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"Fault detection and identification methodology under an incremental learning framework applied to industrial electromechanical systems"

Thesis submitted in partial fulfilment of the requirement for the PhD Degree issued by the Universitat Politècnica de Catalunya, in its Electronic Engineering Program.

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Abstract

Condition based maintenance is a program that recommends actions based on the information collected and interpreted through condition monitoring of the asset under supervision, and has become accepted since a decade ago by the industry as a key factor to avoid expensive unplanned machine stoppages and reach high production ratios. Among the condition based maintenance strategies, data-driven fault diagnosis methodologies have gained attention because of the high performance and widen range of applicability, mainly, due to less restrictive constrains in comparison to other approaches. Currently, an increased effort is been made to study reliable methodologies that could diagnose multiple faults on a machine with initial applications in controlled environments at laboratory scale.

However, applying those methods to industry applications still represent an ongoing challenge due to the multiple limitations involved and the high reliability and robustness required. One of the most important challenges in the industrial sector refers to the management of unexpected events, in respect of how to detect new faults or anomalies in the machine. In addition, the information initially available of the monitored industrial machine is usually limited to the healthy condition, therefore is not only necessary to detect these new scenarios but also incorporate this information to the initial base knowledge. The industrial applicability is also troubled by two important factors, the availability of small number of measurements corresponding to unexpected conditions, since once a machine fault operation is detected immediate corrective actions are applied and, also, the need of accumulate knowledge, since all the characterized fault conditions along time can reappear during the remaining machinery useful life.

In this regard, this thesis presents a series of complementary methodologies that leads to the implementation of a fault detection and identification system capable to detect multiple faults and new scenarios of industrial electromechanical machines under an incremental learning framework to include the new scenarios detected to the initial base knowledge while achieving a high performance and generalization capabilities. Initially, a methodology to increase the performance of novelty detection models to detect unexpected events applied to electromechanical system is proposed. Next, a methodology to implement an enhanced sequential fault detection and identification system composed by a novelty detection and a fault diagnosis stages with high accuracy is proposed. Finally, two different methodologies are proposed to provide the sequential fault detection and identification system the capacity to include new scenarios to the base knowledge depending on the availability of database. The analysis and validation procedures have been carried out by means of experimental data from electromechanical systems, at laboratory scale, in order to identify the proposed methodology performances and, also, at industrial scale, in order to analyze the competency of the method under significant environmental conditions.

Keywords

Artificial Intelligence	*Feature Calculation*	*Feature Extraction*
Condition Monitoring	*Industrial Machines*	*Novelty Detection*
Fault Diagnosis	*Machine Learning*	*Incremental Learning Framework*

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Acronyms and their definitions

AI	Artificial Intelligence
ANN	Artificial Neural Networks
CA	Correspondence Analysis
CBM	Condition Based Maintenance
CPS	Cyber-Physical Systems
FTPC	Fault-Tolerant Process Control
GA	Genetic Algorithms
MoG	Mixture of Gaussians
NN	Neural Network
OEE	Overall Equipment Effectiveness
PDF	Probability Density Function
RUL	Remaining Useful Life
SME	Small Medium Enterprises
SOM	Self-Organizing Maps
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TTF	Time to Failure
ZDM	Zero-Defect Manufacturing
NTFM	Normalized Time Frequency Maps
OC-SVM	One-Class Support Vector Machine

1.

Introduction

This chapter outlines the basis on which this thesis research is engaged. It starts from the introduction to the research topic and current limitations, to the objectives and the hypotheses of this thesis research. This chapter includes also a brief description of the content in the subsequent chapters.

CONTENTS:

1. Introduction

1.1 Research topic

Over the last five years, pushed by the global industrial competition and market demands, the industrial processes, affected by the global economic crisis, have include into their objectives the increase of reliability, effectiveness, accuracy and robustness of their manufacturing assets [1]. Indeed, the related industrial machinery has undergone a series of updates to increase manufacturing ratios and decrease machinery life costs. Hence, a more competitive product. This evolution has been possible due to advances in different engineering fields such mechanics and robotics, but also electronics, instrumentation and signal processing among others.

Thus, taking into account the current industrial scenario, unscheduled machinery stoppages represents a critical issue, leading to a loss of productive efficiency. Indeed, **the increase of manufacturing assets efficiency** is, currently, a research and technologic trending objective in which a great deal of resources is being considered, supported by governmental and private initiatives. In this regard, it is emphasized by the European Union small-medium enterprises report 2015/2016 [2], that the SME industries involved in the manufacturing sector reach around 60-70% of Overall Equipment Effectiveness (OEE), of all plant equipment, due to poor plant performance. The OEE is the standard for measuring manufacturing productivity. Simply put, it identifies the percentage of manufacturing time that is truly productive. An OEE score of 100% means that only ”good parts” are being manufactured, as fast as expected, with no ”stop time”, which are related to maintenance actions. This fact has a direct impact on production and, therefore, in the economic performance. In order to address such current industrial sector demands, scientific and technological efforts must be done toward a more efficient and more reliable **machinery monitoring systems**.

In this regard, the Condition Based Maintenance (CBM), has become accepted since a decade ago by the industry as a key factor to avoiding expensive unplanned machine stoppages and reaching high production ratios. The CBM is a program that recommends actions based on the information collected and interpreted through condition monitoring [3]. Thus, by means of CBM strategies, the maintenance actions can be carried out optimally, that is, considering the actual condition of the machine under monitoring.

Several machinery monitoring approaches for condition based monitoring have been proposed in the literature, which can be generally categorized into model-based fault diagnosis, signal-based fault diagnosis and knowledge-based fault diagnosis [4], [5]. For model-based approaches, a system model, which explicitly describes the relationship among the system physical signals, is available to the expert. Based on the model, fault diagnosis schemes can be designed and, then, implemented on-line for monitoring and diagnosing the real-time system [6]. A significant study of such approach was presented by Gadsden *et al.* in 2013 [7], where two interacting multiple model strategy is presented to monitor different operating modes of an electro-hydrostatic actuator. The proposed approach is compared with popular modelling approaches, such as the extended Kalman filter, showing significant improvement over classical approaches. For signal-based methods, specific signal patterns of a system are characterized, and the fault diagnosis is carried out by checking the consistency between the signal patterns and the signal symptom of the real-time process [8]. Ghorbanian and Faiz in 2015 [9], propose three different analysis procedures to detect rotor broken bars by means of the time, frequency or time-frequency domain analysis. The capability of the proposed fault indicators and classical approaches are studied deeply in order to investigate their applicability at different conditions. Other important contributions in this approach are also the studies that include the fusion of specific signal patterns from different physical magnitudes. Tran *et al.* [10], and Li *et al.* [11] present approaches where information from different physical magnitudes (current, vibration and acoustic signals) are analyzed in different domains (time, frequency and time-frequency), to extract specific patterns from the monitored machine (gearbox or induction motor) to diagnose different faults. Knowledge-based fault diagnosis methods start from where a large volume of historic data is available. Applying a variety of artificial intelligent techniques to the available historic data of the industrial processes, the underlying knowledge, which implicitly represents the dependence of the system variables, can be extracted. The consistency between the observed behavior of the operating system and the knowledge base is, then, checked, leading to a fault diagnosis decision with the aid of a classification algorithm, as stated by X. Dai and Z. Gao in 2013 [12]. Related with electromechanical condition based monitoring, the work of Widodo *et al.* [13] introduces the main features of such approach by descripting a data-driven methodology based on a classifier to diagnose faults in different machine condition monitoring, for example: bearings, induction motors, machine tools, pumps, an stamping machine, etc. This work not only enlightens the generalization capability of data-driven approaches under different scenarios if enough stored information is available, but also makes emphasis on the relatively easy implementation compared to the signal based and model based approaches.

Among the proposed approaches, **knowledge-based fault diagnosis**, which is also known as data-driven fault diagnosis, has gained increased attention because the high performance and widen range of applicability due to less restrictive constrains than the other fault diagnosis approaches. A knowledge-based condition based monitoring program consists of five key stages as shown in **Fig. 1.1.1**, data acquisition, data processing and condition assessment.

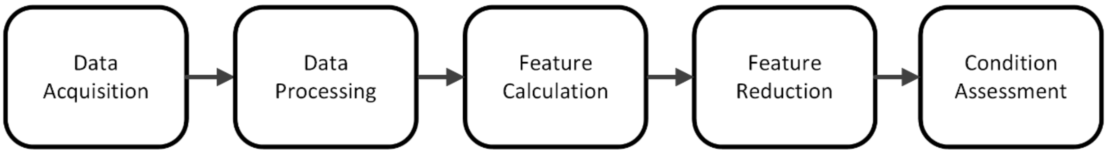

Fig. 1.1.1 Five main stages in a knowledge-based CBM program to facilitate the maintenance decision making.

Data acquisition considers collecting and storing digitalized data from different sources of the monitored asset, i.e. information of sensors connected to the machine or process to be monitored. Data processing consists of a series of procedures to manipulate and transform the data acquired to characterize the physical magnitudes acquired. Apart from filtering, formatting, etc., this stage also includes the analysis of the data in time-domain, frequency-domain and/or time-frequency-domain. After the data is processed, in the next stage, a set of numerical features from the identified relevant domains are calculated, then, in the following stage, the set of numerical features are reduced, by means of feature reduction approaches, to highlight specific characteristics/patterns from the feature set.

Condition assessment consist on analyzing the acquired and subsequent processed data to determinate the condition of the monitored asset. Techniques for condition assessment in a CBM program consist of fault diagnosis approaches, which are capable of identifying the condition of the machine among several scenarios that are known beforehand.

An early approach implementing a CBM program to detect faults on machinery was applied in **electromechanical machinery,** that is, machinery based on an electric motor, and coupled to screws, external bearings and/or gearboxes among others. The initial challenges focused on analyzing and characterizing individual faults, which led to the development of strategies to increase the robustness of the machines for specific operating scenarios [14]. As the topic has been gaining attention in the research community, an increase of effort is been made to develop algorithms, methods and strategies that could **diagnose multiple faults on a machine** [15]. Thus, different CBM schemes are being tested but, mainly, on controlled environments, carrying out a complete characterization of the healthy operation modes and different controlled faults [1]. Indeed, regarding the **industrial applicability** of such method, the complete characterization of all possible operating scenarios, that is, different operating modes of speed and torque under multiple fault conditions, is not feasible. The technical difficulties and, in most situations, the impossibility to modify the machine working regime, makes mandatory the management of novel operating scenarios during the CBM strategy.

Indeed, this challenge leads to the consideration of a specific research framework, the **novelty detection**. Novelty detection focus on the development of algorithmic capable of detecting if the behavior of a monitored system differs, in some respect, from the one considered during the initial CBM design [16]. The incorporation of novelty detection capabilities to classical CBM strategies represents a highly impacting solution to cope with the challenges of current industrial applications. Thus, providing the capability of **diagnose the condition of the machinery under monitoring among a set of previously known conditions, but including the identification capabilities of novel operating scenarios.**

A CBM scheme with such capabilities is known as a **Fault Detection and Identification System** (FDI). The development of fault detection and identification systems widens the applicability of CBM strategies and represents one step beyond current diagnosis capabilities, closer to the industry sector demands. Nevertheless, even if trough FDI systems additional levels of CBM reliability and robustness can be reached, the novel operating scenarios identified must be considered for continuous learning, that is, an adaptive CBM to the machinery under monitoring. To cope with this fact a new framework has been recently considered by the related research community, the **incremental learning framework**, in which different improvements and adaptions of the classical methods, algorithms and techniques are developed to provide the capability to add new operating scenarios to the considered knowledge [17].

The integration of such trending subjects around industrial electromechanical system diagnosis define the research topic in which this thesis is carried out: **fault detection and identification methodology under an incremental learning framework applied to industrial electromechanical systems**.

1.2 Research problem

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

Classical CBM methodologies consist on using a classification algorithm to determine the machine condition [18]. This algorithm is, previously, trained with representative data of different operating scenarios of the machinery (under availability). During the evaluation of a new measurement acquired from the system under inspection, the algorithm analyses the signature of the physical magnitudes, and outputs a label as result of the association with one of the different operating modes of the machine learned during the training process. This approach is known as fault diagnosis or fault identification [1]. Important examples of such approach were presented by Seshadrinath *et al.* in 2013 [19], and Toma *et al.* in 2014 [20], where the condition assessment of an induction machine are performed by neural networks previously trained by a dataset composed by measurements of the machine working in healthy and faulty conditions. However, generally, if a new measurement, corresponding to a condition not presented during the training is evaluated by the algorithm, the label output can only be one of the scenarios presented on the training and, therefore, leading to an incorrect diagnosis.

To provide the CBM scheme the capacity to deal with insufficient information, the detection of novel scenarios represents a first step to cope with the demands of high-performing industrial applications. In this regard, specific research is been doing towards strategies able to monitor the system and detect new operating scenarios, thereby avoiding an incorrect assessment of the condition of the machine. As aforementioned, this research topic is called novelty detection, and can be defined as the task of recognizing that the data under analysis during the diagnosis procedure differ, in some respect, from the available data during the training, that is, the detection of new operating scenarios [21]. Its practical importance and challenging nature have led to many approaches being proposed. These methods are typically applied to datasets in which a very large number of examples of the “normal”, or nominal, condition are available, and where there are insufficient or unavailable data to describe “abnormal”, or new, operating scenarios, due to faults or modifications over the operating set points [22].

The application of novelty detection to electromechanical system monitoring is not simple, there are many conditions that limit the applicability of these algorithms in this application domain. Novelty detection was initially applied on image processing, video surveillance, text mining and network intrusion, where a large amount of data is available to characterize the monitored asset [23]. However, in industrial applications of electromechanical systems, the number of measurements available to characterize the machine is usually limited, that is, in front of a fault condition, the maintenance actions are rapidly applied or even the related machinery is stopped. This fact implies the capture of, generally, initial fault or operating deviation stages under a short period of time. Therefore, **novelty detection approaches, capable of deal with reduced number of samples per condition**, are required.

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

Taking in consideration that the number of adequate algorithms to perform novelty detection in this application domain are limited and that the numerical features and signal processing strategies proposed in the literature to characterize an electromechanical system are mainly focused on the fault diagnosis task, the reliability and robustness of the novelty detection task is a challenging research problem. Indeed, all of these requirements lead to new questions that the state of the art is currently addressing:

- **What signal processing and numerical features estimation procedures are most suitable for novelty detection?, furthermore, Is the optimum feature set dependent of the available operating scenarios?**

- **How to obtain a reliable performance from the novelty detection?, moreover, Is the resulting novelty detection stage robust enough?**

- **What novelty detection approach is appropriate considering electromechanical systems?**

The combination of the novelty detection with the fault diagnosis is not trivial and not properly addressed around electromechanical CBM schemes to date. On the literature, systems capable to perform novelty detection and fault diagnosis are known as fault detection and identification systems, and the concept have been already presented in some applications such as network intrusion detection and industrial plant monitoring among others [22]. Nevertheless, their implementation to electromechanical systems in industrial applications still present some problems that need to be addressed. Classical approaches propose the execution of both tasks in one single stage, performing novelty detection and fault detection with one algorithm or an ensemble of the same algorithm, however, this approach, while easy to implement, leads to **limitations of detection and identification performances** [24] . Separating both stages not only opens the opportunity to analyze different features on each stage, but also limits the number of algorithms that can be used for each task. As mentioned above, the features analyzed for each task could represent a window of improvement to increase the applicability of these methodologies, but still some unanswered questions arise from such approach:

- **Should the novelty detection assessment be performed simultaneously or independently from the fault diagnosis?, even so, Is the same numerical feature set appropriate for both detection and identification tasks?**

- **Since the fault diagnosis stage is not reliable under the presence of new scenarios, How does the result of the novelty detection stage and the fault diagnosis can be combined if they are implemented independently?, Does the novelty detection stage affects the performance of the diagnosis stage?**

The reliability and robustness of a FDI system to be implemented over an electromechanical system can be improved by addressing the previous questions, nevertheless, a static framework is being considered currently [25]. That is, the incursion of new operating scenarios once identified, to the novelty detection or the fault diagnosis stages is not considered. As mentioned before, in industrial applications the initial information available corresponds, generally, only to the nominal operating scenario, therefore, **fault detection and identification methodologies capable to include new scenarios under automatic or semi-automatic methodologies** is a required competency. Indeed, to work under an incremental learning framework, the algorithms for novelty detection and fault diagnosis in a FDI methodology must be capable to include new scenarios, this framework leads to a new series of challenges that represents an undergoing research problem. While adaptive or evolving algorithms for fault diagnosis is, recently, being considered in the research topic, performing novelty detection under an incremental learning framework is completely a new challenge, especially regarding the incorporation to the FDI system. The introduction of an incremental learning framework to the FDI systems lead to a new series of questions that the literature have not yet addressed:

- **What incremental learning strategies are more appropriate for the considered application domain?**

- **Are the novelty detection algorithms capable of detecting the underlying distribution to characterize a new scenario with a limited number of measurements per condition?**

- **How to manage the algorithms reconfiguration when new scenarios are included?**

In summary, although electromechanical condition based monitoring has been classically an active research field, currently, critical requirements are being expected from the industrial sector in regard with their application capabilities. In this regard, the scientific community is being doing an effort to study and define new contributions, where further research should be made in order to propose a coherent and viable **fault detection and identification methodology under an incremental learning framework for industrial electromechanical systems, capable of detect and incorporate new operating scenarios while providing a diagnosis about the available conditions.** It must be taken into consideration that this topic represents a modern research field and highly novel its application into electromechanical condition based monitoring framework, which implies the need of addressing all the aforementioned questions.

1.3 Hypotheses

Considering the state of the art in the corresponding topic, collected in the following chapter, and the identification of the current limitations and problems, the following hypotheses have been formulated as a starting point for this research work:

H1 The performance of the novelty detection task can be increased by including a signal processing and a feature calculation stages focused on extracting general information of the monitored asset. If several scenarios apart from the nominal condition are available, the consideration of features that contribute in the characterization of such conditions would improve the performance of the novelty detection task.

H2 In order to improve the reliability and robustness of the novelty detection task, the degree of novelty of a measurement can be estimated, providing more information over the novelty detection assessment. An uncertainty region in regard with the available data can be defined to reduce the false alarm ratio.

H3 Domain-based methods represent the most adequate solution for novelty detection considering the limitations presented in the application domain, mainly, the limited number of samples and non-connected data distribution clusters.

H4 A separate implementation of the novelty detection and fault diagnosis tasks allows an optimal selection of features for each task that will improve their individual performance. Moreover, the overall performance can be increased by initially performing a reliable novelty detection task that, in consequence, increases the performance of the fault diagnosis task.

H5 If a repository database is available where the monitored measurements are stored, domain-based and non-parametric statistical-based algorithms for novelty detection represent the most adequate choice in terms of flexibility incorporating new scenarios without analyzing the underlying distribution of the data corresponding to the new scenarios.

H6 If a repository database of the measurements is not available, an ensemble of domain-based algorithms for novelty detection and evolving classifiers for diagnosis represent the most adequate choice by providing an optimal trade-off between computational burden and accuracy.

H7 To include a new scenario, the addition of a specific model for that scenario for novelty detection and the addition of a representative prototype with a new fuzzy rule of the new scenario for fault diagnosis, represent the simplest solution with a competitive performance for the incursion of new classes to the base knowledge.

These exposed assumptions represent the basis of the resulting thesis research. The hypotheses are investigated by means of the research work reflected in this thesis document.

1.4 Aim and objectives

The aim of this proposed thesis is to progress in the state of the art of CBM applied to electromechanical machinery considering industrial requirements. This objective is approached by the development of novel methodologies and criteria to construct a fault detection and identification system capable to detect multiple known faults, identify novel operating modes and adapt itself according to the identification of the novelty scenario detected.

Thus, to successfully accomplish the thesis purpose, the following specific objectives are considered:

- **The research, proposal and validation of a suitable feature calculation and reduction scheme alongside with the selection of the most adequate algorithms to achieve a high reliability and robustness in novelty detection applied to electromechanical systems.**

- **The research, proposal and validation of an adaptive feature reduction scheme to increase the performance of the novelty detection task whenever a new scenario is incorporated.**

- **The research, proposal and validation of independent suitable feature calculation and feature reduction stages to increase the reliability and robustness of the novelty detection and the fault diagnosis tasks in a FDI system.**

- **The research, proposal and validation of a robust and reliable methodology for a FDI system to work under an incremental framework when a repository database is available.**

- **The research, proposal and validation of a robust and reliable methodology for a FDI system to work under an incremental framework when a repository database is not available.**

The research methodology carried out in this thesis includes the analysis and validation of the proposed contributions over electromechanical platforms. In this regard, four different experimental test benches are used in this work: two laboratory-scale test benches and two industrial-scale test benches.

The two laboratory test benches are used to test and validate the performances of the proposed methods over electromechanical systems under a controlled environment, which leads to an in-depth study and comparison of the proposed contributions with classical approaches presented in the literature. The first one is the PRONOSTIA experimental platform [26], which consist on an accelerated bearing degradation experiment and accelerometers signals recording. This test bench is open access and is often used by the research community, which allows an easy comparison of the methodologies proposed in this work with the methodologies proposed by other authors. The second laboratory-scale test bench consist of a regular kinematic chain composed by an induction motor coupled to a reduction gearbox, and a DC generator as a mechanical load. From this test bench, measurements from different fault conditions can be extracted, including a variable load, rotating speed configurations and fault scenarios. Vibrations and stator current signals are acquired from the experiments for posterior analysis.

The two industrial-scale experimental setups are used to test and validate the robustness and reliability of the methods under a relevant and challenging environment. Both test benches correspond to industrial electromechanical systems with non-traditional mechanisms for the specific industrial process performed, therefore the monitoring of such specialized mechanism in an electromechanical system have not been previously studied on the literature, which implies that there is no specific strategy to extract relevant features to characterize them. Also, the measurements extracted from those test benched were performed in an industrial environment, which means that the data is exposed to a certain risk of noise and uncertainty in the measurements. The first one is a complicated system present at numerous industrial machineries as the motor-gearbox-camshaft chain. The high-speed ratios, the mechanisms time-overlapping and the smoothing inertia effect make such systems a challenging application field for classical approaches. The test bench is composed by an induction motor connected to a reduction gearbox that rotates a camshaft to activate the mechanisms corresponding to the manufacturing process. The current signals from the induction motor are acquired to analyze the effects of the cam operations to the current. Different fault scenarios and abnormal conditions are available for the analysis.. The second one is an End-of-Line (EoL) test machine that takes part on an industrial process of the automotive sector. The machine under study performs a friction test over the manufactured parts (steering systems), and is composed by a servomotor, a gearbox, an encoder, a torque transducer and a pneumatic clamp to hold the intermediate shaft of the steering system. The torque signal of the friction test performed by the machine is acquired to assess the condition of the machine. Several 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. Additionally, a sliding malfunction is also provoked to have a set of tests corresponding to an abnormal behavior of the machine.

The details of these experimental test benches can be found in the Annex I of this thesis document.

1.5 Chapters' description

This thesis document has been divided into different stages, which are reflected in the chapters described below.

A literature review of previous works of novelty detection and fault diagnosis is presented in **Chapter 2**. In this chapter, the progress regarding novelty detection and the different algorithms proposed in the literature are analyzed. Then, preliminary works regarding the formulation of a fault detection and identification system are presented to identify and clarify the motivation behind this research. After that, initial approaches that work under an incremental learning framework in other application domains are presented. As a result, this chapter concludes with an explanation of the current limitations of the state of the art of these topics. Such limitations are addressed in the following chapters covering all the explained objectives.

In **Chapter 3**, a study regarding the required adaptation of novelty detection to industrial applications is presented. A multi-modal scheme is proposed where several novelty detection models analyze simultaneously the machine to increase the accuracy of the novel scenarios. A thorough study of the impact of the features used to detect anomalies in electromechanical systems is performed, multimodal and re-formulation methodologies are proposed.

The challenges of combining a novelty detection stage and a fault diagnosis stage are addressed in **Chapter 4**, where a methodology that performs both task separately is proposed. The proposed methodology presents a separate set of features for each task to increase the performance of the monitoring approach.

In **Chapter 5**, the challenges of a FDI system working under an incremental learning framework are addressed. A methodology capable to perform a CBM scheme when the initial information of the machine consist only of the healthy condition is proposed. Then, algorithms for novelty detection and fault diagnosis that can include new scenarios with and without needing a repository database for re-training are analyzed to formulate a FDI system capable of work under an incremental learning framework.

Although each chapter concludes with a partial conclusion focused on its respective topic, in **Chapter 6** the thesis work is analyzed from a general point of view, and the conclusions and contributions are collected.

Finally, the publications and collaborations resulting from the research work development are presented in **Chapter 7**.

2.

Novelty detection and Fault Diagnosis

State of the art

The different aspects related to an implementation of a fault detection and identification system in electromechanical systems, with special attention to the novelty detection task and the incremental learning framework, are reviewed to define the state of the art in the thesis research field.

