International Journal of Engineering Research And Management (IJERM)
ISSN : 2349- 2058, Volume-03, Issue-01, January 2016

Fault Detection System in Induction Motor Using Artificial Neural Network (ANN) Embedded into FPGA Processor

Cesar da Costa, Christian Oliveira Santin

***Abstract*— Electric induction motors have been used since the second industrial revolution in the nineteenth century to the present time in the model "automatic industrial production." This demand for more modern and efficient engines makes searching for predictive maintenance more important in industrial settings. Failures in motors are due to a wide range of possible defects such as unbalanced rotor misalignment between devices, deformations on an equipment frame, lubrication failures, bearing failures, short-circuit between turns, phase imbalance, and broken-bar rotor fault. This paper proposes an automatic detection of broken-bar and bearing faults in induction motors. The study was conducted using motor current signature analysis based on the fast Fourier transform, and failure detection was processed by an artificial neural network (ANN) method embedded into an FPGA processor.**

***Index Terms*— Diagnostic, Digital signal processing, Rotating electrical machine.**

I. INTRODUCTION

The monitoring, fault detection, and automatic diagnosis of induction motors are becoming major challenges in the field of electrical machinery maintenance. Various methods ranging from new signal processing techniques currently available to new analytical methods for the analysis of induction motor stator current are used. Machine monitoring plays a crucial role in the detection of incipient faults, and thus, the maintenance process is now a critical factor in the industrial environment. Therefore, an optimum combination of techniques and procedures and the implementation of new tools for analysis and diagnosis of equipment faults with new technologies must be constantly reviewed.

Special attention has been devoted to non-invasive methods that are capable of detecting faults using measured signals without disassembling a machine and its structural parts [1] – [6]. Motor current analysis can be considered as one of the most promising methods for fault detection in induction motors with capacity to detect several types of faults in an induction rotary machine.

This method is based on the spectral analysis of a current signal in the steady state of a stator in a frequency domain. The spectral analysis of the stator current using the fast Fourier transform (FFT) is applied for the diagnosis of the rupture of a rotor bar. According to Ref. [2], when a three-phase induction motor with squirrel-cage rotor bars breaks or cracks in the rotor termination ring, disturbances are caused in the magnetic flux generated by changing the rotor power spectrum.

Often, the visual inspection of frequency domain features (spectral analysis) of current signals is adequate to identify faults. However, this method is time consuming and costly because it requires a specialist technician to make the visual analysis of a current spectrum. There is a need for a reliable, fast, and automated procedure of fault diagnostic of electric induction motors in automatic industrial production. Artificial neural networks (ANNs) have potential applications in automated detection and diagnosis of machine conditions and show high accuracy for fault detection in induction motors [7] – [10].

The motor fault detection problem can be solved using an ANN method approach based on easy accessible measurements, without the need for expensive equipment or accurate mathematical models that are required from conventional fault detection techniques.

Among several neural network methods proposed in the literature, one can distinguish between supervised and unsupervised ones. Supervised methods require previous learning before they actually perform fault detection. A training problem can be overcome with continual online training [10]. Heurist training can also be considered. Unsupervised methods [8], [9] do not require previous training but usually involve previously computed FFT. These methods usually decide whether there is a fault by clustering techniques.

In the last decade, many studies reported successful applications of neural networks implemented on a computer in the diagnosis of induction motor faults [8]-[10]. The present study proposes the use of neural networks for automatic fault diagnosis in induction motors and the implementation of an embedded FPGA processor based on neural networks.

This paper is organized as follows. Section II gives a brief description of rotating machine faults. Section III presents the artificial neural network method. Section IV presents materials and methods. Finally, section V presents the conclusion.

Manuscript received Jan 16, 2016

Cesar da Costa, Electrotechnical Engineering, IFSP – Federal Institute, São Paulo, Brasil

Christian Oliveira Santin, IFSP - Federal Institute, Sao Paulo, Brasil ,01109-010

II. ROTATING MACHINE FAULTS

A rotating machine is considered as a robust and fault-tolerant machine. An induction motor is a rotating electric machine that is designed to operate from a three-phase source of alternating voltage. It is important to perform current measurement and real-time continuous monitoring of machine variables to diagnose the state of a machine before it enters into a fault mode.

