Document downloaded from:

Repositorio Documental de la Universidad de Valladolid (https://uvadoc.uva.es/)

This paper must be cited as:

I. Martin-Diaz, D. Morinigo-Sotelo, O. Duque-Perez, R. J. Romero-Troncoso, Early fault detection in induction motors using AdaBoost with imbalanced small data and optimized sampling, in IEEE Transactions on Industry Applications, vol. 53, no. 3, pp. 3066-3075, May-June 2017, doi: 10.1109/TIA.2016.2618756

The final publication is available at:

https://doi.org/10.1109/TIA.2016.2618756

https://ieeexplore.ieee.org/abstract/document/7593238

Copyright: Institute of Electrical and Electronics Engineers

© 2017 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works."

Early Fault Detection in Induction Motors Using AdaBoost With Imbalanced Small Data and Optimized Sampling

Ignacio Martin-Diaz, *Student Member, IEEE*, Daniel Morinigo-Sotelo, *Member, IEEE*, Oscar Duque-Perez, and Rene de J. Romero-Troncoso, *Senior Member, IEEE*

***Abstract*—Intelligent fault detection in induction motors (IMs) is a widely studied research topic. Various artificial-intelligence-based approaches have been proposed to deal with a large amount of data obtained from destructive laboratory testing. However, in real applications, such volume of data is not always available due to the effort required in obtaining the predictors for classifying the faults. Therefore, in realistic scenarios, it is necessary to cope with the small-data problem, as it is known in the literature. Fault-related instances along with healthy state observations obtained from the IM compose datasets that are usually imbalanced, where the number of instances classified as the faulty class (minority) is much lower than those classified under the healthy class (majority). This paper presents a novel supervised classification approach for IM faults based on the adaptive boosting algorithm with an optimized sampling technique that deals with the imbalanced experimental dataset. The stator current signal is used to compose a dataset with features both from the time domain and from the frequency domain. The experimental results demonstrate that the proposed approach achieves higher performance metrics than others classifiers used in this field for the incipient detection and classification of faults in IM.**

***Index Terms*—Classification algorithms, condition monitoring, data analysis, fault diagnosis, induction motors (IMs), rotors, sampling methods.**

Manuscript received June 15, 2016; revised September 3, 2016; accepted October 10, 2016. Date of publication October 19, 2016; date of current version May 18, 2017. Paper 2016-EMC-0356.R1, approved for publication in the IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS by the Energy Systems Committee of the IEEE Industry Applications Society. This work was supported in part by the doctoral scholarship 598078 from the Mexican Council of Science and Technology (CONACyT); in part by the Universidad Autonoma de Queretaro, sabbatical scholarship 2015–2016; in part by the Universidad de Guanajuato, DAIP, Grant 733/2016; in part by the Universidad de Valladolid grant for foreign professors in the doctoral program 2015–2016; in part by the mobility grant from the Universidad de Valladolid for doctoral students, and in part by the by the Spanish "Ministerio de Economía y Competitividad" and FEDER program in the framework of the "Proyectos I+D del Subprograma de Generación de Conocimiento, Programa Estatal de Fomento de la Investigación Científica y Técnica de Excelencia" Grant DPI2014-52842-P. *(Corresponding author: Rene de J. Romero-Troncoso.)*

I. Martin-Diaz is with the Escuela de Ingenierías Industriales, University of Valladolid, Valladolid 47011, Spain, and also with the CA Telematica at DICIS, University of Guanajuato, Salamanca 36885, Mexico (e-mail: imartin@hspdigital.org).

D. Morinigo-Sotelo and O. Duque-Perez are with the Escuela de Ingenierías Industriales, University of Valladolid, Valladolid 47011, Spain (e-mail: daniel.morinigo@eii.uva.es; oscar.duque@eii.uva.es).

R. de J. Romero-Troncoso is with the CA Telematica at DICIS, University of Guanajuato, Salamanca 36885, Mexico (e-mail: troncoso@hspdigital.org).

NOMENCLATURE

ANFIS	Adaptive neuro-fuzzy inference system.
CBM	Condition-based monitoring.
CV	Cross Validation.
DT	Decision Tree.
FDD	Fault detection and diagnosis.
FN	False Negative.
FP	False Positive.
f_{LSH}	Frequency of the left sideband harmonic.
f_{RSH}	Frequency of the right sideband harmonic.
f_1	Feeding frequency.
IM	Induction motor.
NB	Naive Bayes.
RMS	Root Mean Square.
S	Induction motor slip.
TN	True Negative.
TP	True Positive.
VSI	Voltage Source Inverter.

I. INTRODUCTION

ELECTRIC motors are the most employed electromechanical equipment in industry these days, especially induction motors (IMs) due to their reliability, low cost, and robustness. Consequently, their usage requires condition-based monitoring (CBM) to minimize the costs originated by unexpected faults that cause production loss [1]. One of the benefits of predictive maintenance is the reduced risk of forced outages, and it permits the scheduling and prioritization on the rotary machines inspection in large industries [2]. The monitoring of electric signals has several advantages, such as remote sensing, low implementation cost, online monitoring, etc. In industrial applications, it is usual that motors with frequent starts or large load variations due to thermal gradients and large thermo-mechanical stress suffer rotor cage failures. This, normally in its incipient phase, causes cracks in the joint of bar and end ring [2]. Therefore, it is relevant to appreciate the characteristic changes produced in the previous stages to the fully broken bar.

Fault detection and diagnosis (FDD) systems can be conceived from two perspectives: model-based methods and data-driven methods. The former gives good results for well-controlled environments whereas the latter offers a powerful mean to extract useful information for the design of motor monitoring systems as those based on the motor current signature analysis (MCSA) [3]. MCSA can extract practical information at an early stage to avoid subsequent catastrophic failures. This technique has advantages over the vibration analysis for the difficulty to quantify the rotor severities due to the different mechanical stiffness between the electromagnetic forces by damaged bars and the location of vibration sensors [4].

Nowadays, with the increasing use of ac drives in industries, the CBM and FDD strategies demand intelligent monitoring techniques to take advantage of the easily acquired data [5], [6]. Most of the recent monitoring algorithms are computationally efficient and can be developed on hardware to diagnose multiple IM faults or also discriminate among different types of faults [7], [8]. Thus, the artificial-intelligence-based techniques are currently supplanting the conventional knowledge since these may be demanded to automate IM diagnostic procedures. Moreover, the supervised scheme permits us, by training a classifier with an appropriate number of observations, to generate enough knowledge to identify an incorrect behavior of the squirrel-cage rotor.

