Broken Bar Fault Diagnosis of Induction Motors Using MCSA and Neural Network

S. Guedidi, S.E.Zouzou, W. Laala, M. Sahraoui, K. Yahia

***Abstract*--** **Early detection and diagnosis of incipient faults are desirable to ensure an operational effectiveness improved of an induction motors. A novel practical detection and classification method, using motor current signature analysis (MCSA) associated with a neural technique is developed to detect rotor broken bar faults. In this method, only one phase current is used. Following current spectrum study on hundreds of experimental observations, it was established that the mixed eccentricity harmonic f_{ecc_mix} has the largest amplitude around the fundamental, under different loads and state (healthy or defective). However f_{ecc_mix} is related to the slip and the mechanical rotational frequency. It becomes obvious that the detection of the rotor broken bars harmonic is made easy. The amplitude of this harmonic and the slip (detection criterion) are used as the neural network inputs. The last provides reliably, its decision on the state of the machine. Experimental results prove the efficiency of the proposed method.**

Index Terms: **Induction motor, broken bars, diagnosis, Motor current signature analysis, Digital signal processing, Neural networks.**

I. INTRODUCTION

Induction motors are the most used type of motors in industrial applications. The use of induction motors is widespread. They are generally used in petrochemical industries, chemical and domestic appliances industries. In critical application such nuclear plants, aerospace and military applications, induction motors are also often used. Reliability must be high of standard in these applications [1]. Although these motors are reliable and robust, stresses of various natures (thermal, electrical, mechanical or environment) can affect the life span of this one by involving the occurrence of stator and/or rotor faults [2]. For instance the stator winding is subject to the failure of insulation, as a consequence of mechanical vibrations. Also, bearings may be subject to wear or damage because of bad lubrication, excessive load or misalignment. Finally, the bars of the squirrel-cage rotor may be subject to faults as a result of internal mechanical stresses. Incipient faults will affect the performance of the machine before major failures occur. A single broken or cracked rotor bar may cause its neighbours to fail dues to increased currents in adjacent bars and consequently increased thermal and mechanical stresses.

These faults cause considerable economic losses. However, to obtain a high level of reliability for an electric drive with induction motors, a diagnostic system is necessary.

In the last decades, several researches on methods of monitoring and diagnosis on the condition of induction motors were proposed. A great number of papers have reported the enormous success of the application of the motor current signature analysis (MCSA) for stator and rotor faults detection [3]-[5].

Also, there are many techniques used to detect motor faults by Artificial Intelligence [6]-[8] such as the Artificial Neural Networks [8]-[11], Fuzzy Logic [12]-[16] and Neuro-Fuzzy [17].

This paper proposes a monitoring and diagnosis process composed of two complementary algorithms. The first has the task to detect the eccentricity harmonic on the allowed frequency range and the slip calculation. The second deals with identification and automated classification based on an Artificial Neural Networks (ANN).

II. HARMONICS RELATING TO SOME DEFECTS

With reference to the electrical and mechanical faults of an induction motors; it is well known that a stator current signal contains potential fault information [5], [18]-[21]. The literature reports that each defect is characterized by a harmonic in the stator spectrum of current. However, a great number of formulas, met in the literature, expressed theoretically and confirmed in experiments, shows that the rotor asymmetries, the bearings faults, the short-circuit faults or the air-gap eccentricity faults, etc., depend implicitly or explicitly on the slip. The knowledge of this parameter with a precision, allowing a great reliability to the diagnosis system, is then essential. In our work, we aim broken bar diagnosis, consequently, only the formulas which depend on rotor asymmetry and mixed eccentricity faults are presented.

A. Asymmetry of Rotors

An induction machine rotor asymmetry introduced by broken bars produces spectrum lines at frequencies:

$$f_{bb} = (\nu \pm 2ks) f_s \qquad (1)$$

Where f_s is the electrical supply frequency, s is the per-unit slip, $\nu = 1,3,5,...,$ and $k = 1,2,3,...,$ respectively.

