Chapter

Smart Monitoring Based on Novelty Detection and Artificial Intelligence Applied to the Condition Assessment of Rotating Machinery in the Industry 4.0

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Abstract

The application of condition monitoring strategies for detecting and assessing unexpected events during the operation of rotating machines is still nowadays the most important equipment used in industrial processes; thus, their appropriate working condition must be ensured, aiming to avoid unexpected breakdowns that could represent important economical loses. In this regard, smart monitoring approaches are currently playing an important role for the condition assessment of industrial machinery. Hence, in this work an application is presented based on a novelty detection approach and artificial intelligence techniques for monitoring and assessing the working condition of gearbox-based machinery used in processes of the Industry 4.0. The main contribution of this work lies in modeling the normal working condition of such gearbox-based industrial process and then identifying the occurrence of faulty conditions under a novelty detection framework.

Keywords: smart monitoring, condition assessment, novelty detection, artificial intelligence, Industry 4.0, rotating machinery

1. Introduction

Nowadays industrial applications are straightly involved with intelligent manufacturing processes, and the importance of this issue is reflected in many different activities of the human being, for example, in health, economy, and even comfort. Thus, it is possible to say that most of the daily activities carried out by humans have a direct relationship with those elements produced in the industry that facilitate its making. On the other hand, during the last years, industrial sites have been continuously subjected to several transformations, aiming to improve the effectiveness of its processes and to increase the production quality. Consequently, the integration of multiple technologies in the industry has been performed by the composition of actuators and sensors with cyber-physical systems and Internet of Things devices. Such integration leads to the Industry 4.0 that is the fourth phase of manufacturing and industrial sectors where the automated manufacturing and process monitoring have been enhanced [1]. Consequently, under the integration of such complex systems, it should be highlighted that it is important to ensure its safety and reliability by the implementation of condition-based monitoring approaches. Thereby, in order to guarantee the proper operation in manufacturing processes and aiming to avoid undesirable downtimes, the working condition of the machine components must be continuously assessed. Commonly, most of the industrial applications and processes are involved with the use of mechanical and electrical rotating machines, where electric motors and gearboxes represent the most used elements to perform specific manufacturing processes [2].

In fact, this statement is validated and justified because electric motors, gearboxes, couplings, and shafts represent approximately more than 90% of the elements that compose any industrial process [3]. Indeed, these elements that integrate the main operating system of industrial machinery are also considered, and also known, as the electromechanical machine system. In this sense, electric motors are considered as the most important element in electromechanical systems since its performed functions cannot be carried out and replaced by any other element; additionally, these elements play also an important role in most of the industrial applications because two-thirds of the total electricity is consumed by them. Therefore, these issues make suitable the application of condition monitoring approaches to avoid the occurrence of unexpected breakdowns; even more, it must be noted that under the appearance of a faulty condition, such damaged element can also have influence over the proper operation of the whole elements that are linked to the electromechanical system and crucial damages may be produced [4].

As it has been mentioned, industrial sites have been subjected to several transformations, and through the integration of multiple technologies, a significant improvement in the production efficiency has been obtained. Accordingly, complex electromechanical systems compose most of the industrial machinery that is used in different applications of modern industry. In this regard, several condition monitoring-based approaches have been developed aiming to guarantee the appropriate working condition of industrial machinery. Thus, data-driven condition monitoring strategies represent the most common and suitable approach for carrying out the condition assessment in electromechanical systems; this approach has been preferred since it only takes into account the use of information of available data; therefore, based on known and available information, an accurate diagnosis of the machine under inspection is obtained [2, 4, 5].

In this sense, most of the data-driven approaches mainly include the continuous monitoring of different physical magnitudes that contain significant information related to the machine working condition. Indeed, stator current signals, vibrations, temperatures, and operational rotating speeds, among others, are some of the most accepted and reliable magnitudes used in condition monitoring strategies. On the other hand, aiming to provide the condition assessment, such monitored signals are then analyzed by different signal processing techniques, where time-domain analysis, frequency-domain analysis, and time-frequency domain analysis have been commonly implemented in several condition monitoring strategies [5]. However, although there exist different signal processing, it has been demonstrated that statistical time-based domain features contain significant information that describes the behavior related to the rotating machine working condition. Thereby, the calculation of a high-performance set of features is achieved because statistical time domain-based features have advantages for describing changes and trends of time-domain signals [6].

On the other side, although other sophisticated techniques such as fast Fourier transform (FFT) and discrete wavelet transforms (DWT), among others, also lead to the calculation of features related to the machine condition, the implementation of such techniques considers additional knowledge and experience about the proper usage of the techniques and also complete information of the parameters of the machine operation. Accordingly, it should be highlighted that it is not totally true that sophisticated and complex signal processing may always lead to the estimation of the most representative set of features to describe the machine condition. In this regard, from a practical application viewpoint and based on practical experience, the simplest way to evaluate and identify the early occurrence of faults is by means of analyzing trends of physical magnitudes acquired during the continuous working operation of the machine. Thus, as aforementioned, the appropriate early detection of faults may help in the reduction of monetary losses caused by unscheduled maintenance task.

