Fault diagnosis of rolling element bearings from current and vibration measurements

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ABSTRACT

As rolling element bearings are used in many rotary machines, it is crucial to monitor their response in order to apply condition-based maintenance. One of the main tasks consists in carrying out the diagnosis process, i.e., to do fault detection, localization and identification. Thus, the replacement of rolling element bearings can be done once the diagnosis process gives relevant information that is not only valid for maintenance purposes, but also to design purposes when the causes of the faults appearing in the system are analysed. There are many ways to study the state of these components, which vary from vibration analysis until acoustic emissions, through current or thermal analysis, among others.

In this work the vibrational response of rolling element bearings as well as the current of the motor that drives the motion of these components are analysed. A test rig consisting of a drive motor, a couple of gearboxes and a load motor is used. Damaged bearings have been used in the first gearbox, in such a way that their response is studied and compared to that of a healthy bearing. Some indicators are extracted from both the vibration and current signals that can be used for diagnosis purposes. Moreover, the effect of other factors such as the size of the damage or the position of the damaged zone on the vibrational and electrical response is also studied.

1. INTRODUCTION

Condition monitoring (CM) has become a significant element of condition based maintenance. CM is defined as the continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance (BS 3811:1984). Typically CM is the main tool for preventing catastrophic failure in rotating machinery coming from a breakdown maintenance approach, and for avoiding the unnecessary maintenance actions coming from a preventive maintenance approach, leading to a reduction of associated costs. Thus, CM is used to determine the healthy or damaged state of the machinery and schedule maintenance activities according to its condition. To ensure the in service maximum utilization of assets, CM has been identified as a valuable tool, as it gives relevant information to establish the optimum repair and maintenance periods. Therefore the benefits of CM include, among others, increase in equipment availability, reduce lifecycle cost, reduce risk, reduce wastage and rework.

Often continuous data acquisition is need for CM, combined with analysis and pre-established warning/alarm levels. Continuous work on CM, and the development of less costly and more reliable data acquisition hardware have improved the diagnostic capabilities of CM. Sensor technologies have also advanced, improving sensitivities, size and cost. The above mentioned has allowed that CM has been introduced in manufacturing processes.

An implementation of a CM program must be integrated by three key steps:

1. Data acquisition: To obtain data, relevant to the health state of the system.
2. Signal processing: To handle the data collected in step 1.
3. Feature selection: It gives the means to interpret the data. It must be able to detect the fault, locate it in the system, and identify the typology of the fault.

Commonly, a range of technologies applied to a system will allow the operators/maintenance engineers to take the best decision. The degradation of a system can monitored and predicted, obtaining the remaining useful life, before the system has a failure.

There are many technologies that can be used for condition monitoring, including:

- Oil analysis (Randall, 2011)
- Thermography (Randall, 2011)
- Acoustic emission (Caesarendra, 2016)
- Vibration analysis (Randall, 2011)
- Motor current analysis (Benbouzid, 2000)

In the work that is presented an analysis of the health state of a gearbox is done. One of the bearings is substituted by some versions in different health states. Thus, vibration analysis and motor current signature analysis are performed to determine the state of the bearing. Both analysis are executed being able to draw conclusions from both type of analysis.

This paper is structured as follows: section 2 shows the equipment used for the experimental work; the vibration analysis and the motor current analysis performed in this work are presented in section 3 and section 4, respectively; and, finally, some conclusions are explained in section 5.

2. EXPERIMENTAL

The test rig, test procedure and the bearings used in this paper are described in this section.

2.1. Test rig

The different bearings were tested in the gearbox prognostic simulator (GPS) test rig, manufactured by Spectra Quest Inc, shown in figure 1. A benefit of using the test rig is that it allows the testing of faults that otherwise would be difficult to test in real machinery.

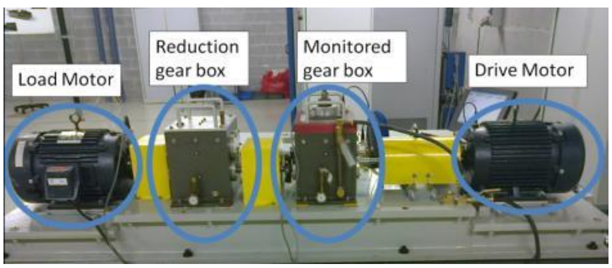

Figure 1. GPS test rig.

The GPS test rig is formed by two motors that are confronted; one works as the diving motor (whose current is being measured) while the other motor provides the load. In addition, two gearboxes are used, the monitored and a reductor for the load motor. Both motors are identical; they have three-phases, two pair of poles and are asynchronous.

