2018 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC 2018). Ixtapa, Mexico

Condition Monitoring Strategy Based on Spectral Energy Estimation and Linear Discriminant Analysis Applied to Electric Machines

Mayra Ramirez-Chavez, Juan Jose Saucedo-Dorantes, Rene de Jesus Romero-Troncoso, Roque Alfredo Osornio-Rios, Luis Morales-Velázquez
HSPdigital CA-Mecatronica
Engineering Faculty, Autonomous University of Queretaro
San Juan del Rio 76806, Mexico

Miguel Delgado-Prieto
MCIA Research Center
Department of Electronic Engineering, Technical University of Catalonia (UPC)
Barcelona, Spain

***Abstract*—Condition-based maintenance plays an important role to ensure the working condition and to increase the availability of the machinery. The feature calculation and feature extraction are critical signal processing that allow to obtain a high-performance characterization of the available physical magnitudes related to specific working conditions of machines. Aiming to overcome this issue, this research proposes a novel condition monitoring strategy based on the spectral energy estimation and Linear Discriminant Analysis for diagnose and identify different operating conditions in an induction motor-based electromechanical system. The proposed method involves the acquisition of vibration signals from which the frequency spectrum is computed through the Fast Fourier Transform. Subsequently, such frequency spectrum is segmented to estimate a feature matrix in terms of its spectral energy. Finally, the feature matrix is subjected to a transformation into a 2-dimentional base by means of the Linear Discriminant Analysis and the final diagnosis outcome is performed by a NN-based classifier. The proposed strategy is validated under a complete experimentally dataset acquired from a laboratory electromechanical system.**

Keywords—Condition monitoring, fault detection, induction motor, feature extraction, signal processing.

I. INTRODUCTION

The application of condition monitoring strategies applied to fault diagnosis in rotating machinery plays an important role to ensure its availability and its proper working condition. In this regard, induction motors (IM) represent the most reliable electric machines used in industrial applications due to its robustness and low cost [1]. However, the sudden appearance of unexpected faults is inherent to its working condition, indeed, the most common faults in IM are related to problems in bearing elements, rotors, stator windings, misalignments, unbalances, among others [2]. Therefore, the development new technologies applied to the solution of problems in modern industry has to be addressed in order to ensure the proper working condition the machinery.

Different physical magnitudes have been used in condition monitoring strategies, however vibration signal analysis remains as the most reliable approach to assess the working condition in rotting machines; indeed, through its appropriate application significant results may be obtained [3]. Classical analysis based on the calculation of the Root Mean Square (RMS) value from the measured vibration signal have been successfully implemented [4]-[5]; moreover, other signal processing involves the calculation of frequency spectrum through the Fast Fourier Transform (FFT) [6]. In this sense, the application of the FFT to vibration signals is for analyzing specific fault-related frequency components; although a different vibration response is generated in function the working condition, it could happen that different fault produce similar frequency components, and the distinguish between them represent a critical problem due to the fault-related frequencies appear overlapped.

Condition monitoring strategies based on different signal processing approaches represent a coherent solution to perform the assessment of the rotating machine condition. Thereby, time domain, frequency domain and time-frequency domain represent the most used techniques, yet, although, significant results may be obtained through its application, most of the times low-performance results could be estimated when the identification of multiple faults is addressed [7]. To overcome this issue, the calculation of high-dimensional feature sets to increase the capability of characterization has been also considered in condition monitoring strategies [8].

Although the calculation of high-dimensional set of features increase the discriminative capability between different conditions, the calculation of non-useful, significative and redundant information is inevitable; thus, the performance of the final diagnosis outcome may be affected instead of increase. In this regard, the application of dimensionality reduction techniques may lead to obtain a high-performance characterization avoiding overfitted responses [9]. The most well-known techniques used with dimensionality reduction approaches are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), and the application of these techniques

This research work was partially supported by CONACYT, Mexico, under the master's degree grant number 291236.

