Novelty Detection based Condition Monitoring Scheme applied to Electromechanical Systems

M. Delgado-Prieto[1*], J. A. Carino[1], J. J. Saucedo[2], R. A. Osornio[2] , R. Romero-Troncoso[2] and L. Romeral[1]
[1] MCIA Research Center, Department of Electronic Engineering, Technical University of Catalonia, Barcelona, Spain
[2] HSPdigital CA-Mecatronica, Engineering Faculty, Autonomous University of Queretaro, San Juan del Rio, Mexico
[*]jsaucedo@hspdigital.org

***Abstract*—The investigation towards advanced predictive maintenance strategies is being required by the industrial sector to enable an actual implementation of the Industry 4.0, in which digitized industrial assets must provide advanced industrial maintenance capabilities. In this regard, this study is focused on the performance analysis resulting from the application of machine learning methods in data-driven maintenance systems for the industrial sector. The study aims to clarify current challenges dealing with classical electromechanical system monitoring approaches applied in industrial frameworks, that is, the presence of unknown events and the limitation to the nominal healthy condition as starting knowledge. Thus, an industrial machinery condition monitoring methodology based on novelty detection and classification is proposed in this study. The proposed methodology is divided in three main stages. First, a dedicated feature calculation and reduction over each available physical magnitude is proposed. Second, an ensemble structure of novelty detection models based on one-class support vector machines to identify not previously considered events. Third, a diagnosis model supported by a feature fusion scheme in order to reach high fault classification capabilities. The effectiveness of the proposed fault detection and identification methodology has been compared with the classical single model approach, and verified by experimental results obtained from an electromechanical machine at laboratory facilities.**

Keywords— Condition Monitoring; Fault Diagnosis; Industry applications; Machine Learning.

I. INTRODUCTION

A high performance demand in industry applications of Condition Based Maintenance (CBM) schemes leads to an intensive research to increase the reliability and robustness of current CBM methodologies. Being reliability in this case defined as the degree to which the result of the assessment of the machine can be depended on to be accurate, and robustness as the ability to withstand or overcome adverse conditions or rigorous testing maintaining the same degree of performance.

Classical CBM methodologies consist on using a classification algorithm to determine the machine condition [1]. This algorithm is, previously, trained with representative data of different operating scenarios of the machinery (under availability). During the evaluation of a new measurement acquired from the system under inspection, the algorithm analyses the signature of the physical magnitudes, and outputs a label as result of the association with one of the different operating modes of the machine learned during the training process. This approach is known as fault diagnosis or fault identification [2]. Important examples of such approach were presented by Seshadrinath *et al.* in 2013 [3], and Toma *et al.* in 2014 [4], where the condition assessment of an induction machine are performed by neural networks previously trained by a dataset composed by measurements of the machine working in healthy and faulty conditions. However, generally, if a new measurement, corresponding to a condition not presented during the training is evaluated by the algorithm, the label output can only be one of the scenarios presented on the training and, therefore, leading to an incorrect diagnosis.

To provide the CBM scheme the capacity to deal with insufficient information, the detection of novel scenarios represents a first step to cope with the demands of high-performing industrial applications. In this regard, specific research is been doing towards strategies able to monitor the system and detect new operating scenarios, thereby avoiding an incorrect assessment of the condition of the machine. This research topic is called novelty detection, and can be defined as the task of recognizing that the data under analysis during the diagnosis procedure differ, in some respect, from the available data during the training, that is, the detection of new operating scenarios [5]. Its practical importance and challenging nature have led to many approaches being proposed. These methods are typically applied to datasets in which a very large number of examples of the “normal” or nominal condition are available, and where there are insufficient or unavailable data to describe “abnormal” or new operating scenarios, due to faults or modifications over the operating set points [6].

The application of novelty detection to electromechanical system monitoring is not simple, there are many conditions that limit the applicability of these algorithms in this application domain. Novelty detection was initially applied on image processing, video surveillance, text mining and network intrusion, where a large amount of data is available to characterize the monitored asset [7]. However, in industrial applications of electromechanical systems, the number of measurements available to characterize the machine is usually limited, that is, in front of a fault condition, the maintenance actions are rapidly applied or even the related machinery is stopped. This fact implies the capture of, generally, initial fault or operating deviation stages under a short period of time. Therefore, novelty detection approaches, capable of deal with reduced number of samples per condition, are required.