Diagnosis of broken bars is a mature research field where many contributions have been presented. Saidi *et al.* [9] propose two higher order spectra techniques showing that bispectrum patterns can lead to better results than those obtained by the power spectrum. In [10], Soualhi *et al.* deal with the difficulty of the influence of frequency converters which introduce undesirable harmonics. It produces a distorted stator current signal that complicates the feature extraction, and therefore the diagnosis. They suggest an approach based on signal processing and an unsupervised classification technique (artificial ant clustering). By contrast, in [8], an automatic decision-based structure is designed for the detection of broken rotor bars and broken end rings in three-phase squirrel cage IMs. This approach consists of a neural network for the classification of rotor faults where the accuracy metric is employed to analyze the performance. Following the idea of these biological-inspired models, Ghate and Dudul [11] develop a radial-basis function multilayer perceptron with a cascade connection for the detection of small- and medium-size IM considering different simultaneous faults. Other studies deal with the broadly used support vector machines with similar purposes [12]. This classifier has been demonstrated to have proper generalization capability, and it has shown good performance for separable and nonseparable data using appropriate kernels. Furthermore, there are studies which combine a set of fuzzy *if–then* rules that have the skill to approximate nonlinear functions, and decision trees to elaborate models of induction rules from empirical data. Tran *et al.* [13] propose a two sequential step approach. First, a decision-tree-based method is utilized for feature selection. Second, the previously obtained crisp rules are converted to fuzzy rules to find the structure of adaptive neuro-fuzzy inference system (ANFIS) classifier. The dataset is constructed with vibration and current signals. Lei *et al.* [7] also apply an ANFIS-based system to diagnose faults of rolling element bearings. It shows a good generalization, and the accuracy metric is used to measure the classifier's performance.

It has to be taken into account that the motor runs actually in its usual healthy condition. Therefore, when an incipient fault occurs, the classifier has to deal with an imbalanced dataset, that is, the number of available instances of the healthy class outnumbers the ones related to the faulty class. Additionally, the available amount of data from the faulty class is limited. However, as far as the authors' knowledge, there are no published studies for the diagnosis of IM faults on imbalanced datasets and much less considering a limited number of faulty tests. Accordingly, there is a necessity to develop a classifier that takes into account this imbalanced small data distribution.

An adaptive boosting (Adaboost) classifier can deal with this imbalanced dataset situation, and it is presented for constructing a stronger decision-based approach using weak learning algorithms. The AdaBoost algorithm has resulted in a promising way to classify imbalanced datasets in other research fields [14], [15]. This ensemble consists of reweighting a training set to improve the results of classification, which is based on a weighted vote from a linear combination of the weak classifiers. Imbalanced datasets do not have enough faulty class observations, and hence, additional approaches are required beyond those algorithm level-based ones. Sampling techniques (data level approaches) add a preprocessing step where the data distribution is rebalanced to decrease the effect in the learning process of the underrepresented faulty class distribution [16]. Some of these techniques are undersampling, oversampling, or the method known as synthetic minority oversampling technique (SMOTE) [17]. For this reason, Adaboost, in conjunction with a sampling technique, provides an adequate classification scheme to deal with the aforementioned fault diagnosis scenario.

This paper presents the development of an efficient classification ensemble, applicable for scenarios that combine an online monitoring with a following diagnosis stage. During experimentation, destructive tests are carried out for different rotor severities in an IM that is fed from an inverter and the line. The information from the current signal is reduced into useful knowledge that leads to the collection of representative features about the motor condition. Various statistical and frequency-domain parameters are used to handle the problem at steady state. The combined approach is formed by an optimized sampling procedure and an Adaboost algorithm for the diagnosis of IM faults. The fault classification is improved in terms of generalization when limited data are used for the training period, which also ends with satisfying results for imbalanced sets. The experimental results show the classifier performance under balanced and imbalanced situations, with and without the sampling technique SMOTE. Finally, the outcomes obtained per rotor fault severity are compared with state-of-the-art algorithms by using appropriate metrics. It is expected to achieve an improvement in performance to illustrate the suitability and effectiveness of this contribution.

II. Fault Diagnosis Features Extraction

The AdaBoost-based proposed classification scheme is summarized in Fig. 1. First, considering the MCSA technique, the data are acquired from the stator current of the machine during a steady-state regime. Next, important features are computed using the signal information of one-phase stator current in both time and frequency domain by developing a convenient preprocessing stage. Once a collection of appropriate variables is ob-

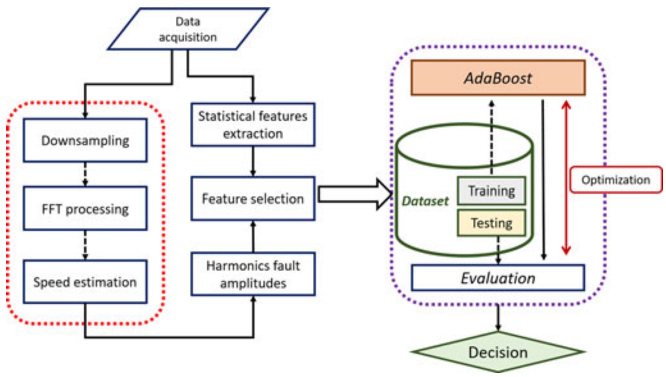

Fig. 1. Proposed classification scheme.

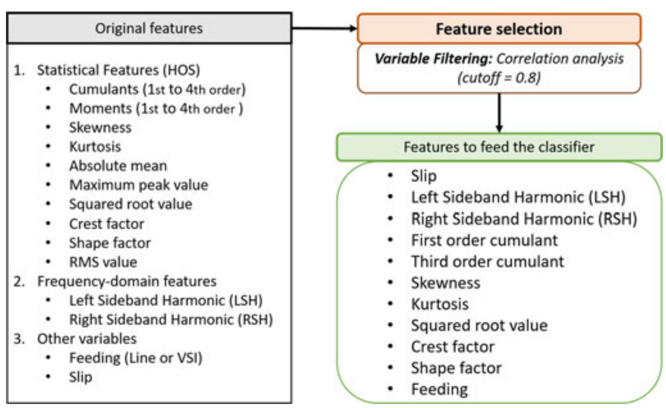

Fig. 2. Feature selection flowchart.

tained (see Fig. 2), a feature selection method is used to choose the most pertinent features, which is detailed in Section IV-B. Then, the data are divided into training and testing sets to calibrate the algorithm parameters. This process finishes once the optimal parameters are chosen according to the maximum number of successes (faults detected) by a cross-validation method. For the sake of comparative reasons, this strategy is applied to several datasets depending on the imbalanced ratio (IR) and on the size of the dataset. With the help of proper evaluation metrics, the results for every case are presented in the corresponding section.

The diagnosis system uses time-domain statistical features, along with others from the frequency domain, that have been suggested as meaningful input data for diagnosis objectives [11], [18]. Some of the higher order statistical (HOS) parameters have the property of being sensitive to non-Gaussian distributed measurements. Nevertheless, the lower-order statistics, those that use from constant to quadratic terms (e.g.. first and second moments) are significantly more robust. Particularly, this study focuses on statistics calculated from the discrete current signal during a constant load condition. As it can be seen in Fig. 2, the set of statistics includes from the first moment (mean) to the fourth, the first four cumulants, the absolute mean, the crest factor, etc. Also, there are HOS measures such as skewness and kurtosis, which use the third or higher power of the discrete sample. The kurtosis tries to reveal the proportion of variance explained by the extreme data combination with regard to the mean, in contrast to those much less deviated from the mean. On the other hand, the skewness measures the degree of asymmetry from the probability distribution of the current values about its mean.

