APPLICATION OF SOME ARTIFICIAL INTELLIGENCE TECHNIQUES IN INDUCTION MOTOR FAULT DIAGNOSIS

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***Abstract* - In spite of the advantages of the use of the induction motor in a large number industrial applications, various stresses natures like thermal, electrical, mechanical or environmental could affect the life span of this induction motor drive. In recent years, monitoring and fault detection of electrical machines have moved from traditional techniques to artificial intelligence techniques. This paper gives examples of application of nine AI techniques already applied to induction motor fault diagnosis: neural networks, fuzzy logic, neural-fuzzy, genetic algorithms, vector support machine, particle swarm optimization, artificial immune system and gaussian bootstrap process. Functions that can be accomplished by them are highlighted.** [1]

***Keywords* - Diagnosis Technique, Artificial Intelligence Methods, Induction Motor Fault Diagnosis**

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I. INTRODUCTION

Due to its reputation of robustness and its low cost of manufacture, the induction motor has been increasingly used in industry. In spite its advantages, various faults due to different reasons may occurs not only at the machine but also at the power converter stage in case of motor drive system, largely used in many industrial applications.

Among all defects, a three-phase induction motor drive could generate three kinds of problems: rotor faults (broken rotor bar or broken end rings, eccentricity), bearing faults, stator failure (inter-turn short-circuits or disconnection of one phase). In the converter could occur: short-circuit or open-circuit in one or more switches, intermittent misfiring [1].

In order to avoid costly unplanned maintenance schedule, due to faults, the reliability and the safe operating system have to be considered. Along the years, many diagnostic procedures have been proposed. Main steps of a diagnostic procedure can be classified as signature extraction, fault identification, and fault severity evaluation and have been focused on for some decades. Different techniques have been developed to accomplish the required tasks for the converter or motor diagnosis, based on the key fault types normally verified in the industry applications.

Considering only monitoring and fault detection of asynchronous machines, it is important to note that line current signature has been widely used to deal with faults occurring in its stator and the rotor and that the frequency components feature can be associated with different rotor faults. One can find in the motor theory that broken bar faults, as well as eccentricity, rotor asymmetry or shaft speed oscillation, show sideband frequencies [2]. However, in recent years, the monitoring and fault detection of electrical machines have moved from these conventional techniques to artificial intelligence techniques [3-6].

There are many types of AI-based techniques applied to a wide area of applications. Some of these techniques applied to motor diagnosis: Expert Systems (ES), Artificial Neural Networks (ANNs), Fuzzy Logic System (FLS), Genetic Algorithms (GAs), Support Vector Machines (SVM) [5] have been well cited in survey papers. However, other techniques, less employed, include possibilities for optimization and/or classification in the automation of the motor diagnostic procedures: Artificial Immune System (AIS), Particle Swarm Optimization (PSO), Bootstrap Gaussian Process. Besides giving improved performance, these techniques are easy to extend, modify, and can be made adaptive by the incorporation of new data or information [7]. In addition, they can combine with each other and also with traditional techniques.

This paper gives examples on the application of some of the mentioned AI techniques, or their combination, making brief comments and highlighting functions that can be accomplished by their use.

II. AI-BASED TECHNIQUES

Among many AI techniques applied to induction motor fault diagnosis nine techniques have been chosen to be discussed in the following.

A. Expert Systems (ES)

The expert system is basically a computer program embodying knowledge about a narrow domain for the solution of problems related to that domain. An ES mainly consist of a knowledge base (containing domain knowledge, which may be expressed as any combination of "IF-THEN" rules, factual statements, objects, procedures and cases) and inference mechanism that manipulates the stored knowledge for producing solutions.

The system can determine a fault situation doing the signals extraction and fault identification from the combined derived information from behavior of various harmonic components and the machine operating conditions [8]. A

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demerit of ordinary rule-based ES is that they can not handle new situation not covered explicitly in their knowledge bases. However, they can be improved when used in combination with other techniques.

B. Artificial Neural Network (ANN)

An ANN is a computational model of the brain. It assumes that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel, thus known as parallel distributed processing systems. Implicit knowledge is built into a neural network by training it. ANN can be trained by typical input patterns and corresponding expected output patterns. The error between the actual and expected output is used to strengthen the weights of the connections between the neurons.

