Bravo-Imaz, Iñaki, Baglee, David, García-Arribas, Alfredo, Ferreiro, Susana and Fernandez, Santiago (2014) Mechanical fault detection in gearboxes through the analysis of the motor feeding current signature. In: Comadem 2014 - Implications of life cycle analysis in asset and maintenance management , 16-18 Sep 2014, Brisbane Convention and Exhibition Centre, Australia. (Unpublished)

COMADEM 2014

16 – 18 September 2014 | Brisbane Convention and Exhibition Centre, Australia

27th International Congress of Condition Monitoring and Diagnostic Engineering

# Mechanical fault detection in gearboxes through the analysis of the motor feeding current signature

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## PAPER TEXT

The knowledge of the state of health of machinery gears helps developing cost effective maintenance plans, preventing costly down times caused by catastrophic failures. The widest spread strategy in industry to avoid faults and failures is based on preventive maintenance. Only its combination with a condition-based maintenance can detect early signs of potential machinery failures.

Often, accurate information about the state of health of a piece of equipment is difficult to obtain. Strategies based on intelligent predictive maintenance could improve this situation. The most established method to gather information in mechanical systems using gearboxes relays in the use of accelerometers, which are expensive and whose installation is usually troublesome.

The analysis of the electric signature of the electric motor that drives the gearbox provides a non-intrusive method, based on readily available information. Changes in the speed and load conditions of the gearbox produce correlated variations in the feeding current and voltage of the motor. A detailed analysis of these electrical signals can produce useful information about the state of health of the system.

In this paper, a gear prognosis simulator (GPS) test bench equipped with a multistage gearbox is used to analyze different types of mechanical faults in the gears. Three fault families have been identified, high damage, moderate damage and low damage. Specific working conditions of the test bench have been selected to mimic the operation of different mechanical systems, such as machine tools or electro-mechanical actuators.

The motor electrical current signature in the different conditions is analyzed to determine the health state of the gearbox. Signal descriptors (such as rms, kurtosis, peak-to-peak value, impulse factor, shape factor, etc.) are obtained from stationary speed. A selection of the most relevant descriptors has been carried, doing a one-way analysis.

The results obtained reveal appreciable differences between the different faulty and nominal states of the gears, making possible the detection of the health state of the system using different advance data analysis techniques.

Keywords: Condition monitoring; Motor current signature analysi; Multi-stage gearbox Asset Management

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## 1. Introduction

Condition monitoring (CM) refers to the measurement and analysis of information that relates to the condition of a machine. CM has grown to become a significant element of any predictive or proactive maintenance strategy  Condition monitoring (CM) is typically defined as a means of preventing catastrophic failure in critical rotating machinery by providing the information required to determine accurately the optimal schedule for maintenance activities. In addition, condition monitoring of plant and equipment has now been identified as a major technique in establishing the optimum repair and maintenance periods to ensure in service reliability and maximum utilization of assets. This often requires continuous data acquisition, combined with some form of analysis and some established warning/alarm levels. The diagnostic capabilities of CM technologies have increased in recent years. The advances in sensor technologies, component sensitivities, size reductions, and most importantly, cost, has allowed manufacturing processes, especially where once this technology was 'missing', the opportunity to enter a new and necessary area of diagnostics. A successful programme consists of three key steps:

- Data acquisition, to obtain data relevant to the system health
- Signal processing, to handle the data or signals collected in step 1 for better understanding and interpretation of the data
- Maintenance decision making, to recommend efficient maintenance policies based on diagnosis and prognosis extracted from the data.

The benefits of condition monitoring therefore include, but are not limited to, increased equipment availably, reduced lifecycle costs, reduced risk of secondary failure and reduced wastage due to scrap or rework. There are several types of condition monitoring technology including:

- Vibration analysis
- Oil analysis
- Infrared thermography
- Motor current analysis

Typically, a range of technologies applied to any given piece of equipment, which allows the operator/maintenance engineer to make the most informed decision. The continuous or periodic monitoring and diagnosis of equipment in order to forecast component degradation can be performed prior to equipment failure. However, not all equipment conditions can be monitored and therefore, it is important to identify which equipment needs CM techniques.

## 2. Experimental

Load fluctuations involve speed changes in electric motors. As a result of speed variations, adjustments in the per unit slip happen which in turn cause shifts in the sidebands across the line frequency [1]. This is the principle in which the motor current analysis relies.

In particular, motor current signature analysis has been used mainly for the diagnosis of electric motor condition [2]. Using this technique, the condition of the winding, broken rotor bars and the internal bearings has been assessed. These problems were identified using signal analysis. The most common trend in current signal analysis is time domain analysis (using characteristic values), spectrum analysis, as well as Cepstrum analysis.