Certainly, the detection and identification of faulty operating modes involve a critical procedure in which the signal processing or feature calculation must be carefully performed. Another important issue to perform and improve the condition assessment is the consideration of artificial intelligence (AI) for carrying out the automatic fault diagnosis. Indeed, the use of AI in condition monitoring strategies has been rapidly increased, and its application to identify the occurrence of faults in rotating machinery is an adequate and coherent option to obtain high-performance results. Additionally, it has been shown that an appropriated application of AI in condition monitoring approaches provides a powerful capacity for detecting and classifying the appearance of single or multiple faults in electromechanical systems. This potential provided by AI is reached because the limitations of classical space-transform techniques, when nonlinearities characterize the analyzed system, are overcome [6].

Hence, several AI techniques have been addressed with the main purpose of being applied in monitoring tasks of industrial machinery, for instance, artificial neural networks, genetic algorithms, fuzzy logic, support vector machines, Bayesian networks, self-organizing maps (SOM), and case-based reasoning, among others, represent some of the most techniques used in condition monitoring approaches [7]. However, there are still great challenges for developing new condition monitoring strategies; indeed, the use of AI techniques has increased because the main challenge of the condition assessment in industrial sites is that nonlinearities are inherent to the working operation [8].

Thereby, the contribution of this chapter lies in the proposal of a condition monitoring strategy for detecting and assessing unexpected working conditions in rotating machines. Such proposal performs the condition assessment under a novelty detection approach based on self-organizing maps. Thus, the proposed condition monitoring method includes the estimation of a statistical time-based set of features from acquired vibration signals; then, the data modeling is carried out through SOM and then the evaluation of novelty detection events. Finally, if novelties are detected, a retraining and incremental learning procedure is considered by including a dimensionality reduction stage by means of the linear discriminant analysis. This proposal is validated and applied to a real laboratory gearbox-based electromechanical system.

2. Fault detection and identification

The condition monitoring assessment is involved with the behavior analysis of the machine working operation; thus, the consideration of stator currents or vibrations as informative physical magnitudes for condition monitoring represents the most preferred and accepted approaches in the related literature. Also, although different information fusion levels are considered, such as signal-level or decision-level, dealing with electromechanical condition monitoring, the feature-level represents the most appropriate, since many numerical fault indicators from aforementioned physical magnitudes have been proposed as suitable fault indexes in multiple studies [9, 10]. In this regard, time-domain, frequency domain, and time-frequency domain are the three feature estimation approaches widely applied during the physical magnitude characterization process. Although techniques based on frequency and time-frequency domain, such as classical Fourier transform or wavelet analysis have been widely applied, most of these techniques require a deep knowledge of the fault effects over the resulting frequency distributions of the physical magnitudes. Indeed, as stated by Zhang et al. in [11], dealing with complex electromechanical systems, where the resulting interaction among multiple parts is reflected in the acquired physical magnitudes, the consideration of statistical time-domain features represents a performing trade-off between computational simplicity and characterization capabilities of general patterns. Such feature-level fusion scheme needs to consider the processing of a high-dimensional set of numerical features estimated during the characterization of the available physical magnitudes that, although increases the fault detection and identification capabilities, inevitably contain redundant and nonsignificant information.

Dimensionality reduction procedures are applied in order to avoid low fault diagnosis performances and overfitting responses of the condition monitoring schemes. In this regard, classical dimensionality reduction techniques have been widely applied, as the principal component analysis (PCA). However, PCA aims to identify orthogonal components that maximize the preservation of the data variance. That is, PCA seeks for global data representation; thus, considering the unsupervised operation, a set of non-connected data clusters have a negative impact over the resulting representation. Other classical approaches, as linear discriminant analysis, overcome such data topology limitation by means of a supervised approach, as the LDA, where the resulting set of features is a mathematical combination of the original ones maximizing distances among classes [12, 13].

Finally, the classification algorithms, play an important role in data-driven condition monitoring schemes to perform the automatic and final diagnosis outcome. In this regard, neural networks and fuzzy inferred systems classically represent the most used classifiers, but also classifiers like decision trees and support vector machines have been widely applied [14–16]. The use of these techniques, however, is related with the maximization of the classification ratio by means of the feature set decomposition following supervised training schemes. According to Shannon's rate-distortion theory, mutual dependencies among various sources and between the input and output spaces contain the actual intrinsic dimension of the data and allow avoiding over-fitted responses. Thus, unsupervised learning approaches applied over the available feature space represent the most coherent processing procedure in order to maintain the underlying physical phenomenon of the system under monitoring. Concerning this problem, manifold learning methods have been applied in the last years to preserve the information in a lower dimensional space. Among them, the self-organizing map, SOM, is the most used, which is based on developing a neural network grid to preserve most of the original distances between feature vector representations in the original feature space [17]. Indeed, the SOM allows a high-dimensional input data mapping over a two-dimensional output layer while preserving as much as possible the structure of the input data. Although SOM leads to model the original data distribution following an unsupervised approach, each of the neuron units used during the original space characterization can be later associated with a class label; thus, through distance criteria, the diagnosis can be estimated during the assessment of a new measurement. Thus, both fault detection and identification tasks can be faced at the same time and, what is more important, considering the same criteria for both outcomes, that is, topological aspects of the data distribution.

