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Condition Monitoring Method for the Detection of Fault Graduality in Outer Race Bearing Based on Vibration-Current Fusion, Statistical Features and Neural Network

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Abstract: Bearings are the elements that allow the rotatory movement in induction motors, and the fault occurrence in these elements is due to excessive working conditions. In induction motors, electrical erosion remains the most common phenomenon that damages bearings, leading to incipient faults that gradually increase to irreparable damages. Thus, condition monitoring strategies capable of assessing bearing fault severities are mandatory to overcome this critical issue. The contribution of this work lies in the proposal of a condition monitoring strategy that is focused on the analysis and identification of different fault severities of the outer race bearing fault in an induction motor. The proposed approach is supported by fusion information of different physical magnitudes and the use of Machine Learning and Artificial Intelligence. An important aspect of this proposal is the calculation of a hybrid-set of statistical features that are obtained to characterize vibration and stator current signals by its processing through domain analysis, i.e., time-domain and frequency-domain; also, the fusion of information of both signals by means of the Linear Discriminant Analysis is important due to the most discriminative and meaningful information is retained resulting in a high-performance condition characterization. Besides, a Neural Network-based classifier allows validating the effectiveness of fusion information from different physical magnitudes to face the diagnosis of multiple fault severities that appear in the bearing outer race. The method is validated under an experimental data set that includes information related to a healthy condition and five different severities that appear in the outer race of bearings.

Keywords: condition monitoring; fault severity; bearings; feature calculation; feature extraction; information fusion; neural network; Linear Discriminant Analysis

1. Introduction

A great deal of the applications in the modern industry is composed of electromechanical systems or kinematic chains that generally involve electrical rotating machinery. In fact, it has been reported by the International Energy Agency (IEA) that electric motors demand more than half of the global electricity [1,2]; additionally, it has been estimated that such electrical demand may grow approximately 2.1% per year. On the other side, it is expected that electric motors used in the industry will represent more than 30% of the total growth until 2040 [2,3]. In this regard, the Induction Motor (IM) is the most used electric machine in the industrial sector; although IM is included in a wide range of industrial applications due to its reliability, robustness, and efficiency, the occurrence of

faults during its operation represents a critical issue since unexpected stoppages are produced and affect the efficiency of the production lines [4–6]. Consequently, aiming to face these issues, the development of condition monitoring strategies focused on fault detection and identification in IM, and its linked components, is being one of the priorities addressed by new research works.

The IM faults occurrence is commonly produced by electrical or mechanical stresses that finally produce damages over the mechanical or electrical parts of the IM. Thus, within the most common faults that influence the IM operation are those damages that affect the stator, rotor, and the bearing elements [7–9]; specifically, the occurrence of faults in IMs is mainly associated with these elements (stator, rotor, and bearings) representing around 32%, 10%, and 40%, respectively [10,11]. That is, a high percentage of fault occurrence in IMs is produced by its associated bearings; consequently, bearings play an important key role that may affect the operation, reliability, and efficiency of IMs. As it has been reported in the literature, bearings have finite life that is limited by their resistance to fatigue; thus, the occurrence of faults is inherent to its operation, even under ideal operating conditions [12,13]. In this sense, most of the common faults in bearing may be attributed to the following causes: (i) overload, which may be generated by static load and/or unbalances or misalignments; (ii) excessive or insufficient lubrication; (iii) external contamination; (iv) inappropriate installation and/or design; and (v) electrical discharges passing through the bearing [14,15]. Hence, electrical discharges are considered one of the most critical causes that may produce the gradual degradation of bearings in IMs.

A large number of diagnosis strategies have been proposed and focused on the identification and diagnosis of bearing failures, where the acquisition of different signals such as the occurrence of vibrations, stator current signatures, voltages, temperatures, and thermal imaging have been analyzed aiming to provide the condition assessment of bearings [16–19]. Despite different signals may be analyzed to achieve the fault diagnosis in bearings, the vibrations signals remain the most preferred that has been accepted by the industrial sector [5,20,21]. In this regard, in [22], a diagnosis strategy to identify impulsive bearing failures from variable-speed vibrations by means of measuring the short-term spectral components from vibration signals is proposed; although effective results are obtained through the application of the method, additional knowledge is mandatory for setting the optimum parameters that are required for the considered techniques in order to obtain high-performance results. Similarly, in [23], the combination of the spectral and permutation entropy of vibrations signal for assessing different types of damage on bearings during low-speed conditions is analyzed; despite different bearing conditions may be assessed, the proposed method seems to be designed to face the fault identification for specific operation conditions, such as continuous speed and load. On the other side, the identification of faults in bearings can be also performed through classical approaches based on MCSA (Motor-Current Signature Analysis); in this sense, in [24], stator current-based bearing fault diagnosis using fractional wavelet denoising and deep learning algorithms is presented; although through the proposed method is possible to identify the damage of outer and inner races of bearings, the application of the methods is focused on the detection of a unique fault severity. Likewise, in [25], a novel methodology for fault size estimation of ball bearings using stator current signals is proposed, where the fault-excited harmonic components and amplitudes in stator current are estimated, and the FHD (Fault-excited Harmonic Distortion) evaluated to achieve the fault size estimation. Even though different fault sizes can be detected, the estimation of undesired frequency components that may appear overlapped with the fault-related components may lead to infeasible detections. Therefore, the separate analysis of vibrations and stator currents may lead to the identification and detection of bearing damages, and the analysis of both signals present particular advantages that may contribute to improving the condition assessment of bearing faults if both signals are analyzed together. Although several works have been proposed to perform the bearing fault detection and diagnosis, some challenges still exist that have not been addressed in the field of bearing fault assessment, which are

(i) the bearing fault detection from the viewpoint of severity detection has not been extensively studied; thus, the identification of fault graduality may be difficult whether physical magnitudes, such as stator current, show small changes and/or variations in amplitude, and (ii) the occurrence of bearing faults may be confused with other faulty components since fault-related patterns overlapping is a common effect in rotating machines.

Additionally, it must be mentioned that others have tried to overcome these challenges through ensemble learning, parallel Neural Networks, and transfer learning-based solutions; however, complex condition monitoring structures are needed to achieve good performance results. In this regard, for example, in [26], a diagnosis method that first includes a higher-order spectral analysis and multitask learning-based convolutional neural network is proposed for the identification of the bearing health condition, and second, identifying bearing fault conditions by means of a transfer learning-based approach in the presence of multiple crack conditions. However, although this proposal leads to the efficient diagnosis of bearing faults, prior knowledge about the implementation and configuration of deep learning (DL) techniques is the main limitation to develop complex structures that are also based on ensemble learning approaches [27]. Moreover, recent DL-based approaches have to overcome some challenges that must be avoided for practical applications. These limitations are: (i) the operation is limited to the amount of data that are not easy to obtain in industrial sites; (ii) difficulties and unclear understandable interpretation for practitioners; (iii) generalization-based approaches to avoid overfitted responses and solutions; and (iv) the strategical hyper-parameter tuning procedures to enable its easy access and configuration. Nevertheless, even though good performance results are obtained, the use of ensemble learning-based on DL results in a complicated task; thus, these challenges can be overcome by the proposal of strategies that incorporate proper processing techniques, i.e., analysis in the time-domain and frequency-domain, and by considering multiple signals that contain different information, but its fusion leads to highlighting those representative fault-related patterns.

