Multi-fault diagnosis method applied to an electric machine based on high-dimensional feature reduction

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***Abstract* – Condition monitoring schemes are essential for increasing the reliability and ensuring the equipment efficiency in industrial processes. The feature extraction and dimensionality reduction are useful preprocessing steps to obtain high performance in condition monitoring schemes. To address this issue, this work presents a novel diagnosis methodology based on high-dimensional feature reduction applied to detect multiple faults in an induction motor linked to a kinematic chain. The proposed methodology involves a hybrid feature reduction that ensures a good processing of the acquired vibration signals. The method is performed sequentially; first, signal decomposition is carried out by means of Empirical Mode Decomposition. Second, statistical-time based features are estimated from the resulting decompositions. Third, a feature optimization is performed to preserve the data variance by a Genetic Algorithm in conjunction with the Principal Component Analysis. Fourth, a feature selection is done by means of Fisher score analysis. Fifth, a feature extraction is performed through Linear Discriminant Analysis. And, finally, sixth, the different considered faults are diagnosed by a Neural Network-based classifier. The performance and the effectiveness of the proposed diagnosis methodology is validated experimentally and compared with classical feature reduction strategies, making the proposed methodology suitable for industry applications.**

Index Terms— Induction Motor, Condition Monitoring; Multiple Faults; Feature Reduction; Vibrations.

I. INTRODUCTION

Induction motors (IM) represent the most common rotating electrical machines used in industry due to its robustness and competitive cost [1]-[2]. However, unexpected faults may occur during the useful life of the IM, causing unscheduled downtimes of the whole components associated to the kinematic chain. Typical faults in IM may be due to mechanical and electrical stresses. Mechanical stresses caused by overloads can produce bearing defects, rotor bar breakage, rotor unbalance and misalignment in couplings, whereas electrical stresses associated to problems in the power supply cause stator faults like short circuits in the stator winding [3]. Thus, the related condition monitoring plays a key role in the reliability and safety strategies of several industry applications [4]-[6]. Although different physical magnitudes have been investigated for IM condition monitoring [3], [7]-[9]; vibration analysis remains as the most industrially accepted approach. The vibration analysis is a useful and reliable tool to assess the IM condition since the characteristic vibration modes of any rotating machine changes in presence of faults [10]-[13]. Yet, although several methodologies applied to diagnose faults in electric motors have been presented during the last decades, most of these methodologies are focused on the analysis of a specific fault mode [7], [10], [14]-[15]. Indeed, the application of such health monitoring schemes to industrial scenarios presents new challenges that must be addressed, where different faults may appear hiding or overlapping the expected characteristic fault patterns.

Typically, it is estimated the root mean square (RMS) from the vibration signal as a numerical indicator to assess the general condition of the machine [16]-[18]. In order to consider improved characterization of the vibration signal, the numerical set of features is extended to additional statistical time-domain, frequency domain, and also time-frequency domain [19]-[21], [22]. Yet, although fast Fourier transform and Cohen's class time-frequency distributions have been successfully applied [22]-[23], the simplicity and low computational cost of the statistical time-domain features exhibit a high characterization potential dealing with regular stationary speed cycles in the industry [24].

Condition monitoring strategies that use a high-dimensional set of features to characterize the properties of faults inevitably contain redundant and non-significant information. Recently, approaches of signal decomposition are widely used in condition monitoring schemes. Different decomposition techniques can be used; and the signal decomposition approach by means of Empirical Mode Decomposition (EMD) has being applied due to its self-adaptive capabilities to extract a set of Intrinsic Mode Functions (IMF) from the raw signal. The estimation of numerical features from each IMF represents a good opportunity to obtain a potential high-dimensional set of features for diagnosis purposes [20]. Yet, dimensionality reduction procedures must be applied to avoid low fault diagnosis performances and overfitting responses of the classification algorithm [21], [25]. In this regard, classical techniques of dimensionality reduction have been integrated in

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condition monitoring schemes; for instance, Principal Component Analysis (PCA) [20], [26], and Linear Discriminant Analysis (LDA) [27], are the main techniques used for reducing high-dimensional sets of features. However, each dimensionality reduction approach is based on a specific objective function; that is, PCA aims to identify orthogonal components aligned with the maximum data dispersion direction, whereas LDA aims to maximize the distance among different data sets [28]. Such difference of criteria leads to multiple works in which the selection of the dimensionality reduction approach is carried out by a performing ratio when combined with the classification algorithm [29]-[30].

Moreover, dealing with multiple faults, such classical dimensionality reduction approaches are usually combined with complex hierarchical classification structures in order to compensate the loss of performance. In this sense, in [23], a set of features, estimated by means of wavelet decomposition from vibration signals, is used in a hierarchical deep belief based network to classify different bearing defects. Although this methodology exhibits good results, the proposed multi-stage network implies multiple trainings, one for each specific condition to be solved. In [22], a bi-spectrum set of features estimated from vibration measurements is reduced through PCA technique and then, used by a hierarchical classifier based on Support Vector Machine (SVM). Although this scheme assesses different bearing condition, the proposed approach involves the use of the same number of SVMs as the same number of considered faults.

Thereby, the contribution of this work lies on a novel multi-fault diagnosis methodology, and the verification of the proposed hybrid high-dimensional feature reduction method to increase the diagnosis performance dealing with multiple faults in an induction motor linked to a kinematic chain.

Originality of the work includes the empirical mode decomposition of the available vibration signals, the estimation of statistical-time-features, and the validation of the proposed hybrid high-dimensional feature reduction method. Indeed, the resulting high-dimensional set of features is analyzed by means of a novel multi-stage dimensionality reduction approach, in which, an optimization is performed by a Genetic Algorithm (GA) in conjunction with the PCA to seek an optimal set of IMFs that best preserve the data variance, afterwards, a selection of the best discriminative statistical features is carried out by means of the Fisher score, and then, the select features are compressed and transformed into a 2-dimensional space through LDA based feature extraction. Such multi-stage dimensionality reduction, allows using a simple Neural Network (NN) -based classification algorithm as diagnosis estimator, including class identification and membership probability.

The proposed diagnosis methodology is validated under a complete set of experimental vibrations acquired from an electromechanical system, where five different mechanical faults are considered. In this context, novelties of this work include the validation that the application of hybrid feature reduction strategies (selection and extraction), represents a high-performance information analysis procedure, which improves the classification capabilities compared with the use of classical approaches, such as PCA and LDA, as a unique technique to high-dimensional feature reduction. Notice that this proposed hybrid feature reduction methodology has not been study in multi-fault diagnosis so far and the results are promising.

