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Bearing Fault Diagnosis in Mechanical Gearbox, Based on Time and Frequency - Domain Parameters with MLP-ARD

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Abstract: Gearboxes are one of the most important parts of the rotating machinery employed in industries. Their function is to transfer torque and power from one shaft to another. If faults occur in any component (bearings) of these machines during operating conditions, serious consequences may occur. Consequently, condinuous monitoring of such subsystems could increase reliability of machines carrying out field operations. Recently, research has been focused on the implementation of vibration signals analysis for the health status diagnosis in gearboxes having as a base the use of acceleration measurements. Informative features sensitive to specific bearing faults and fault locations were constructed by using advanced signal processing enabling the accurate discrimination of faults based on their location.
This work presents a fault diagnosis method for a mechanical gearbox with time and frequency - domain features by using a Multilayer Perceptron with Bayesian Automatic Relevance (MLP-ARD) Neural Network.
The time and frequency-domain vibration signals of normal and faulty bearings are processed for feature extraction. These features from all the signals are used as input to the MLP-ARD. The experimental results show that the proposed approach (MLP-ARD) presents very high accuracy in different bearing fault detection. This approach will be extended as regards real-time fault detection of rotating parts in agricultural vehicles where the anticipation of detection of incipient failure can lead to reduced downtime.
Key words: Gearbox, fault detection, neural network, bearing, vibration

INTRODUCTION

Industrial systems are becoming more complex due, in part, to their growing size, and to the integration of new technologies. With ageing, these systems become more vulnerable to failures, and their maintenance activities are difficult and expensive. All the moving parts of rotation machines produce vibrations during operation. Each machine has a specific vibration signature related to the construction and the state of the machine. The vibration signature of the machine will also change if the state is change. A change in the vibration signature can be used to detect incipient defects before they become critical. Good product design is of course essential for products with high reliability. However, no matter how good the product design is, products deteriorate over time since they are operating under certain stress or load in the real environment, often involving randomness. Maintenance has, thus, been introduced as an efficient way to assure a satisfactory level of reliability during the useful life of a physical asset (Heng et al. 2009).

All these are essential elements of several condition monitoring methods in rotation machines or in there individual mechanisms. Machine condition monitoring is gaining importance in industry because of the need to increase reliability and to decrease the possibility of production loss due to machine breakdown. The use of vibration and acoustic emission (AE) signals is quite common in the field of condition monitoring of rotating machinery. Condition monitoring of bearings using vibration signals can lead to the detection of bearing defects at a much earlier point than the crack propagation stage.

By comparing the signals of a machine operation in normal and faulty conditions, detection of faults like mass unbalance, rotor rub, shaft misalignment, gear failures, and bearing defects is possible. These signals can also be used to detect the incipient failures of the machine components, through the online monitoring system, reducing the possibility of catastrophic damage and the downtime (Shiroishi et al., 1997; Antoni and Randall, 2002; Al-Balushi and Samanta, 2002).

An experienced operator can monitor the machine condition by sensing the vibrations or listening the sound variations. However, this method is not reliable because faults at the beginning cannot be perceived in this way. These faults can develop into a destructive machine very quickly, even before the operator realizes variation in vibration or noise. In these cases the development of diagnostics which will be based on the diversification of vibration signature were found more than necessary to protect machinery of enormous value without considering the caused damage by a possible interruption of production (Rafiee et al., 2007).

The vibration signals are widely used in condition monitoring and in fault diagnosis in basic structural machine elements or mechanism (Bouillaut et al., 2001; Wilson et al., 2001; Monsen et al., 1993). They can be used as a detection tool with great success due to the straightness and the rich information they contain. However, for the damage detection the frequencies range is often large and in accordance with the sampling Shannon's theorem requires a high sampling frequency and a large sample of sizes to detect faults in rolling bearings. Therefore, due to the existence of additional elements there is a requirement for pre- processing in order to extract the appropriate features, which is necessary for the appropriate method supply.

