Non-invasive sound-based classifier of bearing faults in electric induction motors

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Abstract
Induction motors play a major role in the industry nowadays due to their simple construction, uncomplicated maintenance, and cost efficiency. As the motor operates for repeated hours, some faults may occur and, depending on the process sensitivity, can cause significant losses to the industrial production. In this context, an alternative method is proposed to detect and classify bearing faults using acoustic emission signals generated by the machines and simple features obtained from them. A pair of condenser microphones was used to acquire these signals and audio feature extraction is performed to obtain time and frequency patterns to characterize healthy and faulty machines. The major differences of the acoustic signals regarding the fault frequency signatures are discussed by analyzing specific peaks observed in their spectra. Several coupled load values and levels of power supply voltage unbalance were considered in the experimental tests, which emulate common situations encountered in industrial environments, obtaining accuracy rates over 97% of success. Finally, a comparison is presented of machine learning techniques for bearing faults classification under different load values and voltage unbalance levels.

1  |  INTRODUCTION

Three-phase induction motors (TIM) are the main rotating machines in industry nowadays. These motors operate for long non-stop periods of time in environments that can be aggressive to the their mechanical parts, what demands regular maintenance. When a machine component suffers damages, general efficiency decreases, causing financial loss, accidents, and possible unscheduled interruptions. As described in the literature, the main causes of TIM failures are faults in the stator and rotor [1].

A vital component in rotors is the bearing, which is the source of the most common TIM faults on the industrial environment, thus being widely researched [2]. Many approaches for bearing fault prognostics are presented in recent works [3]. Most of these methods are based on using features from vibration or current signals that can capture fault signatures [4, 5]. In [6], besides current signals, that were analyzed in transient, as well as, in steady state, thermography data is also used to qualitatively assess the motor condition.

Specifically for bearings, the faults cause the creation or modification of specific frequency components of those signals, whose magnitudes can be used as indication of the faults [7]. An example is presented by [8], where these fault frequency signatures are identified in vibration signals and used to detect multiple bearing faults. A similar procedure is performed by [9], using current signals. Also, a method using intrinsic mode functions and Hilbert–Huang transform applied to the stator currents is shown in [10]. The probabilistic spectral density of healthy and faulty motors are compared and fault detection is performed considering the whole signal spectra.

Recently, acoustic emission (AE) techniques are being employed for TIM fault detection [11, 12]. Evidences point that the same bearing fault signatures in frequency components of vibration signals are also observed in AE signals [13]. Hence, these signals, which are recorded by microphones and processed online or offline, can be used as an alternative to current or vibration signals for fault detection. These methods have the advantage of being non-invasive and portable because of the...
sensors characteristics. This results in a low cost strategy for the industrial environment, since the method may be implemented in a simple embedded system that can be used in the entire production line.

A system for fault diagnosis of single-phase motors using audio feature extraction is presented in [14], considering bearing and stator short circuits faults. Two types of microphones were employed, connected directly to a personal computer sound card using 44.1 kHz sampling rate. Features were extracted from audio segments of 1 s and used for comparing the signals spectra between healthy and faulty motors. As a result, the authors present the performance of three different intelligent classifiers, obtaining classification accuracy rates between 65.7 and 95.3%, depending on the classifier and set of input features.

A specific system for bearing fault prognostic is presented in [15]. The authors discuss fault frequency signatures and use a wide band AE sensor that operates from 125 kHz to 1 MHz mounted directly on the bearing housing. Signals are acquired using a data acquisition device (DAQ). Based on entropy values, the method obtained correct classifications for all the investigated situations.

Similarly, a bearing fault detection method for slow TIM speeds is presented in [16]. Piezoelectric sensors were used to acquire the signals, at 100 samples per second, and amplified by 40 dB. The analyzed features were obtained by signal intensity estimator and root mean square levels. The conclusion was that feedforward artificial neural networks (ANN) had some advantages over other classifiers for the proposed method.

In addition, a large memory storage retrieval deep learning network with self-organizing maps (SOM) is shown in [17]. The method is based on AE signals feature extraction using short time Fourier transform. These signals are acquired by a sensor attached to the bearing housing with glue. The motor speed varies from 2 to 60 rpm. The inputs are clustered by a Kohonen SOM and classified with a decision module. The method was shown to be useful for low speed bearing detection, where five different bearing conditions were analyzed with accuracy rates over 96%.

