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Analysis of the influence of crack location for diagnosis in rotating shafts based on 3 x energy

M.J. Gómez [*], C. Castejón, E. Corral, J.C. García-Prada

MAQLAB Group, Mechanical Dept. University Carlos III of Madrid, Av. de la Universidad, 30, 28911, Leganés, Madrid, Spain

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Abstract

The aim of condition monitoring is to detect faults before a catastrophic failure occurs. Cracks in rotating shafts are especially critical. The present work studies vibration signals obtained from a rotating shaft under different crack depths and locations. Tests were performed in a rig called Rotokit at steady state at different rotation speeds. Signals obtained are analyzed by means of energy using the Wavelet Theory, specifically the Wavelet Packets Transform. Nine crack depths in the shafts were tested, from 4% to 50% of the shaft diameter. Previous related work showed good reliability for crack diagnosis using 3 x energy for cracks in the middle section. In the present work, previous results are compared to the obtained for a crack in a change of section at one side. In both crack locations, large changes in energy are observed at 3 x at high speeds. Energy levels at this harmonic were used for the inverse process of crack detection, and Probability of detection curves were calculated by thresholding. Cracks with depths above 12% can be detected with reliability in the locations tested using this method.

Key words: , Condition monitoring, Vibration analysis, Crack detection, Wavelet Packets Transform

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1 Introduction

Cracks in shafts are specially critical since they can lead to a catastrophic failure. Dynamic behaviour of cracked rotors has allowed the diagnosis of cracks in some cases, however there is no a standard methodology to detect cracks

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[*] Corresponding author: mjggarci@ing.uc3m.es

and detection not always takes place with time enough to avoid the failure. Besides, in some cases the results are theoretical and difficult to translate to experimental systems. This issues were highlighted in [1].

Acoustic Emission (AE) signals have been applied for condition monitoring since they contain information related to crack growth. Typical frequencies associated with AE activity range are from 20 kHz to 1 MHz. They have been used in shafts in works as [2] and [3]. In [4], a comparison between vibration and AE signature is carried out, and in both cases features related to the crack were found. Nevertheless, most of the work published is focused in vibration signals.

Studies about cracked rotors have been carried out with different methods to select proper features indicators of the presence of a crack. Fast Fourier transform (FFT) and Hilbert transform (HT) are traditional techniques used to observe changes in the dynamical response (1 x, 2 x and 3 x vibrational frequencies) or in eigenfrequencies when a crack appears, as can be consulted in the review by Sabnavis et. al. in [5]. In the last years, time-domain techniques, such as Hilbert-Huang transform (HHT) and Wavelet transform (WT) have showed their effectiveness in this field. HHT has been applied to study transient vibration response in works as [6] and [7]. It was found that HHT appeared to be a good tool for crack detection in a transient rotor, even better than fast Fourier transform and continuous Wavelet transform. The WT theory was applied to experimental vibration signals obtained from cracked shafts at steady state in works as [8], and [9]. Nevertheless, the Wavelet theory application is not a straightforward issue. There are several different methods when applying Wavelet Transform, such as continuous Wavelet transform (CWT), Multiresolution analysis (MRA) or Wavelet Packets transform (WPT). Besides in each of them, the wavelet function and the range scales must be selected, and there are not standard methods to do those selections. All these drawbacks were stated in the review of the Wavelet theory to fault detection carried out by Peng and Chu in 2004 [10].

CWT coefficients were used in [11], [12] and [13], using sub-critical peaks and the first harmonics of the rotation speed. MRA coefficients have been applied in [14] and in [15], to signals coming from experimental system and to signals obtained from a Jeffcott rotor model. Features related to WPT coefficients have been also applied for crack detection in works as [16], [17] and [18], showing that WPT is a powerful tool for detailed feature extraction.

After the features extraction stage, a classification system is needed to interpret the information obtained. Thresholding methods can be used if the features are simple enough, as in [8]. When the features are complex, intelligent classification systems are required. Some examples are artificial neural networks (ANN) [19], Fuzzy Logic (FL) [20], Genetic Algorithms (GA) [21] and

Support Vector Machines (SVM) [22] have attracted considerable attention. The results of the classification system are useful to estimate the reliability of the technique. Examples of works using ANN for crack detection can be consulted in [23,18], and SVM were used in [24].

