

Motor current signature analysis for gearbox health monitoring: Experiment, signal analysis and classification

Iñaki Bravo-Imaz¹, Alfredo García-Arribas², Susana Ferreiro³, Santiago Fernandez⁴ and Aitor Arnaiz⁵

^{1,3,4,5} *Intelligent Information Systems, IK4 - TEKNIKER, Eibar, 20600, Spain*

inaki.bravo@tekniker.es¹

² *Departamento de Electricidad y Electrónica and BCMaterials, Universidad del País Vasco UPV/EHU, Bilbao 48080, Spain*
alf@we.lc.ehu.es²

ABSTRACT

Preventing downtimes in machinery operation is becoming fundamental in industrial standards. The most common strategy to avoid costly production stoppages is the preventive maintenance, combining it with reactive maintenance in detected malfunctions. Condition-based maintenance can reduce costs, and help maintaining the quality of the produced goods. Gearboxes, as crucial elements in industrial machinery, are conventionally monitored using accelerometers, which are expensive and can be hard to install in place to provide useful information.

Motor current signature analysis overcomes these inconveniences. This analysis technique provides a non-intrusive method, and it is based on readily available signals. Changes in the input voltages are related with variations of the speed and/or load of the electric motor. The health state of the gearbox can be examined through an exhaustive analysis of the input currents.

A gear prognosis simulator (GPS) test bench has been used to perform an extensive experimentation campaign. This test bench is particularly convenient due to the flexibility it provides. Different sets of sensors can be placed in different positions, and multiple combinations of speeds and loads can be established. Three damage categories in the gears have been analyzed, high damage, moderate damage and little damage. The test parameters have been selected to simulate the working conditions of electromechanical actuators and machine tools. Constant speed and transient tests have been performed. In the transient tests, fast speed changes are performed to produce acceleration, to investigate the concomitant changes produced in the signal. The analysis has been performed in both the time and the

frequency domain, and complementarily, using the wavelet decomposition. The results obtained allow discerning the different type of defects on the gears, thus allowing detecting the different fault conditions and enabling the assessment of the health state of the gearbox.

1. INTRODUCTION

Regarding machinery maintenance, different strategies are usually followed. The most ordinary trend is the preventive maintenance, combined with reactive or corrective maintenance. There is a great pressure for a better equipment management; a cradle-to-grave strategy to preserve equipment functions, avoid the consequences of failure, ensure the productive capacity and maintain the quality of produced goods (Dhillon, 2002). The use of so-called condition-based maintenance tries to help achieve these objectives. The main obstacle for the implementation of condition-based maintenance is the cost and the knowledge required to properly install sensors. Sensors and other monitoring techniques are not so standard and require costly and, sometimes, hard implementations.

Machinery internal signals, in some cases, are readily available, and can give information of the health state. Avoiding the expenditure and implementation problems of adding sensors. Internal signals give an economical approach to condition monitoring; although they may require complex signal processing. Internal signals are typically controlled in most of the machines and could be available in an easy way.

Gear boxes are crucial elements in industrial machinery. A defect can cause costly downtimes. Gearboxes have been monitored in the past, using the vibration signal (Randall, 2002). But using the vibration signal involves installing accelerometers, with which are often costly and hard to install. This research has been carried out to monitor the

Iñaki Bravo-Imaz et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

health state of gearboxes using electrical motor current (Kar & Mohanty, 2006). If a fault condition does exist, the effective load torque varies with the rotor position. Subsequently, these variations produce spectral components in the current consumed by the driving motor (Hachemi 2000). As a first approach to the use of internal signals, in this paper the current signal is obtained by means of external sensors.

In this paper we present the investigation carried on a gearbox test rig. Three health states are included in this investigation (Severe damage, Medium damage and little damage). The current is analyzed extracting features from the signal, and by previously using a wavelet decomposition, showing the suitability of the preprocessing technique.