Most of the proposed studies that have analyzed and identified the occurrence of faults in bearings are commonly focused on analyzing those faults that are related to the electrical erosion phenomenon [13,15,28]. In this regard, in the research field, the faults produced by electrical erosion are artificially produced by drilling a hole in the outer race, inner race and/or by damaging the rolling elements of the bearing [29–31]. Additionally, most of the times, the initial damage of bearings can start with small holes that may grow gradually until producing irreversible damages; thereby, the importance of studying the evolution of faults in bearings is an interesting topic that should continue to be studied. On the other side, it should be highlighted that most of the reported works in regard to the detection of different severities of bearing faults are validated under experimental datasets, where critical damages are produced on the bearing elements, i.e., excessive damages produced by drilling holes in the outer race with a diameter higher than 6 mm [32]. During the analysis of the occurrence of bearing faults, it would be interesting to study the evolution of the fault occurrence, which is a more gradual effect that can happen in industrial environments.

The proposal of condition monitoring strategies have been supported by the use of different signal processing techniques that can be based on different domain analyses, i.e., time-domain [33,34], frequency-domain [21], and time-frequency domain analysis [35]. For the time-domain analysis, the estimation of statistical time-domain features is taken into account for many of the proposed diagnosis methods. Statistical time-domain features are preferred due to its simplicity of calculation and its effectiveness to model changes and trends of signals [18,33]. Despite that, most of the classical approaches aim to perform the diagnosis of bearing faults by carrying out the analysis of the characteristic fault-related frequency components through the FFT (Fast Fourier Transform) [34]. Furthermore, although the analysis of the fault-related frequency components produced by bearing failures leads to achieving the occurrence of faults, additional knowledge and experience is necessary to distinguish between multiple frequency components that tend to

appear as the fault-related frequency patterns. Additionally, time-frequency analysis represented by complex techniques, such as the Hilbert transform, has been included in condition monitoring strategies [8]. In this regard, Artificial Intelligence (AI) algorithms and Machine Learning (ML) techniques have been also incorporated in condition-monitoring strategies; thus, diagnosis and classification structures can be based on Neural Networks (NNs), Support Vector Machines (SVMs), decision trees, among others, to achieve the automatic fault diagnosis [16,35,36]. Conversely, the use of ML techniques is implemented as feature extraction and feature reduction techniques [37]. Even heuristic search algorithms, such as Genetic Algorithms (GA), are also used in condition monitoring approaches to solve optimization problems that commonly focus on procedures to select those significant features [38]. Accordingly, the consideration of both AI algorithms and ML techniques in condition monitoring strategies can lead to improve the resulting fault diagnosis; even more, if the proposal of condition monitoring methods is based on the fusion of information.

Bearings are the elements that allow the rotating movement in rotating machines, and the sudden occurrence of faults is inherent to its operation. Additionally, the occurrence of faults in bearings may initially occur by its degradation, and then, several damages may appear over the inner race, outer race, and the balls of the bearing. Thus, there are different fault severities that occur from the initial failure to its most critical degree. In this regard, a condition monitoring methodology designed for identifying different severities of the outer race bearing fault in an IM is proposed in this work. The proposed method is supported by tools, such as Machine Learning (ML) techniques and Artificial Intelligence (AI), that facilitate the fusion information of different physical magnitudes. Indeed, the contribution and novelty of this proposal include the processing of different signals through different domain analyses, that is, the time-domain and frequency-domain. In fact, an important aspect of this approach is the calculation of statistical features that are obtained to characterize the acquired vibration and stator current signals; the estimation of statistical features in different domain analyses leads to a high-performance signal characterization. Additionally, the fusion of vibrations with stator current information is carried out by subjecting their characteristic statistical features to a dimensionality reduction procedure. Thereby, the dimensionality reduction is achieved by the LDA, which is classic technique that leads to achieve the maximum linear separation between multiple classes and allows the visual representation into a 2D space. Finally, the automatic diagnosis and fault severity identification is performed through a classical NN-based classifier. The proposed method is validated under a complete set of experimental data that was acquired from a self-designed test bench. Moreover, the effectiveness of this proposal is proved since six different bearing conditions are effectively diagnosed and identified. The assessed conditions comprise a healthy condition and five different severities of fault that appear in the outer race of a bearing with a damage of 1 mm, 2 mm, 3 mm, 4 mm, and 5 mm, respectively.

2. Theoretical Background

2.1. Bearing Faults in Electric Motors

The rotating movement of the electrical machines, such as IM, is produced by means of the bearing elements; therefore, its proper operation ensures the availability of such electric machines [14]. The occurrence of failures in bearings may be to different sources; indeed, different types of failures may appear in bearings; in this sense, the most studied faults in bearings are related to problems that appear in the inner race, outer race, cage, and balls. Although the common occurrence of faults in bearings can be produced by overloads, the electrical discharge is also considered a critical issue that can lead to the appearance of faults in bearings [15].

This issue is also known as electrical erosion, and it is considered as a phenomenon produced by the current leakage; specifically, this phenomenon produces a micro-scaling

of the rolling surfaces [39]. Thereby, the current leakage usually occurs during the IM operation generating small craters on the bearing surfaces (outer and/or inner races), and this damage appears since the leakage of currents travels through the rolling elements (bearing balls) from the outer race to the inner race, as shown in Figure 1a. Subsequently, on the contact surfaces, a similar process to the electric arc welding arises, that is, a high current density on small contact surfaces, as Figure 1b depicts. Then, as shown in Figure 1c, the material is heated to high temperatures, where the bearing material may experiment with a temperature ranging from the temper level to the melt level. As a consequence, the appearance of discolored areas and the appearance of craters occur in those areas where the material has been melted and removed due to the rotation of the rolling element. Finally, the excess material that adhered to the rolling elements of the bearing wears away, as shown in Figure 1d.

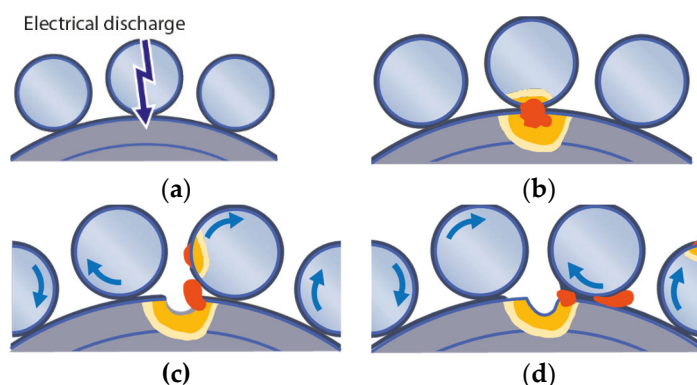


Figure 1. Electrical erosion produced on the bearing surfaces by means of the current leakage phenomenon that consist of: (a) the crossing of the electric current through the rolling elements; (b) the electric arc welding occurs between the rolling elements and bearing surfaces; (c) the molten material solidifies and then separates; (d) the excessive material in the rolling elements wears away.

In this sense, electric erosion is considered one of the main causes of the gradual degradation of bearings in electric machines such as IMs; indeed, such phenomenon may produce the sudden appearance of damages on the outer and/or inner races of the bearing [13]. Although, initially, the failures produced on the outer and/or inner races may not affect the operation of the electric machines; the quick evolution of the bearing degradation can cause several issues in electric machines, even their unexpected breakdown. Thereby, in real applications, when craters are produced in the outer race and/or the inner race of the bearing, the generation of impacts when the rolling elements pass through them is produced. In fact, as it is known and according to the theoretical basis of bearings operation, when they are working under the influence of defects in the inner-race and/or outer-race, it affects the whole bearing system due to the influence of the induced impacts that result from balls coming into contact with the damaged area during the rotating operation of bearings. Even though these impacts are usually generated at intervals of time that are influenced by the severity (size) and shape of the fault, its occurrence may or may not appear depending on the severity of the damage [40].

