Enhanced Industrial Machinery Condition Monitoring Methodology based on Novelty Detection and Multi-Modal Analysis

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***Abstract*— This paper presents a condition-based monitoring methodology based on novelty detection applied to industrial machinery. The proposed approach includes both, the classical classification of multiple *a priori* known scenarios, and the innovative detection capability of new operating modes not previously available. The development of condition-based monitoring methodologies considering the isolation capabilities of unexpected scenarios represents, nowadays, a trending topic able to answer the demanding requirements of the future industrial processes monitoring systems. First, the method is based on the temporal segmentation of the available physical magnitudes, and the estimation of a set of time-based statistical features. Then, a double feature reduction stage based on Principal Component Analysis and Linear Discriminant Analysis is applied in order to optimize the classification and novelty detection performances. The posterior combination of a Feed-forward Neural Network and One-Class Support Vector Machine allows the proper interpretation of known and unknown operating conditions. The effectiveness of this novel condition monitoring scheme has been verified by experimental results obtained from an automotive industry machine.**

Index Terms*— *Condition Monitoring; Fault Detection; Machine Learning; Novelty Detection.

I. INTRODUCTION

The industry of the future is part of the paradigm called Industry 4.0, which seeks the coherent integration of production processes with novel information technologies [1], [2].

In highly competitive industrial manufacturing sectors, as the automotive industry, the evolution towards the Industry 4.0 foresees the optimization of the industrial processes analytics and the interpretation of their operating condition [3], [4].

Indeed, in the field of industrial machinery monitoring, a great deal of approaches in regard with health monitoring schemes have been proposed during the last decade, where information of the monitored machine working under nominal (healthy), and faulty conditions, are analyzed to train a classifier capable of assess the condition of the machine [3], [5]–[7], these approaches have demonstrated to be a reliable option as fault diagnosis strategies applied to electromechanical systems. However, the practical integration in the industry 4.0 requires dealing with challenging scenarios that classical fault diagnosis methodologies are not able to solve by themselves. Unexpected events, in the form of not previously considered fault scenarios, or deviations over the nominal operation of the machine, will take place during the useful life of the machinery under monitoring. In industry applications, it is not feasible to have data regarding all the possible undesired operating conditions of the monitored machine, therefore the maintenance support of classical approaches is limited. Novel operating scenarios must be identified in order to avoid diagnosis misclassifications and incorrect maintenance scheduling. In this sense, the task of detecting patterns that differs from those available during the training of the monitoring scheme, is called novelty detection [8], [9].

The framework of Industry 4.0 demands solutions capable to provide a fast intervention in fault situations, and optimal maintenance scheduling. In order to successfully develop and implement systems with such capabilities, the methodologies applied must be able to identify novel operating conditions (novelty detection), while continue the identification of the known fault scenarios previously available (fault diagnosis). In this regard, the integration of novelty detection strategies to fault diagnosis methodologies is the first step to develop a condition monitoring system able to answer the demands of the industry 4.0. A great deal of scientific effort is being focused on the study of such approaches [10]–[12]. A state of the art of these methodologies is further discussed in section II.

Thereby, the contribution of this study consist on the development of a novelty detection and fault isolation approach applied to an end-of-line (EOL) test machine that takes part on an industrial process of the automotive sector.

This work represents an important step to the introduction of novelty detection techniques and advanced classification structures, to the development of industrial system diagnosis procedures, being the first time that the propose methodology is applied in real automotive industry machinery. The contributions of this papers are as follows:

1) A multi-modal feature reduction scheme to increase the performance of novelty detection and fault diagnosis tasks.
2) An application to an EOL test machine to achieve optimal machine scheduling when an unknown event is detected.
3) A validation and comparison analysis of the proposed approach in front of multiple operating scenarios, including known and unexpected conditions.

Indeed, originality of this work includes a torque signal processing and numerical feature estimation scheme from where the measurements are characterized. A positioning segmentation is employed, and a set of statistical time-based features is estimated from each segment for characterization. A feature reduction study is proposed in this work to highlight

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relevant indicators and avoid data overfitting. An exhaustive comparison is performed between the aforementioned classical state of the art approaches and the proposed methodology in order to highlight the advantages of the multi-modal scheme and novelty detection. A set of quantitative metrics are proposed and analyzed to identify the performance of the proposed methodology. The proposed approach exhibits more than 10% of accuracy increase in comparison with classical approaches proposed on different applications in the literature.

This paper is organized as follows. A background regarding the state of the art of approaches combining novelty detection and fault diagnosis is described in Section II. In Section III, theoretical aspects of the proposed method are described. The experimental setup and the friction test are described in Section IV. In Section V, the proposed method is explained. The results obtained are presented and discussed in Section VI. Finally, conclusions are summarized in Section VII.

II. Background

A priori, the knowledge of characteristic fault patterns of specific industrial machinery is commonly limited, and highly difficult to estimate trough theoretical approaches. Thus, condition monitoring strategies capable of detecting novel operating conditions alongside with classification of the several available known conditions, represents the most convenient solution [13]–[16], [10], [12] to reach optimal maintenance scheduling and fast interventions in fault situations.