Additionally, the frequency-domain predictors can be obtained due to the appearance of the sidebands around the main supplying frequency harmonic because of rotor asymmetries [19]. For instance, when an incipient rotor-bar breakage develops, a resultant backward rotating field appears at a slip frequency with respect to the forward rotating rotor. This opposite rotating field induces a voltage and a current in the stator winding at characteristic frequencies. This induced current causes torque and speed pulsations until two sidebands around the fundamental frequency emerge in the frequency spectrum [19]. For this reason, the amplitude of these sidebands is considered as a fault severity indicator on the rotor. There are more sidebands that also appear around some higher order harmonics [20]. However, for the purposes of this study, the left-side harmonic (f_{LSH}) and the right-side harmonic (f_{RSH}) around the fundamental frequency are enough for their usage as BRBindicators [19], whose expressions are, respectively, presented as

$$f_{\mathrm{LSH}} = (1-2\mathrm{s})f_1 \tag{1}$$

$$f_{\mathrm{RSH}} = (1+2s)f_1. \tag{2}$$

The damaged rotor bars do not cause immediate failures of an IM. Nonetheless, its unpredictable failure evolution may provoke future catastrophic failures to any internal motor parts. This is critical for large industrial motors where a timely detection of the rotor fault can avoid catastrophic consequences.

III. Proposed Classification Approach

Imbalanced datasets are becoming more and more common in real-industry applications leading to machine learning (ML) classifiers far from optimal performance. In addition, when the available data is small, overfitting becomes almost unavoidable, and the noise, together with outliers, turns into a patent concern. Researchers have studied carefully how to deal with this problem through feature-selection strategies from the root (level data) to approaches to the algorithm level [17]. There is no systematic way to either address the problem of imbalance classes or well-defined methods that assist in the choice of the strategy to follow under the challenging conditions of limited samples. For this reason, the use of an appropriate classifier results in one of the fundamental points for the diagnosis stage design. In this paper, AdaBoost is used to enhance generalization, and a cross-validation method aims to reduce the data variability during the fitting phase. This section introduces an attempt to face this imbalanced small data classification problem. The overview of the proposed methodology can be seen in Fig. 3. First, a sampling technique to rebalance an initial dataset is presented. Then, a cross-validation technique for assessing the generalization of the results from a statistical perspective is applied. Finally, a novel algorithm for the diagnosis of IM faults is described to deal with the issue already presented.

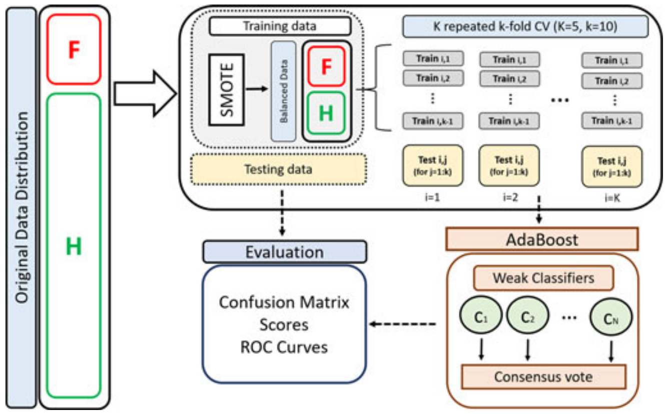

Fig. 3. Proposed methodology for the diagnosis of incipient rotor-bar breakage.

A. Sampling Techniques

Various groups of techniques have been introduced to address the problem of imbalanced classification in which the number of observations of one class is much larger than those from the minority class (faulty observations). Many different approaches have been proposed to solve this problem in other fields, and the literature is extensive in this sense [21]. One of the mainstream methods is based on sampling, where the objective is to sample a balanced training set from an original imbalanced dataset [16], [21]. These methods are based on either undersampling or oversampling of one class in a random manner [16]. The random sampling has some disadvantages that may suppose a worsening of the diagnosis. On one hand, undersampling techniques lose valuable information obtained during the data acquisition phase, possibly useful for the classifier induction. On the other hand, oversampling techniques made literal copies of the minority class observations what may lead to the classifier incurring in overfitting [21]; that is, for instance, when either a rule-based or a decision-tree-based classifier is built seemingly accurately, whereas it is actually concealing a replicated instance. Similarly, there is a method known as SMOTE [17], which combines the oversampling of the unusual (minority) class with the undersampling of the normal (majority) class through the synthetic generation of additional examples. With all of this in mind, an approach to the construction of IM-supervised classifiers from imbalanced datasets to broaden the decision regions of the faulty rotor state can be considered. For this purpose, the implementation of SMOTE for a real dataset formed by processed laboratory tests is approached in following sections. This algorithm, proposed in [17], consists in an oversampling of the minority class by creating synthetic instances avoiding to duplicate known faulty observations. SMOTE is motivated by a technique that demonstrated to be successful in other fields as, for example, handwritten character recognition [22]. However, with this technique, the synthetic observations are produced in the predictor space rather than with the primary data. The faulty instances are oversampled by taking each faulty tuple of predictors with its respective target variable and introducing synthetic examples along the line segments joining any or all of the k-nearest neighbors from the faulty class. The number of k-nearest neighbors is optimized according to the number of detected faults by the classifier in question, and it depends on the amount of oversampling required. The generation of synthetic additional samples follows these steps.

1) Compute the difference between the faulty sample (vector of predictors) under consideration and its k-nearest neighbors of the same class. For categorical features, the majority vote procedure is chosen to assign the values.
2) Multiply this value by a random number in the range (0,1), and add it to the feature vector previously examined.

This procedure causes the selection of a random point along the line segment between two specific feature vectors and thus, it creates a synthetic group of new samples. The algorithm effectively forces the decision region of the faulty class to become more general, within a coherent margin. The pseudo-code of the SMOTE algorithm can be consulted in the original article [17]. The synthetic samples cause the classifier to create larger and less specific decision regions, rather than smaller and more specific regions. Consequently, the learning algorithm can be trained with more number of fault-related observations by means of synthetic instances generation, regarding the case where healthy class observations outnumber the faulty ones under an imbalanced scenario.