As it has been reviewed, there are a lot of works published based on different methodologies that resulted successful when they were applied to diagnose cracks. The aim of condition monitoring is to establish a general method. Therefore there is a need of works benchmarking the techniques applied at different conditions (mounting, speed, load, multiple faults, different location of the fault). POD curves [25] are a universally accepted parameter to evaluate a Non Destructive Evaluation technique. POD curves can be defined as the probability of detecting a crack within a certain range of sizes under specific conditions and procedures that can be used for measuring the capability of an inspection method.

The present work studies the robustness of the technique proposed in [8] that was used for diagnosing cracks located at the middle section. In this case, previous results are compared to those obtained when it is applied to cracks located in a change of section at one side, where they are more kind to appear. Experimental vibration signals obtained from a mechanical system at steady state under different crack depths (from incipient to severe) are analyzed. WPT energy and threshold methods are used for the analysis. Results can be used for crack detection, showing that different phenomena occurs depending on the location of the crack. Probability of detection curves are obtained for each case to quantify the results.

2 The Wavelet Transform

The WT is a modern mathematical development that treats signals and obtains information both in time and in frequency domain. Most of the techniques derived from FFT are inappropriate to treat non stationary signals due to the absence of temporary information. WT is specially useful to carry out local analysis of non stationary signals, or patterns changing with time. The same way as FFT obtains correlation coefficients of the signal with a sinusoidal function, the WT obtains the correlation of the signal with the wavelet function selected. There are a lot of of different families of wavelet functions, as Daubechies, Coiflet, Symlet, Morlet o Meyer. Coefficients obtained depend on the scale and position of the wavelet function. The WT can be applied in a continuous way, (Continuous Wavelet Transform (CWT)), or discrete, (Discrete Wavelet Transform (DWT)).

CWT allows the analysis of structures of the signals through the correlation

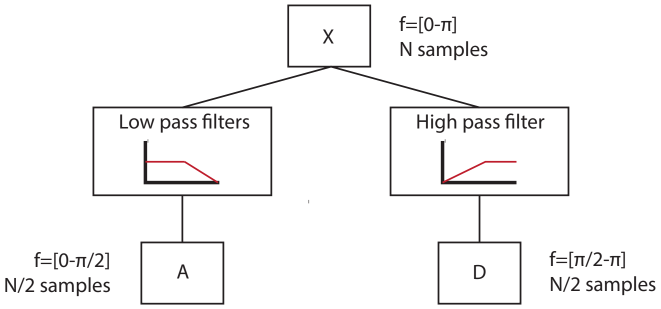


Fig. 1. DWT procedure of decomposition in approximation and detail information through low pass filters and high pass filters

coefficients, instead of using the whole signal. The mathematic formulation of the CWT is shown in eq. 1.

$$T(a,b;\psi) = w(a) \int_{-\infty}^{\infty} x(t)\psi^{*}(\frac{t-b}{a})dt \tag{1}$$

Where $x(t)$ is the temporary signal, ψ is the wavelet function, and $w(a)$ is a weighting function. The parameter a is related to the scale and b to the position of the wavelet function. $T(a,b;\psi)$ represent the resulting coefficients, as a function of a, b and the wavelet function ψ.

Nevertheless, the application of the Wavelet theory by means of the DWT using the developments of Mallat in [26] is more effective. Those developments are based on the use of filters related to the wavelet function. The decomposition is carried out using a low pass filter g, which obtains information of $aproximation(A)$, and a high pass filter h, which obtains information of $detail(D)$, according to figure 1.

After applying filters to a signal S of a frequency band $[0,\pi]$ and number of samples N, the frequency band is halved obtaining both approximation information (A) $[0,\pi/2]$ and detail information (D) $[\pi/2,\pi]$. Therefore, applying Nyquist rule [27], it is justified downsampling by two without losing relevant information, resulting the number of samples is $N/2$ [28].

The recursive application of DWT decomposition derives in Multirresolution Analysis (MRA) and Wavelet Packets Transform (WPT). The MRA decomposes the information of approximation of a signal recursively, until the decomposition level selected, and the divisions generated have different frequency resolution.