978-1-5386-5935-9/18/$31.00 ©2018 IEEE

depends of different criteria; PCA aims to maximize the data variance, while LDA aims to maximize the linear separation between different classes [8]-[10]. Moreover, by means of reducing an original database space, the classification task is facilitated to the considered classification algorithm.

Therefore, the contribution of this research work lies in the proposal of a novel condition monitoring strategy based on the spectral energy estimation and LDA for the identification of different faults in an IM-based electromechanical system. The proposed method is based the calculation of a feature matrix where the discriminative capabilities of vibration signals are enhancing by estimating the spectral energy. Contributions and novelties include the validation of the proposed method as a suitable patter characterization method that allows to obtain a data visual representation supported by the LDA for feature extraction and dimensionality reduction. Moreover, the proposed method is validated under a complete experimentally dataset acquired from a real laboratory electromechanical system, where five different operating conditions are tested. The obtained results make the proposed methods suitable for being applied for the condition monitoring and fault identification in electric machines used in industrial applications.

II. Theoretical Basis

A. Feature calculation

Most of the proposed data-driven condition monitoring strategies include a feature calculation stage, indeed, the feature calculation represents the most important stage from which the pattern recognition and condition assessment is performed. Therefore, by means of applying a feature calculation, the available physical magnitudes, such as stator current signatures, mechanical vibrations, temperatures, among others, are transformed into more characteristic and representative information [11]-[12]. Regarding the condition monitoring and fault assessment in electromechanically systems, the feature calculation plays a key role that allows to highlight characteristic information that has the most useful, representative and discriminative capabilities related to specific working condition. Certainly, different approaches and techniques applied for signal processing can be also considered and used previous to the feature calculation, this is with the aim of representing the data in different ways [14]-[15.]

In this regard, time domain, frequency domain and time-frequency domain techniques are the most well-known approaches that have been widely considered during signal processing. However, frequency-based features estimated through classic techniques such as FFT have been successfully used in condition monitoring strategies to assess the working condition of electric machines. In this sense, the condition assessing is classically performed by analysing the amplitude increase of specific fault-related frequency components [15]-[17].

B. Feature extraction

Feature extraction is another important stage that may be considered in condition monitoring strategies, a feature extraction approach aims to reduce the dimensionality space of an initial set of features into a reduced subset of features; where the resulting subset is mainly composed by the combination of different weights of the initial set of features [8]. The application of feature extraction techniques depends of different criteria; in this regard, its applications mainly differs of whether the considered technique is supervised or unsupervised. Both techniques, supervised and unsupervised, differs in the availability of the considered labels that distinguish between different classes [9].

Thus, linear discriminant analysis (LDA) is one of the most well-known supervised techniques and it has been widely used for extracting a subset of features and for reducing the initial dimensionality of the original set of features in problems where multiple classes are considered [9], [15]. The LDA aims to find a new projection into a low-dimensional representation where the most discriminative information is contained. That is, LDA attempts to maximize the linear separation between data points clusters which belongs to different classes [8]-[9]. Due to LDA pays attention to differences known classes, its appropriate application in condition monitoring strategies is suitable to assess different operating conditions in electromechanical systems.

III. Proposed Method

The proposed diagnosis method for assessing different operating conditions in an IM-based electromechanical system is manly composed by four stages, as flow char of Fig. 1 depicts.

First, in the data acquisition, two vibration signals that belong to the perpendicular plane of the IM rotating axis are continuously acquired during the experimental evaluation of each considered condition, in this regard, one hundred IM vibration measurements are acquired for each evaluated condition, where, each measurement characterizes one second of the electromechanical system working condition.

Second, the feature estimation, each acquired vibration signal is characterized by estimating the spectral energy from their corresponding frequency spectra. In this sense, for each condition, the vibration signals are first segmented in equal parts of two seconds; then, by means of the FFT is computed the frequency spectrum for each segmented part. Thus, each computed spectra represent a bandwidth from 0 Hz to 1500 Hz, subsequently; each spectra is also segmented in fifteen equal parts representing a small slices with a bandwidth of 100 Hz from which the spectral energy is estimated. Consequently, the vibration signals from each evaluated condition are represented by a characteristic feature matrix composed by fifty samples with thirty different values that are in terms of the spectral energy.