The investigation carried out in this paper constitutes a step forward in our quest for using internal signals for condition based maintenance in gear boxes. The information obtained in this research will permit the identification of fault conditions, hopefully allowing in a close future to implement prognosis. The possibilities of using the time-frequency domain analysis are being explored.

2. EXPERIMENTAL

For the procurement of experimental results a Gear Prognostics Simulator (GPS) test rig was used, from Spectra Quest. The data obtained from the test rig are of capital importance as it is in effect, real machinery. So it is perfect for the validation of our algorithms. The most suitable working conditions were selected. In this way the translation from the test rig to actual machinery may be less costly. It is remarkable that it permits the testing of defects that can be hard or impossible to be tested in real machinery.

The GPS consists mainly of two confronted motors, a reduction gear box for the load motor and the monitored gearbox. One of the motors acts as a drive and the other motors acts as the load. The drive motor provides the speed that is commanded by the control. And the load control supplies de torsion load applied to the gearbox. Both motors are three-phase, two pair of poles asynchronous motors.

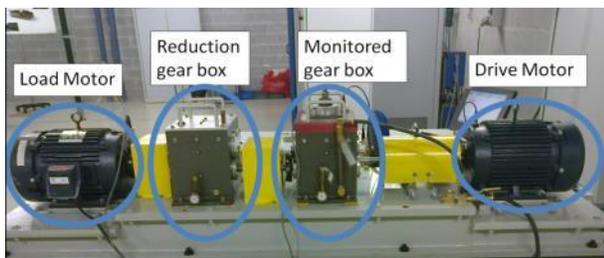


Figure 1 Description of the Gear Prognostics Simulator Test rig.

The monitored gear box is composed by three shafts with different gears. The gear that is being tested in this work is right the first one after the motor.

The test rig allows a fast gear change, so different gears with different defects have been studied. Another property is the adaptability of the gear box that permits the installation of diverse sensors. Hence accelerometers, current sensors, torque sensors, load cells and encoders have been installed.

There are several factors that affect the tests. Operating conditions don't only affect the test, but also the current signals measured. Speed and load are two of those operating parameters, to avoid their effects they are set to 1500 rpm and no load condition. To reduce the effect of other unwanted contributions the tests are carefully performed using the same conditions. For reassurance in avoiding the effect of parameters that could not have been identified and, to get statistical robustness, several repetitions of each gear test are performed.

2.1. Gears tested

A collection of gears have been tested. All of them are spur gears. Different gears with different faults are present in this collection.

Several sensors are installed in the test rig, accelerometers, current sensors, torque sensors and encoders. In order to classify the faulty gears, the signal obtained from the acelerometers has been analyzed. Unsupervised learning techniques combined with tribological expertise have been applied to the tests, after a vibration signal pre-processing, in order to find hidden similarities and to group them. As a result, three different categories have been identified: severe damage, moderate damage and little damage.

Gear number	Health assessment
0003G	Severe damage
0005G	Severe damage
0007G	Severe damage
0010G	Severe damage
0011G	Little damage
0012G	Moderate damage
0013G	Moderate damage and little damage
0014G	Little damage

Table 1. Classification of the gears using the information from the accelerometers.

2.2. Test procedure

Each test was done with a length of 15 seconds to allow the slowest gear in the gear box to be able to perform at least 10 revolutions.

Each test condition was repeated 15 times to enable statistical robustness. And each repetition was independent to the rest as between two repetitions the speed is taken to zero, and the test is re-launched. But all of the tests were

performed in the same speed and load conditions, thus eliminating the influence of these two parameters.

3. DATA PROCESSING TECHNIQUES

At naked eye differences between little damage and severe damage gear's current is indistinguishable, hence making data processing mandatory.

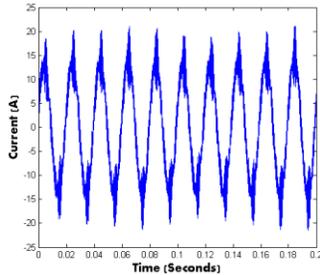


Figure 2 Current raw signal from the 0003G, U channel.

The data that have been processed are the data from the channel U of the drive motor.

