Development of a Methodology for Prediction of Unbalance Using Vibration Analysis and Artificial Neural Networks

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Abstract. Nowadays the high competitive scenario, predictive techniques for diagnosing the mechanical failure increased. These techniques, when correctly applied, they can be the solution to increase equipment availability, decrease the number of assets in the warehouse and the cost with maintenance. In this context, this paper studies vibration analysis with Artificial Neural Network (ANN) to help diagnosing unbalance motor at low speed of rotation. Thus, it was used an electric motor connect into frequency inverter and an unbalanced rotor, in which it was possible to simulate different level of unbalance. The algorithm purposed is capable of identify four different levels of unbalance, that are: not exist (balanced), low, medium, and high. A Multilayer Perceptron (MLP), a type of ANN, with fitness function as sigmoid and radial basis, was used in this classification. Inputs were: only radial, and radial and axial simultaneously. ANN that had inputs radial and axial at the same time got better accuracy than ANN that had only radial data. At the literature, it is said that for the unbalance failure is used just radial data, however, training network with addition of token data from axial direction brought accuracy to in terms of classification.

Keywords: Artificial Neural Network. Multilayer Perceptron. Predictive Maintenance. Vibration Analysis. Severity in Unbalance Failure

1. INTRODUCTION

Over the last decade, there was a significant increase in industrial competitiveness and economic development, which led to a concern with the maintenance of equipment. Due to component repairs or replacement, unexpected production stoppages result in significant capital losses (Dias *et al.*, 2009). In order to minimize accidents and financial losses caused by failures, the need to monitor them was created. With the monitoring, it is possible to detect a defect in its initial phase, when there are no risks of stops, allowing the maintenance time to plan (Dias *et al.*, 2009). Among the mechanical defects, the unbalance defect is one of the most important due to its high recurrence. It comes from several causes: corrosion, cavitation, deposition of subject in the rotor, manufacturing defects, eccentricity, cracks, breaks, and many others. As a consequence, the predictive maintenance of unbalanced axes is increasing in maintenance management, since the identification of this defect prematurely avoids the irregular wear of other mechanical components.

Therefore the accompaniment of the mechanical vibration became one of the most considerable methods of prediction. Such methodology provides adequate periodicity for the monitoring of the defect and the monitoring of its severity. According to Silveira, Souza and Cavalcanti (2011), the use of this type of analysis can avoid the early replacement of mechanical components or unexpected stops of the equipment. Thus, the better planning and control of the maintenance, better will be the availability of the equipment and reduction in the costs of the maintenance.

The autonomous methods of detecting failures in rotary motors have been studied, using different classification algorithms, according to Silva (2014). Among these algorithms, Artificial Neural Networks (ANN) present as an excellent tool due to their ability to solve various typs of problems.

Considering the importance of the monitoring, detection and diagnosis systems of unbalance faults in low speed rotary axes and the increasing use of signal processing, this work describes the automatic classification of faults in a DC motor using ANN. In addition, concepts of mechanical vibration, signal processing, fault diagnosis, MLP type RNA with sigmoid and radial basis as activation function will be addressed, as well as the comparison of results between them.

2. METHODS

In this work, mechanical vibration will be analyzed as a path of identifying the need for maintenance. The system for monitoring mechanical failures allows the identification of faults in their initial state, provides more information on the type of failure and its severity, and helps in the decision making before an intervention; in short, automatic recognition prevents unexpected shutdown of equipment Silva (2014).