A significant work has been published, mostly in the last 30 years, on the diagnosis of mechanical equipments by vibration analysis methods. Different methods of fault diagnosis have been developed and used effectively to detect the machine faults at an early stage. One of the principal tools for diagnosing rotating machinery problems is the vibration analysis (Samanta and Al-Balushi, 2003). Through the use of some processing techniques of vibration signals, it is possible to obtain vital diagnosis information from the vibration signals. However, many techniques available presently require a good deal of expertise to apply them successfully.

Simpler approaches are needed which allow relatively unskilled operators to make reliable decisions without the need for a diagnosis specialist to examine data and diagnose problems. Therefore, there is a demand for techniques that can make decision on the running health of the machine automatically and reliably (Jardine et al., 2006).

Among the various methods for machinery condition monitoring are Artificial Neural Networks (Artificial Neural Networks). This method offers the advantage of automatic failure conditions detection and identification in machine and do not require in-depth system behavior knowledge (Jack and Nandi, 2002; Samanta, 2004).

The object of this paper is to create a practical ball and roller bearing fault detection system. This system based in two Multilayer Perceptron with Bayesian Automatic Relevance Neural Networks (MLP-ARD). The system is able to monitor the gearbox operating condition, to diagnose if there is a problem and to detect the bearing in which the problem occurs.

MATERIALS and METHOD

In this paper a prototype experimental setup was used. It was designed and constructed at the Department of Biosystems Engineering of the Technological Educational Institute of Thessaly (Figure 1). This experimental setup consists of a 6 speed mechanic gearbox (5 forward speeds and 1 reverse speed), a three phase AC motor, a hydraulic dynamometer for the gearbox loading and a complete vibration data acquisition system (Brüel & Kjær, Figure 2).

In order to collect the vibration data, which are used as input to the diagnostic system, two types of accelerometers (2 triaxial and 4 monoaxial) were placed at selected locations on the gearbox. Specifically, as shown in Figure 3 the triaxial accelerometers were placed on the gearbox at the front and the rear vertical axis and the monoaxial accelerometers were placed on the gearbox at the front and the rear horizontal axis.

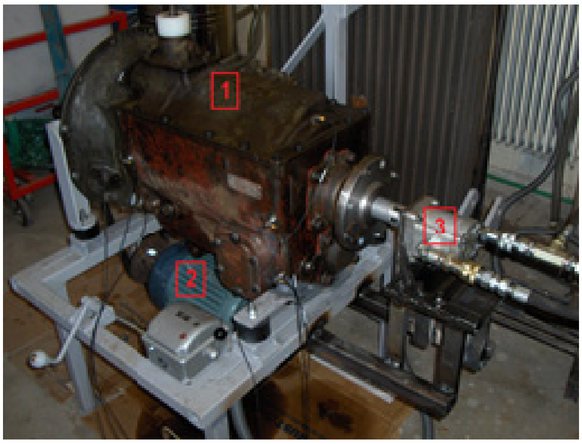

Figure 1. Experimental setup. (1-mechanical gearbox, 2-three phase AC motor, 3-hydraulic dynamometer)

Figure 2. Vibration data acquisition system

Figure 3. The points on which the accelerometers were placed

Three different loads were decided to apply at gearbox output axis (0Nm, 5Nm and 10Nm). The speed at gearbox input shaft was defined at 2700rpm. The health condition of the gearbox (vibration signature) was obtained in all forward speeds. The sampling frequency was 65536Hz and the recording duration was 10 seconds. Two different types of faults were simulated, in ball bearing with No. 1 and in roller bearing with No. 2) (Figure 4).

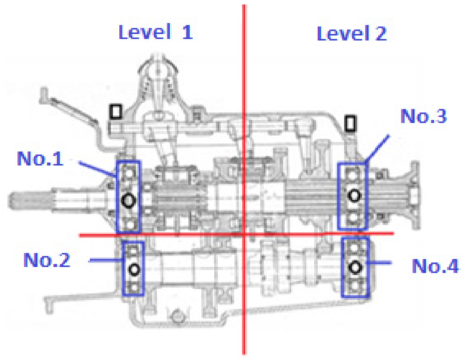

Figure 4. Gearbox intersection. (□ - triaxial accelerometer mounting locations, O - monoaxial accelerometer mounting locations)

All the bearing faults were based after extensive research in literatures. All the faults were artificial faults similar to the real faults (Figures 5 and 6).