S. Guedidi , W. Laala, S. E. Zouzou, and K. Yahia are with Laboratoire de Génie Electrique de Biskra (LGEB), Med Khider University, Biskra 07000,Algeria (e-mail: zouzou_s@Hotmail.com, guedidi.salim@hotmail.fr, laala.wid@hotmail.fr).

M. Sahraoui is with Mentouri University, Constantine 25000, Algeria (e-mail: s_moh78@yahoo.fr

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B. Abnormal Air-Gap Eccentricity

Eccentricity components are caused by many different factors like small misalignment between the motor shaft and the electromagnetic brake used as load for the induction motor, bearing wear, bent rotor shaft and mechanical resonance at critical load. The frequencies for these components can be determined from the following equation by [22]-[25]:

$$f_{ecc\_mix} = \nu f_s \pm m f_r \tag{2}$$

with $\nu = 1,3,5,\ldots$, $m = 1,2,3,..$ and $f_r = (1-s) f_s / p$ the mechanical rotational frequency.

III. THE EXPERIMENTAL TEST BENCH

The test bench used in the experimental investigation is available at the LGEB in university of Biskra-Algeria (Fig.1). The experimental tests were carried out on three-phase induction machines (1.1 kW, 50 Hz, 4 poles, 28 bars, Y connected). Only one stator was used for the tests with rotor interchangeability possibility: healthy, with one broken bar (1bb) and two broken bars (2bb). The acquisition is fixed to 10 seconds at the 10 kHz frequency through a D-Space 1104 board. For each type of rotor, 40 tests were carried out at different times and for three loads ranges: low, medium and full load. That is to say 120 tests for each rotor type of which 60 (20 for each load range) were used for the neural network training and the 60 remainders were left as test set for the neural network after training.

Fig. 1. The experimental test bench.

IV. CHOICE OF THE MIXED ECCENTRICITY AND SLIP CALCULATION

In experiment results, certain degree of an inherent eccentricity existence was observed even in healthy machine, whatever the care taken to its manufacture. This inevitable defect was exploited positively in our work. As mentioned above, the preceding relations depend all on the slip; an incorrect estimate of this parameter will induce a bad diagnosis. When the processing of the motor diagnosis is included in the motor-drive systems, slip frequency is easily obtained from the outputs of speed sensors such as encoders. However, if diagnosis processing is independent of motor-drive systems, slip frequency is gathered only from the stator-current spectra in an MCSA-based diagnosis system, consequently its estimate in an optimal way proves to be necessary. One of the best means of obtaining information on the slip, is to exploit the harmonics of the mixed eccentricity inherent in any machine as quoted at the top, given by the relation (2) instead of those used by [5], [18], [26]-[29]. This conviction comes from study on hundreds of experimental observations on follow-up of this harmonic around the fundamental. The experimental results show that this harmonic has the greatest amplitude for any load in its frequency existence band. This effect is observed at healthy and faulty motors, from where the choice of this harmonic (fig.2, 3 and 4). Each figure is attributed to a rotor where each one shows the superposition of three spectra. Each spectrum is assigned to a load.

The algorithm built from these observations uses thus the relation (3) as a formula for the mixed eccentricity harmonic detection:

$$f_{ecc\_mix} = f_s \pm f_r \tag{3}$$

obtained for, $\nu = 1$ *and* $m = 1$, knowing that :

$$s = \frac{\omega_s - \omega_{re}}{\omega_s} \tag{4}$$

with $\omega_s = 2\pi f_s$, $\omega_{re} = p\omega_r$ *et* $\omega_r = 2\pi f_r$ (5)

The combination of these relations leads to another slip formulation on which algorithm of eccentricity harmonic detection and the slip calculation rests. This one is given by the following formula:

$$s = 1 \mp p \pm p \frac{f_{ecc\_mix}}{f_s} \tag{6}$$

who is reduced, for $p = 2$, and by choosing mixed-eccentricity harmonic on the left side of the fundamental, to :

$$s = -1 + 2 \cdot \frac{f_{ecc\_mix}}{f_s} \tag{7}$$

In this form, it is clear and obvious that slip calculation became very easy. It suffices on the basis of experimental observations evoked above to locate the mixed-eccentricity harmonic by its inherent presence at any healthy or faulty machine. This fact is of great importance because it could be used to detect other defects. Therefore slip calculation is carried out without speed sensor help. Moreover speed can be estimated from this result. A strong point in this algorithm is that, the slip determination is not any more of the field stochastic but of the determinist. The following algorithm summarizes all the stages:

- Detection of the fundamental harmonic f_s.
- Detection of the eccentricity harmonic $f_{\_ecc\_mix}$.
- The slip calculation s.
- Detection of the rotor asymmetry harmonic f_{bb}.

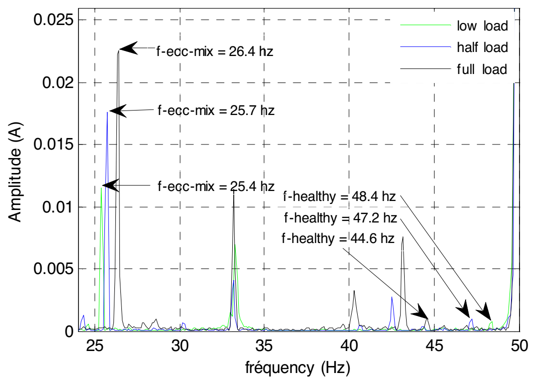

Fig. 2. Superposition of three stator currents spectra; healthy rotor: mixed-eccentricity harmonics and rotor asymmetry harmonics.

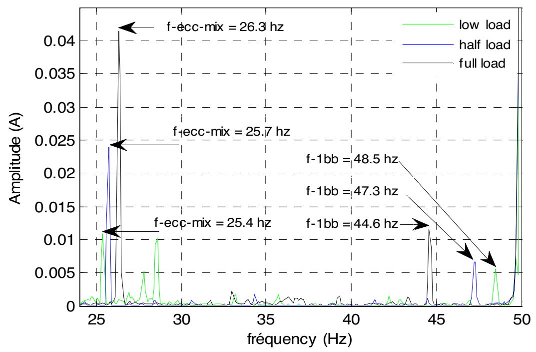

Fig. 3. Superposition of three stator currents spectra; 1bb rotor: mixed-eccentricity harmonics and rotor asymmetry harmonics.

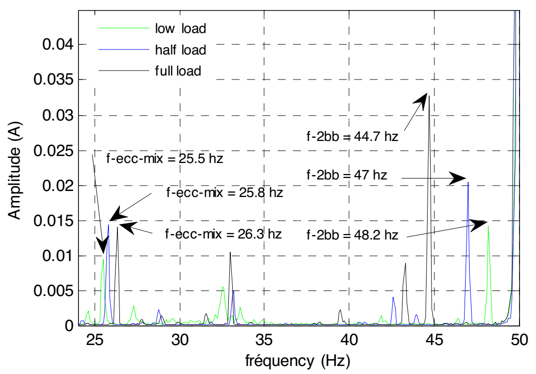

Fig.4. Superposition of three stator currents spectra; 2bb rotor: mixed-eccentricity harmonics and rotor asymmetry harmonics

V. NEURAL NETWORK CLASSIFICATION SYSTEM

A. Introduction

The pattern classification theory has been a key factor in the development of fault diagnosis methods. However, these last decades, new techniques using the artificial neural networks have attracted the researcher's attention in many fields. Excellent results were obtained in various industrial applications such as pneumatic, chemical, aerospace and renewable energy. Also the electric equipment sector had a great part of the research works on parameters identification, control systems and particularly induction motor fault diagnosis. The neural networks had much success because of their less model dependence of the process and in their generalization capacity. They give satisfaction to data not making parts of training set. Moreover neural networks are constantly available to receive new learning data. This remains true as long as the good choice was made on the inputs representing the defects. Therefore, the fundamental requirement for successful implementation of a fault diagnosis technique based upon neural networks is the availability of relevant rich information, which is set of input data for each fault in question. That is why the inputs of the neural networks have to be meaningful indicators of fault. Selecting such a data set from a seemingly infinite of information is a difficult task. However, the best choice of suitable fault indicator is to find the parameters that give the most information about the condition of the system and discard the rest [6]-[9], [30].