In particular, motor current signature analysis has been proposed for monitoring gears [3]. The signal analysis techniques used in this previous work were similar to the techniques used in the case of detecting problems in the motor itself, such as time domain analysis and frequency domain analysis. In another paper [4] time-frequency analysis was suggested, although in the publication load fluctuations are analyzed.

The different gears were tested in the gearbox prognostic simulator (GPS) test rig, from the spectra quest company. The test rig permitted the use of machinery data, not simulations. And the working conditions have been selected to mimic real machinery working conditions. 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.

The GPS test rig is composed of two confronted motors, one that works as the diving motor (which is monitored) while the second motor provides the load. In addition, two gear boxes are used one is monitored while the second is the reductor for the load motor. Both motors are equal; they have three-phases, two pair of poles and are asynchronous.

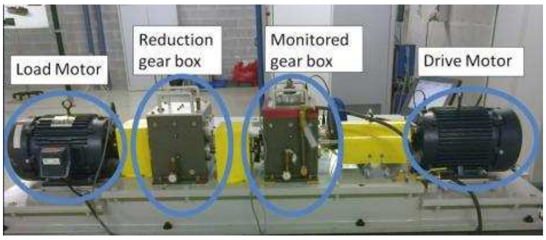



**Figure 1.** Description of the GPS test rig.

The gear under test is the first one located after the driving motor. The monitored gear box is constituted by three shafts.

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.

### 2.1. Gears tested

Ten different gears have been tested. All of the tested gears are spur gears.

As was it mentioned before, several sensors are installed in the test rig. So, taking profit of the accelerometers, an already established method for gear box health determination, the signals obtained with the gears were classified. As a result, three different categories have been identified: severe damage, moderate damage and little damage. There are two exceptions: the first one is the gear numbered 0001G, whose surface has been degraded (machined) on porpoise, and the gear numbered 0006G which has an eccentricity, but no degraded surface. Each of the tested gears has it's a unique code. In the next table the classification can be seen.

**Tabla 1.** Code and health assessment of the gears used.

| Gear number | Health assessment |
|---|---|
| 0001G | Degraded surface |
| 0003G | Severe damage |
| 0005G | Severe damage |
| 0006G | Eccentricity |
| 0007G | Severe damage |
| 0010G | Severe damage |
| 0011G | Little damage |
| 0012G | Moderate damage |
| 0013G | Moderate damage and little damage |
| 0014G | Little damage |

2.2. Test procedure

For statistical robustness reasons the length of the data files is enough to allow at least ten revolutions of the slowest shaft in the gear box. As a result, the time span of the data is 15 seconds long. Beside this, each of tests conditions is repeated 15 times.

In order to assure the independence of each repetition, the speed was brought to zero before launching the next test.

## 3. Data processing technique

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

A time-frequency domain analysis has been performed [5] [6]. The wavelet 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 [7] [8].

The mother wavelet used for the decomposition was the Daubechies 44 [9]. So as to select the most useful descriptor of the most appropriate decomposition level, a one-way analysis of the variance was carried out, due to the high number of descriptors and levels to be analyzed. The variables with the biggest F number are selected; the magnitude of the F value is the ratio of the variance calculated among the means to the variance within the samples. That is why a higher F ratio involves more difference from the rest of the population.

## 4. Results

The results were firstly analyzed using windowing. The data sets were divided in one second length chunks and were analyzed using the wavelet decomposition. However, there has been a problem with the border effect of the wavelet decomposition. In the case of such short signal chunks, the border effects are too notorious and they do not permit an accurate classification of the different gears in the gear collection.

Nevertheless, analyzing the whole signal produced significant results. In the next image the highest value of each decomposition level can be seen.

The most interesting values of the variables in level 1 are the shape factor, the variance and the crest factor. For the case of level 4 decomposition, the skewness, the average and the ratio

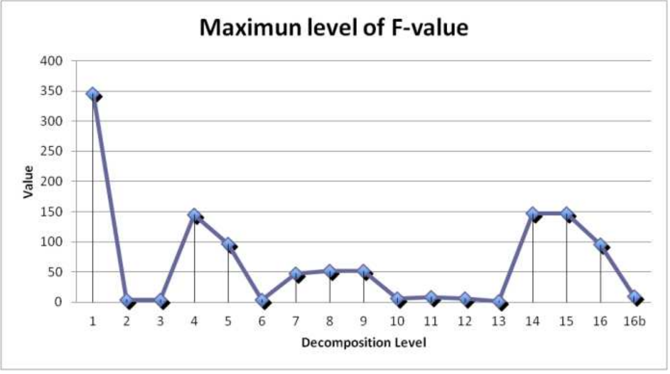



**Figure 2.** The maximun level of the F value in each of the decomposition levels.

are the most interesting. In level 15, the ratio, the clearance factor and the median provide the information.