CONTENTS:

2. Novelty detection and Fault diagnosis – State of the art

2.1 Introduction

During the last years, the data-driven approach in CBM program applied to electromechanical machine has carried out by means of a standard structure.

First, the acquisition of at least one physical magnitude to monitor the machine or the component is carried out. In this regard, some of the physical magnitudes monitored from an electromechanical system include the vibration, the current of the motor, acoustic emissions, temperature, etc. Among them, the vibrations and the current of the motor have been widely used and studied in the literature due to their capacity to reflect the condition of the machine and highlight certain type of faults [20], [27]–[29].

Second, a signal processing stage is applied to these physical magnitudes to gain resolution in the analysis. The analysis of raw physical magnitudes present some intrinsic limitations that complicate the identification of a faults in this application domain, therefore two common stages of data processing are applied, a first one to clean the raw signals and the second one to process the information to highlight certain type of faults in the machine. While the first one is a standard procedure to verify the consistency of the measurement, the second stage is key in order to ensure a high performance of the subsequent stages. Many techniques have been proposed in the literature to increase the resolution of what can be observed in a machine, and therefore, highlight certain fault patterns that were not evident in the raw signals. The physical magnitude can be represented on the time, frequency or time-frequency domains, and each one have their own advantage and disadvantages, a discussion among the characteristics of each approach is discussed later on this chapter.

After that, a set of features are extracted from the processed signals. Depending on the domain of the monitored signal, these features could consist of a statistical characterization, specific frequency bands or coefficients that characterize the properties of the signal. After a set of features is obtained, a feature reduction technique is applied to discard irrelevant features or to obtain a representative reduced set that properly represent the behavior of the signal. The feature calculation and reduction stage are critical in regard the performance of the whole condition based monitoring system. If the information analyzed from the machine doesn't reflect in a significant manner the faults on the machine the performance of the models would be drastically affected. Due to the significance of this stages, some of the most used feature calculation and reduction strategies are presented.

Finally, a classification algorithm is implemented to detect a concrete fault or one kind of fault in the system. There is a great deal of classifiers in the literature, and, after years of research, most of them represent a valuable option for this task. Among the most popular classifiers, the Artificial Neural Network stands out for its non-linear characterization of faults and the high performance presented [19], [20], [30].

As can be seen, the classical scheme of a CBM program only includes the detection of multiple faults, therefore the next step to enhance the monitoring capabilities is to include the capacity to detect anomalies by novelty detection models. Therefore, three groups of novelty detection models are presented in this chapter, alongside with the most relevant models of each family. Each group presents their own advantages and disadvantages, therefore, it is important to analyze them to properly select the most adequate model that facilitate the implementation to electromechanical systems.

The following step to enhance the CBM program consist on including the novelty detection model to the CBM program, which requires an analysis to identify which is the most appropriate strategy of incorporation to maximize the performance of both tasks. In this sense, the fault detection and identification systems presented on the literature are analyzed to evaluate the possible options among the proposed methodologies.

Once the fault detection and identification systems proposed in the literature are analyzed, the incremental learning framework is studied. The incorporation of new scenarios is just one part of such framework, which is the characteristic that is desired to incorporate to the CBM program, therefore, the analysis of the state of the art of this stage is limited to only models that are capable to perform such task.

2.1.1 Feature calculation

Feature calculation is an essential procedure in order to transform or process the information acquired from the physical variables. However, it is also one of the most difficult steps, mainly because the acquired data could contain irrelevant information and also be affected by external factors such as electrical noise. Appropriate features need to be identified from signals before they can be used for health assessment.

As mentioned before, features are extracted after the acquired signals of the machine after the data processing stage, which delimits the features that can be calculated. The acquired signals can be represented on the time, frequency or time-frequency domain.

Time domain techniques are more effective when the component is analyzed under stationary conditions, but are also helpful for some non-stationary conditions. Statistical features are usually calculated from this domain, and they provide basic information about the signal acquired such as signal shape, tendencies, frequency ranges, etc. It is the easiest way to process the acquired data, in order to have a first approach, due to their low computational cost. The time domain techniques include statistical and stochastic methods, data filtering techniques, time-synchronous average and others. The most used statistical features are shown in Table 2.I.1.

Table 2.1.1. Statistical features

Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n}(x_k)^2}$	**Eq. 2.1.1**
Shape Factor	$SF = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	**Eq. 2.1.2**
Crest Factor	$F = \frac{\max(x)}{RMS}$	**Eq. 2.1.3**
Skewness	$S_k = \frac{\sum_{k=1}^{n}(x_k - \bar{x})^3}{n\sigma^3}$	**Eq. 2.1.4**
Kurtosis	$k = \frac{\sum_{k=1}^{n}(x_k - \bar{x})^4}{n\sigma^4}$	**Eq. 2.1.5**

A Frequency-domain analysis is based, first, on the transformation of the acquired temporal array to the frequency-domain. The classical spectral analysis (by Fourier transform) allows the analysis of a temporal signal in terms of individual frequency components by computing the relative presence of each component. These techniques allow discovering spectral information hidden under the temporal form of the signal, but are not able to deal with non-stationary conditions. The main techniques are non-parametric methods such as Discrete

Fourier Transform, parametric models and high resolution methods. Usually, the features extracted from this domain consist on specific frequency bands that highlight a specific fault.

Time-Frequency domain analysis performs, simultaneously, time and frequency analysis, mainly useful in case of transients of speed in the machine, where FFT causes averaging mistakes as it has been shown before. The time and frequency resolutions are the main reasons to select a specific time-frequency technique. The major drawback is that these methods require a huge computational cost making them unavailable for dealing with big datasets. Statistical features can also be calculated in this domain with a proper segmentation of the time-frequency maps to obtain enough resolution. The main techniques are Short-Time Fourier Transform, Wavelet Transform, Discrete Wavelet Transform, Hilbert Huang Transform, Empirical Mode Decomposition, and others. Usually, the features extracted from this domain depend on the technique used, since each one has their own characteristics. Statistical features are also a popular choice in this domain.

Among the three approaches for signal processing, the time domain have been constantly used on recent works, since it represents an adequate tradeoff between simplicity of implementation, low computational cost and generalization capabilities, nevertheless, if the monitored machine requires a more thorough analysis, for example non-stationary process, then the other domains represent a more adequate solution.

2.1.2 Feature reduction

Working with high dimensional datasets complicates the learning task of novelty detection and fault diagnosis 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 [31].

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 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 [32]. 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 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 [33]. 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. A similar reduction approach to the LDA is the Fisher score selection [34], which also attempts to maximize the linear separation between data points belonging to different classes. The same criteria is used, with is to obtain the lowest within-class scatter and the largest between-class scatter, nevertheless, in comparison to the LDA that extract a linear mapping for a low-dimensional representation, this technique ranks the features available and select the most appropriate ones, with the restriction number given by the user.

Another feature reduction technique that could be performed in a unsupervised or supervised environment is the Laplacian Score [35] which is fundamentally based on the Laplacian Eigenmaps and Locality Preserving Projection [36]. The basic idea of LS is to evaluate the features according to their locality preserving power. The motivation for this technique is that, in many real world classification problems, data from the same class are often close to each other, therefore, by preserving the topology of the data a subset of features could be obtained to discriminate among the different scenario without overfitting the models.

The aforementioned linear feature reduction techniques exhibit different objectives (data variance preservation, topology preservation or data discrimination), and method of employment (unsupervised or supervised), and have been widely used in the literature with successful results [31], [37], [38], [34].

2.2 Novelty detection

Novelty detection can be defined as the task of recognizing that test data differ in some respect from the data that are available during training. Its practical importance and challenging nature have led to many approaches being proposed [23]. These methods are typically applied to datasets in which a large number of examples of the normal condition (operation modes available) is available and where there are insufficient data to describe anomalies (new operation modes or faults).

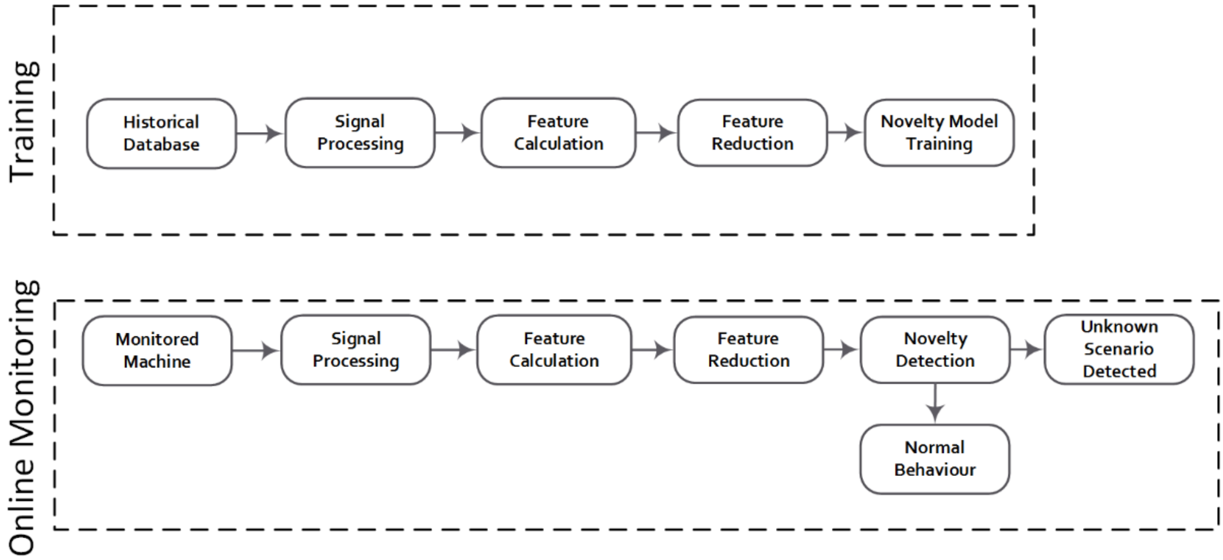

Fig. 2.2.1 Classical approach to implement a novelty detection model, including offline stage (Training) and Online stage (Continuous monitoring).

A classical step flow to implement novelty detection, as shown in **Fig. 2.2.1**Error! Reference source not found., starts with the processing of the information available (database) of the phenomena analyzed (feature calculation, reduction, etc.), then the novelty model is characterized with it, this part depend entirely of the model nature (training for classification, extraction of relevant statistical characteristics of the dataset, delimitation of boundaries, etc.), consequently the novel model will be able to analyze new acquisitions of the phenomena monitored and determinate if new data obtained correspond to the normal operation modes previously learned or detect if the new acquisition presents different characteristics and can be considered novel (detection of an outlier). The final step of the implementation of a novel model consist on a delimitation of a series of criteria to determinate the relevance of the novelty detected, reconfiguration criteria (if supported by the model selected), curse of action towards the monitored criteria (alarm activation in case the monitoring is for fault detection), label of a novel operation mode (if consequent acquisitions are detected with the same novel properties), etc.

An example of a novelty detection basic represented by a space delimited by two features is presented **Fig. 2.2.2**. The model is trained with a set of samples which led to a creation of a criteria to identify the normal operation modes, in this case a limitation of the space bounding a normal operation region; when new samples are acquired the novelty model analyses them and determinates, this time ruled by their position in the feature space, if they represent novel acquisitions or the behavior is still considered normal. If a significant amount of novel acquisitions with the same characteristics are detected, then a novel operation mode is detected and, depending on the application, an evaluation of the phenomena is required.

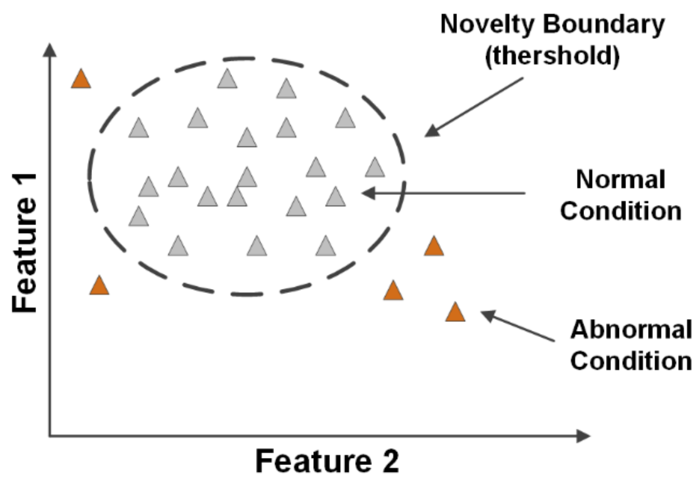

Fig. 2.2.2 Delimitation of a boundary by a novelty detection model.

Detecting novel events is an important ability of any signal classification scheme. Given the fact that we can never train a machine learning system on all possible object classes whose data the system is likely to encounter, it becomes important that it is able to differentiate between known and unknown object information during testing. It has been realized in practice by several studies that the novelty detection is an extremely challenging task. It is for this reason that there exist several models of novelty detection that have been shown to perform well on different data. It is clearly evident that there is no single best model for novelty detection and the success depends not only on the type of method used but also statistical properties of data handled.

2.2.1 Probabilistic methods

Probabilistic approaches to novelty detection are based on estimating the generative probability density function (PDF) of the data [39]. The resultant distribution may then be thresholded to define the boundaries of normality in the data space and test whether a test sample comes from the same distribution or not. Training data are assumed to be generated from some underlying probability distribution which can be estimated using the training data. This estimate usually represents a model of normality. A novelty threshold can then be set using the estimation in some manner, such that it has a probabilistic interpretation.

The estimation of some underlying data density from multivariate training data is a well-established field. Broadly, these techniques fall into parametric and non-parametric approaches, in which the former impose a restrictive model on the data, which results in a large bias when the model does not fit the data, while the latter set up a very flexible model by making fewer assumptions. The model grows in size to accommodate the complexity of the data, but this requires a large sample size for a reliable fit of all free parameters. Opinion in the literature is divided as to whether various techniques should be classified as parametric or non-parametric. For the purposes of providing a probabilistic estimate, Gaussian mixture models (GMMs) and kernel density estimators have proven popular. GMMs are typically classified as a parametric technique, because of the assumption that the data are generated from a weighted mixture of Gaussian distributions. Kernel density estimators are typically classified as a non-parametric technique as they are closely related to histogram methods, one of the earliest forms of non-parametric density estimation.

2.2.1.1 Gaussian mixture models

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities [40]. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in diverse applications. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation from a well-trained prior model.

A Gaussian mixture model is a weighted sum of M component Gaussian densities as given by the equation,

$$p(x \mid \lambda) = \sum_{i=1}^{M} w_i g(x \mid \mu_i, \textstyle\sum_i), \qquad \textbf{Eq. 2.2.1}$$

Where x is a D-dimensional continuous-valued data vector (i.e. measurement or features), w_i are the mixture weights, and $g(x \mid \mu_i, \sum_i)$ are the component Gaussian densities. Each component density is a D-variate Gaussian function of the form,

$$g(x \mid \mu_i, \textstyle\sum_i) = \dfrac{1}{(2\pi)^{D/2} \left| \sum_i \right|^{1/2}} \exp\left\{ -\dfrac{1}{2} (x - \mu_i)' \textstyle\sum_i^{-1} (x - \mu_i) \right\}, \qquad \textbf{Eq. 2.2.2}$$

with mean vector μ_i and covariance matrix $\sum_i$. The mixture weights satisfy the constraint that $\sum_{i=1}^{M} w_i = 1$. The complete Gaussian mixture model is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities. These parameters are collectively represented by the notation,

$$\lambda = \{ w_i, \mu_i, \textstyle\sum_i \} \quad i = 1, \ldots, M. \qquad \textbf{Eq. 2.2.3}$$

There are several variants on the GMM shown in **Eq. 2.2.2.3**. The covariance matrices, $\sum_i$, can be full rank or constrained to be diagonal. Additionally, parameters can be shared, or tied, among the Gaussian components, such as having a common covariance matrix for all components, The choice of model configuration (number of components, full or diagonal covariance matrices, and parameter tying) is often determined by the amount of data available for estimating the GMM parameters and how the GMM is used in a particular application.

In novelty detection applications GMMs estimate the probability density of the target class (here the normal class), given by a training set, typically using fewer kernels than the number of patterns in the training set. The parameters of the model may be estimated using maximum likelihood methods (via optimization algorithms such as conjugate gradients or expectation-maximization, EM) or via Bayesian methods. Mixture models, however, can suffer from the requirement of large numbers of training examples to estimate model parameters. A further limitation of parametric techniques is that the chosen functional form for the data distribution may not be a good model of the distribution that generates the data. However, GMMs have been used and explored in many studies for novelty detection.

One of the major issues in novelty detection is the selection of a suitable novelty threshold. Within a probabilistic approach, novelty scores can be defined using the unconditional probability distribution z(**x**)=p(**x**), and a typical approach to setting a novelty threshold *k* is to threshold this value; i.e., p(**x**)=k. This method has been used for novelty detection in several applications. However, because p(**x**) is a probability density function, a threshold on p(**x**) has no direct probabilistic interpretation. Some authors have interpreted the model output p(**x**) probabilistically, by considering the cumulative probability *P* associated with p(**x**); i.e., determining the probability mass obtained by numerically estimating the integral of p(**x**) over the region **R** for which the value of p(**x**) is above the novelty threshold *k*. For unimodal distributions, one can integrate from the mode of the probability density function to the probability contour defined by the novelty threshold p(**x**)=k, which can be achieved in closed form for most regular distributions.

2.2.1.2 Multivariate kernel density estimators

Multivariate kernel density estimations are flexible approaches to estimate the densities of a given data distribution on which no information is available on the type of the underlying distribution [23]. They are also referred to as Parzen windows or Parzen-Rosenblatt windows.

The approach of kernel density estimation has some similarities to histogram building. One of the main differences of the construction principles of the kernel density function to those of a histogram is that the density calculation is based on an interval placed around the observed value and not on an interval that is placed around a predefined bin center.

For multi-dimensional datasets, multivariate kernel density estimations are applied. Given a *d*-dimensional random vector $\mathbf{X} = (X_1, \dots, X_d)^T$ where $X_1, \dots, X_d$ are one-dimensional random variables, the vector $\mathbf{X}_i$ represents the *i*-th observation of the *d* variables: $\mathbf{X}_i = (X_{i1}, \dots, X_{id})$, where $i = 1, \dots, n$, and *n* correspond to the total number of observations. The variable X_{ij} is the *i*-th observation of the random variable X_j, where $j = 1, \dots, d$. The probability density function (*pdf*) of $\mathbf{X}$ is given by the joint *pdf* of the random variables $(X_1, \dots, X_d)^T$:

$$f(\mathbf{X}) = f(X_1, \dots, X_d) \qquad \textbf{Eq. 2.2.4}$$

The kernel functions are applied to the scaled distances, in a one-dimensional case: $u = (x - X_i)/h$, where h is the smoothing parameter called bandwidth and x is the currently analized observation. In the multivariate version, the bandwidth can be set individually for each distance $(x - X_i)$, obtaining a *d*-dimensional bandwidth: $\mathbf{h} = (h_1, \dots, h_d)$.

There are different approaches to form a multi-dimensional kernel $K(\mathbf{u}) = K(u_1, \dots, u_d)$, as an example is the multiplicative kernel: $K(\mathbf{u}) = K(u_1) \cdot \dots \cdot K(u_d)$.

Using this approach, the density estimator can be given as:

$$f_{\mathbf{h}}(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \left\{ \prod_{j=1}^{d} h_j^{-1} K\left(\frac{x_j - X_{ij}}{h_j} \right) \right\} \qquad \textbf{Eq. 2.2.5}$$

The *pdf* highly depends on the selection of the bandwidth parameter vector. Several approaches have been proposed in the literature on setting the bandwidths, such as Silverman's rule of thumb [23]. Another approach is to set the bandwidths through least squares cross-validation:

$$IMSE(h_j) = \int \left\{ f_{h_j}(x_j) - f(x_j) \right\} dx \qquad \textbf{Eq. 2.2.6}$$

By this approach, each bandwidth h_j is selected so to minimize the integrated mean square error between the estimated and actual distributions.

2.2.2 Domain-based methods

Domain-based methods require a boundary to be created based on the structure of the training dataset. These methods are typically insensitive to the specific sampling and density of the target class, because they describe the target class boundary, or the *domain*, and not the class density [41]. Class membership of unknown data is then determined by their location with respect to the boundary. As with two-class SVMs, novelty detection SVMs (most commonly termed "one-class SVMs" in the literature) determine the location of the novelty boundary using only those data that lie closest to it (in the transformed space); i.e., the support vectors. All other data from the training set (those that are not support vectors) are not considered when setting the novelty boundary. Hence, the distribution of data in the training set is not considered which is seen as "not solving a more general problem than is necessary".

SVMs are a popular technique for forming decision boundaries that separate data into different classes. The original SVM is a network that is ideally suited for binary pattern classification of data that are linearly separable. The SVM uses a hyperplane that maximizes the separating margin between two classes. The training points that lie near the boundary defining this separating margin are called *support vectors*. Since the introduction of the original idea, several modifications and improvements have been made. SVMs have been used for novelty detection in two related approaches described below.

2.2.2.1 Support Vector Data Description

A Data domain description method, inspired by the support vector machine, called the support vector data description (SVDD), also called support vector domain description, can be used for novelty or outlier detection [41]. A spherically shaped decision boundary around a set of objects is constructed by a set of support vectors describing the sphere boundary. It has the possibility of transforming the data to new feature spaces without much extra computational cost. By using the transformed data, this SVDD can obtain more flexible and more accurate data descriptions. The error of the first kind, the fraction of the training objects which will be rejected, can be estimated immediately from the description without the use of an independent test set, which makes this method data efficient.

The minimizing problem to delimitate the radius of the sphere is expressed as the Lagrangian:

$$L = \sum_i \alpha_i (x_i \cdot x_i) - \sum_{i,j} \alpha_i \alpha_j (x_i \cdot x_j) \qquad \textbf{Eq. 2.2.7}$$

Under the constraints of $0 \leq a_i \leq C, \sum a_i = 1$ Where a_{ij} are the Lagrange multipliers, x_{ij} are the data training points, the variable *C* gives the trade-off between simplicity (or volume of the sphere) and the number of errors (number of target objects rejected). For those objects the coefficients a_{ij} will be non-zero and are called the support objects.

The spherically shaped decision boundary is defined in its simpler way by:

$$(z-a)^T (z-a) \leq R^2 \qquad \textbf{Eq. 2.2.8}$$

To determine whether a test point *z* is within the sphere, the distance to the center of the sphere has to be calculated. A test object *z* is accepted when this distance is smaller than the radius, where a is the center of the sphere and *R* is the radius.

Expressing the center of the sphere in terms of the support vectors, objects are accepted when:

$$(z\cdot z)-2\sum_{i}\alpha_i(z\cdot x_i)+\sum_{i,j}\alpha_i\alpha_j(x_i\cdot x_j)\leq R^2 \qquad \textbf{Eq. 2.2.9}$$

Only these objects are needed in the description of the sphere. The radius R of the sphere can be obtained by calculating the distance from the center of the sphere to a support vector with a weight smaller than C. Kernels could be applied to soften the margins of the sphere.

Some extensions to the SVDD approach have recently been proposed to improve the margins of the hyperspherically shaped novelty boundary. The first extension is proposed in [42], where the authors present a "small sphere and large margin "approach that surrounds the normal data with a hypersphere such that the margin from any outliers to the hypersphere is maximized.

2.2.2.2 One-Class Support Vector Machine

OC-SVM was proposed by Schölkopf *et al.* [43], 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 $X=[x_i,\dots,x_N]^T\in R^{NxM}$, which denotes the normal data set, and $x_i, i=1,\dots,N$ denotes training samples (available measurements) characterized by *M* numerical features, then, in order to obtain the boundary, an optimization model is considered as follows

$$\min\left\{\frac{\|w\|^2}{2}+\frac{1}{Nv}\sum_{i=1}^{N}\xi_i-\rho\right\} \qquad \textbf{Eq. 2.2.10}$$

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

$$f(x)=w\cdot\Phi(x)-\rho \qquad \textbf{Eq. 2.2.11}$$

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

$$K(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right), \qquad \textbf{Eq. 2.2.12}$$

In order to solve the optimization problem, Lagrange multipliers $a_i\geq 0$ and $\beta_i\geq 0$ are introduced and the Lagrange equation is formed as

$$L(w,\xi,\rho,a,\beta)=\frac{\|w\|^2}{2}+\frac{1}{Nv}\sum_{i=1}^{N}\xi_i-\rho \qquad \textbf{Eq. 2.2.13}$$

$$-\sum_{i=1}^{N} a_i (w \cdot \Phi(x_i) - \rho + \xi_i) - \sum_{i=1}^{N} \beta_i \xi_i \qquad \textbf{Eq. 2.2.14}$$

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

$$w = \sum_{i=1}^{N} a_i \Phi(x_i) \qquad \textbf{Eq. 2.2.15}$$

$$a_i = \frac{1}{N\nu} - \beta_i \qquad \sum_{i=1}^{N} a_i = 1 \qquad \textbf{Eq. 2.2.16}$$

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

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

$$\text{subject to} \quad 0 \le a_i \le \frac{1}{N\nu} \qquad \sum_{i=1}^{N} a_i = 1 \qquad \textbf{Eq. 2.2.17}$$

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

$$H_{ij} = K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j) \qquad \textbf{Eq. 2.2.18}$$

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

$$\rho = \frac{1}{n_s} \sum_{i=1}^{n_s} \sum_{j=1}^{N} a_j a_i K(x_i, x_j) \qquad \textbf{Eq. 2.2.19}$$

where n_s is the number of support vectors.