2.1 Vibration Analysis in Rotation of Rigid Bodies Around a Fixed Axle

Vibration is present in any system when it responds to an excitation, in which it can be expressed in terms of displacement, velocity and acceleration. Vibration measurement is a non-destructive method of monitoring the condition of the machine during the turning on, shutdown and normal operation of the machinery (Kardec and Nascif, 2013). The vibration signal contains a large amount of information about the machine, such as the presence of mechanical failures and even the state of deterioration of the component. Thus, according to the increase of the vibration level of a rotating machine in conjunction with the analysis of the frequency spectrum, it is possible to identify the cause of the emergence of the new dynamic forces. The vibration of the machine can be analyzed in the time domain and the frequency domain, as seen in Figure 1. In the time domain, the abscissa axis represents the time, whereas in the frequency domain, it is the frequency. In both, the ordinate axis represents the amplitude of the signal.
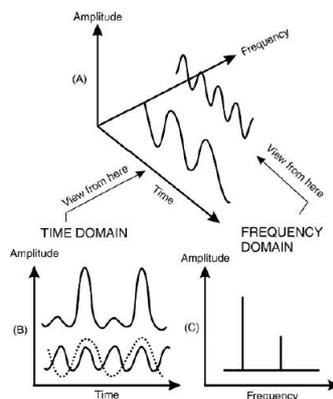

Figure 1. Fourier Transform
Available from:Scheffer and Girdhar (2004)

When analyzed the signal in the time domain, it is possible to identify, through trend lines, the emergence and the development of some fault. However, it is not possible to identify the type of failure. On the other hand, by analyzing the signal in the frequency domain, this also called the frequency spectrum, enables more detailed information on the machine state (Costa, 2015). The parameters used in the spectral analysis are amplitude and frequency. The first one indicates the seriousness of the problem, and the second can inform about the component or type of defect. Before the spectral analysis, it is necessary to acquire the vibration signal by an accelerometer. The signal obtained in the time domain will be transformed to the frequency domain through the Fast Fourier Transform (FFT). Then, the spectrum is analyzed and peaks can indicate the failure of a component, according to the harmonics, it is possible to identify the type of fault present in the equipment (Lopez, 2014). Unbalance is listed as one of the most common mechanical failures that cause undue vibration problems on rotary machines (Lopez, 2014). The unbalance in rotating rigid axle is defined as the non-concordance between the center of mass and the center of rotation. The distance between the unbalanced mass and the center of rotation is called eccentricity. The product of unbalanced mass and its eccentricity is what we call unbalance (IME, 2006).

2.2 Artificial Neural Network

Artificial Neural Networks (ANN) were developed from the influence of natural neural networks, according to Mc Culloch and Pitts (1943) and Cowanand Sharp (1988) (apund varoto2008). Neurocomputation began with the development of neurons as a unit that processed logical operations, contributing to the creation of the first digital computers Finocchio (2014). ANNs are one of the main tools used in Machine Learning Dormehl (2017). Thus, it is possible to perform learning experiments, made from a learning algorithm, by means of modified and ordered synaptic weights in order to achieve the desired result (Matsunaga, 2012). For the network to be able to learn or generalize a content, there is the training sample. This sample consists of information organized in pairs - input / output - forming a database, in order to respond adequately when a new input, not present in the training sample, is presented to the network.

The artificial neuron model is based on the biological neuron model, in which the artificial one has several inputs and makes synaptic connections with other neurons, and finally, the output is the weighted sum of all the outputs. This model is shown in Figure 2, and it can identify the inputs (x), the syntactic process (w), the bias (favoring or not the activation of the neuron), then the function of activation, and then the output. The activation function may be, for example, threshold type, linear or signoid (Matsunaga, 2012).
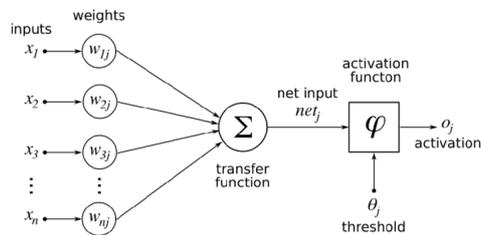

Figure 2. Artificial Neuron Model
Available from:Matsunaga (2012)

In 1986, the learning algorithm backpropagation was developed, through which it was possible to train networks with hidden layers resulting in Multi-layer Perceptron (MLP). In this paper will be used this type of ANN with activation function Sigmoid and Radial base.