This paper is structured as follows. Section II describes the theoretical aspects of the proposed method and section III describes the diagnosis methodology. The experimental test bench used to assess and validate the method is presented and discussed in sections IV and V, respectively. Conclusions and future work are summarized in Section VI.

II. Feature Reduction

The feature set is a critical aspect that compromises the performance of classification algorithms; thereby, a reduced number of features will not contain enough information to describe and to characterize the machine working conditions. Therefore, the addition of new features is an option to increase the capability of discrimination, and it is commonly believed that the classification performance will improve. Yet, an increase of the number of features may not offer additional information to the machine condition, and the performance of classification will be degraded instead of improved. Thus, misclassifications can be obtained because of the redundant and useless information contained in large sets of features. Working with a high-dimensional set of features complicates the fault identification task of the multi-class classification methods. Besides, it is required a high computational cost and the use of redundant and useless information could compromise the proper convergence of the algorithms [21]. For that reason, procedures of feature reduction are implemented in condition monitoring schemes [14]. Mainly, it is possible to remove redundant or non-discriminative features by means of two reduction strategies: feature selection and feature extraction.

Regarding feature selection, it is a filtering strategy in which all the features are independently evaluated by considering only their individual descriptive capabilities; thus, the features are ranked in terms of their relevance, and even though a specific feature cannot be useful by itself, it can be very useful when it is combined with others. Filtering strategies do not require a particular learning algorithm, making, them effective and easy to compute. Most of these algorithms are based on general characteristics of the data such as distance, dependence, and consistency among others [17]. Consequently, the implementation of feature selection strategies in condition monitoring schemes is used to preserve the most discriminative features; in this sense, the filtered features are those that best described the machine working condition [20].

On the other hand, feature extraction differs in the question of whether a technique is supervised or unsupervised. The main difference between both techniques is the availability of labels to distinguish the different classes.

PCA is a well-known and the most common used technique for unsupervised dimensionality reduction and feature extraction [15]. This technique projects a high-dimensional data set into a new uncorrelated set of features; therefore, no redundant information is present. These projections, named principal components, are linear combinations in which the variability of the data is better captured. PCA is based on statistical analysis and even though it does not concern in the separation of different classes, it has advantage in feature extraction due to preserving the variability of the data. Therefore, the consideration of PCA analysis is helpful in condition monitoring schemes to discard redundant information that is not required to detect faults in a system.

LDA is one of the most well-known supervised techniques used in multi-class problems for linear dimensionality reduction and feature extraction [20]. LDA aims to find a projection into a low-dimensional representation in which it is contained the most discriminant information attempting to maximize the linear separation between data points belonging to different classes. LDA is a suitable feature extraction technique to be considered in condition monitoring schemes because it pays attention to differences of known classes; thus, through the proper application of this technique it is possible to obtain the parameters that correctly indicate the machine working condition.

Feature selection and feature extraction approaches provide complementary feature reduction effects; therefore, there is not a clear criterion for choosing a specific technique: the reduction stage is typically implemented in order to fulfill with a required data processing.

III. Diagnosis Methodology

The proposed multi-fault diagnosis methodology is composed by six steps as depicted in Fig. 1. First, the signal decomposition with the estimation of the IMFs from the vibration signal is done by the EMD. Second, the calculation of a set of statistical-time based features from each IMFs is done. The proposed hybrid high-dimensional feature reduction method follows. Thus, third, a feature optimization approach of the available set of features is done by selecting the most significant IMFs to maximize the data variance preservation. Fourth, a feature selection by filtering the set of statistical-time features trough the analysis of the Fisher score is done. Fifth, a feature reduction with the extraction of a reduced set of features to maximize the fault discrimination is performed. Finally, sixth, the classification stage based on NN is performed, where the different considered faults are diagnosed.

In this work, six different conditions have been considered to be evaluated in terms of the induction motor: healthy (HLT), bearing defect (BD), half-broken rotor bar (1/2 BRB), one broken rotor bar (1 BRB), unbalance (UNB) and misalignment (MAL). For each considered condition, ninety axial vibration measurements have been acquired. Each measurement corresponds to one second of the machine operation.

A. *Signal decomposition and features calculation*

The decomposition of the acquired vibration signal is performed by means of EMD; such decomposition is applied to each considered condition and allows obtaining a set of IMFs which are automatically adapted to the corresponding vibrational pattern.

Afterwards, each resulting set of IMFs is characterized by estimating 15 statistical time-based features: mean, maximum value, RMS, square root mean, standard deviation, variance, RMS shape factor, square root mean shape factor, crest factor, latitude factor, impulse factor, skewness, kurtosis, and normalized fifth and sixth moments. Therefore, a resulting number of 150 numerical features are estimated for each considered condition. The proposed set of statistical features is shown in Table I. These statistical-time features have been successfully used for fault detection in electrical motor due to their high-performance source of information and their capabilities to analyze general trends of the signal [19].

TABLE I
STATISTICAL TIME-BASED FEATURES

Mean	$\bar{x} = \frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert$	(1)
Maximum value	$\hat{x} = max(x)$	(2)
Root mean square	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(3)
Square root mean	$SRM = \left(\frac{1}{n} \cdot \sum_{k=1}^{n} \sqrt{\lvert x_k \rvert}\right)^2$	(4)
Standard deviation	$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \bar{x})^2}$	(5)
Variance	$\sigma^2 = \frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \bar{x})^2$	(6)
RMS Shape factor	$SF_{RMS} = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(7)
SRM Shape factor	$SF_{SRM} = \frac{SRM}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(8)
Crest factor	$CF = \frac{\hat{x}}{RMS}$	(9)
Latitude factor	$LF = \frac{\hat{x}}{SRM}$	(10)
Impulse factor	$IF = \frac{\hat{x}}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(11)
Skewness	$S_k = \frac{E[(x_k - \bar{x})^3]}{\sigma^3}$	(12)
Kurtosis	$k = \frac{E[(x_k - \bar{x})^4]}{\sigma^4}$	(13)
Fifth moment	$5thM = \frac{E[(x_k - \bar{x})^5]}{\sigma^5}$	(14)
Sixth moment	$6thM = \frac{E[(x_k - \bar{x})^6]}{\sigma^6}$	(15)

