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VIBRATION-BASED CONDITION MONITORING OF INDUCTION MOTORS USING ARTIFICIAL NEURAL NETWORKS

Aline Elly Treml
Rogério Andrade Flauzino
University of Sao Paulo, USP
alinetreml@usp.br, raflauzino@usp.br

Geraldo Carvalho Brito
Western Paraná State Universisty, UNIOESTE
geraldo.brito@unioeste.br

Abstract. *Induction motors are very used in electromechanical energy conversion equipment, as they are robust and reliable machines. One of the main techniques for identifying incipient faults in these rotary machines is vibration-based condition monitoring. This paper consists of the development of a computational tool dedicated to a diagnostic system for broken rotor bars in Three Phase Induction Motors. Artificial Neural Networks for multi-class classification and detection were configured to receive indices derived from the processing of mechanical signals and then identify normal motors and faulty motors. Besides that, the fault severity is also diagnosed, which represented by the number of broken rotor bars. Experimental data were tested in order to evaluate the proposed method. Signals were obtained from induction motors operating with different torque levels. The results demonstrate the effectiveness of the computational tools developed the diagnostic system since the indices correlated with fault phenomenon.*

Keywords: *Fault Diagnosis, Induction Motors, Vibration-Based Condition Monitoring, Artificial Neural Networks*

1. INTRODUCTION

The industrial sector is the one that demands the most energy in the world. Electric motors are responsible for the consumption of up to 80% of the total energy required in all industrial sections, which may vary accordingly to each country. In Brazil, electric motors are responsible for half of the industrial consumption of electricity (Hasanazzaman et al., 2011). In addition, electric motors are also widely used in renewable energy systems; specifically represent the largest portion of electric vehicle traction engines that corresponds to a sector in full expansion (Carunaiselvane and Chelliah, 2017). Thus, obtaining a robust monitoring system would have a positive impact on the reliability and efficiency in a system in which the electric motor is applied.

Vibration-based condition monitoring (VCM) plays a major role in detecting defects and developing flaws before the equipment fails and potentially damages other related equipment and to avoid unwanted breakdowns and downtimes. Vibration analysis can help increase the lifetime of the equipment when the faults are diagnosed at the right time. This is because, according to Randall (2011), the vibratory pattern of healthy machine changes with the advent of damage, so the alteration analysis allows the detection and diagnosis of the damage.

In this paper the analysis is focused on detecting rotor broken bar fault, using vibration-based condition monitoring. For this purpose, an experimental test rig was used to test induction motors containing specifics faults. Motor vibrations signals were analyzed and treated with the tools of computational intelligence to identify an anomaly and its severity through torque modulation, thus contributing to actions of orientation in predictive maintenance.

2. VIBRATION-BASED CONDITION MONITORING

The method of detection and diagnosis of defects in the time domain can be implemented to verify abnormal changes in the characteristics of the machine. The great advantage is the simplicity of implementation, however, has little sensitivity (Rao, 2011). To overcome this difficulty, complementary techniques of selected attributes and computational intelligence will be used.

Satisfactory results have already been obtained by Zarei (2012) who proposed the use of time domain features to detect bearing faults in induction motors. The pattern recognition algorithms based on neural networks. This method proved to be simple, accurate, reliable and economical. In this paper, a similar methodology was applied, but for broken rotor bars in three-phase induction motors.

The first vibration descriptor that can be used to assess the condition of rotation machines is Root Mean Square (RMS). The RMS value of vibration signals is usually credited as a direct indicator of the damage extension in a machine operating at steady-state condition (ISO 2041, 1975).

The peak value is the value of the largest amplitude present in the signal. When its value increases it is an indication that impacts began to appear on the equipment. The crest factor, according to Scheffer and Girdhar (2004), is an important parameter used to monitor the operating condition of a machine, and this is defined as the ratio between the peak value and the RMS value.