In the third step, feature extraction, the estimated feature matrices representing all the considered conditions are

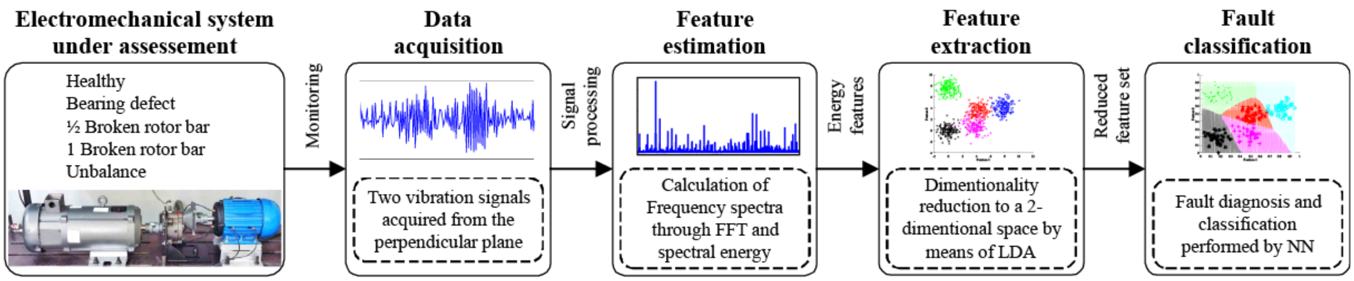


Fig. 1. Proposed diagnosis methodology used for assessing different operating condition in an IM-based electromechanical system.

subjected to a dimensionality reduction and base transformation process by means of the LDA technique. This procedure allows to compress the available information into a 2-dimentiona space from which it is also possible to obtain a graphical representation of all the considered conditions; moreover, these new extracted features facilitates the classification task.

Finally, in the fourth step, the fault classification and diagnosis outcome if carried out by evaluating the extracted set of features through a NN-based classifier. In this regard, due to the high-performance signal characterization, the proposed classifier has a simple structure with two input neurons that belongs to the two dimensional representation of all considered conditions; in the hidden layer, ten neurons are considered as in classic applications is recommended; and in the output layer, five neurons are used to represent the considered conditions.

IV. Experimental Test Bench

The experimental test bench used to validate the proposed method is based on al electromechanical system that consist of a 1492-W three-phase IM model WEG00236ET3E145T-W22, a 4:1 ratio gearbox model BALDOR GCF4X01AA and a DC generator model BALDOR GCF4X01AA that is used as a mechanical load. A picture of the experimental test is shown in Fig. 2, as it can be seen, the IM is mechanically coupled and drives the gearbox; which in turn, is coupled and drives the DC generator. A variable frequency drive (VFD) model WEGCFW08 is used to feed and control the IM, on the other hand, the DC generator comprises around 20% of the nominal load during the IM working condition.

The vibration signals from the perpendicular plane of the IM rotating axis are continuously monitored and acquired through a triaxial accelerometer model LIS3L02AS4 attached on the top of the gearbox, such accelerometer is mounted on a board with its corresponding signal conditioning and anti-alias filtering. The data acquisition is performed by a 12-bit 4-channel serial-output sampling analog-to-digital converters model ADS7841 which is used on board of the data acquisition system (DAS). Such DAS is a proprietary, low-cost design, that is based on field programmable gate array technology (FPGA). The design of the DAS under FPGA technology allows to acquire the occurrence of vibrations in the electromechanical system with high accuracy and resolution, thereby, a sampling frequency of 3 kHz is used to acquire the occurrence of vibrations, as a result 300 kS are stored in a personal computed during 100 seconds of continuous sampling in the steady state of the working condition of the IM.

