Copyright IPCO-2014
Vol.2
ISSN : 2356-5608

Conférence Internationale des Energies Renouvelables (CIER'13)
Sousse, Tunisie - 2013

Optimization of Vibration Data Using Particle Swarm Optimization Applied to Induction Machine Faults

Abla Bouguerne [#1], Abdesselam Lebaroud [*2], Aziz Boukadoum [#3]
[#1] *Laboratory LGEC Constantine, Department of Electrical Engineering, University of Constantine, Algeria*
bouguerneabla@yahoo.fr
[*2] *Laboratory LGEC Constantine, Department of Electrical Engineering, University of Skikda, Algeria*
lebaroud@yahoo.fr
[#3] *Department of Electrical Engineering, University of Tebessa, Algeria*
azizboukadoum@yahoo.fr

Abstract— **This article focuses on a new method the classification of bearings faults of induction motor, that's as it happens the time-frequency dependent class signal "RTFDCS", the first we are normalized the analytical vibration signals of bearing faults. by Hilbert transforms; The main advantages of the PSO algorithm are: simple concept, easy implementation, robustness and computational efficiency compared with the mathematical algorithm and other optimization heuristics. We will use the PSO to optimize the size of the vectors extracted forms the RTFDCS.**
.

Keywords— ***component; classification; time-frequency representation; bearing faults; axial vibration analytic signals(AVAS),;Hilbert transform,;PSO algorithm.***

I. INTRODUCTION

Fault diagnosis is often confronted with the problem of extracting vectors forms (Commonly known as a characteristics vector) that are relevant to the small size and best possible representation of the fault state. Several approaches have been discussed in the literature is the most a view pattern recognition [1], principal component analysis (PCA) and time-frequency representation [2].

In the traditional classification, data were often transformed into a Time-Frequency Representation (TFR) standard (eg the spectrogram or the Wigner-Ville TFR),then a projection was applied to the TFR for reach a reduced dimension of space [3]. In diagnosis of rotating machinery, vibration analysis is widely known to be one of the most effective techniques. This stems from the fact that oscillation is an inherent characteristic of rotating machines and different components of these types of machinery such as shafts, bearings and gears produce vibration energy with different characteristics. Any deterioration in the condition of such components can affect their vibratory attributes and manifest itself in the vibration signature. This allows diagnosis of machine faults by analyzing the vibration signature of the system.

For improved and authentic fault diagnosis using vibration analysis techniques it is necessary that the acquired vibration signals be 'clean' enough that small changes in signal attributes due to an impending fault in any component can be detected. To tackle this problem, we have developed a method based on the cloud points dispersion parameter.

In this article we used the vibration analytical signals normalized by Hilbert transform of bearing fault of induction motor, then the extracting vibrational vectors forms from RTFDCS. It is deliberately designed to maximize separability between classes and minimize the intra-class variance. Fisher contrast is used to design the kernel nonparametric RTFDCS, and recently the optimization of the size of these vectors by the PSO algorithm.

II. VIBRATORY DATA TREATMENT BY HILBERT TRANSFORM

Vibration Analytics Signal method use the principle of the analytical signal obtained by Hilbert transform. Hilbert transform finds a companion function $y(t)$ for a real function $x(t)$ so that [3] : The Hilbert transform of a signal $y(t)$ can be written as:

$$y(t) \xrightarrow{TH} \tilde{y}(t) = \tilde{y}_{\mathrm{Re}}(t) + j\tilde{y}_{\mathrm{Im}}(t) \quad (1)$$

Where

$\tilde{y}_{\mathrm{Im}}(t)$ is the Hilbert transform of the signal $\tilde{y}_{\mathrm{Re}}(t)$

The amplitude modulation $A(t)$ of the time signal $y(t)$ is calculated by using the following relationship:

$$A(t) = \sqrt{\tilde{y}_{\mathrm{Re}}(t)^2 + \tilde{y}_{\mathrm{Im}}(t)^2} \quad (2)$$

we get :

$$V(t) \xrightarrow{TH} \tilde{V}(t) = \tilde{V}a_{\mathrm{Re}}(t) + j\tilde{V}a_{\mathrm{Im}}(t) \quad (3)$$

Where

$\tilde{V}a_{\mathrm{Im}}(t)$ presents the Hilbert transform of the vibration signal $\tilde{V}_{\mathrm{Re}}(t)$.