2.2.3 Distance-based methods

Distance-based methods represents a novelty detection approach similar to that of estimating the PDF of data. Distance-based methods such as nearest neighbors or clustering are based on well-defined distance metrics to compute the distance, as similarity criteria, among data points.

Distance-based approaches do not require a priori knowledge of the data distribution and share some common assumptions with probabilistic approaches. Nearest neighbour-based techniques, however, rely on the existence of suitable distance metrics to establish the similarity between two data points, even in high-dimensional data spaces. Furthermore, most of them only identify novel data points globally and are not flexible enough to detect local novelty in data sets that have diverse densities and arbitrary shapes. Generally, in high-dimensional data sets it is computationally expensive to calculate the distance between data points and as a result these techniques lack scalability.

Probabilistic and distance-based approaches rely on similar assumptions. They attempt to characterise the area of the data space occupied by normal data, with test data being assigned a novelty score based on some sort of distance metric. These techniques require a distance measure computation between a pair of data points. These techniques, when applied to novelty detection, assume that the distance measure can discriminate between novel and normal data points.

2.2.3.1 Nearest neighbors

The main idea rear this technique is that the *normal* data is projected near their neighborhoods, while novelties will be projected far from their neighbors [44]. That is, considering an unknown data point *x*, this point is accepted as normal if the distance to its nearest neighbor *y*, in the training set is less than or equal to the distance from *y* to the nearest neighbor of *y* in the training set. Otherwise, *x* is considered as a novelty. Euclidian distance is the most popular choice for univariate and multivariate continuous attributes,

$$\|x - y\| = \sqrt{\sum_{i=1}^{D}(x_i - y_i)^2} \qquad \textbf{Eq. 2.2.20}$$

Several well-defined distance metrics to compute the distance (or similarity measure) between two data points can be used, which can broadly be divided into distance-based methods, such as the distance to the *k*-th nearest neighbor, and local density-based methods in which the distance to the average of the *k* nearest neighbours is considered [11].

2.2.4 Comparison and summary

In summary, novelty detection approaches differ on the assumptions made about the nature of the available data. Each approach exhibits its own advantages and disadvantages, and faces different challenges for complex datasets. Table 1 collects the main characteristics of the considered methods. Thus, probabilistic methods makes use of the distribution of the training data to determine the location of the novelty boundary. Domain-based methods determine the location of the novelty boundary using only those data that lie closest to it, and do not make any assumption about the data distribution. Distance-based methods require the definition of an appropriate distance measure for the given data.

Table 2.2.1. Summary of main characteristics of novelty detection approaches.

Method	Advantages	Disadvantages
Domain-Based *i.e. One-Class SVM*	Robust to labeled outliers in training by forcing them to lay outside the description. Robust to unlabeled outliers in training.	Several configuration parameters. Sensitive to the scaling of the feature values. Requires a minimum number of training.
Probabilistic, parametric *i.e. Gaussian mixture models*	Great advantage when a good probability distribution is assumed. Provides a more flexible density method.	Requires a large number of training samples to overcome the curse of dimensionality. The distribution of the data is assumed. Unlabeled outliers in training affects the estimation of the covariance matrix.
Probabilistic, non-parametric *i.e. Kernel density estimator*	Flexible density model. Possible configuration of the kernel width *h* on each feature direction. Low computational cost for training. The density estimation is only influenced locally.	Requires a large number of training samples to overcome the curse of dimensionality. Expensive computational cost for testing. Limited applicability of the method when large dataset in high dimensional feature spaces.
Distance Based i.e. *k*-NN	Rejects parts of the feature space which are within the target distribution. Lack of configuration parameters, besides *k*, therefore, it relies completely on the training samples.	Scale sensitive due to the use of distances in the evaluation of test objects. Performance affected when unlabeled outliers are presented in training. Sensitive to noise.

2.3 Fault detection and identification systems

In highly competitive industrial manufacturing sectors the evolution CBM systems requires the optimization of the industrial processes analytics and the interpretation of their operating condition [45], [46].

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 [11], [45], [47], [48], these approaches have demonstrated to be a reliable option as fault diagnosis strategies applied to electromechanical systems. However, the practical integration in the industry 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 [23], [49].

Nowadays, industry applications 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. A state of the art of these methodologies is discussed in the following subsections. *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 [22], [25], [50]–[53] 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* [54], 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 [55], where one one-class classifier is considered for each class [56], [57], [33], [58]. 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. The scheme of the classical approach can be seen in **Fig. 2.3.1**.

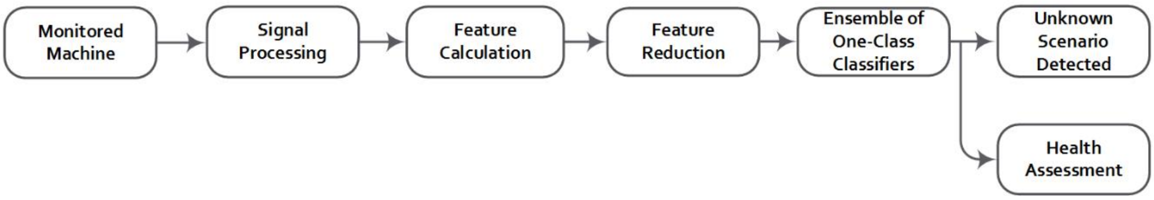

Fig. 2.3.1 Classical approach of a FDI system where the novelty detection and the fault diagnosis task are both performed by an ensemble of One-Class classifiers.

Lazzaretti *et al*. in [25], 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.

2.4 Incremental learning framework

Most of the related works available up to now in fault detection and identification systems, correspond to static approaches where the healthy and a set of fault conditions are previously characterized following a classical diagnosis approach, and uncorrelated events are detected and set apart [2]. Nevertheless, in most of industrial applications, just the nominal operating condition is available (the healthy condition), which, from one side, makes unfeasible a previous characterization of fault conditions and, from the other side, requires the proposal of adaptive CBM schemes capable of update its available knowledge and, then, its diagnosis capabilities.

Among the available works, stands out the proposed by Costa *et al.* in [53], where a two-stage methodology for real-time novelty detection and fault classification applied to an industrial plant is presented. Specifically, the initial novelty detection is supported by density analysis in the data space, and the classification stage is designed by the auto-class fuzzy-rule-based classifier. However, the advantage of such algorithms are based on their computational efficiency for on-line monitoring and adaptive capabilities to novel scenarios incorporation, rather than accuracy and generalization capabilities. Another disadvantage of the method presented is the need of sufficient samples to properly calculate the density of the data, such availability of measurements is proper from industrial monitoring applications but is not guaranteed to occur in electromechanical machines. The work also emphasize the need of an *ad hoc* signal processing, estimation of numerical indicators and feature reduction procedures for the specific plant under test.

Filev *et al*. in [50], propose an autonomous equipment monitoring and diagnosis framework, emphasizing the need of a generic structure that is relatively independent of the type of physical equipment under consideration. The results presented are promising but the algorithms are limited to the detection of two different types of faults, incipient or abrupt. Finally, Wang *et al.*, in [59], present a novelty detection scheme in order to improve the boundaries resulting from the characterization of a set of initially available data. The novelty detection presents increased capabilities to adapt the boundaries when new information is available, but the incorporation of new classes is not considered.

As can be seen most of the proposed approaches focus their contributions on the limitations presented on their respective application domain, being the computational complexity of the incremental learning framework and the continuous improvement of the training stage of the models their primary focus.

Indeed, an important limitation of classical approaches is that the possibility of incursion of new classes to the base knowledge is not considered. That is, traditional data-driven CBM methodologies face the knowledge increase by means of a batch scheme, where a complete retrain of the whole diagnostic model structure is carried out with the data combining the initial and new knowledge. However, storing all the measurements is not a desired solution and, moreover, the complexity of the retraining process is increased as the data is accumulated, which represents an unsustainable approach. As alternative, adaptive strategies for novelty detection are being proposed, first, ensemble-based, and second, incremental approaches [60]–[62]. The objective of both is to provide a more flexible option capable to work in on-line mode. That is, the advantages of these methods focus in lessen the computation efforts of the models, decrease the number of configuration parameters, and provide the capability to update the models without necessity of the base knowledge used for the initial training. Dealing with fault diagnosis, a third strategy is being also considered, the evolving approach. Indeed, considering the need of data labelling for diagnosis purposes, such evolving strategy offers the possibility of model growing while optimizing the global computational complexity.

Such adaptive approaches for novelty detection and fault diagnosis, however, present important restrictions regarding their application domain. The processing of the available signals and estimation of relevant features to analyze the machine condition can only be performed with information of the healthy condition. Therefore, the characterization process of faults to emphasize specific patterns is not an affordable option. A discussion of adaptive approaches for novelty detection and fault diagnosis to perform a FDI system under an incremental learning framework is performed in the following subsections.

2.4.1 Novelty detection under an incremental learning framework

In regard with the implementation of a novelty detection stage under an incremental learning framework, two strategies are considered mainly in the literature: incremental models and ensemble of one-class classifiers.

Incremental novelty detection models are commonly used in data streaming applications to cope with classical problems as the so called concept-drift, by including forgetting and adaptive capabilities to their structures [63]. For instance, Krawczyk *et al*., in [64], proposed an incremental one-class support vector machine based on a weighting matrix to adapt the knowledge' boundary to variations in the incoming data. This weighted approach lead to an improvement in classification of different data streams, especially with the presence of an incipient data drift. Similarly, Al-Behadili *et al.*, in [17], proposed an incremental parzen window kernel density estimator to address also the data drift problem. This approach obtained better results than the standard Support Vector Data Description (SVDD), nevertheless, to keep it computational efficient the user needs to define an initial number of clusters, in this case applying *k*-means algorithm, for each class. Indeed, most of the studied incremental approaches are developed to adapt models to current conditions of the monitored system, which means that past knowledge is considered obsolete and discarded [64].

The ensemble of one-class classifiers is the other main alternative based on training one novelty detection model for each available new data set, combining later the outputs to determinate if the measurement under analysis corresponds to *known* condition or differs in some aspect from the available knowledge. In this sense, the work presented by Lazzaretti *et al.*, in [25], presents an ensemble of one-class classifiers to perform an automatic classification of voltage waveforms in electrical distribution networks. In such work, there is no clear division between the novelty detection and the fault diagnosis stages, therefore, both tasks are performed by an ensemble of Support Vector Data Descriptions (SVDD). Like most of the works dealing with novelty detection, the incursion of novel information is not faced; nevertheless, the method allows the addition of new SVDD models if data regarding a new type of fault is available.

2.4.2 Fault diagnosis under an incremental learning framework

Regarding fault diagnosis, the same both discussed strategies are also applicable with their respective modifications. Indeed, there is considerable literature on incremental learning and ensemble-based classifiers, and most of the characteristics discussed in the novelty detection side applies also for fault diagnosis [65]–[69]. Indeed, incremental and ensemble approaches have their variants for multi-class classification problem, mainly, the incremental Support Vector Machine (SVM) [70], and the ensemble of SVM classifiers [71], respectively. Other proposed models for incremental or ensemble fault diagnosis include an incremental version of probabilistic neural network (PNN) [72], a combination of discriminant analysis (DA) and principal component analysis (PCA) [73], decision trees based techniques [74], AdaBoost [75], Bagging [76] or Learn++ [66], among others. The differences and characteristics of the aforementioned incremental or ensemble models are focused on the classification accuracy improvement by modifying the training procedure, basically, adding robustness to outliers and improving the rules regarding the number of classifiers used in the ensemble-based scheme. It is important to note that, in general, such methods work under a supervised or semi-supervised environment, where the labeling process of a new data set as well as the model tuning is carried out manually and off-line.

However, as it has been aforementioned, dealing with fault diagnosis purposes, the evolving strategy is being considered as a superior adaptive approach in multiple studies [62]. For instance, in [53], an evolving approach is used for fault detection and identification. For novelty detection, the Recursive Density Estimation (RDE) calculation is used to detect outliers, meanwhile for fault identification an unsupervised evolving classifier AutoClass is used. Indeed, the fault diagnosis stage requires the consideration of a more complex data boundary structure. Unlike novelty detection problem, where a binary scenario is considered, the fault diagnosis applied to electromechanical system requires the consideration of a multi-fault scenario.

A family of fuzzy-rule based evolving classifiers have been used in recent works, as for example in [77], based on eClass algorithms, in [78], based on simpleClass, or in [53], based on AutoClass. All of them provide an evolving and online solution for fault diagnosis under low-computational cost requirements.

eClass0 and eClass1, are two well-known and used evolving classifiers. Both approaches are Fuzzy-Rule-Based (FRB) and work under an online unsupervised framework. A set of prototypes (focal points) are selected from the stream of data with a Gaussian membership function to generate the corresponding fuzzy rules. A set of measurements, like the potential and age of the prototypes, are determined to change the fuzzy rules in case new measurements are available for re-training. Their architecture is different regarding the actions performed when a new measurement is evaluated after the activation of the rules; while eClass0 follows the typical construct of an FRB classifier with class labels as direct output, the eClass1 regresses over the feature vector using first-order multiple-input-multiple-output evolving Takagi-Sugeno (MIMO-eTS) models (MISO is also possible for two-class problems9i) and the normalized outputs per rule can be interpreted as the possibility of the data sample belonging to a certain class. It is important to stress that both methods are capable of including new classes as new information is presented and automatically tune the dynamically adapting parameters to define the classification boundaries for each class. A specific discussion about advantages and disadvantages of these methods can be found in [62], [77].

2.4.3 Comparison and summary

Incremental models are mainly applied within big data analytics, where a great deal of continuous data is available. The performance of such approach over electromechanical systems may be limited, considering the low inertia of multiple wear based faults and the necessity of multi-fault patterns recognition.

In general terms, the use of an ensemble of one-class classifiers provides more design flexibility in comparison of the incremental based models. That is, dealing with an ensemble-based approach, a new model can be created when a new data set is detected; therefore, there is no loss of previous knowledge because it is retained within the set of models. In this sense, the discard of knowledge is user-dependent, by selecting the specific model to remove. Moreover, any novelty detection technique can be used to be part of an ensemble-based scheme. In this sense, dealing with electromechanical condition monitoring, where relative small sets of training data are usually available, a suitable option are the domain-based approaches One-Class Support Vector Machine (OC-SVM) or Support Vector Data Description (SVDD). For example, in [79], a method using SVDD is used to deal with an unbalanced and small sampled dataset for rotor severity classification. Dealing with ensemble approaches, some disadvantages are present as well, for instance, the necessity of an offline training stage for each new model. This fact requires that a representative set of data must be identified and temporally stored to train manually the corresponding new model.

Regarding fault diagnosis approaches, the conclusions of some studies suggest that the computational complexity of an ensemble-based approach for diagnosis can lead to unfordable structures after different adaptions to new data sets. Evolving strategies, however, allow the possibility of modify the structure of a unique model in function of the different boundaries to be considered. Indeed, this evolving strategy avoids the risk of a complex ensemble-based fault diagnosis structure, in which the relations among the multiple models must be defined manually depending on their labels.

3.

Novelty Detection

The incursion of novelty detection to CBM schemes represents the first step into this thesis research. In this regard, this chapter presents three contributions to increase the novelty detection accuracy and robustness by specific methodologies based on enhanced selection and reduction of features for this task.

CONTENTS:

3. Novelty Detection

3.1 Introduction

In the past chapter, an overview regarding the classical approach to perform novelty detection was described. Two key components from the novelty detection task can be improved to increase the reliability and robustness of the novelty detection task: the first one is the novelty detection model used and the second one is the feature calculation and reduction stage.

In the literature review, most of the related works focus on the improvement of the novelty detection model by proposing different strategies to detect anomalies or proposing improvements over the structure of the established models. For example, S. Wang et al. [59] propose a parameter optimization estimation scheme to reduce the false alarm rate and increase the detection accuracy for the support vector data description model in tapered roller bearings. Also, S. Ma et al. [80] propose a novelty detection approach based on assigning threshold in extreme value distributions to reduce the uncertainty in vibration signals from rotating machinery. In the same direction, M. Wong *et al.* [81], propose a modification to the self-organizing map for automated novelty detection in vibration signals by adopting multidimensional dissimilarity measure.

From the state of the art, it can be seen that, by modifying a specific novelty detection model, the novelty detection task can be successfully performed in a specific electromechanical system under some circumstances that were initially disadvantageous to this model. This is a valuable contribution to the state of the art in novelty detection, nevertheless, modifying a novelty detection model to make it viable for a specific task is not an approach that would lead to a generalized implementation. Indeed, one of the objectives of this thesis is to provide high reliability and robustness to the novelty detection task in electromechanical machines and, to accomplish this, a more generalized solution is necessary rather than the formulation of a model for each limitation encountered in order to improve novelty detection capabilities in front of unexpected conditions.

Being aware of the characteristics of the challenges presented in the electromechanical systems, two novelty detection models are selected in this thesis to be employed as the basis of the improved solution for electromechanical systems in terms of detection capabilities, the One-Class Support vector machine (OC-SVM) and the multivariate kernel density estimators (MKDE). As analyzed in the state of the art, these models provide advantages that ease the implementation of novelty detection models in this application domain, nevertheless the performance obtained from these models alone is not enough to reach the industrial demands.

It is well known that the performance of the novelty detection models are strictly dependent of the quality of the features calculated; if the features analyzed are not representative enough to characterize the machine, any novelty detection model won't be able to detect the new scenarios. In this sense, a study and proposal of a suitable feature calculation and reduction stages for the novelty detection task appears to be a more performing solution to obtain high reliability and robustness ratios. Therefore, in this chapter, a series of contributions are proposed in the feature calculation and reduction stages to increase the robustness and reliability of the novelty detection task.

3.2 Feature calculation and reduction for novelty detection in electromechanical systems

In order to accomplish with the practical requirements of an industrial implementation, some considerations must to be taken into account. Unexpected events, in the form of not considered fault scenarios or deviations over the normal operation will take place during the useful life of the machinery. These situations must be identified in order to avoid misclassifications and allow the learning of new scenarios. Due to its practical importance, many approaches have been proposed to detect anomalies. However, taking into consideration the unknown characteristics of the unexpected scenarios, a critical stage is the design of the feature space in which the measurements are projected. Indeed, the set of features not only have influence over *what we see* from the system, but also over *how we see it*.

In the following subsections three different methodologies regarding the selection of the feature space for novelty detection in electromechanical systems are proposed.

The first one correspond to an analysis regarding the limitations of novelty detection in a continuous degradation environment, which is performed via the implementation of novelty detection algorithms to a run to failure experiment. The ideal characteristics of the features commonly used in this type of experiments involve a continuous evolution over time that reflects the degradation of the analyzed component, therefore it is an ideal situation to evaluate how sensitive are the novelty detection models in the presence of variations over a set of features.

The second one is a multi-modal scheme to increase the resolution of the novelty detection task by monitoring different aspects of the machine simultaneously. This is accomplished by calculating several sets of features and incorporating a single novelty model for each one working in parallel instead of overfitting a single model with a very high number of features.

The third one is a methodology to reformulate the features each time a new scenario is incorporated to the base knowledge of the model. The appearance of new scenarios during the monitored fault can provide information that could improve the characterization of the monitored machine. In this methodology, the information provided from these new scenarios is exploited by continuously changing the selection of features for a more appropriate set each time new information is available.

3.2.1 Remaining Useful Life time estimation by means of novelty detection models

One of the bases of an effective CBM strategy is the accurate assessment of machine component condition. A common strategy involves obtaining the condition profile of the component to be monitored by the acquisition of some significant physical magnitude and, then the remaining useful life (RUL) time of the component could be identified or predicted. In this case, the RUL is defined as a percentage indicating the condition of the component according the remaining life-time of the component. The RUL is commonly used to estimate the degradation of components used in electromechanical systems. The value of the RUL would be 100% at the start of the experiment and decrease linearly to 0% at the end of the useful life, which implies the component is no longer functional. A graphical explanation of the RUL interpretation is shown in **Fig. 3.2.1**.

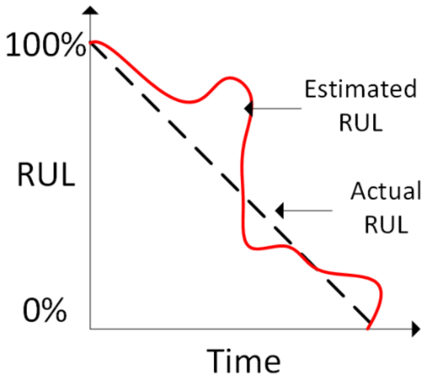

Fig. 3.2.1 Definition of RUL of electromechanical components. The time axis represent the duration of the experiment until the component is no functional.

Numerous methods can be used to determinate the RUL's value with promising results. These methods can be classified into two principal approaches: model-based and data-driven. Model-based uses mathematical models to represent bearing dynamic behavior and degradation phenomenon. One drawback of these methods is that you must have a reliable physical model for the fault degradation. For most real-life signals and systems, a reliable physical model for the degradation process is not available. The data-driven approach uses measured data extracted from the sensor as source for getting a better understanding of the monitored component.

In data-driven methods, a set of numerical feature are calculated and a feature reduction technique is often used to discard unnecessary features and obtain a better representation of the data, aiming to obtain a data distribution where the current state of the monitored component could be clearly identified. Then, a classifier is trained with the degradation profile, in order to identify the corresponding percentage of degradation of the component at the current moment. As in other data-driven based methodologies, some these methods still lack of generalization capabilities to estimate the RUL with test sets that are different from the training set, or rely on feature reduction techniques that does not exploit the appropriate characteristics to estimate the RUL.

Due to the nature of novelty detection to characterize in the feature space with a certain degree of tolerance, the applicability of these models represent a viable option to provide the traditional data-driven RUL estimation methodologies an alternative with more generalization capabilities, particularly the OC-SVM model.

The general idea for developing this methodology is to focus on the intrinsic characteristics of the phenomenon studied, and select an appropriate set of features to characterize it, then, implement a model with significant generalization capabilities to estimate the degradation for different cases and calibrate the output to obtain a desired parameter or characteristic, in this case, the remaining useful life. **Fig. 3.2.2** shows a scheme of the proposed methodology.

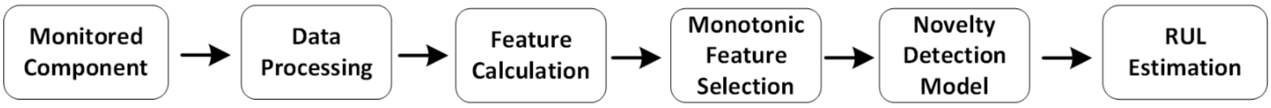

Fig. 3.2.2 Proposed scheme to estimate the RUL by means of novelty detection models.

The proposed scheme begins with the traditional data processing and feature calculation stages to characterize the monitored component. The monotonic feature selection stage extract relevant features that highlights the component degradation profile. This fact allows a better management of the physical behavior of the component under monitoring, from the numerical feature selection point of view. Next, the features selected are analyzed by a novelty model to characterize the degradation profile of the monitored component. Finally, the outputs of the novelty model are calibrated to directly estimate the RUL.

Case Study: RUL estimation of Ball Bearings by Means of Monotonic Score calibration and Novelty detection

To validate the proposed scheme, the RUL estimation methodology is applied to the PRONOSTIA experimental platform, which consist on an accelerated bearing degradation experiment and accelerometers signals recording. A more in-depth description of the PRONOSTIA test bench can be found in **Annex II**. The proposed methodology is shown in **Fig. 3.2.3**.

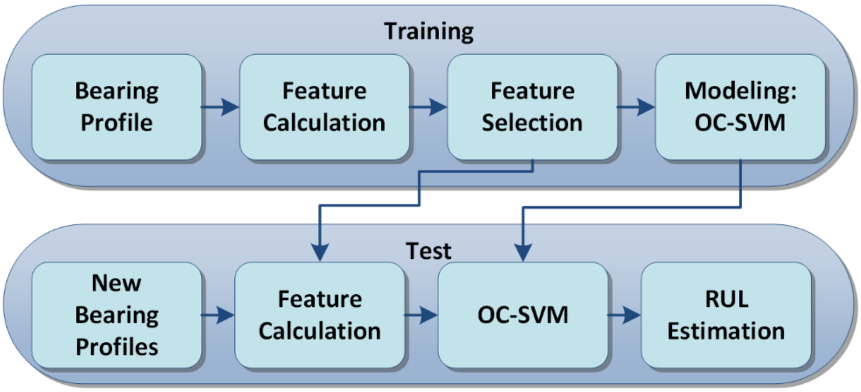

Fig. 3.2.3 Proposed methodology for RUL estimation. A bearing degradation profile is used to identify the relevant features and training the OC-SVM, then different bearing degradation profiles are used to test the methodology.

