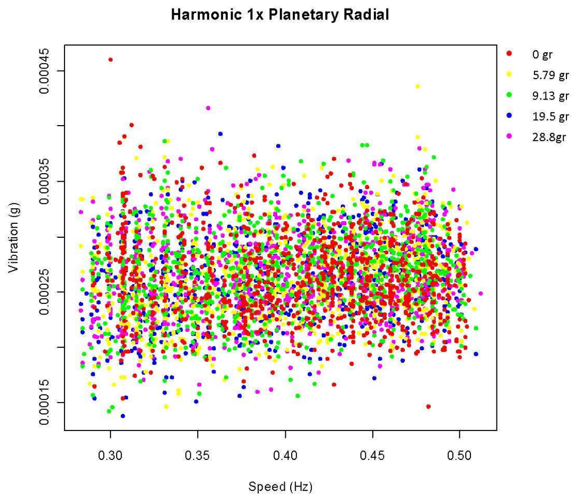

Figure 5. Vibration level harmonic 1X planetary radial (unbalance)

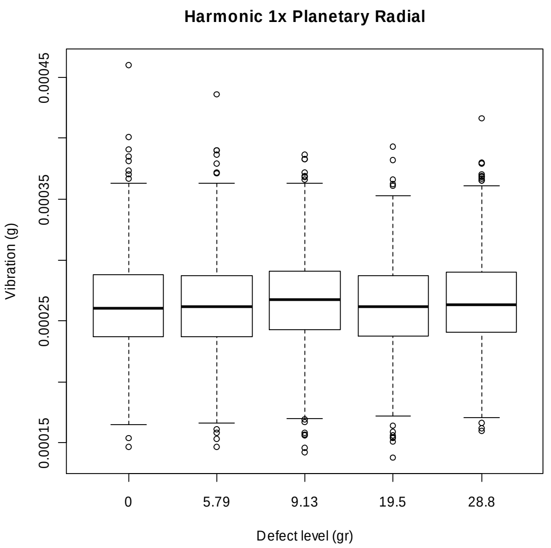

Figure 6. Box-plot harmonic 1X planetary radial (unbalance)

If the same data (radial vibration level of first harmonic) is modeled with a linear model that takes into account the speed, load and the unbalance level the resulting parameters are not significant (table 3).

The equation of the model is

$$Y = (b_0 + b_3\ F) + b_1\ S + b_2\ L \qquad (2)$$

Where Y is the vibration dependent on the speed, load and defect, $b_0 + b_3\ F$ is the intercept, $b_1\ S$ is the slope as a function of speed and $b_2\ L$ is the slope as a function of load.

Table 3: Coefficients modeling harmonic 1X planetary radial (unbalance)

	Estimate	Std. Error	t value	Pr(>|t|)	
b0	2.202e-04	4.208e-06	52.322	< 2e-16	***
b1	8.313e-05	9.484e-06	8.766	< 2e-16	***
b2	-1.895e-05	2.262e-06	-8.377	< 2e-16	***
F=5.79	-2.645e-07	1.819e-06	-0.145	0.88438	
F=9.13	4.686e-06	1.814e-06	2.583	0.00982	**
F=19.5	-8.896e-07	1.824e-06	-0.488	0.62582	
F=28.8	2.527e-06	1.810e-06	1.396	0.16274	
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

It must be said that for the case of unbalance, due to the small amount of added mass that can be practically used, the slow speed (below 0.5 Hz) and the wide range of working conditions (speed and load) the classical parameter used, that is the radial vibration at the first order, is not statistically conclusive. Therefore it is necessary to rely on other parameters like for example the 6x order. Although the defects cannot be distinguished directly (figure 7) with this parameter and are not statistically different (figure 8), the default parameter is significant if the vibration of 6x order is modeled using the speed, load and defect level (table 4).

