Incremental learning framework-based condition monitoring for novelty fault identification applied to electromechanical systems

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***Abstract*— A great deal of investigations are being carried out towards the effective implementation of the 4.0 Industry new paradigm. Indeed, most of the machinery involved in industrial processes are intended to be digitalized aiming to obtain enhanced information to be used for an optimized operation of the whole manufacturing process. In this regard, condition monitoring strategies are being also reconsidered to include improved performances and functionalities. Thus, the contribution of this research work lies in the proposal of an incremental learning framework approach applied to the condition monitoring of electromechanical systems. The proposed strategy is divided in three main steps, first, different available physical magnitudes are characterized through the calculation of a set of statistical-time based features. Second, a modelling of the considered conditions is performed by means of self-organizing maps in order to preserve the topology of the data; and finally, a novelty detection is carried out by a comparison among the quantization error value achieved in the data modelling for each of the considered conditions. The effectiveness of the proposed novelty fault identification condition monitoring methodology is proved by means of the evaluation of a complete experimental database acquired during the continuous working conditions of an electromechanical system.**

Keywords*— condition monitoring, fault detection and identification, industry applications, machine learning, self-organizing maps.

I. Introduction

The condition monitoring assessment is playing an important role to improve the machinery working conditions in industrial applications. In this regard, most of the industrial processes are based on electromechanical systems where electrical and mechanical components, such as electric motors and gearboxes, are involved to perform specific tasks. Thereby, although most of these elements are robust and reliable, the sudden appearance of malfunctioning operating conditions, produced by different sources, may generate machinery breakdowns that, consequently, produce economical losses [1]-[3].

Most of the classical condition monitoring strategies include the estimation of numerical sets of features from available physical magnitudes such as vibrations, stator currents or temperatures, among others. Then, the posterior processing of these features allows to characterize the behaviour of the physical magnitudes during the operation of an electromechanical system [4]-[6]. Thus, in order to perform the diagnosis, such numerical sets of features are presented to a classification algorithm; and during this procedure, the classification algorithm is trained with representative data describing such operating conditions of the electromechanical system. Thereby, during the normal operation of data-driven based condition monitoring scheme, each new acquired measurement is transformed to a numerical set of features that is compared with previous patterns for similarities assessment [7]-[8].

However, from a practical point of view in regard with industrial applications, only the normal or nominal operating condition is initially available, the so called healthy condition. This assumption makes unfeasible a previous characterization of faulty conditions, which represents a significant disadvantage that has not been addressed by classical static diagnosis schemes where the healthy and faulty considered conditions (classes) are previously available and characterized [9]-[10].

Indeed, the main limitation that must be overcome by new condition monitoring schemes is the capability of detect new conditions and include them to the available database knowledge. Most of the advanced incremental learning condition monitoring strategies increase the knowledge through batch schemes, where a complete retraining of the whole detection and identification model structure is required [11]-[12]. However, the continuous storage of all available measurements is not a desired solution. In this regard, it is necessary the proposal of an adaptive condition monitoring strategy capable of updating the available knowledge related to the machine condition under monitoring and, thus, increase the diagnosis capabilities [13]-[15].

Thereby, the contribution of this work is the proposal of a condition monitoring scheme for the novelty detection and fault identification applied to an electromechanical system. Originality of the proposed work includes the analysis of information related to the different faults identified during the monitoring process under an incremental learning framework. Thus, aiming to characterize the operating working condition, a set of statistical-time based features is calculated from the available physical magnitudes. The novelty detection is performed by means of the quantization error assessment provided by the self-organizing maps during the data modelling. The proposed method is evaluated under an experimentally database acquired from a laboratory scale electromechanical system, where different faulty conditions are induced and vibration signals from two accelerometers and one stator current signature are used to characterize the operating working condition. The obtained results show that the proposed condition monitoring can be suitable for the detection and identification of faults under an incremental learning approach applied to electromechanical system fault assessment.