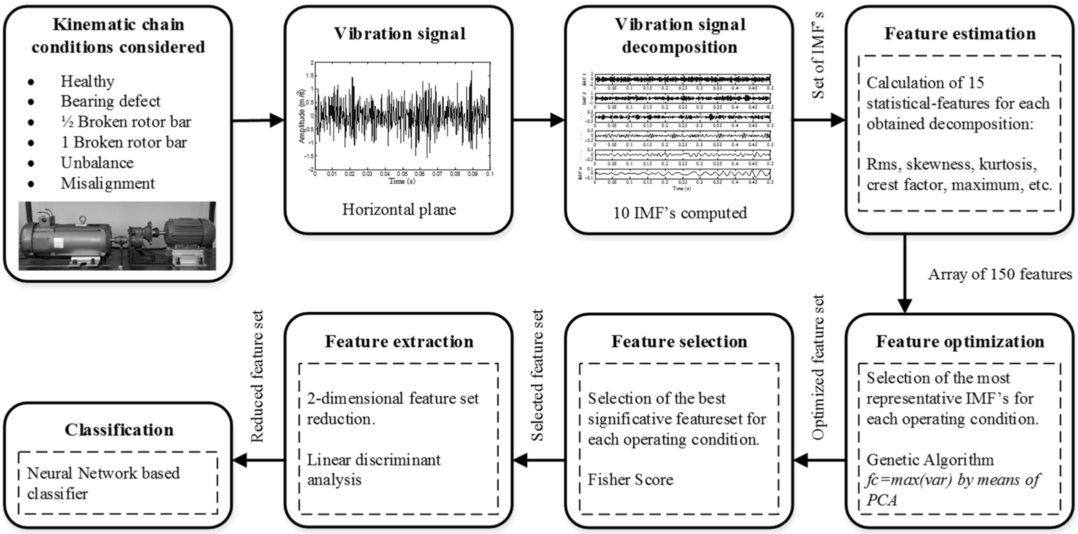

Fig. 1. Proposed diagnosis methodology based on hybrid feature reduction for the detection of multiple faults in electromechanical systems.

B. *Multi-stage dimensionality reduction*

The estimated high-dimensional set of features contains a large portion of the information related to the working condition on the kinematic chain, but only some contain representative information. First, considering the obtained set of IMFs, an optimization process is performed by a GA in conjunction with the PCA technique in order to seek a subset of IMFs that provides a better representation of each one of the considered conditions. This optimization is carried out, individually, for each considered condition as follows: a logical vector with ten elements are the chromosomes of the GA, in which, every element represents each one of the obtained IMFs. Then, an initial population is randomly generated by considering that at least one of the elements contained in the logical vector has to be selected to be evaluated; also more than one element can be evaluated. Once defined the initial population, the fitness function is assessed, which is based on the accumulation of the data variance. Then, the IMFs to be evaluated are now represented by their corresponding statistical-time set of features. In this sense, the cumulative variance of the selected IMFs is computed through PCA, and the fitness function comprises the cumulative variance of the two and three first principal components. Afterwards, another population is generated using the Roulette wheel selection, moreover the GA applies a mutation and based on the Gaussian distribution the new population is chosen, then the process is iteratively repeated until finding the best set of IMFs that best accumulate the data variability; the stop criteria considered for the algorithm is controlled by different goals like achieving a maximization of the variance or reaching a maximum number of generations. In this process, each fault condition is faced to the healthy condition; as a result, the sets of IMFs are optimized by removing those redundant information, and just the discriminative information related to each condition is retained in the optimized IMFs.

Second, in the feature selection, an analysis of the individual discriminative capabilities is applied to the statistical-time features with the objective to filter and preserve the most discriminative features. In this process the considered statistical time-features are those that belong to the optimized set of IMFs. The feature selection is performed by computing the Fisher score that is a relative measure in terms of the distances between data points in different classes, which means, statistical features with a large Fisher score represent largest distances while small Fisher score represent smallest distances. Consequently, the features are ranked in terms of their relevance, in other words, the best ranked features are considered the best discriminative features whereas the worst ranked are the non-discriminative features. The feature selection is a combinatorial problem; in this regard, the Fisher score is computed by combining all the statistical time-features, where subsets of two and three features are considered. As in the optimization stage, in this process the faulty conditions are faced to the healthy condition. After computing the Fisher score for each feature, the three first ranked features in terms of Fisher score ranking are considered the most significant set of features that better describes the machine working condition.

These two first stages correspond to a filtering process of the initial high-dimensional set of features. Thus, for each considered fault condition it is computed a set of features containing the most significant and discriminative information of the kinematic chain working condition.

Finally, in a feature extraction stage, all the filtered sets of statistical features are subjected to a compression process and a base transformation by means of LDA. Through this compression process a new set of features are extracted, and these extracted features are a combination of different weights from the selected set of features. Consequently, the extracted features are projected in a 2-dimensional space allowing a visual interpretation of the considered conditions. Moreover, this resulting 2-dimensional representation facilitates the classification task, since just two inputs must be managed. With this approach the most discriminative features are projected in a reduced dimensional space in which their discriminative capabilities between all the considered conditions are retained.

C. *Classification*

The proposed diagnosis methodology is based on a consecutive processing of the original set of features, and during this process those features that are significantly important to represent the characteristic failure patterns are preserved. Therefore, high performance is obtained by applying the proposed hybrid feature reduction to the high-dimensional set of features. It must be noted that the proposed hybrid feature reduction allows a simpler configuration of the classification stage since the input vectors are reduced to two dimensions.

In this sense, a simple structure of a NN-based classifier is used to obtain the diagnosis estimation of all the considered conditions. Indeed, the classifier has a classical three-layer structure. The input layer is composed by two neurons corresponding to the two dimensional features vectors resulting of the proposed hybrid feature reduction methodology. The hidden layer has ten neurons following classical recommendations [31]. The output layer is composed by six neurons, one for each considered condition. This simple and classical NN structure has been successfully implemented in different condition monitoring schemes [32]-[33]. In addition to the resulting classification, the proposed NN also offers the diagnosis probability due to the sigmoid function is used as activation function in the output layer, thus, the classification result in the NN is related with a probability value. The training uses the back-propagation rule for the gradient estimation and the scaled conjugate gradient as minimization technique.