Awadallah and Morcos [4] remind that ANNs have been densely applied in the area of motor condition monitoring and fault diagnosis performing one or more of the following tasks: pattern recognition, parameter estimation, and nonlinear mapping applied to condition monitoring; training based on both time and frequency domain signals obtained via simulation and/or experimental results; real time, online unsupervised diagnosis; dynamic updating of the structure with no need to retrain the whole network; filtering out transients, disturbances, and noise; fault prediction in incipient stages due to operation anomalies; operating conditions clustering based on fault types.

Example

In the following an example of pattern recognition is described: ANN is applied to vibration signals in order to detect mechanical faults. Unbalance, shaft misalignment, and mechanical looseness have been compared with the "healthy" operation for two different ANN techniques: Global Multilayer Perceptron (MLP-global) and Perceptron Linear Predictive (PLP) [9]. A multi-objective method has been used to improve the generalization capacity of the global MLP network. For investigation, a random choice of training and validation groups was done taking into account the sets dimension: 67% for training patterns and 33% for validation. Deterministic frequencies (fr, 2fr, 3fr, 4fr) and measurement with sensors in six different positions for four cases (healthy, unbalance, misalignment, and mechanical looseness) have been considered, in a total of 978 training and 312 validation patterns.

The bed test that undergoes the experiments consists of a 5 HP, 220/380 V, 60 Hz, four poles, 1730 rpm, squirrel cage. The mechanical load was provided by a separate DC generator feeding a variable resistor. The mechanical structure, in which the motors are settled, offers the possibility to move the two machines, in a way that the system can be either aligned or misaligned at different degrees, for test. An accelerometer was used for vibration spectra acquisition. The signals were taken from the accelerometer fixed at vertical, horizontal and axial positions at either the fan cooling side or the motor coupling side (six positions), that is: P1- Vertical position over the cooling fan (VCF); P2 - Axial position in the front of the cooling fan (ACF); P3 - Horizontal position by the cooling fan (HCF); P4- Vertical position over the motor coupling (VMC); P5 - Axial position in the front side of the motor coupling (AMC); P6 - Horizontal position by the motor coupling (HMC). The signals were filtered and only the multiple rotation frequencies were chosen: fr, $2f_r$, $3f_r$ and $4f_r$.

B1. Global MLP Network

The Global MLP network, Figure 1, has two binary outputs for four situations: 00 – healthy; 01 - misalignment; 10 -unbalance; 11 - mechanical looseness. The layers activation functions are sigmoid and weights have also been updated via back propagation. The method was applied with the acceleration sensor fixed at any of the six positions. It was observed that the best result was obtained for the sensor in the vertical position, in which the vibration levels are more significant in case of mechanical faults. The total success rate was 86.16% for training and 82.37% for validation.

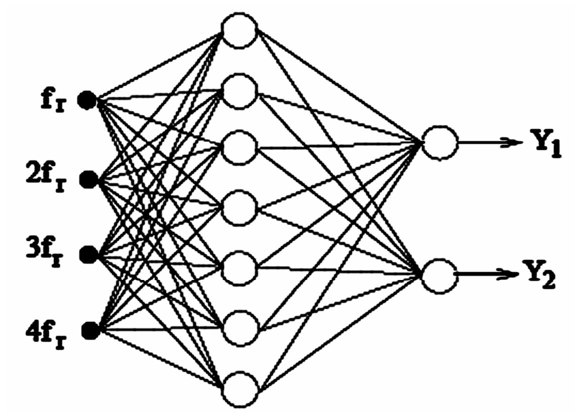

Fig.1: Scheme for the global MLP network.

A well trained network must adequately respond not only to the pattern used for training but also to all other pattern submitted to them. This is known as network generalization capacity. At the training stage the generating function of data is based on possible realizations of the training sets for same task. This variety of solutions is named variance, which must be minimized to guarantee a good network generalization. On the other hand, the number of possibilities increases with the model dimension. A reduction of dimension, by reducing the number of parameters, solves this problem. However, it can originate polarization, which reduces the generalization capacity of the network. It is said that the polarization occurs when even for different realizations of the training process in the reduced dimension space the solution is practically the same. Polarization of solutions must be minimized to preserve the generalization capacity. Therefore, a point of equilibrium must be achieved.