Machine learning techniques are commonly used for fault diagnosis and classification, as shown in [18, 19]. These methods rely on a set of input features used to distinguish characteristics from different classes of signals obtained from the motors. In recent literature, two of the most common classifiers are support vector machine (SVM) and ANN. Examples are SVM with motor vibration [20], voltage and current [21], and motor current signature [22]; and ANN applied to temperature signals [23] and Hilbert footprint analysis [24].

Because of that, our contribution is presenting an alternative TIM bearing fault detection method that is not invasive and based on a simple signal acquisition setup. The proposed features are easily obtained from the AE signals and the experimental tests cover several typical situations in industrial environment, such as power supply voltage unbalance and coupled load variations. Our approach is based on a pair of electret condenser microphones (ECM), which are non-invasive, low cost, and mobile sensors. The features used to capture fault signatures are obtained from time and frequency domains of AE signals using correlations and fast Fourier transform (FFT), respectively. This approach results in a low computational cost compared to many AE methods shown in the literature. The features behavior, with respect to the TIM conditions, is discussed using SOM clustering. Finally, TIM bearing fault detection is performed using two classifiers, SVM and multilayer perceptron (MLP) ANN, which are compared considering their accuracy rates for AE signal classification.

After this brief context of the state-of-the-art, the paper is divided into five more sections. In Section 2, we present concepts about TIM bearing faults and power supply voltage unbalance, their effects and characteristics, concluding with details about the features extracted from the AE signals. Then, in Section 3, the SVM and MLP classifiers are described along with SOM applied to feature analysis. In Section 4, the test bench and its components are detailed. Also, we explain the methodology and test configurations, as well as analyze features characteristics. In Section 5, the results obtained with the classifiers are presented and compared. Finally, in Section 6, we provide our conclusions regarding this study.

2 | MOTOR FAULTS AND FEATURES

In this section, we present the vibration characteristics of TIMs with bearing faults and power supply voltage unbalance. Also, the time-frequency characteristics used as features for fault classification are described.

2.1 | Bearing faults

Bearings are elements that roll at the motor speed. Their particular vibrations characteristics are dependent on their mechanical construction. When the bearing has faults, the load distribution is unbalanced and impose more vibration at determined frequencies. In this work, bearing outer race faults are studied. Such faults produce a frequency peak in the vibration signal spectrum called ball pass outer raceway frequency (BPOF) that is characterized by (1) [1, 13].

\[
\frac{f_{BPOF}}{f_r} = \frac{N_B}{2} f_r \left(1 - \frac{D_B}{D_C} \cos \theta \right).
\]  

In that equation, \( f_r \) is the rotor frequency or motor speed, \( N_B \) is the number of balls in the bearing, \( D_B \) and \( D_C \) are the ball and cage diameters, respectively, and \( \theta \) is the ball contact angle. A representation of the elements of an eight-ball bearing is shown in Figure 1.

2.2 | Power supply voltage unbalance

Voltage unbalance in the TIM power supply causes irregular machine rotation. These irregularities result in periodic vibrations of the motor and, as the vibrations occur, the mechanical parts emit sound waves that propagate through air.
In [25], the theory of $2f$ vibration was introduced, which states that motors operating with voltage unbalance inflict an air gap distortion because of a lack of electromagnetic balance. The $2f$ vibration is proportional to twice the frequency of the machine power supply. Vibration of the air gap of an unbalanced magnetic pull can be represented by a Fourier series. As the eccentricity increases, the harmonic resonance in the vibration also increases [26]. This characteristic is also expected to be present in AE signals.

In addition, as explained in [27], voltage unbalance is a cause of mistakes in TIM fault diagnosis, especially for systems based on current signal analysis. That is because the signatures created by voltage unbalance tend to be similar to those created by incipient faults. Therefore, it is essential to consider such issues when creating a robust fault detection system.