In this study five different conditions are assessed in the IM: healthy (HLT), bearing defect (BD), half-broken rotor bar (½ BRB), one broken rotor bar (1 BRB) and misalignment (MAL). In this regard, the considered faulty conditions are artificially produced as follows: the bearing is damaged by drilling, with a tungsten, a drill hole with 1.191 mm of diameter on the bearing outer race. In Fig. 3a is shown the damaged bearing, model 6205-2ZNR, used in the experiment. The BRB conditions are produced in two different IM rotors, and both are damaged by drilling a hole with 6 mm of diameter; where the drilled hole of the ½ BRB condition covers around 22% of the transversal section of the rotor bar (approximately 3mm of depth). And, For the 1 BRB fault, a through-hole is made (approximately 14 mm of depth) to drilling the complete transversal section of the rotor bar. In Fig. 3b and Fig. 3c are shown both damaged IM rotors, ½ BRB and 1 BRB, respectively. Finally, the MAL condition appears when the centerlines of coupled shafts are not perfectly aligned with each other; consequently, the increase of dynamic loads is produced by the affectation of bearings and couplings. Hence, to produce the MAL condition, an angular

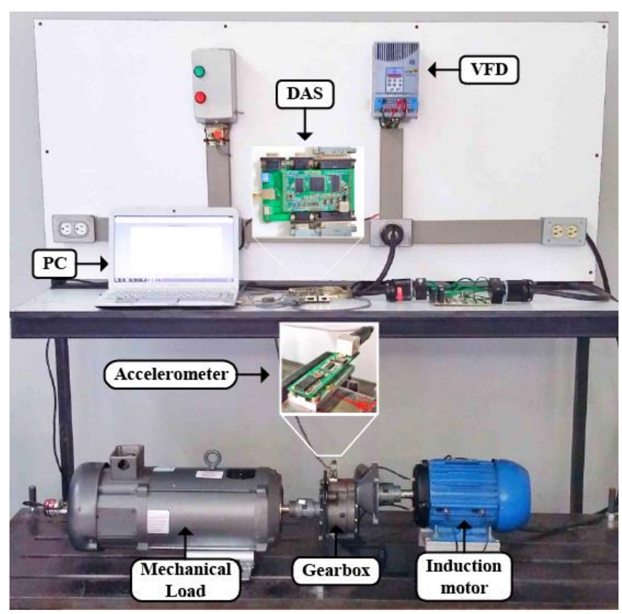
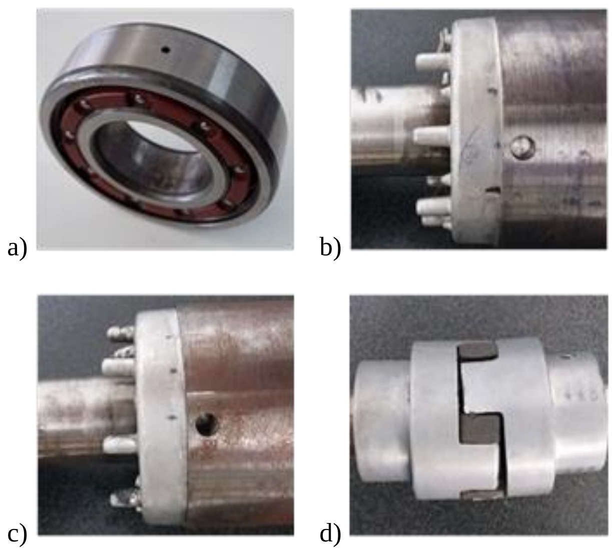


Fig. 2. Experimental test bench used to assess different conditions in the IM.

misalignment is produced by moving the free end of the IM (approximately 5 mm on the horizontal plane); such misalignment, produced between the coupled shafts, is shown in Fig. 3d.

