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# Neural Network technique for induction motor rotor faults classification –Dynamic eccentricity and broken bar faults-

S. Hamdani, O. Touhami, R. Ibtouen and M. Fadel

**Abstract -- This paper presents an artificial neural network (ANN) based technique to identify rotor faults in a three-phase induction motor. The main types of faults considered are broken bar and dynamic eccentricity. The feature extraction based on the frequency and the magnitude of the related fault components in the stator current spectrum is performed automatically by a Matlab script. Features with different speed and load levels are used as input for training a feedforward layered neural network. The laboratory results show that the proposed method is able to detect the faulty conditions with high accuracy and to separate between deferent types of faults.**

**Index Terms-- induction motor, neural network, rotor fault, current spectrum, classification.**

## I. INTRODUCTION

Among electrical machines, induction motors are the most widely used in industry because of their rugged configuration, low cost, and versatility. With their great contributions, induction motors are called the “workhorse of industry”. Because of natural aging processes and other factors related to their operating conditions in industrial applications, induction motors are subject to various faults, such as rotor faults. These faults can be induced by electrical failures such as a bar defect or bar breakage or mechanical failures such as rotor eccentricity. The first fault occurs from thermal stresses, hot spots, or fatigue stresses during transient operations such as start-up, especially in large motors. A broken bar changes torque significantly and became dangerous to the safety and consistent operation of electric machines [1].

The second type of rotor fault is related to air gap eccentricity. This fault is a common effect related to a range of mechanical problems in induction motors such as load unbalance or shaft misalignment. Long-term load unbalance can damage the bearings and the bearing housing and influence air gap symmetry. Shaft misalignment means horizontal, vertical or radial misalignment between a shaft

and its coupled load. With shaft misalignment, the rotor will be displaced from its normal position because of a constant radial force. Depending on whether the minimum air gap is spatially fixed or not, air gap eccentricity is described as being either static or dynamic. For static eccentricity, the rotor shifts from its normal position at the centre of the stator and rotates around its own centre. For dynamic eccentricity, the rotor shifts from its normal position, but still rotates around the centre of the stator. Air gap eccentricity may result from the assembly and manufacturing processes. For example, static eccentricity is caused by manufacturing tolerances between the centre of the stator bore and bearing centres. Dynamic eccentricity in a new motor is controlled by the total indicated reading (TIR) of the rotor [2, 3, 4].

The research in detecting rotor faults began in the 20th century. Existing detection schemes are classified by the type of monitoring parameters. Examples of monitoring parameters include stator current, torque, flux and vibration signal. The stator current is a very convenient medium because of the ease of its measurement. It can be monitored very easily without interfering with the machine, simply by fitting a clip-on current transformer around the supply cable to the motor. By analysing the frequency spectrum of the stator current input to the motor, a considerable amount of information can be gained on the motor condition. This method is well known in the literature as the motor current signature analysis (MCSA) and it has been developed from about thirty years [5]. Though the MCSA is known and a lot of papers using this technique have been published, the problem of automatic faults classification is still open.

The use of Artificial Neural Network (ANN) for induction motor fault diagnosis was first proposed by Chow and Y. [6-8]. They have used ANN for external faults identification on induction motors. Simulation results of induction motors have been used as neural network inputs for faults classification in the work of Filippetti [9, 10]. Using a mathematical formula, they obtain also the number of broken bars in the motor. ANNs with unsupervised learning were used in [11] where the load torque variation was examined. The features extraction was achieved by time-frequency analysis of the stator current. Wavelet technique is used for bar defect, bearing and eccentricity fault detection task and neural network for identification and classification task in [12, 13]. It is noticed that neural networks are often used for faults classification phase and the features extraction can be achieved with different techniques where the stator current is often used.

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In this paper, two rotor faults, namely: broken bars and dynamic eccentricity will be identified using a feedforward network. The features extraction is performed by choosing the most significant component in the stator current spectrum. Through experimental tests where the machines operate under different load levels and for different velocities, a database will be built and used for neural network training and test validation.