2.2. Classic Fault-Related Patterns Produced by the Occurrence of Faults in Bearings

The identification of bearing faults through vibration-based analysis has been considered as a reliable diagnostic approach that has been widely accepted by the industrial sector. On the other hand, the analysis of vibrations by means of frequency-domain techniques, such as the FFT, has been widely implemented because this technique allows representing the discrete and periodic components of signals into a frequency plane, where the characteristic and most representative frequency components are projected [34]. Accordingly, dealing with the diagnosis of bearing faults, the vibration spectra are used for

detecting the occurrence of faults in bearings. As it is known, the common failures in bearings are associated to defects in the outer race, inner race, rolling elements, and the cage. Thereby, the occurrence of any of these faults may produce a characteristic pattern that can be associated a specific frequency component. Hence, to assess the faults in the bearings, it is mandatory to know fault-related frequency components that are produced by the sudden occurrence of bearing faults [12]. In this regard, the identification of bearing defects can be performed by locating their fault-related frequencies over the vibration spectrum; in fact, high amplitudes on the fault-related frequency components are due to the fault appearance. Therefore, the mathematical equations to identify defects in the outer race, inner race, and balls of bearings are related to the fault-related components of Equations (1) and (2), respectively. With the calculation of the BPFO (Ball Pass Frequency of the Outer race) and BPFI (Ball Pass Frequency of the Inner race) components, it is possible to locate the fault-related frequency components in the frequency spectrum and determine the presence of bearing faults on the outer race and inner race. It should be noted that these fault-related frequency components are computed in terms of the number of rolling elements (balls), N_b ; the ball diameter, BD ; the pitch diameter, PD ; the contact angle, θ ; and the rotational frequency, f_{rm} , [41].

$$BPFO = \frac{N_b}{2} f_{rm} \left(1 - \frac{BD}{PD} \cos \theta \right) \quad (1)$$

$$BPFI = \frac{N_b}{2} f_{rm} \left(1 + \frac{BD}{PD} \cos \theta \right) \quad (2)$$

2.3. Machine Learning-Based Feature Reduction

Most of the proposed condition monitoring approaches include the estimation of high-dimensional sets of features as a part of the diagnosis procedure. Precisely, the feature calculation is carried out aiming to obtain the characteristic patterns associated to malfunction operations. Thus, the sets of features are obtained from signals that describe the behavior of a system, i.e., an electromechanical system. Subsequently, unhelpful and correlated information may be estimated if a large number of features is estimated. In this sense, the application of machine learning-based feature reduction techniques represents a practical solution to retain the most significant and representative information.

Thus, the Principal Component Analysis (PCA) and the Linear Discriminant Analysis (LDA) are within the best well-known techniques used to reduce the dimensionality of a high-dimensional set of features. The PCA is an unsupervised linear method that allows reducing the dimension of a correlated data set to a linear space of unrelated indicators while preserving the greatest possible variance. The application of the PCA results in the extraction of a new set of features that are sorted according to the cumulative variance that preserves and are known as principal components [5,11,42]. On the other hand, the LDA is a supervised linear method that allows a dimensionality reduction by extracting a new set of features, in which the maximization of the data separability is achieved for a C number of considered classes. Although both methods have been widely used in several condition monitoring strategies, the implementation of the LDA is appropriated to be applied in multi-class problems leading to high effectiveness during the condition assessment [19,37].

3. Proposed Method

The proposed condition monitoring method for the detection of different fault severities in the outer race of bearings is based on the flowchart in Figure 2. The assessment of different fault severities in the outer race of bearings is carried out by characterizing the available physical magnitudes, vibrations, and stator current through the estimation of a significant set of hybrid features that include statistical features from different domains. Moreover, the information fusion and data compression are considered fundamental parts of the proposed method. In this sense, the estimated hybrid features are fused and represented in a 2-dimensional space by means of applying one of the most well-

known machine learning techniques, the LDA. Finally, the automatic assessment and detection of different fault severities on the outer race bearing of an IM are achieved by means of an NN-based classifier. The diagnosis methodology is proposed by following a step-by-step scheme that allows its practical application over electromechanical systems that are related to rotating machinery, such as IM, gearboxes, shafts, among others. Under this consideration, the proposed diagnosis methodology represents an approach that leads to the characterization of the bearing operation and its posterior recognition.

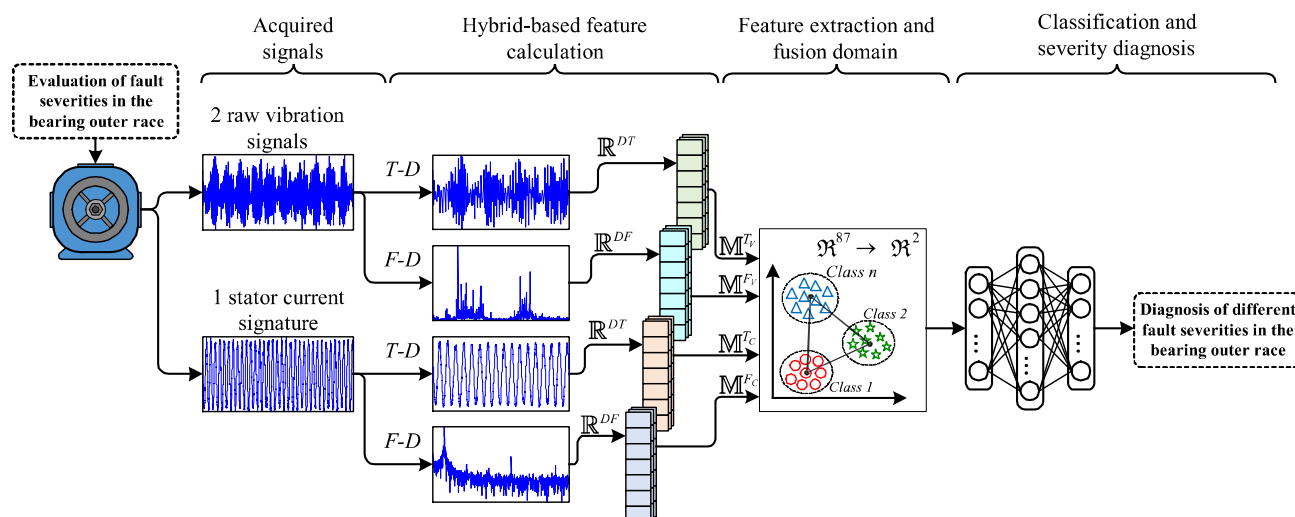


Figure 2. A flow chart of the proposed condition monitoring method for the diagnosis and detection of multiple fault severities that may occurred in the outer race of bearings in IM's.

3.1. Hybrid-Based Feature Calculation

The proposed method supports different or multiple physical magnitudes, despite vibration signals being the most preferred physical magnitude to diagnose the fault occurrence in bearings. In this proposal, the processing of different signals to achieve an improved characterization of the electromechanical system condition is considered, which, in turn, is related to the bearing condition. Thus, in the first stage, the three available signals (two vibration signals and one stator current) are characterized with the aim of computing a meaningful set of hybrid features. Subsequently, the processing of the available signals is carried out in two domains, that is, the time-domain (TD) and frequency-domain (FD). During the characterization procedure, the acquired signals are segmented into equal parts of one second; the consideration of this temporal period guarantees sufficient statistical consistency in most of the practical applications.

