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APPLICATION OF ROOT-MUSIC AND SVM TO INDUCTION MOTOR FAULTS DIAGNOSIS

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Abstract- The use of Support-Vector-Machine based on classification algorithms provides a system for rotor fault diagnosis of a cage induction motor. The Root-MUSIC method is presented which uses motor current signal analysis (MCSA) as input. It is used to extract the frequency spectra derived from the stator current signal, consequently one will obtain powers at lateral frequencies around the fundamental. To separate the different requirements of motor rotor failure, these powers are made available to a multi-class classifier based on a support vector machine to make the decision of the nature and type of the motor failure based on MAP (Maximum-Posterior-estimation). A series of three-phase motor failures (e.g., broken bars) from different experiments are used to provide data and test the operating state of the classifier and to demonstrate the reliability of the both methods namely Root-MUSIC and SVM.

Keywords: MCSA, Root-MUSIC, FFT, SLT, SVM, MAP.

1. INTRODUCTION

Fault detection techniques in induction motors have gained great interest over the past few decades. Performance, efficiency and reliability requirements are imposed in industrial systems for the purpose of hardware safety. In this context, the detection of motor faults, whether they come from mechanical or electrical causes, is essential for the smooth running of an industrial process. Bearing faults and rotor bar breakage are mainly produced by sudden changes in the load that the motor can support. On the other hand, electrical failures which are mostly related to the power supply generally cause short circuits in the motor stator [1, 2].

In general, induction motor failures come from bearing faults. From experience, bearings are by far responsible for the majority of engine faults; then come the short circuits of the stator; Do not ignore failures due to breakage of rotor bars and end rings [3]. With advances in automation, fault detection techniques have become more effective, among these techniques- vibration-analysis or Motor-Current-Signature-Analysis which can easily tell us about the state of the motor. through the spectra measured and compared to spectra of healthy motors [4, 5].

The use of artificial intelligence techniques (here we will mention the Artificial-Neural-Networks, and the Support-Vector-Machine (SVM) has also grown rapidly for fault diagnosis. The major goal is to be able to model the problems of nonlinear systems, in particular to map the input-output states of an anonymous system. Nevertheless, there are differences between the two techniques (ANN and SVM), indeed the minimization of risks differs from one technique to another [6]. Indeed, and according to the studies made before [7, 8], SVMs represent a method of more or less precise classification provided that the entries would be well defined; thus, the choice of the technique to extract the feature from the electric signature in particular the stator current would be of primary importance for their best performance.

The spectral analysis of different spectra of motors with faults or breakdowns can shed light on the origin of the fault. However, fault frequencies are also visible in healthy motors, which makes it difficult to know whether the measured fault spectra really tell us about a fault or not whether the measured characteristic fault frequencies correspond to a fault or not [9 - 11]. Results from several experimental data have proven the advantage of high-resolution spectral analysis of stator current, compared to FFT [12] spectral analysis. One of the methods of high-resolution spectral analysis is the method of Root-MUSIC algorithm which is used to isolate default powers and frequencies.

2. PRINCIPLE OF THE MONITORING SYSTEM BASED ON THE SVM

The monitoring is a function which aims at detecting the operating mode of an induction motor starting from a whole of the vectors of observation taken of the motor considered (current i_a, i_b and i_c), it thus acts to seek the membership of an observation which arises on line and to classify it according to a function of preset decision. From this, the intention comes to use the technique of classification by SVM in the field of the monitoring since it answers well the formality and the requirements requested by the function of diagnosis.

SVMs are a classification method based on the search for an optimal hyper- plane which separates as well as possible from the sets of data. We regarded this method as a technique of detection and localization of the faults. This technique uses the data sensors like a vector of entry and using a base of training; we can classify each new vector and determine then the operating mode of the system to supervise at every moment as shown in Figure 1.