2.3 Acoustic emission features

For fault detection and classification, it is necessary to extract features from the AE signals. As explained before, each fault has its particular spectrum signatures. In this work, we investigate AE signals for bearing fault detection under balanced and unbalanced power supply voltages and different coupled load values in the TIM shaft. The features that characterize the motor state are described in this section and are based in time and frequency aspects of the signals.

According to [4, 5], TIM faults have frequency signatures in current and vibration signals that are reliable for diagnosis. Also, a similar behavior is observed in AE signals [12]. Since AE from electrical machines is a periodic signal, abnormal behaviors or frequency peaks may indicate the presence of bearing faults and power supply voltage unbalance. Thus, besides time-domain patterns, some frequency characteristics were also used as features for the classifiers.

Many faults modify the magnitudes of vibration signals spectra in the vicinity of the supply frequency [5, 13], that was 60 Hz for the experimental tests in this study. Therefore, we selected a feature based on the spectral peaks in the neighborhood of such frequency from the AE signals. In addition, as explained in Section 2.2, voltage unbalance creates vibration that oscillates at twice the supply frequency, hence the spectral peak in the neighborhood of 120 Hz was also considered. Higher frequencies presented too much variation on the collected AE signals, probably caused by noise, then were not used. Finally, since bearing faults were demonstrated to cause vibrations in the vicinity of 30 Hz in [14], another feature was obtained from the spectral peak on that frequency vicinity. These attributes were extracted from the signals spectra and labeled $f_1$ to $f_4$ for ECM 1 and $f_5$ to $f_8$ for ECM 2, as described below:

- $f_1$ and $f_5$: 30 Hz neighborhood not normalized peaks
  The TIM under study in the test bench, as detailed ahead in Section 4.1, has nominal speed of 1730 rpm. Abnormal rotation in the motor shaft, that is caused by faults, increases the slip, resulting in shifts and oscillation of these spectral peaks.
- $f_2$ and $f_6$: 60 Hz neighborhood not normalized peaks
  The motor drive frequency is 60 Hz, therefore a relevant component is expected in this region of the signals spectra. Irregular rotation caused by bearing faults and/or power supply voltage unbalance may result in oscillations of this peak when compared to values of healthy TIMs.
- $f_3$ and $f_7$: 120 Hz neighborhood not normalized peaks
  As described in Section 2.2, unbalanced power supply causes an increase of the second harmonics of the power supply frequency of the vibration signals spectra, which is 120 Hz in this work. Thus, we investigate if this characteristic is present in the AE spectra and the reliability of this feature for detection of unbalanced power supply.
- $f_4$ and $f_8$: Modulated bearing fault neighborhood not normalized peaks
  Bearing faults appear as a modulation in the vibration signal spectrum. Thus, they can be detected by signal processing techniques like envelope demodulation. This process is usually applied to discriminate bearing faults, such as outer race, inner race, or ball pass [28]. A TIM bearing fault generates modulated high-frequency peaks at the same location in the spectrum, usually higher than 2.4 kHz, therefore being reliable for the detection of bearing faults.

On the other hand, the time features were obtained through cross-correlation between the ECM signals. Equation (2) represents the cross-correlation of two signals $x_1$ and $x_2$ with length
\( N \), where \( m = 0, 1, \ldots, N - 1 \) and \( x_1(n) \) and \( x_2(n) \) are the signal values at sample \( n \).

\[
R_{x_1x_2}(m) = \sum_{n=0}^{N-m-1} x_1(n + m)x_2(n). \tag{2}
\]

The following time features were labeled \( f_9 \), \( f_{10} \), \( f_{11} \) (for ECM 1), and \( f_{12} \) (for ECM 2).

- \( f_9 \): Between microphones cross-correlation peak
The first time feature is the peak of the cross-correlation between the signals of each microphone. This feature tries to capture the similarity of the signals, which may vary when there is an eccentricity located near one of the sensors elements.

- \( f_{10} \): Between microphones sample-delay
The second time feature is the sample delay between the signals of the microphones. Cross-correlation sample delays are useful for locating a signal source, such as a fault element.

- \( f_{11} \) and \( f_{12} \): Autocorrelations
The third and fourth features are the peaks of the autocorrelation of each ECM signal. The higher the periodicity of the signals, the larger these values are.