The presented methodology is divided in training phase and test phase. On the training phase, only a representative set of a bearing degradation profile is used, this will be called training set. The objective of this phase is to train a model capable to estimate the RUL of the bearing profile used as training set with enough generalization to accurately estimate the RUL on different testing sets.

Previous to the model training, a feature calculation step is required, which is an essential procedure in order to characterize each measurement and highlight the degradation patterns. Numerical features can be calculated by using different signal processing methods based on time-domain, frequency-domain and/or time-frequency-domain.

Taking into consideration practical industrial applications, usually, the electromechanical system works under specific stationary conditions among its useful life, this condition allows the use of time domain features as condition indicators for the characterization of the degradation, which is the domain used in this work. Among the possible choices, it is possible to distinguish the maximum value, the Root Mean Square (RMS), the variance and the kurtosis as general physical magnitude descriptors used in different applications.

Once the feature calculation stage is done, and a set of features is obtained for each measurement, a feature selection stage is introduced. Feature selection is an important step in the fields of pattern recognition and data mining technology. It identifies a meaningful feature subset, *k*-feature set, from the original one *q*-feature set, where *q*>*k*, by removing redundant or non-significant information. This dimensionality reduction allows reducing the training complexity, while simplifying the classification space.

An important part of this methodology is the criteria to make the feature selection. Based on the assumption that a feature that monotonically increases over time is the ideal degradation signal, *Spearman*'s rank correlation coefficient was used to assess how strong the monotonic relationship was between the set of features calculated and the time duration of the experiment.

Spearman coefficient is a non-parametric measure of statistical dependence between two observational stochastic sequences. It assesses the relationship among the sequences in which the coefficient can be depicted using a monotonic function as:

$$\rho_s = 1 - \frac{6\sum d^2}{n(n^2-1)} \qquad \textbf{Eq. 3.2.1}$$

Where ρ_i denotes the Spearman Rank correlation coefficient, d is the difference between the sequences, and n is the number of the sequences. Basically, a high Spearman coefficient of the feature analyzed will imply a strong monotonic relationship of the feature and the time duration of the experiment, which is the ideal case for estimating the RUL. Under this criterion the two features with highest coefficient ranking will be selected to characterize the degradation profile.

It must be noticed that the capability of the model to estimate the RUL of the bearing will be directly related to the monotonic relationship over time of the features selected, which will be assessed with the Spearman coefficient.

Once the feature set is reduced, a model is trained. In this case OC-SVM with calibrated output is selected. OC-SVM is usually used for one class classification problems, but with calibration of the classification score (output), the classifier could be employed to characterize an incremental degradation profile on the feature space with generalization capacities, which means, it will detect increment in all axis of the feature space.

It is important to stress that common classification algorithms delimit the feature space for classification and can work properly only on the regions in which the training was involved and also their performance is good only with tests in which the behavior of the phenomenon is very similar to the training. In this sense, OC-SVM with calibration of classifier scores provides a more generalized point of view, assuming the monotonicity of the features, the incremental degradation profile will not always follow the same pattern over time, but still, regardless of the pattern, an incremental in any feature selected is detectable.

The classification scores, which are the output of the classifier, are lineally escalated using **Eq. 3.2.2**:

$$s(x) = \frac{f(x) - b}{a - b} \qquad \textbf{Eq. 3.2.2}$$

where *f*(*x*) is the classification score, *s*(*x*) the linear re-scaled score to [0, 1] and [*b, a*] are the minimum and maximum classification score obtained from the training set. This will help the interpretation of results and help the future association of the classification score with the RUL, but still an isotonic regression is employed to fit the degradation profile in an isotonic function (which is ideal to the application), to directly obtain the RUL on future test sets, and to avoid ambiguity on the interpretation of results, that is, same associated RUL to several classification scores due to training error.

At this point, a model trained with the selected features is obtained, and the classification scores are linearly scaled and then fitted with an isotopic regression. This model now can be tested with new bearing degradation profiles, which is the second phase of the methodology. On this test part, there is no need to calculate all features, but only the selected to be monotonically relevant identified in the training part, and posteriorly test the new profiles with the trained and calibrated OC-SVM and obtain the RUL estimation. The performance of the OC-SVM is evaluated by means of the Root Mean Squared Error (RMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad \textbf{Eq. 3.2.3}$$

Where *N* is the size of the dataset, $y_i\hat{y}_i$ corresponds to the estimated RUL, and, $\hat{y}_i$ to the real one.

In order to evaluate the performance of the proposed methodology, experimental data from a laboratory test-bench has been used. This data corresponds to a so called run-to-failure experimental approach, where the elements are forced to work beyond their nominal values and then, the degradation profiles can be extracted. Next, the proposed methodology is applied, the results are discussed and, additionally, some variants of the methodology are proposed and analyzed.

The characteristics of the selected datasets for this experimental validation and the distribution among training and test set can be seen in **Table 3.2.1**:

Table 3.2.1. Characteristics of the dataset and distribution of experiments.

Set	Experiment	Duration	Conditions
Training	Bearing 1_1 (70% of acquisitions)	28000 sec	1800 Rpm 4000 N
Validation	Bearing 1_1 (30% of acquisitions)	28000 sec	
Test	Bearing 1_4	14000 sec	
	Bearing 1_5	24000 sec	
	Bearing 1_6	24000 sec	
	Bearing 1_7	22000 sec	

For training, 70% of the acquisitions from the Bearing 1_1 experiment are used, and to validate the model trained 30% of the acquisitions from the same experiment are used. For testing the methodology 4 different test sets are used, corresponding to test Bearing 1_4 to Bearing 1_7. It's important to clarify that each acquisition of the bearing condition was measured every 10 seconds, so the number of acquisitions available for each set correspond to the duration of the experiment divided by 10.

Each acquisition of the training set is characterized by an array of twelve time-domain statistical features: max. value, RMS, variance and kurtosis for both accelerometers (*x* and *y* axis) and temperature, then, each feature is normalized (standard deviation equals to one, and zero mean).

At this point, a dataset of 12 features calculated is obtained from every acquisition of the training set. As considered in the proposed methodology, a feature selection step is applied. The *Spearman*'s correlation coefficient is calculated from the 12 features and the results are sorted to select the two features with the highest ranking. In this bearing degradation experiment, the RMS of the temperature with ρ_i= 0.91 and the RMS of the accelerometer in X axis with ρ_i= 0.86 are selected due to its monotonic behavior. As can be seen the coefficient is high (being 1 the highest value of the coefficient possible), which implies a strong monotonic relationship between the features and the time of the experiment. These two selected features will be used to train the model, validate it and test it with the different tests sets. **Fig. 3.2.4** shows the training set represented by the two selected features. To include the time variable on the plot, each acquisition was labeled with a gray scale. As it was expected, it can be seen a strong monotonic behavior over the time of the experiment in both axis.

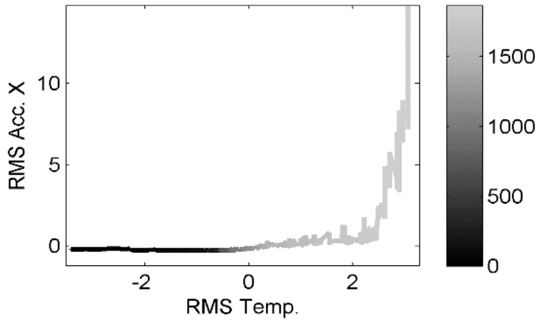

Fig. 3.2.4 Training set represented by the two features selected, with time variable included in a gray scale plot of the acquisitions just for visualization purposes.

The OC-SVM is trained with this feature space. The kernel used is the *Gaussian* and the value of the configuration parameter will be tuned to minimize the error in the validation parting from σ=2, which is a value used in several applications. The objective is to train the OC-SVM with whole training set but center the *Gaussian* at the start of the acquisitions, so the classifier could be able to have resolution in the feature space containing all the degradation profile and have monotonic scores over the degradation. This can be done labeling as outliers part of the dataset.

As it can be seen in **Fig. 3.2.5**, the classification score is presented in a contour plot, in which the value of the score in the feature space is shown in gray-scale.

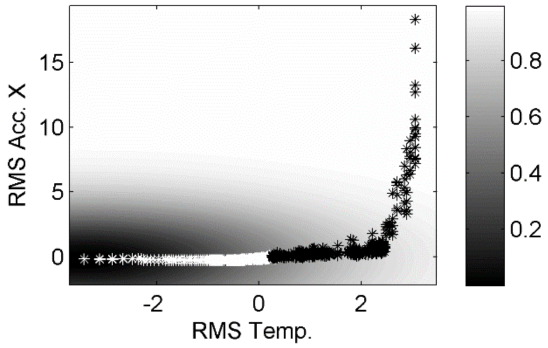

Fig. 3.2.5 Classification score over the feature space and acquisitions of the training set (half of the test is plotter white and the other black for visualization purposes).

The lowest values correspond to the center of the *Gaussian*, which is placed at the start of the degradation profile (first acquisitions) and the classification score increases as the acquisitions are spreading over the feature space. This ensures that, if the test sets have different degradation profile (but still with monotonic properties on the features), the classifier will estimate the RUL. Notice that the classification score is scaled from 0 to 1 (as can be seen in the gray-scale values). The next step is to fit the classification scores with an isotonic regression and associate them with a RUL percentage, the result is shown in **Fig. 3.2.6**.

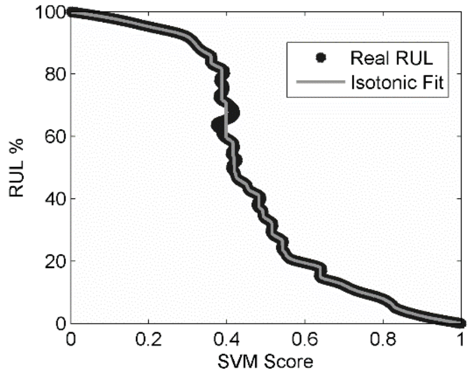

Fig. 3.2.6 Mapping classification scores into RUL percentages using isotonic regression.

Training set was evaluated with the OC-SVM and each acquisition was designed a RUL percentage, assigning the first one 100% RUL and the last one of the test 0%, which correspond to what was previously defined as real RUL. As can be seen in the figure 6 around the score 0.4, the model will have trouble to estimate the RUL, because none of the feature selected presented a monotonic behavior on that part of the test, which correspond to 80% to 50% of the RUL. Once the fitted function is obtained, the model is validated using 30% of the training test. Results are shown in **Fig. 3.2.7**.

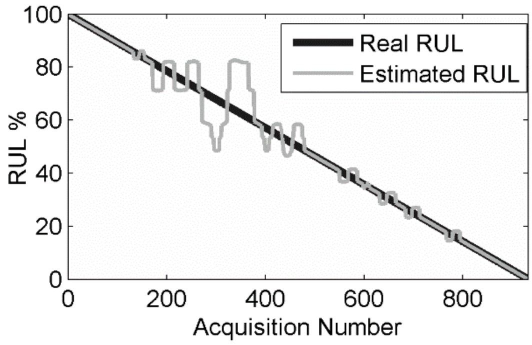

Fig. 3.2.7 Comparison of the estimated RUL versus the real RUL of the validation test.

As expected, an estimation error is obtained around 80% to 50% of the RUL, but in the other parts of the validation set the model had no trouble to estimate the RUL. These percentages are related to the stationary part of the test where the features calculated doesn't change, so it's not possible to accurately identify changes on this part of the degradation profile. The RMSE value is 5.99%. With the same trained OC-SVM and the fit function four different test sets were used. The result of the estimation of set Bearing 1_4 is shown in **Fig. 3.2.8**.

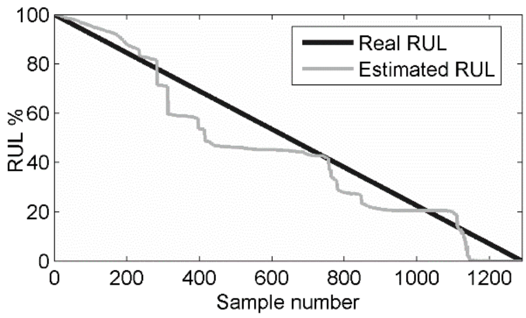

Fig. 3.2.8 Comparison of the estimated RUL versus the real RUL of set B*earing1_4*.

As we can see in figure 8, the estimation of the RUL presents some problems again around the same percentages of the RUL as in validation but still follows with reasonable approximation the real RUL. The error in this test is 8.45%. The error percentages of the validation and all the other sets are presented in **Table 3.2.2**.

Table 3.2.2. RMSE Error percentages of the different experiments

	Bearing 1_1	Bearing 1_4	Bearing 1_5	Bearing 1_6	Bearing 1_7
RMSE	5.99%	8.45%	24.60%	11.23%	22.69%

Taking into account that each test of bearing degradation is different, the proposed methodology is validated by accomplishing a significant generalization performance on the different test with reasonable error percentages. An improvement of the results would be achieved if features with higher *Spearman*'s coefficient would be used.

The methodology presented was limited to certain configuration, for example, the feature selection associated to the *Spearman's* coefficient and the features selected are limited to two. In order to enhance the validation of the methodology several test were performed with some variants, including using Principal Component Analysis (PCA), as a feature reduction technique and testing the methodology proposed but selecting three features instead of two. The results of adding a third feature to the methodology presented are shown in **Table 3.2.3**.

Table 3.2.3. RMSE Error percentages of the different experiments using three features.

	Bearing 1_1	Bearing 1_4	Bearing 1_5	Bearing 1_6	Bearing 1_7
RMSE	6.33%	9.19%	22.25%	11.41%	22.42%

The results in table III show that adding a third feature does not significally improve the estimation of the RUL. The reason is that the third feature added does not provide resolution in the percentages of the RUL estimation where the OC-SVM fails to estimate.

The results of changing the feature reduction approach to PCA are shown in **Table 3.2.4**.

Table 3.2.4. RMSE Error percentages using the PCA

	Bearing 1_1	Bearing 1_4	Bearing 1_5	Bearing 1_6	Bearing 1_7
RMSE	19.03%	19.92%	28.23%	24.13%	19.93%

The results shown in table IV proves that using PCA as a reduction technique does not exploit the characteristics of the features that improve the estimation of the RUL for this methodology.

Conclusions

A methodology to estimate the RUL applied to bearing degradation has been presented. The proposed method is based on the detection of monotonic properties of features calculated of the bearing degradation profiles to make a selection of best features to characterize the phenomenon. Then, a OC-SVM is trained to learn the degradation profile and the output of this model is calibrated to directly estimate the RUL.

Experiments performed with a dataset of bearing degradation indicate that the proposed strategy can estimate the RUL of the bearing with a reasonable error and with enough generalization to be applied to different test sets with different degradation profiles. Also a comparison between another feature reduction technique and increasing the number of features selected were introduced to give more versatility to the study. It must be noticed that the performance of the proposed methodology will be directly related to the monotonic behavior of the selected features.

3.2.2 Multi-modal scheme for novelty detection

The classical approach to perform novelty detection consist on calculating a set of features from the monitored machine and training a single model to assess the condition of the machine. While this approach is adequate in most of the cases, it is highly dependent on the quality of the features calculated from the monitored machine. The ideal scenario is to obtain a reduced set of features that properly reflect the condition of the machine by varying with enough resolution when the machine is working in abnormal conditions. Nevertheless, since the objective of novelty detection is to detect new scenarios in which there is no *a priori* information regarding the repercussion of the fault over the monitored signals, the delimitation of a reduced set of features that could include all the possible new scenarios results in a difficult task. This problem was initially handled by increasing the number of physical magnitudes monitored from the machine and also increasing the number of features calculated from them, therefore, different aspects of the machine are monitored and the capability to detect anomalies increased. However, a very high dimensional dataset with a reduced number of measurements due to the limitations of the application domain not only complicates the selection an appropriate configuration parameters of the model, but also could lead to an overfitted model producing a high number of false alarms.

As a solution for this problem, a multi-modal scheme is proposed in order to increase the resolution of the novelty detection task without compromising the performance by avoiding overfitting. **Fig. 3.2.9** shows a scheme of the proposed methodology, which includes the incursion of different set of features with a specialized model for each one. The first step is to process the data of the monitored machine to characterize the known operation conditions, then, instead of a single set of features, different sets are calculated from the processed data. By training a specialized novelty model for a specific set of features, the resolution of what can be monitored from the machine would increase without overfitting the models. The number of feature sets and novelty models represent a tradeoff between resolution in the analysis and complexity of the approach.

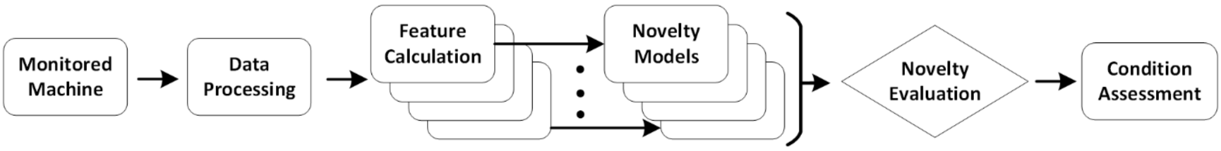

Fig. 3.2.9 Proposed scheme for a multi-modal novelty detection approach.

By having different sets of features, each model monitors different parts of the machine, therefore the detection of anomalies by each model is equally important. To handle the results of the novelty models, a novelty evaluation module is also included that provides the final assessment the condition of the machine. Since the anomalies are not necessary reflected in all the features, the machine can be considered working under a new scenario if at least one novelty model detects it.

Case Study: Multi-modal scheme for Novelty Detection applied to a camshaft-based machine

To validate the proposed scheme, the multi-modal novelty detection methodology is applied to monitor the condition of a camshaft-based machine. The high-speed ratios, the mechanisms time-overlapping and the smoothing inertia effect make such systems a challenging application field for classical approaches. The test bench is composed by an induction motor connected to a reduction gearbox that rotates a camshaft to activate the mechanisms corresponding to the manufacturing process. The current signals from the induction motor are acquired to analyze the effects of the cam operations to the current. A more in-depth description of the camshaft-based machine can be found in **Annex III**. The proposed methodology is shown in **Fig. 3.2.10**.

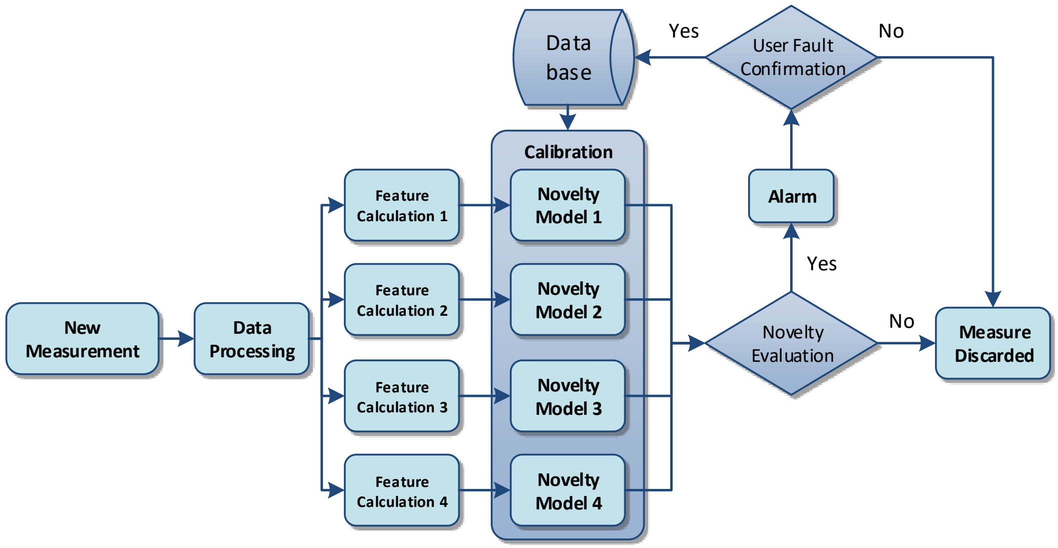

Fig. 3.2.10 Proposed methodology for a multi-modal novelty detection approach. OC-SVM models are used to identify novel behavior of the machine, then their scores are evaluated to determinate if an alarm is activated to assess the process of the machine.

The data processing step consist of obtaining a NTFM, from the signals measured from the motor current of the camshaft-based machine. The calculation of the NTFM is made by using the STFT, of the machine, but normalized in regard to the reference STFT (healthy state). Indeed, a NTFM calculated over a healthy condition will show values close to 0. Comparatively, a NTFM calculated over a novel condition will exhibit differences throughout the t-f representation. A more in-depth explanation regarding the signal data stage and the algorithms to calculate the NTFMs can be found in **Annex III**.

The resulting frequency map will show an increment or decrement in those points in which the behavior of the analyzed signal differs from the reference. In order to improve the resolution of the analysis, the resulting NTFM is divided in *N* different regions considering both time and frequency axes. To facilitate the comprehension of the posterior analysis, each region is identified by a number from *1* to *N*. A large number of regions imply the processing of more information which complicates the structure of the approach, so the selection of *N* will be a trade-off between resolution in the analysis and complexity of the approach. After the data is processed and the NTFM are calculated and divided in regions, statistical features are calculated. In this case of study the RMS is used, due to the fact that the objective is to detect variation of energy in the regions.

Once the features are calculated from each region, the novelty models, conformed in this case by OC-SVM's, are trained and validated with measurements of the normal operation of the machine. The input of the novelty models is the information of the features, and the output is a novelty score that determinates how different is the new scenario analyzed compared to the one which has been trained (the reference). Hence, a high novelty score implies that the new data differs in great scale from the trained one.

To enhance the information obtained from the models about the behavior of the machine, a visual representation of the measurements in the feature space is desirable. Each model will be trained with two features, so a two dimensional representation will be obtained. This approach implies that the number of models created will depend of the number of features. If one feature is obtained from each region, *N/2* models will be trained.

Once the models are trained, new acquisitions of the machine are obtained and evaluated to detect anomalies. In order to manage the resulting novelty scores of all the models an evaluation module is proposed. This module will assess if any of the models detects anomalies in their respective analysis of the regions. To perform this evaluation a novelty threshold is proposed, which in this case of study a constant value representing the boundary between the interpretation of normal and abnormal data is used. Thus, if the threshold is surpassed, the analyzed measurement is considered a novel behavior of the system. Initially, each model enclosures the trained data to create a description of the distribution, and defines a novelty score with a value less or equal than 0 to the data that lies in this description (the know behavior), and a value greater than 0 to data that lies outside of the description. This predefined threshold can be modified according to the application needs. A closed boundary may generate some false alarms but an open boundary may provide less resolution to the detection. In order to avoid false alarms, two premises are taken into account to detect an anomaly. The first one is that the novelty scores of any module surpasses the novelty threshold, the second one is that the threshold is surpassed in several consequent measurements (depending on the application). If both premises are accomplished, an alarm is activated, contrary, the measurement is discarded.

It is important to mention that, due to the lack of information of the possible faults of the machine, this alarm is associated with the aid of an expert to monitor the performance of the machine. Two outcomes are possible after an expert assess the machine: first is that a fault is detected, the second is that the machine is operating normal and the evaluation is caused by a false alarm. Dealing with a false alarm, the threshold limit could be increased to provide more robustness, or the models could be re-trained to incorporate such information. If a fault is detected, the models are re-trained incorporating this information, the process of re-training of the models implies the use of a database where representative measurements of the operation modes of the machine are stored. If no abnormal behavior is detected the process restart with the acquisition of new data from the machine until an anomaly is detected.

In order to validate the proposed methodology, three different experimental cases are considered in this study: a healthy or normal condition, and two faulty conditions by inducing effort disturbances. The first fault condition, F_1, involves the decrease of 25% of the effort pattern related with the first cam, C_1, through the adjustment of the thumbscrew related to the load grip by means of a dynamometric key. The second fault condition, F_2, includes a decrease of 25% of the effort pattern related to both of the cams, C_1 and C_2, also by the adjustment of the thumbscrew related to the load grip. It must be taken into account that the induced fault scenarios correspond to common degradation patterns due to the continuous machine operation. Thus, although the effort disturbances induced by the fault conditions can be considered incipient deviations, it is expected to extract by the proposed methodology the corresponding affectation over the motor stator current. From each of the considered scenarios, 30 camshaft revolutions were acquired, considering both currents and encoder.