IV. Experimental Test Bench

The experimental test bench used to validate the proposed diagnosis methodology and the data acquisition system used to capture the vibration signals are shown in Fig. 2. The test bench consists on a kinematic chain and it is composed by a 1492-W, three-phase IM (WEG00236ET3E145T-W22), with its rotational speed controlled through a variable frequency drive (VFD) (WEGCFW08). It also consists of a 4:1 ratio gearbox (BALDOR GCF4X01AA) that is used for coupling the motor drive to a DC generator (BALDOR CDP3604). The DC generator is used as a non-controlled mechanical load comprising around 20% of the nominal load. The vibration signals from the perpendicular plane of the IM axis are acquired using a triaxial accelerometer (LIS3L02AS4), mounted on a board with the signal conditioning and anti-alias filtering. A 12-bit 4-channel serial-output sampling analog-to-digital converters (ADS7841) is used on board of the data acquisition system (DAS). The DAS is a proprietary low-cost design based on field programmable gate array technology (FPGA). The sampling frequency is set to 3 kHz for vibration signals acquisition, obtaining 270 kS during 90 seconds of continuous sampling in the IM from start-up to steady state.

Regarding the six different conditions considered, the artificial damage on the bearing is produced by drilling a hole with 1.191 mm of diameter on the bearing outer race using a tungsten drill bit. The artificially damaged bearing, model 6205-2ZNR, used in this experimentation is shown in Fig. 3a. The artificial damage in both rotor bar elements are produced by drilling a hole with 6 mm of diameter. For the ½ BRB fault, the hole has a depth of 3mm that corresponds mostly to the 22% of the section of the rotor bar. For the BRB fault, a through-hole is produced with 14 mm of depth, which corresponds to the complete section of the rotor bar. These faults are shown in Fig. 3b and Fig. 3c respectively. The presence of the UNB condition is related to the mechanical load distribution in the IM; thus, a non-uniform load distribution takes the center of mass out of the motor shaft. To do this, the UNB condition is produced by attaching a bolt in one of the IM coupling, as Fig. 3d shows. Finally, the MAL condition is present when the centerlines of coupled shafts do not coincide with each other; consequently, the dynamic load on bearings and couplings increases. Therefore, an angular misalignment is carried out by moving the free end of the IM, so that a misalignment of 5 mm on horizontal plane is produced only from the free end, Fig. 3e shows the misalignment shaft coupling.

In most of the considered fault conditions, the experiments are carried out by replacing the healthy elements with each one of the damaged elements alternatively. Only the MAL condition is induced by moving the free end of the IM as explained above. The operational frequency of driving IM controlled by the VFD is set to 60 Hz, which causes an average rotating speed of 3585 rpm in the IM.

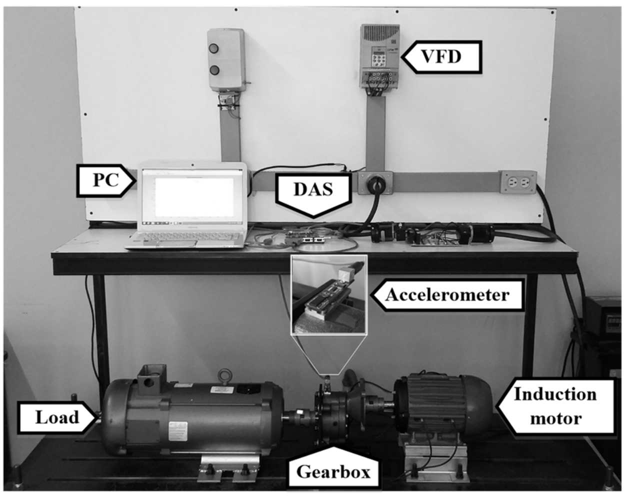

Fig. 2. Experimental test bench used to validate the proposed diagnosis methodology.

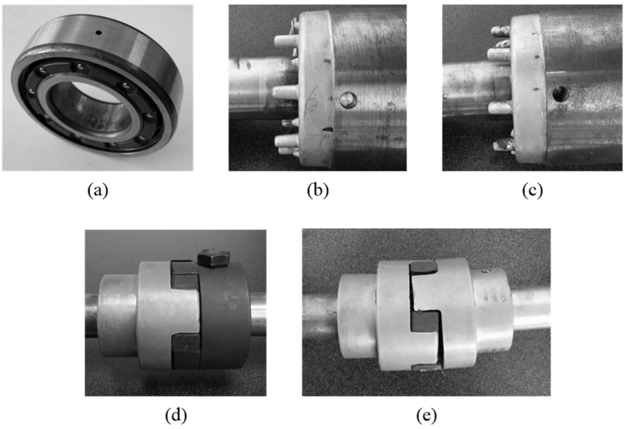

Fig. 3. Arrangement of the different faults produced in the experimental test bench. (a) Bearing defect. (b) ½ Broken rotor bar. (c) 1 Broken rotor bar. (d) Unbalance. (e) Misalignment.

V. Validation of the Method

The proposed diagnosis methodology is implemented under MATLAB, which is used for processing the acquired signals and to provide the fault diagnosis. As some researchers report, the related information to the working condition of rotational machines is reflected in the appearance of perpendicular vibrations on the rotating axis [3], [17], [28]. Thus, the acquired and stored vibration measurements belong to the perpendicular plane to the IM rotating axis. As aforementioned, the stored information consist of ninety seconds of kinematic chain working condition under the considered conditions; then, each acquisition is segmented in ninety parts of one second with the aim to generate a set of consecutive samples.

Afterwards, the signal decomposition is carried out by means of EMD. That is, the decomposition is iteratively obtained from each segmented part; as a result, an adaptive characteristic set of IMFs is computed for each considerer condition. Thus, each vibrational pattern is represented by a set of 90 samples with 10 IMFs. After performing the signal decomposition, each function of the resulting sets of IMFs are then characterized by the estimation of a number of 15 statistical-time based features. Consequently, a high-dimensional set of features is estimated for each considered condition. Thus, all of the high-dimensional sets are composed by 90 samples with 150 statistical-time features.

Although the estimated high-dimensional set of features contains a large portion of the information related to the kinematic chain working condition, only some will have representative information. In this sense, the estimated high-dimensional set of features is then analyzed through the proposed hybrid feature reduction methodology in order to retain the most discriminative features.

First, as previously described, the optimization process is performed by means of a GA in conjunction with the PCA. The main setting parameters of the GA are defined as: a population of 10 for the number of individuals, the maximum number of generations is fixed to 50 and the algorithm uses the Roulette wheel selection scheme with mutation and based on the Gaussian distribution as the selection operator. Meanwhile, in the PCA two and three principal components are considered to compute the cumulative variance. The optimization process is applied individually to the considered conditions; it should be noticed that the faulty conditions are faced to the healthy condition. Thus, the optimized set of IMFs contains those functions with greater variability and relevant information related to the considered fault condition.