II. THEORETICAL BACKGROUND

A. *Feature calculation*

The feature calculation is an important stage that has been widely included in most of the condition monitoring strategies. Thus, through its application, the acquired physical magnitudes are transformed into more representative information. In this regard, dealing with the condition monitoring assessment in electromechanical systems, the feature calculation allows to highlight some of the most potentially discriminative, relevant and useful information related to a specific operating condition. Indeed, different signal processing techniques may be also applied previous to the feature calculation aiming to represent the data in a different way.

Thereby, time domain, frequency domain and time-frequency domain techniques represent the most well-known approaches that have been considered for signal processing. Nevertheless, statistical-based features estimated from the acquired physical signals have been prove to be suitable to characterize and emphasize working condition patterns in electromechanical systems. Thus, statistical-time based features represent an advantageous set of parameters that provides significant information related to the electromechanical system condition [4].

B. *Self-Organizing Maps*

The Self-Organizing Maps (SOM), also known as Kohonen Maps, are based on a neural network grid which aims to retain the topological properties of a *D*-dimensional input data space. The resulting output space generated by SOM application is predefined as a two-dimensional regular grid. The use of hexagonal or rectangular grids represent the most preferred neural structures for such representation.

Each neuron that composes the SOM grid represents a potential Matching Unit (MU). Thus, for each of the *N* neurons considered in the grid, n_i, $i=1...N$, a *D*-dimensional weight vector wn_i is defined. The coordinates of the neurons in the original input space are represented by *D* weights, that is, the space composed by the set of estimated features from the available physical magnitudes. Thus, the mapping is performed by assigning each input data vector, din_j, $j=1...M$, to one of these neurons, namely the one whose weight vector is the closest, which is called the Best Matching Unit (BMU). The position vector of each input data in the output space, $dout_j$, is, then, given by the grid position of the corresponding BMU [13]. The cost function to be minimized during the training procedure corresponds, then, to the error estimation function (1).

$$E_{SOM} = \sum_i \sum_{din_j \in wn_i} \left\| din_j - wn_i \right\| \qquad (1)$$

The E_{SOM} represents the squared distance from an input data vector to its representative BMU. The minimization of the E_{SOM} expresses the objective of the training and is performed with respect to the weight vectors wn_i. For each iteration, *l*, the gradient descent approach leads, classically, to the updating rule (2) based on a learning rate, *α*.

$$wn_i^{(l+1)} = wn_i^{(l)} - \alpha^{(l)}\left(\nabla E_{SOM}^{(l)}\right)_i \qquad (2)$$

During the training process, the $\alpha(l)$ is decreased monotonically, then, preserving the local topology for each neuron unit. Classically, the performance of a trained SOM is evaluated by the average quantization error, *Eq*. The *Eq* means the average distance from each input data vector to its BMU, that is, the so called local topology mean error estimated following (3).

$$E_q = \frac{\sum_M^{j=1} \left\| din_j - dout_j \right\|}{M} \qquad (3)$$

III. PROPOSED DIAGNOSIS METHODOLOGY

The proposed condition monitoring strategy for the novelty detection and fault identification in an electromechanical system is composed by five stages as Fig. 1 depicts.

First, it is assumed that, initially, the available data is related to the healthy condition of the electromechanical system under analysis. Although additional physical magnitudes could be considered, the available ones in this study result from the continuous monitoring of two vibration signals and one stator current.