The experiments are carried out by replacing iteratively each of the damaged elements with the healthy ones. Only the MAL condition is that produced by moving the free end of the IM as above explained. Moreover, during the performance of experiments, three different operating conditions are set in the VFD to drive the IM, the set frequencies are 50 Hz, 15 Hz and 5 Hz that produce an averaging rotating speed of 2985 rpm, 890 rpm and 294 rpm in the output shaft of the IM, respectively.



a) b) c) d)

Fig. 3. Set of considered faults assessed in the IM: a) BD, b) ½BRB,

V. Validation of the Method

The proposed diagnosis method is implemented under Matlab in which the signal processing is carried out to provide the final diagnosis outcome. Therefore, with regard to the proposed method and as aforementioned, the data acquisition is performed by carrying out different experiments. Moreover, three different operating frequencies are set in the VFD to drive the IM during the experimental evaluation of the considered conditions, then, the proposed diagnosis methodology is sequentially implemented for all the operating frequencies. Thus, the acquired and stored datasets consist of one hundred seconds of the continuous working condition of the IM during the steady-state regime; latter, the acquired signals are segmented in equal parts of two second with the objective of producing a consecutive set of samples.

Subsequently, through the feature estimation a feature matrix in terms of the spectral energy is obtained, that is, the frequency spectrum from each is segmented part is first obtained by means of a 4096-point FFT; where the bandwidth of each obtained frequency spectrum is between 0 Hz and 1500 Hz due to a sampling frequency of 3000 Hz is used during the data acquisition.

Then, each resulting frequency spectrum is in turn segmented in equal parts of 100 Hz; hence, each frequency spectrum is divided in fifteen equal parts from which the spectral energy is calculated. Such spectral energy is estimated by using the formulation of the Parseval's theorem that says that it is always possible to compute a signal's energy in the time domain as well as in the frequency domain as follows:

$$\sum_{n=0}^{N-1}|x[n]|^2 = \frac{1}{N}\sum_{k=0}^{N-1}|X[k]|^2 \quad (1)$$

Therefore, for each considered condition is estimated a feature matrix composed by fifty samples where each sample also consists of thirty different spectral energy values (fifteen values per vibration signal). And due to different operating frequencies are also considered, from each considered condition are estimated three feature matrices. In Fig. 4a and Fig. 4b are shown a graphical representation of the obtained frequency spectrum and its corresponding spectral energy obtained from a sample of two seconds for the HLT and MAL condition, respectively. As it can be seen, the spectral energy between both condition has different behavior, and this modification represent significative discriminant information that may lead to perform the identification and classification of the considered conditions with high-performance accuracy.

Afterwards, all the estimated feature matrices that represent the considered conditions are subjected to a compression procedure through the LDA, and such features are transformed into a new base. Thus, by means of the LDA