A multi-objective algorithm approach minimizes both the sum of squared error and the norm of network weight vectors to obtain the Pareto-optimal solutions [10]. Since the Pareto-optimal solutions are not unique, there is a need of a decision phase in order to choose the best final solution by using a validation set. The final solution is expected to balance the network variance and bias and, as a result, to generate a solution with high generalization capacity, avoiding over and under fitting. Once a large topology is defined, the algorithm generates a set of solutions with a variety of norms and minimized error for each one, and selects the best response in relation to the validation set. Calculation of network efficiency confirmed the vertical position of the sensor as the most significant, and reached a success rate of 98.

B2. Parallel Layers Network (PLP).

A Parallel Layers Perceptron was proposed in [11] and replaces the original input of the Adaptive-network-based fuzzy inference system (ANFIS) by parallel perceptrons, Its main objective is to overcome the limitation of working with multiple inputs imposed by the classical ANFIS network due to the resulting exponential increase of operations when each input is combined. In Figure 2 is shown the PLP topology, where $\beta(.)$, $\gamma(.)$ and $\Phi(.)$ are activation, v_{ji} and p_{ji} are components of the weight matrices P and V, x_{it} is the i_{th} input for the t_{th} sample, where x_{0t} is the perceptron bias, and y_t is the t_{th} position of the vector output y. Similarly to the traditional multi-layer perceptron, all network parameters can be adapted using the backpropagation method. However, some differences must be highlighted. Firstly, in the MLP case, the network uses function of functions to input–output mapping. The PLP is mainly based on product of functions. Moreover, as can be seen in Figure 2, the proposed topology is composed of parallel layers. This feature simplifies the network implementation in parallel machines or clusters. The method was applied for the case of the sensor fixed at any of the six positions, as described before. Again, the vertical position of the sensor is confirmed as the most significant and the success rate percentage was 94%.

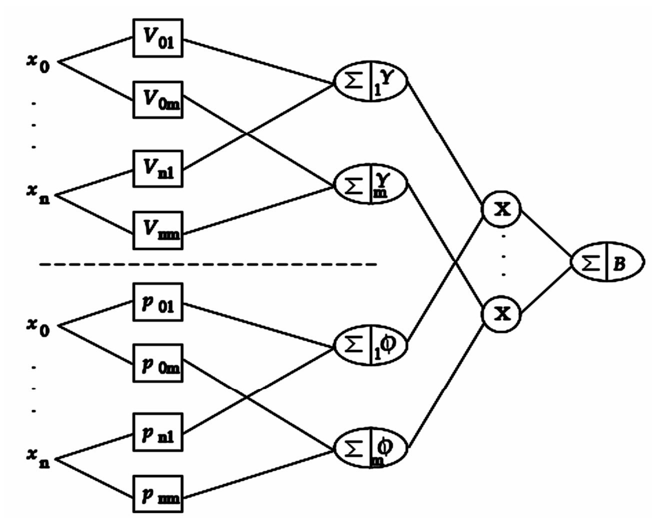

Fig. 2. Parallel Layers Network scheme

C. Fuzzy Logic System (FLS)

The FLS are based on a set of rules. One advantage of FLS is that the rules allow the input to be fuzzy, i.e. more like the natural way that human express knowledge. In contrast to ANNs, they give a very clear physical description of how the function approximation is performed (since the rules show clearly the function approximation mechanism).

Awadallah and Morcos [4] presented an extensive list of references, indicating some of the fuzzy and adaptive-fuzzy systems applications to motor fault diagnosis: evaluating performance using linguistic variables; predicting abnormal operation and locating faulty element; utilizing human expertise reflected to fuzzy *if—then* rules; system modeling, nonlinear mapping, and optimizing diagnostic; fault classification and prognosis.

Example

The aim of this example is the diagnosis of signatures of rotor broken bars when the induction machine is fed by an unbalanced line voltage. It is known that, in this case, the motor generates components in both the forward and the backward system. Considering f_s the supply frequency and s the known induction motor slip, the interesting components to monitor are: $f_1=[s-2]f_s$; $f_2=[-2s-1]f_s$; $f_3=-f_s$; $f_4=[2s-1]f_s$; $f_5=[1-2s]f_s$; $f_6=f_s$; $f_7=[1+2s]f_s$ and $f_8=[2-s]f_s$. The spectrum in Figure 3 shows these eight line components in the case of a 50 Hz fundamental frequency.