3. Novelty detection and diagnosis methodology

The proposed condition monitoring strategy that is applied to the condition assessment of an electromechanical system under a novelty detection framework is composed of five important stages as depicted in **Figure 1**.

The first stage is based on the fact that initially the machine condition is known; in this sense, it is considered as an initial condition that only the available information belongs specifically to the behavior of the healthy condition of the electromechanical system under evaluation. This assumption is asserted and taken into account since all the machinery used in most of the industrial applications starts its life cycle from an initial healthy condition, which means that all elements work properly. Therefore, under this assumption, such available information is obtained from the continuous monitoring of one vibration signal that is monitored during the working operation of the electromechanical system.

In the second stage, the characterization of the machinery behavior is performed; thus, the available vibration signal is processed and analyzed, aiming to carry out a characterization of the machine working condition and also with the aim of highlighting those representative features that can represent the occurrence of abnormal operations. Precisely, the calculation of a representative set of eight statistical time-based domain features is estimated from the acquired vibration signal; this proposed set of features consists of some well-known statistical features such as mean, rms, standard deviation, variance, shape factor, crest factor, skewness, and kurtosis. Indeed, and as it has been mentioned, statistical time-based domain features provide meaningful information leading to the estimation of high-performance feature characterization due to its capability of describing trends and changes in signals; additionally, this proposed set of statistical features has been included in several condition monitoring approaches to perform the assessment of the operating working condition of electromechanical systems used in industrial application [3, 11, 16]. The corresponding mathematical equations of such numerical features are shown in **Table 1**.

Subsequently, in the third stage, the set of statistical features estimated from vibrations is modeled through SOM; the data modeling is performed by SOMs since

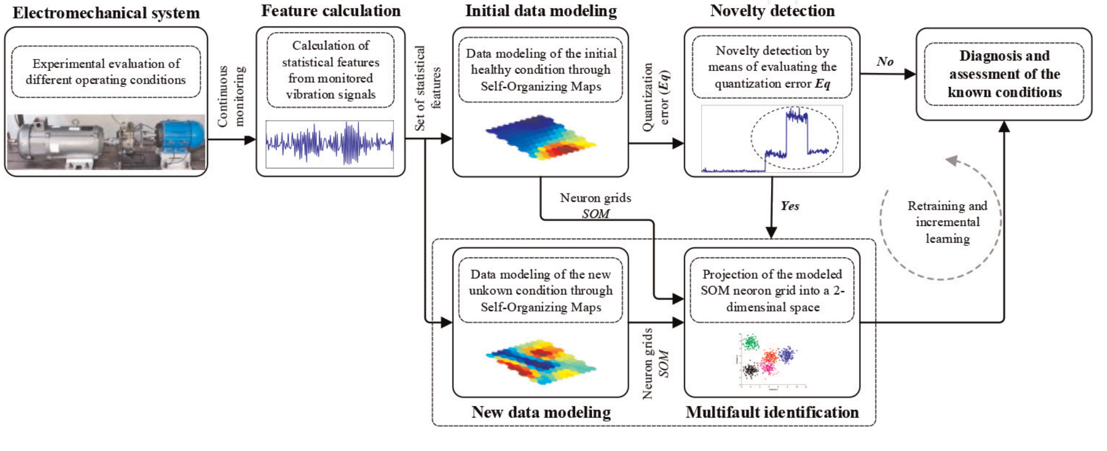

Figure 1.
Rotating machinery-based electromechanical system used to demonstrate the practical implementation of the proposed method.

Mean	$\overline{x} = \frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert$	(1)
Root mean square	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(2)
Standard deviation	$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \overline{x})^2}$	(3)
Variance	$\sigma^2 = \frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \overline{x})^2$	(4)
Shape factor	$SF_{RMS} = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(5)
Crest factor	$CF = \frac{\hat{x}}{RMS}$	(6)
Skewness	$S_k = \frac{E\left[(x_k - \overline{x})^3\right]}{\sigma^3}$	(7)
Kurtosis	$k = \frac{E\left[(x_k - \overline{x})^4\right]}{\sigma^4}$	(8)

Table 1.
Set of statistical time-domain features.

this approach allows to preserve the data topology. Due to the proposed condition, monitoring strategy is based under a novelty detection framework, and the initial and available information is modeled, aiming to represent the initial known condition which is the healthy condition. As a result, a pre-defined neuron SOM grid model is first obtained to characterize the healthy condition of the electromechanical system. Then, in case additional conditions appear, the data modeling is also performed by a specific neuron SOM grid model for each one of the additional operating condition.

