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An Experimental Comparative Evaluation of Machine Learning Techniques for Motor Fault Diagnosis Under Various Operating Conditions

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Abstract—The diagnosis of electric machines, such as induction motors, is one of the key tasks that needs to be performed to guarantee their right operation as electromechanical energy converters in most industrial facilities. The ability to reliably identify a mechanical fault occurrence before it becomes catastrophic can reduce risks related to the productive chain. Recently, different intelligent approaches have been proposed to develop feature-based methods for automatic rotor fault diagnosis of induction motors. This paper provides an experimental comparative evaluation of different machine learning techniques for rotor fault identifications. The classifiers are tested with data obtained under different operating conditions of the ones used to train them, as it is usual in industry. The input information is obtained from current signals of an induction motor with two states of rotor bar degradation under two preestablished load levels.

Index Terms—Condition monitoring, fault diagnosis, induction motors, inverters, machine learning, rotors.

NOMENCLATURE

Acc	Accuracy.
AdaB.	AdaBoost.
ANN	Artificial neural network.
AUC	Area Under the ROC Curve.
Bag.	Bagging.

BRB	Broken rotor bars.
CBM	Condition-based monitoring.
FPR	False positive rate.
IM	Induction motor.
k-NN	K- nearest neighbors.
LSH	Left sideband harmonic.
ML	Machine learning.
MLP	Multilayer Perceptron.
NB	Naive Bayes.
ROC	Receiver operating characteristic.
RSH	Right sideband harmonic.
s	Induction motor slip.
SVM	Support vector machine.
Sens.	Sensitivity.
Spec.	Specificity.
TPR	True positive rate.

I. INTRODUCTION

MOTOR Current Signature Analysis advantages [1] along with the increasing storage capacity of fault patterns records with CBM, during the whole IM lifetime, facilitates the fault detection study through methodologies based on statistical concepts [2], [3]. Although some studies in the past reported the distribution of rotor faults as a small figure compared with bearings and stator faults, there is a current interest in rotor-related faults [4], [5]. Usually, the most indicative features about the IM rotor condition can be extracted through signal processing techniques in most practical cases [6]. However, factors such as the type of feeding and load level complicates the fault diagnosis procedure [6]. Several authors have proposed fault indicators that allow tracking reasonably the rotor state. In [7], the sum of the amplitudes of the two sideband components around the fundamental one in the current spectrum provided useful information to detect and quantify the rotor breakage. In [8], rotor bar fault indicators for inverter-fed squirrel cage IM were proposed (various ratios obtained from the fifth, seventh, eleventh and thirteenth harmonics). These fault patterns are independent to load conditions and drive inertia and with sufficient rejection to frequency variations, but their ability to detect intermediate bar breakages has not been studied.

Intelligent diagnosis approaches, combination of classification algorithms, and signal processing techniques, had produced promising results [2], [9]–[12]. There are different strategies to

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deal with rotor faults depending on the studied signal [11]. Karvelis *et al.* [9] automated a method for the detection of broken bars based on the start-up transient of the current using wavelet approximation. They isolate the fault component and then apply an intelligent icon like approach so that the information can be handled by a k-NN classifier. Gardel *et al.* [13] used an ANN, whose inputs were current spectrum data and some statistical features in the time domain. Both types of data were compared. Some works explore the use of different signals together. In [12], Widodo *et al.* apply Independent Component Analysis for feature extraction and later classify the new observations with a SVM using the sequential minimal optimization algorithm, using current and vibration signals. A research on smart classifiers for BRB detection through the stator current signal in the time domain is presented in [14]. The tested techniques include fuzzy ARTMAP network, SVM, k-NN, and ANN. The problem is stated as a multiclassification approach in which the classes under analysis are one, two, and four BRB.

Few works in the literature approach the classification of various faults [10], [12]. However, there is no work considering the variability that can be introduced by different inverter feedings in the diagnosis of rotor faults. This concern is interesting since not all industries use the same type of inverter to regulate the speed of the application and even inverters with similar characteristics can present differences in the actual performance of the diagnosis system. Therefore, for a real industrial environment, it is important to develop robust intelligent diagnosis approaches for providing accurate predictions if any of the elements of the system undergo major changes in relation to the conditions under which the diagnosis tool was built. However, some of them normally adjust too many fitting parameters leading to modeling noise instances as true underlying relationships. This fact makes that complex models trained with a reduced set of fault observations may provide false indications.

This paper deepens into this aspect by analyzing classifiers from different families under various feeding conditions, which is useful for permanently installed IM. The novelty of this study is summarized in three points: no information is available on how a wide set of classifiers will behave against unknown information such as the case of an inverter change, even when a classifier is trained with data from different power sources; no evidence is known whether data corresponding to different load levels can lead to the same conclusions for the same feeding conditions; it is important to find which algorithm families are more robust to data different from the training data. The latter can help to construct more efficient diagnosis tools, since the computational cost of the training phase may result high for some learning algorithms and, thus, for an online diagnosis. This paper is an extended version of the contribution presented at [15]. It includes a wider set of intelligent fault diagnosis algorithms with additional experimental trials concerning an added incipient severity of the rotor condition. Besides, lighter load conditions are considered and more types of IM supplies are analyzed.