In this regard, for the TD analysis, the available signals are characterized by estimating a set of $T = 15$ statistical features, and as a result, two representative T -dimensional feature matrices are obtained from the considered signals. Thereby, the characteristic feature matrix in the TD for the vibrations signals is M^{Tv} and for the stator current is M^{Tc} , where $T \in \mathbb{R}^T$. On the other side, for the FD analysis, from each segmented part of the available signals, its corresponding frequency spectrum is computed through the classical application of the FFT technique. Subsequently, from each achieved frequency spectrum for each considered signal, a set of $F = 14$ statistical features is estimated aiming to obtain a numerical representation of the previously estimated frequency spectra. After applying the FD analysis, two significant F -dimensional feature matrices are obtained separately for the vibration signals and the stator current. The characteristic feature matrices in the FD are M^{Fv} for vibrations and M^{Fc} for stator current, where $F \in \mathbb{R}^F$.

The characterization of signals by means of its processing through different domain analyses, such as TD and FD, allows improving the characterization of the fault-related patterns because it has been proved to ensure that promising results are achieved in the condition assessment when a meaningful set of hybrid features is estimated. Regarding

the statistical features that are proposed to be estimated during the processing of the vibration and stator current signals in TD and FD analyses, the corresponding mathematical equations of the proposed sets of statistical features are summarized in Tables 1 and 2; these proposed sets of features have been usually considered in several condition monitoring approaches [33–35]. Thus, the statistical features computed in the TD are represented by Equations (3)–(17), while those computed in the FD are represented by Equations (18)–(30). The estimation of these sets of statistical features provides several advantages in condition monitoring strategies, that is, high-performance signal characterization due to its ability of modeling trends and changes in signals when its estimation is performed in TD, whereas the calculation of statistical features in FD allows modeling changes in the main frequency components with a high convergence to the power spectrum. Furthermore, in regard to the computational burden, the easy computation of statistical features shows an advantage over other complex signal processing, such as DWT and MUSIC, among others [10,21].

Table 1. The proposed set of statistical features for the characterization of the available signals during the processing in the time-domain analysis, where $x(i)$ is a sample for $i = 1, 2, \dots, N$, and N is the number of points for each acquired signal.

Statistical Time-Domain Feature	Mathematical Equation
Mean	$T_1 = \frac{1}{N} \cdot \sum_{i=1}^N x_i $ (3)
Maximum value	$T_2 = \max(x)$ (4)
Root mean square	$T_3 = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^N (x_i)^2}$ (5)
Square root mean	$T_4 = \left(\frac{1}{N} \cdot \sum_{i=1}^N \sqrt{ x_i }\right)^2$ (6)
Standard deviation	$T_5 = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^N (x_i - T_1)^2}$ (7)
Variance	$T_6 = \frac{1}{N} \cdot \sum_{i=1}^n (x_i - T_1)^2$ (8)
RMS Shape factor	$T_7 = \frac{T_3}{\frac{1}{N} \cdot \sum_{i=1}^N x_i }$ (9)
SRM Shape factor	$T_8 = \frac{T_4}{\frac{1}{N} \cdot \sum_{i=1}^N x_i }$ (10)
Crest factor	$T_9 = \frac{T_2}{T_3}$ (11)
Latitude factor	$T_{10} = \frac{T_2}{T_4}$ (12)
Impulse factor	$T_{11} = \frac{T_2}{\frac{1}{N} \cdot \sum_{i=1}^N x_i }$ (13)
Skewness	$T_{12} = \frac{\sum[(x_i - T_1)^3]}{T_5^3}$ (14)
Kurtosis	$T_{13} = \frac{\sum[(x_i - T_1)^4]}{T_5^4}$ (15)
Fifth moment	$T_{14} = \frac{\sum[(x_i - T_1)^5]}{T_5^5}$ (16)
Sixth moment	$T_{15} = \frac{\sum[(x_i - T_1)^6]}{T_5^6}$ (17)

Table 2. The proposed set of statistical features for the characterization of frequency spectra estimated from each available signal during its processing in the frequency-domain analysis, where $s(k)$ is a spectrum for $j = 1, 2, \dots, M$, and M is the number of lines with f_j as the frequency value of the j th spectrum line.

Statistical Feature	Mathematical Equation
Mean	$F_1 = \frac{1}{M} \cdot \sum_{j=1}^M s(j) \tag{18}$
Variance	$F_2 = \frac{1}{M-1} \cdot \sum_{j=1}^M (s(j) - F_1)^2 \tag{19}$
Third moment	$F_3 = \frac{1}{M(\sqrt{F_2})^3} \cdot \sum_{j=1}^M (s(j) - F_1)^3 \tag{20}$
Fourth moment	$F_4 = \frac{1}{M(\sqrt{F_2})^2} \cdot \sum_{j=1}^M (s(j) - F_1)^4 \tag{21}$
Grand mean	$F_5 = \frac{\sum_{j=1}^M f_j s(j)}{\sum_{j=1}^M s(j)} \tag{22}$
Standard deviation 1	$F_6 = \sqrt{\frac{\sum_{j=1}^M (f_j - F_5)^2 s(j)}{M}} \tag{23}$
C Factor	$F_7 = \sqrt{\frac{\sum_{j=1}^M f_j^2 s(j)}{\sum_{j=1}^M s(j)}} \tag{24}$
D Factor	$F_8 = \sqrt{\frac{\sum_{j=1}^M f_j^4 s(j)}{\sum_{j=1}^M f_j^2 s(j)}} \tag{25}$
E Factor	$F_9 = \frac{\sum_{j=1}^M f_j^2 s(j)}{\sqrt{\sum_{j=1}^M s(j) \sum_{j=1}^M f_j^4 s(j)}} \tag{26}$
G Factor	$F_{10} = \frac{F_6}{F_5} \tag{27}$
Third moment 1	$F_{11} = \frac{\sum_{j=1}^M (f_j - F_5)^3 s(j)}{M F_6^3} \tag{28}$
Fourth moment 1	$F_{12} = \frac{\sum_{j=1}^M (f_j - F_5)^4 s(j)}{M F_6^4} \tag{29}$
H Factor	$F_{13} = \frac{\sum_{j=1}^M (f_j - F_5)^{1/2} s(j)}{M \sqrt{F_6}} \tag{30}$
J Factor	$F_{14} = \frac{(F_7 + F_8)}{F_1} \tag{31}$

3.2. Feature Extraction and Fusion Domain

The second stage of the proposed method is focused on performing the information fusion and data compression by means of the LDA technique. In this sense, it must be highlighted that the evaluated condition is represented by the available signals that are characterized by a high-dimensional set of hybrid features, where this meaningful set of features comprises the characteristic patterns of the available signals that are processed in different domains. Even though the characterization of signals through a hybrid set of features leads to a high-performance characterization in condition monitoring strategies, the estimation of correlated and non-useful information is inevitable even if complex signal processing is implemented.