In pattern recognition and machine learning framework, this kind of scenario is known as *open set recognition problem* [17], where only a set of known classes are contained in the initial dataset during the training stage, and, then, novel (unknown) classes may appear during testing stage.

The classical approach to deal with such *open set problems* consists on one-class classifiers [18], where one one-class classifier is considered for each class [19]–[22]. Thus, each new measurement from the system under monitoring is analyzed by the one-class classifiers set. If the measurement fits into more than one class, post-processing schemes based on similarity analysis are typically used to assign the definitive class. If the measure does not fit into any of the available classifiers, the measure is considered novelty. In [10], Lazzaretti *et al.*, follows this approach to perform an automatic classification of voltage waveforms in electrical distribution networks. The classification method is based on Support Vector Data Description (SVDD), in order to identify the waveforms class from multiple known options and, at the same time, detect novel voltage waveforms not previously considered.

Other studies have approached the *open set problem* by a separate analysis of multi-class classification and novelty detection [14], [12], [23], [24]. Multi-class classification and novelty detection algorithms are trained with the same available data set; however, the resulting models have different targets. Thus, each new measurement from the system under monitoring is analyzed first by the novelty detection algorithm. If the measure fits in the model of data knowledge, the measure is then assessed by the classification algorithm. Costa *et al.* [12], propose a two-stage methodology for real-time novelty detection and fault classification of industrial plants. Specifically, the initial novelty detection is supported by density analysis in the data space expressed by a *Cauchy* function, and the classification stage is designed by the AutoClass fuzzy-rule-based classifier. Although the advantage of such algorithms is based on their computational efficiency for on-line monitoring and adaptive capabilities to novel scenarios incorporation, the work emphasize the need of *ad hoc* signal processing, estimation of numerical indicators and feature reduction procedures for the plant under test.

Lazzaretti *et al.* in [23] have addressed the comparison of such two *open set problem* methodologies by including different data based algorithms. The experimental results obtained by means of the classical one-class classifiers approach exhibits better results in overall terms, basically, due to the high processing capabilities using as much classifiers as considered classes. However, the potentiality of methodologies separating fault diagnosis and novelty detection, has not been properly exploited yet, and represents, not only the most computationally optimized approach, but the most coherent solution in industrial applications. Indeed, since multi-class classification and novelty detection tasks are supported by different algorithms, there is a potential opportunity for a separate processing of the available data. Thus, the selection of the numerical feature set used to characterize the measurements could be treated independently attending the different targets of the models. The methodology proposed in this work attempts to cover all those deficiencies by including a multi-modal approach during the feature reduction stage, maximizing the performance of both models, novelty detection and classifier.

Many approaches have been proposed as novelty detection models, including: probabilistic approaches like the Multivariate Kernel Density Estimation (MKDE) or Mixture of Gaussians (MoG), distance-based methods like the K-nearest neighbour (NNDD) and, domain-based methods like the Support Vector Data Description (SVDD) or One-Class Support Vector Machine (SVM). The main difference of the methods lies in the formulation of the novelty threshold that serves as a reference to label the data among known or novel; a detailed description of the methods and a comparison between advantages and disadvantages of each one can be found in [9], [18].

For the proposed methodology, the One-Class Support Vector machine (OC-SVM) has been chosen as novelty detection model since it has been successfully employed on different reported industrial applications [25] due to the ability to work with a small amount of samples for training, and exhibits similar performance than the SVDD when the same kernel is used [9]. The Neural Network (NN), is used as a multi-class classification algorithm due to its well-known performances dealing with pattern detection [26]. Both, the OC-SVM and the NN, are used in the reported literature as standard references to analyze the detection rate of the different methodologies compared.

III. Theoretical Considerations

A. One-Class Support Vector Machine

OC-SVM was proposed by Schölkopf *et al.* [27], for estimating the support of a high-dimensional distribution. The

OC-SVM classification objective is to separate one class of target samples from all other class samples. In this type of problem one class is characterized properly, called target class; while for the other class, usually, no measurements are available.

Considering $X = [x_1,..., x_N]^T \in R^{NxM}$, which denotes the normal data set, and x_i , *i=1…N* denotes training samples (available measurements) characterized by *M* numerical features, then, in order to obtain the boundary, an optimization model is considered as follows

$$\min\left\{\frac{\|w\|^2}{2} + \frac{1}{Nv}\sum_{i=1}^{N}\xi_i - \rho\right\} \qquad (1)$$

Subject to

$$w \cdot \Phi(x) \geq \rho - \xi_i, \qquad \xi_i \geq 0$$

where *v* is a regularization parameter and ξ_i is the slack variable for the point x_i. The constants w and ρ are the normal vector and offset of the hyperplane, respectively. Thus, the decision boundary can be formulated as

$$f(x) = w \cdot \Phi(x) - \rho \qquad (2)$$

where $x \in R^M$, and Φ is a higher dimensional projection vector. For the classification problem of two categories, the data sets are not always linearly separable in the original space, then, Φ projects the original data sets into a higher dimensional space, the so-called feature space, where the data sets can be linearly separable. However, Φ is inexplicit in the practical application, and only the dot product from $\Phi(x_i) \cdot \Phi(x_j)$ is necessary to be known. *K* represents the kernel function $\Phi(x_i) \cdot \Phi(x_j)$. The most commonly used kernel functions is the Gaussian