## II. MOTOR CURRENT SIGNAL ANALYSIS TECHNIQUE

Among existing methods in induction motor condition monitoring, motor current signal analysis (MCSA) is the most commonly used technique [14]. The advantages of this scheme include low cost and easy operation. In most applications, the stator current of an induction motor is readily available to protect machines against destructive over-currents, ground currents, etc. Therefore, an MCSA scheme can be implemented at no additional cost. For this reason, MCSA is often referred to as sensorless condition monitoring. This technique is based on the monitoring of stator current spectra. The appearance of new harmonics or increase in magnitude of some other at specific frequencies indicates a fault in the machine. So, the signal given by current sensors must be correctly analysed in both healthy and faulty conditions.

Monitoring of stator current can be used to indicate motor defects such as cracked rotor bars, cracked rotor end rings, bent shaft, coupling problems, interturn shorts and airgap eccentricity. Broken bars cause special harmonics in the power spectrum of the stator current at the frequency given by  $(1 \pm 2.k.g).f_s$ , when the dynamic eccentricity can be detected by monitoring components with frequency  $(f_s \pm f_r)$ , where  $f_s$  is the supply frequency,  $g$  is the slip,  $f_r$  is the rotor mechanical frequency and  $k$  is an integer.

## III. NEURAL NETWORK CLASSIFIER

Artificial Neural Networks (ANN) represent information processing systems formed by interconnecting simple processing units called neurons. Each neuron is an independent processing unit that transforms its input via a function called activation function. The connections between neurons are characterized by weight values that represent the memory of the network. By modifying these weights according to some learning rule, the ANN can be trained to recognize any pattern given the training data [15].

The network architecture or topology, plays a very important role in the performance of the ANN, and usually depends on the problem at hand. Several types of neural network structures have been proposed in literature [16-18] for diagnosis purpose, the most popular one is the Multilayer Perceptron (MLP) which is used in our study. This network with a simple architecture may be used for both modelling and classification tasks. The layers are fully interconnected in one direction, from the input layer toward the output layer. The number of neurons in the input and output layers are governed by the number of inputs and outputs of the pattern

to be recognized. However, the number of neurons in the middle layer can be selected depending upon the application [19]. Input patterns are exposed to the network whose output is compared to the target values to calculate the error, which is corrected in the next pass by adjusting the synaptic weights. Several training algorithms have been designed; the most commonly used being the Levenberg–Marquardt (LM) backpropagation algorithm, which is a natural extension of LMS algorithms for linear systems.

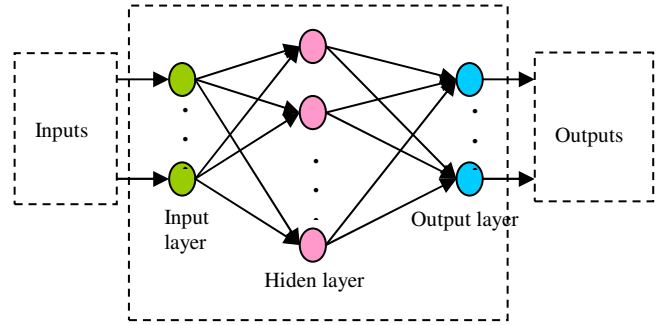


Fig. 1. Multilayer feedforward neural network architecture

## IV. PROPOSED FAULT DIAGNOSIS SYSTEM

The proposed system is based on three steps that include data acquisition, features extraction and data base creation and fault classification. In the data acquisition stage, the analog signal of the stator current from current transducer is measured and transmitted to the data acquisition board where the signal is low-pass filtered to eliminate harmonics with frequency above the Nyquist frequency and then digitized by an A/D converter. The signal is then fed to the pre-processing unit where it is transformed to time-frequency domain using the power spectrum of the stator current. Matlab script is developed for detection and identification of the frequency and the magnitude of the special harmonics related to the faults. Once, these features are extracted, a data base is created and used for training the neural network classifier.