In this regard, the LDA technique is applied over all the resulting feature matrices (M^{Tv} , M^{Fv} , M^{Tc} , and M^{Fc}) estimated from analyzing the vibration and stator current signals in two different domains, TD and FD. The main objective of the LDA is reducing the original high-dimensional space of the hybrid set of features into a low-dimensional

space, where the features of the hybrid set are fused during the dimensionality reduction procedure. The information fusion and/or feature fusion is symbolized by the linear combination, in different weights, of the original set of features (high-dimensional set of hybrid features) that is intended to be projected into a new and reduced dimensional space (i.e., 2D or 3D spaces). The new resulting features projected in the new reduced space are also known as the extracted features.

Consequently, the fusion of vibrations and the stator current is represented by the new extracted features, and the resulting projection contains the fusion of information provided by statistical features estimated from different signal processings in both domains, TD and FD. On the other hand, the LDA is a suitable machine learning technique to be applied in condition monitoring methodologies due to the projection of the extracted features into a 2D space allows the visualization of all considered conditions. Additionally, it may deal with multi-class problems, but this peculiarity is an advantage since the LDA may maximize the linear separation as much as possible between clusters of different classes.

3.3. Classification and Severity Diagnosis

Finally, in the third stage, the automatic fault detection and severity diagnosis by means of a classical NN-based structure are performed. It should be highlighted that an interesting advantage of the proposed hybrid-based feature calculation in conjunction with the feature extraction and fusion domain is that it leads to a reduction in the complexity related to the configuration of the required classification algorithm; that is, a high-performance pattern characterization of the considered conditions is achieved facilitating the classification task.

In this regard, the following parameters are taken into account for the proposed NN-based classifier: (i) the structure consists of a simple multi-layer NN that comprises three-layers: the input, hidden, and output layers; (ii) the number of neurons for each layer are defined as two, ten, and six neurons for the input, hidden, and output layer, respectively; (iii) the backpropagation is used as the training algorithm; (iv) the sigmoid function is used as the activation function; (v) 50 epochs are the number of iterations. Specifically, the number of neurons considered in the input layer is equal to the number of features extracted by means of the LDA technique, and for this proposed work, the features extracted by the LDA are represented in a 2D space. For the hidden layer, the number of neurons is fixed to ten neurons, which have been defined by following the literature suggestions [43,44]. Such literature suggestions are supported by the results obtained in practices of performance analysis based on trial and error for the selection of the number of neurons in the hidden layer [45]. In the output layer, a number of neurons equal to six are considered, where each neuron considered in the output layer represents each one of the evaluated conditions that are associated to a particular fault severity in the outer race of bearings. Moreover, it should be mentioned that the proposed NN-based classifier is trained and tested under a k -fold cross-validation scheme to obtain statistical and significant results. During the training and testing of the NN-based classifier, the sigmoid function is used as the activation function, and the backpropagation is used as the training algorithm during 50 epochs. Additionally, even though optimization algorithms can be optionally used to improve the performance of some NN-structures during the training procedure. The proposed multi-layered NN-based classifier is not supported by any optimizer algorithm since it is a simple multi-layer construction. In Figure 3, the structure of the proposed multi-layer NN-based classifier is shown.

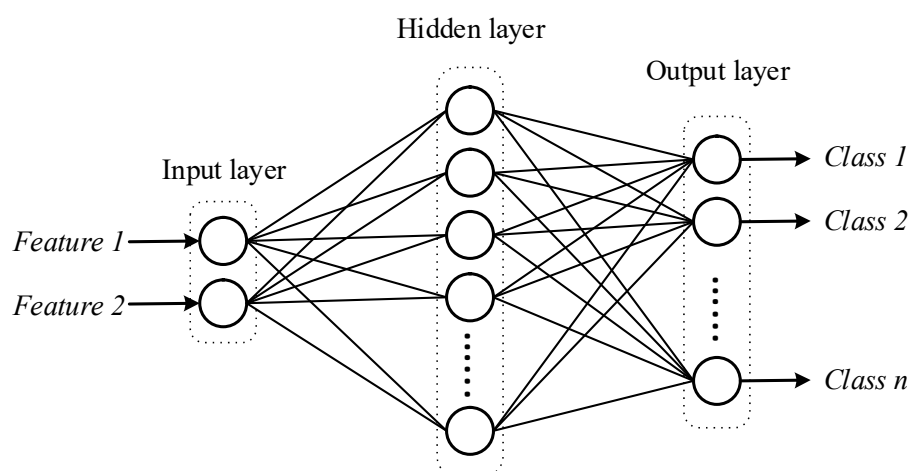


Figure 3. The multi-layer structure of the proposed NN-based classifier for assessing the different bearing conditions under study.

4. Experimental Setup

4.1. Electromechanical Test Bench Based-System

The proposed methodology is validated under a complete set of experimental data. In this sense, an electromechanical test bench-based system is used to evaluate different fault severities in a bearing element. The electromechanical system is a self-designed laboratory test bench, and it is based on a pulley-belt system as the flow chart in Figure 4. shows. The electromechanical system includes a 971-W three-phase induction motor (IM) (model is WEG00136APE48T) with one pair of poles, and the IM is fed through a variable frequency driver (VFD) (model WEGCFW08) with 220 VAC as a power supply; the use of the VFD allows controlling the rotational speed of the IM. Additionally, a conventional alternator is used as a mechanical load, and it is coupled to the IM using the pulley-belt system, as Figure 4 shows; the alternator comprises approximately 25% of the nominal load of the IM.

Regarding the acquired signals, the occurrence of vibrations in the IM and the stator current consumption of one of its three phases are continuously monitored and acquired by a data acquisition system (DAS), which is a proprietary low-cost design based on FPGA (field-programmable gate array) technology. The proprietary DAS has a serial-output sampling analog-to-digital converter with 12 bits and 4 channels (model ADS7841). Thus, the mechanical vibrations that are produced in the electromechanical system are acquired through an accelerometer sensor model LIS3L02AS4 that is placed on the top of the IM case; in this sense, the acquired vibrations are those produced on the perpendicular plane of the rotating axis of the IM shaft, as illustrated in Figure 4. On the other hand, the stator current of one of the three phases of the IM is measured through a hall-effect sensor from Tamura Corporation (model L08P050D15); such a sensor is capable of measuring up to 50 Amps with a high linearity response (1%). Thereby, the hall effect sensor is placed between the VFD and the IM in power supply lines, as is shown in Figure 4. Each of the considered sensors is individually mounted on a PCB that includes the corresponding anti-alias filter and signal conditioning. The sampling frequencies used to acquire the occurrence of vibrations and the stator current consumption were set to 3000 Hz and 6000 Hz, respectively.

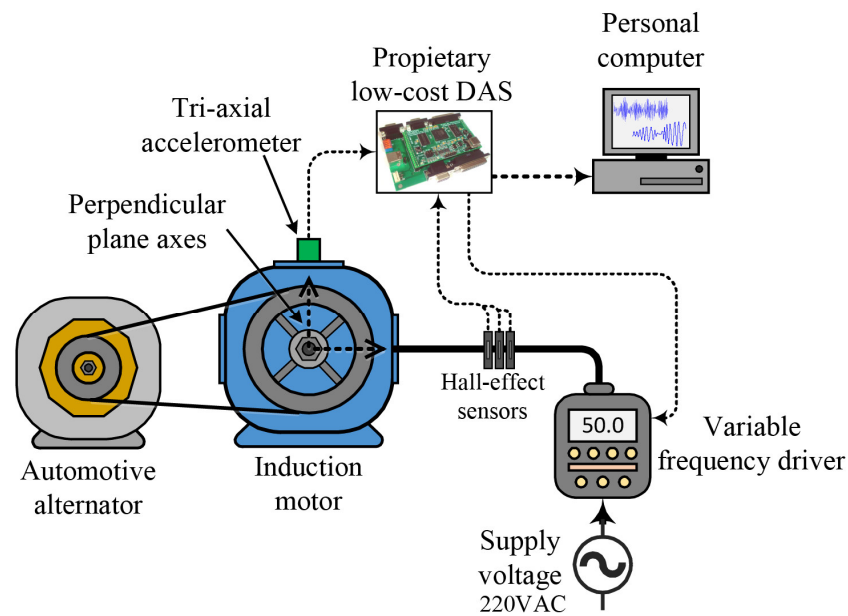


Figure 4. A flow chart of the electromechanical system based on a pulley-belt system and its wiring to perform the acquisition of vibrations signals and the stator current signature.