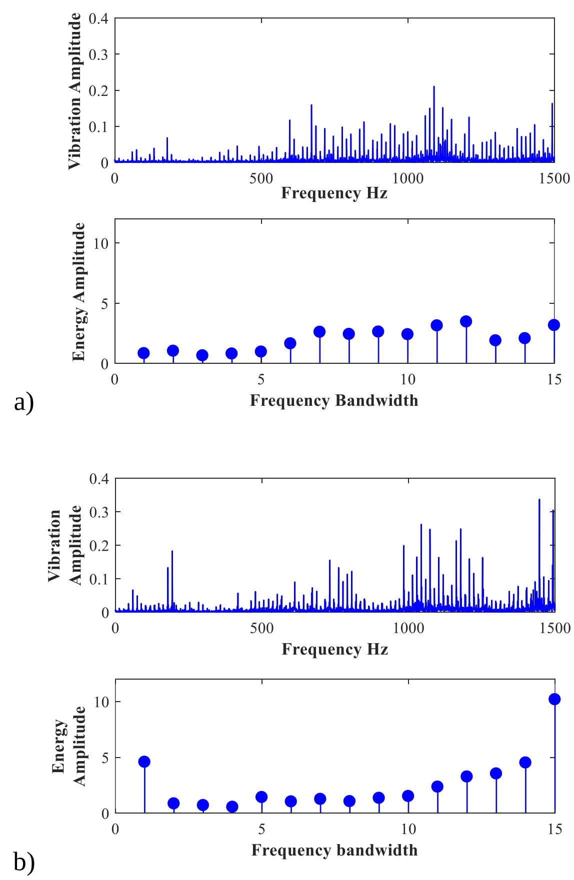


Fig. 4. Vibration spectrum and its correspoending spectral energy representation obtained from a two second sample of the: a) HLT condition and b) MAL condition.

application, a new subset of features that may be projected into a smaller dimensional base are extracted; indeed, through these extracted features the linear separation between the considered conditions is maximized. Moreover, the application of the LDA allows to obtain a new subset of features composed by the combination of different weights of the estimated spectral energy from both vibration signals. Since the feature extraction also allows to obtain a visual representation of the considered conditions in a 2-dimensional space, in Fig. 5 is shown the resulting projection of the extracted subset of features by means of the LDA for all the considered conditions when the IM is driven to different operating frequencies (5 Hz, 15 Hz and 50 Hz).

Although the conditions of DB and 1 BRB are slightly overlapped, the HLT condition is clearly cluster and separated from the considered fault conditions, indeed, it should be mentioned that this graphical representation does not have any sense over the analyzed conditions; that is, the physical magnitudes lose the sense of their units due to the base transformation. Additionally, the classification task is facilitated due to the high-performance characterization obtained by using the estimated spectral energy matrices and LDA.

Finally, in regard to the classification, a multilayer NN-based classifier is used to perform the final diagnosis outcome. Thus, as aforementioned, the considered NN structure has two neurons in the input layer represented by the extracted subset of features, ten neurons in the hidden layer, and five neurons in the output layer are considered for representing the evaluated conditions. In the output layer a probabilistic sigmoid function is used as activation function and the proposed NN-based structure is trained during 70 epochs through the back-propagation rule.

Consequently, aiming to obtain statistical significant results, the NN-structure is trained and validated under a five-fold-cross validation scheme. In this regard, by taking into account all the evaluated conditions, the original database is composed by 250 samples, 50 samples per condition, is then divided in two different datasets for training and validation purposes. Therefore, the first dataset used for training is composed by 200 samples, 40 samples per condition; whereas, the dataset used for validation consist of 50 samples, 10 samples per condition.

The consideration of the five-fold cross-validation scheme allows to analyze the performance of the classification due to all the variability of the data is used during the training and validation. Hence, five classification rations performed under this consideration, then, such classification ratios are averaged and the classification ratios achieved during the training and validation procedure are 98.5%, for both procedures, training and validation. The confusion matrix obtained during the training and validation are summarized in Table I and Table II, respectively.

Besides providing the achieved classification rates, the classification regions are also estimated through the proposed NN-based classifier. Then, a visual representation and interpretation of the reached classification performance during the training and validation may be provided by such visual representations. The resulting classification regions and projected samples, considering the first fold partition for the training, is projected and shown in Fig. 6.

Therefore, the obtained results are in advantage regarding with classical condition monitoring strategies from which the diagnosis outcome is performed by comparing the amplitude of specific fault-related frequency components in a frequency spectrum. In addition, the obtained results makes the proposed condition monitoring strategy suitable to be used in the working assessment of electric machines used in industrial applications.