In regard with the available samples characterization, it should be noted that the numerical features calculated from the measured physical signals determinate what can be observed in the machine. Most of the features calculated for fault diagnosis are selected to highlight a specific fault, nevertheless, for novelty detection there is no information regarding what is necessary to monitor for these unknown scenarios. Moreover, the electromechanical operating conditions shown, generally, and non-connected data distribution. That is, dealing with different sources of faults, the effects into the acquired physical magnitudes are different, and, then, scattered in the considered numerical feature space representation. Therefore, adequate strategies are required for signal processing and feature calculation to detect anomalies or to delimit the boundaries of the available knowledge.

The combination of the novelty detection with the fault diagnosis is not trivial and not properly addressed around electromechanical CBM schemes to date. On the literature, systems capable to perform novelty detection and fault diagnosis are known as fault detection and identification systems, and the concept have been already presented in some applications such as network intrusion detection and industrial plant monitoring among others [6]. Nevertheless, their implementation to electromechanical systems in industrial applications still present some problems that need to be addressed. Classical approaches propose the execution of both tasks in one single stage, performing novelty detection and fault detection with one algorithm or an ensemble of the same algorithm, however, this approach, while easy to implement, leads to limitations of detection and identification performances [8]. Separating both stages not only opens the opportunity to analyze different features on each stage, but also limits the number of algorithms that can be used for each task. As mentioned above, the features analyzed for each task could represent a window of improvement to increase the applicability of these methodologies.

In summary, although electromechanical condition based monitoring has been classically an active research field, currently, critical requirements are being demanded from the industrial sector in regard with their application capabilities. In this regard, the scientific community is being doing an effort to study and define new contributions, where further research should be made in order to propose a coherent and viable fault detection and identification methodology under an incremental learning framework for industrial electromechanical systems, capable of detect and incorporate new operating scenarios while providing a diagnosis about the available conditions. It must be taken into consideration that this topic represents a modern research field and highly novel its application into electromechanical condition based monitoring framework, which implies the need of addressing all the aforementioned questions .In this regard, two main contributions are proposed in this study. First, a new fault detection and identification methodology in order to enhance the detection of novel operating conditions, thus, improving the fault identification capabilities. The proposed novelty detection based condition monitoring methodology is suitable to start from data corresponding only to the nominal healthy condition of the electromechanical system under analysis. Second, the identification of the performances and limitations of the numerical features analyzed from different physical magnitudes in respect of the incursion of new fault scenarios. Different features fusion schemes are proposed for each of the considered condition monitoring tasks: novelty detection and diagnosis. Finally, the validation of the proposed methodology in front of multiple conditions is considered, including known and unknown events, measured from an electromechanical system emulating an industrial machine.

This paper is organized as follows: Section II describes the theoretical aspects of the proposed novelty detection technique; Section III describes the proposed novelty detection based CBM method; Section IV includes the experimental system description used for validation; Section V presents the experimental results and discussion; finally, Section VI includes conclusion remarks.

II. One-Class Support Vector Machine

Current novelty detection strategies differ on the assumptions made about the nature of the available data. Each of the three main approaches exhibit their own advantages and disadvantages, and faces different challenges for complex datasets. Thus, probabilistic methods makes use of the distribution of the training data to determine the location of the novelty boundary. Distance-based methods require the definition of an appropriate distance measure for the given data. Finally, domain-based methods determine the location of the novelty boundary using only those data that lie closest to it, and do not make any assumption about the data distribution.