II. FAULT DIAGNOSIS AND FEATURE SELECTION

The methodology to evaluate different intelligent approaches is shown in Fig. 1. First, the stator current signal is acquired from

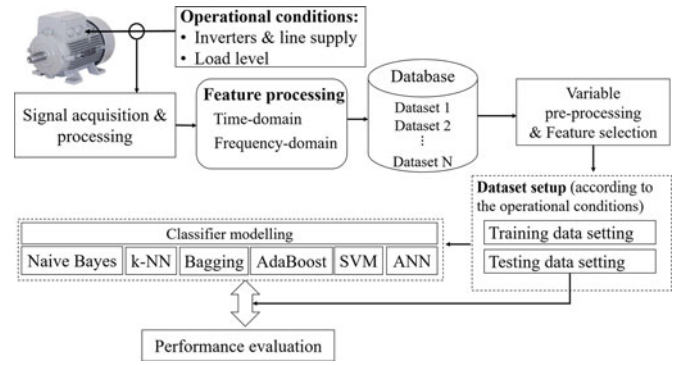


Fig. 1. Intelligent fault diagnosis methodology of evaluation for BRB faults.

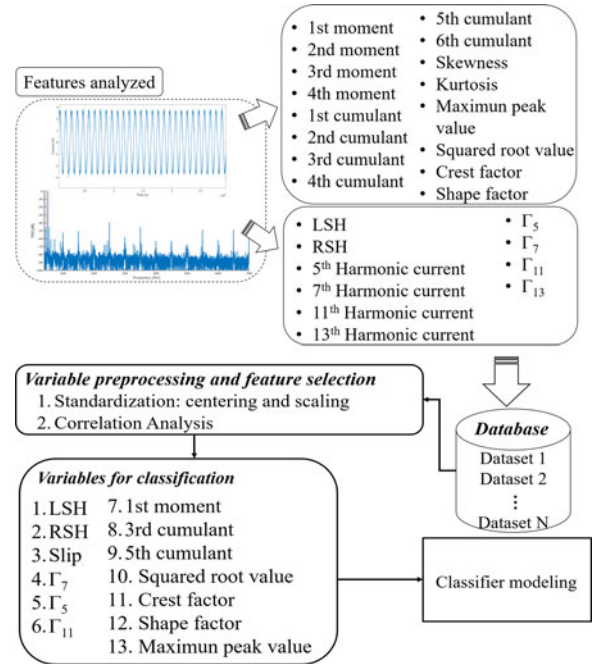


Fig. 2. Feature preprocessing and feature selection.

various operational settings at steady-state conditions. Later, the feature processing is performed to produce a complete database. Then, appropriate features in both time and frequency domains are computed from one-phase stator current. Next, prior to the classification phase, a variable preprocessing and feature selection is carried out. Once a suitable collection of features is obtained (see Fig. 2), a feature selection method is implemented. Then, according to the case of study, a classifier modeling procedure based on the AUC is carried out. The classifier model is validated and its tuning parameters are chosen. Finally, each model is tested with features obtained under different conditions from which it was trained.

A. Features Used for the Diagnosis

Usually, the input features or signatures are obtained from statistical measures on the time domain of the signal [16], amplitudes of fault-related frequencies [7], or some derived ratios [8].

1) *Frequency-domain features*: Several authors have suggested useful frequency-domain features to predict the state

of an inverter-fed cage IM [7], [8] as the left sideband harmonic (LSH), and the right sideband harmonic (RSH). However, Bruzzese [8] proposed new ones, which are defined as follows:

$$\Gamma_5 = \frac{I_{(7-2s)\omega}}{I_{5\omega}} \quad (1)$$

$$\Gamma_7 = \frac{I_{(5+2s)\omega}}{I_{7\omega}} \quad (2)$$

$$\Gamma_{11} = \frac{I_{(13-2s)\omega}}{I_{11\omega}} \quad (3)$$

$$\Gamma_{13} = \frac{I_{(11+2s)\omega}}{I_{13\omega}} \quad (4)$$

where the numerators are the amplitude of the fault-related sidebands around the 5th, 7th, 11th, and 13th harmonics, and the denominators are the amplitudes of these same harmonics. The sidebands are separated from the harmonics a distance in Hertz, that depends on the motor slip, s . In [8], it is stated that Harmonic current sideband-based indicators for the detection of BRB show rejection to frequency variations, as well as load level, inertia, and motor parameters. It can be noticed that the indicators based on the fundamental component of the signal are highly dependent on these conditions [7], [8]. The main advantages of the indicators are [8]:

- 1) increase insensitivity to disturbs such as load torque, drive inertia, and frequency variations;
- 2) low dependence on the machine parameters (except the pole number);
- 3) linear dependence on fault severity. Also, they can be directly applied on motors fed by open-loop control strategies.

2) *Features from the time-domain stator current signal:* The classifiers evaluated also use time-domain statistical features that have proven to be useful for diagnostic purposes [16]. Some of the higher order statistics-based parameters have sensitive properties to non-Gaussian distributions [2], and others are significantly robust. Fig. 2 shows the higher order statistics used in this paper.

B. Feature Selection

The process to choose the most useful features for the classification stage is not straightforward, and it depends on several considerations, mainly, data acquisition costs, performance, and speed of the classifier, and even statistical aspects as interpretability, redundancy, and predictive power (stability of parameters, noise, and overfitting) [17]. In this paper, the pre-processing step is independent, uses a filter method, and does not interfere with the classification phase. The used method consists in the analysis of correlation using the Pearson correlation coefficient, which is defined in (5) and quantifies the linear dependence between two continuous variables X_1 and X_2 . The selected cutoff criterion is 0.8. The reduced set of variables used for the classification phase can be seen in Fig. 2

$$\rho_{X_1, X_2} = \frac{\text{cov}(X_1, X_2)}{\sigma_{X_1} \sigma_{X_2}}. \quad (5)$$

Algorithm 1: Pseudocode of Naive Bayes (NB) algorithm.