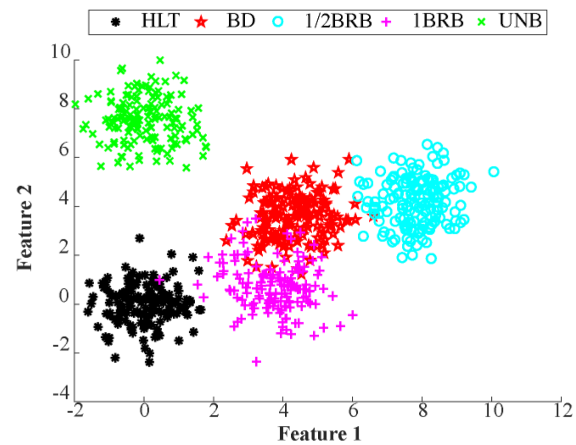


Fig. 5. Resulting projection of the extracted subset of features byapplying the LDA to the estimated spectral energy feature matrices for all the considered conditions when the IM is driven at different operating frequencies (5 Hz, 15 Hz and 50 Hz).

TABLE I
OBTAINED CONFUSION MATRIX DURING THE TRAINING OF THE NN-BASED CLASSIFIER FOR ALL CONSIDERED CONDITIONS

		Actual				
		HLT	BD	½ BRB	1 BRB	MAL
Estimation	HLT	40	0	0	0	0
	BD	0	39	0	2	0
	½ BRB	0	1	40	0	0
	1 BRB	0	0	0	38	0
	MAL	0	0	0	0	40

TABLE II
OBTAINED CONFUSION MATRIX FOR THE VALIDATION OF THE NN-BASED CLASSIFIER FOR ALL CONSIDERED CONDITIONS

		Actual				
		HLT	BD	½ BRB	1 BRB	MAL
Estimation	HLT	10	0	0	0	0
	BD	0	9	0	2	0
	½ BRB	0	1	10	0	0
	1 BRB	0	0	0	10	0
	MAL	0	0	0	0	10

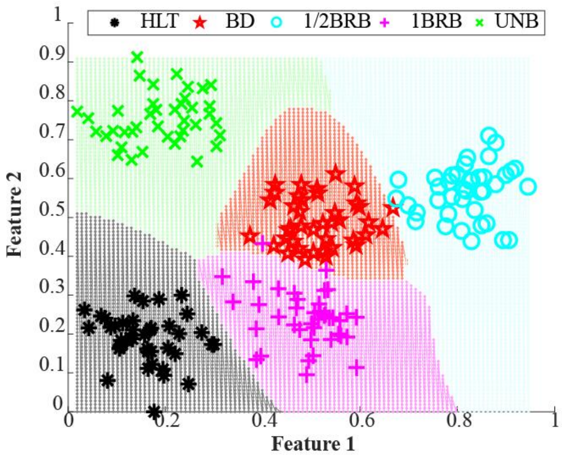


Fig. 6. Projection of classification regions for the fault identification correspopnding to test of the first cross validation performed by the proposed NN-based structure.

VI. Conclusions

In this work is presented a novel condition monitoring based on spectral energy estimation and LDA applied to assess different working conditions in an IM-based electromechanical system. There exist three important aspects that must be highlighted. First, is the estimation of the spectral energy from the computed frequency spectrum permits to obtain a proper characterization of the considered conditions that lead to perform the correct identification. Second, the application of a dimensionality reduction and base transformation approach allows to obtain a graphical representation of the considered conditions into a 2-dimentional space; simplifying the classification task. Third, the high-performance characterization leads to obtain averaged classification ratios around 98.5% through the use a simple NN-based classier algorithm. The obtained results are in advantage with regard to classic approaches where only the amplitude increase of the fault-related frequency components is analyzed; which also represents a tedious process. Finally, the obtained result by considering the experimentally database show that the proposed method is suitable for being applied to the condition monitoring and fault assessment in electric machines such as IM.

References

[1] F. J. Villalobos, and R. Alvarez, "Algoritmo robusto para el diagnóstico de fallas eléctricas en el motor de inducción trifásico basado en herramientas espectrales y ondeletas," Revista Iberoamericana de Automática e Informática industrial, vol. 12, pp. 292-303, 2015.