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \qquad (3)$$

In order to solve the optimization problem (1), Lagrange multipliers $a_i \geq 0$ and $\beta_i \geq 0$ $(i = 1,..., N)$ are introduced and the Lagrange equation is formed as

$$\begin{aligned} L(w,\xi,\rho,a,\beta) &= \frac{\|w\|^2}{2} + \frac{1}{Nv}\sum_{i=1}^{N}\xi_i - \rho \\ &- \sum_{i=1}^{N} a_i (w \cdot \Phi(x_i) - \rho + \xi_i) - \sum_{i=1}^{N}\beta_i \xi_i \end{aligned} \qquad (4)$$

The partial derivatives of the Lagrangian equation with respect to w , ξ and ρ are set to zero. Then, w and a_i can be formulated as

$$w = \sum_{i=1}^{N} a_i \Phi(x_i) \qquad (5)$$

$$a_i = \frac{1}{Nv} - \beta_i \qquad \sum_{i=1}^{N} a_i = 1 \qquad (6)$$

Substitute (5)-(6) into Lagrangian equation (4) and its dual form is presented as

$$\min\ a^T H a$$

$$\text{subject to} \quad 0 \leq a_i \leq \frac{1}{Nv} \qquad \sum_{i=1}^{N} a_i = 1 \qquad (7)$$

where $\boldsymbol{a} = [a_i ... a_N]^T$, and H is the kernel matrix and the factor of H , i.e. H_{ij} , which can be expressed as:

$$H_{ij} = K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j) \qquad (8)$$

Solve the optimization problem (7) to get $\boldsymbol{a}$ and then ρ can be given as

$$\rho = \frac{1}{n_s}\sum_{i=1}^{n_s}\sum_{j=1}^{N} a_j a_i K(x_i, x_j) \qquad (9)$$

where n_s is the number of support vectors.

Tax *et al.* [28] proposed another form of OC-SVM which is called Support Vector Data Description. The basic idea of SVDD is to construct a minimum-volume hypersphere in a high dimensional feature space to enclose as much as normal data points. Both of these two forms of SVM have equivalent solution if the diagonal entries of kernel matrix *H* are equal.

B. Dimensionality Reduction Techniques

Working with high dimensional datasets complicates the learning task of novelty detection and multi-class classification methods, not only because of possible presence of non-significant and redundant information in the data, but also because a proper convergence of the algorithms could be compromised. Indeed, the empty space phenomenon states that to cover the whole space it is needed a number of samples that grows exponentially with the data dimensionality. Thus, the curse of dimensionality implies that in order to carry out a successful learning stage, it is needed a number of available training measurements that also grows exponentially with the dimensionality. The “concentration of measure” phenomenon seems to render distance measures not relevant to whatever concept is to be learnt as the dimension of the data increased. For these reasons, there is a necessity to apply dimensionality reduction techniques in condition monitoring applications [29].

Dimensionality reduction strategies differ in the question of whether the learning process is supervised or unsupervised. The difference between both learning processes is the availability of labels to distinguish the different classes. Principal Component Analysis (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 [30]. By working on the projections that maximize the variance of the data, it is possible to highlight the anomalies that could appear during monitoring, therefore, PCA is used often in novelty detection. Linear discriminant analysis (LDA) is one of the most well-known supervised techniques for linear dimensionality reduction in multi-class problems. 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 [21]. 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 aforementioned linear feature reduction techniques exhibit different objectives (data variance preservation or data discrimination), and method of employment (unsupervised or supervised), and have been widely used in the literature with successful results. This difference in the data analysis represents the opportunity to increase the performance of novelty detection and classification models.

IV. EXPERIMENTAL SETUP

The machine under study performs a friction test over the manufactured parts (steering system). Note that the machine applies its own algorithm to determine the healthy state of the part but the aim of this work is to monitor the proper function of the machine.

A picture of the end-of-line machine under monitoring is shown in Fig. 1, where a 1.48kW synchronous servomotor with 4 pair of poles, 3000 rpm of rated speed and a rated torque of 4.7Nm is connected to a 60:1 reduction gearbox.

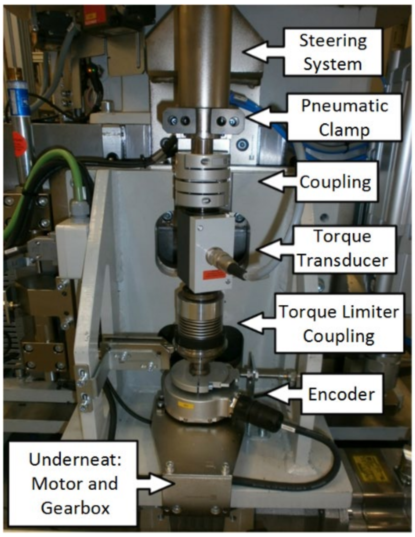

Fig. 1. Machine that performs the end-of-line test composed by a servomotor, a gearbox, an encoder, a torque transducer and a pneumatic clamp to hold the intermediate shaft of the steering system.