Afterward, the novelty detection is performed in the fourth stage; in this sense, there exist different approaches for carrying out the detection of novel events. Classic novelty detection approaches are based on the evaluation of numerical threshold values, and the definition of such values depends on different criteria. Thereby, for this proposal, the novelty detection is performed by evaluating the average quantization error, *Eq*, obtained during the data modeling through SOMs; indeed, the novelty detection based on the *Eq* is a coherent option according to the data modeling to detect whether the electromechanical system condition is known or unknown. Certainly, because the healthy condition is initially the unique known and available condition, the evaluation of any other new measurement that does not belong to the known condition will exhibit a different *Eq* value. Thus, any change presented in the *Eq* value should be analyzed because this value is an important measurement related to the occurrence of unexpected and unknown events which results in the novelty detection. Otherwise, the diagnosis and condition assessment of the known conditions is carried out if any change is presented in the *Eq* value.

Finally, the last stage is carried out in case of novelty detection; thus, this stage considers a retraining process where an incremental learning is performed with the aim of updating the available information with new data that belongs to new operating conditions. In this sense, during the detection of a novelty event, the available information that describes such novel condition is also processed, and from the acquired vibration signal, the statistical time-domain features are also estimated. Then, such new available information represented by the estimated statistical features is modeled through SOMs, and a new neuron SOM grid represents the new condition. Accordingly, as aforementioned, each new operating condition detected under this novelty detection approach has to be modeled by a specific neuron SOM model. Finally, when novelty detection occurs, such neuron SOM grids are subjected to a dimensionality reduction procedure by means of the linear discriminant analysis in order to obtain a maximum linear separation between the considered conditions and also with the aim of obtaining a visual representation the assessed conditions.

4. Case study

In order to demonstrate the practical implementation of the proposed smart monitoring based on novelty detection in an industrial application, a case of study is proposed next.

A rotating machinery-based electromechanical system has been considered; such electromechanical system includes a three-phase IM of 1492-W (model WEG00236ET3E145T-W), a gearbox with 4:1 ratio (model BALDOR GCF4X01AA), and a DC used as a mechanical load (model BALDOR CDP3604). The IM is coupled shaft to shaft to the gearbox, and the gearbox is also coupled shaft to shaft to the DC generator, and a VFD (model WEGCFW08) is also used to feed and control the different operating frequencies of the IM. Besides, the DC generator is used as a non-controlled mechanical load representing around 20% of the nominal load. A picture of the second electromechanical system based on a gearbox is shown in **Figure 2**.

Aiming to detect and assess the appearance of unexpected conditions, a database of different experiments is generated. The data acquisition is carried out by means of a data acquisition system (DAS) that is a proprietary low-cost design based on a field programmable gate array; such DAS uses two 12-bit 4-channel serial-output sampling analog-to-digital converters, model ADS7841 from Texas Instruments. Different physical magnitudes have been acquired during the experiments; that is,

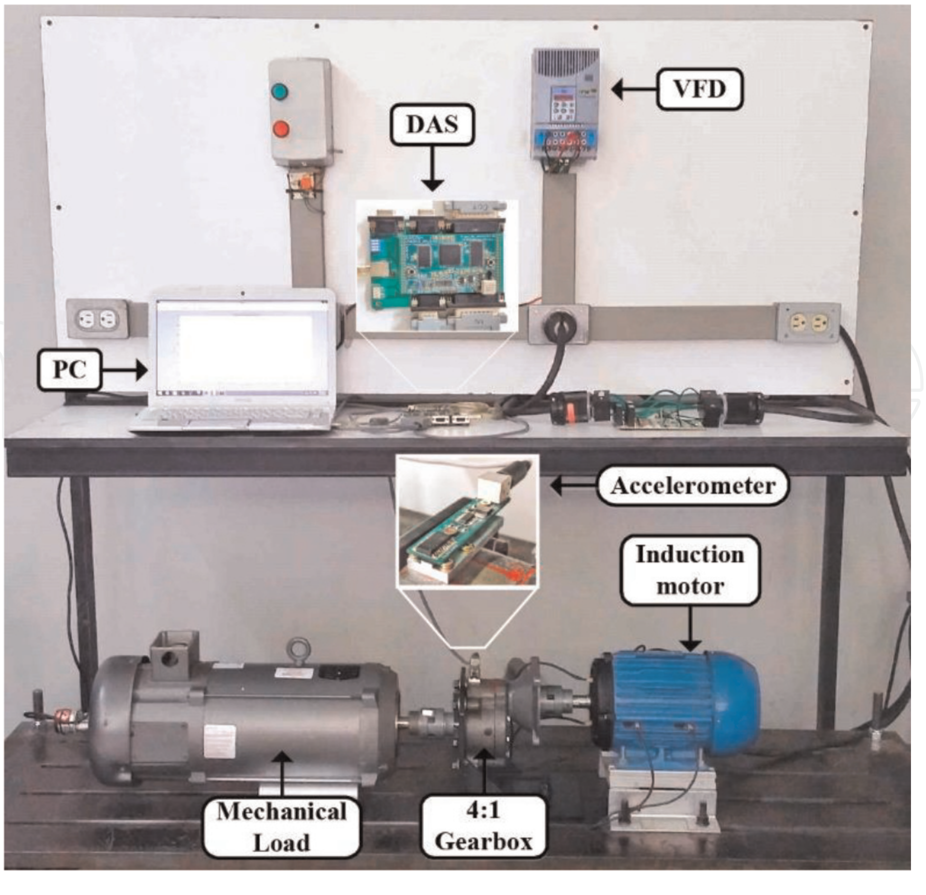

Figure 2.
Rotating machinery-based electromechanical system used to demonstrate the practical implementation of the proposed method.