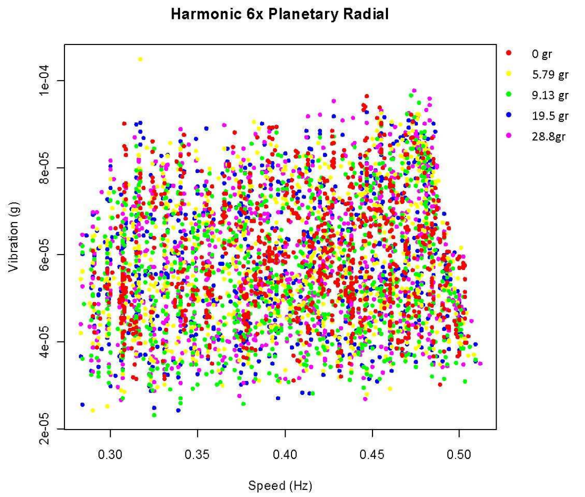

Figure 7. Vibration level harmonic 6X planetary radial (unbalance)

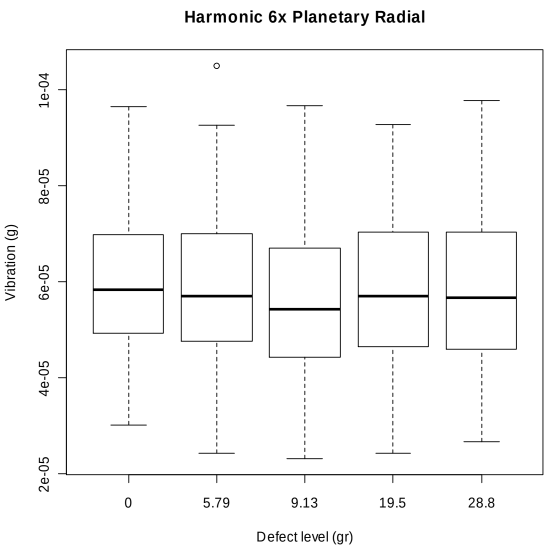

Figure 8. Box-plot harmonic 6X planetary radial (unbalance)

Table 4: Coefficients modeling harmonic 6X planetary radial (unbalance)

	Estimate	Std. Error	t value	Pr(>|t|)	
b_0	2.159e-05	4.378e-07	49.31	<2e-16	***
b_1	2.902e-05	9.866e-07	29.42	<2e-16	***
b_2	-5.538e-05	2.353e-07	-235.31	<2e-16	***
F=5.79	-2.987e-06	1.892e-07	-15.79	<2e-16	***
F=9.13	-5.409e-06	1.887e-07	-28.66	<2e-16	***
F=19.5	-2.864e-06	1.898e-07	-15.09	<2e-16	***
F=28.8	-2.940e-06	1.883e-07	-15.61	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

With the modeling parameters of speed, load and defect can be determined which variables are most sensitive to failure and they are to be monitored. Based on this analysis, a selection of the most significant variables for the detection of the faults has been done resulting in a final set of 45 variables (table 5).

Table 5. Selected variables to be monitored for unbalance

Type of variable	**Number of variables**
Statistical variables	1
Electrical variables	0
Order 1X to 10X	10
Gears	5
Common orders for the 4 accelerometers	17
Common frequency bands for the 4 accelerometers	9
Planetary Axial	0
Planetary Radial	1
Parallel Axial	0
Parallel Radial	2

6.2 Misalignment analysis

In the case of misalignment, the results obtained from the visual and the statistical analyses are similar to the unbalance, that is, with the analysis of the vibration level alone cannot be differentiated statistically the amount of misalignment of the harmonic 1x axial (Figures 9 and 10) and radial (Figures 11 and 12) or 2x axial (Figures 13 and 14) and radial (Figures 15 and 16).