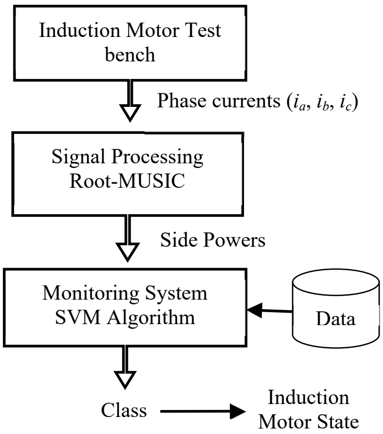


Figure 1. Monitoring principle by SVM

This method is completed in four stages, represented in Figure 2, namely:

- The construction of the input vector
- Preparation of the data base
- The phase of training
- The classification or the decision-making

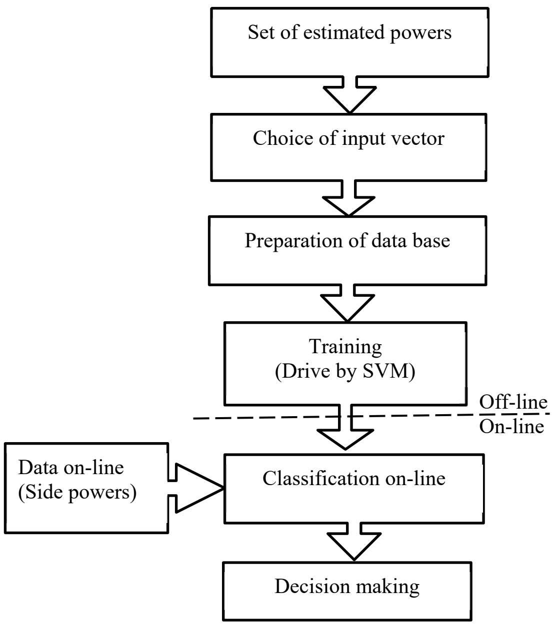


Figure 2. Stages of monitoring by SVM

The entry of the process of classification is a vector characterizing an operating mode. It contains the estimated data (side Powers around the power of frequency source). The phase of classification, applied in real time, is preceded by a phase of training off line for the determination of the separating functions. The system thus contains a base of training. It is about a sample of vectors whose decisions (classes) are known beforehand.

3. FEATURES EXTRACTION

3.1. Introduction

The spectral components of the characteristic vector of the fault conditions generally inform us about the desired state of the motor. In the first place, techniques based on spectral analysis based on FFT were by far the most used, however, and with the advent of techniques based on artificial intelligence, new methods have emerged; this of course to remedy the drawbacks of the first methods (leakage of some spectra which contribute to the growth of the error range). In the paper we have chosen the Root-MUSIC-Method, which is a dominant tool to extract, significant powers and frequencies from the motor stator current signal Figure 3. This method offers a very precise means of resolution since it is based on the linear algebraic concept of subspaces.

3.2. High Resolution Method Root-MUSIC

The high-resolution methods or "HR" appear in the years 1970 in the fields of underwater acoustics (W.S. Ligget), of seismic (V.F. Pisarenko) and of radioastronomy (I.N. El Behery) [14]. The popularity of these methods in signal processing started, in 1980 after the publications brought closer and independent of two algorithms based on an identical principle.

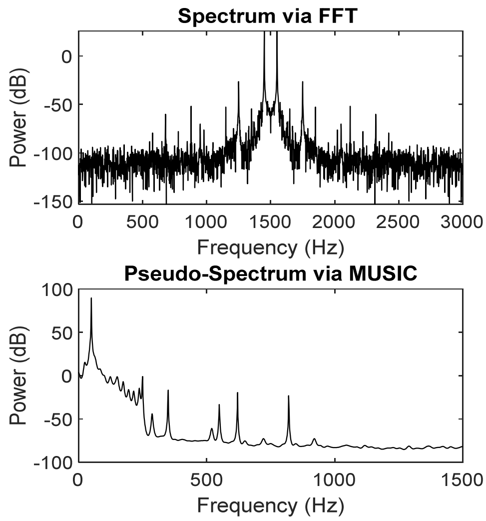


Figure 3. Spectrum estimate via FFT and MUSIC

It is about algorithm MUSIC of Schmidt, and the method of Bienvenu and Kopp. From the features of the autocorrelation matrix of the observations, these two methods decompose the space of the observations into two orthogonal vectorial subspaces [14]. Algorithm MUSIC exploits decomposition properties in eigenvectors of the autocorrelation matrix related to vector observations. This decomposition makes it possible to separate space from the observations in two orthogonal vector spaces: the subspace signal and its orthogonal complement, subspace noise. Root-MUSIC indicates the polynomial version of the MUSIC algorithm [15]. We assume the stator current $I_s[n]$ as follows:

$$E\wedge\ E^H = \sum_{k=1}^{L} l_k e_k e_k{}^H + \sum_{k=L+1}^{M} l_k u_k u_k{}^H \qquad (1)$$

where, $w_k = \frac{2pF_k}{F_s}$; n=0, 1, 2,…, N-1 where, N is the number of sample data and N_G represents the white noise with a zero mean (Gaussian white noise).