These features capture regularity and similarities between the ECM signals, what is useful to decrease the influence of random noise and interference sounds generated by other sources.

\section{Pattern Classifiers and Visualization}

In this section, we present a brief description of the intelligent systems employed in this work: two classifiers, SVM and MLP, and a feature visualization tool, Kohonen SOM. Pattern classifiers have been regularly used for bearing fault detection and they validate the efficiency of the feature extraction methods [29–31]. In this study, the inputs of these tools are the features obtained from the AE signals presented in the previous section. In this case, a comparison of two popular classifiers is performed for motor state classification in order to find the most suitable for this application.

The SVM and MLP classifiers are supervised learning methods. For these systems, a training group is initially defined with sample feature vectors randomly taken from the experimental data set, which must cover all the data domain. Then, for each of the classifiers, different topologies are employed and tested using \( k \)-fold cross-validation method [32], with \( k \) equal to 10. The configuration with the best classification results for the test group was selected.

On the other hand, the Kohonen SOM is an unsupervised method that can be used for feature visualization. Using the map, it is possible to analyze characteristics of the features and their ability to separate the data classes. Each of these tools is briefly described in the next sections.

\subsection{Multilayer perceptron}

Recent researches show the application of ANNs in bearing fault classification [16, 19, 33]. Specifically, MLP is an ANN that can be used for universal function approximation, identification and process control, system optimization, time series forecasting, pattern recognition, among others [32]. This network is characterized by the presence of an output layer containing one or more neurons and intermediate hidden layers, which may have any number of neurons. The training is supervised and uses a set of samples and their targets, iteratively updating the neurons weights by a learning method called backpropagation until a stopping criterion is reached.

A general neuron output is expressed in (3), where the vector of input features is \( x = \{x_1, x_2, \ldots, x_M\} \), \( M \) is the input dimension, \( w_j \) is the vector of associated weights of neuron \( j \), \( b_j \) is the bias of neuron \( j \), \( f_j(\cdot) \) is the activation function of neuron \( j \), \( y_j(n) \) is the output of neuron \( j \) for iteration \( n \). The input can be a training sample or the output from a previous layer.

\[
y_j(n) = f_j\left(\sum_{i=0}^{M} x_i w_{ji} + b_j\right). \tag{3}
\]

The MLP training process consists in applying the inputs to the network, as in (3), a feedforward process. This step produces adjustments of weights and biases in order to minimize the error between input samples and the desired responses (supervised training). This process is based on the actual difference between the output and the desired value, expressed in (4), where \( y_j(n) \) is the output of the \( f^{th} \) neuron for training sample \( n \) and \( d_j(n) \) is the desired output for that sample.

\[
E_j(n) = \frac{1}{2} \sum_{j=1}^{N} (d_j(n) - y_j(n))^2. \tag{4}
\]

\subsection{Support vector machines}

SVM is a classifier that works with supervised training and relies on statistical learning theory [34]. This algorithm is based on maximizing the separation margins between the samples of the classes under analysis by a hyperplane decision surface. One limitation is that the method can only be used to separate two classes, but combinations are possible [35]. SVM is a popular tool for bearing faults classification [9, 36, 37].

This classifier also relies on the backpropagation training algorithm that uses optimization of a convex quadratic function for maximum practical performance. Using the input values, the algorithm seeks a non-linear boundary hyperplane that divides the feature space in two distinct regions. This optimization problem can be expressed as in (5) [34], where \( C \) is the threshold of error, \( \lambda \), is the solution for the dual problem, solved for Kühn-Tucker conditions, and \( y_i \) is the classifier output for
sample $i$.

$$\max w(\lambda) = \sum_{i=1}^{N} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{N} y_i y_j \lambda_i \lambda_j (x_i x_j),$$  \hspace{0.5cm} (5)$$

subject to

$$\begin{cases} 
0 \leq \lambda_i \leq C \\
\sum_{i=1}^{N} \lambda_i y_i = 0, \hspace{0.2cm} i = 1, 2, \ldots, N.
\end{cases}$$

### 3.3 Self-organizing maps

Kohonen SOMs are used for pointing similarities, regularities, and correlations between input samples [32], which is achieved by clustering these samples. Each cluster has its particular features behavior, which represents the relationship between inputs and classes.