The reasons behind failures in rotating electrical machines have their origin in assembly, installation, nature of load, and maintenance schedule. Similar to other rotating electrical machines, induction motors are subjected to both electromagnetic and mechanical forces. The design of a motor is such that interactions between these forces under normal conditions lead to stable operation with minimum noise and vibration. When a fault occurs, the equilibrium between these forces is lost, leading to further enhancement of the fault. Induction motor faults can be categorized into two types: mechanical and electrical [1], [2]

A. Rotor Broken Bar Failures

Spectral analysis refers to the representation of current signals in the frequency domain. The Fourier transform (FT) defines that a periodic waveform in the time domain can be represented by a weighted sum of sines and cosines. The same waveform can then be represented in the frequency domain as an amplitude–phase pair for each frequency component.

Spectral analysis of stator current using the FFT is applied to the diagnosis of rotor broken-bar fault. According to [5], in a three-phase induction motor with a squirrel-cage rotor, the rotor broken bars or crack in the rotor ring termination bars disturb the magnetic flux and the rotor frequency, thus, altering the motor current spectrum.

Several works such as [1], [2], and [3] have used FFT for spectral analysis of stator current to diagnose rotor broken bars. From these works, internal faults of rotor broken bars may be detected in the stator current spectrum. On the whole, owing to the rotor asymmetry, the following frequencies appear in the spectra of different signals: $(1 \pm 2ks)f_0$ in the stator current and instantaneous power signals, $(2k-1)sf_0$ in the rotor current signal, $2ksf_0$ in the velocity and torque signals, and ksf_0 in the axial flux signal, where $k = 1, 2, 3...$

Rotor broken-bar failures can be diagnosed by determining the sidebands of twice the slip frequency ($2sf_0$) on the fundamental supply frequency of the motor (f_0) from the stator current spectrum [2].

B. Rolling Bearing Failures

The common faults of rolling bearings include corrosion in inner race, outer race and rolling elements, fatigue pitting, and cage damage. Any faults of inner race, outer race, and rolling elements will cause modulation phenomenon. If there is a fault in either inner or outer race or rolling elements, mechanical impulse with higher amplitude will be incurred while shaft rotating. This impulse will motivate the natural frequency of the inner race, the outer race, and the rolling elements [4], [5].

For a particular bearing geometry, inner race, outer race, and rolling element faults generate vibration spectra with unique frequency components. These frequencies, known as the defect frequencies, are functions of the running speed of the motor and the pitch diameter to ball diameter ratio of the bearing. Outer and inner race frequencies are also linear functions of the number of balls in the bearing. Given the geometry of the bearing in Figure 1, for an angular contact ball bearing in which the inner race rotates and the outer race is stationary, the four characteristic frequencies is presented in Table I. The outer race is fixed; f_i is the rotation frequency of shaft in hertz; D is the pitch diameter; d is the ball diameter; α is the contact angle; Z is the number of balls. The contact between the balls and the inner and outer race is assumed to be a pure rolling contact [8], [10].