Input: Training data: $\mathbf{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$

Output: Posterior probabilities

```

1: for  $i = l$  to  $k$  do
2:    $\mathbf{D}_i \leftarrow \{x_j \mid y_j = c_i, j = 1, \dots, n\}$ 
3:    $n_i \leftarrow |\mathbf{D}_i|$ 
4:    $\hat{P}_i(c_i) \leftarrow \frac{n_i}{n}$ 
5:    $\hat{\mu}_i \leftarrow \frac{1}{n} \sum_{x_j \in \mathbf{D}_i} x_j$ 
6:    $\mathbf{Z}_i = \mathbf{D}_i - 1\hat{\mu}_i^T$ 
7: end for
8: for  $i = l$  to  $d$  do
9:    $\hat{\sigma}_{i,j}^2 \leftarrow \frac{1}{n_i} \mathbf{Z}_{i,j}^T \mathbf{Z}_{i,j}$ 
10:   $\hat{\sigma}_{i,j} = (\hat{\sigma}_{i,j}^2, \dots, \hat{\sigma}_{i,j}^2)$ 
11: end for
12: return  $P$ 

```

III. INTELLIGENT FAULT DIAGNOSIS ALGORITHMS

Several state-of-the-art ML algorithms used for electrical machine diagnosis are evaluated, and they are described next.

A. Bayesian Learning

This learning approach consists in computing the posterior probabilities of each target class (rotor state) with the known training data and input features, to build a predictive model, which is based on the Bayes theorem [18]. The NB classifier is a probabilistic approach that permits the estimation of the posterior probability distribution of the features for an unknown observation. The assumption for numeric features is that they are normally distributed for each class c_i . Through the independence assumption, the joint probability can be decomposed into a product of the probability along each dimension, as can be seen in the pseudocode of Algorithm 1. Since NB uses the sample mean and the diagonal sample covariance matrix for each class, the total number of parameters to be estimated is twice the dimension of the features. Given a training set \mathbf{D} , the algorithm estimates the prior probability and mean for each class. Next, it computes the variance for each feature \mathbf{X}_j . The variance of each feature is obtained after centering. Finally, the testing samples are predicted by returning the class with the maximum posterior probability. NB can be used for developing supervised classifications. It permits to work easily with any number of features [19]. In practice, NB can work suitably even when the independence assumption is violated. The performance results by NB classifier are not affected by small amounts of noise data. The undesired classification bias may increase if there are highly correlated features. Consequently, the removal of the redundant features using correlation analysis can improve the NB performance results [19].

B. Instance-Based Methods

k -NN is a well-known instance-based method with the following characteristics: 1) adaptable to unseen observations; 2) nonparametric; 3) nondemanding of prior knowledge about

the classes; and 4) useful in cases where the samples Gaussian distribution is difficult to assume. The mathematical foundation of k-NN is in [15]. A k-NN model needs training after standardization of the features and the choice of a distance metric.

C. Bootstrap Aggregating: Bagging

Small changes in the data, which is usual, can result in variable splitting criteria, complicating the interpretation and, thus, the decision making. Bagging is an ensemble classification method [18], which averages many trees to reduce their variance. This improvement is achieved with the bootstrap sampling [18]. Bagging creates slightly different training sets D_i , with $i = 1, 2, \dots, K$. Different base classifiers C_i are trained on each D_i . Let the number of classifiers that predict the class of x as c_j be defined as

$$v_j(x) = |\{M_i(x) = c_j \mid i = 1, \dots, K\}|. \quad (6)$$

For a binary classification, the predicted class of the test sample is through majority voting of every base classifier

$$M_c(x) = \text{sign}\left(\sum_{i=1}^K M_i(x)\right) \quad (7)$$

where the class labels are given by $\{+1, -1\}$.

D. Boosting Algorithms: AdaBoost.M1

Boosting is also an ensemble-based technique that builds base classifiers on different training samples, becoming more beneficial for weak classifiers [19]. Unlike Bagging, Boosting uses weighted samples to construct different training sets, with the current sample depending on a previous stage. Adaptive boosting (AdaBoost) is a ML technique, which is one of the most popular versions of boosting. The motivation for AdaBoost was a round-based procedure, which uses the outputs of many weak base learners to improve the accuracy of predicting the correct target class from a set of variables. Because of its learnability, AdaBoost yields an exponentially decreasing empirical error. As Bagging, this process will be repeated K times. Let it denote the iteration and α_{it} the weight for the it th classifier M_{it} , where w_i^{it} denote the weight for x_i with $w^{it} = (w_1^{it}, w_2^{it}, \dots, w_n^{it})$ being the weight vector over all samples at each iteration. Initially all samples have equal weights, i.e., they have the same probability. AdaBoost has been previously used for IM fault diagnosis in [2]. During each iteration, the training sample D_{it} is obtained via weighting resampling using the updated weight in the previous iteration. This is an important fact since it allows the classifier to focus on those observations that were misclassified in previous rounds. The classifier M_{it} is trained on D_{it} and compute its weighted error rate ϵ_{it} on the entire input dataset \mathbf{D} as

$$\epsilon_{it} = \sum_{i=1}^n w_i^{it-1} I(M_{it}(x_i) \neq y_i) \quad (8)$$

where I is an indicator function that is 1 when its argument is fulfilled; α_{it} can be set using the Freund or Breiman expressions [2]. The weight for each sample x_i remains invariable if the predicted class matches correctly with the true class label.