An encoder of 9000 points of resolution follows the gearbox and is coupled to a 10Nm torque transducer by a torque limiter coupling. The other side of the torque transducer is coupled to the steering system. A scheme of the parts composing the friction test machine is shown in Fig. 2. The measurement equipment, in order to monitor the machine, is focused on the acquisition of the torque signal of the transducer and the rotatory shaft position from the encoder. Data acquisition is done at 1 kHz of sampling frequency by a NI cDAQ-9188 composed by the modules NI 9411 and NI 9215.

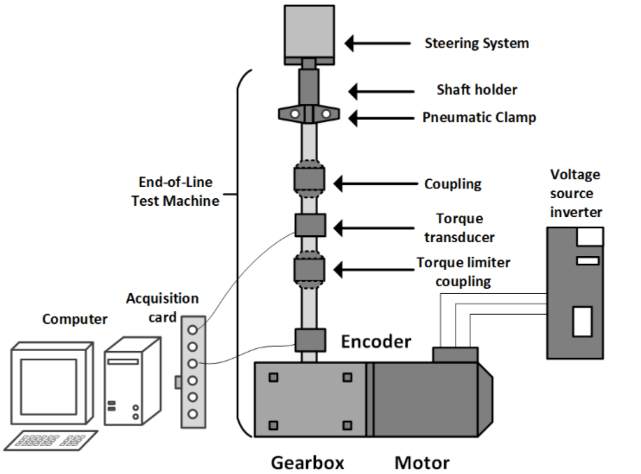

Fig. 2. Schematic of the end-of-line machine under monitoring and the acquisition system.

A. *Description of the friction test*

The purpose of friction test is to quantify the DC value of the torque to rotate the steering system. The EOL machine forces the steering system column to follow a predefined speed profile which consist of a complete clockwise turn (CW) and a complete counter clockwise turn (CCW). The speed profile performed by the test machine is shown in Fig. 3.

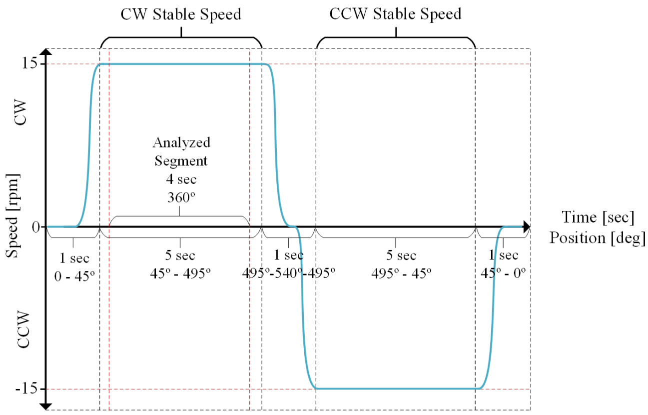

Fig. 3. Speed profile applied by the EOL test machine.

The test starts smoothly in a clockwise direction for the first 45º until a speed set point is reached. The acceleration time depends on the drive capability. During the next 455º the speed is fixed at the set point, in this case 15 rpm. Then, the same procedure is employed to return to the original start point in the opposite direction. This speed profile (see figure 3) provokes a torque in the shaft that it is measured by the torque transducer. An example of the torque measurement of a complete test under machine healthy conditions and the analyzed segment of three different conditions are shown in Fig. 4.

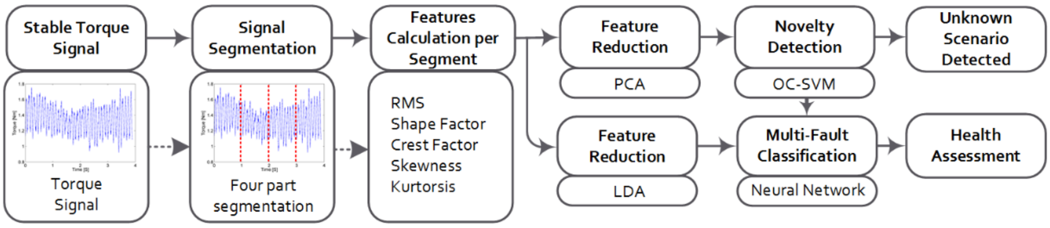

Fig. 5. Proposed methodology for the EOL test machine. The monitoring method is composed by a signal processing stage where statistical features are calculated and analyzed by a novelty detection and a multi-fault classification models to assess the condition of the machine.

As can be seen in Fig.4, malfunction in the test machine modify the torque signal form and its statistical properties (RMS value, crest and shape factor, etc.). The objective of the signal processing stage and the methodology is to highlight these alterations to perform the assessment of the machine without altering the part test itself, therefore, the methodology can be applied online. In order to characterize the condition of the friction test machine, a segment of 4 seconds is extracted of each torque signal measurement corresponding to the CW stable speed period. That is, the torque signal corresponding to the stationary speed set point during 360º rotation.