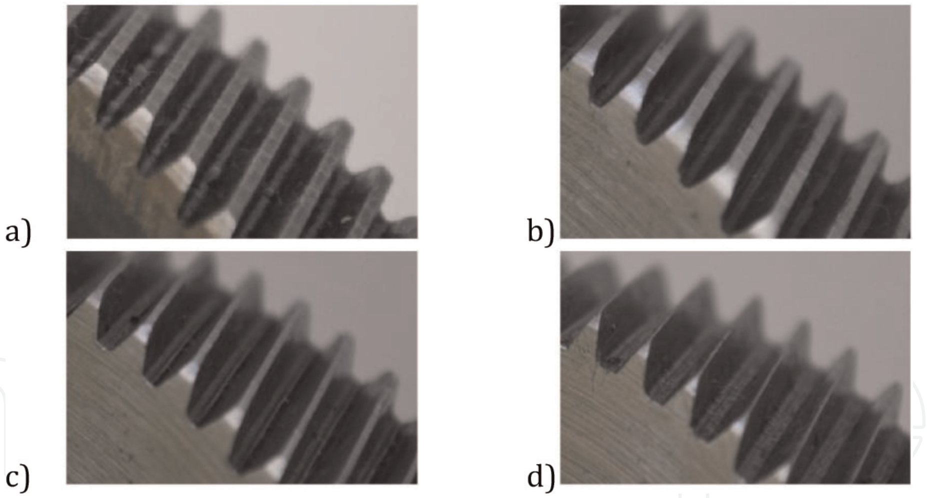

Figure 3.
Set of the faulty conditions evaluated in the gearbox-based electromechanical system: (a) healthy gear, (b) 25% of uniform wear, (c) 50% of uniform wear, and (d) 75% of uniform wear.

the appearance of mechanical vibrations is acquired by means of a triaxial accelerometer (LIS3L02AS4). In this regard, the accelerometer sensor is fixed on the top of the gearbox. For this proposed work, the occurrence of vibrations is analyzed because they are inherent to the rotating condition of the rotating elements that compose the electromechanical system, i.e., electric motors, gearboxes, and bearings, among others [2].

The accelerometer sensor is individually mounted on a board with its corresponding signal conditioning and anti-alias filtering. During the acquisition of vibration signals, the sampling frequency is set to 3 kHz; as a result, 270 kS are stored during 90 s of continuous sampling of the working condition, in the steady-state regime, of the electromechanical system are stored. Furthermore, the IM of the experimental test bench is driven at different operating frequencies during the experimentations; specifically, the operating frequencies are set at 5, 15, and 50 Hz.

During the experimentation, four different operating conditions are also evaluated: healthy (HLT), 25% of uniform wear in the gearbox (W25), 50% of uniform wear in the gearbox (W50), and 75% of uniform wear in the gearbox (W75). In this regard, the gearbox with 4:1 ratio is composed of two gears, the driver gear and the driven gear which has 18 and 72 teeth, respectively. The wear was artificially induced uniformly in all teeth of three similar driven gears: from **Figure 3a–d**, the set of gears tested in the gearbox-based electromechanical system. The experiments are performed by replacing iteratively the healthy gear with the damaged ones.

5. Competency of the method/results

The proposed condition monitoring strategy is based on a novelty detection approach; the implementation of such proposal has been done in Matlab that is a sophisticated software used in several engineering applications. Indeed, the use of Matlab facilitates the signal processing for carrying out the condition assessment of the electromechanical system. Thus, the available vibration signal is first continuously monitored and acquired during the operating condition of the electromechanical systems, and then the statistical set of features is estimated from the vibration signal.

As aforementioned, the initial condition belongs to the healthy condition; in this sense, the data modeling is carried out aiming to obtain a neuron SOM grid model that represents such initial condition. As a result of the data modeling, the first

SOM_1 model obtained and this SOM model only characterize the healthy condition of the electromechanical system. During the data modeling, an average *Eq* error of 0.4932 has been obtained during the training procedure, and during the evaluation the *Eq* error reaches a value of 19.4419. It should be noted that during the evaluation different data information has been used; indeed, the evaluated data belong to a faulty condition tested in the gearbox. In **Figure 4**, a visual representation of the novelty detection achieved by the first modeled neuron SOM_1 grid is shown.