B. Adaptive Boosting

Classifier ensemble learning consists basically in constructing multiple classifiers from an original data distribution and, after collecting each classifier prediction, deciding the label of the unknown samples based on a consensus rule (usually majority voting). Consequently, by using redundant ensembles, the generalization ability is enhanced because each base classifier does not commit the same errors on a limited training set to which it is fitted. This fact allows learning different patterns by each classifier. The AdaBoost algorithm was proposed as a boosting algorithm by Freund and Schapire [23]. The main concern related to ML classifiers is to achieve a reasonable bias-variance tradeoff from a statistical point of view. The bias reveals the classifier ability to generalize correctly to a testing set, whereas the variance expresses the sensitivity of the classifier prediction due to the training data. Generally speaking, boosting combinations usually have resulted in being useful for the variance reduction owing to the averaging by the ensemble, which in turn indicates a decrement of overfitting. AdaBoost is also recognized for achieving a meaningful reduction in bias as well. The justification is because weak base learners can predict slightly better than random guessing without fitting excessively [23]. Hence, there is a statistical reasoning behind it, which makes it suitable rather than standard learning methods that perform vaguely on the minority class. The core concept is based on weak classifiers focusing their efforts on those instances misclassified previously. The AdaBoost algorithm samples sequentially with replacement, by taking the sample importance into account and prioritizing those that are most often misclassified by the preceding classifiers on previous rounds. That is, AdaBoost initially chooses every sample with equal probability. In each iteration, a new weak learner is added to the ensemble and a weighting vector adjusts

Algorithm 1 AdaBoost pseudocode

Input:

Set of m observations $(x_1, y_1) \dots (x_m, y_m)$ with labels $y_1 \dots y_m, y \in \{1, -1\}$

Weak classifier: Decision Tree (CART) $h: x \to [1, -1]$

Optimized number of iterations T

Error function $E(f(x), y, i) = e^{-y_i f(x_i)}$

Initial weights: $D_{1,1} \dots D_{m,1}$ set to $\frac{1}{m}$

for all t in $1 \dots T$ **do**

Call Weak classifier $h_t(i)$ using distribution $D_t(i)$

Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_i D_{i,t} E(h_t(x), y, i)$

Choose learning coefficient (Breiman) $\alpha_t = \frac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t} \right)$

Add to ensemble: $F_t(x) = F_{t-1}(x) + \alpha_t h_t(x)$

Update weights distribution: $D_{i,t+1} = D_{i,t} e^{-y_i \alpha_t h_t(x_i)}$ for all i

Renormalize $D_{i,t+1}$ such that $\sum_i D_{i,t+1} = 1$

end for

Output: the final classifier:

$$H_f(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

Fig. 4. AdaBoost algorithm (pseudocode).

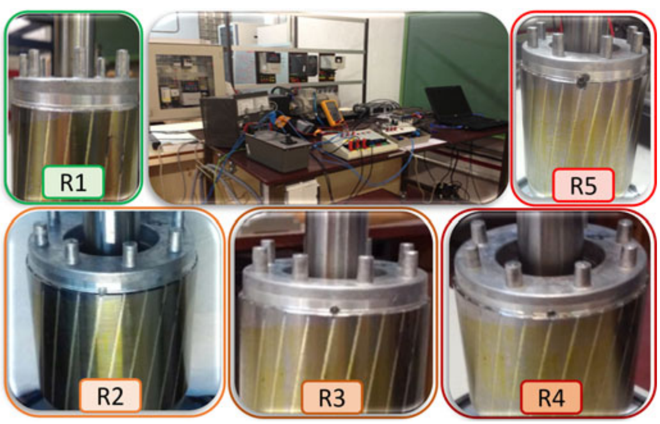

Fig. 5. Experimental setup and diferent rotor conditions.

adaptively to the errors of the weak classifiers to later update the probability distribution. A sample that is correctly classified receives a lower probability to be drawn in the next iteration, and a misclassified sample receives a higher probability. The pseudocode of the AdaBoost algorithm is shown in Fig. 4.

IV. Fault Classification With AdaBoost

A. Laboratory Setup and Data Description

A layout of the laboratory setup can be seen in Fig. 5. An IM, star connected and fed both directly from the line and an inverter supply is tested in a laboratory to collect data for this study. The motor and the inverter have the specifications shown in the Appendix. The motor is loaded with a magnetic powder brake and tested under two load conditions. The operating frequency is 50 Hz. The stator current is acquired by a Hall-Effect current transducer by LEM. A National Instruments NI cDAQ-9174 base platform with an NI 9215 acquisition module is used for data acquisition with a sampling frequency of 80 kHz and a sampling time of 10 s. The motor is tested first under healthy conditions (R1). Fault conditions are produced by drilling a hole in one of the rotor bars. An incipient fault is obtained by

TABLE I
Descriptions of the Imbalanced Datasets

Label of classification	Condition	IR	Number of samples
R1	Healthy	1, 2, 5, 10	60 (IR = 1), 120 otherwise
R2	Slightly BRB	1, 2, 5, 10	60, 60, 24, 12
R3	Half-BRB	1, 2, 5, 10	60, 60, 24, 12
R4	Thinner BRB	1, 2, 5, 10	60, 60, 24, 12
R5	Thicker BRB	1, 2, 5, 10	60, 60, 24, 12

drilling a 4.2-mm hole with a diameter of 2.5 mm in one of the bars (R2). Next, a partially broken bar was produced with a depth hole of 9.4 mm and the same diameter (R3). Then, a more developed bar breakage (R4) was achieved by drilling an 18 mm hole with the diameter unchanged. Finally, the R4 hole diameter is widened to 3.5 mm to attain the last severity (R5). The datasets formed according to a particular IR and the already explained rotor severities (also considering the number of tests per case), are presented in Table I. The IR of a dataset [16] is defined as the number of healthy class observations divided by the number of faulty cases of each rotor condition. The IRs considered in this study are 1, 2, 5, and 10, forming binary sets for the target variable (rotor condition). The healthy class is always present in the mentioned sets. This selection of IR serves to analyze the influence of the level of imbalance under this particular small data problem. The IR chosen is influenced by the available observations obtained from the experimental setup.

B. Feature Selection From the Initial Variables

Feature selection (or variable selection) is a useful step in a diagnosis methodology. It serves basically to remove irrelevant variables to the classification stage. The benefits of variable selection procedures are three-fold: increasing the prediction performance of the variables, providing faster and less costly predictors, and sometimes it helps to better understand the underlying process of the bar breakage in the diagnosis of IM. Thus, a filter method, known as correlation analysis [24], is considered. First, the correlation matrix of all variables is constructed. Then, the highly correlated attributes (with a cutoff of 0.8) are eliminated, as it can be seen in Fig. 2. It has been observed that different features are selected in this stage depending on the dataset under study. The common features chosen for all cases are shown in Fig. 2 and these are the variables used to train the classifiers.

C. Optimized Sampling for Small Imbalanced Data

According to the procedure explained in Section III, the SMOTE sampling technique is applied to various imbalanced datasets with different IR, as it is described in Table I. The tuning parameters of this technique are the number of nearest neighbors and the number of randomly generated faulty samples. The first is optimized using a cross-validation procedure regarding the faulty cases detected once a balanced dataset is achieved with SMOTE. The second depends on the number of faulty synthetic instances required to balance the dataset, which depends on the