However, if the sample is misclassified

$$I(M_{it}(x_i) \neq y_i) \quad (9)$$

and

$$w_i^{it} = w_i^{it-1} \left(\frac{1}{\epsilon_{it}} - 1 \right). \quad (10)$$

This means that if the error rate ϵ_{it} is low, consequently x_i suffers a greater weight increment. If the error of a classifier is close to 0.5, as the case of classifiers with a performance similar to random guessing, then there is a slight change in weight, and it is expected to misclassify many observations. Thus, this is the motivation to understand the usage of weak base classifiers. Then, the sample weights w_{it} are updated and renormalized. Finally, when the boosted classifiers are available along with their respective weights, the label on the test sample x is obtained by majority voting. Let $v_j(x)$ be the weighted vote for class c_j over the K classifiers

$$v_j(x) = \sum_{it=1}^K \alpha_{it} I(M_{it}(x) \neq c_j). \quad (11)$$

The combined classifier that predict a binary classification problem can be similarly obtained as in (7).

E. Artificial Neural Networks

ANN-based methods are learning algorithms that are characterized by their nonlinear weighting approach and capability of parallelization in a similar fashion as the human brain neurons [20]. The main elements of a ML neural model are the set of synapses with its respective weights, the adder for summing the input signals, and the activation function for limiting the neuron output. A multilayer perceptron (MLP) neural network is used in this paper, which is characterized by completely connected feedforward networks where the number of hidden layers is optimized. The main function of these layers is to disclose gradually the noticeable features that describe the training data, storing such associated knowledge. The approach to minimize the evaluation criterion to stop the training stage is the backpropagation algorithm [18]. The objective of the backpropagation algorithm [20] is to adjust the weights matrix of the network to minimize the performance measure. However, it is important not to overparametrize the model by taking into account the following:

- 1) the starting values of the weights;
- 2) the overfitting problem;
- 3) the scale of the input features;
- 4) choosing an appropriate number of hidden units to capture the nonlinearities in the data;
- 5) avoiding to fall in local minima because the error function is nonconvex by randomizing the starting configuration.

The use of ANN to detect faults has been a topic of interest within the research community on electrical machines [13], [21], [22]. These tools may be effective under scenarios with a high signal-to-noise ratio. However, it does not permit to construct an interpretable prediction model.

F. Support Vector Machines

SVMs are a type of statistical models used for converting linear classifiers into models capable of producing nonlinear decision boundaries. This classifier builds a model that assigns new observations to one of the classes using an optimization problem to find the best hyperplane that separates most the target classes. Vapnik [23] investigated this statistical technique and introduced the margin metric, which is the distance between the classification boundary and the closest training set sample. The margin metric defined by these samples can be quantified and used to evaluate possible models for its later maximization. As aforementioned, this algorithm can deal with nonlinear boundaries by enlarging the feature space using quadratic or higher order polynomial functions, which is also known as the kernel trick. The optimization problem consists in finding the margin that best separates both classes. According to [18], and having a set of training samples of length n , $(x_1, y_1), (x_2, y_2), (x_i, y_i), \dots, (x_n, y_n)$ with $x_i \in \mathbb{R}^p$ and $y_i \in \{-1, 1\}$, a generic hyperplane $h(x) = 0$ to separate the provided data and thus optimize such problem, can be defined as (13)

$$\min_{\beta, \beta_0} \frac{1}{2} \|\beta\|_2 + C \sum_{i=1}^n \xi_i \quad (12)$$

subject to

$$\begin{cases} y_i(\beta^T \phi(x_i) + \beta_0) \geq 1 - \xi_i \\ \xi_i \geq 0, \end{cases} \quad i = 1, 2, \dots, N \quad (13)$$

where β^T is a dimensional weight vector, β_0 is a scalar called bias, and C is a constant that represents the cost tuning parameter. The mentioned optimization problem can be expressed in terms of Lagrange multipliers as

$$L(\lambda) = \sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i,j=1}^N y_i y_j \lambda_i \lambda_j x_i^T x_j \quad (14)$$

subject to

$$\begin{cases} 0 \leq \lambda_i \leq C \\ \sum_{i=1}^N \lambda_i y_i = 0, \end{cases} \quad i = 1, 2, \dots, N \quad (15)$$

and maximizing (14), the optimization problem can be solved at the SVM training stage [24]. The performance of SVM classifiers clearly depends on the kernel function selection, kernel parameters, and regularization parameter [10]. In the literature, one of the most frequently used kernel functions is radial basis function, which is used in this paper and it is defined as follows:

$$K(x, x_i) = \exp(-\sigma \|x - x_i\|_2), \sigma > 0. \quad (16)$$

Basically, what this function does is to give access to spaces of higher dimension instead of using the mapping function $\phi(x_i)$. In this paper, a binary classification is addressed to evaluate each classifier behavior for the diagnosis of incipient faults for both, half broken rotor bar and a full broken rotor bar.