Second, the available information is processed in order to highlight and characterize the known and eventual unknown conditions of the electromechanical system. Thus, a set of six numerical statistical-time features is calculated from each of the

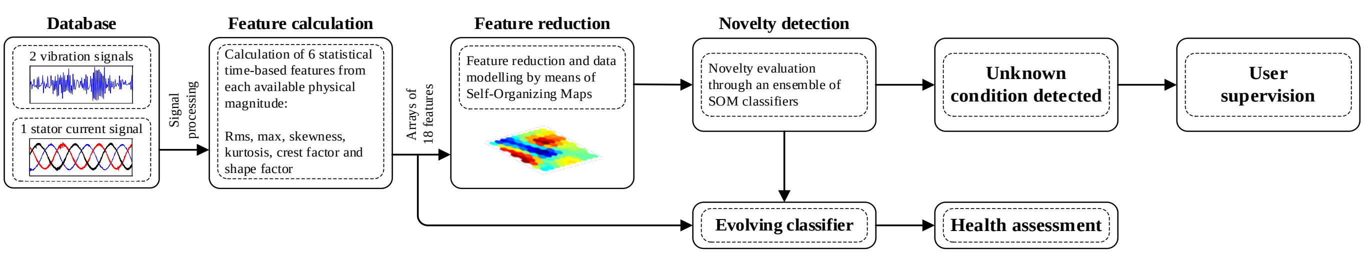

Fig.1. Proposed diagnosis methodology for the novelty detection and fault identification in electromechanical systems.

acquired physical magnitudes. Specifically, the proposed statistical-time set of features is composed by: rms, maximum value, skewness, kurtosis, crest factor and shape factor. The equations of these proposed numerical features are listed in Table I. It must be noticed that the capabilities of such features to characterize general trends and changes in signals has been proved by different studies and, although limited in information, they have been effectively use in condition monitoring schemes to assess different operating conditions in electromechanical systems [5], [7], [10].

The third stage involve the feature reduction and data modelling by means of SOM. This dimensionality reduction allows the compression and data visualization in a reduced 2-dimensional space. Thus, this proposed condition monitoring strategy has initially composed by a framework with only one SOM in which the available data related to the first known condition, the healthy condition, is modelled. The number of considered SOM in the framework may increase as novel operating conditions are detected since, consequently, a new SOM would be used to model the novel condition.

Next, in the fourth step, the novelty valuation model is designed. In this regard, there are several novelty detection models proposed in the literature that have been shown proper performances in certain circumstances. In this work, and in coherence with the data modelling approach through SOM, the average quantization error, *Eq*, is proposed to be used to evaluate whether a measurement under analysis is novel or not. Specifically, to perform the novelty detection, first, the available data represented by the estimated statistical-time features is modelled; and as a result, a SOM neural network grid is obtained representing the original data topology. Then, a new measurement, also represented by the set of statistical-time features, is presented to the first SOM; as a result of this evaluation the *Eq* value is obtained and the novelty degree evaluated. Thus, a novelty will be identified if the *Eq* exhibits high values.

Finally, if an unknown (novelty) condition is detected, the new available data is included in the available knowledge through a new SOM; thereby, the condition monitoring framework is increased. The consideration of a new SOM will affect the number of involving classifiers, where all the available information related to known conditions is evaluated. Otherwise, if unknown conditions are not detected, the diagnosis assessment is directly performed. The performance of such detection and identifications scheme is proposed to be measured by means of the classification error, which is also computed though each one of the considered SOM.

IV. EXPERIMENTAL SETUP

Aiming to demonstrate the effectiveness of the proposed condition monitoring strategy, an experimental database has been generated through a laboratory scale electromechanical system. The experimental test bench is based on two face to face identical electric motors. One of the electric motors is the motor under study and the other one is the motor used as a mechanical load. Both motors are linked by means of a screw shaft and a gearbox, all the elements compose the test bench. The motor under study drives the input shaft of the gearbox, and consequently, the output shaft of the gearbox drives the screw shaft which in turn, performs a displacement of a movable part. Both motors belong to the model ABB-SPMSMs with 3 pairs of poles, a rated torque of 3.6 Nm, 230 Vac, and a rated rotational speed of 6000 rpm. To drive these motors ABB power converters model ACSM1 are used.