The gearbox under test is the first one located after the driving motor. The monitored gearbox is a two stage gearbox, composed by three shafts, as shown in Figure 2. The test bearing is one of the two located in the second (intermediate) shaft.

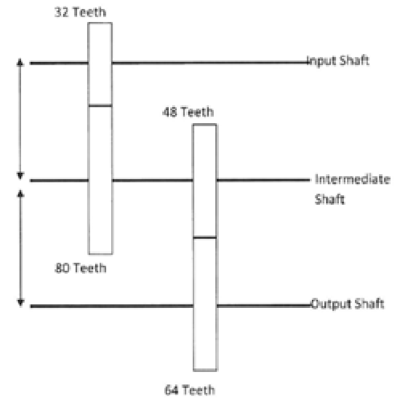

Figure 2. Schema of the monitored gearbox.

Due to the high versatility and adaptability of the GPS test rig, several sensors have been installed: accelerometers, torque sensors, load cells, encoders and current sensors. Specifically, the signals acquired by the following sensors have been used for this study:

- Current sensors: Lem HTA 100 hall sensors.
- Encoder: Scancon type SCH68B, in the input shaft.
- A uniaxial IPC accelerometer, model 608A11, at the top of the monitored gearbox measuring in the vertical direction.
- Two uniaxial IPC accelerometers, model 608A11, near the housing of the monitored bearing measuring in the radial directions.
- A triaxial PCB 356A17 accelerometer at the housing of the monitored bearing.

2.2. Tested bearing

The bearing under test is a ER16k bearing form the Rexnord manufacturer. It is a radial ball bearing for a 1 inch diameter shaft. It is classified as standard duty. It has a seal and its own lubrication by grease. The dimensions of the monitored bearing are shown in Table 1.

Bearings in different conditions have been tested in this work. Thus, a healthy and three damaged bearings have been used. The damages have been seeded to the outer ring by a drilling process from its outer surface until its raceway, taking care not to damage any other component of the bearing. The seeded damages have different diameters: 0.6

mm, 1 mm and 2 mm, denoted as DO1, DO2 and DO3, respectively, whereas the healthy state is denoted as H throughout this paper. Figure 3 shows ones tested bearing with a damage DO2.

Table 1. Specifications of the REXNORD ER16K bearing.

Parameter	**Value**
Number of balls, Z	9
Ball diameter, D_w	7.94 mm
Inner race diameter, d_i	31.38 mm
Outer race diameter, d_o	47.26 mm
Pitch diameter, d_m	39.32 mm
Race groove radius, r	4.1 mm
Material density, ρ	7750 kg·m^{-3}
Elastic modulus, E	210 MPa
Poisson's ratio, v	0.25

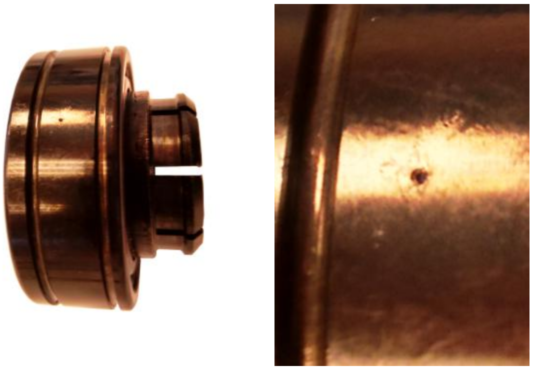

Figure 3. Bearing with DO2 damage.

2.3. Test procedure

Three different values for the load applied by the second motor have been used: no load, 30% of the load applied by the drive motor, and 60% of the load applied by the drive motor. Moreover, four different levels have been defined for the speed of the drive motor: 250 rpm, 500 rpm, 1000 rpm and 1500 rpm.

For statistical robustness reasons the length of the tests is enough to allow at least sixty revolutions of the intermediate shaft in the gearbox. As a result of this condition and the speed used in the tests, the time span of the data is 36, 18, 10 and 10 seconds long, respectively. Besides this, each of tests conditions is repeated 24 times. To make each repetition independent, the speed was brought to zero before launching the next test.

The sampling speed used for the measurements is 50000 Hz except from the case of the last accelerometer listed before, where a sampling speed of 10000 Hz is used.

3. VIBRATION ANALYSIS

The techniques used to process the data, to compute features from the processed data and to select the most relevant features are explained in this section, as well as the algorithm used for classifying the features. Then, the results obtained with this analysis are presented.