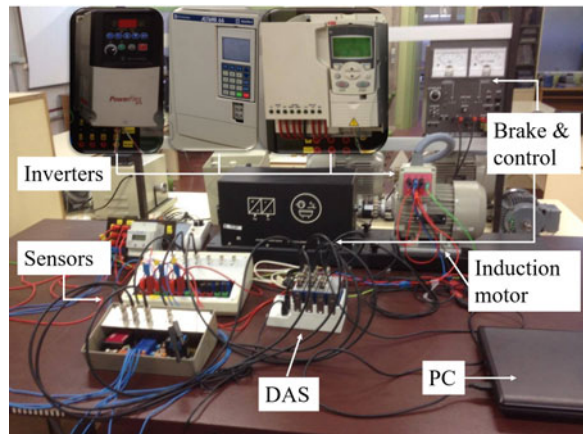


Fig. 3. Experimental test bench.

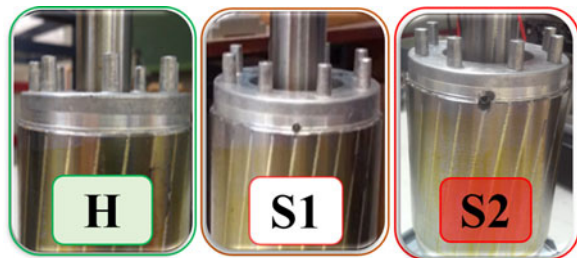


Fig. 4. Rotor conditions.

IV. EXPERIMENTAL TEST BENCH

A set of experimental trials is conducted to develop a rotor early-state checking approach for providing an automatic detection of IM faults. Fig. 3 shows a layout of the laboratory setup. A three-phase IM, star connected, is tested in a laboratory environment to acquire data related to its condition. The IM is fed from the line and three types of inverters, whose specifications are shown in the Appendix. These inverters are the following: 1) ABB; 2) Allen Bradley (A.Br.); and 3) Telemecanique (TM). Unlike ABB and A.Br. inverters, TM inverter is characterized by an inherent floor noise level higher than the rest of inverters [6]. The three are programmed with a V/f linear control. The motor is loaded through a magnetic powder brake and tested for two load levels, considered as medium (LL1) and high (LL2), respectively. The operating frequency is 50 Hz, and one-phase stator current is measured 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 50 kHz where the data collection have been performed for a stationary period of time for 10 s. The evolution of the bar breaking is simulated by drilling a hole in one of the rotor bars, as Fig. 4 depicts. Three conditions are considered. The rotor is healthy (H) in the first test. Next, a 4.2-mm depth hole is drilled in one of rotor bars, and this is the incipient faulty condition of the rotor (Half-broken rotor bar, S1). The diameter of the hole is 2.5 mm. Then, a more severe fault condition is produced by drilling a complete hole in the

TABLE I
DESCRIPTION OF THE CASES OF STUDY ACCORDING TO THE DATASET USED FOR TRAINING AND TESTING

Case Study	Data for training	Data for testing	# of samples for training	# of samples for testing
1	ABB, Allen Bradley, Line-fed	Telemecanique	90	30
2	Telemecanique, Allen Bradley, Line-fed	ABB	90	30
3	Telemecanique, ABB, Line-fed	Allen Bradley	90	30
4	Telemecanique, ABB, Allen Bradley	Line-fed	90	30

TABLE II
CHOSEN TUNING PARAMETERS FOR EACH CASE OF STUDY ONCE THE TRAINING AND VALIDATION PROCEDURE IS PERFORMED

Severity	Load level	Case Study	k -NN	Bagging		AdaBoost			MLP	SVM		
				k	N_{trees}	T_{depth}	N_{trees}	T_{depth}	Learning Coef.	size	σ	C
S1	LL1	1	3	9	5	9	7	Freund	3	0.5331	0.0464	
			7	9	5	9	11	Freund	6	0.1176	5.0734	
			5	9	3	9	11	Freund	7	0.1973	0.5107	
			5	9	11	9	7	Freund	7	0.5723	162.993	
	LL2	1	7	9	5	9	9	Freund	9	0.0102	3.6169	
			9	9	9	9	9	Freund	9	0.1780	0.5107	
			7	9	7	9	9	Freund	6	0.1940	0.5107	
			5	9	11	9	7	Freund	7	0.5723	162.993	
	S2	LL1	1	7	3	1	3	1	Breiman	3	0.3152	0.0464
				9	9	5	9	7	Freund	7	0.0059	18.0341
				5	9	11	9	11	Freund	6	0.0292	22.8643
				7	9	11	9	11	Freund	9	0.0225	79.3369
LL2		1	7	3	1	3	1	Breiman	3	0.3043	0.0464	
			9	9	7	9	7	Freund	5	0.0410	0.9034	
			9	9	5	9	11	Freund	5	0.2073	326.94	
			9	9	9	9	3	Freund	5	0.9034	0.9034	

same rotor bar (Broken rotor bar, S2) with a depth equivalent to the thickness of a bar.

V. RESULTS AND DISCUSSION

Experimental tests were managed for the diagnosis of the incipient (S1) and for the developed fault (S2). Several case studies were carried out with the previously described test bench. In Table I, each case of study is detailed according to the organized database with the experimental tests. The number of samples used for training and testing purposes is specified along with the IM supply used for each case. The distribution of the classes (rotor conditions) for both training and test sets is the same. The ML algorithms are tuned using training data from various power supplies and for different load cases. The classifiers are tested to evaluate their performance with data from another IM supply, not employed in the training stage. Finally, the testing set is employed to evaluate the performance of each classifier by means of tools such as: scores derived from the confusion matrix and the ROC curve, including its AUC metric.