TABLE I. SET OF CONSIDERED STATISTICAL TIME-BASED FEATURES

Root mean square	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(4)
Maximum value	$\hat{x} = max(x)$	(5)
Skewness	$S_k = \frac{E[(x_k - \bar{x})^3]}{\sigma^3}$	(6)
Kurtosis	$Ku = \frac{E[(x_k - \bar{x})^4]}{\sigma^4}$	(7)
Crest factor	$CF = \frac{\hat{x}}{RMS}$	(8)
Shape factor	$SF_{RMS} = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(9)

Regarding the database, different physical magnitudes such as mechanical vibrations and a stator current have been acquired by using an accelerometer transducer and current probe, respectively. The accelerometer transducer and current probe were connected to a PXIe 1062 data acquisition system provided by National Instruments. During the data acquisition, the sampling frequency was fixed at 20kS/s during 1 second for each measurement acquisition. A diagram of the electromechanical system used for experimentation is shown in Fig. 2. In this work, four different working conditions have been considered to be evaluated. Initially, the healthy condition (HLT), of the electromechanical system has been evaluated. A second condition of a degraded bearing (BD), has been mounted, in which the non-end bearing inner as well as outer races have been scraped thoroughly in order to cause a generalized roughness defect. The third condition considers a partially demagnetized in the motor (DEM), this demagnetization correspond to the 50% of nominal flux reduction in one pair of poles. Finally, the fourth condition, a static eccentricity (ECC) has been induced by attaching a screw in the output shaft of the gearbox. Each one of these considered conditions have been individually evaluated during the experimentation of two speed set points considered, 1500 rpm and 3000 rpm. These speeds, in turn, were combined with two torque patterns set points, 0 % and 50 % of the rated torque. Thereby, four different operating regimes have been experimentally evaluated for each considered condition. During the experimentation of each different condition, fifty complete measurements were performed.

V. RESULTS AND DISCUSSION

The condition monitoring strategy proposed in this work is implemented in Matlab, in which the processing of the database composed by the available physical magnitudes stored during the experimentation has been performed. In order to analyse the effectiveness and performance of the proposed method, the four

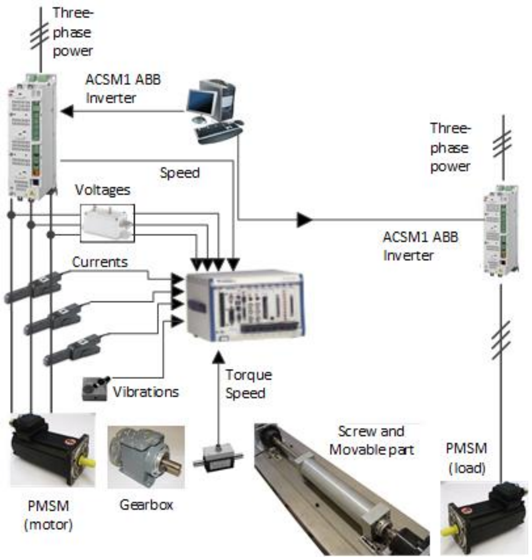

Fig. 2. Experimental test bench used to validate the proposed diagnosis methodology.

different operating conditions are experimentally evaluated in the electromechanical system. Table II summarizes the performed tests considered during the training and validation for the analysis of the proposed detection and identification of the proposed condition monitoring methodology.

In regard with the proposed methodology, the available physical magnitudes are characterized by calculating the statistical-time set of features; then, the data modelling is performed by means of the SOM. Thus, as a part of the novelty detection approach, only the HLT operating condition is initially available; under this assumption, the first data modelling is performed by a SOM_1 grid which only considers information related to the HLT condition. Thereby, the first data modelling represented by SOM_1 results from the consideration of the Test 1 during the training procedure.