Two types of analysis were performed. One for the case of the raw signal, in the time domain, and another one for the time-frequency domain of the wavelet decomposition signal.

In the case of the raw signal analysis, 14 features from the signal were obtained. The features are: rms, average, peak value, crest factor, skewness, kurtosis, median, minimum, maximum, deviation, variance, clearance factor, impulse factor, shape factor (Chandran, Loksha, Majumder, Raheemv, 2012). They have been obtained from the each repetition, and a median of all of the results is calculated.

On the other hand, time-frequency domain analysis is performed, in comparison with frequency analysis, it overcomes problems such as frequency resolution and magnitude accuracy (Cusidó, Romeral, Ortega, Rosero, García Espinosa, 2008), (Peng & Chu, 2004). In the work carried out, constant speed signals have been analyzed. Several wavelet decomposition levels have been studied. And in each level the 14 features that were achieved for the time domain case, are also achieved. Also another feature is calculated, this feature represents the difference between one level and the next (Subasi, 2007). Before the average of the features of the different levels a one-way analysis of the variance was performed. The objective is to reduce the number of levels and the number of features.

In this way the variables with the biggest F number, have more difference between the group variability than among within the same group, thus revealing the feature that exposes the most difference between the different gears.

4. RESULTS

Both time domain analysis and time-frequency domain analysis are compared.

4.1. Time domain analysis

After analyzing the several features, we arrive to the conclusion that not all of them provide useful information. Out of the 14 features just half of them give results, good enough to differentiate the good condition gears, and the gears with faults. The useful features are: Average, deviation, maximum, median, peak value, root mean square and variance.

Among those the most significant feature is the variance.

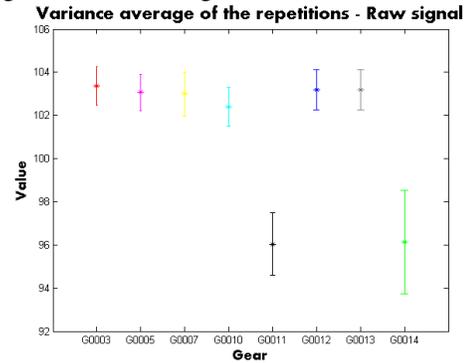


Figure 3 Variance of the raw signal.

In this case the difference between the good condition gears (0011G and 0014G), and the rest (high damage, and moderate damage) is most obvious. It is of about 2 or 3 units. In the case of comparing it in percentage points, the difference is not that pronounced.

It is to be highlighted that the moderate damage gears are not discriminated.

The root mean square value also gives a remarkable difference. However the difference in percentage points is more remarkable, but the absolute variation is not that evident.

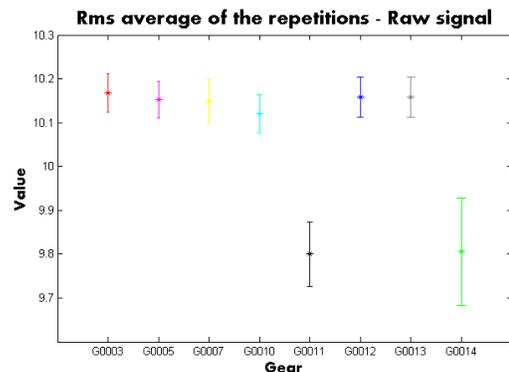


Figure 4. Root mean square of the raw signal.

4.2. Time-frequency domain analysis

The mother wavelet used was a daubechies 44 (Rafiee, Rafiee, Tse, 2010).

As stated before a one-way analysis was performed. All of the gears were introduced in the one-way analysis, instead of the gears representing the failure groups. In the next table the results of this one way analysis are shown.