During the optimization process of the GA, the cumulative variance of the two and three principal components is used to compare the optimized results. Through this comparison it is obtained the same set of optimized IMFs. Although the results are similar, there is a clear difference in the computational resources. That is, when three principal components are considered, the computational load increases, and as a consequence the convergence time increases approximately twice compared with the convergence time when only two principal components are considered. Regarding the cumulative variance, by considering three components the percentage of cumulative variance is around 3% greater than the computed cumulative variance when considering only two components. Thereby, good results with low computational resources are obtained when two principal components are considered in the PCA, as expected. Table II lists the optimized set of IMFs for all the considered conditions. In all the optimized set of features the cumulative variance is in the upper 75%, which reflects a good concentration of the data. Also, Table II summarizes the percentages of the cumulative variance and the detail of the statistical features with greater attribution considered by the two first principal components. Regarding to the optimization process it was stopped because the maximum number of generations was reached, in all the optimization processes it was obtained a good performance; in Fig. 4 are shown the graphics related to the performance achieved in terms of the cumulative variance for the optimization of the IMFs, for all the considered conditions and it is possible to notice that in all the cases after the 20 generations the best individual shows the best result.

In this optimization stage, redundant information is discarded. In order to show the difference between the data variance, the PCA is applied to an optimized set of IMFs and a random set of IMFs of the MAL condition. In this regard, the optimized set of IMFs for the MAL condition is composed by the two first modes (IMF1 and IMF2); thus, their corresponding statistical-time features are used by the PCA to compute the cumulative variance (91.1%). A representation of the scattered data points obtained by the optimized set of IMFs is shown in Fig. 5. It could be believed that a better characterization of the machine working condition can be obtained if there is as much information as possible. In this sense, for the same MAL condition, a random set of the IMFs composed by the last three modes (IMF8, IMF9 and IMF10) is

TABLE II
DETAIL OF THE OBTAINED OPTIMIZED SET OF IMFS BY CONSIDERING TWO PRINCIPAL COMPONENTS IN THE OPTIMIZATION PROCESS

Condition	Optimized set of IMFs	%σ	Statistical-time features with grater attribution in the two principal components
Bearing defect	IMF1, IMF2	82.9%	Maximum value, root mean square, square root mean, standard deviation, variance, RMS shape factor, SRM shape factor, crest factor, latitude factor, kurtosis.
½ Broken rotor bar	IMF1	84.2%	Maximum value, root mean square, square root mean, standard deviation, variance, RMS shape factor, SRM shape factor, crest factor, latitude factor, impulse factor.
1 Broken rotor bar	IMF1	92.3%	Maximum value, root mean square, square root mean, standard deviation, variance, RMS shape factor, SRM shape factor, crest factor, latitude factor, impulse factor, kurtosis, sixth moment.
Unbalance	IMF1	92.4%	Mean, maximum value, root mean square, square root mean, standard deviation, variance, RMS shape factor, SRM shape factor, crest factor, latitude factor, impulse factor, skewness, kurtosis, fifth moment, sixth moment.
Misalignment	IMF1, IMF2	91.1%	Maximum value, root mean square, square root mean, standard deviation, variance, RMS shape factor, SRM shape factor, crest factor, latitude factor, impulse factor, kurtosis, sixth moment.

used to compute its cumulative variance. Thereby, a set of 45 statistical-time features estimated from the random set on IMFs is evaluated through the PCA obtaining the cumulative variance of 36.9%. Fig. 6 shows the scattered data points obtained by the random set of IMFs. From Fig. 5 and Fig. 6 it is possible to notice the difference between the data scatter. Thereby, in both figures it is used the same scale, and the data points from Fig. 5 are widely spread while in Fig. 6 they are concentrated within a smaller area. Moreover, this comparison proves that not all the information related to the machine working condition is useful in condition monitoring schemes, and the performance of such schemes will be degraded instead of improved.

Feature selection is the next process considered in the proposed hybrid feature reduction; in this process, an analysis of the discriminative capabilities of the statistical-time features is carried out by computing the Fisher score. The statistical-time features considered in this selection process are those computed from the optimized sets of IMFs. Fisher score is based on a combinatorial problem; thus, all the statistical-time features are analyzed by considering subsets of two and three statistical features. Moreover, in this process the faulty

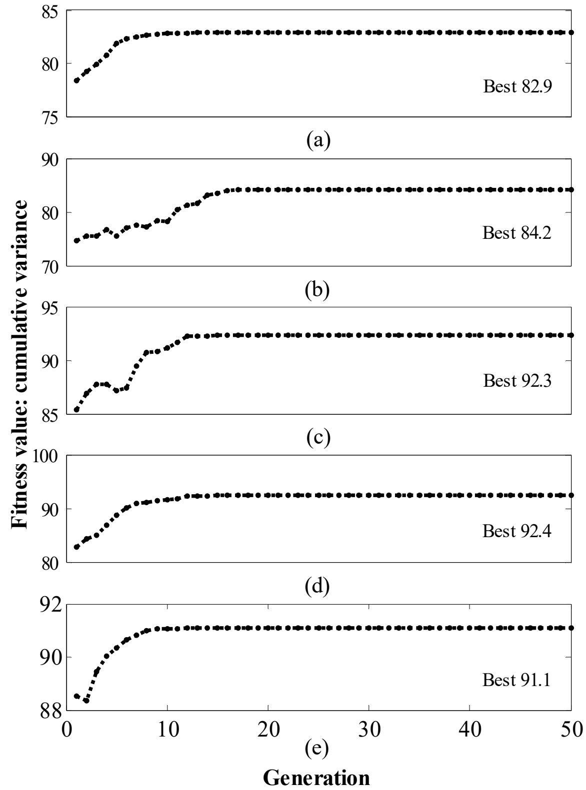

Fig. 4. Performance of the GA-based procedure applied during the optimization of the number of IMFs to represent each considered fault. Evolution and maximum percentage the cumulative variance obtained: (a) Bearing defect. (b) ½ broken rotor bar. (c) 1 broken rotor bar. (d) Unbalance. (e) Misalignment.

conditions are faced to the healthy condition in order to highlight the best discriminative statistical features.

As aforementioned, different subsets are used to compute the Fisher score; thus, the computational resources could be compromised by the number of statistical features used due to this strategy is a combinatorial problem. In this way, all the combinations are performed and the statistical-features are ranked in terms of their relevance; which means that features with largest values are considered the best discriminative feature. Then, the three first ranked subsets of features are considered the best to describe the machine working condition.