[2] Z. Y. Medrano, C. Perez, J. Gomez, and M. Vera, "Novel Methodology of Fault Diagnosis on Bearings in a Synchronous Machine by Processing Vibro-Acoustic Signals Using Power Spectral Density," Ingeniería Investigación y Tecnología, vol. XVII, pp. 73-85, Enero-Marzo 2016.

[3] S. A. McInerny, and Y. Dai, "Basic vibration signal processing for bearing fault detection," IEEE Transactions on Education, vol. 46, pp. 149-156, Febrery 2003.

[4] R. K. Patel and V. K. Giri, "Analysis and interpretation of bearing vibration data using principal component analysis and self-organizing map," *Inter. J. Advanced Design and Manufacturing Technology*, vol. 9, no.1, pp. 111-117, 2016.

[5] M. R. Mehrjou, N. Mariun, N. Misron and M. A. M. Radzi, "Analysis of statistical features based on star-up current envelope for broken rotor bar fault detection in line start permanent magnet synchronous motor," Electrical Engineering, vol. 1, pp. 1-15, 2016.

[6] S. J. Wang, and N. K. Jha "Algorithm-based fault tolerance for FFT networks," IEEE Transactions on Computers, vol. 43, pp. 849-854, July 1994.

[7] R. Langone, O. Mauricio Agudelo, B. De Moor, and J. A. K. Suykens, "Incremental kernel spectral clustering for online learning of non-stationary data," *Neurocomputing*, vol. 139, pp. 246–260, 2014.

[8] R. Joy, U. Rajendra, and L. Choo, "ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform," Biomedical Signal Processing and Control, vol. 8, pp. 437-448, September 2013.

[9] A. Sharma and K. K. Paliwal, "Linear discriminant analysis for the small sample size problem: an overview," *Inter. J. Machine Learning and Cybernetics*, vol. 6, no. 3, pp 443-454, 2015.

[10] M. N. Moreno, L. A. Miguel, F. J. García, and M. J. Polo, "Aplicación de técnicas de minería de datos en la construcción y validación de modelos predictivos y asociativos a partir de especificaciones de requisitos de software," Universidad de Salamanca. Departamento de Informática y Automática, 2001.

[11] L. E. Mendoza, R. D. Castellano, and R. D. Rojas, "Aportes y alcances de las técnicas de procesamiento, clasificación y descomposición de señales electromiográficas," IV Latin American Congress on Biomedical Engineering 2007, Bioengineering Solutions for Latin America Health, vol. 18, pp. 131-135, 2007.

[12] A. F. Quinceno, "Análisis tiempo-frecuencia por métodos no paramétricos orientado a la detección de patologías en bioseñales," Universidad Nacional de Colombia, Grupo de Control y Procesamiento Digital de Señales, 2009.

[13] C. E. Talbot, P. N. Saavedra, and M. A. Valenzuela, "Diagnóstico de la Condición de las Barras de Motores de Inducción," Información Tecnológica, vol. 24, pp. 85-94, 2013.

[14] A. M. Castellino, P. D. Donolo, G. R. Bossio, C. H. De Angelo, and G. O. García, "Diagnóstico de fallas en los rodamientos de motores eléctricos empleando variables eléctricas," XII Reunión de Trabajo en Procesamiento de la Información y Control, Grupo de Electrónica Aplicada, Fac. de Ingeniería, Universidad Nacional de Río Cuarto, Octubre 2007.

[15] S. Yu, J. Qing-Chao and Y. Xue-Feng, "Fault diagnosis and process monitoring using a statistical pattern framework based on a self-organizing map," *J. Central South University*, vol. 2, no. 2, pp. 601-609, 2015.

[16] J. Harmouche, C. Delpha and D. Diallo, "Improved fault diagnosis of ball bearings based on the global spectrum of vibration signals," *IEEE Trans. Energy*, vol. 30, no. 1, pp 376-383, 2015.

[17] L. Saidi, J. B. Ali, F. Fnaiech, "Application of higher order spectral features and support vector machines for bearing faults classification," *ISA Transactions*, vol. 54, pp. 193-206, 2015.