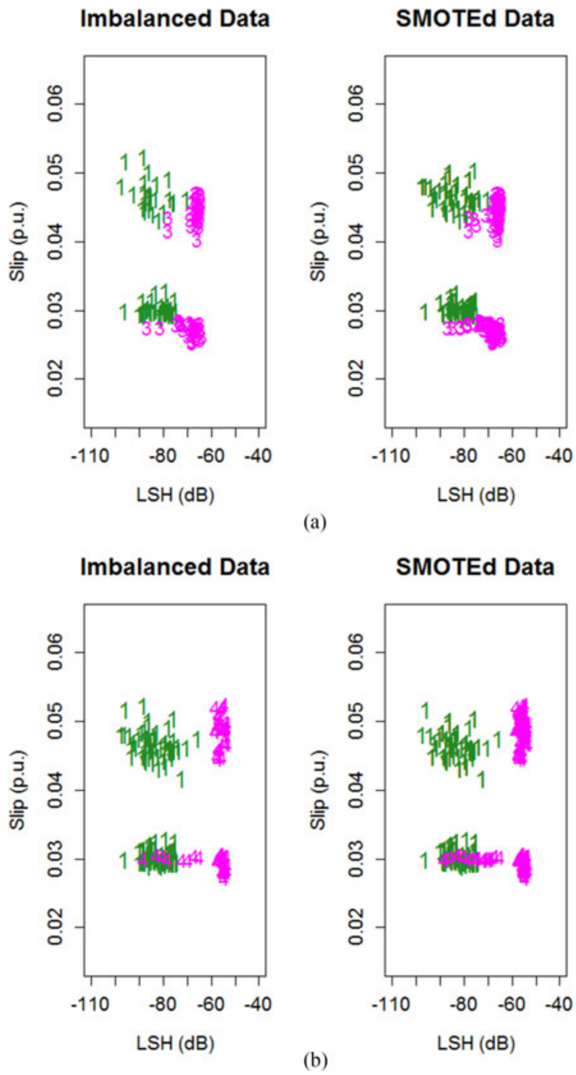

Fig. 6. 2-D scatterplot of imbalanced sets, IR = 2 (left) and the SMOTEd set (right), for (a) R1 and R3 observations, and (b) R1 and R4 observations.

size of the dataset under consideration. In this study, three sizes of datasets per each IR are considered (see Table I). The best results are obtained for one nearest neighbor on all cases. The 2-D scatterplots for R3 and R4 against R1 (healthy) conditions are presented in Fig. 6 before and after applying the introduced technique. Only the left-side harmonic amplitude versus the slip are plotted for clarity reasons.

D. AdaBoost Tuning

As it is described in previous sections, AdaBoost is relatively flexible (it can be combined with any learning algorithm) and it is simpler and easier to program than other state-of-the-art algorithms. Also, it has the advantage that no prior knowledge is required about the weak classifier, and it can provide consistent rules of thumb for both binary and multiclass problems. For the latter, the proposed version is known as AdaBoost.M1 [23]. But there is a rule for the error committed by each weak classifier, ε_t, which must be less than one-half to update the weights of the training samples α, in the right direction. The AdaBoost tuning parameters have been chosen following the criterion based on the detected faulty cases rate, that is, according to the number of faults detected by the classifier and not by the number of correct answers on all classes. For this classifier, the tuning parameters are the following: the number of trees that compose the ensemble, the maximum tree depth and the learning coefficient type (Breiman or Freund). Each learning coefficient updates the weights of the training sample α, differently:

- Breiman: $$\alpha = \frac{1}{2}\ln\frac{(1-\varepsilon_t)}{\varepsilon_t} \tag{3}$$
- Freund: $$\alpha = \ln\frac{(1-\varepsilon_t)}{\varepsilon_t}. \tag{4}$$

During the tuning phase, the most outstanding weak classifier turns out to be the decision tree (CART algorithm). A CART tree is a binary decision tree built by splitting a root node (that contains the variables whole information) into two child nodes, making a recursive partition of the instance space. In the CART algorithm [25], each split depends on the value of only one variable. The growing procedure consists basically in ascertaining each predictor's best split in a stepwise manner toward the following nodes. It must be choose those splits that maximize the Gini Impurity criterion, which is a standard decision-tree splitting metric. Thus, the node must be split using its best split found previously. The algorithm ends once the stopping rules are reached. Each leaf is assigned to a unique class label (rotor condition). Alternatively, the leaf may hold a probability vector indicating the probability of the target attribute having a certain value. Instances are classified by passing them from the root of the tree down to a decision node, according to the outcome of the along the path rules. For the data under consideration, the remaining tuning parameters that get the best AdaBoost performance are a maximum depth of five trees and the Breiman learning coefficient. The training and testing error (by 5-repeated-10-fold CV) evolution of the AdaBoost classifier shows that an acceptable performance can be appreciated when approximately 75 trees are reached for the imbalanced case, but this number is lower for the SMOTEd set. For this reason, a suitable number of trees to build the ensemble are 100 and 50 for the imbalanced conditions and the SMOTE-sampled data, respectively.

V. Results

This section presents the classification results obtained for the experimental data presented earlier. In order to demonstrate the effectiveness of the intended scheme for diagnosis purposes, an AdaBoost performance comparison study, under imbalanced and balanced conditions, is shown. Therefore, under an imbalanced scenario, a satisfying performance of the sampling technique can be determinant to deliver a proper distribution of the provided data to the classifier. Then, the strength of AdaBoost compared with other state-of-the-art algorithms for classifying the previous rotor bar severities is evaluated. The classifiers are implemented in the statistical computing environment known as R, [26]. For these purposes, the one-against-one (OAO) and the one-against-all (OAA) approaches for a binary problem are regarded. These approaches are chosen because of the progressive nature of the rotor-bar breakage, where the classes of the target variable come from the same type of fault unlike for example, faults in bearings.

A. *Performance Analysis of the Proposed Approach.*

The arrangement of the training and testing sets are realized according to a 5-repeated-10 cross-validation method [27], [28], as it is shown in Fig. 3. To observe the adequate performance of the proposed approach, first, the suitability of the sampling technique should be verified. The accuracy measure does not allow a correct interpretation of the classifier performance with each class taken into account, which it is an important fact when discriminating among different severity degrees. In this sense, the use of additional performance metrics is required [29], [30] to appreciate the differences among various classifiers for every damaged rotor condition, and under imbalanced conditions. The scores used are the following:

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{5}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} - \text{FP})} \tag{6}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{7}$$

$$\text{Accuracy} = \frac{\text{FP} + \text{FN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}. \tag{8}$$

Accuracy gives a value related to the overall behavior of the algorithm on all rotor states. Recall (also known as sensitivity in the medical field) and Precision provide more precise information about the classifier performance on the class of interest (faulty rotor). Furthermore, the specificity, also known as true negative rate is necessary to introduce later the ROC curve. In this case, a multiclassification approach is considered, and the classifier is trained with instances from all classes (from R1 to R5). By using SMOTE, the original class distribution is altered due to the additional generation of synthetic examples. With this balancing technique, an increase in the number of faulty instances correctly classified has been observed, as can be seen in Table II. Table II shows the Confusion Matrix (in percentage) and its derived scores for the AdaBoost classifier without and with the SMOTE application for an IR = 2, separated by semicolons, respectively. The Recall and Precision scores are used to analyze the classification performance on the faulty observations. In the first case (AdaBoost without applying SMOTE), poorer results for the R2 severity degree are found. However, when the SMOTE algorithm is used to obtain a balanced set, the classifier performance is quantitatively improved concerning this rotor fault severity, R2.