Signal processing and feature calculation

As it has been explained, the computation of the *NTFM* under *healthy* conditions is performed first, which will be further used for the calculation of the NTFM of new samples when monitoring the machine. Since the mechanical failures that are desired to be detected are related with the rotating speed of the shaft, only the low frequency band of the spectrum has been analyzed. This band goes for 0 to 60 Hz for the speed of 30 cycles per minute. It should be noticed that the temporal axis have been substituted with the associated rotatory position in degrees, from 0 to 360º.

Once the reference maps are obtained, the NTFM is computed over new measurements, and it will be divided in *N* regions. For this application, 8 rectangular uniform regions have been created, fixing with it a temporal resolution of 90 º and a spectral resolution equal to half the bandwidth of the signal. As an example, the NTFM of the system working with a fault scenario, the vertical sealing cam disconnected, $F_{MC,}$ is shown in **Fig. 3.2.11**. It can be appreciated that there is a generalized loss of spectral energy in regions 2 and 6, but the loss of energy in these regions does not ensures that when different faults appear they will be reflected in the same regions. Then, the RMS is calculated from each region. This procedure is repeated during the assessment of a new measurement.

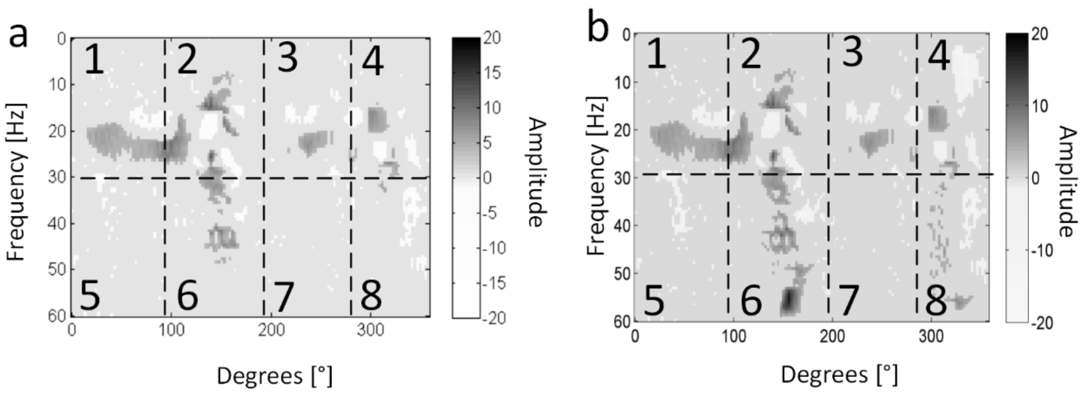

Fig. 3.2.11. Resulting NTFM segmented in 8 regions. a) F_1 b) F_2

Since the NTFM is divided in eight regions, four OC-SVM models are trained, each one is responsible to monitor 2 regions. Each pair of regions is associated to 90° of the rotation of the camshaft, this mean that the first model, $OC\text{-}SVM_1$, will be trained with the features from region 1 and 5, the second model, $OC\text{-}SVM_2$, with features from region 2 and 6, the third model, $OC\text{-}SVM_3$, with features from 3 and 7 and, finally, the fourth model, $OC\text{-}SVM_4$, with features from region 4 and 8.

Novelty detection results

First, the OC-SVM models will be trained with normal operation data; 20 acquisitions of cycles of the machine have been used to train the models, and 10 additional measurements to validate the models. The kernel used is the *Gaussian* with σ=2, which is a value used in several applications. This kernel allows a coherent assumption with the physical phenomena, decreasing the novelty score as a *Gaussian* distribution. The novelty threshold (which is classically set to 0), will be heuristically selected and configured in the corresponding module according to a percentage providing more robustness to the methodology, in this case of study a value of 0.1 has been selected.

The resulting $OC\text{-}SVM_1$ training is shown in **Fig. 3.2.12**. The points in the figure represent several cycles of the camshaft used to train the module. As can be seen in the figure, all the information concerning normal operation is concentrated near zero values, due to the NTFM; the same concentration is presented in the rest of OC-SVM models. The dotted line represents the novelty threshold value, all data lying inside the boundaries of the line is considered normal. The contour plot represent the novelty score evaluation over different regions of the feature map. This evaluation showed in the contour has a Gaussian shape due to the kernel selected, and the novelty data lies in the center of the Gaussian distribution.

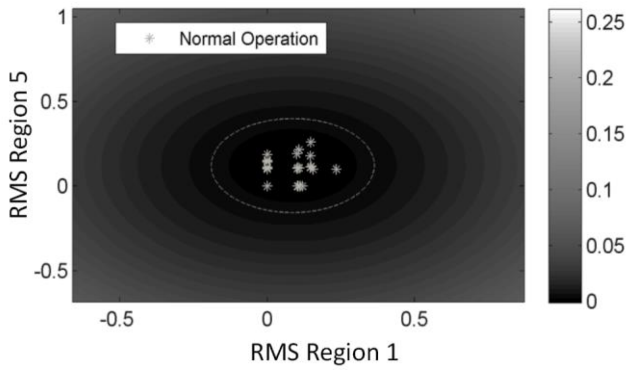

Fig. 3.2.12. *Novelty detection boundary for regions 1 and 5, where* are the measurements of each cycle and – is the limit of the novelty threshold.*

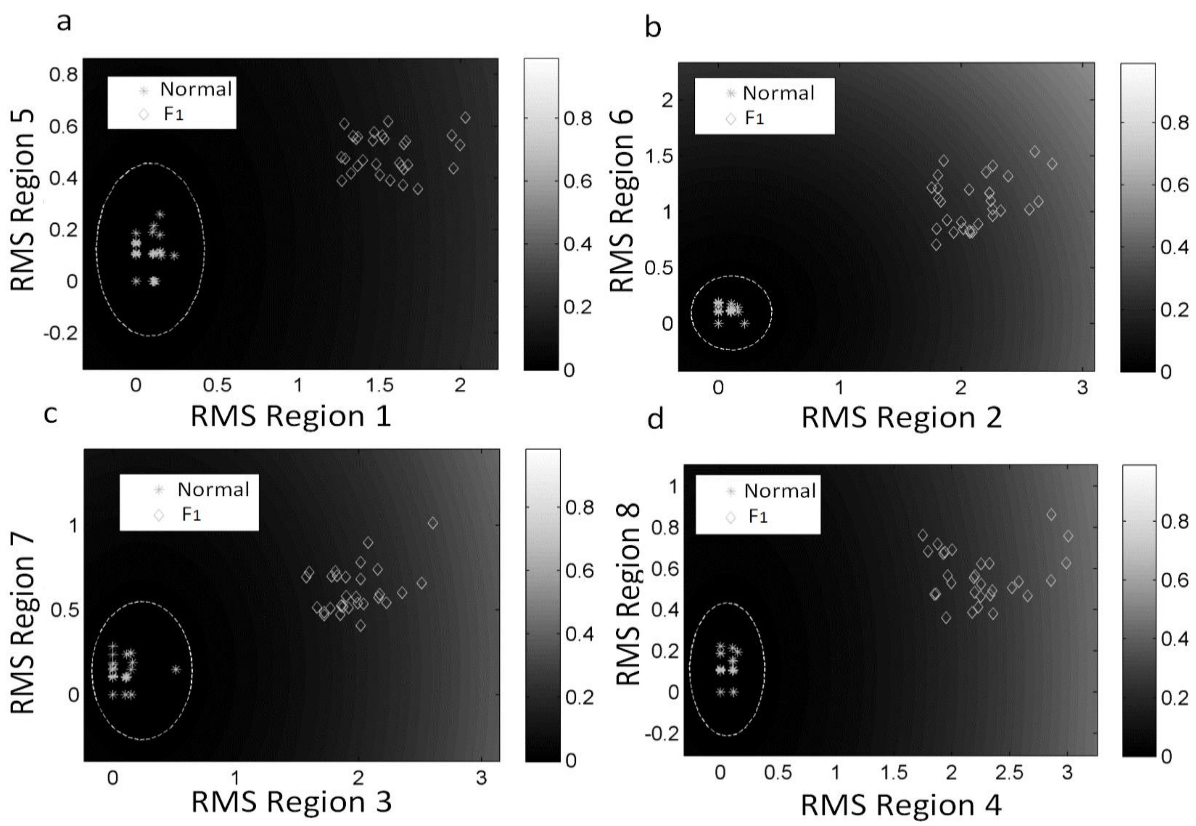

Fig. 3.2.13. *Novelty detection boundary for a) OC-SVM$_1$ b) OC-SVM$_2$ c) OC-SVM$_3$ d) OC-SVM$_4$*

In case of a novel scenario, the measurements will be directly reflected in the novelty detection map. The F_1 scenario has been induced to test the performance of the models. For this case, 30 cycles has been used, and the novelty scores were evaluated to determine if all the acquisitions were detected as novelty. The result is presented in **Fig. 3.2.13** for all four OC-SVM models.

As can be seen in this case, all acquisitions of the fault case are placed outside the novelty boundary, so the abnormal behavior is detected by all models; this means that this fault has impact around all the rotation of the camshaft. Following the methodology an alarm is activated and the novelty condition should be analyzed. A certain number of measurements (30 cycles), should be stored in order to allow the learning by the novelty model. The result of incorporating this fault to the known data distribution is shown in **Fig. 3.2.14**. Only one module is presented since the graphical result is similar in all four OC-SVM models.

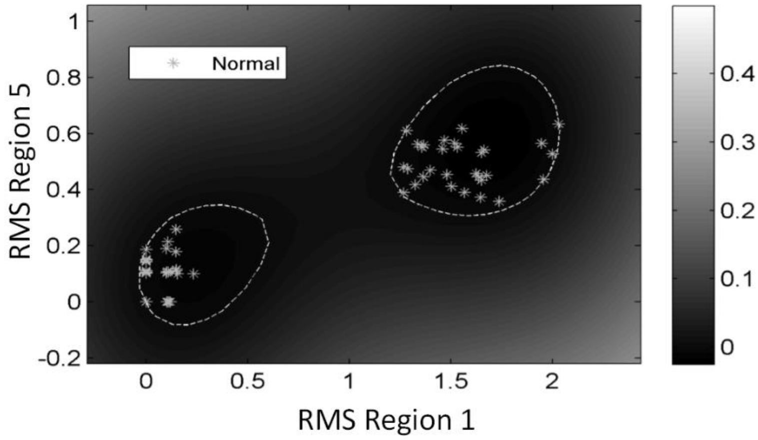

Fig. 3.2.14. *Novelty boundaries of OC-SVM1 after learning F_1*

As can be seen in **Fig. 3.2.14**, the introduction of new data implies a modification of the novelty scores distribution. The Gaussian evaluation formed previously with one lobe, now has two lobes that enclose the zones where the new data distribution is concentrated. The novelty threshold is present in the two data distributions to delimit the new boundaries. An example of the 3D representation of the space partition of the model is shown in **Fig. 3.2.15**.

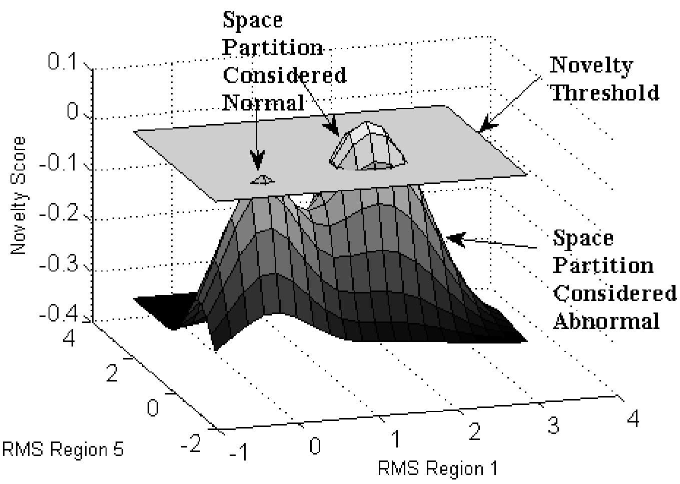

Fig. 3.2.15. *Novelty scores evaluation over the feature space. Space over the threshold limit is considered normal and space above is considered novelty*

It can be appreciated in **Fig. 3.2.15** that the model evaluates the RMS of region 1 and 5 to compute a novelty score in which the peaks with values over the novelty threshold delimits the normal distribution and all the space under the threshold is represented as novelty.

A second novel condition has been introduced, this time F_2. As can be seen in **Fig. 3.2.16**, this fault can be detected only in models *OC-SVM*$_1$ and *OC-SVM*$_2$, this means that the fault has more impact on the regions corresponding from 0° to 180° of the rotating cycle of the camshaft.

This is an example of the restrictions of the framework of novelty detection, when dealing with unknown sources of faults in a machine is difficult to limit the information sources, because it will lose resolution to detect possible faults. If all the regions are not taken into account, or a lower resolution would be used (i.e. 4 regions instead of 8), this novel scenario would not be detected.

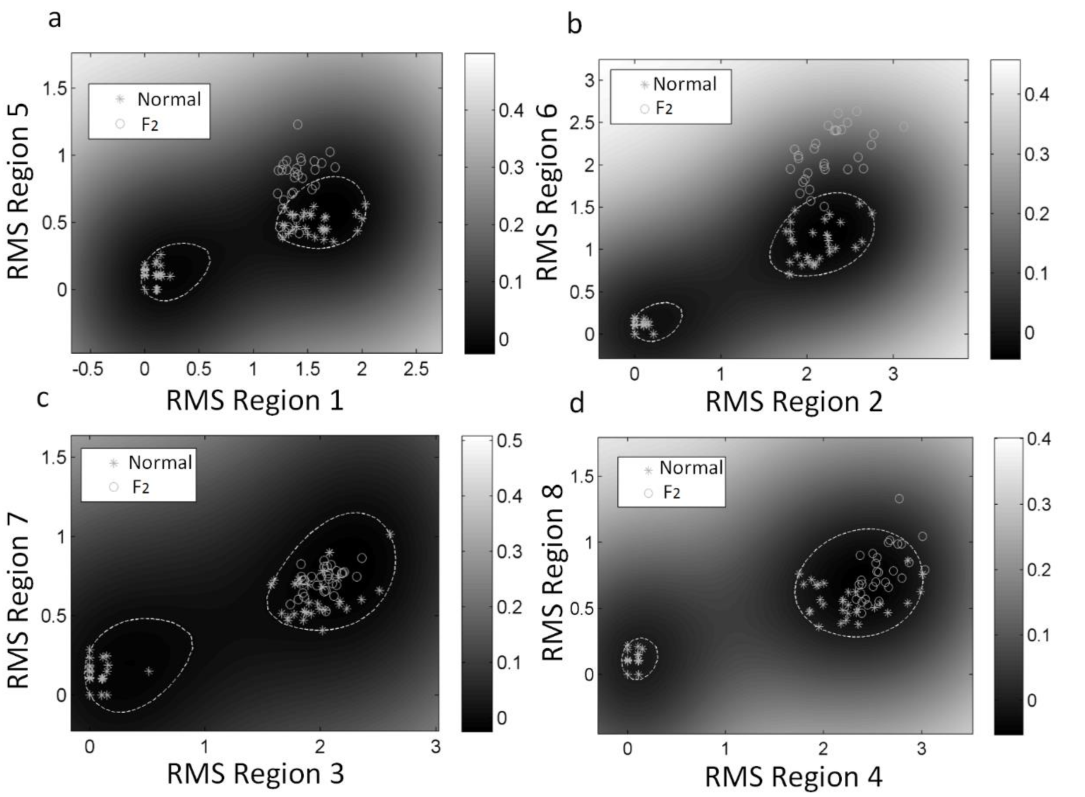

Fig. 3.2.16. *Novelty boundaries after learning F_1 scenario and testing the F_2 scenario a) OC-SVM$_1$ b) OC-SVM$_2$ c) OC-SVM$_3$ d) OC-SVM$_4$*

The procedure repeats activating an alarm, storing the data to characterize the fault and calibrating the models, **Fig. 3.2.17** shows the model *OC-SVM*$_1$ after the learning of the new scenario; the other modules presents similar results. This time the novelty models did not incorporate a new lobe on the feature space, but enhanced the lobe that was next to the fault data.

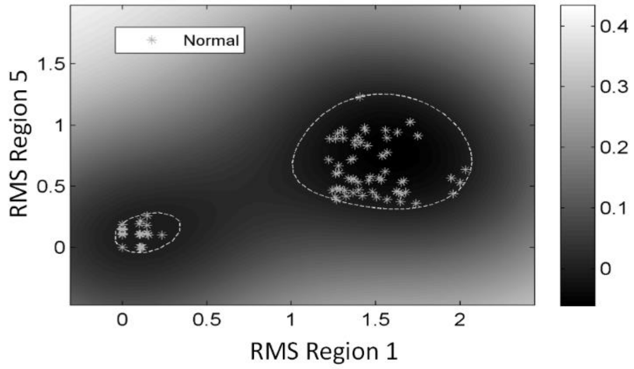

Fig. 3.2.17. *Novelty boundaries of OC-SVM$_1$ after learning F$_2$*

All the faults have been detected and learned successfully with this approach. Due to the fact that this is an expert-aid novelty detection approach, still 2-D representations are needed to have a better understanding of the behavior of the machine during abnormal events over all regions.

Conclusions

The proposed methodology in this section introduces a multi-modal novelty detection approach applied to an industrial camshaft using phase current information from the main motor. Two fault scenarios have been introduced to test the response of the models under abnormal behaviors.

The normalized time-frequency maps used to calculate the features presented high capabilities in order to identify the presence of deviations from the healthy behavior of the system in terms of motor currents and improved the performance of the models.

The novelty detection approach successfully identified both faulty scenarios and the models incorporated the information to avoid generating alarms when similar behavior is detected.

3.2.3 Reformulation of features for novelty detection each time a new scenario is incorporated

Most of the methodologies for novelty detection are limited to a static analysis and the incorporation of the novel information to the novelty detection system is not usually considered. An approach to include adaptability to the novelty framework, based on vibrations, is proposed in [59]. The proposed monitoring scheme include testing data on the boundary of the novelty model, based on Support Vector Data Description, and retrain the model with this information to gain robustness. Nevertheless, this approach does not take into consideration the possibility to include novel scenarios during the monitored process.

Other approaches to develop an adapting condition monitoring scheme were presented by D. Filev *et al*. [50] where a practical framework for autonomous monitoring of industrial equipment based on novelty detection is analyzed; and by B. Costa *et al.* [53], where a two-stage algorithm for real-time fault detection and identification is presented. Both approaches provide the opportunity to incorporate novel detected faults to the monitoring system, nevertheless, in both methods the incorporation is limited to update the known data base, but an adaptation of the numerical features analyzed is not considered.

The performance of a novelty detection system is highly dependent on the numerical features considered. When there is no previous information of the possible faults that can occur, the application of a suitable numerical features analysis strategy represents a critical challenge [23]. Considering a continuous monitoring framework where the initial information available is the healthy operating condition and, later on, different faults are identified progressively when the machine condition deteriorates, all the approaches previously discussed do not modify the initial set of features when new information of faults is incorporated. This static approach have the advantage of providing a most adequate situation for on-line adaptation, nevertheless, analyzing the information of the faults detected during the monitoring process could improve the identification of a most adequate set of features to discriminate the possible upcoming or already detected fault scenarios.

Given that the data initially available is usually related to the healthy condition of the machine under analysis, condition-based monitoring schemes must be designed to overcome two main challenges:

(i) The identification of significant features to deal with the characterization of the known conditions of the machine, under the consideration that the occurrence of additional unknown faults must be detected.

(ii) The adaptation of the condition-based monitoring scheme to update the considered data base of the machine, once unknown fault scenarios have been detected.

Such requirements are addressed in the proposed novelty detection methodology shown in **Fig. 3.2.18**. This methodology represents an important step to the introduction of adaptive novelty detection schemes to the development of electromechanical system diagnosis procedures.

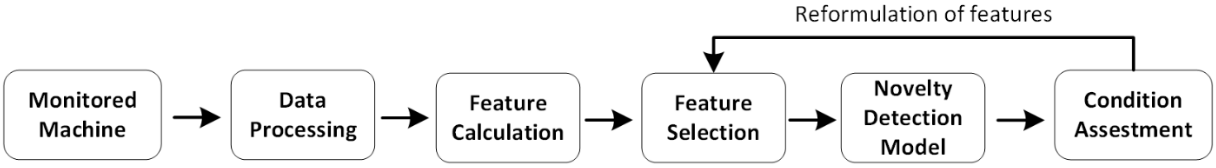

Fig. 3.2.18 Proposed scheme for a multi-modal novelty detection approach.

The contribution of this study is to provide a methodology for novelty detection where the information of identified faults during the monitoring process is exploited to improve the novelty detection task. This is performed by a reformulation of features whenever a new scenario is incorporated to the novelty detection model.

Two new concepts are incorporated in this new methodology in comparison to classical approaches, first, the reformulation of the feature reduction module, second, the incorporation of new scenarios to the novelty model. Taking in consideration that the information initially available consist only on the healthy condition, the feature reduction module, is initially performed by unsupervised approaches; yet, once the information of a fault is available, the feature reduction module could improve its performance by employing supervised methods. The unsupervised approach is replaced by a supervised approach in this methodology to search for a possible discriminative feature space to increase the detection of novel scenarios.

Case Study: Vibration-based adaptive novelty detection method for monitoring faults in a kinematic chain

The proposed method is composed by two stages: an offline stage and an online monitoring stage. The main objectives of the offline stage are, first, the analysis of the information available of the monitored machine to find a reduced set of numerical features to characterize the known machine conditions and, second, the design of the novelty model by means of the selection of the configuration parameters and training. The proposed novelty detection methodology shown in **Fig. 3.2.19.**

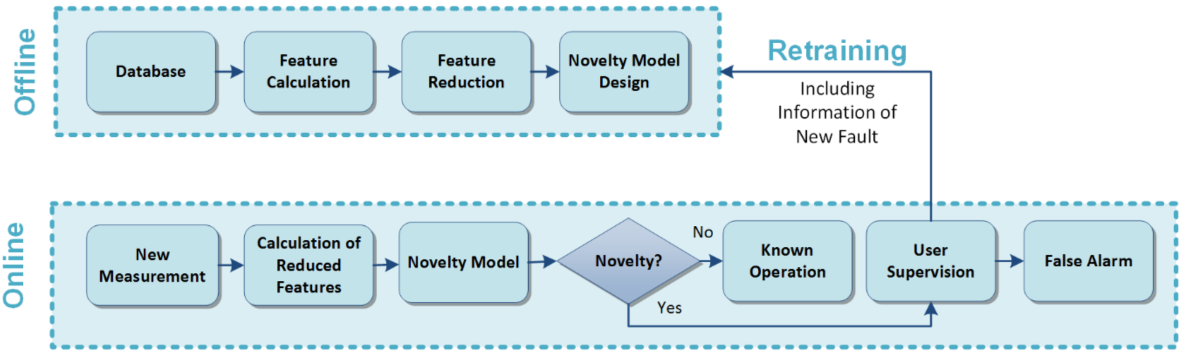

Fig. 3.2.19 Proposed methodology for the novelty detection approach. The monitoring method is composed by an offline stage for initialization and retraining, and an online stage for continuous monitoring.

Once a reduced set of characteristic features is obtained and the novelty model is designed, the online stage is carried out. During the online stage, new measurements are continuously compared with the normality threshold, T_n, defined during the novelty model training in the offline stage. Thus, if a novel scenario is detected, the supervision of an expert user is proposed in order to confirm and label the new condition of the machine; consequently the monitoring system is retrained to include the characteristics of the novel scenario. Detailed information of each stage and the retraining process is described in the following subsections.

Offline Stage Description

During the initialization, it is assumed that only information of the machine operating under healthy condition is available in the database. The first step is the calculation of numerical features from the vibration measurements obtained during the machine operation. Since the information of the possible faults of the monitored machine is not available yet during this initialization, a generic set of statistical time-based numerical features is proposed to be extracted from each available vibration axis measurement. The proposed set of potential features are the Root mean square, the crest factor, the shape factor, the kurtosis and skewness. The formulas to obtain such features can be consulted in **Table 2.1.1** in Chapter 2. These features have been successfully employed for fault detection on the last years [1], [5].

The resulting number of numerical features is proportional to the number of available vibration axis collected during the acquisition. However, in order to allow the compression and visualization of the data, a feature reduction module is implemented. During such offline stage initialization, an unsupervised feature reduction approach must be used, a Laplacian Score Ranking is proposed in this work as a good trade-off between simplicity and performance [35], to rank the features according the topology preservation capabilities. The two or three first ranked features in terms of Laplacian score are selected.

Next, the novelty model is designed. There is a significant number of novelty models proposed on the literature [23], each one demonstrated to be a capable option under certain circumstances. An increasing amount of works imply that domain based novelty detection models present promising results [25], [53]. In this work a standard OC-SVM with Gaussian kernel is used. The design of the novelty model includes the selection of the parameters for configuration, and training employing the known scenarios stored at the database. Then, the initialization of the offline stage finalizes with the design of the OC-SVM.