Kurtosis is also descriptor and corresponds to statistical parameters based on probability theory and statistic, obtained from vibration signals measured in rotating machines, used to detect and diagnostic local faults (Amarnath and Praveen Krishna, 2014). Kurtosis is the normalized fourth statistical moment of the signal; its level is used to provide a measure of the impulsive nature of the signal, i.e. the signal changes from a regular continuous pattern. The kurtosis of any univariate normal distribution is 3, for a DC signal is 0, for a square wave is 1 and pure sine wave has a kurtosis equal to 1.5. Distribution with kurtosis less than expected pattern means to be platykurtic, i.e. it has a probability distribution lower and with fewer outliers than a normal distribution with the same standard deviation. Distribution with kurtosis greater than expected pattern means to be leptokurtic, i.e. it has tails that asymptotically approach zero more slowly than a Gaussian distribution and it produces more outliers than the normal distribution.

3. ARTIFICIAL NEURAL NETWORK

Computational intelligence is a science that seeks, thought the application of techniques inspired by nature, the development of an intelligent system that imitates aspects of human behavior. The Artificial Neural Network (ANN) corresponds to a computational technique inspired by biological neurons. For the detection and diagnosis of defects, the ANN is very employed, since, from the training with historical data, they make possible the prediction of the defect in equipment by pattern recognition. Therefore, the use of intelligent systems is as important as the steps that precede it, which are the steps of acquisition and processing of signals.

The ANN represents information-processing systems formed by interconnecting simple-processing units called neurons. The most widespread artificial neuron model was proposed by McCulloch and Pitts in 1943. Each neuron is shown in Fig.1 is an independent processing unit that transforms its input data $\{x_1\ x_2\ _{...}\ x_n\}$ via activation function *g(.)*. The connections between neurons are characterized by weights values $\{w_1\ w_2\ _{...}\ w_n\}$ that represent the memory of the network. By modifying these weights according to learning rule, the ANN can be trained to recognize any pattern giving the training data (Silva, Spatti and Flauzino, 2016).

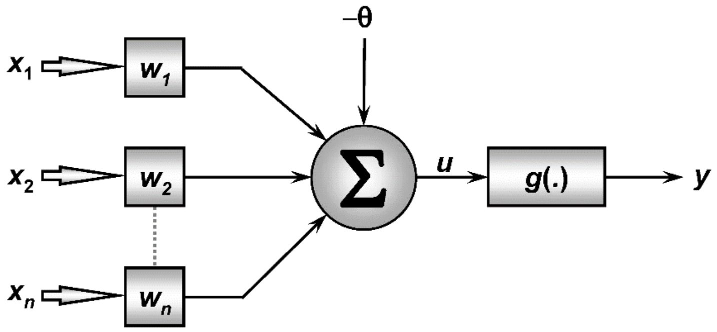


Figure 1. Artificial neuron. Available from: Silva, Spatti and Flauzino (2016)

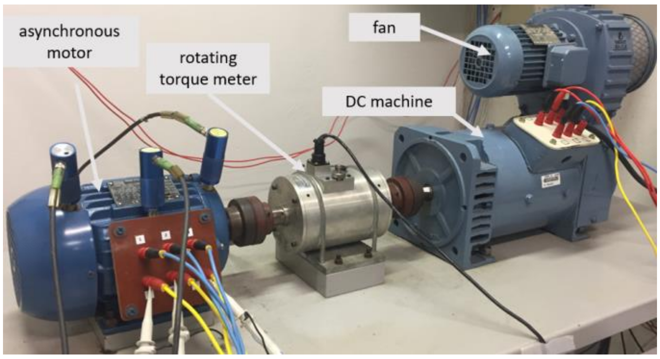
The network architecture, i.e. the arrangement of processing units, plays a very important role in the performance of ANN and usually depends on the problem at hand. Several types of ANN have been proposed in the literature for diagnosis purposes, the most popular one is the multilayer perceptron.

After defining the architecture, it is necessary to specify the number of hidden layers, the number of neurons in each layer and the type of activation function θ of the artificial neuron, defining the network topology. Next, it is necessary to perform the training phase of the network by a learning algorithm, which consists of a set of ordered steps to adjust the synaptic weights and thresholds of activation of the neurons, in order to generalize the solutions produced by the outputs without losing the representativeness of the physical system. In this way, it can be affirmed that knowledge was acquired from experience (Silva, Spatti and Flauzino, 2016).