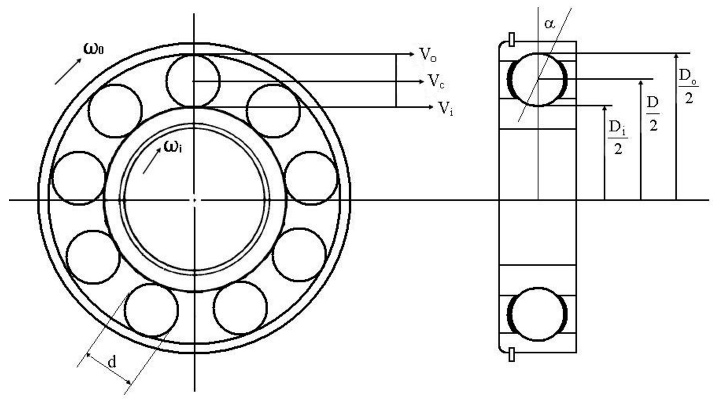

Fig.1. Ball bearing geometry

Table I. Characteristic fault frequencies

Fault frequency of inner race	$f_{bi} = f_i \times \frac{Z}{2}(1 + \frac{d}{D}\cos\alpha)$
Fault frequency of outer race	$f_{bo} = f_i \times \frac{Z}{2}(1 - \frac{d}{D}\cos\alpha)$
Fault frequency of rolling elements	$f_{bs} = f_i \times \frac{D}{2d}(1 - (\frac{d}{D})^2 \cos^2\alpha)$
Fault frequency of cage	$f_c = f_i \times \frac{1}{2}(1 - \frac{d}{D}\cos\alpha)$

III. NEURAL NETWORK

Neural networks are computer models that emulate the structure and functioning of the human brain. ANNs are inspired by biological nervous systems and consist of simple processing elements (artificial neurons) that are interconnected by weighted connections. The predominantly used structure is a multilayered feed-forward network (multilayer perceptron). The nodes (neurons) are arranged in several layers. The information flow is only between adjacent layers [8], [9], and [12]. An artificial neuron is a very simple processing unit. It calculates the weighted sum of its inputs and passes it through a nonlinear transfer function to produce its output signal. The predominantly used transfer functions are so-called "sigmoid" or "squashing" functions, which compress an infinite input range to a finite output range [8], [9]. Through a simple set of processing elements (acting as neurons), connected in parallel for high processing power, they are able to recognize and classify patterns.

A. ANN Method Development

The proposed ANN method for failure detection in induction motors is presented in block diagram in Figure 2. The first step is acquiring data, that is, motor parameters, which may be relevant in the search for information on the motor status. Herein, in particular, stator current will be measured using a current sensor. After measuring the data, the current signal is pre-processed by means of the FFT, and the signal frequency spectrum is obtained to show frequencies of broken-bar fault and bearing fault. Their magnitudes will be extracted with a developed software program. The third step, called Neural Processor, refers to the use of ANN method, implemented in an FPGA that provides the induction motor condition automatically, in real time, without requiring a visual inspection of the frequency domain features (spectral analysis) by a specialist technician for diagnosis and decision.

The structure of a proposed ANN for detection of faults in induction motors is shown in Figure 3. It implements an MLP (Multilayer Perceptron) with two input nodes that receive the information motor condition values (Broken-bar fault and rolling bearing fault), six nodes in the hidden layer, and two output nodes for detection of faults, according to Table II.

Table II. Output of the proposed neural processor (ANN)

Broken-Bar Fault	Bearing Fault	Output 1	Output 2	Condition Motor
0	0	0	0	Healthy
0	1	0	1	Bearing fault
1	0	1	0	Broken-bar fault
1	1	1	1	Broken-bar and Bearing fault

The nodes at the hidden and outputs layers have a "*log–sigmoid*" activation function defined by (1), where α is the sum of the inputs to the nodes [10]. The ANN was trained offline by the back propagation algorithm. The selection of an MLP with back propagation training offers an easy hardware implementation for the proposed ANN.