The signal $\tilde{V}(t)$ is usually called Vibration Analytic signal

The amplitude modulation $A(t)$ is:

$$A(t) = \sqrt{\tilde{V}_{\mathrm{Re}}(t)^2 + \tilde{V}_{\mathrm{Im}}(t)^2} \quad (4)$$

The real and imaginary vibrations are normalized to the module of the Analytic Vibration signal

$$\tilde{V}'_{\mathrm{Re}}(t) = \frac{\tilde{V}_{\mathrm{Re}}(t)}{A(t)} \quad (5)$$

$$\widetilde{V}'_{\text{Im}}(t)=\frac{\widetilde{V}_{\text{Im}}(t)}{A(t)} \tag{6}$$

the average vibration is given by:

$$m_{\widetilde{V}_{\text{Re}}}=\frac{1}{N_{\widetilde{V}'}}\sum_{k=1}^{N_{\widetilde{V}'}}\widetilde{V}'_{\text{Re}}(k) \tag{7}$$

$$m_{\widetilde{V}'_{\text{Im}}}=\frac{1}{N_{\widetilde{V}'}}\sum_{k=1}^{N_{\widetilde{V}'}}\widetilde{V}'_{\text{Im}}(k) \tag{8}$$

The normalized characteristics $\widetilde{V}'_{\text{Im}}\left(\widetilde{V}'_{\text{Re}}\right)$ consists of a cloud points $N_{\widetilde{V}'}$.

The parameter ξ ,that present the cloud dispersion of these points is defined as.

$$\xi=\sum_{k=1}^{N_{va}}\left(A_k-\widetilde{V}'_{\text{Re, Im}}\right)\left(A_k-\widetilde{V}'_{\text{Re, Im}}\right)^T \tag{9}$$

Where

$\widetilde{V}'_{\text{Re, Im}}=\left[\widetilde{V}'_{\text{Re}},\widetilde{V}'_{\text{Im}}\right]$ is gravity center of the assembly

A_k is a point with coordinates $\widetilde{V}'_{\text{Re}}(k)$ and $\widetilde{V}'_{\text{Im}}(k)$.

The parameter ξ is relatively sensitive to different states of the machine such as defected bearings, broken bars or unbalanced feed [4].

III. VECTORS FORMS EXTRACTION BY TFR DEPENDENT CLASS SIGNAL

The kernel $\phi_{opt}(\eta,\tau)$ is designed for each specific classification task. We determine N locations from the ambiguity plane, in such a way that the values in these locations are very similar for signals from the same class, while they vary significantly for signals from different classes[4],[5].

The notation $A_{ij}[\eta,\tau]$ presents the ambiguity plane of the jth training example in the ith class. We design and use Fisher's discriminant ratio (FDR) to get those N locations.

The discrimination between different classes is made by separating the class i of all remaining classes $\{i+1,...,N\}$ .In this case, The bearing fault kernel is designed to discriminate bearing fault class from the healthy motor class.

The kernels are designed by I training example signals from each class with the equation as follows:

$$J_i(\eta,\tau)=\frac{\left(m_i[\eta,\tau]-m_{i-res\tan t}[\eta,\tau]\right)^2}{V_i^2[\eta,\tau]+V_{i-res\tan t}^2[\eta,\tau]} \tag{10}$$

Where:

$m_i[\eta,\tau]$ and $m_{i-res\tan t}[\eta,\tau]$ represent two means of location (η,τ)

$$m_i[\eta,\tau]=\frac{1}{N_i}\sum_{j=1}^{N_i}A_{ij}[\eta,\tau] \tag{11}$$

$$m_{i-remain}[\eta,\tau]=\frac{\sum_{k=i+1}^{4}\sum_{j=1}^{N_k}A_{kj}[\eta,\tau]}{\sum_{k=i+1}^{4}N_k} \tag{12}$$