We will examine the subspace structure of a current composed of L frequency components, starting with investigative its autocorrelation matrix. The autocorrelation sequence of is[n] is expressed as:

$$r_s[k] = E\left(I_s[n].I_s^*[n-k]\right) \qquad (2)$$

And the autocorrelation matrix of $I_s[n]$ is defined as:

$$R_s = \begin{bmatrix} r_s[0] & r_s[-1]_O & \dots & r_s[N-1] \\ r_s[1] & r_s[0]_O & & r_s[-1] \\ M & M & & M \\ r_s[N-1] & r_s[1] & & r_s[0] \end{bmatrix} \qquad (3)$$

It can be shown that the autocorrelation in (2) becomes:

$$r_s[k] = |A_k|^2 e_k e_k^{*T} + s_0^2 d[k] \qquad (4)$$

$$R_s = \sum_{k=1}^{L} |A_k|^2 e_k e_k^{*T} + \sigma_0^2 I = R_{signal} + R_{noise}$$

where, $e_k = \left[1\ e^{jw_k} e^{jw_k 2} \dots e^{jw_k(M-1)}\right]$ is an eigenvector of the matrix R_{signal} with eigenvalue $\lambda_k = M|A_k|^2$. Equation (4) can be written as:

$$R_s = E\wedge\ E^H + \sigma_0^2 I \qquad (5)$$

where, $E = [e_1 e_2 \dots e_k]$ is M×L matrix,

$$L = diag\left(|A_1|^2 |A_2|^2 \dots |A_L|^2\right) \qquad (6)$$

The spectral decomposition of the M×M matrix $E\wedge\ E^H$ (called the clean autocorrelation matrix) is:

$$E\,L\ E^H = \sum_{k=1}^{L} l_k e_k e_k{}^H + \sum_{k=L+1}^{M} l_k u_k u_k{}^H \qquad (7)$$

where, the eigen values λ_k are real-valued and satisfy: $\lambda_1{}^3\lambda_2{}^3\dots{}^3\lambda_L > \lambda_{L+1} = \lambda_{L+2} = \dots = \lambda_M = \sigma_0^2$, the signal and noise subspaces are orthogonal, we thus have:

$$E^H \times u_k = 0 \qquad (8)$$

Accordingly, the "annihilating filter" by the relation:

$$U_i(z) = \sum_{k=0}^{M-1} u_i[k] z^{-k}; i = L+1,\dots,M \text{ and } z = e^{jw} \qquad (9)$$

From this equation we find (M-1) roots for each proper filter, while all these filters have L roots that we can solve through their average. In spectral MUSIC component frequencies can be found, by finding the maxima position, from the estimated signal pseudospectrum [20]:

$$S\left(e^{jw}\right) = \frac{1}{\sum_{k=L+1}^{M} \left|e_k(w)^H u_k\right|} \qquad (10)$$

The Root–MUSIC-Method offers the possibility to find polynomial roots in a simpler way:

$$P(z) = \sum_{i=L+1}^{M} [U_i(z)]\left[U_i^*\left(1/z^*\right)\right] \qquad (11)$$

With respect to the unit circle, its nearest L-roots that fit the possible harmonics are:

$$F_k = \frac{F_s}{2p}.\arg(z_k)\ ,\ k = 1,\dots,L \qquad (12)$$

It should be pointed out that there is a difference between the two methods (ESPRIT and Root-MUSIC). To evaluate the frequencies of the sinusoidal component ESPRIT only uses the signal subspace, while Root-MUSIC only uses the noise subspace. To calculate the powers of each component, the following relationship is used:

$$e_i^{*T} R_s e_i = l_i \qquad (13)$$

by substitution:

$$R_s = \sum_{i=1}^{L} E\left\{A_i A_i^*\right\} s_i s_i^T + \sigma_0^2\ I = \sum_{i=1}^{N} P_i s_i s_i^T + \sigma_0^2\ I \qquad (14)$$

Resulting equations can be solved for P_i [21]. It should be noted that we calculate the power to sort the frequencies and thus to avoid false identifications; this is carried out while being based on the experimental principle which the powers of the faults are above -80 dB [12].