Classically, one of the main characteristics of SOM performance corresponds to the quantization error. The average quantization error describes the average distance from each data vector to its corresponding BMU. In this regard, the quantization error achieved during the training procedure of the SOM_1 is 3.38. In this regard, aiming to evaluate the achieved performance for the data modelling, in the validation procedure a database different to the HLT condition is evaluated through the SOM_1 grid. This new database contains information related to the ECC condition; in consequence, the averaged quantization error achieved by evaluating this fault condition is 17.52. As aforementioned, the increasing in the quantization error implies the appearance of an unknown condition, this fact is generated due to that the topological properties of the evaluated database (ECC condition), are different to the properties with which the SOM_1 was trained (HLT condition); thus, this significant change in the topographic error quantified by the quantization error makes possible the novelty fault detection.

The novelty detection may be better appreciated by the graphical representation of the quantization error *Eq* for both conditions, HLT and ECC. Thus, in Fig. 3 is shown the *Eq* value obtained during the validation where the assessment of both conditions is performed. Thereby, as it is shown in Fig. 3, the first half of the graphical representation belongs to the HLT condition which is in the range of the *Eq* average value. Consequently, due to the HLT condition is always the known condition, the appearance of any different condition will produce a different response that may be identified by the modification of the characteristic pattern; thus, the novelty

TABLE II. PROPOSED TEST SETS FOR THE NOVELTY DETECTION

	Training	Validation
Test 1	HLT	HLT and ECC
Test 2	HLT and ECC	HLT, ECC and BD
Test 3	HLT, ECC and BD	HLT, ECC, BD and DEM

detection is carried out. In this sense, the novelty detection is depicted by the second half of the graphical representation in Fig. 3; specifically, the novelty is detected by the increase over the *Eq* value, above two times the averaged *Eq*, when the ECC condition appears. It must be noticed that four operating conditions are considered in both scenarios.

In order to provide a visual representation of such novelty detection, a 2-dimensional projection is performed by a classic

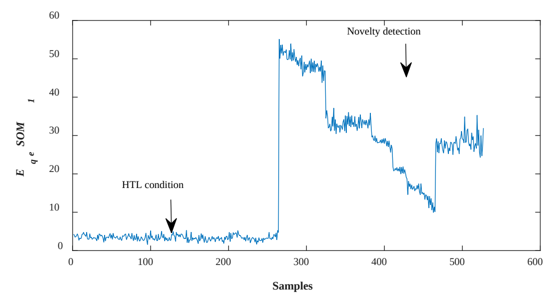

Fig. 3. Quantization error performed during the evaluation of the HLT and ECC conditions through the SOM_1 model which belong to the initially known condition (healty condition).

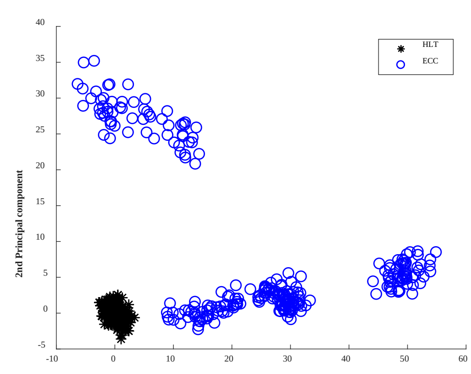

Fig. 4. 2-dimensional projection performed by the PCA for the HLT and ECC conditions.

feature reduction approach based on Principal Component Analysis (PCA). In Fig. 4 the resulting projection that describes the data distribution is shown with an accumulative variance of 86.58%. Different clusters can be observed in the data distribution of the *Ecc* condition, which correspond to the affectation of the operating frequency over the working condition of the considered scenarios.

Once an unknown operating condition has been detected, the database has to be updated, in this regard a new SOM is considered for modelling the new operating condition *Ecc*. In this regard, the database which describes the *Ecc* condition is modelled by a SOM_2. Therefore, the updated condition monitoring structure has two SOM based models. Thus, if a new operating condition is presented, the proposed approach will be capable to detect it and learn such new knowledge to increase its structure.