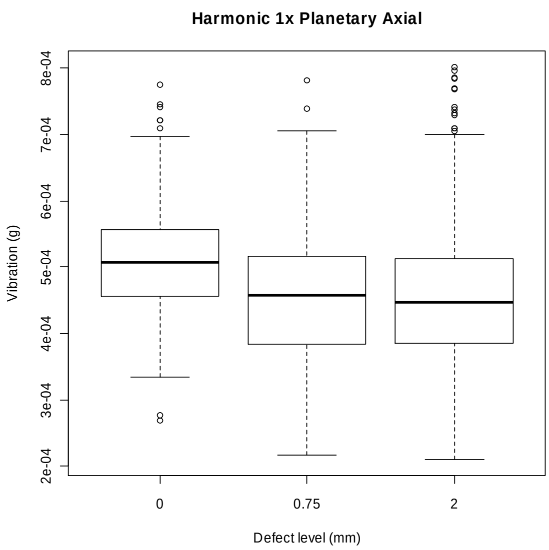

Figure 9. Box-plot harmonic 1X planetary axial (misalignment)

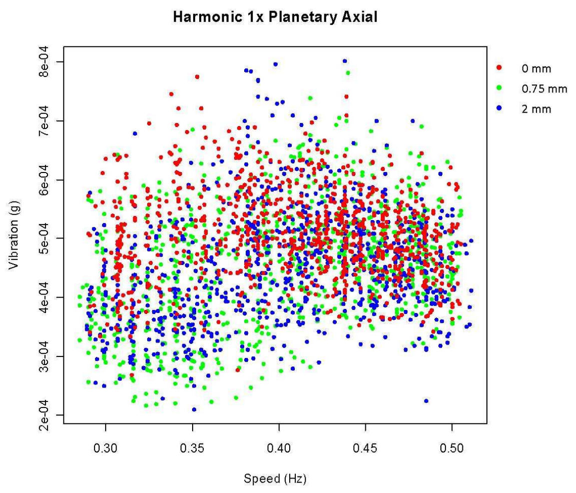

Figure 10. Vibration level harmonic 1X planetary axial (misalignment)

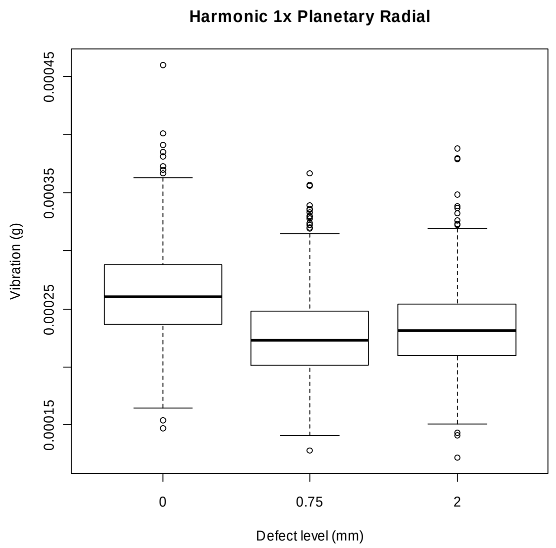

Figure 11. Box-plot harmonic 1X planetary radial (misalignment)

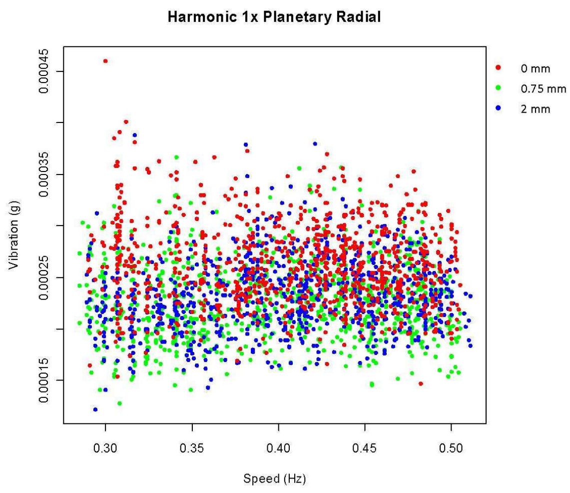

Figure 12. Vibration level harmonic 1X planetary radial (misalignment)