Dealing with electromechanical condition monitoring where relative small sets of training data are usually available, the domain-based approaches represent a suitable option [9]. A domain-based method requires a boundary to be created based on the structure of the training dataset. These methods are typically insensitive to the specific sampling and density of the target class, because they describe the target class boundary, or the domain, and not the class density. Class membership of unknown data is then determined by their location with respect to the boundary. Domain-based novelty detection is approached as with two-class problem in terms of Support Vector Machine (SVM), where it is determined the location of the novelty boundary using only those data that lie closest to it (in a kernel-based transformed space), by means the support vectors. All other data from the training set (those that are not support vectors), are not considered when setting the novelty boundary. Hence, the distribution of data in the training set is not considered, which is seen as an easy novelty detection approach [10]. The original SVM is a network that is ideally suited for binary pattern classification of data that are linearly separable. Indeed, the SVM defines a hyperplane that maximizes the separating margin between two classes. Since the introduction of the original idea, several modifications and improvements have been made. In this regard, the so called One-Class SVM (OC-SVM), proposed by Schölkopf *et al.* [11], aims to separate one class of target samples from all other class samples. In this type of once-class problem, one class is characterized well, called target class; while for the other class no measurements are available. This approach requires to define a priori the ratio of positive data allowed to fall outside the boundaries of the normal class. This makes the OC-SVM more tolerant to outliers in the normal training data. Also, the shape of the domain delimiting the boundaries depend on the kernel selected. In this regard the development of the algorithm is based on the classic SVM approach where it is not considered a specific structure (for example a hypersphere), to delimit the domain, therefore does not automatically optimizes the model parameters by using artificially generated unlabeled data uniformly distributed.

III. METHOD

The main objective in any novelty detection system is the recognition of unknown patterns. In this regard, in this novelty detection based CBM methodology proposed, a multi-modal scheme is considered in order to increase the novelty detection performance as shown in Fig. 1. The first step is to process the data of the machine under monitoring to characterize the normal (healthy) operating condition, then, the estimation of numerical features from the processed data follows in order to that stand out novelties in the electromechanical operation. Considering previous works related with condition monitoring applied to electromechanical systems, the statistical time-domain features proposed are: RMS, standard deviation, variance, shape factor, crest factor, kurtosis and skewness [12].

Once the features are calculated from each physical magnitude available, the novelty models, conformed by OC-SVM, are trained with this information. Each of the proposed OC-SVM are trained and validated with measurements of the normal operation of the machine. Then, the input of the novelty models is the information contained in the features, and the output is a novelty score that determinates how different is the new measurement analyzed compared to the ones which has been trained (the reference). Hence, a high novelty score implies that the new data differs in great scale from the trained one.

The presence of nonsignificant and/or redundant information in high dimensional datasets complicates the learning task of novelty detection as well as pattern recognition of multi-class classification methods. Indeed, the empty space approach states that, in order to cover the whole space, a number of samples exponentially related with the dimensionality, is required. Thus, in order to avoid the curse of dimensionality, a number of training examples also exponentially related with the dimensionality is needed. For these reason, there is a necessity to apply dimensionality reduction approaches in condition monitoring schemes. Thus, in order to analyse the performance of the proposed methodology, a common dimensionality reduction approaches has been applied over the feature vectors proposed in this work, that is, Principal Component Analysis (PCA) for novelty detection, and Linear Discriminant Analysis (LDA) for diagnosis.

Indeed, the dimensionality reduction strategies differ in the criteria applied over the data in order to reach a reduced feature space. PCA is one of the most commonly used technique for unsupervised dimensionality reduction. It aims to find the linear projections that best capture the variability of the data [13]. Another well-known technique is the LDA. The LDA attempts to maximize the linear separation between data points belonging to different classes. In contrast to most other dimensionality reduction techniques, LDA, as a feature extraction technique, finds a linear mapping that maximizes the linear class separation in the low-dimensional representation of the data. The criteria that are used to formulate linear class separation in LDA are the within-class scatter and the between-class scatter [14]. Since LDA is a supervised technique, is not often employed in novelty detection applications, however, is one of the best options for feature extraction in supervised multi-class classification applications.

The consideration of a multi-modal based novelty detection stage represents an enhanced approach in order to detect data distribution deviations during the monitoring process. In this regard, the fusion of the information provided by different magnitudes is proposed to be done at novelty level. However, dealing with the diagnosis the fusion of the information provided by different magnitudes is proposed to be done at feature level, considering a unique classification algorithm, in this case a simple neural network based.