4. SUPPORT VECTOR MACHINES (SVM)

SVM is mainly based on Vapnik-Chervonenkis (VC) theory. The input vectors mapping is done in a linear or non-linear way through one or more spaces. After that we divide in a linear and optimized way in order to build a hyperplane to share the two classes. Thus, and to prevent the result of overfitting, a global optimized solution is sought through SVM training [14]. A separating hyperplane is possible for the linear separable case, its function being:

$wx + b = 0$ which implies: $y_i(wx+b) \geq 1; i = 1,\dots,N$

For the Euclidean norm of w, ‖w‖, to be minimal, the SVM method must find a unique separating hyperplane (in this case the hyperplane is 2/‖w‖ distant from the furthest data points) close to each class. If we introduce Lagrange multipliers $\propto_i$, the problem to be solved through SVM would be convex quadratic. the properties of the result (single optimized solution) will be:

$$w = \sum_{i=1}^{n} \alpha_i y_i x_i \qquad (15)$$

In the case where to $\propto_i > 0$ xi will be the support vectors. After the formation of the SVMs, the decision function will have the following form:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i (x.x_i) + b\right) \qquad (16)$$

The SVM method has the possibility of carrying out a nonlinear mapping (which is solved by the kernel function) of the input vector x belonging to the input space Rd which is included in the Hilbert space which is of higher dimension. To optimize the classification results, we select the different functions of the kernel [14]. So far, we have only been able to process labels with binary classification

(1 and -1). In practice, several classes of faults are encountered in the induction motor. To remedy this problem, several works have found SVM methods of multiple classification, we can cite here the classification one against one, or one against all. In our case, and to improve the speed of training and diagnosis, we will try to use these methods [20, 21].

3. EXPERIMENTAL SETUP DESCRIPTION

To validate our system, we chose broken bar defects. Several experiments are carried out in the LDEE laboratory of USTO-MB. All tests were carried out on a 4 poles motor type ENEL with three-phase network, 50 Hz, its power is 3 kW (Appendix). This motor is squirrel cage, it has 28 uninsulated slashes. The stator current is $I(\Delta) = 7$ A. The load used here is a DC generator. Measuring instruments comprise a Hall effect current sensor (Figure 4).

Figure 4. Experimental setup

To be able to create defects in the bars, tiny holes are made through a drilling. For charging, a torque of 20 Nm is applied for 2 seconds. The frequency resolution is 0.5 Hz (which is equivalent to a sampling frequency of 3 kHz). To be able to compare all results, two distinct operating modes are used:

- Healthy engine
- Engine showing faults of one, two and three bars separately (Figure 5)

At the end, we took two files for the first modes for comparison (checking the existence of the fault) and we collected 66 files corresponding to the second mode. We used 40 files in training and the rest for the test. To highlight the effect of the defect in temporal field (Figure 7), we supported to exploit the combination of the three currents and we chose the direct component whose formula is:

$$i_{sd} = 2\frac{i_a + v i_b + v^2 i_c}{3} \tag{17}$$

where, $v = e^{\frac{j2\pi}{3}}$; i_a, i_b, i_c are the three phases' currents and i_{sd} is a direct component.