2.3 Data Acquisition System

To collect the required data was used the system described below:

- Two vibration sensors of the Piezoelectric type (located at: Axial and Radial);

- Signal Chassis and Chassis, in charge of converting the analog signals to digital;

- Computer with the signal acquisition software (LabView);

Figure 3 shows the connections of the experiment. For each measurement two vibration signals (radial and axial) are acquired. The NI 9234 module is connected to the NI cDAQ 9135 chassis, and then attached to the notebook via the USB cable. The notebook has LabView 2015 software, which allows the recording and compilation of signals.
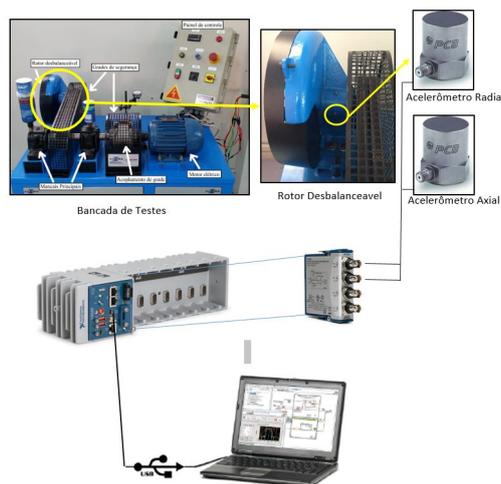

Figure 3. Recording Process Connection Diagram

3. RESULTS

The experiments were grouped as follows:

1. MLP type RNA with sigmoid type activation function to classify the system in: balanced, low unbalance, medium unbalance, and high unbalance, with only radial input;

2. MLP type RNA with sigmoid activation function to classify the system in: balanced, low unbalance, medium unbalance, and high unbalance, with radial and axial input;

3. MLP type RNA with radial base type activation function to classify the system in: balanced, low unbalance, medium unbalance, and high unbalance, with only radial input;

4. MLP type RNA with radial base type activation function to classify the system in: balanced, low unbalance, medium unbalance, and high unbalance, with radial and axial input;

The data collection were created using 27 nuts and 4 screws, generating 33 different cases of unbalance. In addition, the ANN needs to classify the data into 4 classes (balanced, low, medium and high unbalance). The experiments were performed using MATLAB Pattern Recognition and Classification (nprtool). The architecture used is feedforward type and has only one hidden layer. The hidden layer is formed by 10 neurons, with activation function sigmoid or radial base type. Finally, the output layer is formed by 4 neurons, since there are 4 classes to be classified, the function in the output layer is Softmax.

The experiment 1, with the parameters and architecture set, the network was trained 30 times obtaining CE (zero means no errors) average of 6.65 and standard deviation of 0.85; the percentage error (percentage of the examples that were erroneously classified) was 5.73 % and standard deviation 1.03. Finally, the accuracy of the network was 94.26 % with a standard deviation of 0.08. The experiment 2, EC was obtained with a mean of 5.68, with a standard deviation of 1.20; % E of 5.68 with standard deviation of 0.92; finally, the accuracy of 94.61 % and standard deviation of 0.2. The experiment 3 was obtaining a percentage of error (% E) of 5.83 %, with standard deviation of 0.0873; and accuracy of 94.15%, with a standard deviation of 0.0937. The experiment 4, the mean E% of 5.42 % was obtained with standard deviation of 0.165, and accuracy of 94.59%, standard deviation of 0.166.

4. DISCUSSION

The MLP algorithm was able to satisfactorily classify the unbalance defects in four levels of criticality. Analyzing the ROC curve of all experiments, classes 3 and 4 were the ones that presented the worse classification. In class 4 (balanced), the difficulty was caused by the smaller amount of samples in relation to the other classes. Although in class 3, the problem is related to a highest dispersion of the data, also resulting in a bigger number of false positives. With the results of experiments 2 and 4, it was verified that the addition of the axial data in the input sample caused an improvement in the performance of the algorithm, diverging from the current bibliography, in which only the radial data were considered for this type of mechanical defect. Thus, it can be concluded that RNA is able to identify characteristics in the training pair (input-output), which helps to better classify the new inputs. By comparing the results between experiments 1 and 3, and experiments 2 and 4, it was observed that the functions of sigmoid and radial base activation showed a very similar accuracy and average error percentage.

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