On the other hand, WPT decomposes approximation and detail information. Since the decomposition is applied to all the information, all the packets ob-

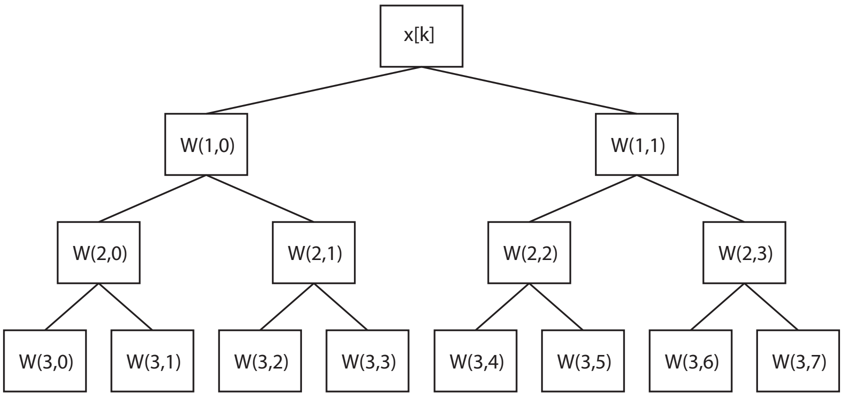


Fig. 2. WPT decomposition process until decomposition level 3

tained have the same frequency resolution. The scheme of decomposition in the WPT is shown in figure 2.

$W(k, j)$ represents the coefficients of the signal in each packet, k the decomposition level, and j the position of the packet within the decomposition level. Then, each correlation vector $W(k, j)$ has the structure of the eq.2.

$$W(k, j) = \{w_1(k, j), ..., w_N(k, j)\} = \{w_i(k, j)\} \tag{2}$$

Where i is the position of the coefficient within its packet.

The reconstruction of the signal must consider the totality of the packets within a certain decomposition level. For example, the reconstruction of the signal from the packets obtained at level three can be made through the eq. 3.

$$W(0, 0) = \sum_{j=0}^{7} \{w_i(k, j)\} \tag{3}$$

2.1 Energy of the WPT coefficients

Calculus of energy using WPT information is similar to calculating it using Fourier Theory [29]. The energy of a specific packet can be calculated according to eq. 4, as the sum of all the squares of the coefficients. The energy of a packet represents the energy contained in the frequency band covered by it.

$$E_{k,j} = \sum_{i} \{w_i(k, j)\}^2 \tag{4}$$

3 Experimental Setup

Vibration signals were obtained from a rig comprising an aluminum shaft, two ball bearings (ER10 from Rexnord) and a motor that drives the shaft through an elastic coupling. The tests were carried out with two shafts at steady state. Both were tested first at healthy condition and later, nine different levels of cracks (a) were induced with saw cuts. To avoid mounting effects, cracks were induced without dismounting the shaft from the rig. For the first shaft, middle section cracks (MSC) were made. For the second one, the test are performed using side section cracks (SSC), that are located in a change of section, as shown in figure 3.

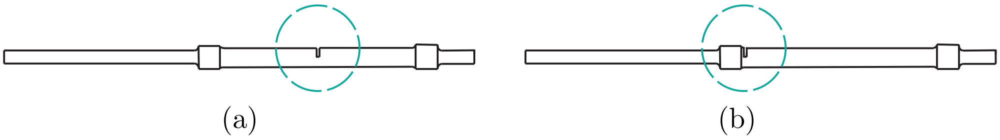

(a) (b)

Fig. 3. Positions of cracks induced in the shaft (a) middle section crack (MSC) (b) side section crack (SSC)

The values of crack depths a are shown in table 1 as the ratio between the crack depth d and shaft diameter D, where $D = 16mm$.

Defect level	1	2	3	4	5	6	7	8	9
Value ($a = d/D$)	0.04	0.08	0.12	0.17	0.22	0.28	0.33	0.42	0.5

Table 1
Crack depths a used for the experimental setup, expressed in relative terms with respect to the diameter of the shaft D.

The rig is shown in figure 4.

Figure 5 show an induced defect level 2 in the middle section, and a defect level 9 in the change of section.

Measurements were obtained at steady state, while the rotational speed was controlled by an optical tachometer and was set to 20 Hz, 40 Hz and 60 Hz. The number of points for each signal measured was 2^{14}, with a sample rate of 6 KHz.

4 Results

The technique applied was detailed in [8]. The present section resumes signal processing applied and results of WPT energy evolution versus crack size for both locations tested. POD curves are also shown.