Online Stage Description

This stage continuously monitors the condition of the machine to detect if an anomaly is present. To accomplish this, new measurements of the machine are acquired each certain amount of predefined time. Each measurement is segmented and a set of features is calculated from each segment. The set of numerical features calculated on this stage are reduced in the offline stage by means of Laplacian Score.

Thus, each new measurement characterized by the numerical features is analyzed by the novelty model. In case of no novelty detection, it is assumed that the machine is working under known conditions. However, if the analyzed measurement is detected as a novelty, an alarm is triggered in order to consider the user assessment. Then, if the occurrence of a new scenario is confirmed the corresponding measurements are stored at the database and a retraining procedure is performed.

Retraining Description

Once the retraining is trigged, the feature reduction and the novelty model design modules are modified at the offline stage. A diagram of the retraining procedure is presented in **Fig. 3.2.20**.

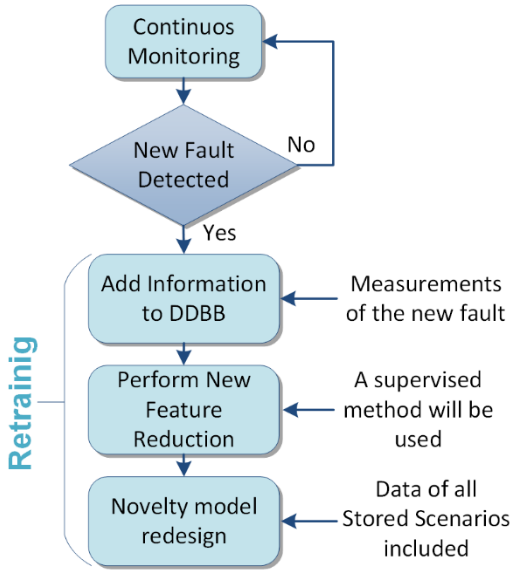

Fig. 3.2.20 Proposed retraining approach. First, measurements characterizing the fault are stored, and then the feature reduction module and the novelty design module are modified to incorporate the new scenario encountered.

It must be noticed that two important contributive aspects are proposed on this retraining approach, first, the reconsideration of the feature reduction module, second, the incorporation of fault scenarios to the novelty model. As it has been explained, the feature reduction module, during its initialization, is supported by an unsupervised Laplacian score ranking due to the lack of additional scenarios; yet, once the information of a fault is available, the feature reduction module could improve its performance by employing supervised methods.

Then, the Laplacian approach is replaced by a Fisher Score ranking approach in this work, where the features are sorted according the Fisher coefficient calculated from each feature. It is important to mention that Laplacian Score can be configured to work also under a supervised framework and could obtain similar results than employing a Fisher approach, similarities between the two approaches are discussed in [35]. Nevertheless, Fisher Score is used on this methodology to search for a possible discriminative scenario to increase the detection of novel scenarios. A comparison of results obtained from both features reduction approaches are presented in the results of this work.

The consideration of a faulty scenario in the novelty model may contradict the principle of anomaly detection, where the objective is to detect healthy behaviors from the rest. Nevertheless, the aim of an adaptive condition monitoring system should be to learn from all the identified conditions to subsequently detect them if they are presented again by a fault detection module. Indeed, some works present a parallel structure for fault detection and novelty detection modules [50], [53], where the novelty module learn the known faults along with the healthy operation because its objective is to detect only new scenarios, while the objective of the fault detection is to identify the condition of the machine, including known faults. This work is based on such parallel structure approach, where the fault scenarios must be taken into consideration to be included in the novelty model, and then they could be identified by a complementary fault detection module with a high confidence level

The test bench used for testing consist of a kinematic chain with different faults and the acquisition system used to capture the vibration signals. A more in-depth description of the kinematic chain test bench can be found in **Annex I**.

Three scenarios are considered to verify the performance of the proposed method, the first one, *H*, is the kinematic chain working under healthy condition and the other two, F_1 and F_2, represent the kinematic chain working under faulty conditions. For F_1 the motor is working with a half broken bar, and for F_2 the motor is working with a fully-broken bar.

The information stored from the kinematic chain consist of an acquisition of 60 seconds of the machine working under the three scenarios mentioned; each acquisition is segmented in 30 parts of 2 seconds and a set of features is calculated from the 30 segmented measurements. Since two axes are taken into consideration, a total of ten features are calculated from each segmented acquisition of the machine working under the different scenarios mentioned. The first step of the methodology is the offline stage, where a reduced set of features is obtained and the novelty model is designed.

Regarding the Laplacian Score configuration, a simple approach is followed for parameter tuning, that is, a value of k=3 is used for constructing the adjacency graph and a "simple minded" weighting approach is followed. Since the proposed approach is be compared to different feature reduction modules, selecting generic parameters settings is useful for the purpose of evaluation, but ignores that there may be dependencies between the feature reduction model and the novelty model. Regarding the design of the novelty model, the kernel used is the *Gaussian* and the value of the configuration parameter is tuned to minimize the error in the validation. In all experiments 80% of the samples are used for training and 20% for validation. To train and adjust the parameter the novelty model a five-fold cross-validation is used.

In order to highlight the contributions and motivation of this work, the outline of the results is presented as follows: first, a test is performed by a classical approach, then the proposed methodology is applied and the results are compared. The classical static approach imply conserving the reduced features set obtained at the offline initialization stage, meanwhile the proposed dynamic approach implies a possible reformulation of the reduced features set during the retraining stage.

During the initialization stage, the reduced set of features selected by means of the Laplacian Score ranking is composed by the RMS of the Y axis and the Kurtosis of the Y axis. The OC-SVM model is trained employing healthy condition data. The resulting OC-SVM during training is shown in **Fig. 3.2.21**. The marks, *, in the figure, represent measurements of the machine used to train the model, on this case and on the subsequence figures only 1 fold of the five-fold cross validation is displayed. The dotted line represents the novelty threshold value, all data inside the boundaries of the dotted line is considered normal. The contour plot represents the novelty score evaluation over different regions of the feature map.

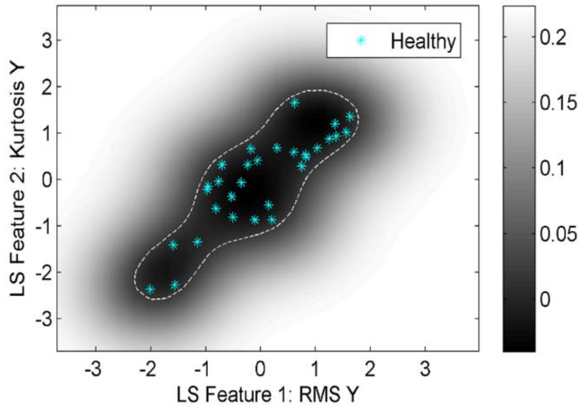

Fig. 3.2.21 Initial novelty model representation. Limit of the novelty threshold, --, and measurements used to train the model, *.

Once the offline initialization stage is finished, the online stage follows, that is, new measurements are obtained to assess the condition of the monitored machine. To give robustness to the novelty detection and avoid false alarms, a batch consisting of 30 measurements are evaluated, if 75% of the analyzed measurements are evaluated as novelty then the alarm is triggered. Next, the F_1 scenario is presented to test the performance of the model. The plot of the scenario and the novelty threshold obtained during training is presented in **Fig. 3.2.22**.

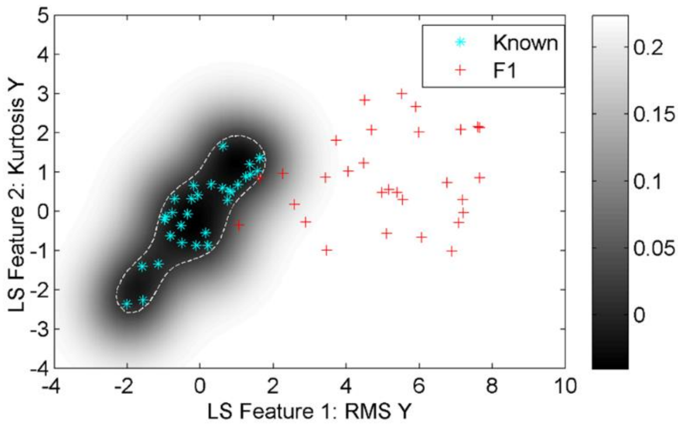

Fig. 3.2.22 Evaluation of the fault scenario F_1. The novelty model is trained employing data from healthy operation condition.

As can be appreciated, the new scenario lays outside the novelty threshold so it is successfully detected as novelty. Once a novel scenario is detected and identified as a fault by the user, it is incorporated to the database to consider it as part of the known scenarios and the novelty model is retrained, without changing the features, to include this information. **Fig.3.2.23** shows the feature space after the novelty model is trained using Healthy and F_1 data as part of the known scenarios.

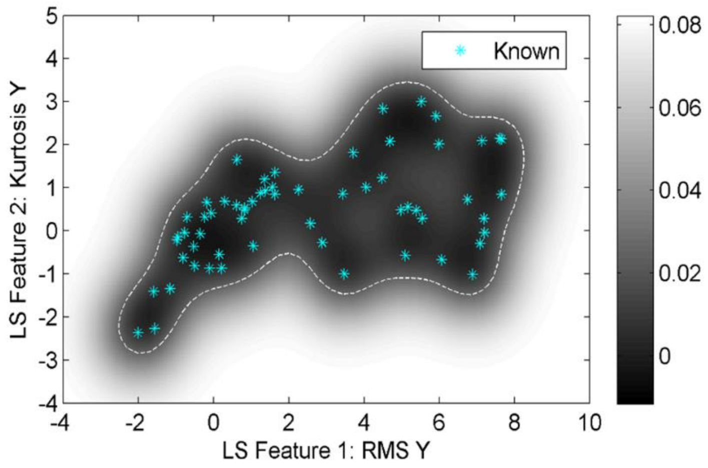

Fig. 3.2.23 Contour plot of the novelty model after including F_1.

Once the model is re-trained, the third scenario, $F_{2,}$ is introduced. The visual representation of the test is presented in **Fig. 3.2.24**, this scenario is not detected as novel because only 50% of the measurements are labeled as novel by the model.

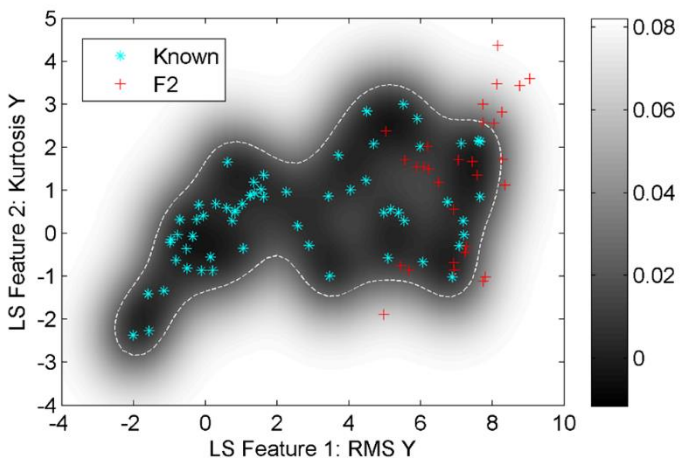

Fig. 3.2.24 Evaluation of the fault scenario F_2. The novelty model is trained employing data from healthy and F_1 scenarios.

A similar result is obtained when the novelty model is trained using Healthy and F_2 data and is tested with data of F_1. A summary of the results of novelty detection maintaining the same features obtained during initialization is shown in **Table 3.2.6**.

Table 3.2.5. Performance of the novelty detection using only healthy class data to reduce the number of features, where D.R. stands for dimensionality reduction. Different scenarios are included according the information available to train and test the novelty model.

D. R.	Performance Using OC-SVM (%)					
	Known	Test	Known	Test	Known	Test
	H	F1 + F2	H + F1	F2	H + F2	F1
LS	95.4 (± 1.1)		57.6 (± 6.7)		43.5 (± 6.4)	

As it can be seen in Table 3.2.6, using the reduced set obtained during initialization is easy to detect the novel scenarios when there is only information of the healthy condition, but when a novel scenario is included in the database and the novelty model is retrained, the reduced set of features initially obtained does not necessarily provide a good representation to detect a new scenario during test.

To improve these results, the methodology presented on this work proposes to evaluate again the feature reduction module each time a retraining is applied. Following the outline presented for results and parting from the first retrain where the scenario F_1 is included in the database, the feature reduction module is applied again but this time including information from Healthy condition and F_1 scenario. Since two scenarios are taken into consideration and the labels are known, a supervised approach can be applied, in this case a Fisher Score ranking for feature reduction is employed. The novelty model using the initial set of features and the novelty model after retraining with the new reduced set of features are shown in **Fig. 3.2.25**.

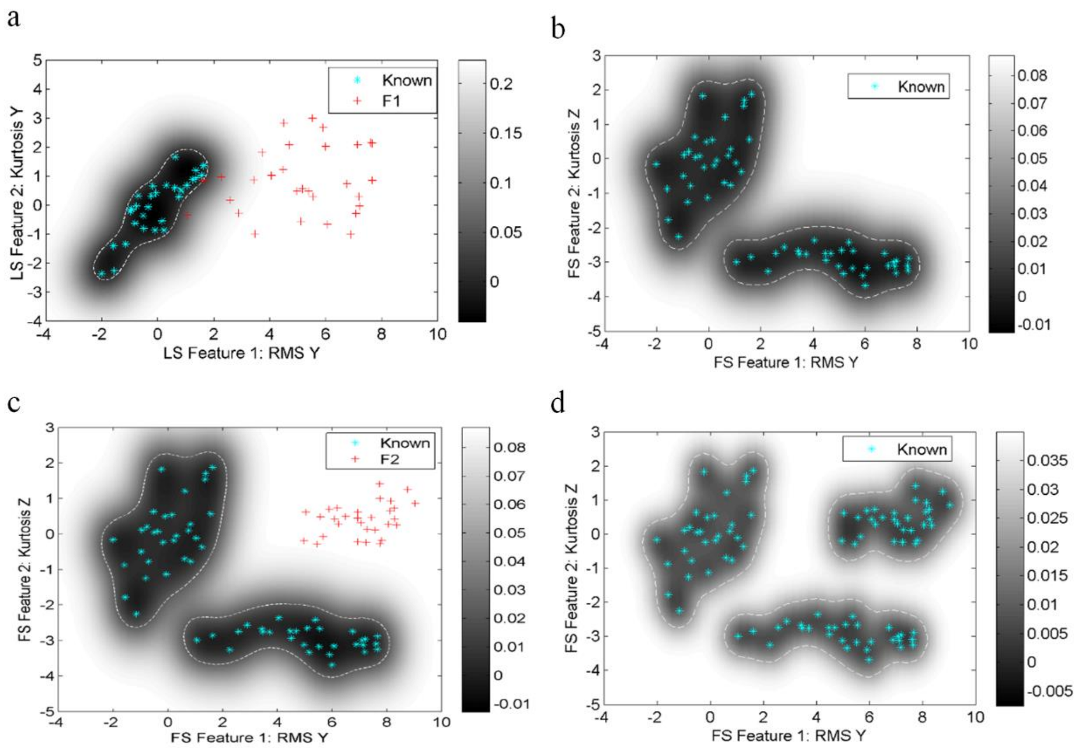

Fig. 3.2.25 Process of evaluation and retraining employing the methodology proposed. (a) Evaluation of the fault scenario F_1. (b) Retraining of the novelty model and reformulation of the reduced set of features including F_1. (c) Evaluation of the fault scenario F_2. (d) Retraining of the novelty model and reformulation of the reduced set of features including F_2.

The new reduced set of features is composed by the RMS of the *Y* axis and the Kurtosis of the *Z* axis, as can be appreciated, the new set of features present a more discriminative distribution of the three scenarios considered. At the last step, **Fig. 3.2.25 (d)**, when F_2 scenario is included, the Fisher Score still ranked the same features of the last retraining, **Fig. 3.2.25 (b)**, as the highest; yet, it would be possible that a different set of features would be obtained. The results obtained demonstrates the advantages of including the Fisher Score reduction module to the retraining procedure, the new distribution of the scenarios avoided an overlapping of the new scenario under test, therefore the novelty model successfully detected as novelty all measurements corresponding to the F_2 scenario.

It is worth mentioning that if initially the scenario F_2 is used for training and the scenario F_1 is used for testing, the new set of features obtained could be different than the aforementioned. The results achieved from both scenarios are shown in **Table 3.2.7**, which also includes a comparative of the results obtained employing PCA, LDA and Laplacian Score dimensionality reduction techniques on the retraining step instead of the Fisher Score proposed.

Table 3.2.6. Performance of the novelty detection employing a reduction of features during retraining. Different scenarios are included according the information available to train and test the novelty model.

D. R.	Performance Using OC-SVM (%)			
	Known H + F1	Test F2	Known H + F2	Test F1
PCA	59.0 (± 5.2)		64.2 (± 5.1)	
LDA	47.4 (± 6.1)		51.2 (± 6.1)	
LS	84.3 (± 2.4)		100 (± 0.0)	
Fisher S.	100 (± 0.0)		100 (± 0.0)	

Regarding the classical feature extraction techniques, PCA and LDA, the test scenario is not identified as novel in both cases. The Fisher Score and the Laplacian Score successfully identified the new scenarios as novel since the percentage obtained in both cases is higher than the 75% predefined threshold in the methodology to activate the alarm. Both techniques achieved high scores, but still the Fisher Score provided a more appropriate selection of features.

As mentioned in Section II, LDA is a feature extraction technique based on the Fisher discriminant coefficient, so similar results between Fisher Score ranking and LDA are expected; however, employing Fisher Score ranking score achieved a better result; this can be caused because the test consist of novel scenarios and LDA finds the directions on the feature space specialized for the two supervised scenarios employed during training, meanwhile Fisher Score ranking provides a more general approach by selecting features.

To test the robustness of the Laplacian Score and Fisher Score approaches, a comparative test is performed where the set of features is increased from 10 to 15 and varying the number of reduced features selected. The five features included to the original set are obtained from the axis X of the accelerometer monitored, where the features calculated are presented on **Table 3.2.8**; these features were discarded initially because they are not part of the perpendicular plane of the motor and does not contribute significantly to the monitoring, in fact it could affect the performance of the feature reduction and novelty detection modules. The results are presented in Table 4.

Table 3.2.7. Performance of the novelty detection increasing the number of initial features from 10 to 15 and varying the number of the reduced set of features.

D.R.	Performance varying the number of features reduced (%)		
	2	**3**	**4**
LS	59.0 (± 4.1)	64.3 (± 3.3)	88.6 (± 2.5)
Fisher S.	100 (± 0.0)	100 (± 0.0)	100 (± 0.0)

The features obtained from the Fisher Score still present a better distribution to detect the new scenarios. The Laplacian Score performance is affected when irrelevant features are included on the feature set but increases when more dimensions are taken into consideration. Since the objective of the Fisher Score is not topology preservation, contrary to LS, it is capable of discarding all the irrelevant features that were included and the performance is not affected.

Conclusions

The methodology is based on the acquisition of vibration signals that are generated in the kinematic chain; along with an adequate signal processing to extract features to characterize the components, and an adaptive novelty detection model to detect anomalies. The method is composed by two sequential stages, an offline stage to initialize and retrain the modules, and an online stage to continuously assess the condition of the machine. During initialization the model is trained employing only information from the machine working under healthy condition and two additional faulty scenarios are introduced to test the performance of the method under unknown operations.

The adaptive novelty detection approach successfully detected both novel scenarios and the model incorporated the information to avoid generating alarms if the same fault is detected. A comparison between the proposed method and classical dimensionality reduction approaches highlights the limitations of maintaining a static set of features during monitoring, instead of reformulating the feature reduction module once new information is available.

On this particular study, employing features reduced by Laplacian Score and Fisher Score obtained similar results; nevertheless, it does not imply that a similar outcome will be present during the analysis of other faults. Fisher Score is encouraged to be employed on this methodology rather than maintaining the Laplacian Score approach due to the similarity between the method objective and the objective function of Fisher Score, on both the ideal case is to find the features to maximize the distance between scenarios while maintaining compact clusters. A specific comparative of performance between LS and Fisher Score was also included, in which the Fisher Score obtained better results when irrelevant features are included to the original set of features and when the dimensionality of the reduced set is increased; this highlights the advantages and robustness of the feature selection approach by Fisher Score compared to the LS.

3.3 Conclusions and discussion

In this chapter the limitations regarding the application of novelty detection to electromechanical systems are analyzed. A first analysis regarding the limitations of novelty detection in a continuous degradation environment, which is performed via the implementation of novelty detection algorithms to a run to failure experiment is performed.

Several RUL estimation methodologies have been presented previously achieving good results, but still some drawbacks are detected, some of the methodologies doesn't make a proper selection of features to ease the estimation but just a general reduction, others over fit the method to certain profile and fail to estimate the RUL of different sets with different patterns or they depend of complex models that makes them difficult to implement on practical applications. The methodology presented in this paper tries to close the gap on these drawbacks detected by introducing a proper feature reduction for this case, the use of OC-SVM, which would be easy to implement, to generalize the RUL estimation in the feature space and an isotonic fit to improve the estimation. An important drawback of this method would be the monotonic properties of the features, if they don't present that property the RUL estimation would tend to fail, but taking into account the phenomenon of degradation this property is expected to occur, if it's difficult to detect, then new features should be calculated to identify this property. This method can be applied on other components, other than bearings, but, in case of other components degradation, an assessment of the monotonic properties of the features will determinate the performance of the methodology.

Some conclusions can be drawn from the analysis performed. The performance of the novelty detection model is heavily influenced by the features used to characterize the monitored component. Improving the feature calculation and feature reduction stage the false alarm rate would decrease. Nevertheless, part of the false alarms are caused by the intrinsic variability of the physical magnitudes acquired, causing an uncertain zone regarding the condition of the monitored component. By identifying and characterizing this uncertain zone the false alarm rate would also decrease and the robustness of the novelty detection task would increase.

These conclusions lead to the development of the subsequent methodologies to improve the reliability and robustness of the novelty detection task. Indeed, two methodologies that improve the feature calculation and feature reduction stages are proposed in this chapter, but the characterization of the uncertain zone is further addressed in chapter 5.

Regarding the improvement of the feature calculation and reduction stage, the first methodology proposed consist of a multi-modal scheme. The objective of this methodology is to improve the resolution of the feature calculation and reduction stage without compromising the performance of the novelty detection models. Taking into account the number of measurements available to characterize a scenario are limited, the increment of features analyzed by the models complicate the training stage and the selection of the configuration parameters. However, by dividing the monitoring task in different segments or parts, (in this case study the rotation angle of the camshaft) it is possible to increase the resolution and detect new scenarios without compromising the performance of the models.

The second methodology proposed consist on the reformulation of the features analyzed each time a new scenario is incorporated to the base knowledge. Taking in consideration that the information initially available consist only on the healthy condition and the novelty detection model is selected beforehand, the feature reduction module, is initially performed by unsupervised approaches. Once the information of a fault is available, the feature reduction module could improve its performance by employing supervised methods. In this case study, a Laplacian Score Ranking is proposed as an initial unsupervised feature reduction approach since it provides a good trade-off between simplicity and performance. Then, the Laplacian approach is replaced by a Fisher Score ranking approach in this work, where the features are sorted according the Fisher coefficient calculated from each feature to search for a possible discriminative feature space to increase the detection of novel scenarios.

It can be concluded that, under the restrictions of a low number of measurements per scenario and a selected novelty model, the performance of the novelty could be improved if a reformulation of features is performed. It is important to notice the limitation that implies the development of the feature calculation and reduction when there is no information of the possible faults that could occur to the monitored asset. This is specially critic in electromechanical systems, where the effects of degradation for different faults could not be detected with the same accuracy in the initial feature space proposed. Indeed, in the performed analysis, the identification of the broken bars faults was performed with higher accuracy by selecting the features that allows a better characterization of the monitored fault.

From an industrial perspective, the proposed method can be extended and improved for further development, this improvement could include a diagnosis method to not only detect anomalies on the kinematic chain, but to identify the fault causing the abnormal behavior.

4.

Fault Detection and Identification Systems

The incursion of novelty detection to the CBM program represent the first step to reach the industry demands. In this regard, this chapter presents the contributions to increase the reliability and robustness of the FDI systems by specific methodologies based on an adequate selection and reduction of features for each task.

CONTENTS:

4. Fault Detection and Identification Systems

4.1 Introduction

In the last years, the industry applications are demanding 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 scenarios (novelty detection), while continue the identification of the known fault conditions previously available (fault diagnosis). In pattern recognition and machine learning framework, this kind of scenario is known as *open set recognition problem* [54], 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. In this regard, the integration of novelty detection strategies to fault diagnosis methodologies is the first step to develop a condition monitoring system capable to deal with the open set recognition problem. A great deal of scientific effort is being focused on the study of such approaches [25], [53], [82].

As mentioned in the presentation of the state of the art, the classical approach to deal with such open set problems consists on one-class classifiers [55], where one one-class classifier is considered for each class [56], [57], [33], [58]. 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.