B. Choice of Pertinent Variables

The choice of the mixed eccentricity harmonic detection comes in fact that one looks for a criterion which would increase the discernment between healthy machine and faulty machine with one or two broken bars. Because at the time of experimental results study, one was confronted with the fact that the harmonics amplitudes corresponding to frequencies of broken bars, as alone distinction criterion between the healthy and faulty machine, or between a faulty machines with one or two broken bars, was insufficient owing to the amplitudes interpenetration of these harmonics. Two amplitudes combinations were carried out on the set of these harmonics. The fig. 5 shows the first classification (class1) while the fig. 6, shows the second classification (class2). These samples sets form the data bases to neural network training as well as its checking.

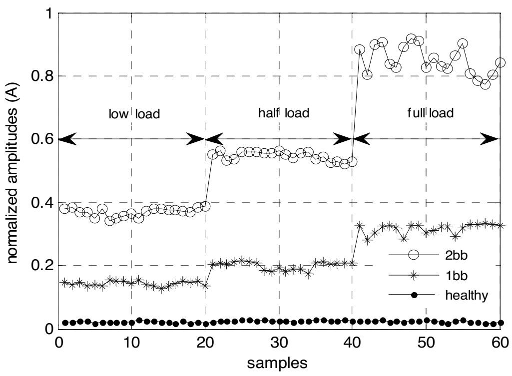

Fig. 5. Normalized amplitudes of the f_{bb} harmonics for: healthy rotor, one and two broken bars. First classification.

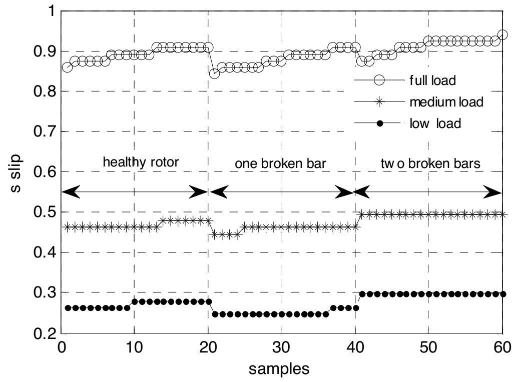

Fig.7. Slip normalized, ascending order

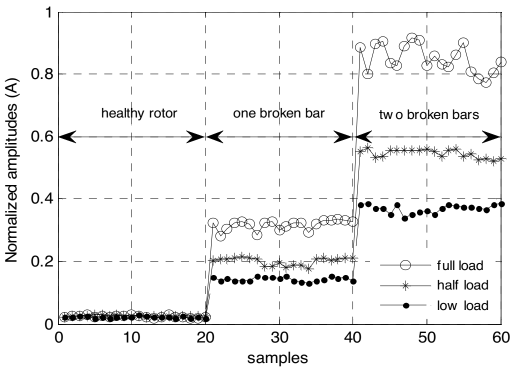

Fig. 6. Normalized amplitudes of the f_{bb} harmonics for the three rotors: healthy, one and two broken bars. Second classification.

Class1 on fig. 5 shows the amplitudes interpenetration on the all load ranges for the healthy rotor. There is amplitudes interpenetration at the full loads for 1bb rotor with those of 2bb rotor at low loads. The established facts are more obvious for the arrangement of the class2 where one collected the different loads for each rotor type. This justifies or obliges, for a highly reliable diagnosis, without error, to consider another criterion or another variable to be added at the neural networks so that the decision-making is the most reliable. After several attempts on the choice of the variables, fulfilling the quoted requirements and, which must be used as neural network inputs, the harmonics f_{bb} amplitudes and the slip s were adopted. The slip (fig. 7) is the variable chosen to be the discernment criterion between various states. In fact, the slip plays a double role. Firstly it helps to locate the rotor asymmetry harmonic and secondly it is used as demultiplexer and discernment input of the neural network.