### A. Data acquisition

In order to use ANN for identifying induction motor fault and no fault conditions, it is necessary to select the proper inputs and outputs of the network and the structure of this network. For this purpose, two experimental setups are used. The first one is located at LRE laboratory of ENP School in Algiers and the second one is in LAPLACE laboratory of ENSEEIHT in Toulouse.

The first experimental setup is illustrated by Fig. 2. It consists of three induction motors of 4kW. The first one is healthy, the second and the third one have one and two broken bars respectively. The machines can be supplied by the main or by an industrial inverter. The current is measured using LA-55P Hall-effect current sensor and simultaneously sampled through channels of 16 bits, 200 kHz PCI data acquisition (DAQ) board and directly stored into a desktop



computer [20]. Using this setup, the three motors were tested for six load levels (from 10 to 80%) and three power supply frequencies (50, 40 and 25 Hz), giving a total of 102 tests.

The second experimental setup is represented in Fig. 3. Two industrial induction motors of 5.5 kW are available. The first one is healthy and the second one is with 40% dynamic airgap eccentricity. The machine under test is supplied by a standard industrial inverter operating in open loop condition. Measured signals include the three line currents, the three stator voltages and the shaft speed. The current is measured by a tachymeter generator. These signals are acquired through a data acquisition board at 25.6 kHz with 24 bit resolution. The board has 8 channels with a separate AD-converter. Anti-aliasing filters are also included.

To elaborate the second database, the two motors were tested for three load levels 10, 50 and 80%. Therefore, 30 additional tests were performed and a general database of 132 elements was created.

**B. Features extraction and database creation**

The main problems facing the use of ANN are the selection of the best inputs and the choice of ANN parameters making the structure compact, and creating highly accurate networks. The choice of potential features is found to have a significant impact on the performance of the network. The selection of the most important components reduces the input dimensions of a network and minimizes the time spent in training. In our study the features extraction is accomplished using a Matlab script which calculates the power spectrum of the stator current, detect the power supply frequency (frequency of the fundamental component), calculates the slip and the RMS value of the current and detect the magnitude and the frequency of the specific components, as indicated by fig.4. At the end of this calculation, this script forms the input vector which contains the following data:

- fundamental frequency  $f_s$ ;
- slip;
- RMS of the stator current;
- The frequency and the magnitude of the left sideband component  $(1-2g)f_s$  ;
- The frequency and the magnitude of the right sideband component  $(1+2g)f_s$  ;
- The frequency and the magnitude the component  $(f_s+f_r)$ ;
- The frequency and the magnitude the component  $(f_s-f_r)$ .

The Supply frequency, the RMS stator current and the slip are the data that gives information on the operating conditions of the induction machine, whereas the other data represent the fault signature. The RMS value of the stator current can be calculated using the following expression:

$$X_{rms} = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \quad (1)$$

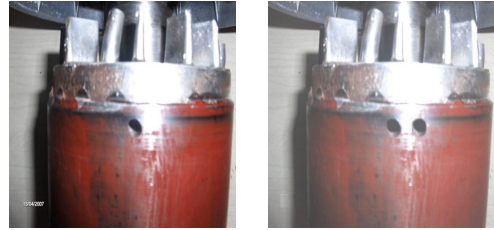


Fig. 2. ENP experimental setup

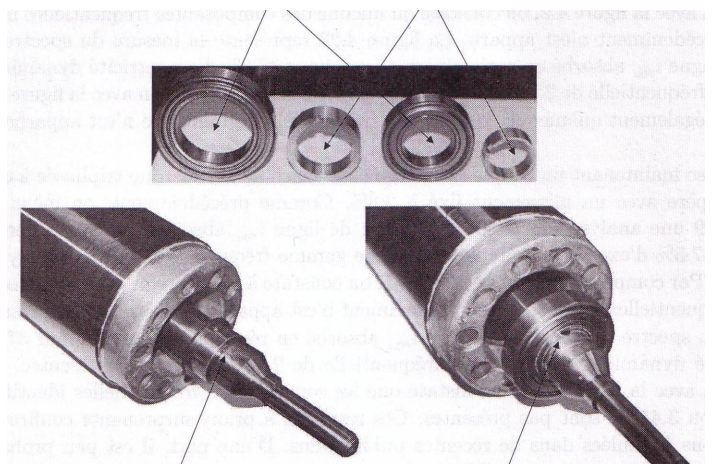


Fig.3. LAPLACE experimental setup

As it was indicated in the second section, the frequency of the specific components is function of the rotor slip of the machine. Thus, automatic calculation of this parameter is necessary to check the presence of these components and perform the diagnosis operation in good conditions. The slip of an induction machine is given by:

$$g = 1 - \frac{p \cdot f_r}{f_s} \quad (2)$$

where  $p$  is the pair poles number. Using the above equation involves the calculation of  $f_s$  and  $f_r$ . To determine the supply frequency, the stator current spectrum is performed and the frequency of the larger component is located as shown by Fig.5. Once the frequency  $f_s$  is known, the rotor frequency can be written in terms of  $f_s$  as follow:

$$f_r = \frac{(1-g) \cdot f_s}{p} \quad (3)$$

Therefore, to calculate  $f_r$  it is necessary to know in advance the slip. To solve this problem, we detect first the component with frequency  $(f_s+f_r)$  as shown by fig. 6. To search this component, two values of the slip are introduced:  $g_{\min}$  and  $g_{\max}$  and two approximate values of  $f_r$  are then calculated as follow:

$$\begin{cases} f_{r \max} = \frac{(1-g_{\min}) \cdot f_s}{p} \\ f_{r \min} = \frac{(1-g_{\max}) \cdot f_s}{p} \end{cases} \quad (4)$$

with these values, it will be possible to define a frequency range in which the component  $(f_s+f_r)$  is evaluated. Thus, knowing  $f_s$  and  $f_r$  it will be easy to calculate the slip  $g$ .

### C. Data normalization

An important feature of the neural network is its capacity of generalization: given several different input vectors, all belonging to the same class, the network will learn to key off of significant similarities in the input vectors, on the contrary the irrelevant data will be ignored. Therefore the neural network will be applied to every induction machine, or at least to a size range of induction machines. To this aim the inputs must be correctly normalized. In this study, the inputs to the neural network are normalized between  $[-1,+1]$  using the equation:

$$y = \frac{(y_{\max} - y_{\min})(x - x_{\min})}{(x_{\max} - x_{\min}) + y_{\min}} \quad (5)$$

where  $y_{\max} = 1$ ,  $y_{\min} = -1$ ,  $x_{\min}$  and  $x_{\max}$  are the minimum and maximum value of the inputs respectively.