Other studies have approached the open set problem by a separate analysis of fault diagnosis and novelty detection [24], [51], [53], [83]. Fault diagnosis 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.

As concluded by the analysis on the previous chapter, the performance of the novelty detection models are strictly dependent of the quality of the features calculated, if the features analyzed are not representative enough to characterize the machine, any novelty detection model will not be able to detect the new scenarios. In this sense, the study and proposal of a suitable feature calculation and reduction stages specifically designed for the novelty detection task appears to be a coherent solution to obtain high reliability and robustness. Therefore, in this chapter, a study of the feature calculation strategies independently for novelty detection and fault diagnosis is performed to propose a series of contributions to increase the robustness and reliability of the novelty detection and fault diagnosis task separately.

4.2 Sequential FDI system with separated stages for novelty detection and fault diagnosis

An initial approach to provide detection capabilities in front of not previously considered faults was proposed by Grbovic *et al.* in 2013 [84], by means of a combination of novelty detection and fault diagnosis models. Indeed, the use of novelty detection models, and a classification (or supervised) models, to deal with the lack of information during training is being currently used in data stream analysis application field [62]. Nevertheless, such methods need a proper adaptation to cope with the challenges presented in an industrial electromechanical system, such as the need of a proper signal processing stage to highlight the faults and considerable lower ratios of available data.

As mentioned before, other studies have approached the open set problem by a separate analysis of fault diagnosis and novelty detection [24], [51], [53], [83], nevertheless, such FDI methodologies deal with their own limitations of their application domain that differ from the ones presented in the electromechanical systems. Furthermore, such approaches does not consider a specialized and separated stages of feature calculation and feature reduction for the novelty detection and fault diagnosis tasks.

In this sense, a FDI system with a specialized feature reduction stage for novelty detection and fault diagnosis is proposed in this chapter. **Fig. 4.2.1** shows a scheme of the proposed methodology.

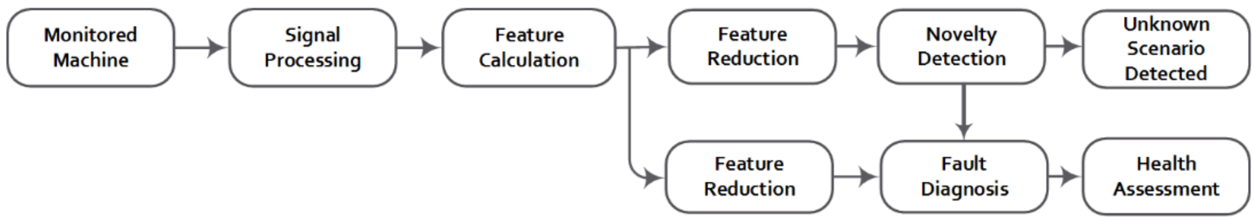

Fig. 4.2.1 Proposed methodology for a sequential FDI system with separated stages for novelty detection and fault diagnosis

The proposed scheme begins with the traditional data processing and feature calculation stages to characterize the monitored machine. As concluded in the previous chapter, increasing the number of features observed from the monitored machine could increase the capacity of the models to detect anomalies or discriminate between faults, nevertheless, in this application domain, generally, the number of measurements available per scenario is limited, therefore, a high number of features per model could compromise the performance of the models. In order to exploit the potentiality of a separate fault diagnosis and novelty detection stages under this restrictions, two different feature reduction approaches are applied over the features sets.

As mentioned before, feature reduction approaches that consider the topology preservation (Laplacian score, self-organizing maps, etc.), or variance maximization (principal component analysis), of the analyzed features are recommended for novelty detection, due to their capacity to consider a more general perspective of the characterized machine. Meanwhile for fault diagnosis, discriminative feature reduction approaches (Fisher coefficient ranking, linear discriminant analysis, etc.), are recommended to maximize the distance of the known scenarios.

It is important to stress that this methodology works under the premise that the healthy condition and several fault conditions are initially available, therefore there is no need to include new scenarios.

To analyze a 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 fault diagnosis model. The output of the model is a label that identifies the analyzed measurement as one of the considered classes.

Case Study: Sequential FDI system applied to an EOL test machine of the automotive sector

To validate the proposed scheme, the FDI methodology by means of separated stages of feature reduction for novelty detection and fault diagnosis is applied to monitor the condition of an EOL friction test machine over the manufactured parts, a steering system in this case study. Note that the machine applies its own algorithm to determine the condition of the steering system under test but the aim of the methodology is to monitor the proper function of the EOL test machine. A more in-depth description of the EOL test machine and the friction test can be found in **Annex IV**. The proposed methodology is shown in **Fig. 4.2.2**.

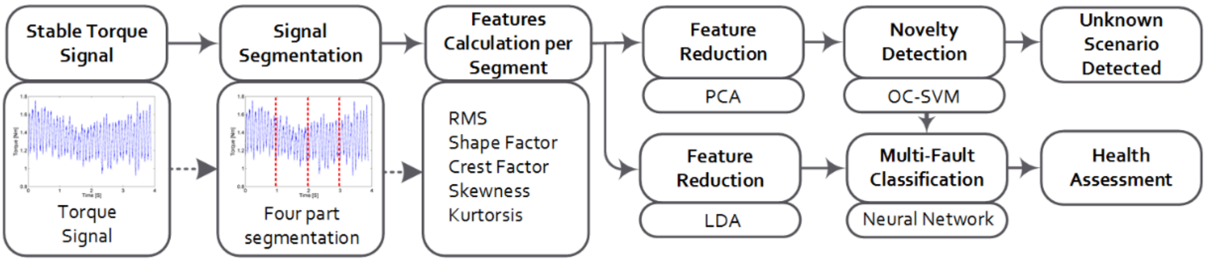

Fig. 4.2.2 Proposed methodology for the EOL test machine. The monitoring method is composed by a signal processing stage where statistical features are calculated and analyzed by a novelty detection and a multi-fault classification models to assess the operating scenario of the machine.

In this case study, the torque signal analysis is carried out during a stationary speed set point, corresponding to a 360º clock-wise turn of the steering system. It is expected, a priori, due to the mechanical nature of the possible malfunctions and anomalies, that these could be reflected in the torque signal during segments of the revolution of the steering system, therefore, the segmentation of such signal is proposed as a viable strategy to gain resolution during the characterization. Thus, the available 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. That is, a larger number of segmentations increases the resolution but also increases the number of features, and could lead to overfitted models, meanwhile choosing a lower number of segments could not provide enough resolution to detect deviations from the healthy operation. The torque signal and the segmentation is presented in **Fig. 4.2.3**.

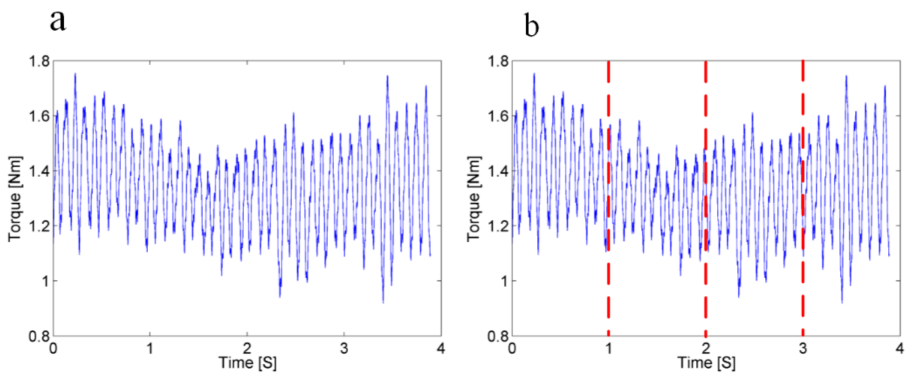

Fig. 4.2.3 Torque signal analyzed a) Stationary part of the torque signal b) Segmentation proposed for this study

A set of five statistical time-domain features are calculated from each segment of the torque signal which consist of the Root mean square, the crest factor, the shape factor, the kurtosis and skewness. The formulas to obtain such features can be consulted in **Table 2.1.1** in Chapter 2. These features have been successfully employed in different studies for electromechanical systems fault detection [18]. Therefore, a total of 20 features are calculated from each torque signal measurement.

Regarding the feature reduction stages, for the novelty detection module, the PCA is proposed 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 operating scenarios. Regarding the fault diagnosis module, LDA is proposed 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.

In this case study, a standard OC-SVM with Gaussian kernel is proposed for novelty detection. 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 fault diagnosis stage, a multi-layer neural network (NN) is proposed. 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 [1].

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.

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

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

The faulty conditions corresponds to different severities degree of Misalignment (MIS) and coupling wear (CW), more details of the EOL test machine and the considered faults can be found in Annex III. There is 80 measurements for each class, therefore, the dataset consist of a total of 640 measurements.

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 classifiers are 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.

Performance metrics

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.

In order to highlight the contribution and motivation of the proposed methodology, the outline of the results will be presented as follows: first, a test is performed by a classical methodologies that consist in an ensemble of one-class classifiers for fault detection and novelty detection. Then a test is performed with a simple approach of a sequential fault detection and identification methodology, where the same feature reduction is used for both tasks. Finally, the proposed sequential methodology with separated stages of feature reduction 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 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 4.2.2**, where the best performance of each metric is highlighted.

Table 4.2.1. Performance of classical one-class classifiers based methodology using three different dimensionality reduction configurations

Classical 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 4.2.2**, 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 4.2.3**.

Table 4.2.2. Performance of a simple sequential fault detection and identification methodology using the same feature reduction for each task.

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 [23]: Multivariate Kernel Density Estimator (MKDE), and Mixture of Gaussians (MoG). The results are shown in **Table 4.2.4**, where the best performance of each metric is highlighted.

Table 4.2.3. 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.

Table 4.2.4. Performance of the proposed novelty detection and multi-fault classification methodology using three different novelty detection models

True Class	Assigned Class							
	Hc	**CW*₁***	**CW*₂***	**CW*₃***	***MIS₅***	***MIS₆***	***MIS₇***	***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

To analyze the performance of each class individually, the confusion matrix of the proposed methodology is shown in **Table 4.2.5**. 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.

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.

4.3 Conclusions and discussion

A methodology with separated stages for novelty detection and fault diagnosis is 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 methodology proposed is compared with two classical methods. The set of key performance metrics are proposed to evaluate 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 fault diagnosis task and the PCA capable of improving the novelty detection task.

Regarding the novelty model accuracy metric, the three methodologies tested 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 applied to this case study, a high novelty model accuracy and high multi-fault accuracy performances cannot be obtained at the same time since the performance of the model is 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.

5.

Incremental learning framework

The incremental learning framework is referred to a structure intended to serve as a procedure to include new information to a given system. In a FDI system, working under an incremental learning framework implies the incursion of new scenarios to a given initial knowledge which implies a new set of emerging challenges.

In this regard, this chapter presents the contributions to successfully implement a FDI system under an incremental learning framework by specific methodologies to cope with the limitations presented in the CBM applied to electromechanical systems.

CONTENTS:

5. Incremental learning framework

5.1 Introduction

One of the most important challenges towards the implementation of reliable Condition-Based Monitoring (CBM) schemes in the industrial sector, refers to the management of unexpected events. As mentioned in the previous chapters, a classical CBM is supported by a set of malfunction conditions that, a priori characterized, can be recognized later during the diagnosis process. However, the presence of faults not previously considered, or even deviations of performance over the nominal behaviour, represent common conditions that lead to diagnosis errors. Indeed, classical CBM schemes are being redefined by the incursion of the Fault Detection and Identification (FDI) systems. Novelty detection became a critical task since the objective is to detect whether the measurement under analysis corresponds to a *known* or *unknown* condition. Then a fault diagnosis model identify the fault. In the past chapter the methodologies to implement FDI systems were discussed and analysed, then, a methodology to improve the accuracy such systems was presented.

However, the FDI methodology previously presented and most of the related works available up to now work under a static framework, where the healthy and a set of fault conditions are initially available and previously characterized following a classical diagnosis approach, and uncorrelated or abnormal events are detected and set apart [1], [25]. Nevertheless, in most of industrial applications, just the nominal operating condition is available (the healthy condition), which, from one side, makes unfeasible a previous characterization of fault conditions and, from the other side, requires the proposal of a FDI system capable of update the models as new scenarios are present.

As discussed in the presentation of the state of the art, most of the proposed approaches in the literature focus their contributions on the limitations presented on their respective application domain, being their primary focus the reduction of the computational complexity of the incremental learning framework. Some of the applications assume that the variables that characterize a monitored asset drift over time, therefore the contributions of the models focus on providing adaptive capabilities to drift changes, which leads to an intrinsic forgetting feature of the systems to discard past information. However, in some application domains it is not desired to discard past information but rather keep accumulating fault scenario to further detect them if they are presented again. In addition, the application to electromechanical systems present other limitations.

The computational complexity of the methods to work in real time is not the primary limitation in this application domain due to the low number of measurements analysed in a selected period of time during the monitoring task and the possibility of an offline re-training, nevertheless, this implies that the models should be able to characterize the new operating scenarios with a limited number of measurements. Another limitation corresponds to the storage of measurements of each scenario detected. Some of the applications include a repository database to store every measurement analysed of the machine under monitoring, therefore scenarios to characterize every new scenario detected are available. If a new scenario is intended to be included in the base knowledge of a model, almost all models for novelty detection and fault diagnosis require to access this repository database to re-train the model and include a new scenario to the already existing ones, therefore, the availability of a repository database represents a critical factor to select the appropriates models for each task. Nevertheless, in some applications a constant storage of measurements of the monitored machine is not available, therefore the models should be able to include new scenarios without needing the measurements previously used to include the previous scenarios.

Taking in consideration the limitations mentioned the adaptation of the incremental learning framework to FDI systems represents a challenging task, which will be further discussed in the subsection of this chapter.

5.2 Methodologies for FDI systems under an incremental learning framework

The incremental learning framework in FDI systems is a new topic and only few works have been published in different application domains. Among the available works, stands out the proposed by Costa *et al.* in 2016 [53], where a two-stage methodology for real-time novelty detection and fault classification applied to an industrial plant is presented. Specifically, the initial novelty detection is supported by density analysis in the data space, and the classification stage is designed by the auto-class fuzzy-rule-based classifier. However, the advantage of such algorithms are based on their computational efficiency for on-line monitoring and adaptive capabilities to novel scenarios incorporation, rather than accuracy and generalization capabilities. Another disadvantage of the method presented is the need of sufficient samples to properly calculate the density of the data, such availability of measurements is proper from industrial monitoring applications but is not guaranteed to occur in electromechanical machines. The work also emphasize the need of an *ad hoc* signal processing, estimation of numerical indicators and feature reduction procedures for the specific plant under test. Filev *et al*. in [50], propose an autonomous equipment monitoring and diagnosis framework, emphasizing the need of a generic structure that is relatively independent of the type of physical equipment under consideration. The results presented are promising but the algorithms are limited to the detection of two different types of faults, incipient or abrupt.

Classical data-driven CBM methodologies for fault detection or novelty detection face the knowledge increase by means of a batch scheme, where a complete re-training of the models structure is carried out with the data combining the initial and new scenarios. However, storing all the measurements is not always possible and, moreover, the complexity of the retraining process is increased as the data is accumulated, which represents an unsustainable approach.

The capacity to continuously store the measurements of the monitored machine represents an important factor regarding what novelty detection and fault diagnosis models can be used. If an repository database is available, traditional novelty detection and fault diagnosis models can be used since a complete re-training of the models structure with the data combining the initial and new scenarios can be performed. Nevertheless, if a repository database is not available to continuously store the monitored measurements, models that can performed a re-training to include the new scenario without the measurements of the initial scenarios are necessary.

In this sense, the implementation of a FDI system working under an incremental learning framework could be defined according the availability of the resources, in this case, when a repository database is available and when isn't available.

In this chapter both cases are studied, and the previously proposed methodology for a sequential FDI system is initially enhanced by including a re-training stage to include new scenario to the novelty detection and fault diagnosis model. Then, an alternative methodology is proposed to cope with the absence of a repository database to re-train the models, where an ensemble of one-class classifiers and an evolving classifier are used for novelty detection and fault diagnosis. Such techniques are capable to include new information without a complete re-training of the models and also without forgetting the base knowledge which consist of the other known scenarios.

5.2.1 Incremental learning when a repository database is available

As mentioned before, classical data-driven CBM methodologies face the knowledge increase by means of a batch scheme, where a complete re-training of the models structure is carried out with the data combining the initial and new scenarios. By assuming that a repository database is available, this approach can be applied in a FDI system to work under an incremental learning framework. Since an offline re-training is used to include new scenarios to the models, this approach allows to use the classical novelty detection and fault diagnosis models discussed in previous chapters. **Fig. 5.2.1** shows a scheme of the proposed methodology, which includes different stages regarding the activity performed, an initial training stage, an online monitoring stage and a re-training stage. The methodology proposed also considers separate stages for novelty detection and fault diagnosis, therefore the advantages of separated stages for novelty detection and fault diagnosis is maintained.

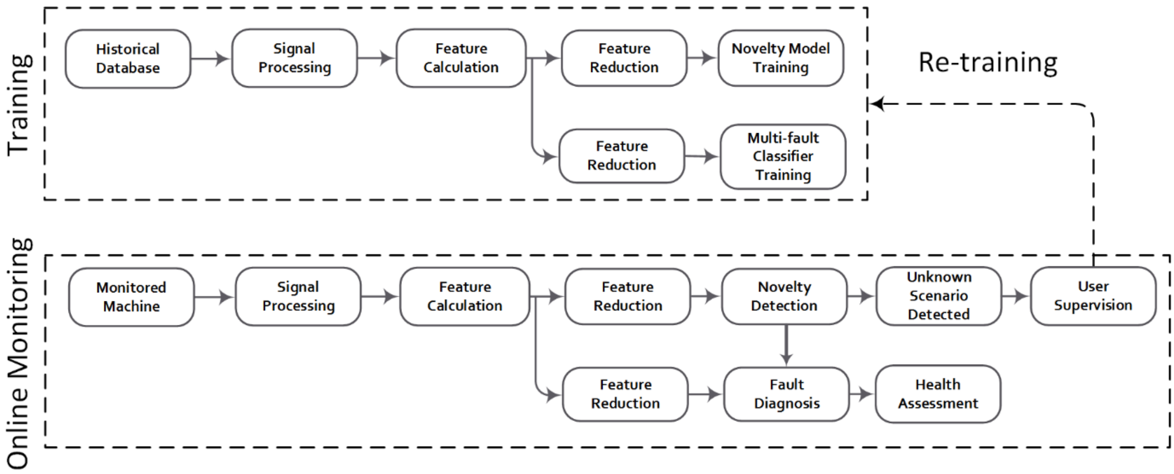

Fig. 5.2.1 Proposed scheme for a FDI system working under an incremental learning framework when an repository database is available.

Taking into consideration that the initial knowledge consist only on the healthy condition, the models are initially trained with this scenario during the training stage. During the online monitoring stage, a batch-type analysis is proposed to evaluate the condition of the machine, where a certain number of measurements are stored and then evaluated by the novelty detection model to identify the machine is working under known or novel conditions. The number of analyzed measurements is empirically selected to provide a robust decision regarding the condition of the machine; if only one measurement is analyzed each time then the rate of false alarm rate could be increased drastically due to outliers.

If the condition of the machine is determined to be known, then the measurements are analyzed by the fault diagnosis model to determinate the condition of the machine. If the condition of the machine is determined to be novel or unknown, a user supervision module is activated. If the user determinates that the novel condition corresponds to a new fault condition, the batch with the corresponding measurements of the new fault are stored in a repository database and a re-training procedure is performed to include the new scenario to the base knowledge of the models. The re-training is performed for both, the novelty detection and the fault diagnosis model, in a classical approach combining the initial and new scenarios to the training set. After the models are re-trained, the online monitoring stage starts again.

It is important to mention that the contributions presented in past chapters, especially the multi modal scheme, can complement this methodology to increase the accuracy of the method.

Case Study: FDI system under an incremental learning framework applied to a camshaft-based machine

To validate the proposed methodology, a FDI system under an incremental framework with a multi-modal scheme for novelty detection is applied to monitor the condition of a camshaft-based machine. The high-speed ratios, the mechanisms time-overlapping and the smoothing inertia effect make such systems a challenging application field for classical approaches. The test bench is composed by an induction motor connected to a reduction gearbox that rotates a camshaft to activate the mechanisms corresponding to the manufacturing process. The current signals from the induction motor are acquired to analyze the effects of the cam operations to the current. A more in-depth description of the camshaft-based machine can be found in **Annex III**. The proposed methodology is shown in **Fig. 5.2.2.**

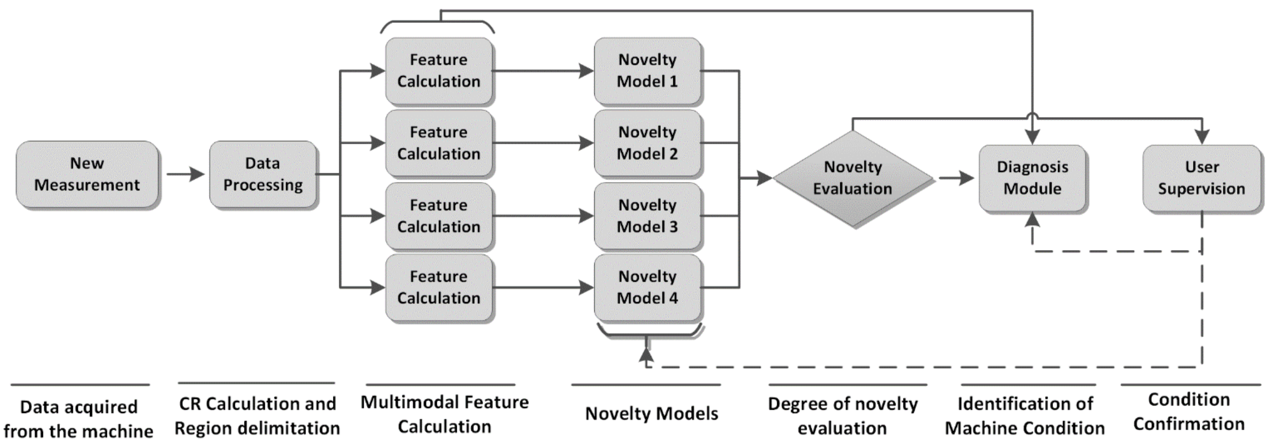

Fig. 5.2.2 Proposed methodology for a FDI system under an incremental learning framework with a multi-modal scheme. The monitoring process starts with data regarding normal operation of the machine and the modules adapt as information of faults are present. The continuous line corresponds to the evaluation of new measurements, meanwhile the dotted line corresponds to the re-training of the models.

In order to highlight the deviations during the operation of the machine, the calculation of a NTFM is proposed as a data processing stage. As aforementioned in previous sections, the NTFM is obtained by means of the Short-Time Fourier Transform (STFT) of the acquired signal but normalized in regard to a reference, which is a STFT over the healthy condition during the calibration process. Each Normalized Time-Frequency Map (NTFM) calculated from the current of the motor has a time window length corresponding to one full shaft turn. A more in-depth explanation regarding the data processing stage and the algorithm to calculate the NTFMs can be found in **Annex III**.

In order to characterize the machine, two sets of statistical time-frequency features are calculated from the NTFM. The NTFM is divided in 8 different regions considering both time and frequency axes. Each region is identified by a number from 1 to 8. The number of regions proposed is empirically selected and represents an adequate tradeoff between resolution and overfitting. A larger number of regions 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. As an example, the NTFM of a measurement corresponding to the first fault, F_1, is shown in **Fig. 5.2.3 (a)** and the corresponding to a second kind of fault, F_2, is shown in **Fig. 5.2.3 (b)**, the characteristics of both faults are further explained in **Annex III.**

It can be appreciated that there is a predominant change of spectral energy respect to the reference in regions 1 to 4, 6 and 8. An analysis of such regions could identify a possible anomaly in the condition of the machine; nevertheless, all regions must be analyzed because different anomalies could generate different affectation patterns distributed through the NTFM.