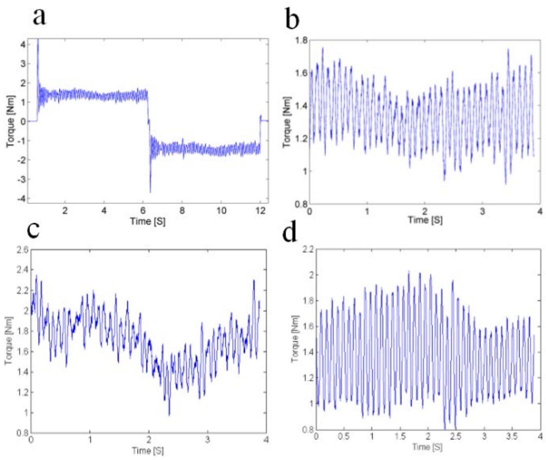

Fig. 4. Torque signal measured during a test a) Complete torque measurement under machine healthy conditions b) Analyzed segment of a healthy machine measurement c)Analyzed segment of a machine misalignment fault d) Analyzed segment of a machine coupling wear fault

B. Machine faults under consideration

In order to validate the proposed methodology, fault conditions have been induced in the machine to provoke two common fault conditions, moreover, three severity levels have been also considered for each fault. Thus, three severity degrees of misalignment, MIS_5, MIS_6 and MIS_7, and three severity degrees of coupling wear, CW_1, CW_2, and CW_3.

The misalignment fault of the shaft has been provoked by the controlled displacement of the base of the fixture holding the steering system. This induces a misalignment of the steering system respect to the shaft holder. Three degrees of severities are considered regarding the distance that the fixture is displaced horizontally: 5mm (MIS_5), 6mm (MIS_6) and 7mm (MIS_7).

The coupling wear fault is emulated by employing three different intermediate elastomers in the torque limiter coupling, each one with different dynamic torsional stiffness (DTS). The values of the DTS of the used elastomers are all lower than the standard used in the healthy machine in order to emulate classical wear.

The DTS values of the three elastomers corresponds to a low degradation degree, 2580Nm/rad (CW_1), intermediate degradation degree, 2540 Nm/rad (CW_2), and high degradation degree, 876 Nm/rad (CW_3).

Additionally, a sliding malfunction is caused by varying the tightening torque of the screws of the coupling between the torque transducer and the pneumatic clamp. The screws are loosened 0.5 Nm from the nominal tightening measured by a torque wrench. To test the capacity of the proposed methodology to detect novel scenarios, the measurements corresponding to this fault are going to be considered as an emerging novelty condition (*Nc*).

V. Methodology

The condition based monitoring approach is aimed to accomplish two objectives:

(i) The calculation of significant features to characterize the friction test machine.

(ii) The detection and isolation of known fault scenarios and detection of possible unknown faults.

Such objectives are accomplished on this work by means of the proposed condition based monitoring methodology shown in Fig. 5.

The torque signal analysis is carried out during the stationary speed set point corresponding to a 360º CW turn of the steering system. It is expected that malfunctions and anomalies could be reflected in the torque signal during segments of the revolution of the steering system, therefore, the segmentation represents a viable strategy to gain resolution during the characterization. Thus, the four seconds torque signal is segmented in four parts of 1 second. The number of segments chosen represents a tradeoff between resolution and total number of features. A larger number of segmentations increase the resolution but also increase the number of features, and could lead to overfitted models, meanwhile choosing a lower number of segments could not provide enough resolution.

A set of five statistical time-domain features are calculated from each segment of the torque signal. The proposed features are listed in Table I. These features have been successfully employed in different studies for electromechanical systems fault detection [31]. Therefore, a total of 20 features are calculated from each torque signal measurement.

TABLE I.
STATISTICAL TIME FEATURES

Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(10)
Shape Factor	$SF = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(11)
Crest Factor (CF)	$CF = \frac{\max(x)}{RMS}$	(12)
Skewness	$S_k = \frac{\sum_{k=1}^{n}(x_k - \bar{x})^3}{n\sigma^3}$	(13)
Kurtosis	$k = \frac{\sum_{k=1}^{n}(x_k - \bar{x})^4}{n\sigma^4}$	(14)

In order to exploit the potentiality of a separate fault isolation and novelty detection stages, two different dimensionality reduction approaches are applied over the features sets.

For the novelty detection module, a PCA is used to extract a reduced set of features that maximize the variance of the dataset. The extracted features could highlight the appearance of outliers and novel faults. Regarding the multi-fault classification module, LDA is used to extract a reduced set of features that maximize the margin between classes and minimize the scatter within classes. That is, the extracted features will lead to a distribution of the data that improves the classification task. The number of reduced features selected of each method vary depending on the information retain, in the case of PCA, and the discrimination capacities for the LDA.