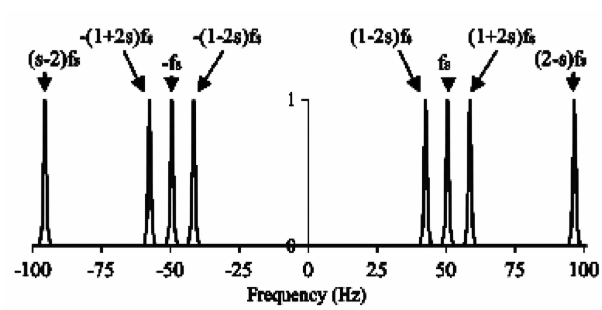

Fig. 3. The stator line currents spectrum in case of one broken bar.

There are four stages in the process: acquisition of the currents, calculation of the Concordia's vector, searching of the defective lines amplitude and computation of diagnosis indexes thanks to an expert system based on fuzzy logic.

The current signatures are given by the complex spectrum modulus of the line current. The amplitudes of all these components are necessary for the fuzzy system fault detector. For this, each input variable was described by membership functions (Small, Medium and High) which can be triangular or take other function shapes. The inference engine was based on the classical Max-Min method determined by the output membership functions. Thanks to the sets of rules, several diagnosis indexes are able to be evaluated we are able to evaluate.

The sense of velocity (positive or negative) is one of them, which can be easily determined through the rules:

IF (I_{f6} is <high>) AND (I_{f3} is <small>) THEN Velocity is <Positive> OR
IF (I_{f6} is <small>) AND (I_{f3} is <high>) THEN Velocity is <Negative>.

Also, the connection of the motor to the line (normal or abnormal) is monitored using
IF (I_{f6} is <high>) AND (I_{f3} is <high>) THEN Current line is <abnormal> OR
IF (I_{f6} is <small>) AND (I_{f3} is <small>) THEN Current line is <abnormal>.

In addition, the load level of operation (Small, Medium, Full) can be determined as a function of the motor slip:
IF (s is <small>) THEN Load level is <Small> OR
IF (s is <medium>) THEN Load level is <Medium> OR
IF (s is <high>) THEN Load level is <Full>.

In the case of a broken bar, the frequency of the current flowing in the bar is sf_s. It is well known that the negative sequence rotor current produces currents of $(1\pm2s)f_s$ frequency in the stator. The detection and the degree of fault severity is proportional to the average amplitude of the two component lines at the right $(1+2s)f_s$ and the left $(1-2s)f_s$ of the main line at the feeding frequency divided by the fundamental current amplitude. This approach gives a sufficient precision about the fault severity.

In the study of the forward and the backward sequence of the supply line, the ratio has to be calculated for the two sequences: I_{rf} and I_{rb}. The set of rules for the expertise of three phase induction motor, in case of broken bar defect, are given by:

IF (I_{rf} is <small>) AND (I_{f6} is <high>) AND (I_{f3} is <small>) THEN Operating Condition is <Normal> OR
IF (I_{rb} is <small>) AND (I_{f6} is <small>) AND (I_{f3} is <high>) THEN Operating Condition is <Normal> OR
IF (I_{rf} is <medium>) AND (I_{f6} is <high>) AND (I_{f3} is <small>) THEN Operating Condition is <Progressive failure> OR
IF (I_{rb} is <medium>) AND (I_{f6} is <small>) AND (I_{f3} is<high>) THEN Operating Condition is < Progressive failure > OR
IF (I_{rf} is <high>) AND (I_{f6} is <high>) AND (I_{f3} is <small>) THEN Operating Condition is <Broken Bar> OR
IF (I_{rb} is < high >) AND (I_{f6} is <small>) AND (I_{f3} is <high>) THEN Operating Condition is < Broken Bar >

The results of this example have been used as the additional inputs for the expert system. However, this technique requires the knowledge of the system behavior for determination of the membership functions.

In order to confirm the effectiveness of the proposed approach, invasive experiments had been performed on one type of induction motor. The first experiments were considered thanks to a healthy induction machine. Several tests were made for the motor operating at 50%, 75% and 100% of the full load level. This served as references in order to test the efficiency of the approach proposed. The second experiments were made with a machine where a partial hole was made in order to simulate a progressive failure in a broken bar. The third experiments were made with a complete hole in order to have one full broken bar. All the results obtained by the fuzzy expert system were in full accordance with the test considered.