C. Neural Network Architecture

The neural networks are known for their capacity of classification. In our work, one requires of neural network to be able to declare after each data reception if the machine is healthy or defective. For that, certain stages must be carried out. The choice of relevant input variables, the number of output variables, layers and neurons in each layer. Several networks were tested. The network selected is composed of two input variables. The first $A_{f_{bb}}$ representing the broken bar harmonic amplitude and the slip s as second input improving the reliability of desired classification (as explained above in *B*). Therefore the network is an multilayer perceptron (MLP) where its architecture is represented on fig. 8. It is composed of two inputs neurons, one hidden layer of five neurons and two outputs neurons. An output neuron, attributing the zero value to the healthy machine, 0.5 to the defect of one broken bar and the 1 value to the defect of two broken bars. The second neuron gives the load range. Value 0 is allotted to the low loads, 0.5 to the half loads and the value 1 to the full loads. All activations functions of neurons are sigmoid.

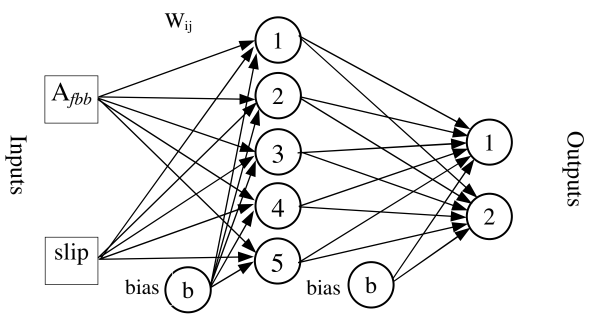

Fig.8 Neural Network Architecture

The training algorithm used is that of the gradient back-propagation. With the inputs chosen, the desired results were acceptable after a few tens of iterations. Let us note that the training data presented at the neural network are classified by ascending order: those of fig. 9 because, after tests, one found that the convergence is faster and the desired results are more reliable than those obtained by random data.

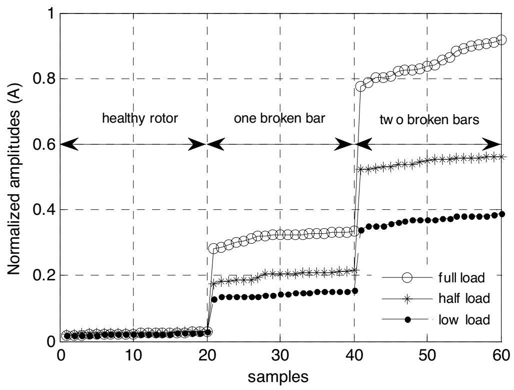

Fig. 9. Normalized amplitudes of the f_{bb} harmonics for : healthy rotor, one and two broken bars. Second classification, ascending order

D. Results to Test Set

After four thousand epochs, the results are spectacular. All the experimental data bases taken at different times were tested by the constructed neural network, the results were more that satisfactory, the network did not fail on all presented cases. The results at test set, instead of tables, are presented at fig. 10 and 11. Each figure gathers the results of the three rotors. They do not require many comments. The results are very conclusive. They vary around the desired values. The results are acceptable to 100%. As fig. 15 shows it, the results of the healthy rotor vary all around zero; those of the rotor to a broken bar vary around 0.5 as envisaged while the results of the rotor with two broken bars also vary around the desired value of 1.

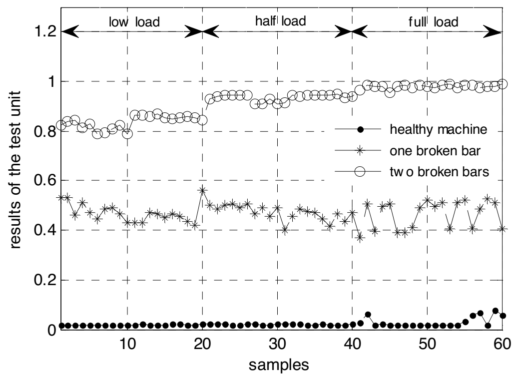

Fig. 10. Results of the test set. M1
out1 or neuron1 : 0 = healthy, 0.5 = 1bb, 1 = 2bb