$$LS(\alpha) = \frac{1}{1+e^{-\alpha}} \, . \tag{1}$$

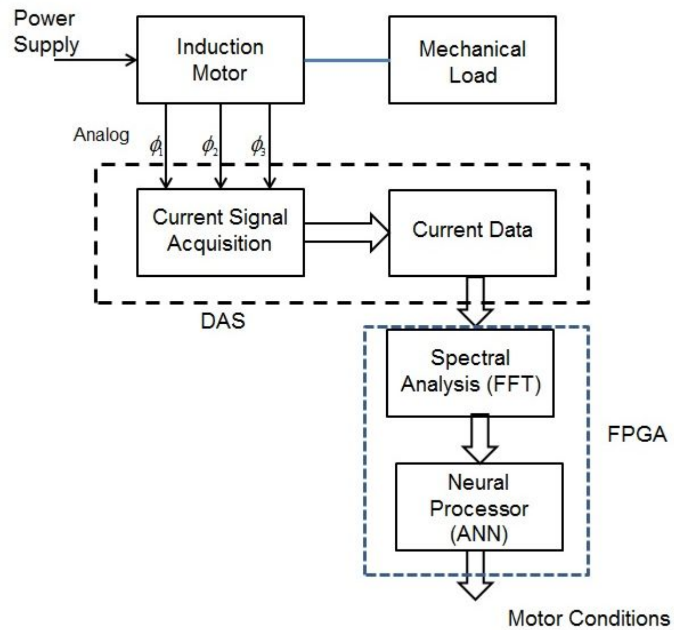

Fig. 2. Block diagram of the proposed ANN.

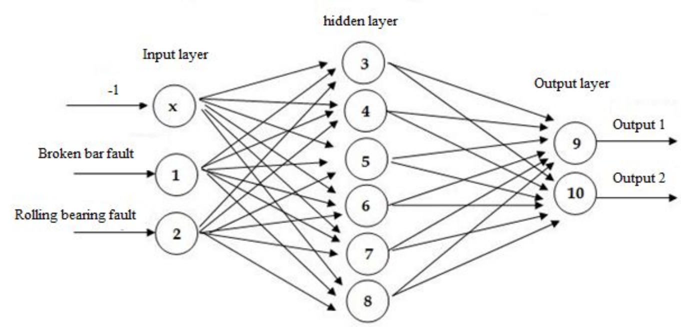

Fig. 3. Structure of a three-layer feedforward neural network.

B. Embedded ANN into FPGA

Embedding a processor inside an FPGA has many advantages. Specific peripherals can be chosen based on the application, with unique user-designed peripherals being easily attached. A variety of memory controllers enhance the FPGA embedded processor system interface capabilities. FPGA embedded processors use general-purpose FPGA logic to construct internal memory, processor busses, internal peripherals, and external peripheral controllers (including external memory controllers). Soft processors are built from general-purpose FPGA logic as well [11], [12], and [13].

The implementation of FFT and ANN algorithms in FPGA is usually done in two steps: in the first step the algorithm is developed and simulated in a development environment such as MATLAB/SIMULINK. Once the development phase and the simulation of the algorithm are completed according to the initial specifications, the second phase begins, which consists in converting the algorithm into a hardware description language (VHDL) and its implementation on FPGA. The complete design flow using MATLAB/SIMULINK and DSP BUILDER/QUARTUS II software is shown in Figure 4.

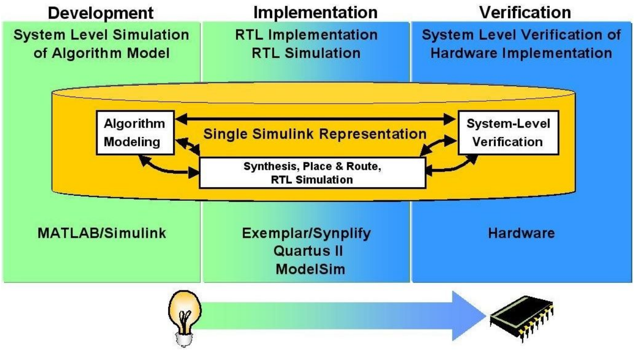

Fig. 4. Development phases of a project with FPGA.

The hardware platform used to incorporate the FFT and ANN method was the Cyclone II EP2C35F672C6 FPGA from ALTERA, in the kit DE2. This board was chosen because it was the less expensive one available that could hold the implementation [12, 13]. The FPGA implementation of the proposed ANN processor in an Altera Cyclone device (Kit DE II) is shown in Figure 5, where a broken-bar defect condition is displayed. The liquid crystal display (LCD) is used as an interface to display the motor condition to the user.