D. Neural-Fuzzy

The idea behind the fusion of Neural and Fuzzy technologies is to use the learning ability of ANN to implement and automate the fuzzy system, which use the high-level human-like reasoning capability. Consider the case of a faulty motor stator, Neural-Fuzzy (NF) fault detection is obtained, which learns the stator faults and the condition under which they have occurred by an inexperienced and noninvasive procedure. Many methods have been proposed for implementing and optimizing fuzzy reasoning via ANN structures [12].

Example

Applications of two known NF structures to solve the induction motor fault detection are presented in [13]: The Fuzzy Adaptive Learning Control/Decision Network (FALCON)-Based Fault Detector (FFD), and the Adaptive-Network-Based Fuzzy Inference System (ANFIS)-Based Fault Detector (AFD).

In a three-phase induction motor framework, stator currents and rotor angular velocity are measured under different motor friction and load torque. The magnitude of motor friction and load torque affect motor operations, which, in turn, affect speed and current measurements. The effects of incipient motor friction faults are highly coupled with effects of load torque. For a balanced friction fault, monitoring stator currents and rotor speed could lead to successful fault detection/diagnosis. In the presence of varying load situations, however, it is observed that the impact of load on motor current and speed is similar to that of the motor friction. For example, an increase in motor friction increases the current, and decreases the speed, which is similar to the effect of an increase in load. Two NN/FZ systems have been employed, which perform motor fault detection under different load conditions, and were able to extract heuristics for the fault detection process [13].

The fault detection process may be viewed as a mapping from the input space to the output space, which maps the operating current, speed, and load torque to motor friction. Both structures provided good fault detection/diagnosis under varying load torque. However, the results of the AFD were slightly more accurate [13].

E. Support Vector Machines

Support Vector Machine (SVM) is derived from the Statistics Learning Theory (SLT) and has attractive features, such as good generalization ability, large dimension robustness, objective function convexity, and well established theory. In fact, the SVM based classifier is claimed to have an efficiency that does not depend on the number of features of classified entities, to have better generalization properties, cost much less time than NN based classifiers and better accuracy (greater than 97%) than Linear Discriminant analysis, K-Nearest Neighbor, Probabilistic Neural Network, Gaussian Mixture Model pattern recognition techniques [14]. However, its accuracy may be drastically affected by choices in SVM implementations, such as kernel function and penalty parameters of the support vector. An improvement can be obtained by tuning these parameters with other optimization techniques, like GA [14], artificial immune system [15], or on particle swarm optimization [16].

The SVMs are essentially binary classifiers (positive and negative classes). Nevertheless, SVM-based multi-class classifier can be constructed using "one against one" technique, which consists in creating k SVMs, k corresponding to the number of classes. In the generation of each machine, a class is fixed as positive while the other are considered as negative. However, the use of "one against one" technique needs a synthesizing scheme to decide the final results according to the results of sub classifiers. In [17] four synthesizing schemes were compared (majority voting;

binary tree decision; neural network and hybrid matrix), while in [18] ten of them were needed.

Depending on what is required in motor diagnosis, there are two possibilities. The first, called simple diagnosis (1-Class), discovers only if the fault has occurred. The second one (complex diagnosis, 2-Class) is able to find, for instance, how many bars have been damaged [19]. The SVM is gaining application in rotating machinery anomaly detection, due to its superb performance with small samples [20-21].

Example

The fault diagnosis of induction machine is a multi-class classification problem. For classification of mechanical faults, as in the ANN example (Global MLP Network, section *B1* and Parallel Layer Network, section *B2*), have been compared to the "healthy" operation [22]. The software developed by [23] was used because this work deals with four classes: SVM1 - No Faults; SVM2 - Unbalance; SVM3 – Misalignment and SVM4 Mechanical Looseness. The one-against all classifier gave the final diagnosis, grouping the four support vector machine. The output was one of the following messages: no fault, misalignment, unbalance or mechanical looseness. The method was applied for the acceleration sensor fixed at any of the six positions described in section *B*. The final results of the nets outputs for each acceleration sensor position for the data used to test the diagnosed system was: P1 (VCF), 96%; P2 (ACF), 90%; P3 (HCF), 92%; P4 (VMC), 92%; P5 (AMC), 92%; P6 (HMC), 92%.