After the first novelty detection, the process and incremental learning is carried out; in this regard, the available data that belong to the first faulty condition (25% of uniform wear) is modeled by a second neuron SOM_2 grid. Thus, the data information related to the working condition of the machine consist of two known conditions which are healthy and 25% of uniform wear. Indeed, during the training of the second SOM model, a *Eq* of 0.8997 is achieved during the training and during the evaluation with available data, which belongs to another unknown condition; the *Eq* error was 7.0773; thus, such significant increase in the *Eq* error depicts that an anormal condition is detected by the novelty detection approach. The visual representation of the *Eq* error is shown in **Figure 5** where it is possible to appreciate the abrupt change due to the occurrence of the unexpected faulty condition.

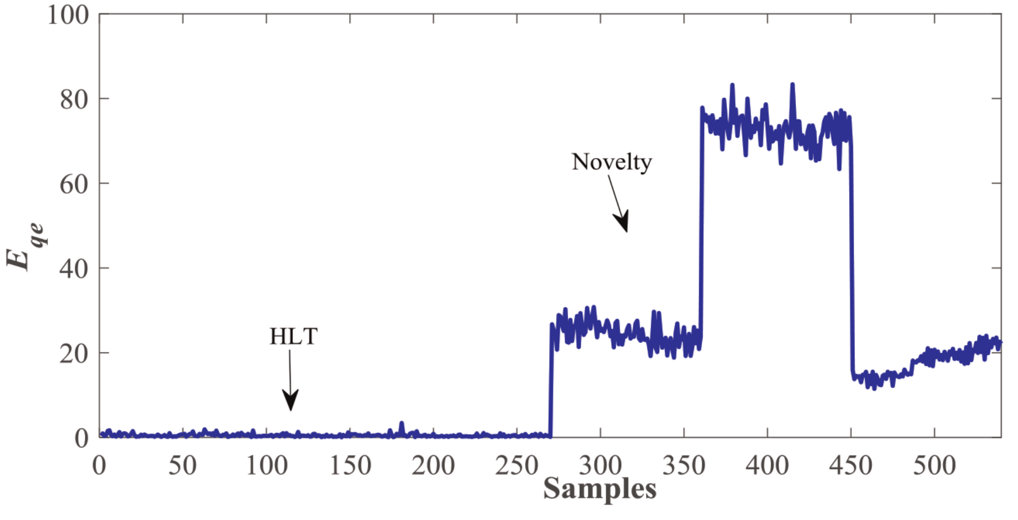

Figure 4.
Novelty detection performed by SOM_1 during the evaluation of the first faulty condition tested in the electromechanical system, 25% of uniform wear in the gearbox.

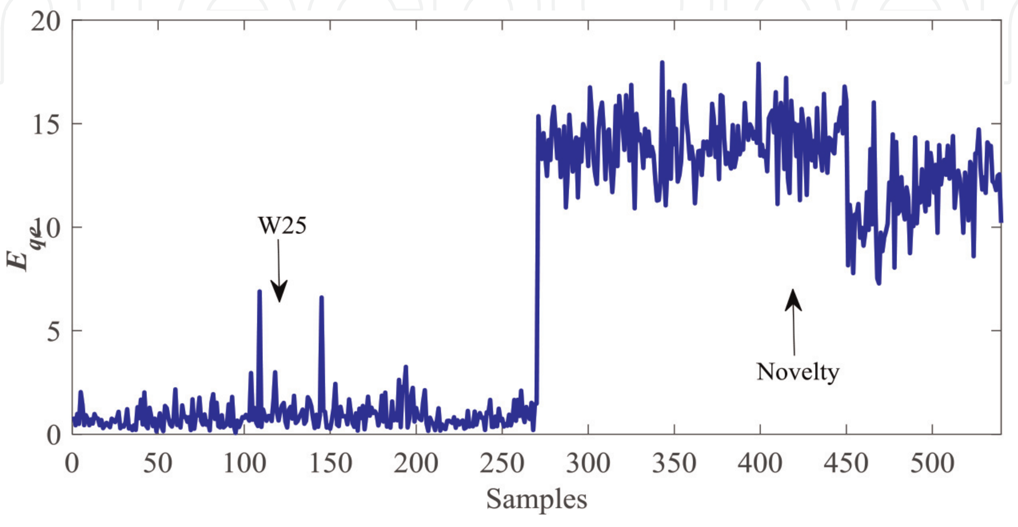

Figure 5.
Novelty detection performed by SOM_2 during the assessment of the second faulty condition, 50% of uniform wear in the gearbox.

The data information to the electromechanical system condition is currently composed of three different conditions, healthy, 25%, and 50% of uniform wear in the gearbox. Later, available information related to another faulty unknown condition is evaluated after performing the retraining process and incremental learning. In this regard, during the training procedure of the third neuron SOM_3 grid, the obtained Eq value was around 0.7077, and during the evaluation of the last faulty condition the achieved Eq was around 6.4367. Thus, the SOM_3 model represents the available information to the third faulty condition that is 50% of uniform wear. In **Figure 6**, the visual representation of the novelty detection performed is shown during the evaluation of the SOM_3 model.