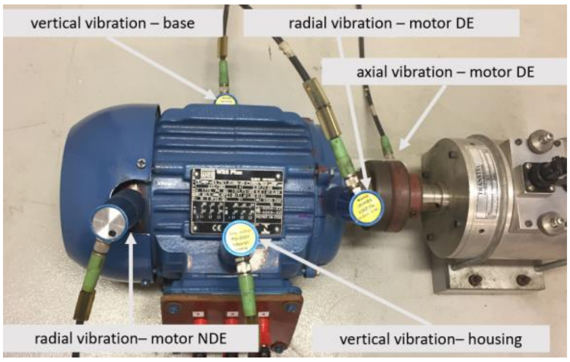
In this paper, the architecture used was multilayer perceptron, sigmoid activation function, with supervised feedforward network training. The computational tool chosen to be used in this research was the Waikato Environment for Knowledge Analysis (WEKA) version 3.8.3, because it’s a free software, developed in Java language, which has established itself as one of the main tools of data mining, performing the task of clustering, association, selection of attributes and, the main objective, in this case, classification (Lausch, Schimidt and Tischendorf, 2015).

4. EXPERIMENTAL TEST RIG

The experimental set up consists of an induction motor coupled to a DC machine, which works as a generator simulating the load, connected by a shaft to a rotating torque meter, as shown in Fig. 2(a). The induction motor has the following specifications: 1 hp, 220/380V, 4 poles, 60 Hz, 4 Nm and the nominal speed of 1715 rpm. DC machine has a nominal capacity of 2 kW, field rated voltage of 190 V, and armature rated voltage of 250 V, using an external fan for forced ventilation. Its drive is made by a field coil supply circuit, which aims to vary the field voltage in favor of changing the torque imposed to the shaft. Finally, the rotating torque meter used in the research has a sensitivity of 2 mV/V and it is limited to 2000 rpm.



(a)



(b)

Figure 2. (a)Experimental set up (b) Vibration monitoring points

Five accelerometers were used to measure vibration signals. Signals were electronically integrated giving a sensitivity of 10mV/mm/s, in the frequency range of 5 to 2000Hz. Accelerometers were fixed using ethyl cyanoacrylate adhesive, allowing vibration measurements in both drive end (DE) and non-drive end (NDE) sides of the motor, axially or radially, in the horizontal or vertical directions. The baffle cap that protects the motor ventilation system was adapted to enable accelerometers assembly, as shown in Fig. 2(b). All signals were sampled at the same time for 18 seconds, but in this paper, only 10s of steady state was used. After that, all signals were processed using Matlab®.

Four different rotors were used in the experimental setup. One rotor was undamaged while the other four rotors were drilled to simulate one, two, three, and four broken bars. Rotor drilling was performed by means of a bench drill, mounted with a 6mm diameter drill bit, to ensure that the hole diameter extrapolated the width of the rotor bar, with the tip centered at half the longitudinal length of the rotor. Broken bars were adjacent to each other, simulating the usual situation in damaged rotors. It shall be noted that the process to simulate broken bars, besides of this fault, also produces a mechanical unbalance in the rotor, which is maximum in the case of four adjacent bars.

5. RESULTS AND DISCUSSION

The success in the detection and diagnosis of defects depends on the monitoring condition and the methodology used for the extraction and processing of the characteristics. Fig. 3 show a generic structure of an intelligent system capable of identifying broken bar defects in electric induction motors.

The first step corresponds to the acquisition of data, which was described in item 4. Next, it is necessary to pre-process these signals. In order to do so, the signal processing techniques are used, which were described in item 2. Finally, Artificial Networks are used, as described in item 3 to aid in decision making, with the answers to the detection and diagnosis of the defect.