The SVM, together with one-against-all technique, has shown an excellent performance. It is shown that the best position for signals acquisition and analysis is vertical over the cooling fan, which is considered useful information for the maintenance workers. This valuable information reduces the number of sensors and also the maintenance time and costs.

F. Genetic Algorithm

Genetic Algorithm (GA) is based on biology and, in particular, by those biological processes that allow populations of organisms to adapt to their surrounding environment: genetic inheritance and survival of the fittest, that is, natural selection as well as evolutionary process. Because GA is a stochastic optimization method, it needs less prior information about the problems to be solved than the conventional optimization schemes, which often require the derivative of objective functions. It also has the unique features of parallel search and global optimization and it is adapted for the simultaneous evaluation of a large number of points in the search space.

GA can be used to determine the coefficients of a regulator [24] or to identify induction machine parameters. It can also be used in the diagnosis of induction motor rotor and stator faults, such as rotor broken bars [25-26], open rotor and stator phase [27], rotor unbalance and misalignment, and bearing loose fault [28].

Although GA based approaches have interesting features when used alone, as compared to Neuro-Fuzzy (NF) based approaches, for instance [27]. GA combined with other AI based approaches will have tremendous scope in future. An example is found in [29] in which in order to improve fault identification accuracy rate, principal component analysis (PCA) and GA are employed to reduce the feature dimensionality of the measured data. PCA extracts the principal components (PCs) from the original features. Then the significant features are selected from the extracted features by GA as inputs to neural network. GA is also used to optimize the ANN parameters. The combined technique have considered broken rotor bar, bowed rotor, bearing outer race fault, rotor unbalance, misalignment and phase unbalance. Results have shown that the combination has fast training procedure, high classification rate and compact structure

Example

Consider the process mentioned in the example of section *C*: acquisition of the currents, calculation of the Concordia's vector, amplitude search of the defective lines and finally computation of diagnosis indexes thanks to an expert system based on fuzzy logic. This example treats of the application of the GA to find the global maximum as well as to solve an optimization problem in the spectral lines identification process in case of a rotor broken bar of an induction motor [25-26]. The N individuals in the case are the supply frequency and the slip frequency and these are the parameters to be found.

In order to find the eight main components in the current spectrum in Figure 3, eight Gaussian functions were used as a window, which only depends on the supply frequency (f_s) and the slip frequency (sf_s) The integral of the product of the current spectrum by the spectral window was used to calculate the fitness.

The approach was tested for a rotor broken bar fault detection. Besides searching lines of the supply frequency GA was used to search the slip frequency, inside of the Concordia's vector spectrum. Figure 4 depicts the results for line currents spectrum with one full broken bar and 100% of full load level. Results are obtained after few interactions. A comparison with the healthy line currents spectrum allows the operator to distinguish the faulty case and also to be aware of a progressive failure in the rotor.

G. Particle Swarm Optimization algorithm

Particle swarm optimization (PSO) is a semi-global optimization algorithm, first introduced by [30]. It simulates social model like those of birds, insects and fish swarm. Its main concept is simulating the movement of these organisms searching for food. Candidates to find the best solution are particles. They move globally into the search space along a search trajectory, sharing their experience, collaborating to each other, suggesting its own solution for the problem. The particles speed is based on particle momentum, the attraction force towards the global and the best local.

PSO is a simple optimization technique without heavy computation and has shown success in solving many optimization problems [31, 32]. The technique does not require the computation of derivatives and hessians nor does not need training with heuristic data and its performance has been continuously improved [33-35].

PSO method has been applied to the following motor faults: broken bar, part of the end-ring broken [31], stator inter-turn and independent winding short circuit [36]. It is an efficient method to solve the optimization problem as to extract information quickly from a frequency. Next it will be shown its ability to estimate the line frequency and the fault line frequencies with the induction motor operating under one full broken bar [31].

Example

Consider the same four stages process mentioned in the example of section *C*. In this example, the search of the defective lines amplitude is accomplished by using PSO Based on a spectrum of current and calculation of the window function and of Fitness with the same equations used in GAS method, the transient of the PSO was examined thanks to several variables. In the estimation of the fundamental frequency the majority of the particles stayed close to the fundamental frequency after about twenty iterations. To estimate the slip s, the population moved along the two sidebands to be found. Both the particle best fitness and the global best performance have been reached after twenty iterations. Bad performance particles disappeared with the increasing value of the number of iterations.