The SOM algorithm consists of a competitive learning process in the training/clustering phase, where the neurons in the network receive all the inputs and their weights are adjusted based on the Euclidean distance to the input sample. The network designer specifies the radius of the neighborhood weight adjustment and the map configuration. For a unitary radius neighborhood, weights are updated as in (6), where $\eta$ is the learning rate, $w^{(v)}$ is the $v$ neuron weight vector, $x^{(k)}$ is the input vector of sample $k$, and $w^{(\Omega)}$ is the weight vector of neighbor neuron $\Omega$.

$$\begin{cases} 
\text{Rule 1:} \hspace{0.2cm} w^{(v)} \leftarrow w^{(v)} + \eta (x^{(k)} - w^{(v)}), \hspace{0.2cm} \text{winner} \\
\text{Rule 2:} \hspace{0.2cm} w^{(\Omega)} \leftarrow w^{(\Omega)} + \frac{\eta}{2} (x^{(k)} - w^{(\Omega)}), \hspace{0.2cm} \text{neighbor}.
\end{cases}$$  \hspace{0.5cm} (6)$$

The training phase is executed repeatedly until a stopping criterion is reached, such as maximum number of epochs or minimum value of weight vector variation, which is obtained using empirical tests. In the operation phase, each sample at the input is classified by each neuron according to their respective Euclidean distance, given by (7).

$$d_j^{(k)} = \sqrt{\sum_{i=1}^{L} (x_i^{(k)} - x_i^{(j)})^2}, \hspace{0.2cm} \text{with} \hspace{0.2cm} j = 1, \ldots, N.$$  \hspace{0.5cm} (7)$$

In that equation, $d_j^{(k)}$ is the distance of the input vector of sample $x^{(k)}$ to the $j^{th}$ neuron with weight vector $w^{(j)}$, $L$ is the dimension of the input and weight vectors, and $N$ is the number of neurons in the map. The outputs are clusters containing similar samples.

### 4 METHODOLOGY

In this section, the test bench used for acquiring the experimental data is described and the proposed method is detailed.
caused by vibration and ventilation. ECM 1 was positioned upside the shaft of the machine and ECM 2 was 14.4 cm backwards, directed to the motor fan, as shown in Figure 3. This configuration created a simple array of sensors focused on the desired source of AE. The interpolation of the ECM reception fields attenuated unwanted signals originated in different directions than that of the motor.

The AE signals were not collected in an industrial environment, but in an electrical machine laboratory, which was usually being used concomitantly for other tests. Therefore, during the experiments, there were other aleatory sources of sound, such as air conditioners, other machines, and people noise due to laboratory usage. In the end, these issues contribute to validate the robustness of the methodology when faced with interference from sounds not generated by the TIM under test.

The sampling rate was set to 96 kHz and, for each configuration, 30 s of AE signals were collected. The faults were induced by replacing healthy motor elements with faulty ones and modifying the power supply voltage levels. Also, the referred faults were emulated by a corrosion of the bearing outer race produced with an abrasive paste.

Voltage unbalance was created in the power supply in four different configurations: (a) 2% lower voltage in phase A, (b) 2% higher voltage in phase B and lower in phase C, (c) 4% lower voltage in phase A, and (d) 4% higher voltage in phase B and lower in phase C.

Table 1 presents the experiments performed in this work. First, the TIM with no bearing faults and balanced power supply was operated in nine coupled load configurations: 0.4 and 1.0 to 4.5 Nm, in steps of 0.5 Nm, labeled #1 to #9 in the table. Then, the power supply voltage was unbalanced in the four configurations described before. The (a) and (b) settings were tested using three load values: 0.4, 2.0, and 4.0 Nm, labeled #10 to #12 and #13 to #15, respectively. Finally, the (c) and (d) settings were tested using all the nine load values, labeled #16 to #24 and #25 to #33, respectively. Then, the process was repeated for the faulty bearings configurations with equivalent labeling from #34 to #54.