$I=N_1\cdot N_2$ is the number of examples per class,

N_2 the number of current examples of same load level and

N_1 the number of load levels,

$V_i^2[\eta,\tau]$ and $V_{i-res\tan t}^2[\eta,\tau]$ represent two variances of location (η,τ):

$$V_i^2[\eta,\tau]=\frac{1}{N_i}\sum_{j=1}^{N_i}\left(A_{ij}[\eta,\tau]-m_i[\eta,\tau]\right)^2 \tag{13}$$

$$V_{i-remain}^2[\eta,\tau]=\frac{\sum_{k=i+1}^{4}\sum_{j=1}^{N_k}\left(A_{kj}[\eta,\tau]-m_{i-res\tan t}[\eta,\tau]\right)^2}{\sum_{k=i+1}^{4}N_K} \tag{14}$$

IV. VECTORS FORMS OPTIMIZATION BY PSO

The particle swarm optimization (PSO) algorithm is a search process based populations where individuals, referred to as particles, are grouped in a swarm. Each particle in the swarm represents a candidate solution to the optimization problem [14], [15], [17]. In a PSO system, each particle is "controlled" in the multidimensional space search, adjusting its position in space according to its own experience and that of neighboring particles [16].

A particle is, therefore, produced by the best position itself and its neighbors to move towards an optimum solution. This shift occurs following a path defined by a fitness function (or objective function) which encapsulates the characteristics of the optimization problem.

Thus, each particle P_i is positioned (randomly or otherwise) in the search space of the problem and is characterized by its current position $x_i(t)$ and its current speed $v_i(t)$. The new position $x_i(t+1)$ of a particle P_i is determined by adding the speed $v_i(t)$ at its current position $x_i(t)$ as follows[10]:

$$x_i(t+1)=x_i(t)+v_i(t) \tag{15}$$

Is the velocity vector $v_i(t)$ that directs the research process and reflects the "sociability" of the particles. Considering N particles of P_i and each particle compares its new position to its best position obtained, it gives the following algorithm , where f is the fitness function which evaluates the quality of the particle.

The main advantages of the PSO algorithm are: simple concept, easy implementation, robustness and computational efficiency compared with the mathematical algorithm and other optimization heuristics. We will use the PSO to optimize the size of the vectors extracted forms the RTFDCS.

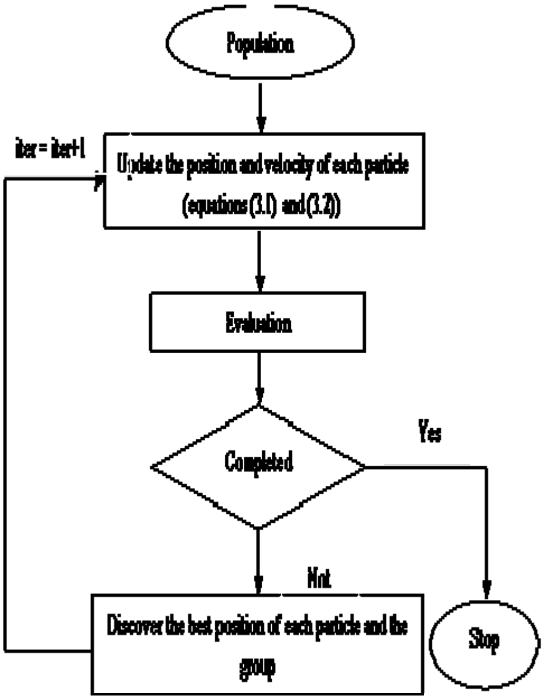

Fig. 1. Based diagram of the PSO

V. OPTIMIZATION OF A ANALYTICAL VIBRATORY BEARING DATA

The vibration data that were used for analysis are obtained from the Case Western Reserve University Bearing Data Center [18]. Reliance Electric's 2-hp motor, along with a torque transducer, a dynamometer, and control electronics, constitutes the test setup. With the help of electrostatic discharge machining, faults of sizes of 0.177 mm (0.07 in) and 0.533 mm (0.21 in) are made. The vibration data are collected using accelerometers placed at the three-o'clock position. The rotational frequency (Fr) is 29 Hz[17].