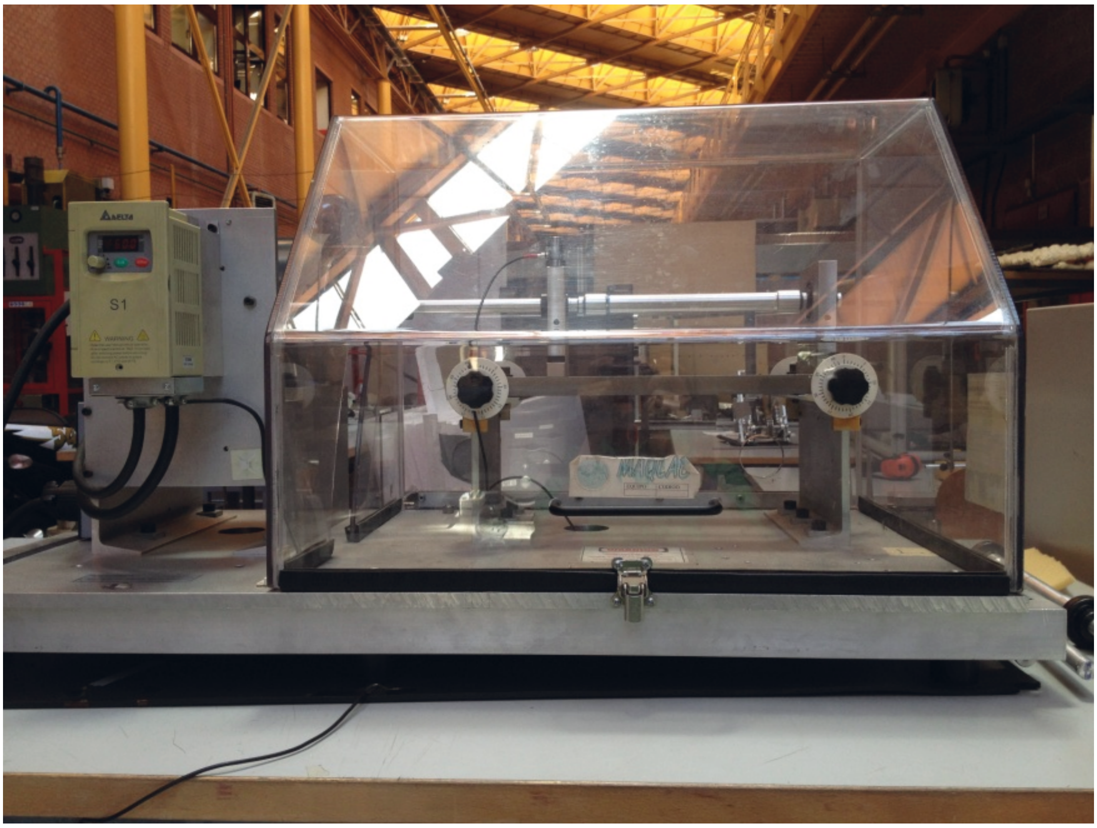
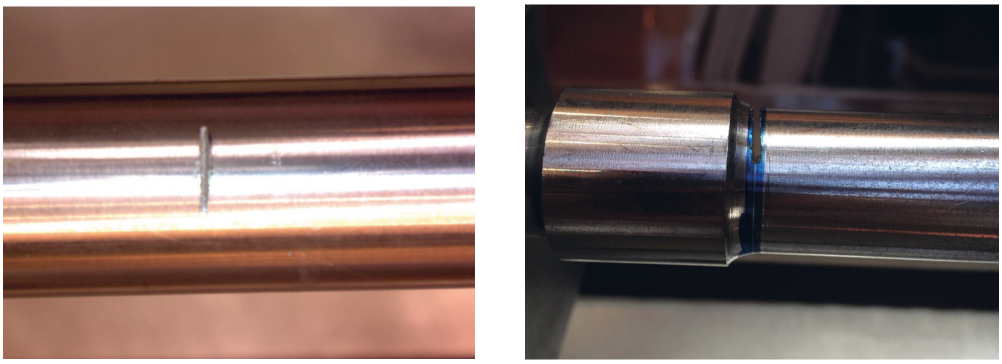


Fig. 4. Fault Simulation rig used



(a)

(b)