A. Classifier Tuning

The computational cost of this stage depends on the number of parameters to be optimized for each intelligent algorithm. The technique for estimating the classification error is also a relevant aspect since it will determine, with the training available data, the corresponding score value. In this paper, the 0.632 plus bootstrap method is chosen for the training and validation

phase, as it is suggested in [25] for small datasets. This analysis is performed with four cases of study, shown in Table I. The classifiers used for the IM diagnosis evaluation are those presented in Section III and are implemented through various R libraries [26], [27]. The NB classification algorithm has not influential tuning parameters. For the k -NN method, the number of neighbors chosen for its tuning are 1, 3, 5, 7, and 9. The Minkowski method is used to calculate the distance. The tree-based methods employed in this paper use the Classification and Regression Trees algorithm. The common tuning parameters for Bagging (Bag.) and AdaBoost.M1 (AdaB.) are the number of trees of the ensemble (N_{trees}) and the maximum tree depth (T_{depth}). N_{trees} varies in the discrete range [1, 9] and T_{depth} takes the discrete values: 1, 3, 5, 7, 9, and 11. For AdaB. an additional parameter, the learning coefficient (Breiman or Freund), is considered [2]. For the MLP algorithm, the values of the number of hidden units (size) of the single hidden layer network vary between 3 and 9. The sigmoid function is used for the purposes of activation. The parameter grid of the SVM algorithm is: $C \in (0, 400)$ and $\sigma \in (0, 1)$. AUC metric was used to select the optimal classifier tuning. In Table II, the selected tuning parameters, for each case of study corresponding to each particular rotor fault severity and load level, are specified.

B. Performance Evaluation I

The following scores are used to evaluate the classifiers [25]: 1) accuracy (Acc); 2) sensitivity (Sens.); and 3) specificity

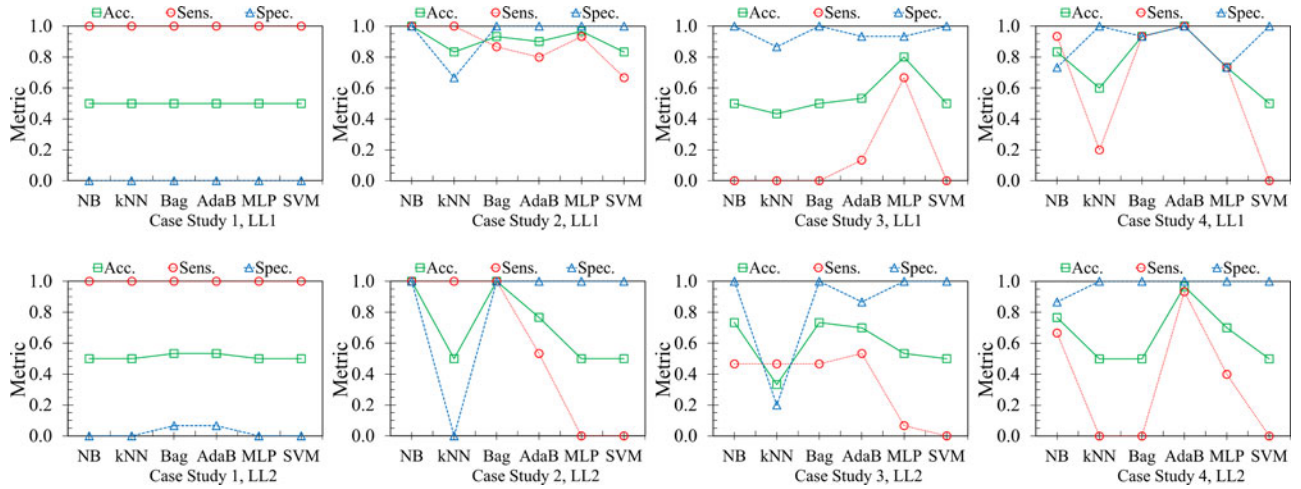


Fig. 5. Classifiers' performance scores for each case study and half-broken rotor bar severity (S1). Top row: Low Load Level (LL1). Bottom row: High Load Level (LL2).