The fig 2 and 3 present respectively ; Bearing vibration data for four signals (healthy bearing, inner race, ball and outer faults bearing) and spectrums for each signals

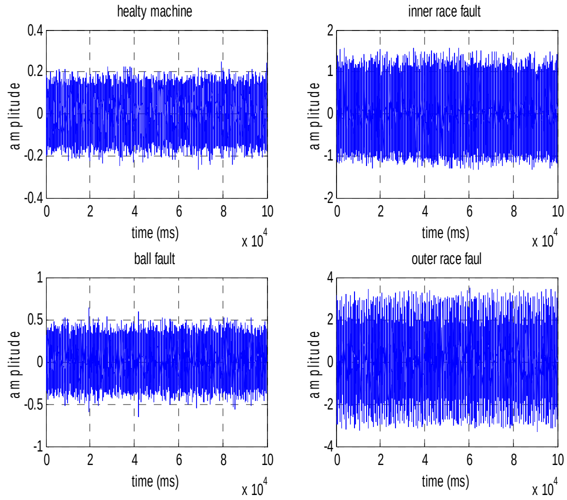

Fig 2. Bearing vibration data

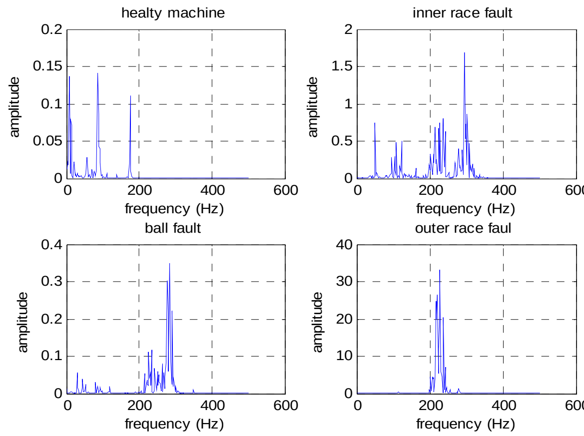

Fig 3 .Bearing vibration data spectrums

Since, we cannot use the Analytics vibration signals (AVS) directly due to their very low values. We have proposed pretreatment methods before TFR. We have proposed a method for calculating a parameter very interesting to know the parameter ξ of the cloud dispersion of points. This parameter is used to calculate the TFR and extraction vectors forms.

A. *Vectors forms optimization by PSO*

The Optimization of vectors forms for four classes healthy bearing, inner race, ball and outer faults bearing will be do by Particle Swarm optimization algorithm. with the optimization criterion, the optimization of vectors forms will be fitting and executing to extract pertinent points.

Variables initialize:

N = 20: size of the swarm

maxit = 50: iterations maximum number .

c1 = 2: cognitive parameter

c2 =4 c1 : social parameter

wmax = 0.9, wmin = 0.4: inertia weight

xmin = 2 xmax = 10: the parameter Limits

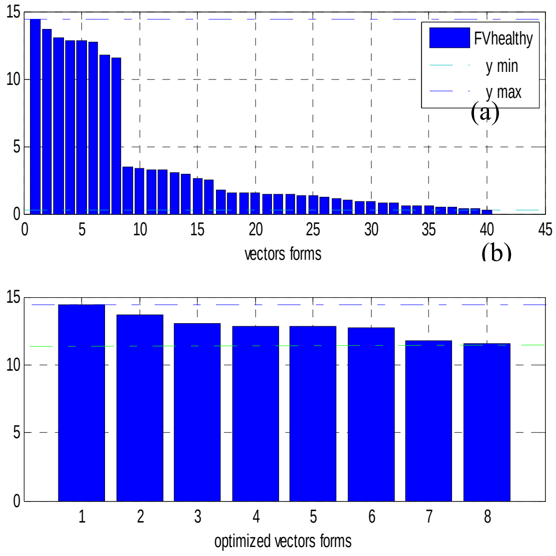

Fig 4. Vectors forms of healthy bearing
(a) before optimization (b)after optimization