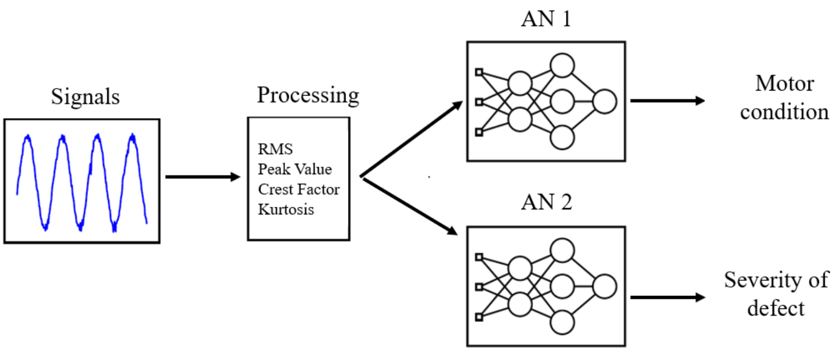


Figure 3. Intelligent system for detect and diagnose broken rotor bar in asynchronous motors.

An induction motor was tested first with a healthy rotor under 12.5, 25, 37.5, 50, 62.5, 75, 87.5 and 100% of full load. The same induction motor that was tested with one, two, three, and four broken rotor bars under the same loading conditions. In every case, ten consecutive measurements were taken to reduce the average noise level.

In Table 1 some of the results obtained by means of the radial velocity transducer of the non-driven side operating in the condition of maximum loading, that is, with a nominal torque of 4.0 N.m. As each assay was repeated ten times, the results are presented in terms of the mean along with the direct measurement uncertainty of type A given by the ratio of the standard deviation to the square root of the number of replicates.

Table 1. Experimental results for vibration analysis in time domain.

Motor Condition	RMS [mm/s]	Peak Value [mm/s]	Crest Factor	Kurtosis
Healthy Rotor	9.928 ± 0.081	17.277±0.133	1.740 ± 0.007	1.564± 0.004
Rotor with 1 Broken Rotor Bar	10.327 ± 0.084	17.239±0.251	1.669 ± 0.013	1.589 ± 0.003
Rotor with 2 Broken Rotor Bar	12.956 ± 0.306	20.565±0.639	1.587 ± 0.016	1.547 ± 0.007
Rotor with 3 Broken Rotor Bar	10.740 ± 0.042	18.607±0.123	1.732 ± 0.013	1.595± 0.006
Rotor with 4 Broken Rotor Bar	13.224 ± 0.076	22.332±0.165	1.689 ± 0.015	1.564 ± 0.004

The RMS value of the vibration signals is usually used as a direct indicator of the extent of the defect in permanent operating equipment (ISO 2041, 1975). Table 1 confirms this statement, despite an anomalous behavior. At this point, it should be noted that in addition to the broken bars, the simulated defects also produce mechanical imbalances due to the removal of material from the rotor. In addition, different rotors were used in each severity condition, with residual imbalance or misalignment of the intrinsic axis. This same behavior is seen, in the other parameters of the waveform, they are: the peak value and crest factor.

Figure 4 shows the vibration signal of the motor in two different conditions, the condition without defect illustrated by the blue signal and the red signal in the presence of the most severe defect. High modulation in the vibration signal is evident with the defect condition. And in both cases, the vibration signal has a sinusoidal characteristic. Therefore, as expected, Table 1 indicates that the kurtosis of the vibration is close to the kurtosis of a sinusoidal signal, that is, 1.5, regardless of the severity of the defect.