Subsequently, after the last retraining and incremental learning, the available information related to the faulty condition of 75% of uniform wear is also modeled

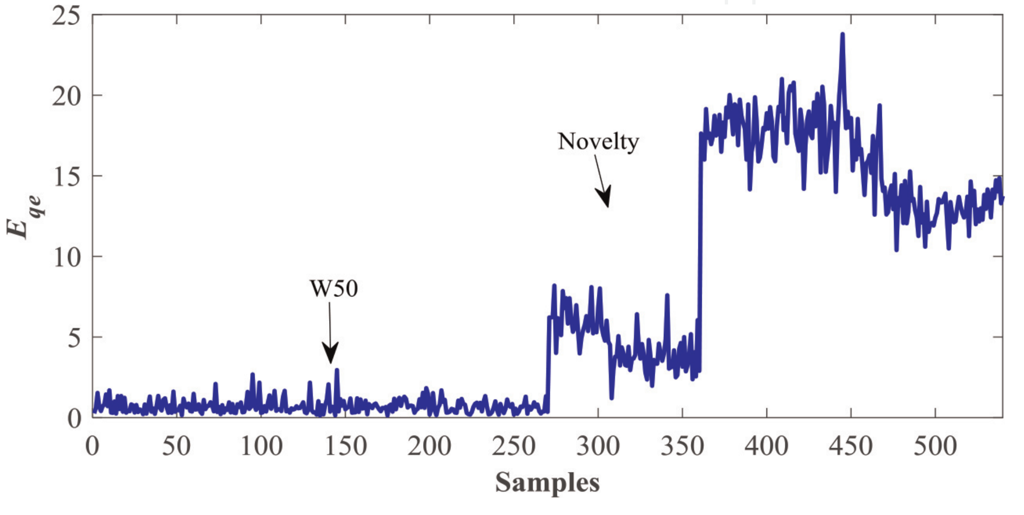

Figure 6.
Novelty detection carried out by SOM_3 obtained for the evaluation of the third faulty condition, 75% of uniform wear in the gearbox.

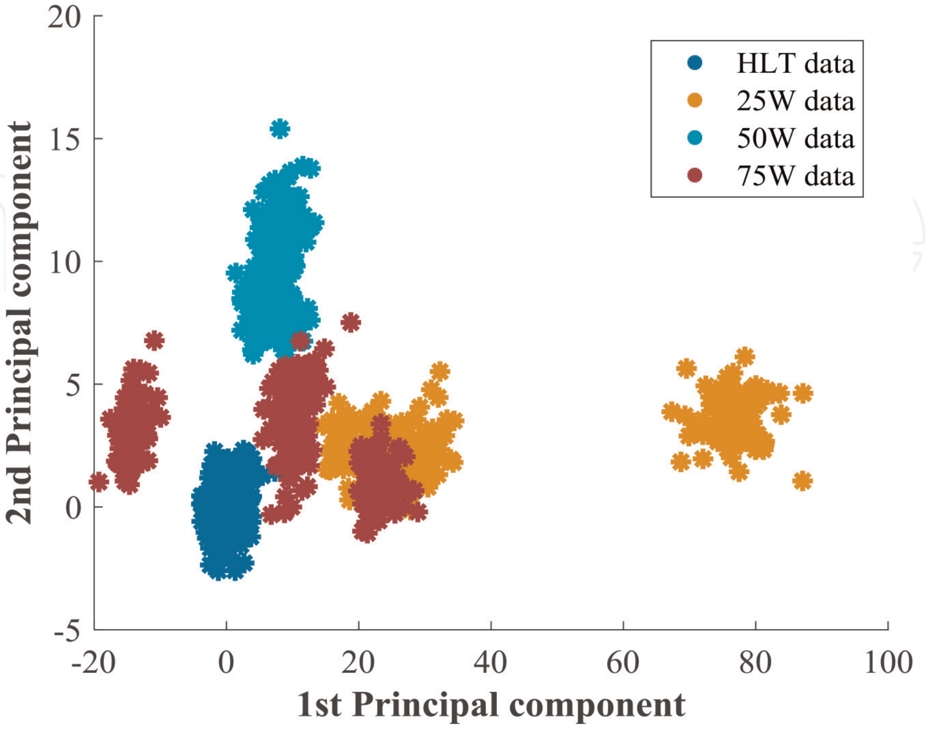

Figure 7.
Resulting two-dimensional projection obtained by considering the four neuron SOM grids modeled for each one of the detected conditions.

by a fourth SOM model, such model is the neuron SOM_4 model, and the E_q error achieved during the training was 0.7700. Because four different operating conditions are detected during the operating condition of the electromechanical system, the final available information stored by the proposed novelty detection approach consist of information capable of detecting four different operating conditions. In case of more novelty detections, the retraining process and incremental learning are again performed, and the information related to the different operating conditions is updated.