The proposed method is divided into the following steps, as shown in Figure 4. First, 30 s of AE signals were recorded by the

| Experiment | Bearing | Voltage unbalance |
|------------|---------|-------------------|
| #1 to #9   | Balanced|                   |
| #10 to #12 | (a) 2% lower in A |
| #13 to #15 | Healthy    | (b) 2% higher in B & lower in C |
| #16 to #24 | (c) 4% lower in A |
| #25 to #33 | (d) 4% higher in B & 4% lower in C |
| #34 to #42 | Balanced  |
| #43 to #45 | (a) 2% lower in A |
| #46 to #48 | Faulty    | (b) 2% higher in B & lower in C |
| #49 to #51 | (c) 4% lower in A |
| #52 to #54 | (d) 4% higher in B & 4% lower in C |

FIGURE 3  Positions of ECM 1 and 2 with respect to the TIM

FIGURE 4  Flowchart of the proposed method, consisting of AE time and frequency feature extraction and TIM fault classification with the MLP and SVM classifiers
two microphones positioned upside the motor along the shaft axis. Then, for the training set, each signal was divided into 45 windows of 3 s of length, with 50% overlap. From each window, the twelve time and frequency features ($f_1$ to $f_{12}$) were extracted, as described before. These features are the classifiers inputs, as listed in Table 2.

The classification was performed based on the mechanical condition of the TIM and also if there was power supply voltage unbalance. This leads to separation in four distinct classes: (1) healthy (HEA), (2) healthy with unbalanced power supply (UNB), (3) faulty bearings (BEA), and (4) faulty bearings with unbalanced power supply (BNB).

Data were divided into training and test sets. For the training phase, signals from the four classes (HEA, UNB, BEA, and BNB) were employed, with load values of 0.4 and 4.0 Nm. For the testing phase, load values of 1.0, 1.5, 2.0, 2.5, 3.0, and 4.5 Nm were used (when available), also from the four classes.

5 | RESULTS AND DISCUSSION

In this section, we discuss the results obtained for TIM bearing fault classification. First, an assessment of the extracted features is presented using mean and standard deviation values. The features had their amplitude normalized between $-1$ and 1. Also, Kohonen SOM is used to visualize the separability of the four classes. After that, the performances of the SVM and MLP classifiers are compared.

5.1 | Analysis of features characteristics

The first analysis considers the classes separability based on the individual behavior of the extracted features. Three conditions were analyzed: healthy, bearing fault, and unbalanced power supply, and divided into four classes, as previously described. Figure 5 shows the features normalized mean and standard deviation values comparing healthy and faulty cases with balanced power supply voltages.

For the faulty case (diamond), both 2.5 kHz frequency features, $f_4$ and $f_8$, have normalized mean values of 0.1346. For the healthy case, this frequency normalized mean value was $-0.6143$. This is caused by the frequency modulation resulting from the TIM bearing fault. Other features have lower values for the faulty case when compared to healthy ones. This fact indicates separability between those mechanical conditions when using the selected features.

Also, in Figure 6, a comparison is presented of the features values for the healthy cases with balanced and unbalanced power supply voltages. The key features are the 120 Hz peaks, $f_3$ and $f_7$, which are the $2f$ frequencies described in Section 2.2. These features had mean values of 0.1561 for the unbalanced case and $-0.4207$ for the balanced one. Other frequency features had similar behaviors for the balanced and unbalanced cases of the healthy TIM.

Similarly, Figure 7 presents a comparison of balanced versus unbalanced power supply voltages for the faulty bearings case. When the motor presents a bearing fault, the values of the

| TABLE 2 | Features extracted from the AE signals |
|---------|----------------------------------------|
| Frequency | Time                                  |
| ECM 1 30 Hz peak ($f_1$) | Crosscorrelation ECM 1 and 2 ($j_6$) |
| ECM 1 60 Hz peak ($f_2$) | Time delay between signals ($j_{10}$) |
| ECM 1 120 Hz peak ($f_3$) | Autocorrelation ECM 1 ($j_{11}$)      |
| ECM 1 2500 Hz peak ($f_4$) | Autocorrelation ECM 2 ($j_{12}$)      |
| ECM 2 30 Hz peak ($f_5$)  |                                        |
| ECM 2 60 Hz peak ($f_6$)  |                                        |
| ECM 2 120 Hz peak ($f_7$) |                                        |
| ECM 2 2500 Hz peak ($f_8$) |                                          |
FIGURE 7  Mean and standard deviation values of the features for the faulty case with balanced and unbalanced power supply voltages

proposed features have no significant difference between balanced and unbalanced supply, which indicates no visible separability for this case.