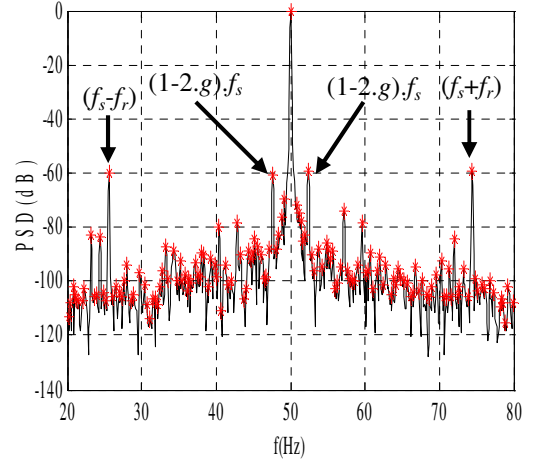


Fig. 4. Features extraction

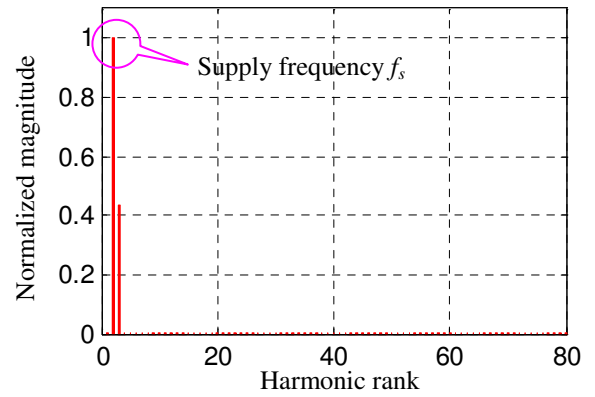


Fig. 5. Stator current spectrum

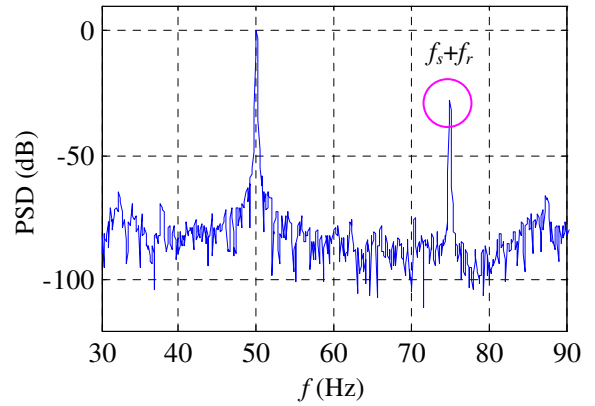


Fig. 6. Extraction of  $f_s+f_r$  component

### D. Machine codification

The artificial neural network output indicates the status of the studied machines. Each machine is assigned by a codification that distinguishes it from the others. Regarding the type of classification, machine codification is performed as follow:

- Separation between two classes: the neural network separates between a healthy and a faulty machine

without specifying the nature of the fault. Therefore, the output layer of the neural network has two neurones and the target vector is defined by [1 0] for the healthy machine and [0 1] for the faulty one.

- Separation between three classes: the output layer of ANN has three neurones and the classification is performed between a healthy machine, a machine with a bar breakage and a machine with dynamic eccentricity. So, the target is [1 0 0], [0 1 0] or [0 0 1] regarding the three machines respectively.

## V. RESULTS AND DISCUSSION

In this study, a multilayer feedforward backpropagation network with four layers is used for faults classification. This network has eleven neurons in the input layer corresponding to the number of the inputs and two or three neurones in the output layer (depending in the type of classification). In order to evaluate the impact of the network structure on the performance of motor fault classification, different architectures have been tested by changing the number of neurons in the hidden layer. Using two-thirds of the data base and 500 epochs, the learning phase was performed by the Levenberg Marquardt algorithm. The learning rate was fixed at 0.005. The initial values of the weights and offsets were randomly assigned. During the training phase, the weights were adjusted repeatedly until the calculated outputs converged sufficiently to the close target and the performance reached. Once, the training phase completed, the network is tested with the remaining data (the third). A sample is considered classified if the deference between the network output and the target does not exceed 30%.

Results for the first type of classification are presented in table 1 which indicates the structure of the neural network, the performance reached by the network, the classification accuracy and the classification error. The classification accuracy is defined as the ratio between the number of the classified samples and the number of the total tested samples. It is noticed that the accuracy of motor fault classification depends on the neural network architecture, ranging from 86% to 92%. In addition of this, the increase of neurons in the hidden layer does not improve the network performance. The later depends essentially on the size of training data. Best result is obtained with the structure [11x13x11x2] which gives 92.11% of classification accuracy.