Level 1		Level 2	
Variables	F-test	Variables	F-test
Shape factor	328.5494	Skewness	159.9297
Variance	287.8911	Average	73.0568
Crest factor	241.6040	Ratio	60.8824
Peak Value	54.8416	Peak Value	10.8254
Impulse factor	12.5476	Crest factor	10.4561
Clearance factor	10.97	Deviation	7.3155
Rms	4.1327	Clearance factor	4.4491
Skewness	2.8228	Impulse factor	3.4263
Deviation	2.264	Median	2.9218
Minimum	1.3558	Shape factor	1.5086
Average	1.159	Maximum	1.4948
Median	0.9807	Minimum	1.0227
Maximum	0.9549	Variance	0.8998
Kurtosis	0.6377	Rms	0.7296
		Kurtosis	0.507

Table 2. Table with the F tests.

The results of the one-way analysis test unveiled that the best levels for the decomposition are the levels 1, 4 and 15.

The most interesting variables for level 1 are crest factor, peak value, shape value and variance. In the case of level 4 are average, skewness and ratio. And last but not least important for the case of the level 15 decomposition the best variables are the clearance factor, the median, the ratio and the variance.

Going through a thoughtful analysis to find among those variables that pointed out the one-way analysis, the ones that provided the most information were selected.

In the next image the difference between the gears is noticeable.

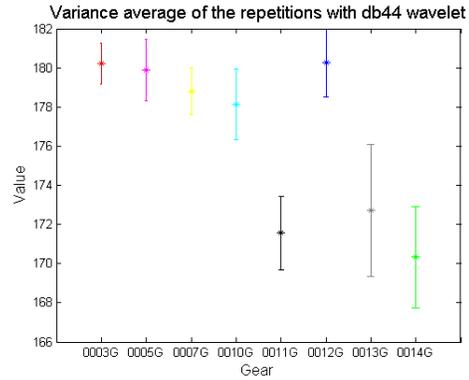


Figure 5. Variance of the signal obtained in the level 15 wavelet decomposition.

It is also remarkable that the results are more in concordance with the classification of the accelerometer data than the analysis of the raw signal. The gear 13 was classified as having some results as moderate damage and others as little damage, and as we can see in the image above the dispersion of this results are in between the high damage area and the little damage area. It is also visible that the gear number 12, classified as moderate damage, has got slightly different values than the gears categorized as high damage. This can also be seen in other variables. And the difference is bigger in value than in the case of the time domain analysis, providing an easier differentiation.

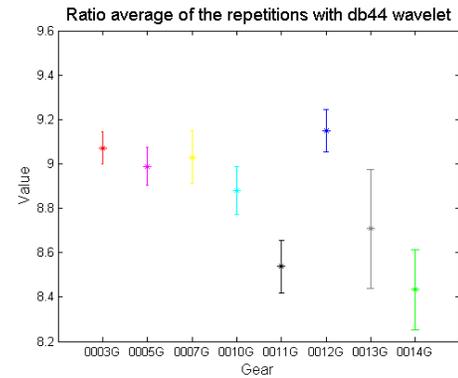


Figure 6. Ratio of level 4 wavelet decomposition.

Though in this case, due to the dispersion of the signal the difference may not be that easily noticeable.

As a result the time-frequency domain produces a differentiation between the gears with a greater match with the results obtained from the vibration analysis.

5. CONCLUSION

It has been shown that the analysis of the signals obtained in the wavelet analysis produces better results than the analysis of the raw signal for the differentiation of the different states of the gears, analyzing the motor current signal. This paper is a step forward for the use of internal signals of machinery in condition based maintenance for gear boxes. Providing a

non intrusive an easy to implement method. The final goal is that the manufacturers implement this method and provide more accurate information on the state of the machinery, provide recommendations on the problems that the client may have and to provide information on the use, so that future designs can be improved. There is still space for more improvement, as the technique will be further perfected. The mother wavelet will be optimized; data from the frequency components of each decomposition level will be analyzed.

ACKNOWLEDGEMENT

The work presented in this paper is part of the research work still in progress in the project Power-OM, funded under FP7 under grant agreement no. 314548, as part of the Factories of the Future initiative.