B. *OAO Performance Evaluation*

As ML algorithms are becoming common as IM diagnosis tools, there is a need to evaluate the performance of algorithms varying in complexity. In this study, the performance metrics mentioned earlier will be used on different fault scenarios, and using the same datasets, to compareAdaBoost against two other ML models. Their fitted parameters and most relevant characteristics are chosen according to the most successful detection rate achieved through the CV procedure. To provide a detailed explanation (but not excessively extensive) of the classifiers behavior, an individual comparison for R2 and R3 rotor severities is presented in Tables III and IV. The R1 state (healthy rotor) versus R2 (slightly BRB) and R3 (half-BRB) classification results are analyzed for the following classifiers: Naïve Bayes, Decision Tree, and AdaBoost. In Table III, performance metrics for the imbalanced problem without optimized sampling with the three classifiers under different IR is presented. Analyzing the R2 case, AdaBoost shows a better performance compared to the rest. However, as the IR increases, its results turn out poorer. This outcome applies equally to the other two classifiers. It is also interesting to analyze the Accuracy values and observe how misleading this score can be. The Naive Bayes (NB) classification results with an IR = 10 are a good example because there is not a single faulty instance correctly classified (value of zero

TABLE II
CONFUSION MATRIX AND PERFORMANCE METRICS FOR THE MULTICLASS CASE WITH ADABOOST: IR = 2 AND SMOTE (IR = 1)

Predicted rotor state (%)	Actual rotor state (%) (IMBALANCED DATA WITH IR = 2; SMOTED DATA)				
	R1	R2	R3	R4	R5
R1	30.3;16.9	4.2;3.3	0.0; 0.0	0.7;0.8	0.0;0.0
R2	2.7;2.5	12.5;16.7	0.3;0.3	0.0;0.1	0.0;0.0
R3	0.3;0.1	0.0;0.0	16.3;19.7	0.0;0.0	0.0;0.0
R4	0.0;0.2	0.0;0.0	0.00;0.00	15.9;19.1	0.4;0.3
R5	0.0;0.0	0.0;0.0	0.0;0.0	0.0;0.0	16.3;19.7
	Scores by class				
Recall	0.91;0.86	0.75;0.83	0.98;0.98	0.96;0.95	0.98;0.98
Precision	0.86;0.80	0.81;0.85	0.98;0.99	0.97;0.97	1.00;1.00

TABLE III
PERFORMANCE METRICS FOR THE IMBALANCED PROBLEM WITHOUT OPTIMIZED SAMPLING WITH THE THREE CLASSIFIERS

Target severity	IR	Classifier	Accuracy	Precision	Recall
R2	10	NB	0.8091	0.0000	0.0000
		DT (CART)	0.9076	0.3333	0.0167
		AdaBoost	0.9561	1.0000	0.5167
	5	NB	0.7681	0.2762	0.2417
		DT (CART)	0.8472	0.5472	0.4833
		AdaBoost	0.9514	0.9885	0.7167
	2	NB	0.6078	0.3801	0.2800
		DT (CART)	0.8167	0.7491	0.6767
		AdaBoost	0.9811	0.9863	0.9567
R3	10	NB	0.9470	0.6923	0.7500
		DT (CART)	0.9712	0.8475	0.8333
		AdaBoost	0.9864	1.0000	0.8500
	5	NB	0.9194	0.6987	0.9083
		DT (CART)	0.9750	0.9554	0.8917
		AdaBoost	0.9917	1.0000	0.9500
	2	NB	0.9078	0.8182	0.9300
		DT (CART)	0.9433	0.9136	0.9167
		AdaBoost	0.9989	1.0000	0.9967

Dataset size (120/12), (120/24), and (120/60) for IR = 10, IR = 5, and IR = 2, respectively.

TABLE IV
PERFORMANCE METRICS FOR SMOTED DATASETS WITH THE THREE CLASSIFIERS

Target severity	IR	Classifier	Accuracy	Precision	Recall
R2	10	NB	0.7150	0.6949	0.7667
		DT (CART)	0.9208	0.9014	0.9450
		AdaBoost	0.9967	0.9934	1.0000
	5	NB	0.6483	0.6440	0.6633
		DT (CART)	0.8642	0.8519	0.8817
		AdaBoost	0.9975	0.9950	1.0000
R3	10	NB	0.9233	0.9364	0.9083
		DT (CART)	0.9550	0.9723	0.9367
		AdaBoost	1.0000	1.0000	1.0000
	5	NB	0.9442	0.9540	0.9333
		DT (CART)	0.9508	0.9640	0.9367
		AdaBoost	1.0000	1.0000	1.0000

Dataset size (120/12) and (120/24) for IR = 10 and IR = 5, respectively.

TABLE V
PERFORMANCE METRICS FOR SMOTED DATASETS WITH THE THREE CLASSIFIERS FOR DIFFERENT SIZES OF THE DATASET

Target severity	IR	Size (H/F)	Classifier	Precision	Recall
R2	10	120/12	NB	0.6949	0.7667
			DT (CART)	0.9014	0.9450
			AdaBoost	0.9934	1.0000
		60/6	NB	0.8328	0.8967
			DT (CART)	0.8036	0.8867
			AdaBoost	0.9967	0.9967
		30/3	NB	1.0000	1.0000
			DT (CART)	0.9571	0.8933
			AdaBoost	1.0000	1.0000
	5	120/24	NB	0.6440	0.6633
			DT (CART)	0.8519	0.8817
			AdaBoost	0.9950	1.0000
		60/12	NB	0.6174	0.7100
			DT (CART)	0.8797	0.9267
			AdaBoost	1.0000	0.9967
		30/6	NB	0.9184	0.9000
			DT (CART)	0.9032	0.9333
			AdaBoost	1.0000	0.9867

for Precision and Recall scores). On the other hand, the classification on R3 achieves better outcomes. In particular, AdaBoost achieves remarkable Precision and Recall values. Finally, with an IR = 2, which is not so severe, more optimistic results for each classifier are shown clearly, as it was expected. Obviously, those values are smaller for R2 due to the difficulty to obtain discriminative differences with the predictor's information.

Table IV shows the classification results after applying the SMOTE technique. The performance seems considerably improved for one classifier to another. However, it appears that a high IR (= 10) corrected with SMOTE better improves the NB and CART classifiers for the R2 severity. But, the outcomes of AdaBoost do not vary too much. Regarding the R3 fault severity, while AdaBoost classifies correctly all instances belonging to this class, NB and Decision Tree (DT) (CART) produce worse results as the IR increases from 5 to 10.

The final analysis, summarized in Table V, tries to study the effect on the classification performance of the size of the dataset, according to each IR. This study is focused on the incipient fault detection, that is, only the R2 severity is considered.

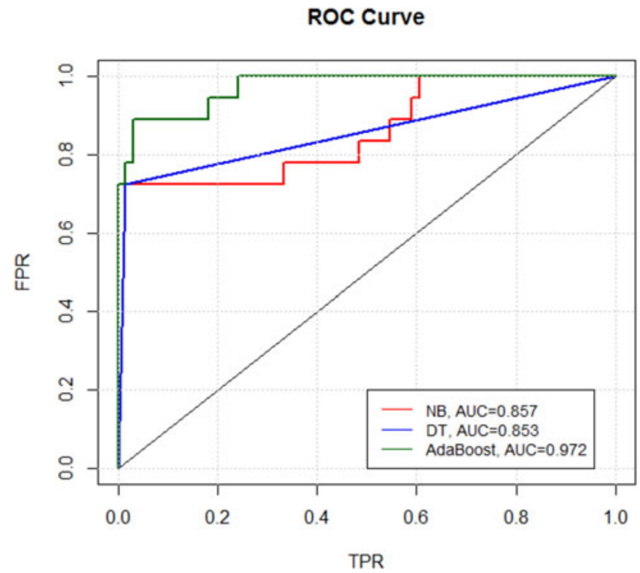

Fig. 7. ROC curves: Classifier comparison after applying SMOTE sampling for the literature classifiers and the proposed AdaBoost ensemble for an IR = 10.