After the corresponding feature reduction, the novelty model and the multi-fault classification algorithms are trained using the healthy data and the faulty scenarios. That is, both models are trained with the same scenarios, however, the labels used for novelty detection and multi-fault fault classification are different. For the novelty detection model, the data labels are unique, which means that the dataset is considered to be one single class. Meanwhile for the multi-class classification model, the labels correspond to each of the considered faults in order to reach the classification among the known scenarios.

To analyze a new torque signal measurement, the corresponding reduced set of features is first examined by a novelty detection model. Then, the measurement can be cataloged as novel or known. If the measurement is catalogued as novel, the machine is considered to be working under unknown conditions. This can be triggered by different scenarios, including outliers, the presence of a new fault or by a new operation condition of the machine. If the measurement is catalogued as known, it means that the machine is working under a previously known scenario, which can be healthy or faulty. To discern between the known scenarios, the measurement is analyzed by a multi-fault classifier. The output of the model is a label that identifies the analyzed measurement as one of the considered classes.

A. Novelty detection and multi-fault classification models

There is a great deal of novelty models proposed on the literature, each one demonstrated to be a capable option under certain circumstances. An increasing amount of studies point out that domain based novelty detection models present promising results. Thus, in this work, a standard OC-SVM with Gaussian kernel is used. The preparation of the novelty model includes the selection of the parameters for configuration and the training of the model. The OC-SVM is trained with information of the known scenarios (healthy and faulty sets), but labeled as a unique class. This means that the model finds a boundary that encloses all the known scenarios, if a new tested sample is within the boundary, then, it is considered known, on the contrary, if it lies outside, it is considered novel.

For the multi-fault classification module, a multi-layer neural network (NN) is used. Neural networks are data-driven self-adaptive information processing method inspired in biological systems, and represents the most commonly data-driven technique found in the literature[31].

VI. EXPERIMENTAL RESULTS

In order to validate the feasibility of the proposed methodology, four different models of steering systems have been tested. The four models possess the same structure described previously, but with different brands of components. It is important to note that all the steering systems used were in healthy state, in order to focus the analysis on the state of the test machine.

The expected torque response is slightly different for each steering system model. The four steering system models have a different reference pattern, therefore it is expected that the performance of the novelty detection and multi-fault classification models are affected by the variability of the torque response of the models. Nevertheless, it is desired to assess the capability of a condition monitored approach to generalize between different models of steering system and correctly identify the machine condition.

Eight classes regarding the condition of the machine are considered on this work:

- Healthy condition: *Hc*.
- Six faulty conditions: MIS_5, MIS_6, MIS_7, CW_1, CW_2, CW_3.
- Novelty condition: *Nc*.

For each one of the 4 models, 20 friction tests are performed, that leads to a total of 80 measurements for each class. Then, the dataset consist of a total of 640 measurements.

A. Model estimation and parameter selection

A 70% of the available measurements per class are used for training. It is important to emphasize that novelties measurements, *Nc*, are used only in the test stage. From the training set, a five-fold cross-validation is used in order to adjust the OC-SVM parameters. The kernel used is the *Gaussian* and the value of the width of the kernel is limited among the following set of discrete values: {1, 2, 3, 5, 10, 15}. Regarding the neural network, a configuration of one hidden layer with 10 neurons is used. The neurons are configured with a sigmoid activation function and the training procedure corresponds to a classical back propagation algorithm using all the training samples.

Once the classifier was trained and adjusted, the final test is done using the remaining 30% of the measurements. This process was repeated five times with five different training-test set distributions, randomly selected and fixed.

B. Performance analysis

To describe the performance metrics, the 8 classes are grouped in two nomenclatures: *novelty class* and *known class*. The *novelty class* corresponds to measurements of the novelty condition *Nc*. The *known class* is composed by the 7 remaining classes: *Hc*, MIS_5, MIS_6, MIS_7, CW_1, CW_2 and CW_3. To analyze the performance of the proposed method, three sets of performance metrics are considered, each set is associated to the stage on which they are calculated: after the novelty model, after the multi-class classifier and the global result. Regarding the results obtained from the novelty detection model, the following metrics are calculated:

- Novelty model accuracy: This metric refers to the number of correctly classified measurements of the *novelty class* and the *known class* divided by the total of test examples. This metric is used to obtain a novelty model global performance. Nevertheless, it is not the ideal metric to assess the performance of the methodology because it does not contemplate the accuracy of discriminating between the different classes composing the *known class* by the multi-fault classifier.

Regarding the results obtained from the multi-fault classification model, the following metrics are calculated:

- Training performance: This metric represents the capacity of the multi-fault classification model to classify the samples used in the training. A low training performance indicates that the model is not able to discriminate among classes, which can be caused by an overlapping of the data in the feature space.
- Multi-fault accuracy: As mentioned in the previous section, the measurements analyzed by the multi-fault classifier are the ones that the novelty detection module classified as *known class.* This metric represents the measurements analyzed by the multi-fault classifier that are correctly classified divided by the total number of measurements that actually belong to the *known class.* This metric is important to measure the capacity of the classifier to classify the test measurements of the known class, but the result can be deceiving if the performance metrics of the novelty model are not analyzed. Since the methodology follows a sequential execution, the error performed by the novelty model by classifying novelties as part of the *known class,* propagates to the multi-fault classifier.