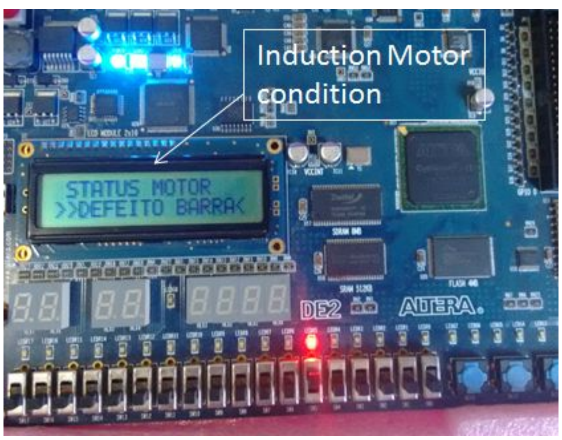

Fig. 5. Interface to show the motor condition to the user.

IV. MATERIALS AND METHODS

A. Simulation of Failures

For validating the feature extraction method that uses motor current signature analysis (MCSA), several tests were performed with: a 4-pole, 3-phase, 60 Hz, 1.5 kW, 220/380 V (rated voltage), 1750 rpm (rated speed), and 28-rotor-bar induction motor. The load was a 2 kW DC machine with a rated speed of 1800 rpm. For the simulation of the broken bars and rolling bearing failures, holes were inserted manually with a 3 mm drill, as shown in Figure 6.

B. Data Acquisition

The first stage of the work consisted of the acquisition of the stator current signal to create a database of faults. The motor operates under steady normal conditions without faults. Several tests under different loads for healthy rotors and faulty rotors, with broken bars and faulty rolling bearings were performed in steady state. The sample rate used was 1024 samples, acquisition time of 1 second, and a sampling frequency of 1024 Hz.

Fig. 6. Simulation of failures: broken bars (a); bearing inner and outer race (b).

C. Processing and Analysis with MCSA Method

Several tests with different loads with rotors without fault and with broken rotor bars were made. In each case, the stator current signal obtained was subjected to a digital processing by means of the FFT to obtain the current frequency spectrum. A developed computer routine, running in MATLAB software transforms data stream in time domain into frequency domain and performs an analysis of the motor current by the method called MCSA. The system calculates the current spectrum, the frequency of broken-bar and rolling bearing faults, and their amplitudes. The spectrum of stator current is shown in Figure 7 for healthy motor; Figure 8 for one broken bar; and Figure 9 for two broken bars.

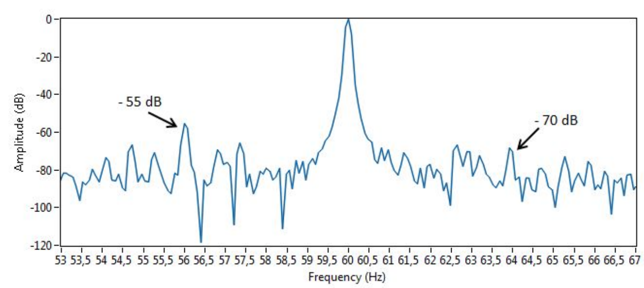

Fig. 7. Current spectrum of motor healthy.

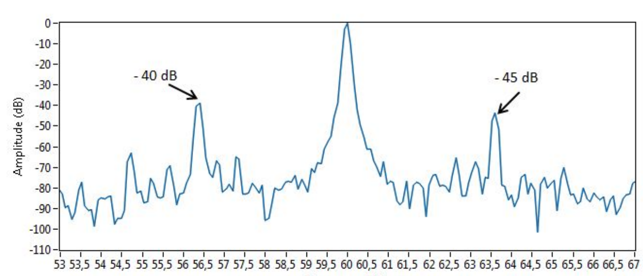

Fig. 8. Current spectrum of motor with one broken bar.