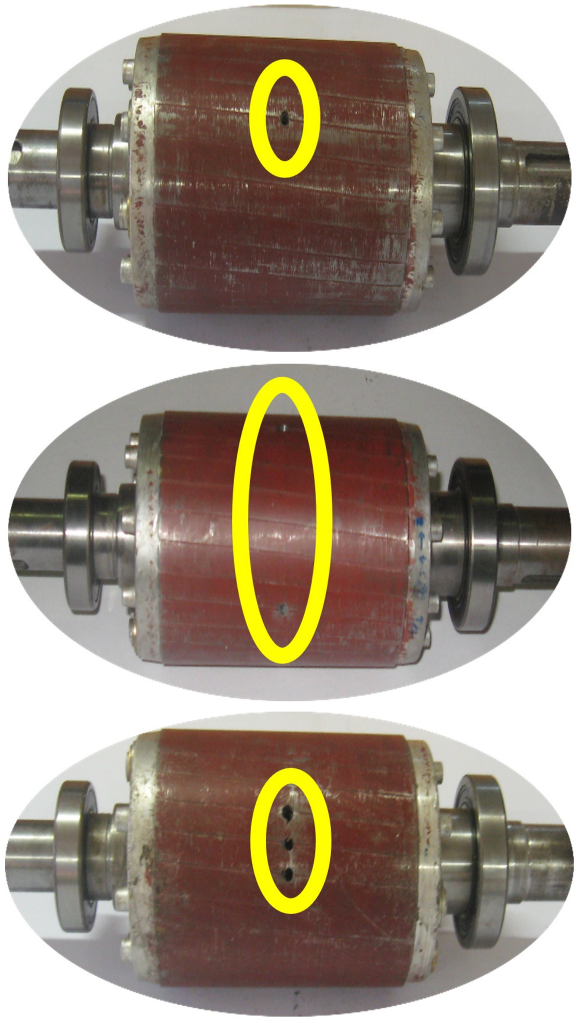


Figure 5: Rotors cage with broken bars

5.1. Feature Extraction

During the various faults, space harmonics arise, this is due to the non-sinusoidal distribution of the stator windings. These harmonics arise in pairs at regular intervals. Harmonic frequencies of the rotor slots are given by the equation:

$$f_{sh} = f_0\left(\frac{k.n_b}{p}(1-s) \mp \rho\right) \tag{18}$$

where, $k = 1, 2, \ldots$ is a positive integer.

The procedure followed in this paper to extract the feature for the broken bars faults diagnosis is exposed as below:

- Check if it is indeed a fault by applying Lissajou to the stator direct component current (i_{ds} in Figure 6)
- Application of Root-MUSIC method to the stator direct component current
- Estimating of slip by determining the first rotor slot harmonic
- Predicting of lateral harmonic frequencies around the fundamental characterizing broken bars faults deduced from the theoretical formula (f_b=$(1\pm2s) f_0$)
- Identification of the predicted lateral harmonic frequencies around the fundamental with those really existing in the stator current spectrum,

• Find the power corresponding to each of the frequencies previously identified, Figure 8.

Given the Figures 7-9, it is difficult to make the difference between the three faults; hence the need to use a means of recognizing the kind of defect such as the SVM.

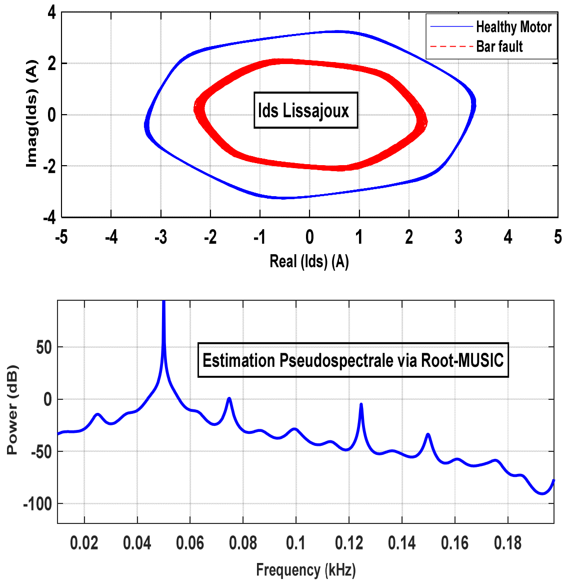


Figure 6. Stator direct current i_{ds} and its spectrum

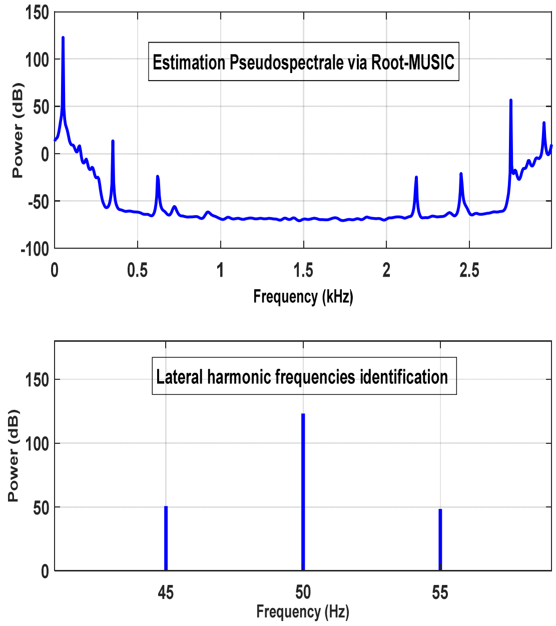
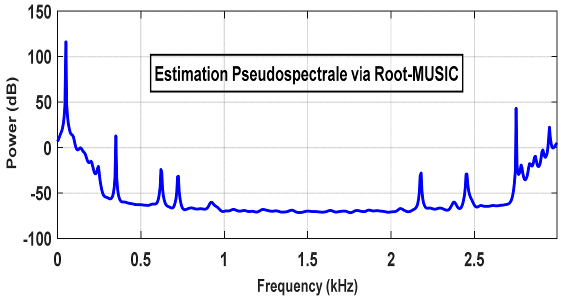