4.2. Considered Conditions under Evaluation

As aforementioned and according to the theoretical basis of the bearing operation, impacts are induced over the whole bearing system when bearings are working under the influence of defects in the inner race and/or outer race, such impacts appear when the balls get in contact with the damaged area during the rotating operation of bearings. Thus, these impacts usually appear at intervals of time that are influenced by the severity (size) and shape of the fault. Therefore, regarding the assessed conditions, different fault severities in one of the bearing elements of the IM are experimentally tested under different rotational speed conditions; specifically, the end-drive bearing of the IM (model 6203) is that bearing under evaluation.

Consequently, six different bearing conditions are taken into account during the experimentation. The evaluated conditions are the healthy condition (HC) and five different fault severities that are artificially induced on the outer race of the bearing. To generate the different fault severities, five identical bearings are damaged with different tungsten drill bits with diameters of 1 mm, 2 mm, 3 mm, 4 mm, and 5 mm; thus, by drilling a completely through-hole that passes the outer race of each identical bearing, five bearing fault severities (S1, S2, S3, S4, and S5, respectively) are produced. In Figure 5, the damaged bearings are shown.

Accordingly, during the experimentation, different values are considered to be set as the supply frequency in the VFD, aiming to produce different rotational speeds in the IM; thus, each bearing condition (HC, S1 to S5) is iteratively tested under different values of supply frequency that are set in the VFD, that is, 5 Hz, 15 Hz, 50 Hz, and 60 Hz. In this sense, for each supply frequency, the vibration signals and the stator current are continuously measured, acquired, and stored in a personal computer for posterior analysis. Therefore, each bearing condition is tested 15 times under each considered supply frequency, and the vibrations and current signals are acquired during 10 s of the steady-state operation of the IM; as a result, for each bearing condition, 150 s of the measured signals are acquired.

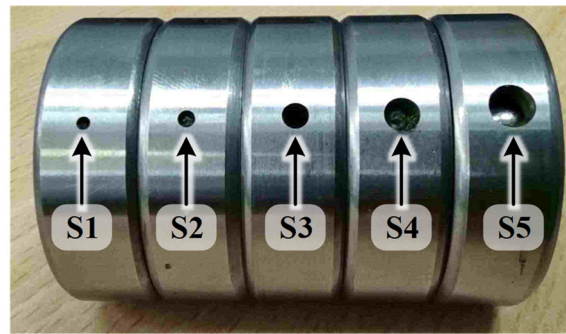


Figure 5. The set of damaged bearings experimentally tested in the IM of an electromechanical systems. The damaged bearings are damaged in their outer race with a severity of damage of: 1 mm (S1), 2 mm (S2), 3 mm (S3), 4 mm (S4), and 5 mm (S5).

5. Results and Discussions

To validate the effectiveness of the proposed method in front of the diagnosis and detection of the different severities of bearing faults, the method is applied to the available signals that are acquired from the pulley-belt electromechanical system; such signals are the two vibration signals and the stator current signature. Hence, as described in Section 3.1, these signals were acquired during 150 s of the continuous operation of the IM, and its processing is carried out under Matlab, which is a dedicated software used in a great deal of engineering applications. According to the proposed method, each one of the acquired signals is segmented into equal 1-second parts to generate a consecutive set of samples; afterward, the multi-domain analysis is performed over each one of the segmented parts of the signals to perform the signal characterization in two different domains, that is, DT and DF. Moreover, the proposed multi-domain analysis leads to achieve high-performance characterization of the electromechanical system operation, which, in turn, is associated with the different bearing conditions.

In this regard, for the TD analysis, the set of 15 statistical features is computed from each segment of each available signal; thus, for both vibration signals, a feature matrix with 30 statistical features and 150 samples ($\dim(M^{Tv}) = (150 \times 30)$) is achieved; meanwhile, the feature matrix achieved from the stator current consists of 15 statistical features with 150 samples ($\dim(M^{Tc}) = (150 \times 15)$). On the other hand, in the FD analysis, from each segmented part of each available signal, the corresponding frequency spectrum is estimated by means of applying the FFT technique, and then, from each resulting spectrum, the set of 14 statistical features is calculated to characterize each corresponding spectrum into a set of representative numerical values. Thereby, for both vibrations signals analyzed in FD, a feature matrix with 28 statistical features and 150 samples ($\dim(M^{Fv}) = (150 \times 28)$) is computed; whereas, for the analysis in FD of the stator current signature, a characteristic feature matrix that contains 14 statistical features with 150 samples ($\dim(M^{Fc}) = (150 \times 14)$) is achieved. Consequently, for each evaluated condition, a high-dimensional set of hybrid features that contain the characteristic patterns is computed. The high-dimensional set of hybrid features includes the four representative feature matrices: M^{Tv} , M^{Tc} , M^{Fv} , and M^{Fc} , which are estimated after analyzing each one of the available signals in two different domains (TD and FD). Hence, the resulting dimension by concatenating the features matrices consist of 87 statistical features in TD and FD with 150 consecutive samples ($\dim([M^{Tv}, M^{Tc}, M^{Fv}, M^{Fc}]) = (150 \times 87)$). Additionally, it should be clarified that these representative feature matrices are estimated for each one of the considered conditions that is experimentally tested under the considered supply frequencies fixed in the VFD (5 Hz, 15 Hz, and 50 Hz).

In order to carry out the information fusion and data compression, the high-dimensional set of hybrid features are subjected to the feature extraction procedure by means of applying the LDA technique. In this sense, the whole resulting feature matrices, consid-

ering all supply frequencies and all bearing conditions, are concatenated, as shown in Table 3. From Table 3, it must be noted that all considered conditions, HC, S1, S2, S3, S4, and S5, are concatenated as row elements, where each condition includes its corresponding feature matrices achieved by analyzing the vibration signals in TD and FD, M^{Tv} and M^{Fv} , respectively, and also includes its corresponding feature matrices achieved by analyzing the stator current signature in TD and FD, M^{Tc} and M^{Fc} , respectively. In regard to the domain of analysis, the resulting feature matrices are concatenated as column elements, as shown in Table 3. Additionally, for the different values of supply frequency, each tested condition includes the corresponding feature matrices that are particularly estimated from the vibrations and stator current signals when the frequencies in the VFD are set to 5 Hz, 15 Hz, and 50 Hz. Such supply frequencies are addressed in Table 3 as @5 Hz, @15 Hz and @50 Hz, respectively.