3.1. Theoretical background

The presence of a damage in rolling element bearings leads to some excitations in their vibratory response. The impulsiveness in a damaged state follows a pattern of periodical shocks when a contact is produced in the damaged area. Thus, for the case with a localized damage in the outer ring, as it is the case study of this work, the response described in Figure 4 occurs, where the time signal is presented above and the envelope of that signal is shown below. The impulsiveness is repeated in both cases with a period of the inverse of the ball pass frequency of the outer ring (BPFO). The BPFO is calculated as (Randall, 2011)

$$BPFO = Z \cdot \frac{n}{2} \cdot \left(1 - \frac{D_w}{d_m} \cdot \cos\phi\right)$$

where n is the shaft speed and φ is the contact angle. Note that, as there is not axial load applied to the bearing, φ is equal to 0.

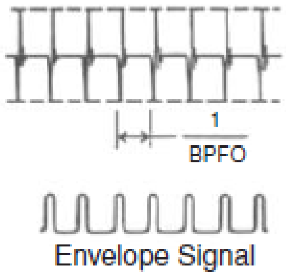

Figure 4. Vibratory response when there is a damage in the outer ring, adapted from Randall (2015).

Thus, it is expected that the frequency-domain response of a bearing whose outer ring is damaged results in impulsiveness in BPFO and its harmonics (Smith & Randall, 2015).

There are many approaches for the analysis of the signals. Regarding time-domain analysis, features such as kurtosis, crest factor or the root-mean-square (RMS), among others, can be computed (Sassi, Badri & Thomas, 2007; Behzad, Bastami & Mba, 2011). Regarding frequency-domain analysis, it should be highlighted the semi-automated bearing diagnostic procedure developed by Sawalhi and Randall (2007) is used in this paper, who proposed a number of techniques that can be used to determine the state of rolling element bearings.

3.2. Data processing techniques

In this study different processing techniques based on the information presented in the theoretical background part are used. First of all, the raw signals acquired by the accelerometers have been weighted by different filters. The former is a low pass finite impulse response filter, taking 150 Hz as passband-edge frequency. This value has been settled as 4-5 times the value of the BPFO for the higher operating speed. The latter filter is the one constructed by the discrete random separation (DRS) technique, which is one of the steps of the semi-automated bearing diagnostic procedure. It has as aim the separation the signal as the sum of the discrete part of the signal and the random part, in such a way that the excitations coming from different sources can be isolated. It should be noted that the excitations coming from the rolling element bearings can be found in the random part (Randall, 2011). DRS consists on finding a filter to carry out the separation process. This frequency response *H(f)* of the filter can be estimated as the *M*-long discrete Fourier transforms of the sequences (Antoni & Randall, 2004):

$$\hat{H}(f) = \frac{\sum_{k=1}^{K} \hat{X}_{k,M}^{d}(f) \cdot \hat{X}_{k,M}(f)^{*}}{\sum_{k=1}^{K} \hat{X}_{k,M}^{d}(f) \cdot \hat{X}_{k,M}^{d}(f)^{*}}$$

where K is the number of sequences that can be used for the estimation, M is the next power of 2 higher than the sequence length N, $\hat{X}_{k,M}$ is the Fourier transform of the k^{th} sequence and $\hat{X}_{k,M}^{d}$ is the Fourier transform of the delayed k^{th} sequence (Antoni & Randall, 2004).

After that, some time-domain and frequency-domain features are computed. Specifically, the following time-domain features have been calculated: mean, standard deviation, skewness, kurtosis, peak value, RMS, crest factor, shape factor and energy operator (Sassi et al., 2007; Behzad et al., 2011). Regarding frequency-domain features, two approaches have been followed based on the fast Fourier transform (FFT) and the envelope analysis. On one hand, some indicators have been computed in the zones close to the BPFO and its harmonics: the averaged RMS, the sum of peak amplitudes and the highest peak amplitude. On the other hand, the kurtograms of the signals extended to a 1/3 binary tree have been calculated (Antoni, 2006) and the five values denoted by K1 to K5 shown in Figure 5 have been used as indicators.

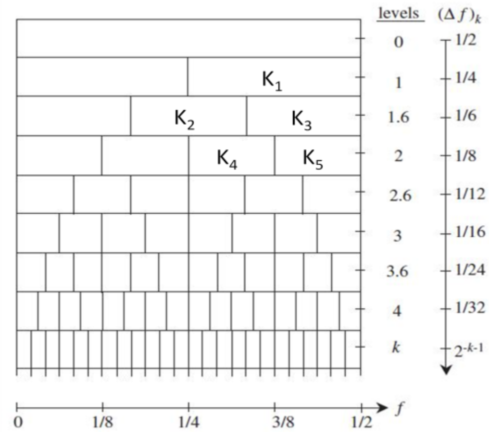

Figure 5. Values obtained from the kurtogram.