Finally, the necessity of evaluating the novelty detection performance is critical. The use of a particular score depends on multiple interests, however, the most useful and common scores in a discrete scenario is the accuracy. Accuracy and classification error (1-accuracy), is one of the most frequent scores used to evaluate discrete classification in electromechanical diagnosis schemes. This score is indicative of the classification error committed evaluating, in case of novelty detection, two classes (1).

$$\text{Accuracy} = (FP + FN) / N \tag{4}$$

where FP is the number of false positives, FN is the number of false negatives, and N, the total number of analysed measures. Two novelty detection approaches could exhibit the same accuracy but provide a different novelty ratio for each class (normal data and novelty data).

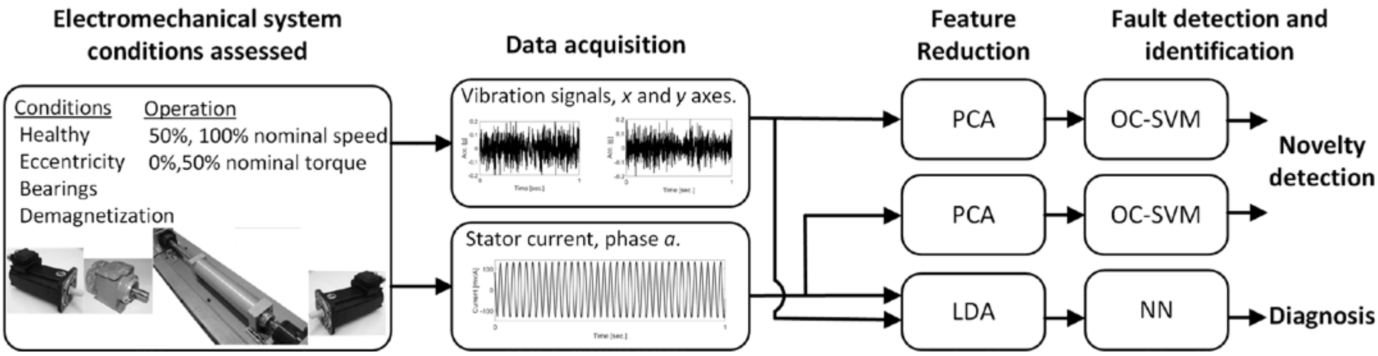


Fig. 1. Novelty detection based condition monitoring scheme, including feature level diagnosis stage and novelty level novelty detection stage.

IV. EXPERIMENTAL SETUP

In order to evaluate the goodness of the proposed methodology, experimental data has been obtained from a test bench based on an electromechanical actuator. The experimental motor bench is based on two identical featured face to face motors, the motor under test and the motor that acts as a load. These motors are connected by means of a screw and a gearbox, constituting the test bench. A motor runs the input axle of the gearbox. The output axle of the gearbox runs the screw, which in turns, displace the movable part. The motors are two SPMSMs with 3 pairs of poles, rated torque of 3.6 Nm, 230 Vac, and rated speed of 6000 rpm provided by ABB Group. The motors were driven also by ABB power converters ACSM1 model. The measurement equipment is focused on the acquisition of stator currents and vibrations. The current probes, as well as the accelerometer transducer, were connected to a PXIe 1062 acquisition system provided by NI. The sampling frequency was fixed at 20kS/s during 1second for each experiment. The experimental arrangement diagram is shown in Fig. 2.

A set of four fault conditions have been considered to complete the experimental arrangements. First of them, a complete healthy electromechanical actuator have been tested. Second, partially demagnetized motor was developed during the manufacture with a 50% of nominal flux reduction in one pair of poles. Third, degraded bearings have been mounted. The non-end bearing inner as well as outer races have been scraped thoroughly in order to cause a generalized rough defect. Fourth, a static eccentricity have been induced through a screw attachment in the gearbox output shaft. Each of these fault scenarios have been experimentally reproduced following two speed patterns, 1500 rpm and 3000 rpm, combined with two imposed torque patterns, 0% and 50% of rated torque. Therefore, four different operating regimes have been tested for each considered condition. For each of the experimental cases, fifty complete acquisitions were carried out.