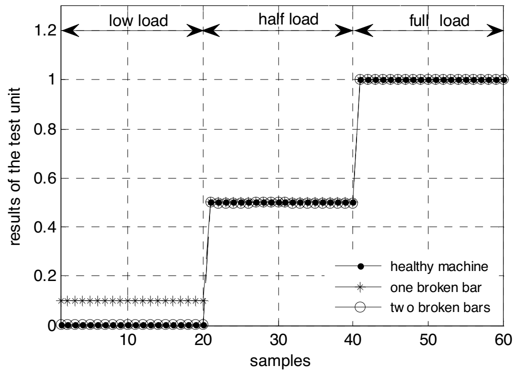

Fig. 11. Results of the test set. M1
Out2 or neuron2 : 0 = low load, 0.5 = half load, 1 =full

VI. CONCLUSION

In the present paper, an efficient diagnosis system which combines MCSA technique and neural network high performances was proposed. Trough the proposed relationship (7), mixed eccentricity harmonic inherent can be detected efficiently. This relation allows precise slip calculation. Then, the slip determination is not any more of the field stochastic but of the determinist. Therefore, rotor asymmetry harmonics could be detected with high reliability. Experimental results show the effectiveness of neural network integration. The neural network didn’t fail in any case of the test set. Therefore the proposed diagnosis process, starting on the eccentricity harmonic detection up to final results, is entirely automatic. One can state that the process needs only one stator current sensor. Following these excellent results, it is possible to apply the proposed diagnosis process to detect others kind of faults.

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VIII. Biographies

Salim Guedidi was born in Biskra, Algeria. He received the D.E.S from the University of Batna, Algeria, the D.E.A from the INPL of Nancy, France and “Magistère” degrees in electrical engineering from the University of Med Khider of Biskra, Algeria. He is interested in the modeling, condition monitoring and faults diagnosis of electrical machines and working toward the Ph. D degree on the same axis. He is the author or coauthor of some national and international papers. Mr. Guedidi is an assistant professor with the University of Biskra and he is a member in the “Laboratoire de Génie Electrique de Biskra”.

Salah Eddine Zouzou was born in Biskra, Algeria on 1963. He received the B.S degree from the “Ecole Nationale Polytechnique d’Alger”, Algeria in 1987 and the M.S and Ph.D degrees from the “École Nationale Polytechnique de Grenoble” France, in 1988 and 1991 respectively. His fields of research interests deal with the design and condition monitoring of electrical machines. He has authored or co-authored more than 40 scientific papers in national and international conferences and journals. Prof. Zouzou is a Professor at the University of Biskra, Algeria and he is the director of the “Laboratoire de Génie Electrique de Biskra” since 2003.

Wided Laala was born in Biskra Algeria. She received the Engineer and the “Magistère” degrees in electrical engineering both from the University of Med Khider of Biskra, Algeria in 1993 and 2001 respectively. She is interested in the modeling, condition monitoring and faults diagnosis of electrical machines and working toward the Ph. D degree on the same axis. She is author or coauthor of several national and international papers. Ms. Laala is an assistant professor with the University of Biskra

Mohamed Sahraoui was born in Biskra, Algeria in 1978. He received the Engineer, “Magistère” and the Ph degrees in electrical engineering from the University of Med Khider of Biskra, Algeria in 2001, 2003 and 2010 respectively. He is interested in the modelling, condition monitoring and faults diagnosis of electrical machines. He has authored or co-authored many national and international scientific conferences and journal papers. Mr. Sahraoui is an assistant professor with the University of Constantine, Algeria since 2005.

Khaled Yahia was born in Biskra Algeria on 1980. He received the Engineer, “Magistère” in electrical engineering from the University of Med Khider of Biskra, Algeria in 2005. He is interested in the Control, condition monitoring and faults diagnosis of electrical machines and working toward the Ph. D degree on the same axis. He is author or coauthor of several national and international papers Mr. Yahia is an assistant professor with the University of Biskra.