Through this feature selection approach, the best subsets of statistical features with a better class separation are obtained, besides of the reduction of the optimized sets of statistical-time features. For all the considered conditions, Table III shows the details of the selected subsets of statistical features obtained by the combinations of two features, their corresponding IMF and the computed Fisher score for each statistical feature. The obtained Fisher scores reveal that there exists a good separability between the conditions of BD, 1 BRB, MAL and HLT. On the other hand, an overlapping could appear between the ½ BRB, UNB and the HLT condition. Thus, to obtain a good separability between classes the expected Fisher score should be higher than one; however, the combination of all the

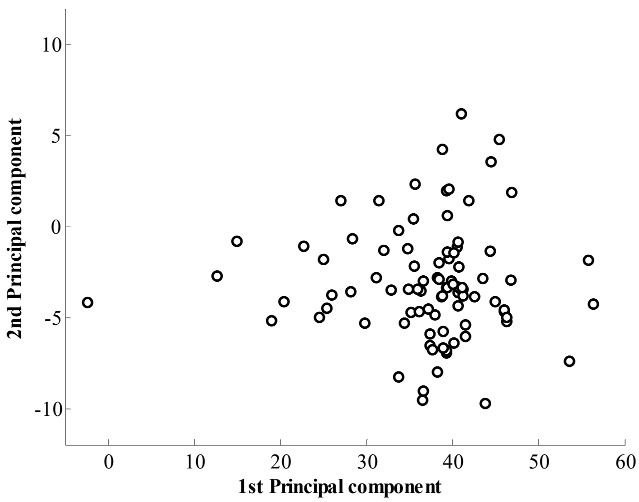

Fig. 5. Scatterplot of the optimized set of IMFs (IMF2 and IMF2) for the misalignment condition using two principal components in the PCA.

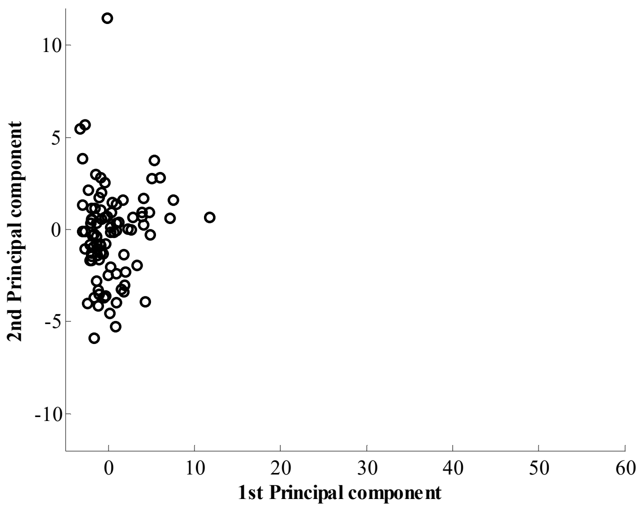

Fig. 6. Scatterplot of the random set of IMFs (IMF8, IMF9 and IMF10) for the misalignment condition using two principal components in the PCA.

selected sets of statistical features will be useful in a feature extraction technique such as LDA. Regarding the use of different subset of features, the results are not significantly different and, when three statistical features are considered the execution time of the technique is at least twice compared when considering two features only.

In the last stage, a feature extraction is carried out by the LDA, in which all the selected sets of statistical features are subjected to the compression procedure. The LDA strategy aims to find a projection by attempting to maximize the linear separation between different classes. Through this approach a new set of extracted features are obtained, and those extracted features are composed by a combination of different weights of the selected set of features. Besides that, the dimensionality of all the selected sets of statistical features is reduced.

Consequently, the extracted set of features is projected in a 2-dimensional space where it is possible to obtain a visual

TABLE III
DETAIL OF THE OBTAINED SELECTED SET OF STATISTICAL-TIME FEATURES BY CONSIDERING COMBINATIONS OF TWO FEATURES IN THE FISHER SCORE CALCULATION

Condition	Statistical-time feature	Optimized IMF	Fisher score rank
Bearing defect	Root mean square	IMF1	76.9
	Standard deviation	IMF1	76.9
	RMS Shape factor	IMF2	62.7
	Kurtosis	IMF2	37.8
½ Broken rotor bar	Square root mean	IMF2	0.13
	Standard deviation	IMF2	0.13
	Kurtosis	IMF2	0.13
	Sixth moment	IMF2	0.11
1 Broken rotor bar	RMS Shape factor	IMF1	12.4
	Kurtosis	IMF1	6.7
	Kurtosis	IMF2	4.8
	Sixth moment	IMF2	2.1
Unbalance	SMR Shape factor	IMF1	0.29
	Maximum value	IMF2	0.16
	Root mean square	IMF2	0.16
	Standard deviation	IMF2	0.15
Misalignment	Root mean square	IMF1	89.0
	Square root mean	IMF1	88.9
	Standard deviation	IMF1	80.0
	SMR Shape factor	IMF2	67.5

interpretation of all the considered conditions. Fig. 7 shows the projection of the extracted set of features resulting from the application of the proposed hybrid feature reduction. Although it is expected an overlapping between the ½ BRB, UNB and the HLT condition by means of the LDA, a separation is obtained. This projection is obtained through a transformation matrix composed by a set of values with different weights. Table IV shows the details of the transformation matrix. The values that compose the transformation matrix prove that the extracted features projected are not specifically concentrated in one or two statistical features, and even though some statistical features have a low weight, these are essential to improve the separability between classes.

Previous to the fault classification, a comparison between the proposed hybrid feature reduction and classical approaches such as LDA and PCA is carried out. That is, the proposed 15 statistical-time features are directly estimated from segmented parts of the acquired vibration signals. Then, for all the considered conditions, a feature extraction is carried out by the classical approaches, and these extracted features are also projected in a 2-dimensional space to have the same basis of comparison. Fig. 8 and Fig. 9 show the projection of the extracted features computed by the PCA and LDA, respectively.