On the other hand, in regard with the diagnosis part, it is possible to obtain misclassifications during the electromechanical systems assessment if the database is not

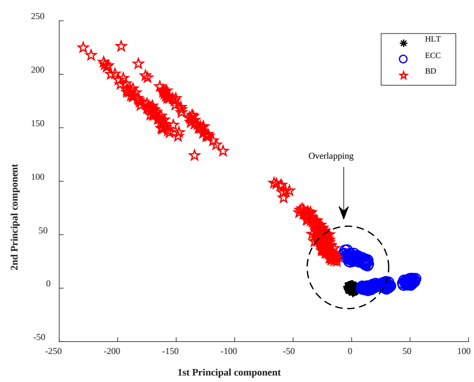

Fig. 5. 2-dimensional projection performed by the PCA for the eventual operating conditions are not considered in the database.

properly updated with information related to the new operating conditions. In Fig. 5, a 2-dimensional projection in which the database knowledge considering information related to the HLT and ECC conditions is shown, as well as a novel operating condition presented, damaged bearing-BD, following the test 2. From Fig. 5 it is possible to infer that an overlapping may occur between samples belonging to ECC and BD conditions and, then, misclassifications would result.

However, after the update of the database through SOM_1 and SOM_2, it is possible to detect the presence of new operating conditions different to the known ones. In order to prove this capability, in Fig. 6a and Fig. 6b the graphical quantifications of the *Eq* values performed by SOM_1 and SOM_2 when the HLT, ECC and BD conditions are evaluated through them are shown. From this *Eq* values it is possible to identify different behaviours that represent the evaluated conditions and make possible the novelty detections.

Thereby, due to a novelty detection is performed when the BD conditions is assessed, a new SOM model has to be included in the structure of this proposed condition monitoring method. In this regard, the final diagnosis is performed by a condition monitoring structure which uses *i* SOM models as *i*

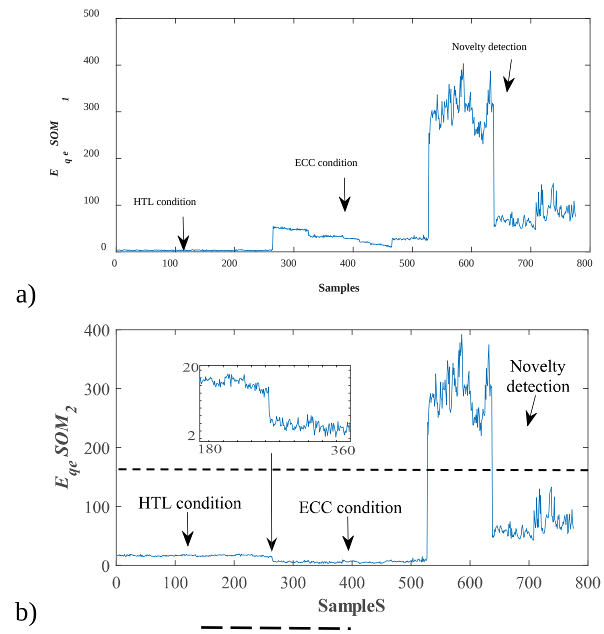

Fig. 6. Performed quantization error during the evaluation of the HLT, ECC and BD conditions through: a) SOM_1 and b) SOM_2.