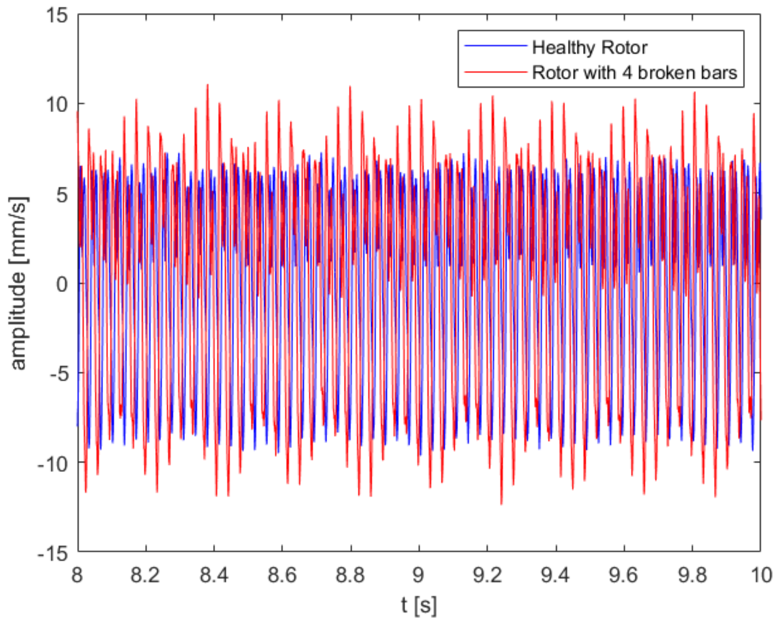


Figure 4. Vibration signal in time domain under higher load.

In order to increase the amount of data available for the analysis and to explore the potential of the methodology, the sliding windowing was used as the artifice, as shown in Fig 5. Thus, the permanent regime of the mechanical vibration signal of 12 s was divided into windows of 4 s, with an overlap of 50%, totaling 5 windows. Thus, with repeated trials 10 times, and each repetition subdivided into 5 windows, totals 50 samples for each engine condition in each loading condition.

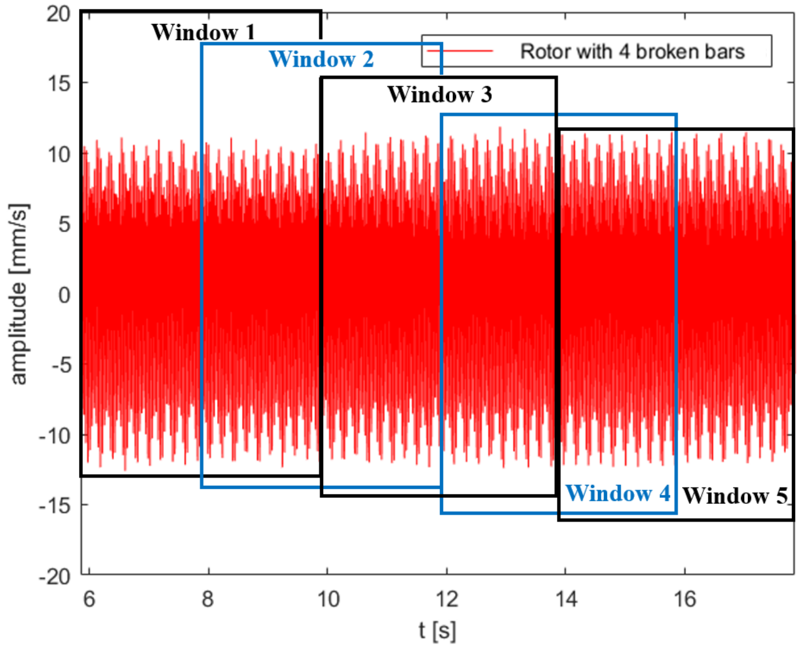


Figure 5. Slip windowing for vibration signal.

The time-slotted and pre-processed data were used as input to a broken bar fault detection system composed of a multi-layered Perceptron neural network with standard WEKA software configuration for the purpose of defining the effective descriptors in identifying the defect. This default configuration consists of 1000 processing times, a learning rate of 0.3, a momentum of 0.2, and a hidden neural layer with the number of neurons equal to the mean given by the number of inputs and the number of classes (WITTEN; FRANK; HALL, 2011).

The system performance was obtained through cross-validation stratified with 10 partitions, performed with 10% of the input data, and with an early stop of 5, which indicates that the validation set error can worsen up to 5 times in a row before the training is terminated, thus avoiding overfitting problems. Tiered validation ensures that each partition maintains the correct proportion of data for each class. In addition, repetitions in different combinations of data improve the results on the repeated evaluation, by reducing the variance of the evaluation.