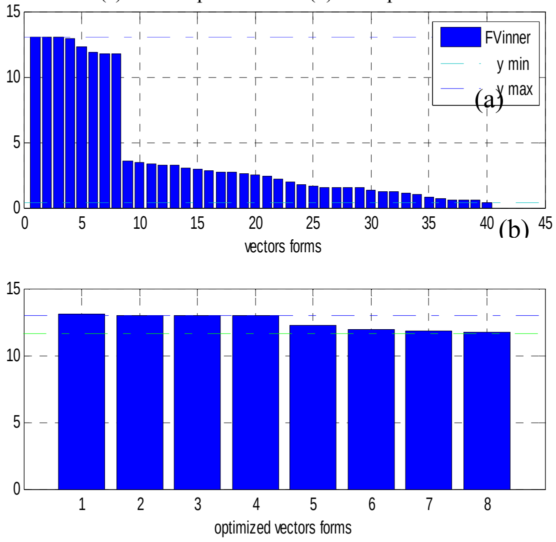

Fig 5. Vectors forms of inner race faults
(a) before optimization (b)after optimization

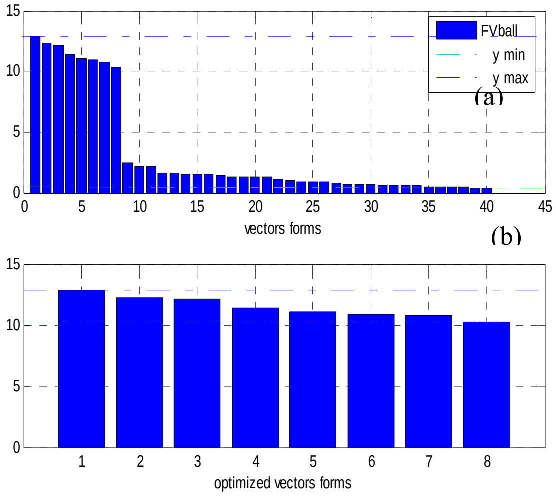

Fig 6 . Vectors forms of ball faults
(a) before optimization (b)after optimization

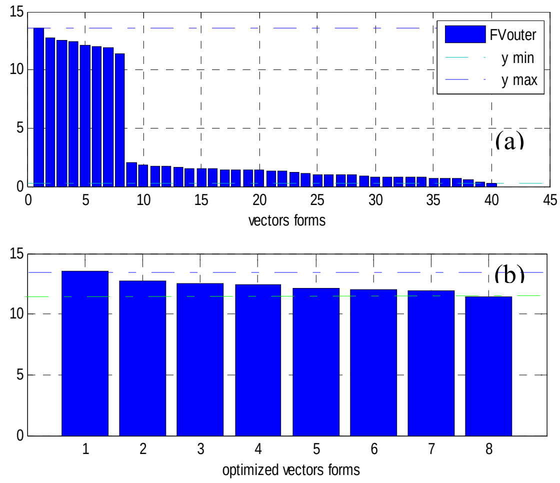

Fig 7 . Vectors forms of outer faults
(a) before optimization (b)after optimization

Fig 4,5,6 and 7 have a representation of vectors forms for four classes healthy bearing, inner race, ball and outer faults bearing before and after optimization by Particle Swarm optimization algorithm. We were able to reduce the size of point in the vectors forms in classes. before optimization, each classes is characterized by four vectors forms and each vectors forms comported ten points (element) relevant called scores or high contrast in the sense of Fisher. after optimization, each classes is characterized by four vectors forms and each vectors forms comported only two points (element) relevant also called scores or high contrast in the sense of Fisher.