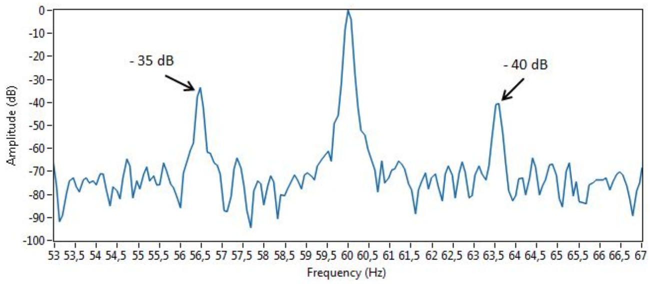

Fig. 9. Current spectrum of motor with two broken bars.

D. Experimental Results with ANN Method

The proposed Neural processor (ANN) embedded into FPGA was developed and trained through a backpropagation algorithm for identifying a healthy induction motor or the presence of other faults. Figure 10 shows the FPGA processor test bench used in the training (offline) tests.

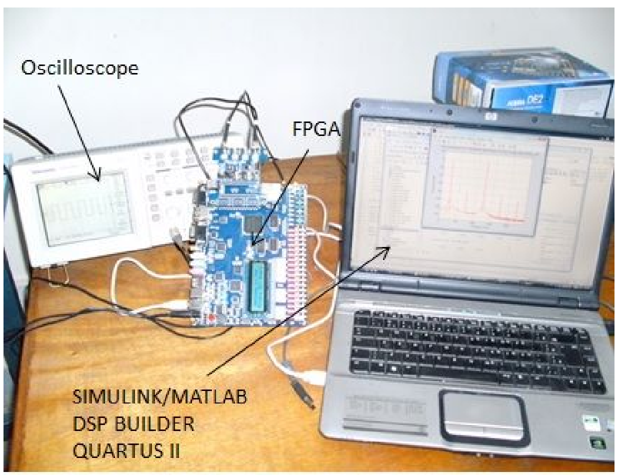

Fig. 10. Experimental set up: FPGA processor

To verify the efficiency of the ANN system, several tests were performed. These tests were performed under different loads and motor conditions: healthy rotor, one broken bar and two broken bars, and rolling bearing failure in inner race and outer race. Table III presents the results reached by the proposed ANN method during the induction motor condition tests. This table shows high efficiency of the ANN method for detection of faults in induction motors.

Table III. Efficiency of the proposed ANN method.

Induction motor Condition	Efficiency (%)
Healthy	100
1 broken bar	80
2 broken bars	100
Bearing fault inner race	90
Bearing fault outer race	90

V. CONCLUSION

In this paper, an online condition-monitoring device based on ANN method was developed and tested. The target controller based on an FPGA processor is capable of measuring non-invasive sensor signals and is capable of identifying and analyzing them for extraction of rotor problems in induction motors. A significant characteristic of the proposed ANN method is the identification of faults in an automatic mode; different from the cited literature where the results have to be interpreted by the user from the current spectrum. The ANN method based FPGA processor is able to detect faults as rotor broken bars, bearing faults in inner and outer race by utilizing real current signals from the induction motor.