Regarding the results obtained considering the whole methodology the following metric is calculated:

- Complete Accuracy: This metric represents the measurements of the *novelty class* correctly classified by the novelty detection model and the measurements of the *known class* correctly classified by the multi-fault classification model, divided by the total of test examples. This performance metric combines the results of the both models and can be used to compare the methodologies. Nevertheless, the other metrics are necessary to have better understanding of the performance, and also, to allow the identification of deficiencies in-between the stages of the methodology.

C. Results and discussions

In order to highlight the contribution and motivation of this work, the outline of the results will be presented as follows: first, a test is performed by the two classical methodologies aforementioned in section I, then, the proposed methodology is applied and the results are compared. The performance metrics are analyzed on each case to highlight the advantages and disadvantage of each methodology. To be able to compare the results obtained between methods, the same novelty detection model is used on all the methodologies, on this case, the OC-SVM.

Different configurations regarding the dimensionality of the features are used to have an insight of the advantages of discarding irrelevant features. Three different configurations are selected: using all the features (no feature reduction applied), applying PCA and, finally, applying LDA. The number of selected features is reduced from an initial 20-dimensional space to a reduced 2-dimensional space, taking into consideration that the reduced set of features fulfill the respective restrictions from each dimensionality reduction approach.

The first classical methodology consists on performing the novelty detection and multi-fault classification by means of a combination of one-class classifiers. The results are shown in Table II, where the best performance of each metric is highlighted.

TABLE II.
PERFORMANCE OF CLASSICAL ONE-CLASS CLASSIFIERS BASED METHODOLOGY USING THREE DIFFERENT DIMENSIONALITY REDUCTION CONFIGURATIONS

First methodology: One-class classifier per class			
Performance Metrics	OC-SVM		
	All 20 Features	PCA	LDA
Novelty model accuracy	0.656(±0.013)	**0.835(±0.023)**	0.773(±0.025)
Training performance	0.788(±0.035)	0.703(±0.019)	**0.846(±0.022)**
Multi-fault accuracy	0.592(±0.021)	0.581(±0.033)	**0.723(±0.038)**
Complete accuracy	0.632(±0.014)	0.712(±0.019)	**0.719(±0.032)**

By comparing the complete accuracy shown in Table II, it is possible to observe that both dimensionality reduction approaches exhibit better results than using all the available features, being the LDA the method with the highest complete accuracy. The characteristics of each dimensionality reduction approach are highlighted by the results of the metrics.

In regard with the novelty detection, by comparing the novelty model accuracy, the PCA approach obtained better results on this task than the LDA, 6% higher with the PCA.

Regarding the multi-fault classification task, an important advantage of the LDA approach can be noticed by analyzing the training performance metric for classification, 15% higher. Since in both cases, PCA and LDA, the methodology is trained with the same measurements, it can be concluded that the low percentage of training performance is caused by an overlapping of the different classes in the feature space, rather than the capacity of the method to perform multi-class classification.

The second classical method analyzed is similar to the proposed methodology, where the novelty detection and multi-fault classification tasks are performed by different models. The same structure of an OC-SVM for novelty detection and the neural network for classification are used for this test, nevertheless, the same dimensionality reduction technique is used for both tasks: novelty detection and multi-fault classification. The results are shown in Table III.

TABLE III.
PERFORMANCE OF THE CLASSICAL NOVELTY DETECTION AND MULTI-FAULT CLASSIFICATION METHODOLOGY USING THREE DIFFERENT DIMENSIONALITY REDUCTION CONFIGURATIONS

Second methodology: Same dimensionality reduction for both models			
Performance Metrics	OC-SVM		
	All 20 Features	PCA	LDA
Novelty model accuracy	0.606(±0.021)	**0.815(±0.007)**	0.761(±0.017)
Training performance	0.851(±0.034)	0.706(±0.019)	**0.906(±0.009)**
Multi-fault accuracy	0.606(±0.048)	0.523(±0.026)	**0.795(±0.014)**
Complete accuracy	0.597(±0.021)	0.643(±0.016)	**0.716(±0.021)**

By comparing the complete accuracy shown in Table III, one can observe that, again, the dimensionality reduction approaches obtained better results than employing all the features, being the LDA the method with the highest complete accuracy. In general, both classical methodologies presents similar results, the PCA reduction also obtained better results for the novelty detection task while the LDA reduction obtained better results for the classification task. Taking into consideration the low training performance metric of the features obtained by the PCA (70%) compared to the training performance obtained by the LDA (90%), the problem regarding the overlapping of measurements of different classes is still present.

Finally, the proposed methodology is also tested. A comparison between other novelty detection models is also performed. Two commonly used models in the literature are chosen [9]: Multivariate Kernel Density Estimator (MKDE) and Mixture of Gaussians (MoG). The results are shown in Table IV, where the best performance of each metric is highlighted.