These previous analyses considered each feature individually; however, the classifiers work with all the features at once in a multidimensional space, trying to obtain hyperplanes to separate the data classes [38]. Since it is not possible to visualize the $f_1$ to $f_{12}$ features in a 12-D graph, we employed the Kohonen SOM to try to capture their relationships in 2-D. SOM is a traditional tool for dimension reduction and visualization of high dimensional data [32].

The Kohonen SOM was implemented with the toolbox presented in [39] using a hexagonal map with $20 \times 30$ neurons. This topology resulted in an efficient visualization for the features characteristics, as presented by Figure 8. The map shows clusters based on the four data classes. At a first glance, two regions are noticeable: the upper cluster, containing samples from the healthy (HEA) and healthy with unbalanced power supply (UNB) classes; and the other, the lower cluster, containing samples from the faulty (BEA) and faulty with unbalanced voltages (BNB) classes.

The existence of such clear separation is an indication that the proposed features are effective for the discrimination of healthy and faulty samples. If this is possible in 2D, the classifiers hyperplanes could easily perform this in higher dimensions. Also, based on the map, three groups of neurons are distinguished inside the upper healthy cluster: two smaller ones, surrounded by darker edges, of balanced voltage samples; and a large one of unbalance voltage samples. This separation shows a reasonable distinction between HEA and UNB classes, but some signals could still be misclassified using the features.

On the other cluster, for BEA and BNB faulty classes, the samples with balanced and unbalanced supply are mixed in the map, which indicates that discrimination is not straightforward using the chosen features. Therefore, the usage of the SOM visualization method, jointly with features dispersion analyses of Figures 5–7, allows the assessment of the features effectiveness to discriminate the classes, indicating that TIM mechanical condition (healthy or faulty) is more easily detectable, however, samples with unbalanced power supply voltage are harder to be diagnosed, specially if they are from a TIM with faulty bearings.

After this initial analysis of features characteristics, in the next sections, we apply the data set to SVM and MLP classifiers in order to obtain a complete bearing fault detection system.

5.2  |  SVM classifier

The SVM was tested using the following kernel functions: linear, polynomial, and radial basis function (RBF). For each of them, the classifier was trained using samples from two coupled load configurations and tested with the remaining cases, as described

FIGURE 8  Experimental data shown in a Kohonen SOM with $20 \times 30$ hexagonal neurons. HEA, healthy bearings; UNB, healthy with unbalanced voltages; BEA, faulty bearings; BNB, faulty with unbalanced voltages
Two SVM structures were combined in parallel to detect whether the features represented a healthy bearing, a faulty bearing, or if there was power supply voltage unbalance, as shown in Figure 9. The SVM classifiers have binary outputs and there are four possible classes. Then, the proposed structure consists of two parallel classifiers. The first, SVM[0], is used to detect whether the motor is healthy or if a bearing fault is present. The second, SVM[1], is employed in power supply unbalance detection. The result of the input features classification is a vector of two binary elements representing one of the four possible classes, as shown in Figure 9. Table 3 presents the accuracy rates of the SVM classifiers versus the kernel functions. SVM was useful for classifying whether the motor presented the bearing fault. Also, with the linear kernel, the accuracy rates were higher than 82% for the detection of power supply voltage unbalance with healthy or faulty bearings. The SVM using the RBF kernel performed better for unbalance detection with healthy motors, but had a worse performance for faulty ones. Overall, the SVM with polynomial kernel had the best performance with 90.8% and 80.0% of correct classification for UNB and BNB classes, respectively.