REFERENCES

[1] C. Kral, A.Haumer, C. Grabner, Modeling and simulation of broken bars in squirrel cage induction machines, Proceedings of the World Congress on Engineering 2009, Vol. I, pp. 435-440, 2014, 2009.
[2] C. Da Costa, C. , M. Kashiwagi, M. H. Mathias, "Rotor failure detection of induction motors by wavelet transform and Fourier transform in non-stationary condition", Case Studies in Mechanical Systems and Signal Processing, Vol. 1, pp.15-26, Jul. 2015.
[3] C. Da Costa, M. H. Mathias, P. Ramos, P. Girão, A new approach for real time fault detection in induction motors based on vibration measurement. Instrumentation and Measurements Technology Conference (I2MTC), 2010 IEEE, Austin (2010), 1164 – 1168.
[4] G. Georgoulas, I. P. Tsoumas, J. A. A. Daviu, V. C. Alarcon, " Automatic pattern identification based on the complex empirical mode decomposition of the startup current for detection of rotor asymmetries in asynchronous machines", Industrial Electronics, IEEE Transactions on, Vol. 61, No 9, pp. 4937-4946, 2014.
[5] S. Pu, C. Zheng, V. Yuriy, Z. Zoubir, "A new detection of broken rotor bar fault extent in three phase squirrel cage induction motor," Mechanical Systems and Signal Processing, Vol. 42, pp. 388–403, 2013.
[6] M. Y. Kaikaa, M. Hadjami, "Effects of the simultaneous of static eccentricity and broken rotor bars on the stator current of induction machine", Industrial Electronics, IEEE Transactions on, Vol. 61, No 5, pp. 2452-2463, 2014.
[7] A. Sadoughi, M. Ebrahimi, M. Moalem and S. Sadri," Intelligent diagnosis of broken bars in induction motors based on new features in vibration spectrum". Diagnostic for Electric Machines, Power Electronics and Drives, IEEE International Symposium, pp. 106-111, Sept. 2007.
[8] L. Eren, A. Karahoca, M. J. Devaney, "Neural network based motor bearing fault detection", In Proc. Instrumentation and Measurement Technology Conference (I2MTC), Vol.3, pp. 1657-1660, May. 2004.
[9] S. Guedidi, S. E. Zouzou, W. Laala, M. Sahraoui, K. Yahia, "Broken bar fault diagnosis of induction motors using MCSA and neural network," in Diagnostics for Electric Machines. Power Electronics & Drives (SDEMPED), 2011 IEEE International Symposium on, pp. 632-637, 2011.
[10] B. Samanta, K. R. Al-Balushi, "Artificial neural network based fault diagnostic of rolling element bearings using time-domain features", Mechanical System and Signal Processing, Vol. 17 (2), pp. 317–328, 2003.
[11] C. Da Costa, M. Kashiwagi, M. H. Mathias, Digital systems design based on DSP algorithms in FPGA for fault identification in rotary machines, Journal of Mechanical and Industry Research, Vol. 2, Issue 2, pp. 1-5, 2014.
[12] E. Cabal-Yepez, M. Valtierra-Rodriguez, R. J. Romero- Troncoso, A. Garcia-Perez, R.A. Osornio-Rios, H. Miranda-Vidales, R. Alvarez-Salas, . "FPGA based entropy neural processor for on-line detection of multiple combined faults on induction motors". Mechanical Systems and Signal Processing, Vol.30, pp. 123-130, 2012
[13] A. Ordaz-Moreno, R. Romero-Troncoso, J. A. Vite-frías, J. RivieraGillen, and A. Garcia-Pérez, "Automatic online diagnostic algorithm for broken-bar detection on induction motors based on discrete wavelet transform for FPGA implementation," *IEEE Trans. Ind. Electron.*, vol. 55, no. 5, pp. 2193–2200, May 2008.

Cesar da Costa was born in Rio de Janeiro, Brasil.
He received the B.Sc. degree in electronic and electrical engineering from the CEFET-RJ, Federal Center of Technological Education Celso Suckow da Fonseca and Nuno Lisboa University in 1975 and 1980, respectively. He received the M.S. degree in mechanical engineering from Taubate University, São Paulo, Brazil and the Ph.D. degree in Mechanical engineering from UNESP-Universidade Estadual Paulista Júlio de Mesquita Filho, Guaratinguetá, SP, Brazil in 2005 and 2011, respectively. He did Sandwich doctoral stage, PDEE - CAPES, in the IST - Instituto Superior Técnico, Lisbon, Portugal, in 2009. He is currently post doctorate and professor of automation and control engineering in the IFSP-Federal Institute of Education, SP, Brazil. His research interests include Fuzzy controller, Artificial Neural Network, machine monitoring, diagnostic, electrical machines and FPGA.

Christian O. Santin was born in São Paulo, SP, Brasil.
He received the B.Sc. degree in Electrical Systems Technology from the IFSP – Federal Institute of São Paulo, SP, Brazil in 2014. He is currently student of electronic Engineering. His research interests include Artificial Neural Network, microprocessor, machine monitoring, and FPGA.