Figure 5. Vertical grooving at No.1 ball bearing's inner ring (3mm width and 1mm depth)

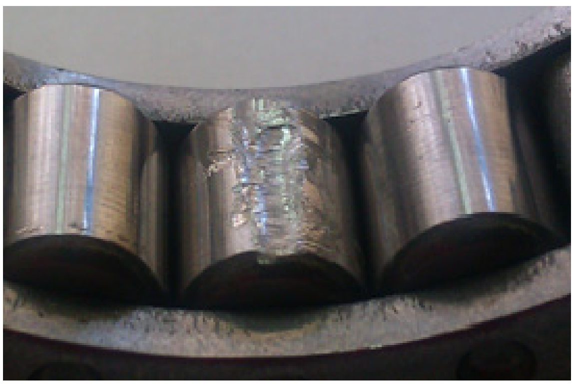

Figure 6. Extended wear on one of the bearing rollers (roler bearing No.2)

After fault bearing assembly at the gearbox, a new vibration signature was carried out in two circumstances (two bearing faults) in two different gearbox speeds (1st and 5th speed) and different loads (0, 5, 10Nm) at the output gearbox shaft.

The recorded vibration signals were used for feature extraction. These features are descriptive or high-order statistical data, which were extracted from the vibration signals in time and frequency domain. In total 26 features were selected. The first 14 in time-domain (Lei et al., 2008; Moshou et al., 2010) and the rest 12 in frequency-domain (Lei et al., 2008).

First, for the extraction of the 26 features the vibration signals were used from the triaxial accelerometers on. Then, the vibration signals from the other four monoaxial accelerometers were used. All these features provide statistical information for the nature of the vibration data and were found that they were quite good for fault detection in bearings. These features were extracted for all the cases and were input to the diagnostic system in order to be trained. The system was trained in all bearing condition circumstances (health condition and bearing faults) for load 10Nm at the output shaft of the gearbox.

The system was trained in all situations (healthy condition and bearing faults) and for 10Nm load at the output shaft. The diagnosis system was based on two Multilayer Perceptron with Bayesian Automatic Relevance (MLP-ARD) with a 10 neurons hidden layer each. The number of neurons at the input level was equal to the number of selected features.

The first set of features (these features were extracted only from the triaxial accelerometers data) was fed to the first neural network. After that, the training of the neural network can carry out fault diagnosis in whichever level (Level 1 or 2). The second set of features (these features were extracted only from the monoaxial accelerometers data) was fed to the second neural network. The training of the second neural network was used to recognize fault at the top or the bottom level of bearing (Figure 4).

The combination of results for both neural network running gives the exact defective bearing. The code of the two neural networks was written in Matlab and it was used for data feature extraction.

RESULTS and DISCUSSION

The tested scenarios included both neural networks running in four different case studies: 1st speed, Damage at bearing No. 1 and No. 2 and selection of 1st and 5th speed gearbox.

1st Scenario: Fault at bearing No. 2The results after both neural networks running are presented in Table 1

Table 1. Results 1st scenario running (Fault at bearing No.2)

1st speed at the gearbox (2700rpm input shaft -300rpm output shaft) Neural network training with 10NMm load at the output shaft					
Using triaxial accelerometers		1st level Bearing without fault	2nd level Bearing without fault	1st level Bearing with fault	2nd level Bearing with fault
Test with 0Nm load	(%)	0	0	100	0
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0
Using monoaxial accelerometers		(Level 1 or 2) **up** bearing **without** fault	(Level 1 or 2) **down** bearing **without** fault	(Level 1 or 2) **up** bearing **with** fault	(Level 1 or 2) **down** bearing **with** fault
Test with 0Nm load	(%)	0	0.61	0.08	99.31
Test with 5Nm load	(%)	0	0	0	100
Test with 10Nm load	(%)	0	0	0	100