The best results obtained for the second type of classification are presented in table 2. Here, the non classification ratio is introduced. This ratio is defined as the rate between the non classified samples and the total samples used for the test. A sample is not classified if the values of the neural network output are not significant to assign this sample to a specified class as the output. For example, the output [0.34683071, 0.05941535, 0.0007094] for the class [0,1,0].

The structure [11x23x17x3] gives the best performances comparing to the structure [11x15x17x3] and the classification errors are 7.89% and 13.16% respectively. Table 3 gives detailed results for the best structure. In this

table, 38 samples are tested. Among 7 samples for healthy machines, five are well classified and two are classified as machines with bar fault. The number of rotor bar fault samples is 21, only one is classified as healthy. Concerning the dynamic eccentricity fault, all samples are well classified.

TABLE I  
PERFORMANCES OF BEST STRUCTURES FOR THE FIRST CLASSIFICATION TYPE

architecture	Performance	Accuracy (%)	Classification error (%)
11x13x11x2	$3.75 \times 10^{-6}$	92.11	7.89
11x10x10x2	$9.64 \times 10^{-6}$	89.47	10.53
11x11x13x2	$8.70 \times 10^{-6}$	89.47	10.53
11x13x13x2	$9.39 \times 10^{-6}$	86.84	13.16

TABLE II  
PERFORMANCES OF BEST STRUCTURES FOR THE SECOND CLASSIFICATION TYPE

architecture	Performance	Accuracy (%)	Classification error (%)	no-classification rate (%)
11x23x17x3	$9.79 \times 10^{-6}$	86.84	7.89	5.26
11x15x17x3	$9.04 \times 10^{-6}$	84.21	13.16	2.63

TABLE III  
PERFORMANCES OF THE ARCHITECTURE [11x23x17x3]

Machine state	Healthy	Bar fault	Dynamic eccentricity
Healthy	5	2	0
Bar fault	1	20	0
Dynamic eccentricity	0	0	10

## VI. CONCLUSION

In the present work, a multilayer feedforward neural network has been proposed for the identification of rotor faults such as bar breakage and dynamic eccentricity on a three-phase induction motor. The paper describes the methodology and presents the different parameters used as inputs for neural network training. Some of these parameters give information on the operating conditions while others stand for the fault signature. The performance of different neural network architectures was compared. The accuracy rate depends on the ANN structure. Furthermore, the increase of neurons did not necessary improve the performance. To increase the accuracy of fault classification, the training set should have a larger data set with higher number of fault cases.

## VII. REFERENCES

- [1] A. H. Bonnett 'Root Cause AC Motor Failure Analysis with a Focus on Shaft Failures' IEEE transactions on industry applications, vol. 36, no. 5, september/october 2000.
- [2] W. T. Thomson, D. Rankin, and D. G. Dorrell, "On-line current monitoring to diagnose airgap eccentricity in large three-phase