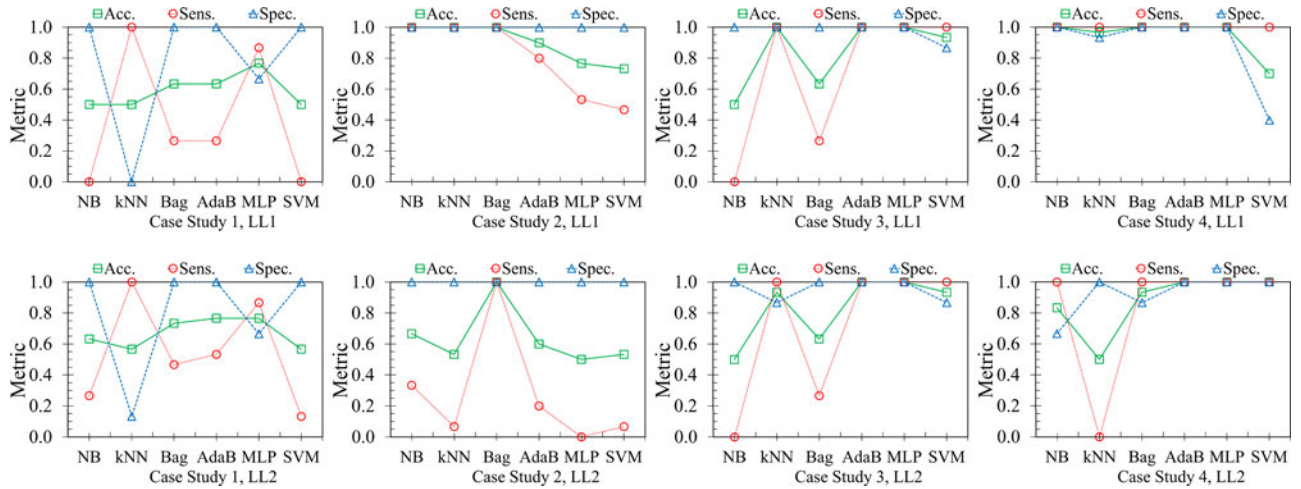


Fig. 6. Classifiers' performance scores for each case study and broken rotor bar severity (S2). Top row: Low Load Level (LL1). Bottom row: High Load Level (LL2).

(Spec.). Acc. defines the average performance of two classes (healthy motor, negative; and faulty motor, positive) combined and is computed with a threshold value of 0.5. Sens. shows the extent to which true positives are not overlooked and Spec. shows the extent to which positives correspond to the condition of interest and not other condition being mistaken for it [25].

1) *Half-broken rotor bar (S1)*: The diagnosis of this severity in an inverter-fed IM is the most complex, as shown in Fig. 5.

Case study 1: This is one of the most complex cases since the testing data come from the TM inverter whose stator current has a high noise content. Fig. 5 shows that no classifier achieves good predictions.

Case study 2: The classifiers perform much better than in the case study 1, being the NB the best (for the two load levels) and k-NN and SVM the worst. MLP shows correct results for the lower load level (LL1), but it is not able to predictive for the higher load level (LL2).

Case study 3: Again, the classifiers performed poorly, especially for low loads. However, Bag. and AdaB. present better performance for high loads.

Case study 4: Despite testing data come from the line-fed IM, the behavior of the classifiers is very different. AdaB. achieves Accuracy values of 1 for both load levels. The rest of classifiers show worst results.

2) *Broken rotor bar (S2)*: The classification is better than for the half-broken rotor bar, as Fig. 6 demonstrates. Case study 4 yields the best results.

Case study 1: The results obtained for both load levels are similar, showing K-NN and SVM the worst performance.

Case study 2: Surprisingly, classifiers perform better for the lower load level, and Bag. presents excellent results in both cases.

Case study 3: AdaB. and MLP present excellent performance for both load levels, followed by k-NN and SVM.