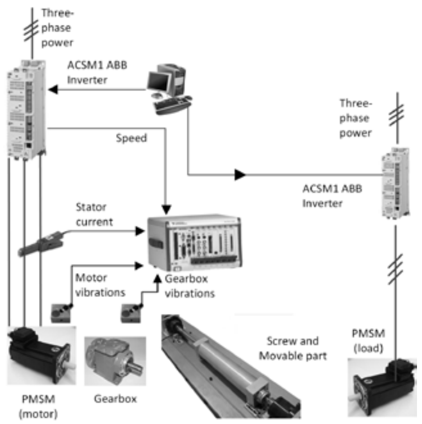


Fig. 2. Test bench diagram used for the validation of the novelty detection based condition monitoring scheme.

V. RESUTLS AND DISCUSSION

Four different test sets have been considered in order to analyse the performance of the proposed novelty detection based condition monitoring methodology. The sets are based on the consideration of different conditions as part the training and test sets. Detail of these four test sets are shown in Table I.

TABLE I. TEST SETS DESCRIPTION

	Training	Test
Test 1	H	B, E and D
Test 2	H and B	E and D
Test 3	H, B and E	D
Test 4	H, E and D	B

Previous to the analysis of the novelty detection behavior, it must be noted the limitation of the diagnosis stage in front of different faults. It is shown in Fig. 3(a) the resulting LDA 2-dimensional LDA projection of two classes, healthy and bearings fault, used during and initial training of the diagnosis stage. As it can be seen in Fig. 3(b), the projection of an eventual operating condition not considered during the training process of the diagnosis stages, as for example the eccentricity fault condition, results in a clear overlapping with previously data, specifically with the bearing fault conditions. This fact, as it can be seen in Fig. 3(c), leads to diagnosis error trough false positives since the measurements corresponding to the eccentricity fault condition will be identified as bearing fault conditions by a classification algorithm.

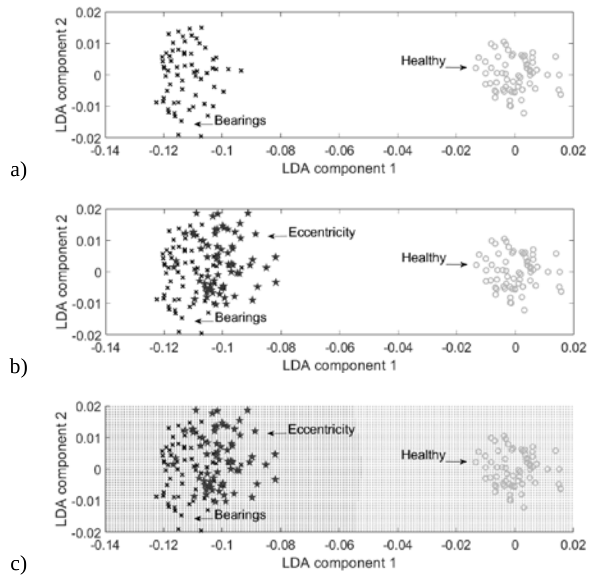
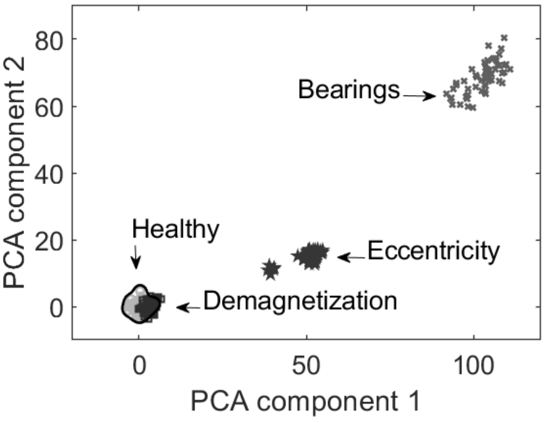


Fig. 3. Resulting two-dimensional projection considering linear discriminant analysis over healthy and bearing fault conditions. (a) Projection of healthy and bearing fault condition. (b) Projection of healthy, bearing and eccentricity fault conditions. (c) Projection of healthy, bearing and eccentricity fault conditions and classification boundary resulting from a neural network application.