Through the application of both classical approaches some disadvantage are present. There is a clear difference between the extracted features computed through the proposed hybrid feature reduction and the extracted features obtained by the classical approaches. That is, in Fig. 8 and Fig. 9 an overlap is presented between the conditions of ½ BRB, 1 BRB, UNB and HLT, while in Fig. 7 these classes show a better separation. Although the conditions of BD and MAL are not overlapped the use of classical approaches of feature extraction such as

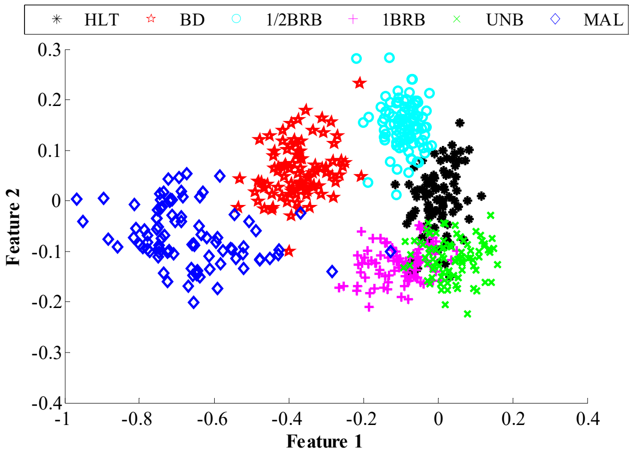

Fig. 7. Projection of the extracted set of features resulting from the application of the proposed hybrid feature reduction strategy.

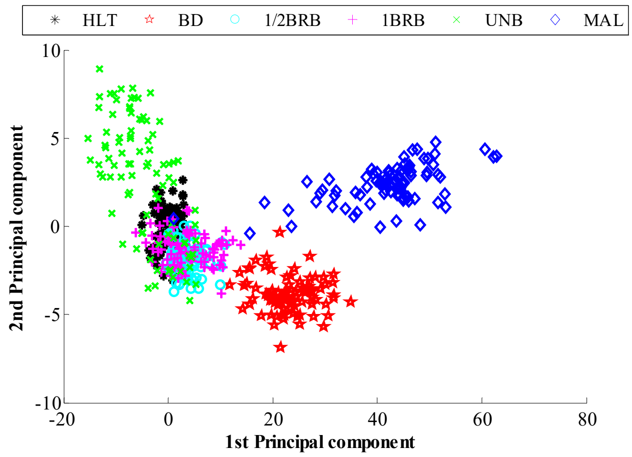

Fig. 8. Projection of the extracted set of features resulting from the classical approach PCA.

TABLE IV
DETAIL OF THE TRANSFORMATION MATRIX COMPUTED BY THE LDA TO OBTAIN A 2-DIMENSIONAL PROJECTION OF THE EXTRACTED FEATURES

Statistical-time feature	Optimized IMF	Column 1	Column 2
Root mean square	IMF1	0.570	0.505
Root mean square	IMF1	0.021	0.026
Standard deviation	IMF1	0.551	0.481
RMS Shape factor	IMF1	0.095	0.055
Kurtosis	IMF1	0.088	0.031
Maximum value	IMF2	0.014	0.001
Root mean square	IMF2	0.297	0.476
Root mean square	IMF2	0.075	0.037
Standard deviation	IMF2	0.376	0.528
RMS Shape factor	IMF2	0.180	0.025
SMR Shape factor	IMF2	0.012	0.010
Kurtosis	IMF2	0.258	0.014
Sixth moment	IMF2	0.131	0.009

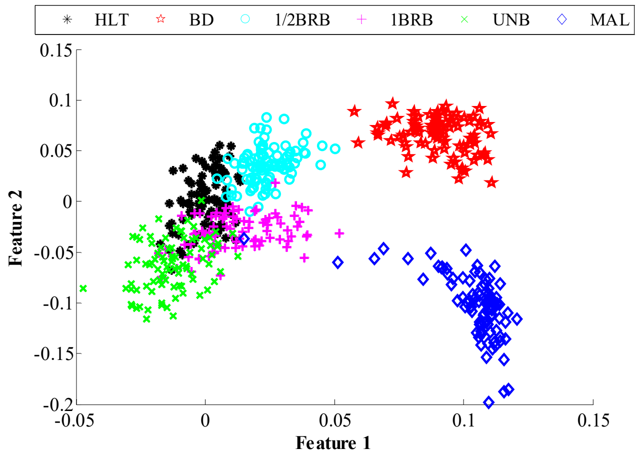

Fig. 9. Projection of the extracted set of features resulting from the classical approach LDA.

PCA and LDA would not be capable to characterize all the considered faults.

Regarding the fault classification, a multilayer NN-based classifier is used to obtain the output classes. Because it is obtained a better performance by the proposed hybrid feature reduction, a simple structure considered in the classifier allows obtaining good results without excessive use of resources. Thus, the classifier has 10 neurons in its hidden layer, in the output layer a probabilistic sigmoid function is used as activation function and 70 epochs are considered for training using the back-propagation rule. These parameters are selected by trial and error tests.

In order to obtain statistically significant results and to prove the performance of the proposed diagnosis methodology, the classifier is trained and tested under a 5-fold cross-validation scheme. Thus, considering all the conditions, the original database is composed by 540 samples, 90 samples of each condition. This database is divided in two different parts, one of them composed by 432 samples for training purposes, 72 samples per condition, and the other one composed by 108 samples for testing purposes, 18 samples per condition. In order to analyze the performance of the classification using all the variance available in the original database, a 5-fold cross validation scheme has been applied, in which five classification ratios are obtained as result of five iterations with complementary partitions of the original database in training and test sets. An averaged classification ratios of 91% for the training, and 92% for the test have been obtained.

It should be also clarified that the classification ratios obtained during the 5-fold cross validation exhibit a stable behavior, that is, within the range of 89.8% to 91.7% in the training stage, and within the range of 90.7% to 92.8% in the test stage. Besides to provide the classification rates, the decision regions are computed by means of the NN classifier. A visual representation of the resulting classification performance reach during the training and test of the NN classifier is provided next. The resulting decision regions and samples projections, using the first fold partition as reference, are projected and shown in Fig. 10, training, and Fig. 11, test.

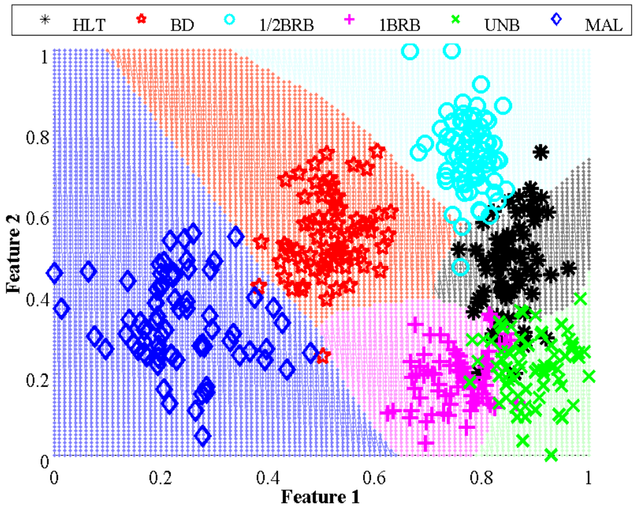

Fig. 10. Projection of the decision regions resulting from the NN-based classification algorithm. Projection of the training data set corresponding to the first cross validation.