VI. CONCLUSION

In this paper , we have Using time-frequency representation dependant class signal (RTFDCS) and particle swarm optimization for Classification Vibration Data of healthy bearing, inner race, ball and outer faults bearing . in the first part, we are used our vibration signal of four classes healthy bearing, inner race, ball and outer faults bearing for the diagnosis, and because of their vibration signals have low values applies the Hilbert transform methods for pretreatment of these vibratory signals before the RTFDCS ,that allow the calculate of the cloud points dispersion parameter ,this parameter shawn clearly the points are very separated for healthy bearing, inner race, ball and outer faults bearing. the following ,the optimization processing, illustrate that each classes is characterized by four vectors forms and each vectors forms comported only two points (element) relevant also called scores or high contrast in the sense of Fisher.

VII. REFERENCES

[1] O. Ondel, E. Boutleux, and G. Clerc, "Feature selection by evolutionary computing: Application on diagnosis by pattern recognition approach," in CAINE, S. Dascalu, Ed., 2005, pp. 219–225.

[2] Lebaroud, Abdesselam, Clerc, Guy " Classification of Induction Machine Faults by Optimal Time-Frequency representations ", IEEE Transactionson Industrial Electronic, Vol.57, n°12, pp.4290-4298,2008.

[3] Castelli Marcelo, Juan Pablo Fossatti and José Ignacio Terra "Fault Diagnosis of Induction Motors Based on FFT" Fourier Transform - nal Processing, Dr Salih Salih (Ed.), 2012.

[4] Atlas L., Droppo J., and McLaughlin J., "Optimizing time-frequency distributions via operator theory," Proc. SPIE, vol. 3162, pp. 161–171, 1997.

[5] Davy M. and Doncarli C., "Optimal kernels of timefrequency representations for signal classification" inProc. IEEE-SP Int. Symp. Time-Freq. Time-Scale Anal., 1998, pp. 581–584.

[6] Wang M., Rowe G. I., and Mamishev A. V., "Classification of power quality events using optimal time-frequency representations—Part 2: application," IEEE Trans. Power Delivery, vol. 19, pp. 1496–1503, 2004.

[7] Y. del Valle et al., « Particle swarm optimization: Basic concepts, variants and applications in power systems », IEEE transactions on evolutionary computation, vol.12, no.2, April 2008.

[8] R. R. Schoen ;T.G.Habetler ; F. Kamran ; R. G. Bartheld; "Motor Bearing Damage Detection Using Stator Current Monitoring". IEEE Transaction on Industry Applications, vol 31, N°6, pp. 1274-1279, November- December 1995.

[9] M. Blǫdt et al. "models for bearing damage detection in induction motors", IEEE transactions on industrial electronics, vol. 55, no. 4, April 2008

[10] B. Yazici, and G. B. Kliman, "An adaptive statistical time–frequency method for detection of broken bars and bearing faults in motors using stator current," IEEE Transactions on Industry Applications 35(2), pp. 442–452. 1999.

[11] H. Ocak, and K. A. Loparo, "Estimation of the running speed and bearing defect frequencies of an induction motor from vibration data," Mechanical Systems and Signal Processing 18(3), pp. 515–533. 2004.

[12] W. Zhou; T. G. Habetler; R. G. Harley; "Stator Current-Based Bearing Fault Detection Techniques: A General Review", IEEE International Symposium on. Diagnostics for Electric Machines, Power Electronics and Drives, pp. 7–10, 6-8 Sept 2007

[13] A. Abido, "Optimal power flow using particle swarm optimization", Int. J. Elect. Power Energy Syst., vol. 24, no. 7, October 2002, pp. 563–571.

[14] F. Bergh and A. Engelbrecht., « A cooperative approach to particle swarm optimization », IEEE Trans. Evol. Comput., vol. 8, no. 3, June 2004, pp. 225 239.

[15] Maurice Clerc., « L'optimisation par essaim particulaire », Tutorial pour PSO 2003

[16] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space", IEEE Trans. Evol. Comput., vol. 6, no. 1, February. 2002, pp. 58–73.

[17] A. Santhana Raj and N. Murali «Early Classification of Bearing Faults Using Morphological Operators and Fuzzy Inference»IEEE Transactions on industrial electronics, vol. 60, no. 2, february 2013

[18] Bearing Data Center, Case Western Reserve Univ., Cleveland, OH.[Online].Available:http://www.eecs.case.edu/laboratory/bearing