Subsequently, the LDA technique is applied over all concatenated matrices, aiming to perform the fusion of information, that is, the fusion of statistical features estimated from multiple signals analyzed in both domain analyses, DT and DF. The information fusion stage is achieved because the LDA is based on a linear transformation that projects the information of the original feature space (87-dimensional space) into a new and reduced feature space (2-dimensional space). The resulting projection symbolizes the linear combination, in different weights, of the original set of features (high-dimensional set of hybrid features), where the most representative information of all considered features is retained. In fact, those features that have a high weight, in the linear combination, have a high influence over the resulting projection. In contrast, those insignificant features may have a lower influence and a low weight that does not have significant influence over the resulting projection.

Table 3. The arrangement of feature matrices that are subjected to the feature extraction and fusion domain procedure.

Considered conditions	HC	$M^{Tv}_{@5Hz}$	$M^{Tc}_{@5Hz}$	$M^{Fv}_{@5Hz}$	$M^{Fc}_{@5Hz}$
		$M^{Tv}_{@15Hz}$	$M^{Tc}_{@15Hz}$	$M^{Fv}_{@15Hz}$	$M^{Fc}_{@15Hz}$
		$M^{Tv}_{@50Hz}$	$M^{Tc}_{@50Hz}$	$M^{Fv}_{@50Hz}$	$M^{Fc}_{@50Hz}$
	S1	$M^{Tv}_{@5Hz}$	$M^{Tc}_{@5Hz}$	$M^{Fv}_{@5Hz}$	$M^{Fc}_{@5Hz}$
		$M^{Tv}_{@15Hz}$	$M^{Tc}_{@15Hz}$	$M^{Fv}_{@15Hz}$	$M^{Fc}_{@15Hz}$
		$M^{Tv}_{@50Hz}$	$M^{Tc}_{@50Hz}$	$M^{Fv}_{@50Hz}$	$M^{Fc}_{@50Hz}$
	⋮	⋮	⋮	⋮	⋮
	S5	$M^{Tv}_{@5Hz}$	$M^{Tc}_{@5Hz}$	$M^{Fv}_{@5Hz}$	$M^{Fc}_{@5Hz}$
		$M^{Tv}_{@15Hz}$	$M^{Tc}_{@15Hz}$	$M^{Fv}_{@15Hz}$	$M^{Fc}_{@15Hz}$
		$M^{Tv}_{@50Hz}$	$M^{Tc}_{@50Hz}$	$M^{Fv}_{@50Hz}$	$M^{Fc}_{@50Hz}$

After applying the LDA technique over the hybrid set of features of all considered conditions, the original 87-dimensional feature space is projected into a 2-dimensional space, where the projected features belong to the new set of extracted features. In Figure 6, a visual representation of the new extracted features achieved by means of the LDA technique is shown. From this resulting projection, it can be appreciated that different clusters appear separated between them; each cluster represents each one of the considered conditions evaluated under different operating supply frequencies (5 Hz, 15 Hz, and 50 Hz). Moreover, although the clear separation between all considered conditions is desired, a slight overlapping appears between the conditions S3 and S5; such overlapping may lead to achieving a lower performance of classification performance during the condition assessment. However, on the other hand, it should be highlighted that the HC is well separated from all faulty conditions, and this fact results in avoiding false negatives during the condition assessment, which is an advantage because the proper working condition of rotating electrical machines is assured. From the obtained projection of Figure 6, it must be highlighted that the proposed signal characterization by means of the statistical

features estimated from different signals in different domains, and its fusion and compression through the LDA can lead to a wide range of operating frequencies that, in industrial environments, cover the common ranges of rotating speeds for any considered electrical machine.

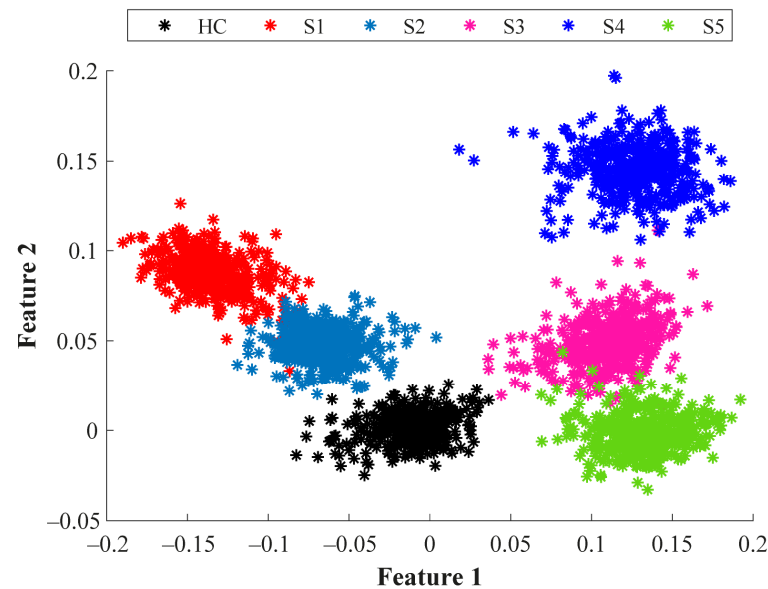


Figure 6. The resulting 2-dimensional LDA projection achieved over all considered conditions, that is, HC, S1, S2, S3, S4, and S5.

Previous to the application of the automatic diagnosis and severity detection, aiming to emphasize the effectiveness of the proposed method in regards to the consideration of different signals and in regards to their processing in different domains, in Figure 7a,b the qualitative representations are shown, which were achieved by means of a PCA projection over the representative feature matrices estimated from analyzing the vibrations signals in both domains, TD and FD, respectively. In both resulting projections, the data distributions of all considered conditions can be appreciated, and from Figure 7a,b, it can be also seen that the characterization of vibration signals in the TD may contribute to the separation of the S2, S3, S4, and S5 conditions. Conversely, the characterization of the vibrations signals through the FD leads to the separation of S1, S2, S3, and S4 conditions. Therefore, the fusion of the information calculated from different signals and different domains will improve the contribution in the face of the separation of the considered conditions.

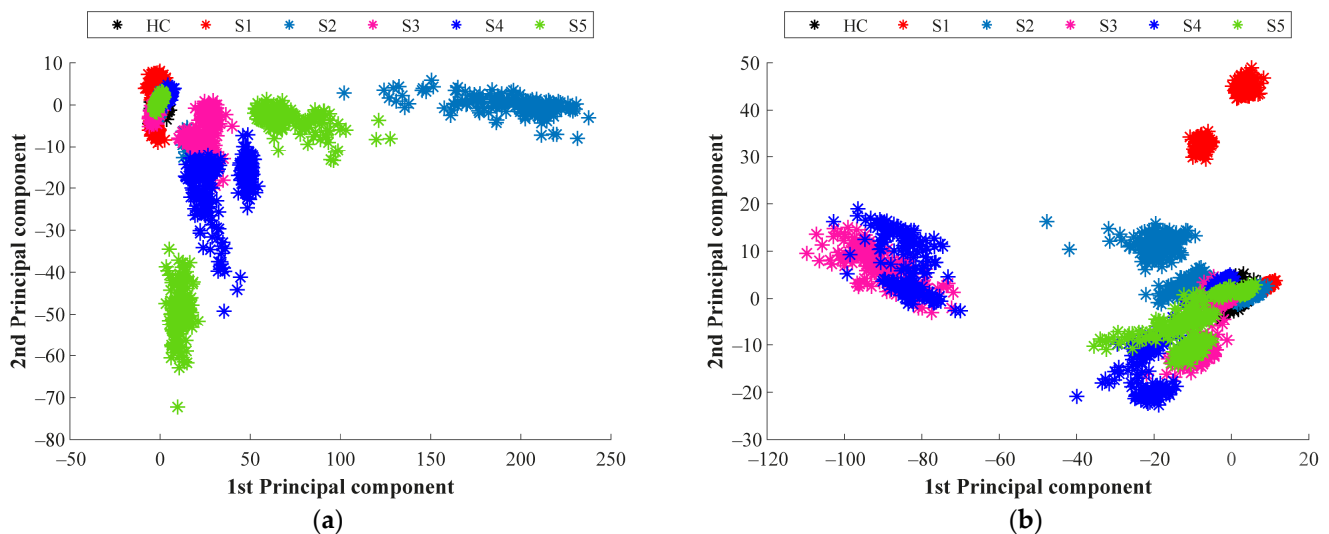


Figure 7. Two-dimensional PCA projection performed over all considered conditions: HC, S1, S2, S3, S4, and S5, and applied to the statistical features estimated from vibration signals in both analysis domains: (a) DT and (b) DF.