TABLE IV.
PERFORMANCE OF THE PROPOSED NOVELTY DETECTION AND MULTI-FAULT CLASSIFICATION METHODOLOGY USING THREE DIFFERENT NOVELTY DETECTION MODELS

Proposed methodology: PCA + LDA			
Performance Metrics	Different novelty detection models		
	MKDE	MoG	OC-SVM
Novelty model accuracy	0.771(±0.052)	0.802(±0.029)	**0.815(±0.007)**
Training performance	**0.906(±0.009)**	**0.906(±0.009)**	**0.906(±0.009)**
Multi-fault accuracy	0.708(±0.022)	0.710(±0.017)	**0.751(±0.021)**
Complete accuracy	0.763(±0.023)	0.774(±0.031)	**0.811(±0.021)**

As can be seen, the proposed methodology obtained an average of 81% of complete accuracy, which is 10% more than the other two methodologies.

As can be expected, the inclusion of the LDA at the multi-fault classification task improves considerably the multi-fault accuracy and, therefore, the complete accuracy.

Regarding the comparison with other novelty detection models, the MKDE obtained the lowest complete accuracy, which is 5% less than the proposed methodology. This can be caused by the different variations of the torque signal, causing several data distributions with limited measurements to characterize them. It is well know that, as a statistical non-parametric model, the MKDE needs a considerable number of samples to adapt to the underlying distribution.

Similar results are obtained by the other two models, the MoG and the OC-SVM, with a difference of 4% regarding the complete accuracy.

To analyze the performance of each class individually, the confusion matrix of the proposed methodology is shown in Table V.

As can be seen in the confusion matrix the misclassification problems are present in-between classes of the same fault, especially between CW_1 and CW_2, which means, the method have difficulties to discern between severities of the same fault but not between different faults. A specialized feature calculation and reduction approach could improve the classification of the CW severities.

TABLE V.
CONFUSION MATRIX OF THE PROPOSED METHOD USING THE OC-SVM.

True Class	Assigned Class							
	Hc	CW_1	CW_2	CW_3	MIS_5	MIS_6	MIS_7	*Nc*
Hc	20	0	0	1	0	0	0	3
CW_1	0	22	2	0	0	0	0	0
CW_2	0	13	8	0	0	0	0	3
CW_3	0	0	0	20	0	0	0	4
MIS_5	1	0	0	0	16	1	0	6
MIS_6	0	0	0	0	0	21	0	3
MIS_7	0	0	0	0	0	0	20	4
Nc	1	0	1	12	2	0	0	64

Regarding the novelty measurements, most of the misclassifications are assigned to CW_3 which means the *Nc* measurements have underlying similarities with the torque signal from this severity of coupling wear.

VII. CONCLUSIONS

In this paper, a novelty detection based condition monitoring methodology applied to the torque signal of an automotive sector end-of-line test machine is proposed. The methodology is capable of assess the condition of the machine under monitoring without altering the undergoing operation.

The two main contributions presented are focused on: (i) the analysis, characterization and proposal of a coherent signal processing stage to extract and select relevant features of the end-of-line test machine, and (ii) the methodology for the analysis of the extracted features to perform the classification of the seven considered known scenarios and the detection of unexpected (novel) scenarios not previously characterized.

The methodology proposed is compared with two classical methods. The most important performance metrics are proposed for the evaluation of the methodologies. By monitoring, globally and partially, the accuracy of the models, it is possible to identify the advantages and limitations of each stage of the methodologies.

The tests performed using the LDA and PCA proved the importance of exploiting the characteristics of the proposed methodology, being in this case the LDA capable of improving the multi-fault classification task and the PCA capable of improving the novelty detection task.

Regarding the novelty model accuracy metric, the classical one-class classifiers based methodology, the classical novelty detection and multi-fault classification based methodology employing the PCA, and the proposed methodology, exhibit similar results, ±2% of accuracy.

However, regarding the multi-fault accuracy metric, the classical one-class classifiers based methodology presents the lowest performance. The classical novelty detection and multi-fault classification based methodology employing the LDA and the proposed methodology exhibit better results, +6% and +4% respectively.

It should be emphasized that in regard with the training performance metric, both classical approaches improve their performance, more than 15% by using LDA feature reduction. That is, in classical approaches high novelty model accuracy and high multi-fault accuracy performances cannot be obtained at the same time since are dependent of the feature reduction approach. Indeed, the proposed approach allowing different dimensionality reduction techniques for novelty detection and multi-fault classification lead to a better overall performance compared to both classical methodologies, obtaining an average of 81% of complete accuracy, which is a 10% more than the classical approaches.

The use of the OCSVM as a novelty model approach in front of MoG and MKDE, results in an increase of the complete accuracy metric of 5% and 4% respectively.

In future work, the study will be expanded using others novelty detection models and dimensionality reduction approaches, in order to analyze the opportunities for an optimized classes boundaries formulation. Also, next steps include the incorporation of adaptive monitoring strategies, where new emerging classes are included on-line to the previous set of known classes (incremental classifiers). This adaptive framework could permit to continuously learn novel scenarios detected and identified during monitoring.

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