Fig. 5. Defects induced (a) level 2 MSC (b) level 9 SSC

4.1 Experimental energy distributions

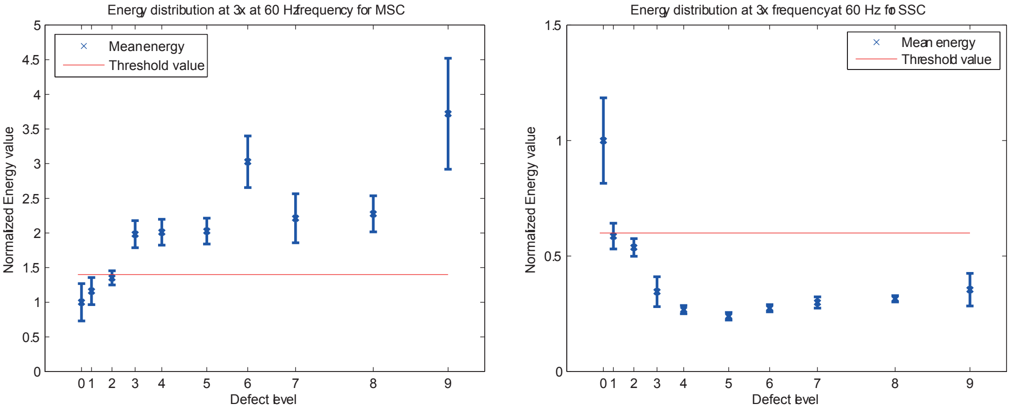
For each shaft, fault condition, and speed setting, 1,500 vibration signals were obtained by groups of 100 consecutively. Features extraction is performed for all vibration signals and later, to reduce random noise, WPT energies were averaged across the 100 consecutive samples. Therefore the number of samples to handle is 15 by condition.

The mother wavelet ‘Daubechies 6’, and the decomposition level are selected in consonance to those in the previous related work [8]. The decomposition level used is 9, thus the frequency resolution of each packet, f_r, is 6 Hz.

Due to the high amount of data measured, energy distributions are considered to be Gaussian, therefore they will be represented using mean and root mean square (RMS) values. On the other hand, tests were performed for two shafts. To normalize values between them and avoid mounting effects, mean energy values at the healthy condition are set to 1. The rest of mean and RMS energy values are processed accordingly.

Energy values at frequencies related to the first harmonics of the rotation speed (1 x, 2 x and 3 x) are evaluated for the three rotation speeds tested. At 1 x and 2 x frequencies at all speeds tested, changes in energy are do not show correlation with the crack size, thus they can not be used for crack detection. Crack effects seem to be hidden at these frequencies by other factors.

On the other hand, when analyzing 3 x energies, it is found that at 60 Hz they show a clear correlation with the crack size. Figure **??** presents energy distributions at 3 x frequencies at 60 Hz, showing both for MSC and SSC cases a clear significant trend with the crack size. For the MSC case, the energy increases with the crack size, and an upper threshold value can be established to separate data from healthy and cracked shaft. For the SSC case, the energy decreases with the crack size, and a lower threshold value can be used to distinguish lower energy values corresponding to cracked shaft data.



(a) (b)

Fig. 6. Energy distributions at frequencies related to 3 x represented by mean and RMS versus the level of crack at 60 Hz (a) MSC (b) SSC

Figure 7 shows superposed cases with the respective upper threshold value (MSC case) and lower threshold value (SSC case) proposed.