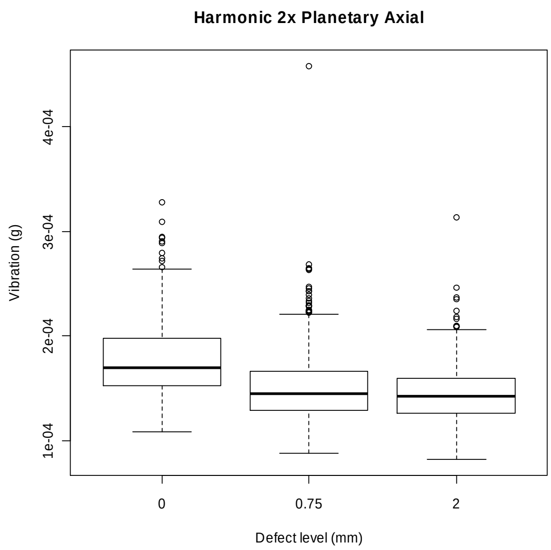

Figure 13. Box-plot harmonic 2X planetary axial (misalignment)

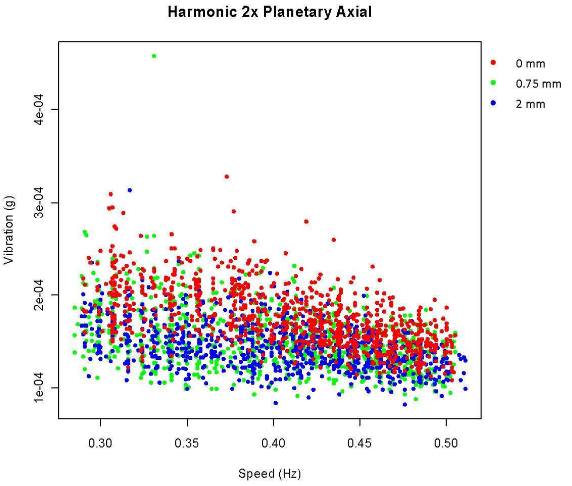

Figure 14. Vibration level harmonic 2X planetary axial (misalignment)

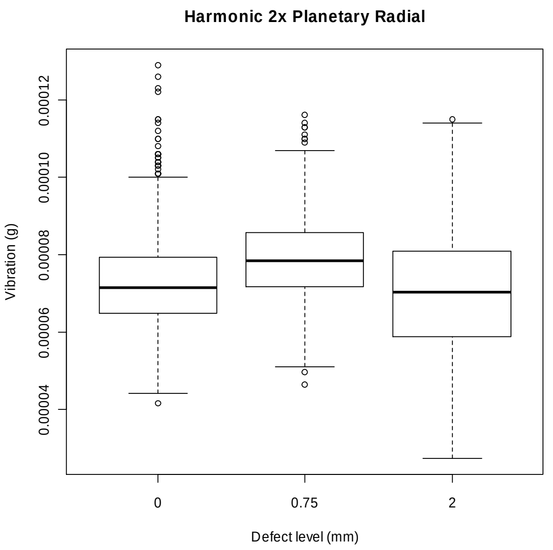

Figure 15. Box-plot harmonic 2X planetary radial (misalignment)

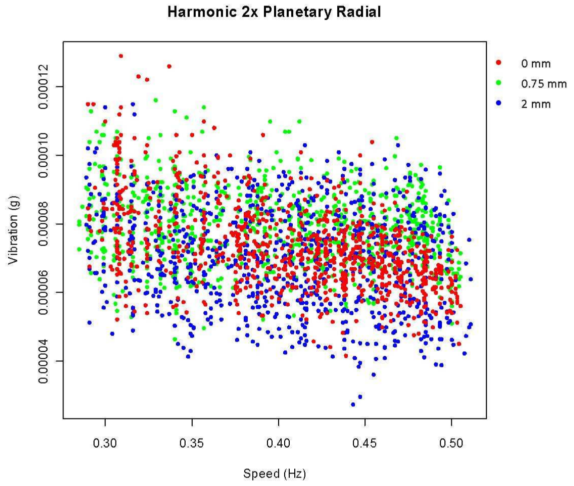

Figure 16. Vibration level harmonic 2X planetary radial (misalignment)

On the other hand, a linear model of the vibration using the speed, load and defect levels as independent variables can lead to a detection and separation of the defect levels, where the significance level for the different defect levels are statistically significative (small p-value) as is shown for the harmonic 1x axial (table 6) and radial (table 7) or 2x axial (table 8) and radial (table 9).