Figure 7. One bar broken spectra



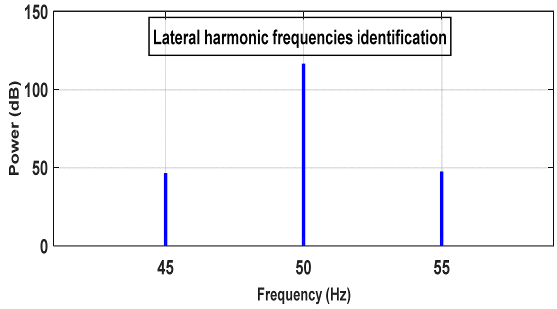


Figure 8. Two bars broken spectra

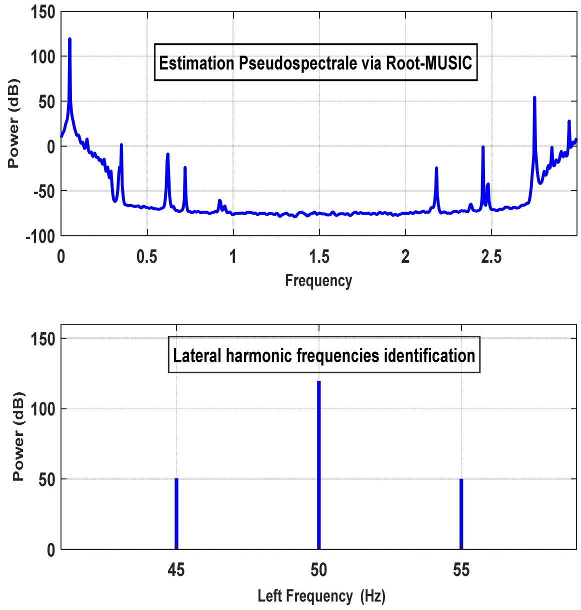


Figure 9. Three bars broken spectra

5.2. Bar Defect type Recognition

SVM results from Statistical Learning Theory (SLT). When we have a small number of samples, machine learning methods. In fact, we constructed firstly the spectrum characteristics (pairs of powers) from the bilateral frequencies around the fundamental and we used secondly them as learning sample vectors for the SVM. After the SVM is trained. With learning sample vectors, so each type of the rotor broken bar faults can be recognized. Indeed, we took 12 pairs of each fault type for learning, Table 1 and the rest of files are used for the test.

Table 1. Power Pairs of each fault type for learning

Powers (dB) for One bar broken		Powers (dB) for Two bars broken		Powers (dB) for Three bars broken	
48.752	51.4366	49.5013	51.7042	49.5944	49.4923
52.1003	47.9411	48.9350	48.5370	50.0085	47.7852
51.9416	47.4957	51.3352	50.1351	49.9069	49.8408
47.6986	48.2643	49.1135	50.5950	47.6278	49.2341
50.5346	50.4033	49.6037	48.5266	50.2183	49.8896
51.3638	47.5008	49.2006	49.1763	51.4591	48.1869
49.8602	49.0970	48.2828	50.2362	49.3591	49.2229
50.5478	48.8412	48.9331	48.9718	51.2003	47.2485
51.7900	46.1926	49.7792	51.3134	49.2978	50.4354
51.6632	48.9048	51.3163	49.5395	50.8065	48.9794
53.2510	49.9289	51.2988	50.8447	50.0568	49.5540
52.5242	52.3247	50.4173	48.9098	48.7497	48.5750