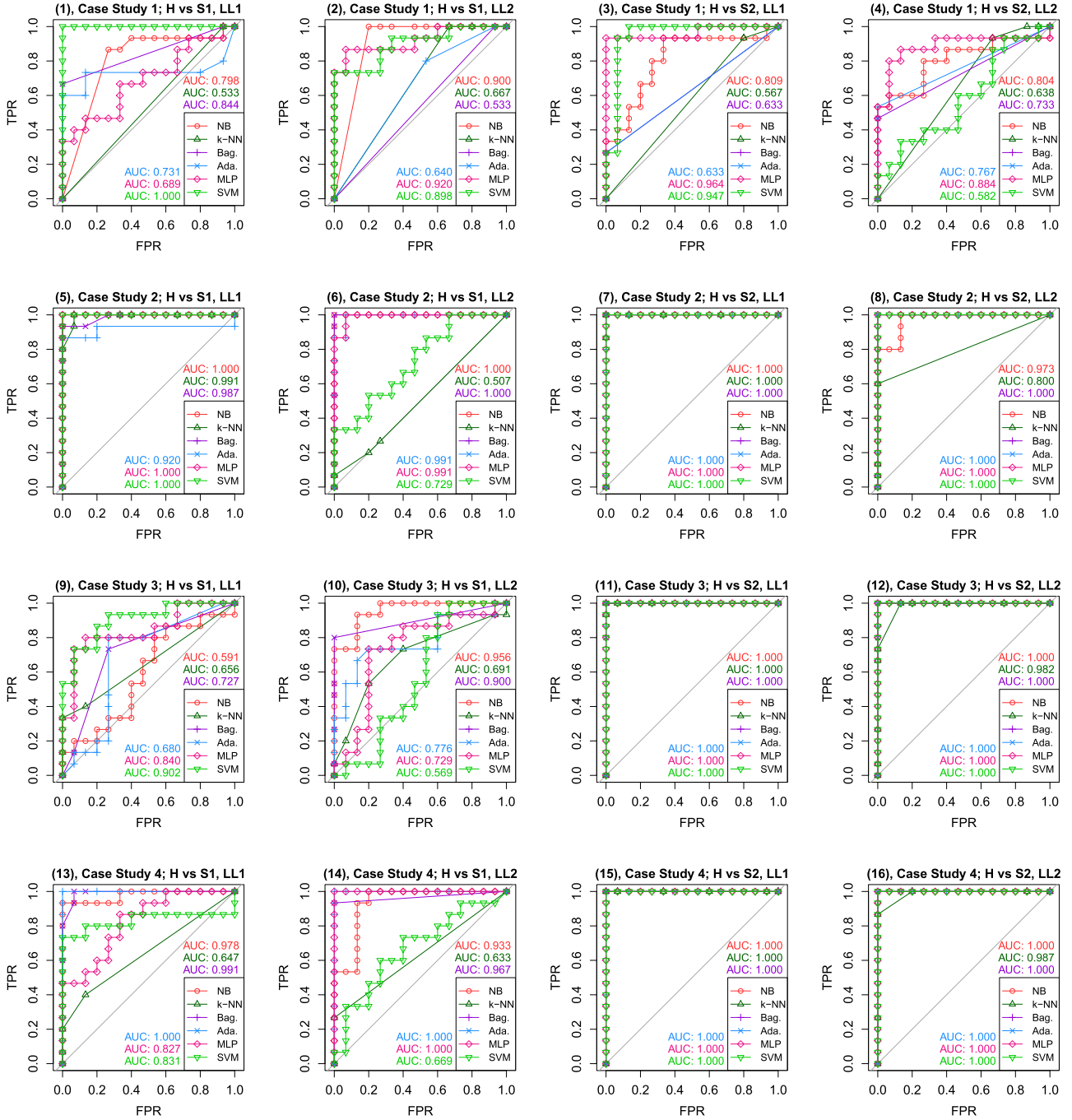


Fig. 7. ROC Curves grouped by the sort of feeding of the testing data. They are organized by rows according to the case study: First row, Case Study 1. Second row, Case Study 2. Third row, Case Study 3. Fourth row, Case Study 4. The title of each panel indicates the condition states compared: H, healthy motor; S1, half-broken rotor bar; S2, broken rotor bar; the two load levels: LL1, low load; LL2, high load.

Case study 4: Only SVM performs worse than the others at low loads. In contrast, k-NN is the worst at high load level, and Bag. suffers a slight deterioration performance.

C. Performance Evaluation II

The performance metrics were calculated for a class assignment threshold of 0.5 that coincides with a loss or cost function in which the two kinds of errors are equally considered, which is seldom the case. For example, it is not the same predicting a

probability of 0.6 and then observing an event than predicting a probability of 0.9 and then observing an event. Undoubtedly, both predictions are true but the first one worse.

However, evaluating the classifier probabilities over all possible thresholds through the ROC curves [25] may be of interest to assess the classifiers implemented. ROC curves evaluate the performance of the classifier by analyzing the class assignment threshold. In a ROC curve, the resulting TPR or Sensitivity is depicted against the FPR for different thresholds [25]. Each point in the ROC curve represents a sensitivity–specificity pair

corresponding to a particular decision threshold. The more the ROC curve is to the upper left corner the better the classifier performance is. On the other hand, a classifier guessing randomly would be represented by a ROC curve close to the 45° line. Fig. 7 shows the ROC curves of the classifiers for the same conditions previously studied.

Case study 1 (first row of Fig. 7): k-NN achieved a low AUC at both load levels, even for the broken rotor bar (S2). Panel 7.1 (half-broken rotor bar, S1, and low load, LL1) shows that SVM and Bag. classified better than the rest (AUC of 1.0 and 0.84, respectively). NB was more stable under changing testing data, fault severity, and load level, as its AUC remained in the range (0.798, 0.900).

Case study 2 (second row of Fig. 7): All classifiers performed well, except SVM (AUC = 0.729) and k-NN (AUC = 0.527), as shown in panel 7.6.

Case study 3 (third row of Fig. 7): All classifiers identified the broken rotor bar at both load level. However, MLP and SVM classified the half-broken bar worst at the higher load than at the lower load.

Case study 4 (fourth row of Fig. 7): The AUC score of the classifiers did not fail below 0.82, except SVM and MLP classifying the half-broken bar. Alike case study 3, no classifier failed to identify the broken rotor bar.

VI. CONCLUSION

We performed an experimental comparative evaluation of ML techniques used for the diagnosis of rotor faults in inverter-fed IM. The fault features are computed (in the frequency and time domains) from the stator electric current. The motor is fed with four different power supplies and loaded at two levels. Two faulty conditions considered are: half broken rotor bar (S1) and a broken rotor bar (S2). The majority of techniques classifies the broken rotor bar condition correctly, regardless of the motor load level. Only the k-NN showed worst results with testing data from the TM inverter. The identification of the half-broken rotor bar presents more difficulties, especially when the motor is inverter-fed. Tree-based algorithms improved their classification results with higher motor load levels in the study cases 2 and 3, unlike MLP and SVM that worsened. The analysis of the results establishes that Naive Bayes and Bagging obtained the best scores and k-NN is the worst classifier. More flexible techniques, like k-NN, MLP, and SVM (RBF), perform worse than the rest. This indicates that the decision boundary in this classification problem is probably linear with those features more correlated with the IM load level. The voltage supply of an industrial IM can change during its lifetime. Automatic identification of a faulty rotor is still a primary concern, despite a voltage supply substitution that can change the fault patterns. Our work is based on only one output frequency, equal to the line frequency, but this study can be extended to different operating frequencies and control strategies.

APPENDIX

SPECIFICATIONS OF THE USED DEVICES

Three-phase squirrel cage induction motor (Siemens), star connection. Rated characteristics: Power = 0.75 kW, $f = 50$ Hz,

voltage = 400 V, current = 1.9 A, rated speed = 1395 r/min, No. of pole pairs = 2. Three three-phase inverters from the brands ABB (model ACS355), Allen Bradley (model PowerFlex 40) and Telemecanique (model Altivar 66) with a power range of 0.37 to 4 kW, 0.4 to 2.2 kW, and 0.75 to 250 kW, respectively. The switching frequency of all inverters is 4 kHz.

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