An analysis of the pre-selected variables has been carried out, selecting among those the ones that provide the most accurate and interesting information. The analysis of the gears should be a multi-parametric analysis, as the analysis of only one parameter may not give full information of the state of the gear.

The analysis of figure 3 throws interesting results. Gears

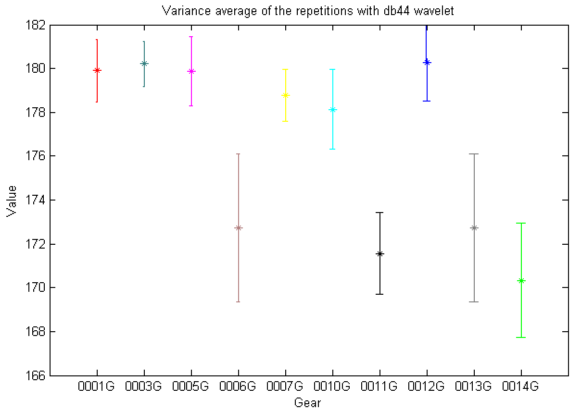
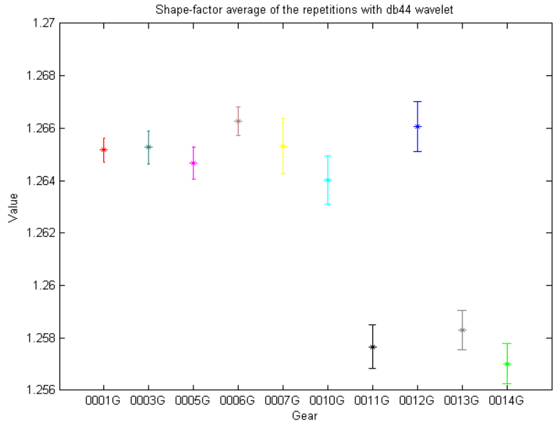



**Figure 3.** Variance of the signal obtained in the level 15 wavelet decomposition.

0011G and 0014G are the good state gears. The 0013G has a number of repetitions classified as moderate damage and other as low damage that is why, it is in the same area as the low damage gears, but has a big deviation. The high damage gears outcome is




in the same area.

**Figure 4.** Shape factor of the signal obtained in the level 1 wavelet decomposition.

As we can see in figure 4, the reason for the position of the gear 0006G results, is that it doesn´t show a big level of superficial pitting, although it has a machined fault, so it is somewhere between the low level damage and the high level damage. The 0013G has shown a large deviation, due to the reason stated in the last paragraph, so the outcomes of the analysis are around the low damage results area.

In the next image the gear 0012G can be seen slightly lower than the gears classified as having high damage.

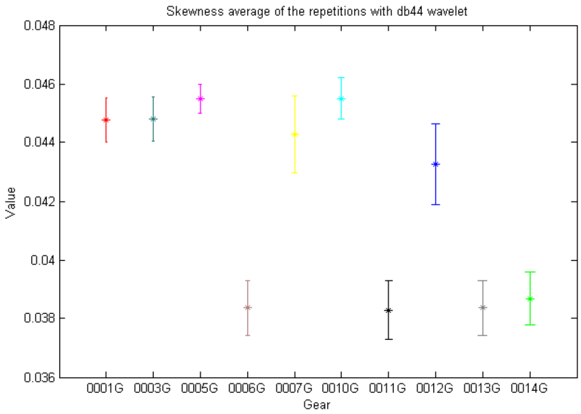



**Figure 5.** Skewness of the signal obtained in the level 4 wavelet decomposition.

## 5. Conclusions

The work shown in this paper is another step forward in an ongoing work to use internal signals in industrial machinery to assess health states of gear boxes driven by electrical motors. Internal signals will provide a non intrusive, and easy to implement method. By means of assessing the state of health, valuable information will be provided to the users, maintainers and manufacturers of the industrial machinery, allowing a better use, less costly maintenance and further improvements in the design respectively. This work has shown the viability of capturing and extracting variations in internal signals. The wavelet analysis and feature selection procedure have shown useful in producing observations correlating with the health state of gears. As future work, there is room for improvement, as further optimization is possible. For instance, wavelet analysis can be improved by using schemes such as zero padding, smooth padding and symmetric extension, and optimizing the window length, among others. For health assessment, the use of data mining techniques, such as classification, may be beneficial.

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