5th speed at the gearbox (2700rpm input shaft -2700rpm output shaft) Neural network training with 10NMm load at the output shaft					
Using triaxial accelerometers		1st level Bearing without fault	2nd level Bearing without fault	1st level Bearing with fault	2nd level Bearing with fault
Test with 0Nm load	(%)	0	0	100	0
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0
Using monoaxial accelerometers		(Level 1 or 2) **up** bearing **without** fault	(Level 1 or 2) **down** bearing **without** fault	(Level 1 or 2) **up** bearing **with** fault	(Level 1 or 2) **down** bearing **with** fault
Test with 0Nm load	(%)	0	0,08	0	99.92
Test with 5Nm load	(%)	0	0	0	100
Test with 10Nm load	(%)	0	0	0	100

In particular, it is observed that the system is able to recognize 100% the level that the fault occurs (Level 1) both in 1st speed and in 5th speed. What is more, although the training was conducted in circumstances with 10Nm load at the output axis the system is able to recognize 100% the fault in different loads (0,5 and 10 Nm) at the output shaft of the gearbox (1st and 5th speed).

Then, the second neural network was run. This neural network detects the exact position of the defective rolling bearing. The accuracy is 99.31% for output shaft load 0Nm and 100% for the other two loads (5 and 10Nm) at 1st speed and 99.92% output shaft load 0Nm and 100% for the other two loads (5 and 10Nm) at 5th speed.

2nd Scenario: Fault at bearing No. 1

The results from the second scenario were presented in Table 2.

As in the previous case, in this case it is observed that the system is able to recognize in high percentage (100%) the level in which the fault occurs (Level 1). By running the second network performs the determination of the exact location of the defective bearing at the gearbox. The accuracy is 67.48% for output shaft load 0NM and 100% for the other two loads (5 and 10Nm) at 1st speed and 97.86% for output shaft load 0Nm and 100% for the other two loads (5 and 10Nm) at 5th speed.

CONCLUSIONS

It has been shown that the neural network MLP-ARD can provide reliable results using as inputs features in time domain and in frequency domain. These features were extracted from vibration signals. These features (according to their nature) can be used with success for fault diagnosis of rolling and roller bearings. The combination of the futures with the appropriate neural network gives a powerful tool for bearing condition monitoring and early fault diagnosis in mechanical gearboxes. Furthermore, the features can identify with sufficient precision the point in which the fault occurs.

The feature extraction from accelerometer signals (triaxial and monoaxial) at vertical and horizontal axis increases the accuracy of fault detection in persentage of 99% for different fault types and in different gearbox points. The system has a strong ability to be trained in a specific load at the output shaft.

In future work the diagnostic system effectiveness will be investigated with more data from different sensors, different type of faults in rolling bearings, gears, and shafts of the gearbox.

Table 2. Results 2ndt scenario running (Fault at bearing No.1)

1st speed at the gearbox (2700rpm input shaft -300rpm output shaft) Neural network training with 10NMm load at the output shaft					
Using triaxial accelerometers		1st level Bearing without fault	2nd level Bearing without fault	1st level Bearing with fault	2nd level Bearing with fault
Test with 0Nm load	(%)	0	0	100	0
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0
Using monoaxial accelerometers		(Level 1 or 2) **up** bearing **without** fault	(Level 1 or 2) **down** bearing **without** fault	(Level 1 or 2) **up** bearing **with** fault	(Level 1 or 2) **down** bearing **with** fault
Test with 0Nm load	(%)	0.15	0	67.48	32.37
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0

5th speed at the gearbox (2700rpm input shaft -2700rpm output shaft) Neural network training with 10NMm load at the output shaft					
Using triaxial accelerometers		1st level Bearing without fault	2nd level Bearing without fault	1st level Bearing with fault	2nd level Bearing with fault
Test with 0Nm load	(%)	0	0	100	0
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0
Using monoaxial accelerometers		(Level 1 or 2) **up** bearing **without** fault	(Level 1 or 2) **down** bearing **without** fault	(Level 1 or 2) **up** bearing **with** fault	(Level 1 or 2) **down** bearing **with** fault
Test with 0Nm load	(%)	0	0	97,86	2.14
Test with 5Nm load	(%)	0	0	100	0
Test with 10Nm load	(%)	0	0	100	0

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