Different classifiers were made to identify the condition of the motor, without fault or fault, one for each parameter processed in the time domain, in order to make the training more compact and allow the comparison of the same. In addition, these classifiers were tested with an unused database for training and validation. It is noteworthy that in this step all the resistive loads of the axis were used.

Thus, the input data matrix for AN 1 training and validation has 750 rows (3 rotor conditions x 5 vibration transducers x 5 windows x 10 repetitions) and 9 columns (8 torque conditions + 1 class). The data matrix for testing has 500 rows (2 rotor conditions x 5 vibration transducers x 5 windows x 10 repetitions) by 9 columns, idem training data matrix, and validation.

In addition, it can be seen from Table 2 that the statistical parameter kurtosis was the only one able to generalize the network with a high hit rate, that is, it allowed the identification of rotors with three broken bars belonging to a non-standard database. used in intelligent system training and validation.

Table 2. System to detect broken rotor bar in time domain.

Descriptor	Train Data	Percentage Classification Accuracy (%)	Test Data	Percentage Classification Accuracy (%)
RMS	HR (5), R2B (2) and R4B (4)	96.67	R1B (1)	58
			R3B (3)	40
Peak Value		94.53	R1B (1)	60
			R3B (3)	40
Crest Factor		96.93	R1B (1)	73.6
			R3B (3)	92
Kurtosis		100	R1B (1)	78
			R3B (3)	100

(1) one broken rotor bars, (2) two broken rotor bars, (3) three broken rotor bars, (4) four broken rotor bar, (5)healthy rotor.

Then, in order to diagnose the defect by identifying its severity, which is a superior hierarchical level and subsequent to the detection, see Figure 1, a diagnostic system composed also by a neural network PMC, with configuration analogous to AN 1 used for the detection, whose adopted terminology was AN 2.

Learning algorithm training and validation were performed using the preprocessed data of all defective rotors, as it is required by the representativeness of each of the four severity classes of the damage. Thus, the separation of the data, necessary to make the tests feasible, was done according to the windowing, and the first three data windows were used to carry out the training and the fifth window used to carry out the tests, as indicated in the header of Tab.2. Thus, window 4 was not used, so as not to characterize data overlap.

Table 2. System to diagnosis broken rotor bar in time domain.

Descriptor	Train Data (windows 1,2,3)	Percentage Classification Accuracy (%)	Test Data (window 5)	Percentage Classification Accuracy (%)
RMS	HR (5), R1B (1), R2B(2), R3B (3) and R4B (4)	90.67	R1B (1)	80
			R2B (2)	100
			R3B (3)	100
			R4B (4)	80
Peak Value		87.17	R1B (1)	90
			R2B (2)	100
			R3B (3)	100
			R4B (4)	80
Crest Factor		93.17	R1B (1)	96
			R2B (2)	100
			R3B (3)	98
			R4B (4)	100
Kurtosis		97.00	R1B (1)	94
			R2B (2)	100
			R3B (3)	98
			R4B (4)	100

(1) one broken rotor bars, (2) two broken rotor bars, (3) three broken rotor bars, (4) four broken rotor bar, (5) healthy rotor.

By means of the results presented in Tab.2, all analyzed parameters obtained from the mechanical vibration signal are able to determine the severity of the defects. Thus, they allow both the detection and the diagnosis of broken bars in induction motors.

6. CONCLUSION

This paper presents a method of diagnosing broken rotor bar based on temporal analysis of vibration and intelligent systems. Experimental results prove the efficacy of the method, because in several resisting torque conditions, including low magnitudes that make it difficult to detect the fault, the motors were classified with high accuracy.

This method demonstrates the application of signal processing with neural network in a problem of great relevance. The method overcomes difficulties of spectral resolution and sampling time, for example, that exists in other techniques in the frequency domain and time-frequency domain.

7. ACKNOWLEDGEMENTS

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