Subsequently, the automatic condition assessment and fault severity identification is carried out by means of the proposed NN-based classifier; thereby, the new features extracted by the application of the LDA are evaluated through the proposed classifier. As mentioned previously, the NN-based structure consists of three layers, where the input, hidden, and output layers have a number of neurons defined as 2, 10, and 6, respectively. Additionally, the NN-based classifier is trained and tested under a k -fold cross-validation scheme with a number of $k = 5$ folds, and the NN is trained and tested during 50 epochs through a probabilistic sigmoid function that is used as the activation function. Hence, each considered condition is represented by a total number of samples equal to 450, from which 360 samples are used for training purposes and the remaining 90 samples are used for validation purposes. As a result, during the training and validations of the proposed NN, global classification ratios around 98.9% and 98.7% are achieved, respectively. In Table 4, the confusion matrix that summarizes the individual classification scores performed by the NN-based classifier is shown. As can be seen, most of the misclassifications are between faulty conditions, which proves that the prediction of false negatives is avoided.

Additionally, for the training of the NN-based classifier, the decision regions of all considered conditions are modeled and estimated to be projected over a 2D plane. Subsequently, in Figure 8, the resulting decision regions is shown, and over these regions, the set of samples that have been considered during the validation process are projected. On the other side, the associated diagnosis probability can also be estimated for those samples that are associated with misclassification problems, and the analysis of such associated diagnosis probability may lead to a re-classification by assigning its appropriated true class.

Table 4. The confusion matrix achieved during the training and validation of the proposed NN-based structure.

Assigned Class		True Class										
		Training					Validation					
		HC	S1	S2	S3	S4	S5	HC	S1	S2	S3	S4
HC	360	0	0	1	0	0	89	0	0	0	0	0
S1	0	351	1	0	0	0	0	89	1	0	0	0
S2	0	9	359	0	0	0	1	1	89	0	0	0
S3	0	0	0	352	0	5	0	0	0	88	0	2
S4	0	0	1	1	360	0	0	0	0	0	90	0
S5	0	0	0	6	0	355	0	0	0	2	0	88

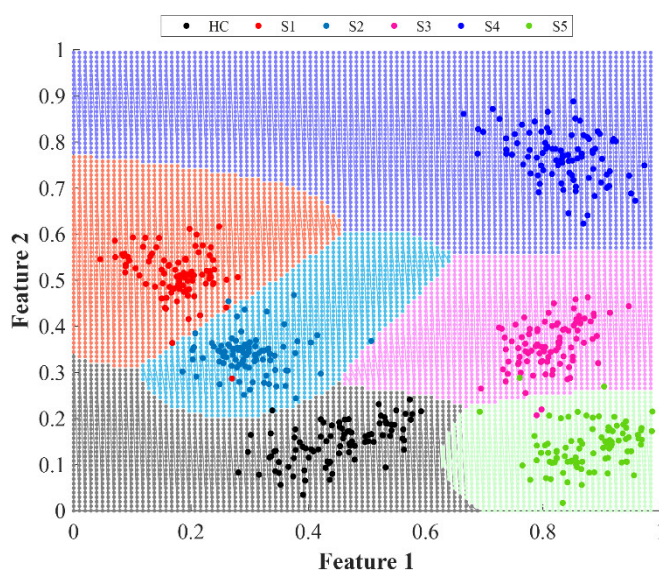


Figure 8. The resulting decision regions achieved during the training of the NN-based classifier for detecting the considered bearing fault severities.

6. Conclusions

Most industrial machines are based on electromechanical systems or kinematic chains that are mainly driven by electrical rotating machines, such as IMs, where bearings are the elements that allow its rotating movement, and the sudden appearance of faults is inherent to its operation. In this regard, in this work, a condition monitoring methodology designed for identifying different severities of the outer race bearing fault in an IM is proposed. The proposed method is supported by tools, such as Machine Learning (ML) techniques and Artificial Intelligence (AI), that facilitates the fusion information of different physical magnitudes and that leads to high-performance pattern characterization. Specifically, this work proposes the fusion information of different physical magnitudes, such as vibrations and stator current, which are characterized through a hybrid set of statistical features that is estimated by the signal processing in two different domains: the time-domain and frequency-domain. This proposal aims to promote the detection of different fault severities in the outer race of a bearing can be effectively performed by the use of multiple physical magnitudes, such as vibrations and stator current, that are processed in multiple domains, leading to high-performance signal characterization. In fact, the detection and evolution assessment of incipient faults that appear in bearings can be a complex task since the fault-related patterns may not show significant changes compared to when several damages are induced; that is, the identification of fault graduality may be difficult whether physical magnitudes, such as stator current, show small changes and/or variations in amplitude. Thus, the main contributions of this work include the use of different

physical magnitudes for estimating the characteristic patterns associated to the bearing condition; indeed, the estimation of statistical features through different domain analyses results in high-performance signal characterization. Moreover, the use of ML techniques, such as the LDA, allows performing the fusion of information because the compression and reduction of information is carried out by mapping, with different weights, the original feature space into a new space of lower dimension (i.e., 2D). Consequently, the characterization of vibration and stator current signal through statistical features from different domains, together with its fusion through the LDA technique, facilitates the classification task performed by the NN-based classifier. In this regard, it is proved that, by means of the proposed method, a global classification ratio higher than 98.7% is obtained during the diagnosis of different fault severities that may appear in the bearing outer race. On the other side, the proposed approach presents a coherent design of the structure that includes Machine Learning and Artificial Intelligence that, in comparison with other related works that propose ensemble learning structures based on Deep Learning, allows correctly identifying different severities in the outer race of bearings. Moreover, it should be highlighted that this proposed methodology has been designed to overcome and face the occurrence of unexpected faults that may appear insignificant but may gradually increase until producing irreversible damages. The proposed method is validated under a complete set of experimental data that considered a healthy condition (HC) and five severities in the outer race of a bearing (S1, S2, S3, S4, and S5). For future work, the analysis of the remaining useful life remains a research topic that must be addressed, and the analysis of combined faults that may occur simultaneously in different parts of bearings also needs to be addressed. Additionally, it has been detected that the proposal of condition monitoring strategies that may be capable of assessing the bearing condition independently of the bearing technology, i.e., metallic, hybrid, and full ceramic bearings, is also necessary. The obtained results make the proposed method suitable for application to condition assessments of machinery involved in industrial applications.

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