The computation of the whole features for all the raw and filtered signals leads to an amount of 882 features. In order to reduce the feature space the minimal-redundancy-maximum-relevance (mRMR) feature selection algorithm has been used (Peng, 2005).

Once the feature selection has been carried out, linear support vector machines (SVMs) have been used with the aim of classifying the data for diagnosis purposes. The 25% of the data has been employed for cross validation purposes.

3.3. Results

The frequency-domain analysis provides results according to what is expected according to Smith and Randall (2015). Thus, the spectral content of one of the acceleration signals acquired when an operating speed of 1500 rpm was applied to the test rig in which a damaged bearing (DO) was mounted is shown in Figure 6. The impulsiveness at BPFO (35.6 Hz) and its first harmonic (71.2 Hz) are clearly identified, as it can be seen with a continuous line and a dotted line, respectively.

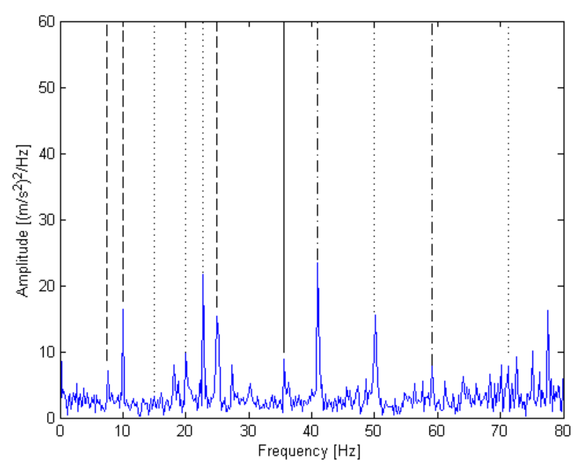

Figure 6. Spectral content of a damaged case.

The classification results obtained by the linear SVMs show that there is a need of using at least 5 of the most relevant features to provide accurate information related to the detection of the presence of damage. It has also been proved that the most relevant features are those related to the frequency-domain. Thus, the classification results have an accuracy of 100 % in the validation process, in such a way that there is not any false positive nor false negative, as shown in the confusion matrix of Table 2. These accurate results are obtained due to the low dispersion of the indicators used for the classification and the great difference in their values for the healthy and damaged cases. Moreover, repeatability between the measurements is found, leading to a reduction of the variability of the data.

Table 2. Confusion matrix for the detection process.

		Predicted class	
		H	**D**
True class	**H**	100 %	0 %
	D	0 %	100 %

When it comes to quantifying the size of the damage, more features are needed to obtain an accurate response of the supervised classification. As it can be seen in Figure 7, the response one indicator individually is not enough to assure the degradation state of a bearing.

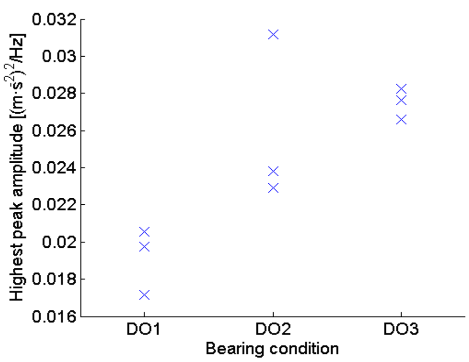

Figure 7. Indicator of bearing degradation.

Thus, the total number of features used to train a SVM giving accurate results is equal to 55. This classification leads to a situation in which classification errors of less than 3 % are obtained, as presented in the confusion matrix of Table 3. It should be highlighted that the misclassification is given by adjoining damage sizes, in such a way that there is not any small damage classified as huge damage and viceversa.

Table 3. Confusion matrix for the damage quantification process.

		Predicted class		
		DO1	**DO2**	**DO3**
True class	**DO1**	100 %	0 %	0 %
	DO2	0 %	97.2 %	2.8 %
	DO3	0 %	0 %	100 %

4. MOTOR CURRENT SIGNATURE ANALYSIS

In this section the information extracted from the motor current analysis is analyzed. A brief description of motor current analysis is made. After that the analysis itself is explained, as well as the techniques used. To finish the results obtained are shown.