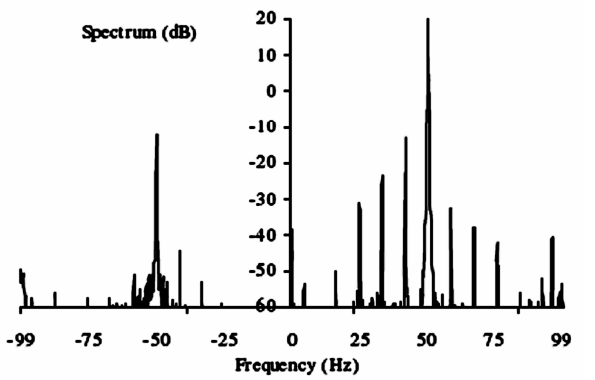

Fig. 4. Stator currents spectrum in case of one broken bar and the motor operating at full load, obtained by using GA.

H. Other Techniques

There are many AI techniques that could be employed in the induction motor fault diagnosis. Two of them, already tested, have been select to illustrate these possibilities.

H1. Artificial Immune System

Artificial immune system (AIS) is an emerging soft computing method inspired by natural immune system. Because the AIS abilities of learning, memory and self adaptive control, this method is used in pattern recognition, classification, optimization and anomaly detection problems. Clonal selection is an artificial immune algorithm used for optimization problems. It has not crossover operator, so this method is different from genetic algorithm. Also, it converges faster than genetic algorithm.

In combination with other diagnosis methods, AIS can effectively improve the accurate rate of fault diagnosis and diagnosis system robustness, bringing into play each of their advantage, so that the accurate rate is improved. Clonal selection has been used to select optimal parameters of SVM, extracted from three phase motor current and constructed based on Park's vector approach. This has been applied to the study of broken rotor bar and stator short circuit faults [15]. Also, AIS method has been combined with neural network for machine fault diagnosis using genetic algorithm to combine diagnosis methods [28, 37-38]. In [39] the IGA is employed to adaptively optimize the structure of an ANN. Four typical fault situations have been studied: bearing fault, stator winding fault, broken rotor bar, and eccentricity [39]. AIS inspired fault detection algorithm has been proposed in [40] for detection of broken bars. The performance of faults detection is improved by using genetic algorithm and fuzzy clustering method.

H2. Bootstrap Gaussian Process

Bootstrap Gaussian Process (BGP) has been proposed from the merge of Gaussian process classifiers (GPCs) and bootstrap methods, as an alternative to other classifiers, like the kernel classifier support vector machine (SVM), which has excellent performance towards this purpose, but it has difficulties to optimize relevant hyper-parameters. GPCs are Bayesian probabilistic kernel classifiers and provide a well established Bayesian framework to determine the optimal or near optimal kernel hyper-parameters. They are largely unexplored for anomaly detection applications and, also, a promising statistical tool for both binary and multi-category classification. Moreover, GPCs proved to outperform SVM [41]. It can be employed to solve a wide range of problems, such as hypothesis tests, model selection and probability distribution estimations. Bootstrap is most useful where little is known about the statistics of the data or too few samples are available to use asymptotic results [42].

In BGP, bootstrap methods are incorporated to improve GPCs' performance for small machinery anomaly samples by re-sampling at random. The fact that GPCs are strong classifiers suggests that small numbers of bootstrap samples might be sufficient to enhance classification performance.

Experiment results for rotating machinery misalignment anomalies detection [43] in which wavelet packet is utilized to perform vibration analysis, show that bootstrap GPCs are highly effective and outperform GPCs and SVM with cross validation for anomaly detection. Thus the proposed approach is promising for rotating machinery anomaly detection.

III. CONCLUSION

This paper treats of the application of nine Artificial Intelligence (AI) methods in induction motor fault diagnosis: neural networks, fuzzy logic, neural-fuzzy, genetic algorithms, artificial immune system, vector support machine, particle swarm optimization, and Gaussian bootstrap process were summarized. Their applications and possibilities of combination were discussed as well. AI techniques are a very strong tool for electrical motors diagnosis studies. Although some investigators indicate that they are not yet supposed to compete with conventional methods, tremendous efforts have been made to develop new methods, as it is the case of bootstrap gaussian process. AI methods become a strong tool when used in combination with other ones.

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