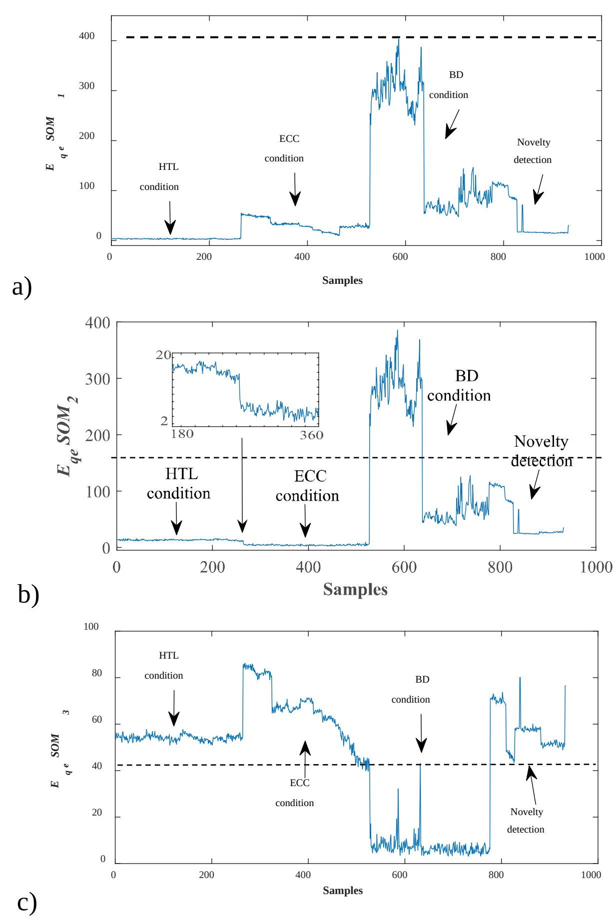

Fig. 7. Resulting quantization errors during the assessment of all the considered conditions, that is, HLT, ECC, DB and DEM through: a) SOM_1, b) SOM_2 and c) SOM_3.

operating conditions are evaluated. Accordingly, the new database that belongs to the BD condition is modelled by a SOM_3 and the condition monitoring structure is also updated. To conclude the assessment, the models SOM_1, SOM_2 and SOM_3 are evaluated under the previous considered conditions HLT, ECC and BD, and also with the DEM condition which represents the novel condition, following the test 3. In Fig. 7a, Fig. 7b and Fig. 7c the resulting *Eq* values by the SOM_1, SOM_2 and SOM_3 during the assessment of all considered conditions are shown.

TABLE III. RESULTING QUANTIZATION ERRORS OF TESTS AND CORRESPONDING DETECTION AND IDENTIFICATION PERFORMANCES

	E_q **training**	E_q **validation**	**Performance**
SOM_1 / $Test_1$	3.38	17.52	100
SOM_2 / $Test_2$	5.85	60.75	100
SOM_3 / $Test_3$	7.15	45.38	94

The three SOM models have been initialized as 2-dimensional hexagonal grids of 5 x 5 neurons, that represents a total of 25 neurons to model the data manifolds during a 100 epochs batch algorithm training. As aforementioned, the novelty detection performance can be measured depending of a specific interest, for this proposed work the performance is measured in terms of the classification error. Thus, in Table III the *Eq* values performed by each SOM model during the training and validation are summarized as well as the classification performances.

In general, the obtained results are in advantage regarding the classical condition monitoring approaches where unknown conditions are not considered. Moreover, these results make the proposed conditions monitoring methodology suitable to be applied in electromechanical systems used in industrial applications as far as repetitive operating conditions are considered.

VI. CONCLUSIONS

This work proposes a condition monitoring methodology for the detection of novel conditions and the identification of the fault based on an incremental learning framework approach applied to an electromechanical system.

The proposed work considers, first, the characterization of the available physical magnitudes by the calculation of significant statistical-time based features. Second, the use of SOM grids for modelling each one of the considered conditions is proposed. The capability of the SOM to preserve the data topology is proposed to represent the data characteristics. Due to such collaborative SOM structure, a novel condition can be easily detected and, then, identified. Finally, third, the consideration of an incremental learning framework leads to avoid classical problems such as overlapping between different operating conditions; in this sense, misclassification problems may be reduced though the incremental learning of knowledge related to new operating conditions.

The obtained results show that the proposed condition monitoring strategy is suitable to be applied during the working condition assessment in electromechanical systems used in industrial applications.

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