The AdaBoost results suffer slightly differences for the metrics presented for each dataset size. However, it seems *a priori* that the dataset size is not determinant to ensure good results for the same IR. The reduction of instances to obtain smaller datasets is done randomly. For this reason, the performance results, which are influenced by the most complicated instances to classify, depend possibly on their presence in the final training set. However, AdaBoost is not so negatively affected, unlike the NB and DT (CART) classifiers, as their performance evaluation demonstrate. It has been observed that their scores vary in a small range without an identified pattern.

C. OAA Performance Evaluation

The ROC curves are one of the most recurrent performance measures because of the graphical information that can be obtained about the classifier behavior. In the ROC space, the true positive rate (TPR, sometimes referred to as sensitivity or Recall) is graphed as a function of the false positive rate (FPR, which equates to 1-Specificity) for different cutoff points of a varying threshold [31]. From the ROC curves, several claims can be gleaned. The closer the curve is to the upper left-hand border of the ROC space, the more accurate the classifier is considered. However, if the curve comes close to the space diagonal, it represents a less accurate classifier. Hence, the area under the curve is also a measure of accuracy. This curve has been demonstrated to be useful to evaluate classifier performances [27]. In order to analyze the OAA case (healthy observations against the whole set of faulty rotor states), a SMOTEd dataset with an IR of 10 is used. Different ROC curves, shown in Fig. 7, are obtained for each classifier. AdaBoost seems to have better performance than others because its ROC curve is graphed closer to the optimal point in the ROC space. It is obvious that all curves are different and that the AdaBoost algorithm outperforms the rest.

In summary, Fig. 7 shows how well each classifier can perform in a generic context where the faulty observations are

TABLE VI
SPECIFICATIONS OF THE IM USED

Manufacturer	Siemens
Rated power	0.75 kW
Rated voltage	400 V
Rotor type	Squirrel cage
Rated current:	1.9 A
Number of pole pairs	2
Rated speed	1395 R/min

TABLE VII
SPECIFICATIONS OF THE INVERTER

Manufacturer	ABB
Model	ACS355
Control Mode	V/f linear
Power range	0.37 to 4 kW

all considered equally important. However, the OAO analysis demonstrated the differences when discriminating among rotor severities. Finally, the use of SMOTE under imbalanced scenarios has shown important results to deal with classification of faults in IMs.

VI. CONCLUSION

A novel approach for imbalanced dataset where the IM healthy observations outnumber those of fault related is presented. The proposed application, based on the AdaBoost algorithm, improves the predictive accuracy of classifiers by focusing on difficult observations that belong to the faulty class. Provided that it is still unclear which sampling method performs best, or what sampling rate should be used, one conclusion is that the SMOTE technique improves the classifier performance once the faulty cases increase their representation. The AdaBoost classifier seems a promising approach to deal with imbalanced datasets. The combined use of SMOTE and Adaboost has demonstrated that, in presence of varying sizes of the dataset (for the same IR) and under different number of IRs, it still presents stable results. However, there are still some issues for improvement as for instance, what the most representative IR is and which features should perform best. In this paper, a filter method for the feature selection is used due to the small set of observations available. However, decision tree-based methods intrinsically perform variable selection to build its set of rules. Under a common framework of experiments, the results indicate that the proposed classification approach results in a better prediction of the faulty class than others classifiers presented in recent literature. The dataset obtained from the experiments contained different intermediate severities previous to a full BRB, which provides accurate diagnosis for incipient rotor faults detection of IM. Finally, future research is needed to address its least explored points, particularly when other competitive predictors are applied within the IM fault diagnosis field.

APPENDIX
NAMEPLATE DATA OF THE IM

See Tables VI and VII, shown at the top of the page.

REFERENCES

[1] O. Ondel, E. Boutleux, and G. Clerc, “A method to detect broken bars in induction machine using pattern recognition techniques,” *IEEE Trans. Ind. Appl.*, vol. 42, no. 4, pp. 916–923, Jul./Aug. 2006.

[2] S. B. Lee *et al.*, “Identification of false rotor fault indications produced by online MCSA for medium-voltage induction machines,” *IEEE Trans. Ind. Appl.*, vol. 52, no. 1, pp. 729–739, Jan./Feb. 2016.

[3] W. J. Bradley, M. K. Ebrahimi, and M. Ehsani, “A general approach for current-based condition monitoring of induction motors,” *J. Dyn. Syst., Meas., Control*, vol. 136, no. 041024, pp. 1–12, Jul. 2014.

[4] W. T. Thomson and M. Fenger, “Current signature analysis to detect induction motor faults,” *IEEE Ind. Appl. Mag.*, vol. 7, no. 4, pp. 26–34, Jul./Aug. 2001.

[5] M. Seera, C. P. Lim, D. Ishak, and H. Singh, “Fault detection and diagnosis of induction motors using motor current signature analysis and a hybrid FMM-CART model,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 23, no. 1, pp. 97–108, Jan. 2012.

[6] O. Duque-Perez, L. A. Garcia-Escudero, D. Morinigo-Sotelo, P. E. Gardel, and M. Perez-Alonso, “Analysis of fault signatures for the diagnosis of induction motors fed by voltage source inverters using ANOVA and additive models,” *Elect. Power Syst. Res.*, vol. 121, pp. 1–13, Apr. 2015.

[7] Y. Lei, Z. He, and Y. Zi, “A new approach to intelligent fault diagnosis of rotating machinery,” *Expert Syst. Appl.*, vol. 35, no. 4, pp. 1593–1600. Sep. 2007.

[8] H. Arabaci and O. Bilgin, “Automatic detection and classification of rotor cage faults in squirrel cage induction motor,” *Neural Comput. Appl.*, vol. 19, no. 5, pp. 713–723, Dec. 2009.

[9] L. Saidi, F. Fnaiech, G.-A Capolino, and H. Henao, “Stator current bi-spectrum patterns for induction machines multiple-faults detection,” in *Proc. IEEE Conf. IEEE Ind. Electron. Soc.*, Oct. 2012, pp. 5132–5137.

[10] A. Soualhi, G. Clerc, and H. Razik, “Detection and diagnosis of faults in induction motor using an improved artificial ant clustering technique,” *IEEE Trans. Ind. Electron.*, vol. 60, no. 9, pp. 4053–4062, Sep. 2013.

[11] V. N. Ghate and S. V. Dudul, “Cascade neural-network-based fault classifier for three-phase induction motor,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 5, pp. 1555–1563, May 2011.