During the training, we chose the Gaussian kernel with the optimization of its parameters (the mean μ, the standard deviation σ) being done automatically by MATLAB (version R2022b) Figures 10 and 11. Once the training of the SVM is completed, we tried the test so we took each of the test files at random and introduced it to our system for identification. The recognition procedure used here is Maximum Posterior estimation (MAP) that can be used to estimate a number of unknown parameters related to a given sample on the basis of empirical data [22]. As a result, Figures 12-14, the one bar broken defect is recognized with 0.34 of probability, the two bars broken defect is with 0.46 and the three bars broken defect is with 0.42; which is acceptable in the context of empirical data. In [24], an intelligent multi-agent system (MAS) is used to make decisions on the fault conditioning of a three-phase squirrel cage induction motor. For one broken bar the performance of the system is between 80.3%- 84.9%, that of the two broken bar is between 86.3%-87.9% and that of the three broken bar is between 84.1%-87.9%.

In [25], they apply an algorithm based on the combination of both the Park's vector approach (PVA) and the extended Park's vector approach (EPVA) for broken rotor bars (BRBs) fault detection and identification. They obtain a simple graphical view of the presence of abnormal operating conditions. However, the structure does not give a precise quantitative conception as to the magnitude of the problem. The main disadvantage of this method is the lack of information about the severity of the fault when the induction motor is unloaded or lowly loaded, although the fault is detected. In [26], they use the wavelet coefficients by the motor current signature analysis to extract the features and SVM for identify the healthy and faulty conditions, among these broken rotor bar. The accuracy is close to 93.33%. Our own is able to recognize successfully all types of bar defect. In fact, the recognition rate is unexpected and fortunately 100%.

6. CONCLUSION

Our aim of this humble work has been finally to carry out a system which is entitled to imitate a human expert in instrumentation; this last from the spectra of stator current will determine the state of the asynchronous motor then to identify the type of the fault if it is failed. In fact, this goal was highlighted thanks to twinning of the spectral approach Root-MUSIC with the procedure of artificial intelligence SVM. Indeed, we also gathered by this marriage the spectral accuracy, the reduction in the set of the necessary data to training as well as minimization of ambiguity in the decision-making concerning the kind and the category of the defect. Lastly, we hope for the implementation of this system in a chip of the type ASIC or FPGA.