4.1. Theoretical background

Motor current signature analysis has been used typically for the diagnosis of electric motor condition (Benbouzid, 2000). This technique can assess the condition of the winding, rotor bars and the internal bearings. For such purpose signal analysis is mandatory. The most common techniques used for motor current signal analysis are time domain analysis (using characteristic values), spectrum analysis, as well as Cepstrum analysis.

For the case of studing mechanical elements out of the motor some papers have been found. In particular, in the present paper motor current signature analysis has been proposed for monitoring bearings out of the motor (Singh et al., 2014). The signal analysis techniques used in this previous work also include time-frequency domain analysis. No commercially available product analyzing mechanical components out of the motor is known to the authors.

4.2. Data processing techniques

The data processed is the data from the U line of the drive motor of the GPS test rig.

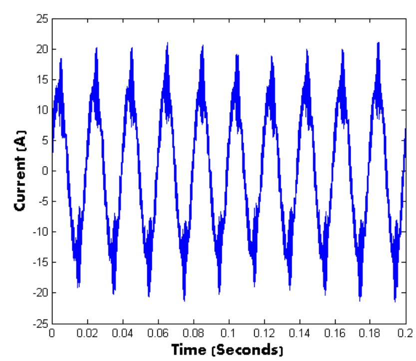

Figure 8. Image of the crude current information from the U channel of the driving motor.

A wavelet analysis was performed. (Cusidó et al., 2008) (Peng et al., 2004). The decomposition has arrived until the 16th level. In every single level, 14 descriptors from the signal have been obtained; rms, average, peak value, crest factor, skewness, kurtosis, median, minimum, maximum, deviation, variance, clearance factor, impulse factor, shape factor and the ratio descriptor (Chandan et al, 2012) (Subasi, 2007).

Having into account the different variables (speed, axial charge and radial charge), 168 descriptors per mother wavelet were obtained. To be able to select the best of the variables an F-test analysis was performed (Stemthal et al., 2008), which gives as a result a score chart, being able to select the descriptor that has most difference among the different sates of health.

4.3. Results

The results obtained were very promising, proving that motor current signature analysis is a valid technique for the analysis of bearings, in gearboxes moved by electrical motors.

The results from the bearings with the smallest faults are not differentiated from the healthy state.

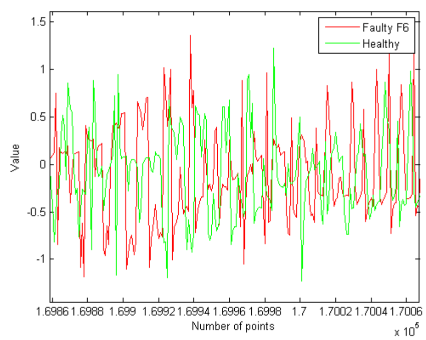

Figure 9. Healthy and faulty signal comparison.

As it can be seen in figure 10, the difference between the healthy state and the results from DO1 is not easy, but the healthy state can be distinguished from the bigger faulty states.

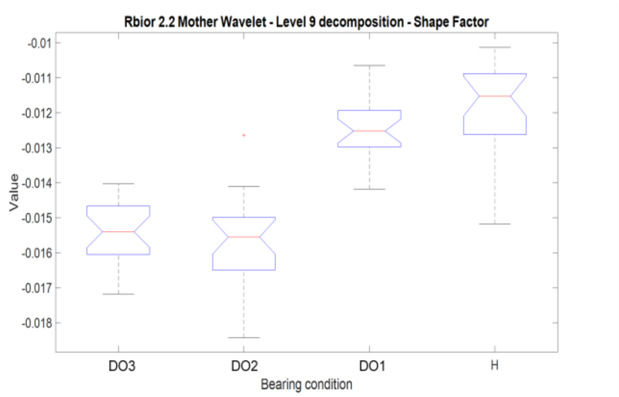

Figure 10. Rbior mother wavelet, level 9 decomposition, values of the shape factor descriptor.

5. CONCLUSION

Experiments have been performed, obtaining data from real machinery, testing different health states of bearings. An analysis of the signal and a classification of the descriptors obtained were performed. An accurate classification of the faults has been performed, proving that the use of vibration analysis techniques used are effective in the detection and classification of faults in bearings, used in gearboxes. The objective with the analysis of the current signal was to acknowledge its potential to assess the health state of bearings in a gearbox, which it has. It provides the means for differentiation for faults big enough, but this technique faces more problems when faults are small. Thus, this study provides a step forward to the implementation of condition monitoring in gearboxes giving information on fault detection, location and identification.

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