REFERENCES

- Chandran P., Lokesh M., Majumder M.C., Raheemv K.F. A. (2012) Application of Laplace Wavelet Kurtosis and Wavelet Statistical Parameters for Gear Fault Diagnosis, *International journal of multidisciplinary sciences and engineering*, vol. 3 (issue 9), pp. 1-8
- Cusidó J., Romeral L., Ortega J.A., Rosero J.A., García Espinosa A. (2008). Fault Detection in Induction Machines Using Power Spectral Density in Wavelet Decomposition, *IEEE Transactions on Industrial Electronics*, vol. 55 (issue 2), pp. 633-643. doi:10.1109/TIE.2007.911960
- Dhillon B.S. (2002). *ENGINEERING MAINTENANCE A modern approach*. USA: CRC Press
- El Hachemi Benbouzid M. A. (2000). Review of Induction Motors Signature Analysis as a Medium for Faults Detection, *IEEE Transactions on Industrial Electronics*, vol. 47, (issue 5), pp. 984 - 993. doi: 10.1109/41.873206
- Kar C., & Mohanty A.R. (2006). Monitoring gear vibrations through motor current signature analysis and wavelet transform. *Mechanical Systems and Signal Processing*, vol. 20 (issue 1), pp. 158-187
- Peng Z.K., Chu F.L. (2004) Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography, *Mechanical Systems and Signal Processing*, vol. 18, pp. 199-221, doi: 10.1016/S0888-3270(03)00075-X
- Rafiee J., Rafiee M.A., Tse P.W. (2010). Application of mother wavelet functions for automatic gear and bearing fault diagnosis, *Expert Systems with Applications*, vol. 37 (issue 6), pp. 4568-4579, doi: 10.1016/j.eswa.2009.12.051
- Randall Robert B. (2002). State of the Art in Monitoring Rotating Machinery – Part 1, *ISMA 2002 conference*, September, Leuven, Belgium.
www.sndv.com/downloads/0403rand.pdf
- Subasi A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model, *Expert model with applications*, vol. 32, pp. 1084-1093, doi: 10.1016/j.eswa.200602.005

BIOGRAPHIES

M.Sc. Iñaki Bravo-Imaz Industrial Engineer, degreed from The College of Engineering of the University of Navarra (TECNUN). M. Sc. at the University of the Basque Country. Currently a member of the Intelligent Information Systems Unit in IK4-Tekniker involved in several statewide projects related to Health Monitoring of industrial equipment, as well as a PhD student in the Faculty of Science and Technology of the University of the Basque Country.

Dr. Alfredo García-Arribas got his Ph.D. degree at the Universidad del País Vasco (Spain) in 1996. He is currently with the Departamento de Electricidad y Electrónica in the same University. He is mainly interested in soft magnetic properties of materials and their application to magnetic sensors and actuators.

Dr. Susana Ferreira got her degree in computing science at the Technical School in the University of the Basque Country (Spain) in 2005. In 2012 she received her PhD (cum laude) in the area of “Probabilistic Models for Artificial Intelligence and Data Mining”. Since 2005 she has been working in Tekniker in national and European projects in the area of health assessment, diagnosis and prognosis applied to different industrial sectors such as manufacturing, aeronautics, chemistry, etc.

Dr Santiago Fernandez received his B.Sc. in Physics from the University of Santiago de Compostela in 1996, and M.Sc. (equiv.) in 1997. In 2001 he received his Ph.D. degree for work in the area of speech perception and acoustic phonetics. After having worked as a post-doctoral researcher in the University College London and at the Dalle Molle Institute for Artificial Intelligence, Switzerland, he joined Tekniker, where he works on intelligent information systems unit.

Dr. Aitor Arnaiz is head of the intelligent information systems unit at IK4-Tekniker. He holds an MSc on ‘Applied Artificial Intelligence’ at Aberdeen University and a PhD at Sunderland Univ. with the thesis ‘Development of Artificial Intelligence Technologies to support automation of condition monitoring tasks’. During last 5 years he has also been head of the diagnostics and prediction unit and responsible of the research line in maintenance and reliability at Tekniker.