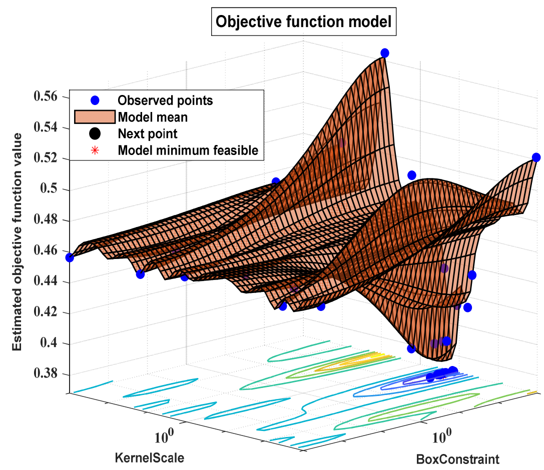


Figure 10. Kernel function optimization

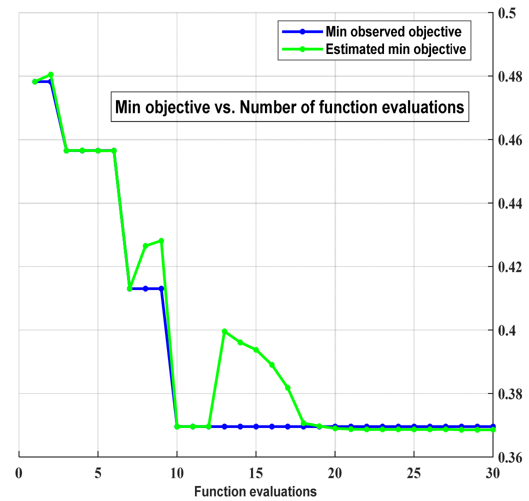


Figure 11. Number of kernel function evaluations optimization

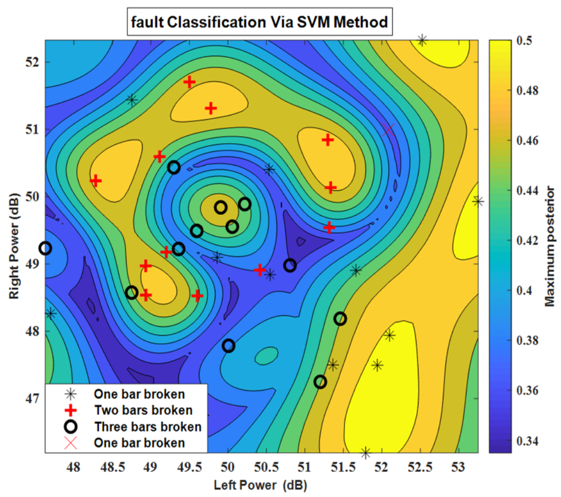


Figure 12. One bar fault recognition

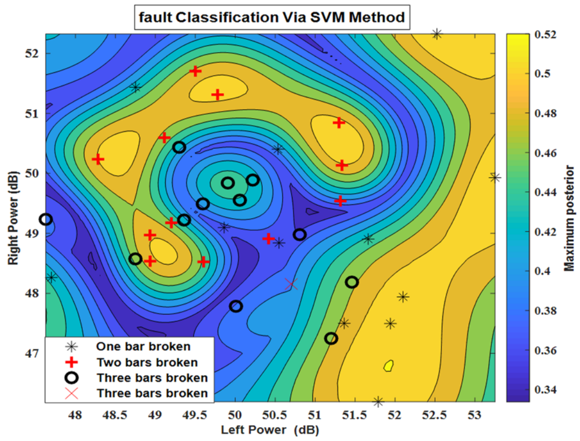


Figure 13. Two bars fault recognition

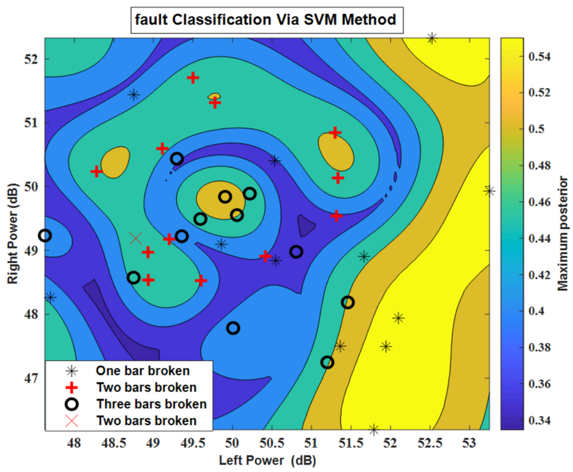


Figure 14. Three bars fault recognition

APPENDIX

Experiments of Induction Motor Characteristics

Description	Value
Power	3 k W
Supply frequency	50 Hz
Input voltage	380
Full load current	7A
Rotor speed	1440 rpm
Number of rotor bars	28
Number of stator slots	36
Power factor	0.83
Number of pair of poles	2

NOMENCLATURE

1. Acronyms

SVM	Support Vector Machine
MCSA	Motor Current signal Analysis
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
FFT	Fast-Fourier-Transform
MUSIC	Multiple-Signal-Classification
MIN-NORM	MINimal NORM
SLT	Statistical Learning Theory
MAP	Maximum Posterior estimation
ESPRITT	Estimation of signal parameters via rotational invariance techniques

2. Symbols / Parameters

I_s : Stator current
A_k: Magnitude and Phase of the k^{th} component
ω_k: The k^{th} frequency
F_s: The sampling frequency
r_s: Autocorrelation sequence of the stator current
R_s: Autocorrelation matrix of the stator current
e_k: The k^{th} autocorrelation matrix eigenvector
λ_k: The k^{th} eigenvalue
Λ: The power matrix of the harmonics
σ_0^2 : White noise variance
I: Identity matrix
S: The estimated signal pseudospectrum
P_i: Power of the component i
$\propto_i$: Lagrange multipliers
x_i: Support vectors
$f(x)$: The decision functions
f_{sh}: Harmonic frequencies of the rotor slots
f_0: Power supply frequency
s: The slip
p: Pole pairs number
ρ: Order time harmonics
n_b: Rotor bars number
i_{ds}: The stator direct component current
f_b: Lateral harmonic frequencies around the fundamental
i_a, i_b, i_c: Three phases' currents

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