- induction motors-industrial case histories verify the predictions," *IEEE Transactions on Energy Conversion*, Vol. 14, No. 4, Dec. 1999, pp1372-1378.
- [3] W. T. Thomson, D. Rankin, and D. G. Dorrell, "On-line current monitoring to diagnose airgap eccentricity-an industrial case history of a large high-voltage three-phase induction motors," *Electric Machines and Drives Conference Record*, 1997, ppMA2/4.1-MA2/4.3.
- [4] S. Hamdani, O. Touhami, R. Ibtouen, M. Fadel et J. Régnier "Inductances Calculation of Induction Machine with dynamic eccentricity fault based on FMM and permeance approach," in Proc ISEF the XIV International Symposium on Electromagnetic Fields in Mechatronics, Electrical and Electronic Engineering, pp. 1-11, September 2009
- [5] C. Demian, G. Cirrincione and G. A. Capolino, "A neural approach for the fault diagnosis in induction machines," *IEEE 28<sup>th</sup> Annual Conference of the Industrial Electronics Society*, Nov. 2002, Vol.4, pp. 3372- 3376.
- [6] S. Kolla and L. Varatharasa, "Identifying three-phase induction motor faults using artificial neural networks," *ISA Transactions*, 39, 2000, pp. 433- 439.
- [7] M. Y. Chow and S. O. Yee, "Using neural networks to detect incipient faults in induction motors", *Journal of Neural Network Computing* 2, 1991, pp. 27-32.
- [8] M. Y. Chow and S. O. Yee, "Methodology for on-line incipient fault detection in single-phase squirrel-cage induction motors using artificial neural networks", *IEEE Transactions on Energy Conversion*, Vol. 6, No. 3, Sept. 1991, pp536- 545.
- [9] F. Filippetti, G. Franceschini et C. Tassoni, "Neural networks approach to electric machine on-line diagnostics," in *Proc. IEEE 9<sup>th</sup> European Conference on Power Electronics and Applications*, Vol. 4, pp. 213- 218, Sep. 1993.
- [10] F. Filippetti, G. Franceschini et C. Tassoni, "neural networks aided on-line diagnostics of induction motor rotor faults," *IEEE Tans. Ind. App.*, Vol. 31, N° 4, pp. 892- 899, Juil/Aout 1995.
- [11] G. Salles, F. Filippetti, C. Tassoni, G. Grellet et G. Franceschini, "Monitoring of induction motor load by neural network techniques," *IEEE Tans. On Power Electronics*, Vol. 15, N° 4, pp. 762- 768, Juil. 2000.
- [12] T. Han, B. S. Yang, W. H. Choi et J. S. Kim, "Fault diagnosis system of induction motors based on neural network and genetic algorithm using stator current signals," *International Journal of Rotating Machinery*, Vol. 2006, Article ID61690, pp. 1-13.
- [13] A. Zhongming and Y. B. Wu, "Online detection of broken rotor bars in induction motors by wavelet packet decomposition and artificial neural networks", *IEEE Transactions on Instrumentation and Measurement*, Vol. 58, No. 7, July 2009, pp 2253- 2263.
- [14] A. Bouzida, S. Hamdani, O. Touhami, R. Ibtouen, M. Fadel and A. Rezzoug, "An experimental study on stator and rotor defects of squirrel cage induction machines", in *Proc. IEEE 19<sup>th</sup> International Conference on Electrical Machines ICEM 2010*, pp. 1-5.
- [15] A. Saxena, A. Saad, "Evolving an artificial neural network classifier for condition monitoring of rotating mechanical systems", *journal of applied soft computing* N°7, 2007, pp. 441- 454.
- [16] H. Su and K. T. Chong, " Induction machine condition monitoring using neural network modelling", *IEEE Transactions on Industrial Electronics*, Vol. 54, No. 1, Feb. 2007, pp 241- 249.
- [17] T. Han, B. S. Yang, W. H. Choi and J. S. Kim, "Fault diagnosis system of induction motors based on neural network and genetic algorithm using stator current signals", *International Journal of Rotating Machinery*, Vol. 2006, pp. 1-13
- [18] J. F. Martins, V. F. Pires and A. J. Pires, "Unsupervised neural-network-based algorithm for an on-line diagnosis of three-phase induction motor stator fault", *IEEE Transactions on Industrial Electronics*, Vol. 54, No. 1, Feb. 2007, pp 259- 264.
- [19] S. Kolla and L. Varatharasa, "Identifying three-phase induction motor faults using artificial neural networks", *ISA transaction journal* N°39; 2000, pp. 433-439
- [20] S. Hamdani, A. Bouzida, O. Touhami et R. Ibtouen "Diagnosis of Rotor Faults in Induction Machine Using the MUSIC Analysis of the Terminal Voltage after Switch-off," in *Proc. IEEE 18<sup>th</sup> International Conference on Electrical Machines ICEM 2008*, pp. 1-5.