The novelty detection represents, then, a critical stage in order to avoid the diagnosis errors due to the assessment of not previously characterized operating conditions. Next figures, Fig. 4, Fig. 5, Fig. 6 and Fig. 7, show the novelty behavior in front of the different test sets previously defined. The novelty model boundary is represented by a solid line.



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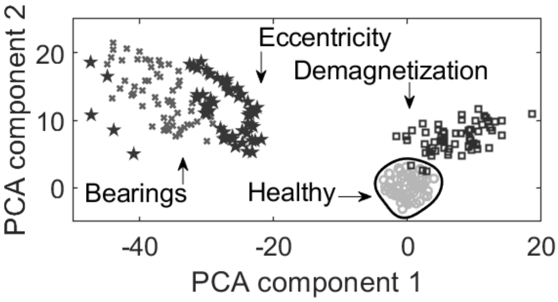

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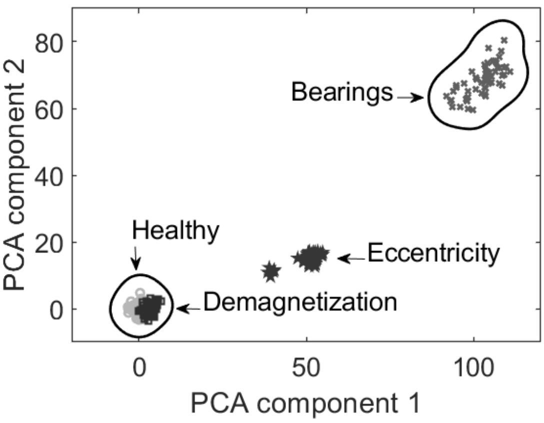
Fig. 4. Two-dimensional projection of the healthy, bearings, eccentricity and demagnetization scenarios by means of principal component analysis corresponding to the test 1.



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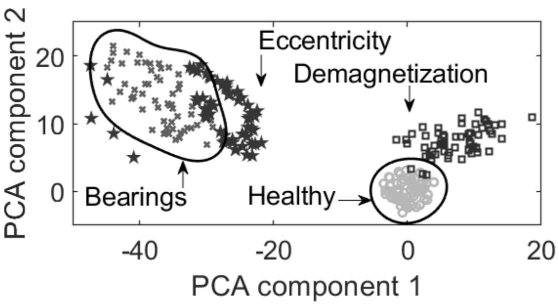

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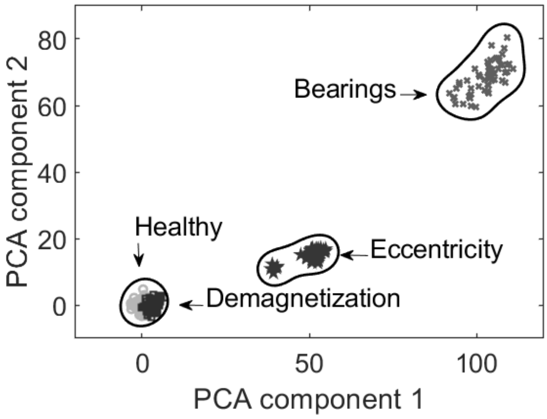
Fig. 5. Two-dimensional projection of the healthy, bearings, eccentricity and demagnetization scenarios by means of principal component analysis corresponding to the test 2.



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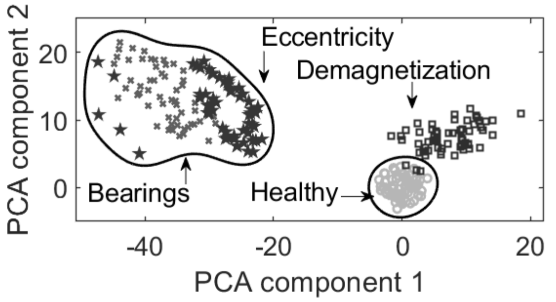