Table 6: Coefficients modeling harmonic 1X planetary axial (misalignment)

	Estimate	Std. Error	t value	Pr(>|t|)	
b_0	3.618e-04	1.267e-05	28.568	<2e-16	***
b_1	3.281e-04	2.877e-05	11.405	<2e-16	***
b_2	-2.358e-05	6.661e-06	-3.539	0.000408	***
F=0.75	-5.325e-05	4.190e-06	-12.709	<2e-16	***
F=2	-5.301e-05	4.224e-06	-12.550	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Table 7: Coefficients modeling harmonic 2X planetary axial (misalignment)

	Estimate	Std. Error	t value	Pr(>|t|)	
b_0	2.713e-04	3.826e-06	70.923	<2e-16	***
b_1	-2.378e-04	8.690e-06	-27.365	<2e-16	***
b_2	-4.248e-06	2.012e-06	-2.112	0.0348	*
F=0.75	-2.818e-05	1.266e-06	-22.264	<2e-16	***
F=2	-3.300e-05	1.276e-06	-25.867	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Table 8: Coefficients modeling harmonic 1X planetary radial (misalignment)

	Estimate	Std. Error	t value	Pr(>|t|)	
b_0	2.436e-04	5.262e-06	46.293	<2e-16	***
b_1	1.833e-05	1.195e-05	1.533	0.125	
b_2	-2.544e-05	2.767e-06	-9.195	<2e-16	***
F=0.75	-3.829e-05	1.741e-06	-21.995	<2e-16	***
F=2	-2.943e-05	1.755e-06	-16.769	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Table 9: Coefficients modeling harmonic 2X planetary radial (misalignment)

	Estimate	Std. Error	t value	Pr(>|t|)	
b_0	9.265e-05	1.710e-06	54.185	<2e-16	***
b_1	-6.068e-05	3.884e-06	-15.623	<2e-16	***
b_2	-1.122e-05	8.992e-07	-12.474	<2e-16	***
F=0.75	4.753e-06	5.657e-07	8.402	<2e-16	***
F=2	-3.239e-06	5.703e-07	-5.680	1.49e-08	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Because cases of misalignment used in these tests are very severe, it is easy to detect with all the variables, however the method presented in this section to determine the most sensitive has reduced the number of variables to 133, in Table 10 shows this result. As the classical parameters used for monitoring misalignment, orders 1X and 2X in radial and axial directions are among this group of 133 variables, these are the variables to be monitored for this type of failure.

Table 10. Selected variables to be monitored for misalignment

Type of variable	**Number of variables**
Statistical variables	5
Electrical variables	0
Order 1X to 10X	10
Gears	12
Common orders for the 4 accelerometers	49
Common frequency bands for the 4 accelerometers	32
Planetary Axial	11
Planetary Radial	2
Parallel Axial	7
Parallel Radial	5

7. CONCLUSION

The present work shows the first results of a statistical analysis of vibration applied to a test-bed working under large variability of speed and load conditions. To solve the problems caused by variations in speed and load, the vibration signals are processed with an angular resampling method developed by the authors. Based on this signal processing technique the classical vibration order parameters can be used to detect incipient faults like small unbalance and misalignments. The authors show how through a statistical vibration analysis taking into account the full working range of the test-bed (speed and load) as independent parameters can be determined which variables are most sensitive to these parameters and to the failure and can be reduced the number of variables to be analyzed do not always coincide with the variables recommended by the theory of vibration analysis.

At present, the authors are working on an automated selection of parameters using computer intelligence methods, and are also working on a prognosis based on statistical significance levels of different models. Another important defect simulation under work is gear failure. The aim of the authors is to implement the prognosis algorithms for the detection of mechanical defects in the drive train of wind turbines.

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