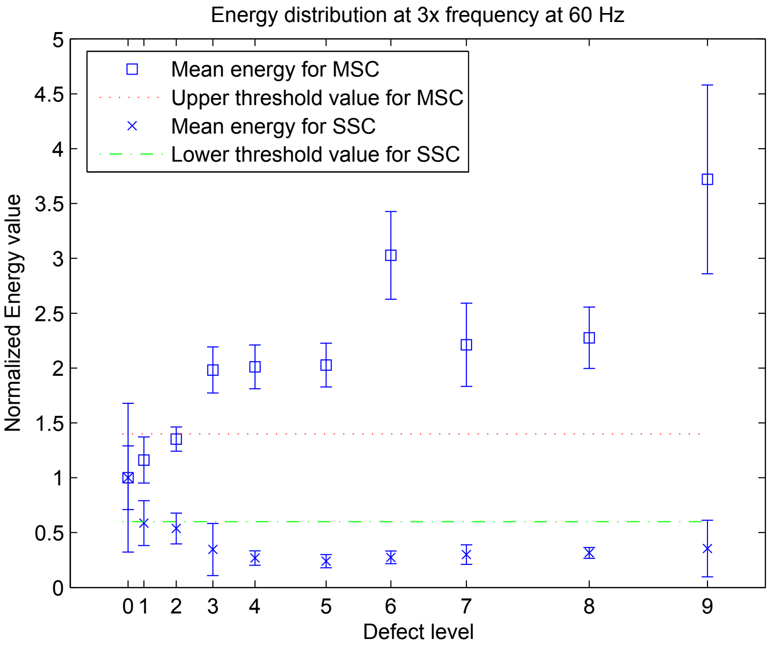


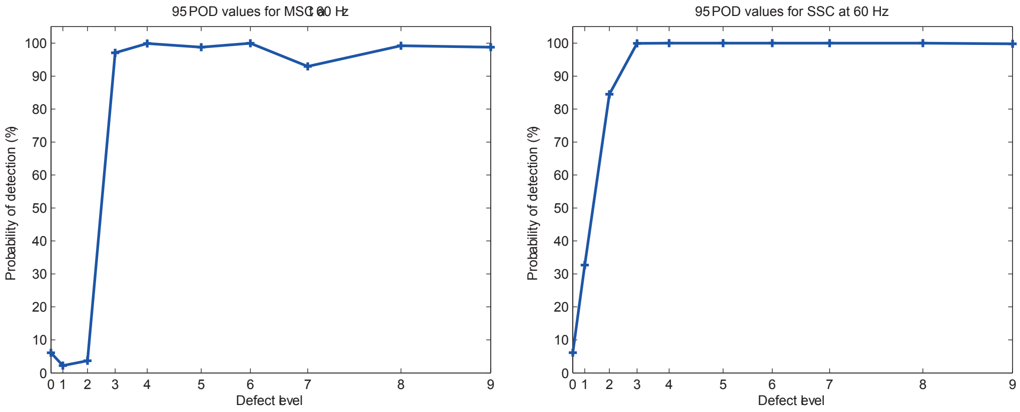
Fig. 7. Energy distributions at frequencies related to 3 x represented by mean and RMS versus the level of crack at 60 Hz for MSC and SSC cases.

As can be concluded from figure 7, for MSC energy values increases and for SSC energy values decreases with the crack size. Nevertheless, it could appropriate to consider that a crack exists when the energy values deviate more than 40% of its mean value at healthy condition. Depending on the sense of the deviation, also location of the crack could be detected.

Using the proposed threshold values, POD curves are calculated for the energy of the packet related to 3 x. The 95% lower confidence limit curves are shown in figure 8 for both locations of crack tested. Results show that cracks above level 3 (12% of shaft diameter) can be detected with very high reliability. However, POD curve for MSC shows a decreasing in detection probability at defect level 7, and its values are slightly lower than for SSC case. POD curve for the SSC is closer to the ideal case. The number of false alarms is admissible for both cases.

5 Discussion

Crack effects are observed in this work at 3 x, where significant changes of energy are observed. Energies at 1 x and 2 x components do not seem to be affected by crack effects. They can be hidden due to the presence of other defects as misalignment or unbalance. The capability of detecting crack effects using 3 x is an advantage to distinguish between types of defects. Crack effects



(a) (b)

Fig. 8. 95% POD curves for energies related to 3x at 60 Hz (a) MSC (b) SSC

that cause changes of energy at 3 x, should cause the same changes at 1 x and maybe at 2 x. However, at 1 x there are more phenomena affecting to that energy that can hide those effects. The crack effects in the vibration signal are compared to the mother wavelet, in this case Daubechies 6. Those crack effects causes increasing of energy at 3 x components. That means that crack effects in the signal have not exactly the same shape than the mother wavelet, and they can be described more accurately using harmonics (in this case odd harmonics, specifically the third). It is also observed that for the MSC case the energy at 3 x increases, and for the SSC case decreases.

The results of the current work confirm that the crack affects to the 3 x component, as found in [8]. However, the present work allows to confirm the robustness of the technique, and to conclude that the crack position is critical to the way the crack affects to 3 x energy. As for the MSC case the energy at 3 x increases and for the SSC decreases, the results can be used not only to detect a crack but also to locate it.

6 Conclusions

This paper presents a methodology for crack detection in a rotating shaft, based on WPT energy analysis. Experimental measurements were taken from a fault simulation machine at steady state at different rotation speeds and at different crack conditions. Nine different crack depths were induced (from 4% to 50% of the shaft diameter) at two different locations (middle section (MSC) and side section (SSC)). After a WPT energy analysis it is concluded that the energy of the 3 x component of the rotation speed is the best indicator of crack for both locations at the highest speed tested (60 Hz). For MSC the 3 x energy increases, and for SSC the energy decreases. Deviations of more than

40% of the mean value at the healthy condition indicates that a crack exists. 95% lower confidence limit of POD curves are calculated finding that at 60Hz, the reliability of the technique is high.

The technique proposed, based in WPT energy at 3 x component, has shown its robustness. It has applications in condition monitoring under stationary conditions. It allows the establishment of parameters that defines a machine working under normal operating conditions, and the detection and location of the presence of a crack if a threshold value is exceeded.

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