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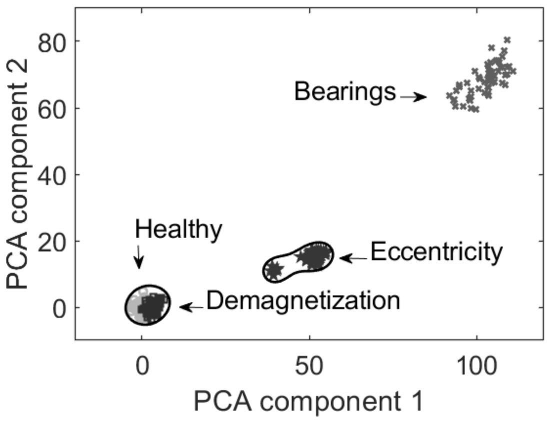
Fig. 6. Two-dimensional projection of the healthy, bearings, eccentricity and demagnetization scenarios by means of principal component analysis corresponding to the test 3.



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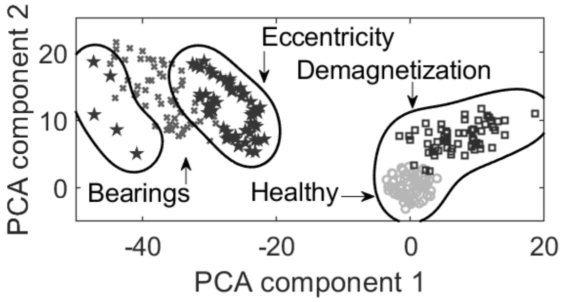

b)

Fig. 7. Two-dimensional projection of the healthy, bearings, eccentricity and demagnetization scenarios by means of principal component analysis corresponding to the test 4.

The results of the multi modal novelty stage are shown in Tale II, where the individual performance of the novelty detection carried out independently by each physical magnitude is shown as well as the aggregate result. It can be seen that the proposed multi-modal novelty detection scheme improves the novelty detection between 5 % and 23 % the novelty detection task depending on the test considered and compared with classical one single model approach.

TABLE II. NOVELTY DETECTON PERFORMANCE

	Current	Accelerometer	Aggregate result	One model
Test 1	92.8	79.4	94.4	85.0
Test 2	62.5	68.3	85.0	62.3
Test 3	85.0	43.3	90.0	85.0
Test 4	63.3	100.0	100.0	93.3

Indeed, the application of dimensionality reduction techniques results in the projection of the data in new axis composed by a weighted relation of the original feature set. In this regard, it is possible to analyse the most significant statistical time-domain features identified by the techniques in order to inspect their characterization capabilities. Thus, for examples, considering the effects of the principal component analysis dealing with stator current signal, one of the most significant features corresponds to the kurtosis. Kurtosis is a measure of how much the data distribution is heavy-tailed or light-tailed relative to a normal distribution. That is, data sets with high kurtosis value tend to have heavy tails, or outliers. Otherwise, data sets with low kurtosis value tend to have light tails, or lack of outliers. Another significant statistical time-domain features for stator current signal are the rms, the variance and the standard deviation. Dealing with the vibration signals also during the principal component analysis, one of the most significant features corresponds to the shape factor, that is, the ratio of the rms value to the mathematical mean of absolute values of all points on the data set. Another significant statistical time-domain features for stator current signal are the rms, the variances and the standard deviation.

VI. CONCLUSSIONS

This paper proposes a methodology for the consideration of novelty detection in a condition based monitoring approach applied to an electromechanical system by analyzing the stator currents and vibration signals.

Taking into consideration that the proposed methodology works under the assumption that only the healthy condition is initially available, the main contributions presented are focused on: (i) the analysis and selection of a separate feature reduction method to increase the performance of the novelty detection and fault classification stages, and (ii) the proposition of an ensemble of novelty detection models in order to proposed a decision level fusion approach.

Regarding the novelty detection stage, the ensemble method of OC-SVMs successfully discerned among the known set and the outlier set of the seven performed tests by considering a specific novelty model for each of the available physical magnitudes in comparison of using a single novelty model approach. An increment of till 23 % of accuracy on the known set is achieved. Regarding the fault identification stage, it is proven that without the novelty detection stage, the risk of false positive outcomes is increased.

In general, the results obtained in this work suggest that this methodology may be also useful for any other industrial machines, with a corresponding signal processing stage to identify a suitable set of features of the monitored machine.

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