### 5.3 MLP classifier

When using an MLP classifier, an important choice is the topology. Depending on that, the backpropagation algorithm may not converge or result in poor classification. Because of that, topologies with one to five hidden layers and configurations with one to fifty neurons were tested, aiming to fit the data into the defined classes. The output layer contained two neurons for every topology. Each configuration was tested ten times and the best results are shown in Table 4. This classifier performed better than the SVM for the detection of power supply voltage unbalance when the motor is healthy using configuration [50 47 2]. Accuracy rates similar to the SVM were obtained for unbalance detection for faulty bearings. The best total accuracy rate was obtained with the [50 47 2] configuration, with 97.6% and 80.6% of correct classification for UNB and BNB classes, respectively.

In the next section, we present a comparison of our technique to other recent studies regarding the kind of measurements, methodology, and classification results.
### 5.4 Comparison with other studies

As mentioned before, in this section, we present a brief comparison of our study to the following works [6, 8, 9, 11–13]. Table 5 presents the main characteristics of these researches, which are better compared below.

Regarding the type of measurements collected from the motors, [6] and [9] used current signals, but the former also employed thermography data. Vibration measures were considered by [8] and [13]; however, the latter also used AE. As commented in Section 1, the majority of motor fault diagnosis systems are based on vibration or current signals, whereas AE is used in recent approaches as in [11–13] and in this work.

All the studies cited in this section focused on bearing faults, along with other faults, as detailed in Table 5. Our methodology considered power supply voltage unbalance and coupled load torque variations, which are common situations in an industrial environment. These conditions influence the motor behavior, especially voltage unbalance, that is a power quality problem that causes modifications to the measurements. Therefore, it is essential to consider them in the analysis, which is only partially performed in some of the references presented in the table.

Regarding the methodology, all the cited works employ some kind of spectral features, since bearing faults have clear signatures in the frequency domain. Despite that, [6, 13] and our approach also considered temporal information of the signals. These two references used time-frequency methods to analyze the measurements, which simultaneously consider both time and frequency domains. However, we used simple cross-correlations of the AE signals to obtain the time features.

Lastly, in [6, 8, 13], the features were analyzed qualitatively, no classifiers were employed to discriminate the classes. On the other hand, [9, 11, 12] and our approach used some classification tools, mainly SVM, nearest neighbor (NN), or MLP, that are the most common classifiers in machine fault diagnosis systems. In all these works, accuracy rates were comparable for similar conditions. However, as demonstrated, our approach considered power supply voltage unbalance and load variations, and also employed features that were easy and fast to estimate.

### 6 CONCLUSION

In this study, we presented an alternative method for the detection of TIM bearing faults from AE signals using time and frequency features that are easily obtainable from the signals and their spectra. The proposed experimental setup is simple and noninvasive, based on two condenser microphones. In order to test the robustness of the presented approach, the tests considered typical situations of industrial environment, such as variation of coupled load torque and power supply voltage unbalance. Also, a comparison was presented of intelligent classifiers, SVM and MLP, using the proposed features.

Based on the results, the proposed method is considered reliable for bearing faults detection in line-connected TIMs operating with several coupled load values. The method depends on the power supply frequency because the features are based on specific peaks of the AE signals spectra, which corresponds to motor speed, supply frequency, and their harmonics. However, if the supply frequency is known, the method can be applied to inverter fed machines.

Considering the proposed time and frequency features as inputs to the classifiers, we obtained accurate diagnosis of outer race bearing faults. The samples from healthy or faulty motors with balanced power supply were all correctly differentiated by the SVM or MLP classifiers. On the other hand, for the unbalanced cases, the best accuracy rates, obtained by SVM, were slightly over 97% and 80%, respectively, for healthy and faulty.
motors. In this work, MLP and SVM had equal accuracy in detecting the fault and MLP performed better in overall for the unbalanced power supply detection. Therefore, the proposed method can be implemented in an industrial environment, since several load conditions were considered, as well as variations of supply voltage unbalance. The system setup is based only on two microphones and an embedded system for signal processing and classification.

For future works, stator and rotor faults will be investigated using the described method in order to design a generalized fault classifier for TIM using AE signals. Also, other features can be extracted using similarity measures, like mutual information, and other signal processing techniques in order to increase the method accuracy for unbalanced power supply classification. Finally, more tests will be performed in industrial environments so as to completely assess the robustness of the proposed method when in the presence of several other sources of acoustic emissions.

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