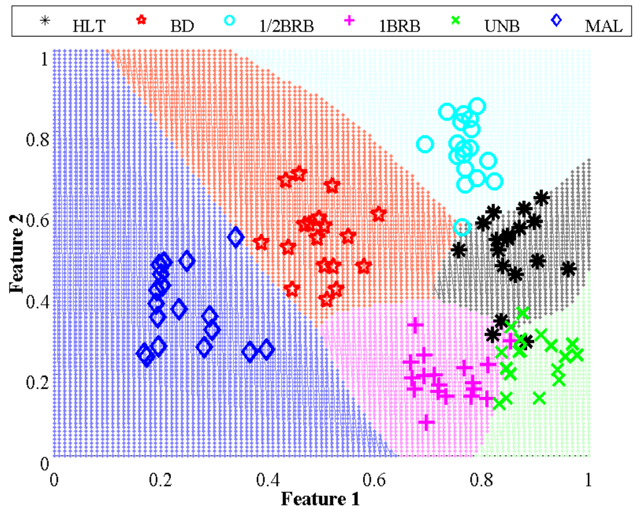

Fig. 11. Projection of the decision regions for the multiple fault classification corresponding to the test of the first cross validation computed by the proposed NN-based classifier.

To analyze the performance of each class individually, the same structure of the NN-based classifier is trained and tested with the extracted features provided by the classical approaches. Table V and Table VI summarize the confusion matrices computed by the classical approaches, PCA and LDA, respectively. As the results show in the confusion matrices of the classical approaches, the misclassification problems are present between the classes of ½ BRB, 1 BRB, UNB and HLT. It should be noticed that the most critical misclassification cases are related to the HLT condition that represents a disadvantage. The classification ratio achieved by the classical approaches PCA and LDA are approximately 80% and 72%, respectively.

Regarding the proposed diagnosis methodology, the resulting classification ratio achieved from the training and test of the NN classifier is 91% and 92% respectively. In Table VII and Table VIII are summarized its respective confusion matrices corresponding to the evaluation of all the considered conditions by using the proposed hybrid feature reduction. Although some misclassifications are obtaining in both training and test of the NN classifier, the results are promising. Considering the results generated during the test of the NN classifier, the global ratio of classification is improved by 12% and 20% in comparison with the classical approaches PCA and LDA, respectively. Respecting the right classification of the healthy condition, which is the most important condition, the proposed approach improved its correct classification by 39% compared to the classical approach PCA, and 11% for the LDA. These results represent a high-performance feature reduction in the development of diagnosis schemes for electromechanical systems.

TABLE V
CONFUSION MATRIX RESULTING FROM THE EVALUATION OF ALL CONSIDERED CONDITIONS USING THE CLASSICAL PCA

Assigned	True Class					
Class	HLT	BD	½ BRB	1 BRB	UNB	MAL
HLT	8	0	2	0	2	0
BD	0	18	0	0	0	0
½ BRB	1	0	14	1	0	0
1 BRB	3	0	2	17	4	0
UNB	6	0	0	0	12	0
MAL	0	0	0	0	0	18

TABLE VI
CONFUSION MATRIX RESULTING FROM THE EVALUATION OF ALL CONSIDERED CONDITIONS USING THE CLASSICAL LDA

Assigned	True Class					
Class	HLT	BD	½ BRB	1 BRB	UNB	MAL
HLT	13	0	1	3	1	0
BD	0	18	0	0	0	0
½ BRB	1	0	13	13	1	0
1 BRB	2	0	4	2	2	0
UNB	2	0	0	0	14	0
MAL	0	0	0	0	0	18

TABLE VII
CONFUSION MATRIX RESULTING FROM THE EVALUATION OF ALL CONSIDERED CONDITIONS COMPUTED DURING THE TRAINING OF THE NN-BASED CLASSIFIER CONSIDERED IN THE PROPOSED HYBRID FEATURE REDUCTION

Assigned	True Class					
Class	HLT	BD	½ BRB	1 BRB	UNB	MAL
HLT	58	0	2	0	3	0
BD	0	70	0	0	0	0
½ BRB	5	0	70	0	0	0
1 BRB	4	0	0	71	14	0
UNB	5	0	0	1	55	0
MAL	0	2	0	0	0	72

TABLE VIII
CONFUSION MATRIX RESULTING FROM THE EVALUATION OF ALL CONSIDERED CONDITIONS COMPUTED DURING THE TRAINING OF THE NN-BASED CLASSIFIER CONSIDERED IN THE PROPOSED HYBRID FEATURE REDUCTION

Assigned Class	True Class HLT	BD	½ BRB	1 BRB	UNB	MAL
HLT	15	0	1	0	1	0
BD	0	18	0	0	0	0
½ BRB	1	0	17	0	0	0
1 BRB	1	0	0	18	3	0
UNB	1	0	0	0	14	0
MAL	0	0	0	0	0	18

VI. CONCLUSIONS

This paper presents a novel methodology to diagnose an IM-based electromechanical system under multiple fault conditions. There are three important aspects in this new method. The first one is the vibration signal decomposition in multiple IMFs. The adaptive capability of the EMD allows the identification of the main vibration modes under the different fault conditions; thus, enhancing the characteristic fault patterns of each fault. The second is the application of a hybrid strategy as feature reduction processing stage. The application of a sequential set of feature reduction procedures over the high-dimensional set of features, allows the consideration of different approximations to the optimum data set, from the elimination of the less contributive features to the compression of the most significant set. The third is the use of a simple classification algorithm based on a unique NN structure able to recognize all the considered conditions. Six different experimental conditions have been considered, which represent an important range of system conditions, including healthy and faulty states. Under all of these experimental conditions, the proposed methodology shows reliable fault diagnosis results. Moreover, the diagnosis outcome is complemented by the probability value, which allows an additional degree of interpretation of the diagnosis outcome. The proposed methodology shows almost 12% and 20% of diagnosis improvement compared with classical approaches PCA and LDA respectively, till 92% of total diagnosis ratio. Note that this is the first time that this methodology and the corresponding analysis with classical approaches is made in electromechanical system diagnosis. The results obtained in this work suggest that this methodology may be also useful for any other rotating mechanical component faults. Future work will focus in the analysis of the multi-fault diagnosis methodology considering different operating conditions of speed and load.

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