Finally, a visual representation of the operating conditions detected during the application of the proposed diagnosis methodology is obtained by means of applying a dimensionality reduction technique, PCA. In this sense, in **Figure 7**, a visual representation of the data distribution of all detected conditions is shown; in this visual representation, it is appreciated that different operating conditions appears. Indeed, different clusters appear for each detected condition because different operating frequencies were considered during the experimental evaluation of the considered conditions.

6. Conclusions

Modern industrial production is characterized by the consideration of machine learning data-based models to support the main aspects of the manufacturing process. In this regard, two main data science challenges related with condition monitoring of electromechanical assets in the Industry 4.0 framework are (i) the premise that only information of the healthy condition is initially available and (ii) the adaptation of the fault detection and identification scheme in order to incorporate new operating conditions. Thus, this paper proposes a new methodology for multi-fault detection and identification based on incremental learning applied to novel fault detection on electromechanical systems by analyzing vibrations and stator current signatures of the electric motor drive.

Moreover, the proposed condition monitoring strategy based on a novelty detection approach is capable of being applied to other electromechanical systems, and also the consideration of other different physical magnitudes can be also included in such proposal.

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Conflict of interest

The authors declare no conflict of interest.

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References

[1] Frank AG, Dalenogare LS, Ayala NF. Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics. 2019; **210**:15-26

[2] Contreras-Hernandez JL, Almanza-Ojeda DL, Ledesma S, Ibarra-Manzano MA. Motor fault detection using quaternion signal analysis on FPGA. Measurement. 2019;**138**:416-424

[3] Saucedo-Dorantes JJ, Osornio-Rios RA, Delgado-Prieto M, Romero-Troncoso RJ. Diagnosis methodology based on statistical-time features and linear discriminant analysis applied to induction motors. IEEE 11th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED). 2017;**2017**:517-523. DOI: 10.1109/DEMPED.2017.8062404

[4] Ribeiro DA, Ferreira DD, Pereira DA, Braga Junior RA, Nunes RD. Mechanical fault detection in electric motors measured by a digital signal processing device in an optical mouse. Measurement. 2019;**138**:350-355

[5] Frini M, Soualhi A, El Badaoui M. Gear faults diagnosis based on the geometric indicators of electrical signals in three-phase induction motors. Mechanism and Machine Theory. 2019; **138**:1-15

[6] Zhao Y, Li T, Zhang X, Zhang C. Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. Renewable and Sustainable Energy Reviews. 2019; **109**:85-101. DOI: 10.1016/j.rser.2019.04.021

[7] Nasiri S, Khosravani MR, Weinberg K. Fracture mechanics and mechanical fault detection by artificial intelligence methods: A review. Engineering Failure Analysis. 2017;**81**: 270-293. DOI: 10.1016/j.engfailanal.2017.07.011

[8] Liu R, Yang B, Zio E, Chen X. Artificial intelligence for fault diagnosis of rotating machinery: A review. Mechanical Systems and Signal Processing. 2018;**108**:33-47. DOI: 10.1016/j.ymssp.2018.02.016

[9] Kang Md. M, Islam R, Kim J, Kim JM, Pecht M. Hybrid feature selection scheme for reducing diagnostic performance deterioration caused by outliers in data-driven diagnostics. IEEE Transactions on Industrial Electronics. 2016;**63**(5):3299-3310

[10] Wang S, Yub J, Lapirac E, Lee J. A modified support vector data description based novelty detection approach for machinery components. Applied Soft Computing. 2013;**13**: 1193-1205. DOI: 10.1016/j.asoc.2012.11.005

[11] Zhang X, Chei W, Wang B, Chen X. Intelligent fault diagnosis of rotating machinery using support vector machine with ant colony algorithm for synchronous feature selection and parameter optimization. Neurocomputing. 2015;**167**:260-279

[12] He Q, Ding X, Pan Y. Machine fault classification based on local discriminant bases and locality preserving projections. Mathematical Problems in Engineering. 2014;**2014**: 1-12. Article ID: 923424

[13] Prieto-Moreno A, Llantes-Santiago o, Garcia-Moreno E. Principal components selection for dimensionality reduction using discriminant information applied to fault diagnosis. Journal of Process Control. 2015;**33**:12-24

[14] Cunha-Palacios RH, Goedtel A, Godoy WF, Fabri JA. Fault identification in the stator winding of induction motors using PCA with artificial neural networks. Journal of Control, Automation and Electrical Systems. 2016;**27**(4):406-418

[15] Manimala K, Getzy David DI, Selvi K. A novel data selection technique using fuzzy c-means clustering to enhance SVM-based power quality classification. Soft Computing. 2015; **19**(5):3123-3144

[16] Sadooghi MS, Khadem SE. Improving one class support vector machine novelty detection scheme using nonlinear features. Pattern Recognition. 2018;**83**:14-33

[17] Li W, Zhang S, He G. Semisupervised distance-preserving self-organizing map for machine-defect detection and classification. IEEE Transactions on Instrumentation and Measurement. 2013;**62**(5):869-879