[12] A. Widodo and B.-S. Yang, “Support vector machine in machine condition monitoring and fault diagnosis,” *Mech. Syst. Signal Process.*, vol. 21, no. 6, pp. 2560–2574, Aug. 2007.

[13] V. T. Tran, B.-S. Yang, M.-S. Oh, and A. C. C. Tan, “Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference,” *Expert Syst. Appl.*, vol. 36, no. 2, pp. 1840–1849, Mar. 2009.

[14] J. F. Diez-Pastor, J. J. Rodriguez, C. Garcia-Osorio, and L. I. Kuncheva, “Random balance: Ensembles of variable priors classifiers for imbalanced data,” *Knowl.-Based Syst.*, vol. 58, pp. 96–111, Sep. 2015.

[15] P. Thanathamathee and C. Lursinsap, “Handling imbalanced data sets with synthetic boundary data generation using bootstrap re-sampling and AdaBoost techniques,” *Pattern Recognit. Lett.*, vol. 34, no. 12, pp. 1339–1347, Sep. 2013.

[16] V. Lopez, A. Fernandez, S. Garcia, V. Palade, and F. Herrera, “An insight into classification with imbalanced data: Empirical results and current trends on using data intrinsic characteristics,” *Inf. Sci.*, vol. 250, no. 20, pp. 113–141, Nov. 2013.

[17] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “SMOTE: Synthetic minority over-sampling technique,” *J. Artif. Intell. Res.*, vol. 16, pp. 321–357, Jun. 2002.

[18] M. D. Prieto, G. Cirrincione, A. G. Espinosa, J. A. Ortega, and H. Henao, “Bearing fault detection by a novel condition-monitoring scheme based on statistical-time features and neural networks,” *IEEE Trans. Ind. Electron.*, vol. 60, no. 8, pp. 3398–3407, Aug. 2013.

[19] A. Bellini, F. Filippetti, G. Franceschini, C. Tassoni, and G. B. Kliman, “Quantitative evaluation of induction motor broken bars by means of electrical signature analysis,” *IEEE Trans. Ind. Appl.*, vol. 37, no. 5, pp. 1248–1255, Sep./Oct. 2001.

[20] J. Faiz, B. M. Ebrahimi, H. A. Toliyat, and W. S. Abu-Elhaija, “Mixed-fault diagnosis in induction motors considering varying load and broken bars location,” *Energy Convers. Manage.*, vol. 51, no. 7, pp. 1432–1441, Jul. 2010.

[21] Y. Sun, A. K. C. Wong, and M. S. Kamel, “Classification of imbalanced data: A review,” *Int. J. Pattern Recognit. Artif. Intell.*, vol. 23, no. 4, pp. 687–719, Jun. 2009.

[22] T. M. Ha and H. Bunke, “Offline, handwritten numeral recognition by perturbation method,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 5, pp. 535–539, May 1997.

[23] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *J. Comput. Syst. Sci.*, vol. 55, no. 1, pp. 119–139, 1997.
[24] I. Guyon, S. Gunn, M. Nikravesh, and L. A. Zadeh, *Feature Extraction: Foundations and Applications* (Studies in Fuzziness and Soft Computing). New York, NY, USA: Springer, 2006.
[25] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees* (Wadsworth and Brooks-Cole Statistics-Probability Series). New York, NY, USA: Taylor & Francis, 1984
[26] R. Core Team. (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, [Online]. Available: http://www.R-project.org/
[27] N. Japkowicz and M. Shah, *Evaluating Learning Algorithms. A Classification Perspective*. Cambridge, U.K.: Cambridge Univ. Press, 2011.
[28] S. L. Salzberg, "On comparing classifiers: Pitfalls to avoid and a recommended approach," *Data Mining Knowl. Discovery*, vol. 1, no. 3, pp. 317–328, 1997.
[29] I. Martin-Diaz, O. Duque-Perez, R. J. Romero-Troncoso, and D. Morinigo-Sotelo, "Supervised diagnosis of induction motor faults: A proposed methodology for an improved performance evaluation," in *Proc. 2015 IEEE 10th Int.* Symp. Diagnostics *Elect. Mach., Power Electron. Drives*, Sep. 2015, pp. 359–365.
[30] G. Santafe, I. Inza, and J.A. Lozano, "Dealing with the evaluation of supervised classification algorithms," *Artif. Intell. Rev.*, vol. 44, no. 4, pp. 467–508, Jun. 2015.
[31] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognit. Lett.*, vol. 27, no. 8, pp. 861–874, Jun. 2006.

Ignacio Martin-Diaz (S'13) received the B.S. degree in industrial engineering from the Escuela de Ingenierías Industriales, University of Valladolid (UVA), Valladolid, Spain, in 2014. He is currently working toward the Ph.D. degree at the UVA and the University of Guanajuato, Guanajuato, Mexico.

He is with the HSPdigital Research Group, Santiago de Querétaro, México. His current research interests include signal processing techniques, monitoring of induction machines, fault diagnosis and detection in electric machines, and machine learning algorithms.

Daniel Morinigo-Sotelo (M'08) received the B.S. and Ph.D. degrees in electrical engineering from the University of Valladolid (UVA), Valladolid, Spain, in 1999 and 2006, respectively.

He was a Research Collaborator on electromagnetic processing of materials with the Light Alloys Division, CIDAUT Foundation, from 2000 to 2015. He is currently with the Research Group in Predictive Maintenance and Testing of Electrical Machines, Department of Electrical Engineering, UVA and with the HSPdigital Research Group, Santiago de Querétaro, México. His current research interests include condition monitoring of induction machines, optimal electromagnetic design, and heuristic optimization.

Oscar Duque-Perez received the B.S. and Ph.D. degrees in electrical engineering from the University of Valladolid (UVA), Valladolid, Spain, in 1992 and 2000, respectively.

In 1994, he joined the E.T.S. de Ingenieros Industriales, UVA, where he is currently a Full Professor with the Research Group in Predictive Maintenance and Testing of Electrical Machines, Department of Electrical Engineering. His main research interests include power systems reliability, condition monitoring, and heuristic optimization techniques.

Rene de J. Romero-Troncoso (M'07–SM'12) received the Ph.D. degree in mechatronics from the Autonomous University of Queretaro, Santiago de Querétaro, México, in 2004.

He is currently a Head Professor with the University of Guanajuato, Guanajuato, México, and an Invited Researcher with the Autonomous University of Queretaro. He has been an Advisor for more than 200 theses, an author of two books on digital systems (in Spanish), and a coauthor of more than 130 technical papers published in international journals and conferences. His fields of interest include hardware signal processing and mechatronics.

Dr. Romero-Troncoso received the 2004 Asociación Mexicana de Directivos de la Investigación Aplicada y el Desarrollo Tecnológico Nacional Award on Innovation for his work in applied mechatronics, and the 2005 IEEE ReConFig Award for his work in digital systems. He is a National Researcher level 3 with the Mexican Council of Science and Technology, CONACYT, México City, México and a Fellow of the Mexican Academy of Engineering. He is part of the editorial board of Hindawi's *International Journal of Manufacturing Engineering*.