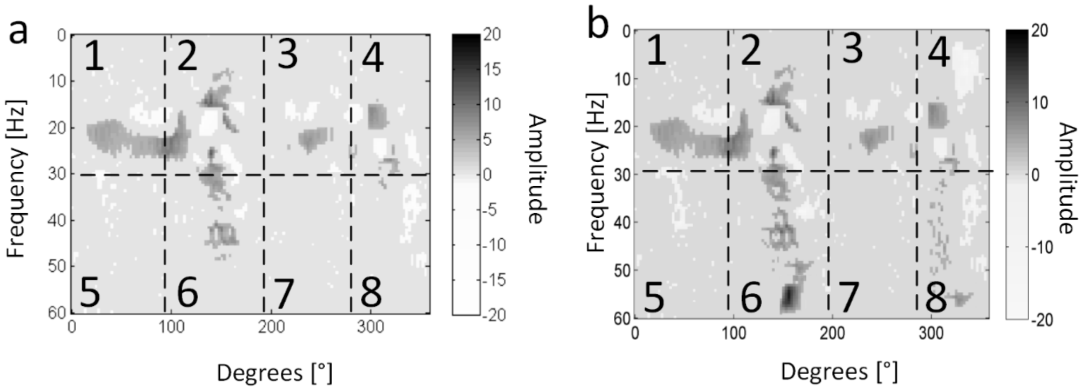

Fig. 5.2.3. Resulting NTFM segmented in 8 regions. a) F_1 b) F_2

Novelty detection and diagnosis have different objectives: novelty detection is focused only on detecting deviations from the known behavior (one-class problem approach), and the diagnosis is focused on identifying and discriminating the different previously labeled scenarios (multi-class problem approach). Therefore, the features for novelty detection are intended to provide a more general analysis (less overfitted), of the behavior of the machine, meanwhile the features for the diagnosis are intended to provide more specific analysis of the known faults.

Novelty models

The full shaft turn is segmented in four parts, each one corresponding to 90 degrees. When an unexpected anomaly is present, it is not possible to anticipate in which part of the full shaft turn is reflected and extracting this information could be important to the operator; therefore, one novelty model is used to monitor each of the four parts of the full shaft turn, meaning that a total of 4 novelty models are used in this study, in this case, the multivariate kernel density estimators.

Each novelty model is trained with the features of the corresponding regions of each 90 degrees of the turn, for example, the first novelty model monitors the regions 1 and 5, the second novelty model monitors the region 2 and 6, and so on. The novelty models detect if a new measurement differs from the known scenarios in which such models have been trained. A probabilistic approach is employed based on the calculation of the pdf, $f_{\mathbf{h}}(\mathbf{X})$, where **X** corresponds to the training dataset characterized by an arrays of features. The assessment of a new measurement, $\hat{\mathbf{x}}$, over the resulting pdf's provides the degree of novelty of the data, $f_{\mathbf{h}}(\hat{\mathbf{x}})$. As an interpretation of the test results, a low $f_{\mathbf{h}}(\hat{\mathbf{x}})$ value implies that the new measurement differs from the data used in training. To enhance the information obtained from the models about the condition of the machine, a visual representation of the measurements in the feature space is desirable. In this study, since only the *rms* is calculated per region for novelty detection, each novelty model is trained with two features, therefore a two dimensional representation is obtained.

Novelty Evaluation

After the 4 models are trained and new measurements of the monitored machine are analyzed, an evaluation procedure is employed in order to process the resulting novelty scores of the models. This procedure assesses abnormal behaviors detected during the analysis of the regions and results in the degree of novelty of the analyzed measurements. A batch-type analysis of 30 NTFMs (which corresponds to 30 full shaft turns) of the monitored machine are stored and then evaluated simultaneously by the models, the novelty scores of each NTFM is then analyzed to diagnose the behavior of the machine. The number of analyzed shaft turns is empirically selected to provide a robust decision regarding the condition of the machine; if only one shaft turn is analyzed each time then the rate of false alarms could be increased drastically due to outliers.

The first step is to label the resulting degree of novelty of the NTFMs as: *Known, Uncertain* or *Novel*. The assignation of the label depends on the assessment of the novelty score $f_{\mathbf{h}}(\hat{\mathbf{x}})$. The possible range of values part from zero to the maximum value determined by the bandwidth, the number of samples used for training and the kernel selected, thus $f_{\mathbf{h}}(\hat{\mathbf{x}}) \in \left[0 \ldots \max\left(f_{\mathbf{h}}(\mathbf{X})\right)\right]$.The labelling process is determined by the novelty score shown in **Fig. 5.2.4**.

The label *known* represents the measurements with a $f_{\mathbf{h}}(\hat{\mathbf{x}})$ score higher or equal than 2/3 of the maximum value of $f_{\mathbf{h}}(\mathbf{X})$. The label *Uncertain* represents all the data with a $f_{\mathbf{h}}(\hat{\mathbf{x}})$ on the interval of 2/3 and 1/3 of the maximum value of $f_{\mathbf{h}}(\mathbf{X})$. The label *Novel* consist of the measurements with a lower or equal $f_{\mathbf{h}}(\hat{\mathbf{x}})$ score than 1/3 of the maximum value of the $f_{\mathbf{h}}(\mathbf{X})$.

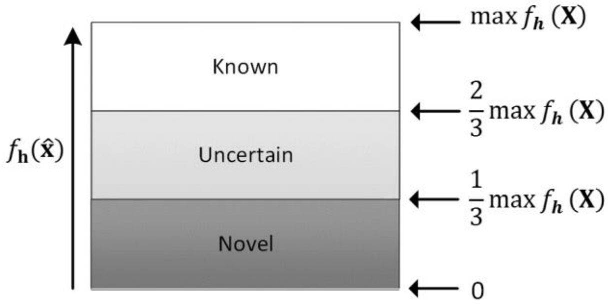

Fig. 5.2.4 Delimitation of degree of novelty according the novelty score.

Those predefined thresholds can be modified according to the application; however, considering that no previous information of the novel conditions is available, such proportional thresholds represent an appropriate configuration. In fact, a higher value for the boundary between *Known* and *Uncertain* may generate some false alarms, whereas a lower value for the boundary may provide less resolution to the detection.

In order to complete the procedure, the labelling process is applied over the 30 NTFMs. Since there are, in this work, 4 novelty models the final label is defined by the analysis of the output label of all the models.

Each NTFM is analyzed by the 4 models obtaining 4 labels, the final label is selected as same as the highest degree of novelty among the 4 different labels obtained by the models. That is, for each analyzed full shaft turn, if at least one of the novelty models detects that the measurement under consideration is *Novel*, then, the final label for this analyzed full shaft turn is selected as *Novel*, even if the 3 other models label the measurement as *Known* or *Uncertain*.

The reason to assign the label with the highest degree of novelty of the four models as the final label of the measurement is because each novelty model analyze a part of the camshaft rotation, and the machine faults are expected to be reflected more significantly in one part of the rotation of the camshaft than another; therefore, it is possible that new faults are only detected by one of the models.

After the 30 full shaft turns are labeled, the current condition of the machine is determined according to the majority of the labels. If the *Known* label represent 50% or more of the measurements, the 30 NTFM are processed by the diagnosis stage to identify the condition of the machine. If the machine is diagnosed as healthy behavior, then, the process repeats, starting from the acquisition of 30 full shaft turns and processing them into NTFMs.

On the other case, if more than 50% of the labels analyzed correspond to *Uncertain* and/or *Novelty*, the corresponding result is shown, and the user supervision is required, where further actions are conducted regarding the opinion of an expert which analyzes the machine. A more detailed explanation regarding the interaction of the user supervision is detailed in further in this subsection.

Fault Diagnosis

The objective is to identify the condition of the machine among the possible scenarios previously characterized and labelled, and this is carried out by means of a classification algorithm. This module is activated when the majority of the labels are detected as *Known* in the novelty evaluation stage or when the user supervision module is activated by a majority of *uncertain* labels.

Although different classifiers can be applied to perform the diagnosis task, the artificial neural network is considered as a convenient option for this methodology. ANN are data-driven self-adaptive information processing methods inspired in biological systems, and they represent the most commonly data-driven technique found in literature [1]. An ANN is composed by a number of interconnected processing elements (neurons) working at the same time to solve a specific problem. The ANN represents a no-lineal, multivariate and non-parametric algorithm approach applied in this methodology for pattern recognition. The ANN combines the information coming from the different parts of the full shaft turn in order to determine the machine condition among the known scenarios.

The ANN is trained with all the features of the 8 regions of the known scenarios and processed in a different way that for the novelty evaluation. The output is the condition of the machine, in terms of healthy state or one of the considered faults. The capacity of the diagnosis module to discern among the different scenarios will be assessed by a validation test of the ANN whenever a new scenario is incorporated.

User Supervision

The user supervision is required previous to the adaptation of the scheme to new data. That is, when *novel* or *uncertain* data is detected. *Novel* data imply a behavior complete different from the one presented so far;

then, a new operating mode of the machine is taking place. In the case of *uncertain* data, it is possible that the presence of a small deviation from the *known* scenarios is detected. The 30 full shaft turns can therefore be analyzed by the diagnosis algorithm in this case with the aim of providing more information to the supervisor user.

Three possible scenarios can be present after the inspection of the results by the supervisor. First, a new fault condition is determined; second, the current scenario is already known by the methodology; and third, false positive detection and the data must be discarded.

If the identified scenario is already known but still the novelty evaluation label the data as novel or uncertain, the novelty and diagnosis models are re-trained to incorporate such information to an already existing scenario. Otherwise, if a new fault is detected, the novelty models and diagnosis models are re-trained incorporating a completely new scenario where the supervisor user will introduce the corresponding label.

In order to validate the proposed methodology, three different experimental cases are considered in this study: a healthy or normal condition, and two faulty conditions by inducing effort disturbances. The first fault condition, F_1, involves the decrease of 25% of the effort pattern related with the first cam, C_1, through the adjustment of the thumbscrew related to the load grip by means of a dynamometric key. The second fault condition, F_2, includes a decrease of 25% of the effort pattern related to both of the cams, C_1 and C_2, also by the adjustment of the thumbscrew related to the load grip. It must be taken into account that the induced fault scenarios correspond to common degradation patterns due to the continuous machine operation. Thus, although the effort disturbances induced by the fault conditions can be considered incipient deviations, it is expected to extract by the proposed methodology the corresponding affectation over the motor stator current. From each of the considered scenarios, 30 camshaft revolutions were acquired, considering both currents and encoder.

To highlight the contributions and challenges described at the beginning of this chapter, the experimental results are presented in three stages. In the first stage, the novelty models are trained and validated only with data corresponding to the healthy condition, *Hc,* and, then, tested with data corresponding to a novel condition, the fault condition F_1. In the second stage, the novelty models are re-trained including information of the fault F_1, and then the novelty models are tested with information of a novel fault condition, F_2. In the third stage, once the fault condition previously tested is detected, the novelty models are re-trained including information of the fault, F_2, and then the diagnosis model is tested with data corresponding to the three scenarios.

As it can be seen by the description of each stage, for organization purposes, the capability of the novelty models to detect and incorporate each novel scenario is tested first and, later the diagnosis performance is analyzed. Nevertheless, the methodology is structured to perform a continuous monitoring, therefore, when is tested in real time applications, the diagnosis model can be triggered each time the data is labeled as *known* during the novelty detection task.

Novelty assessment, availability of healthy data

Initially, the acquisition of the 30 full shaft turns and the computation of the NTFMs under healthy condition are carried out alongside with the calculation of features for each region, then, the novelty models are trained.

Four *pdfs* are calculated (one by each novelty model trained) by pairing the *rms* estimation of each region. Each *pdf* considers one partition of the rotation axis, that is, 90º. Thus, the *pdf1* is obtained with the features from region 1, rms_1, and 5, rms_5, that is, from 0º to 90º, the *pdf2* is obtained with features from region 2, rms_2, and 6, rms_6, from 90º to 180º, the *pdf3* is obtained with features from 3, rms_3, and 7, rms_7, from 180º to 270º and, finally, the *pdf4*, is obtained with features from region 4, rms_4, and 8, rms_8, from 270º to 360º.

For the training procedure, the MVKDE with multiplicative function and Gaussian kernel function are used. The bandwidths are set through least squares cross-validation. The resulting *pdf1* is shown in **Fig. 5.2.5**, where the continuous line represents the boundary of the known data and the dotted line represents the boundary of the unknown data. Everything that lies outside the dotted line is considered novel.

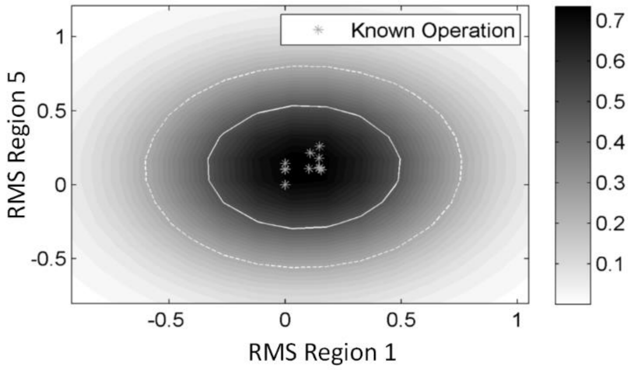

Fig. 5.2.5 The pdf_1 for regions 1 and 5, where * are the measurements of each cycle, the continuous line represents the boundary of known data and the dotted line the boundary of uncertain data, the contour plot represents the *pdf* value.

As it can be seen, all the information regarding to healthy operation is concentrated near the zero value of the both RMS axes. Similar behavior is obtained for the rest of *pdfs*. The contour plot in the same figure represents the novelty score distribution, the $f_{\mathbf{h}}(\hat{\mathbf{x}})$ value. The bandwidths obtained are 0.0653 and 0.0651; since the difference between the values of the consequent measurements is low, the resulting bandwidths have a low value; therefore, the distribution obtained is over-fitted for values close to zero with small variations; to provide more robustness to the initial monitoring phase the bandwidths are increased to a empirically selected value of 0.65, this value represent the tradeoff between avoiding false alarms and gaining resolution on detection so it can be modified according the necessities of the application.

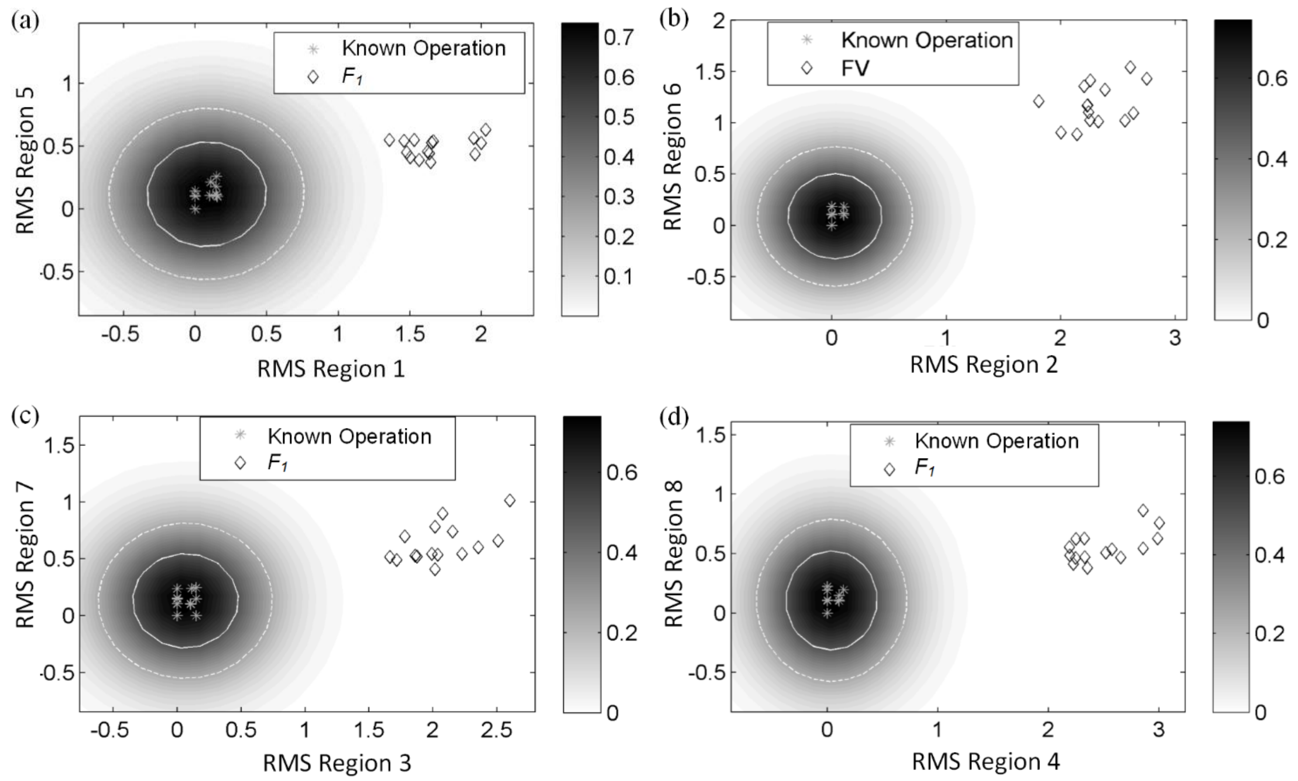

Fig. 5.2.6 Evaluation of a fault scenario on the probability densities obtained of the different regions a) pdf_1 b) pdf_2 c) pdf_3 d) pdf_4

The assessment of the 30 measurements of the F_1 scenario over the initial *pdf* is presented in **Fig. 5.2.6**. It should be noted that the corresponding NTFM is shown in **Fig. 5.2.3 (a)**. The novelty scores are obtained to determine the corresponding novelty degree. The measurements corresponding to the F_1 scenario show a very low novelty score for all four novelty map: <0.01 in all models. Such abnormal behavior is detected by all four models, which implies a significant impact during all the rotation of the camshaft. The 30 full shaft turns are labeled as *novel.* The user supervision alarm is activated and a re-training is performed to include the new scenario detected.

Novelty assessment, availability of healthy data and fault F_1

The adaptation of the novelty maps to the new scenario is shown in **Fig. 5.2.7**, where the resulting pdf_1 is presented. Similar results are obtained for pdf_2, pdf_3 and pdf_4. As it can be seen in **Fig. 5.2.7**, the introduction of new data implies a modification of the novelty score distribution. The pdf_1 obtained previously formed by one lobe, now has two lobes that enclose the zones where the known operations are concentrated. In **Fig. 5.2.8** the resulting pdf_1 is represented with the boundaries planes between *known*, *uncertain* and *novel* data. After the incorporation of the F_1 scenario to the *known operation*, a second scenario is tested corresponding to the second fault F_2. The corresponding NTFM is shown in **Fig. 5.2.3 (b)**.

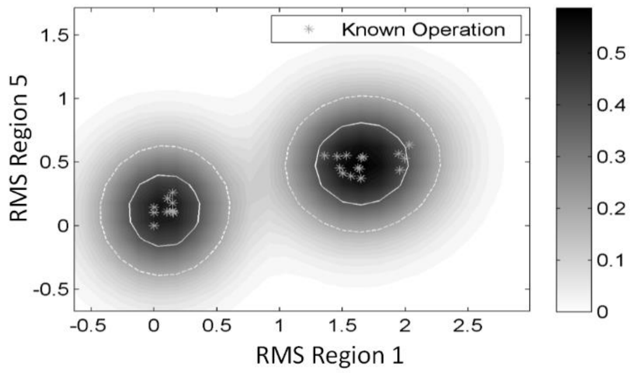

Fig. 5.2.7 Contour plot of the pdf_1 after including F_1

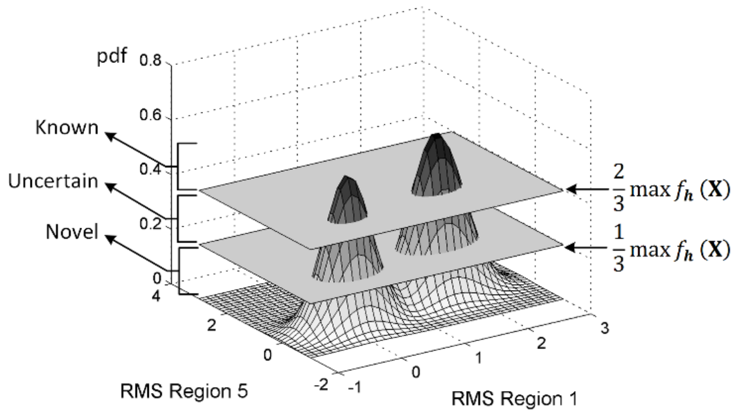

Fig. 5.2.8 Probability density function of regions 1 and 5. The feature space is divided in 3 zones that delimit the degree of novelty according the novelty score.

As illustrated in **Fig. 5.2.9**, this scenario is detected mostly in the novelty models pdf_1 and pdf_2. The resulting novelty scores means that the F_2 scenario impact the first half rotating cycle, from 0° to 180°. Most (29 out of 30) of the full shaft turns are labeled as *novel*; therefore, the user supervision alarm is activated and a re-training is performed to include the new scenario detected.

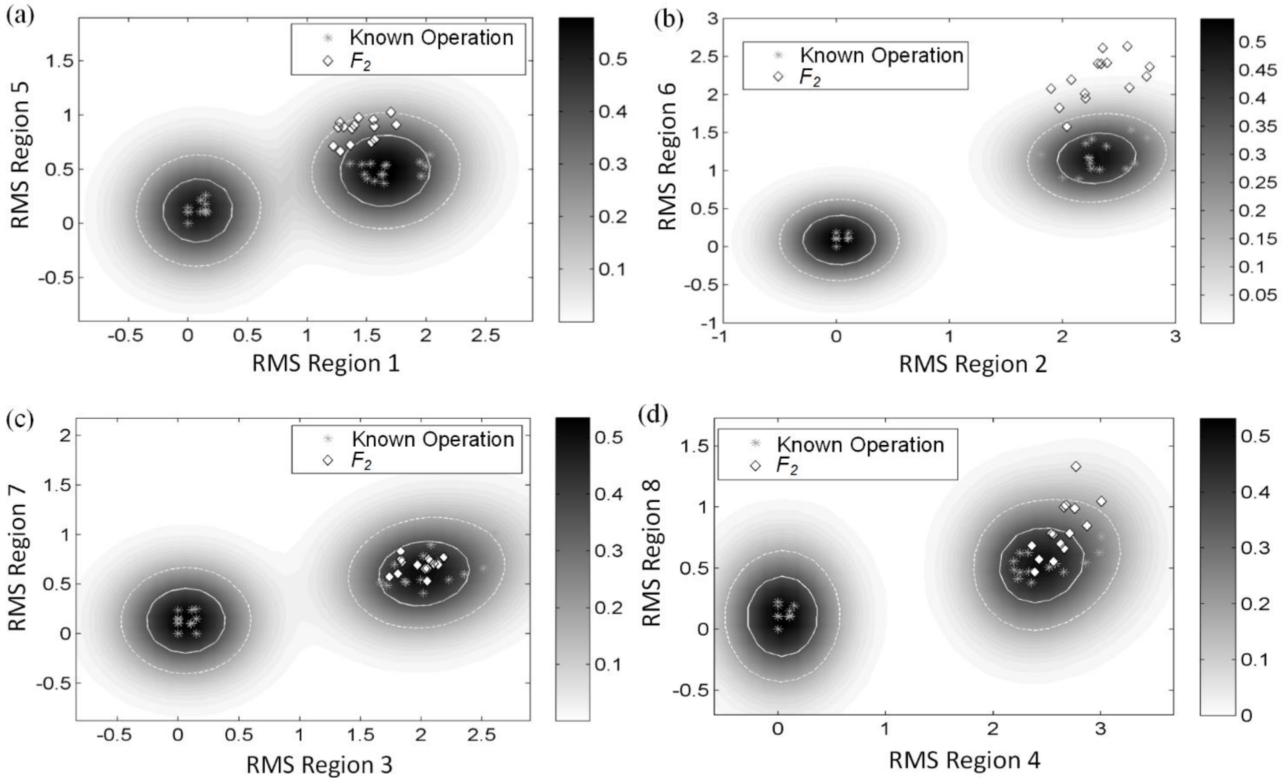

Fig. 5.2.9 Novelty models after incorporating F_1 and analyzing F_2. a) pdf_1 b) pdf_2 c) pdf_3 d) pdf_4

Diagnosis assessment

The procedure repeats activating an alarm, and adapting the novelty models to the new knowledge after the user labelling. **Fig. 5.2.10** shows the pdf_1 after incorporating the last scenario. Similar results are obtained for the rest of pdfs. In this last case, the novelty models do not incorporate a new lobe on the feature space, but extend the lobe next to the previous fault data (F_2). This implies that the new scenario incorporated is not very different, in terms of *rms* of the energy deviations, from one of the known scenarios, which is expected, since the F_2 includes the same cam malfunction analyzed in F_1 plus a malfunction in a different cam.

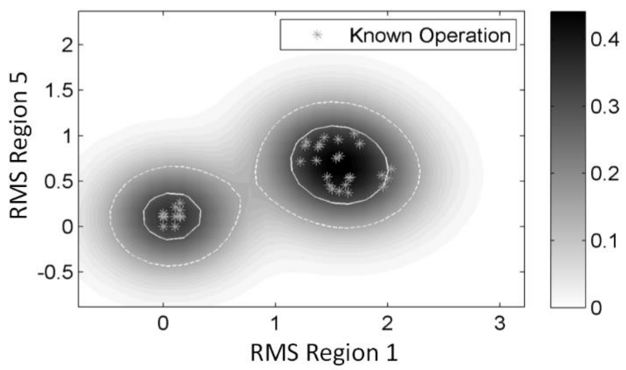

Fig. 5.2.10 Contour plot of the pdf_1 after including F_2.

To test the diagnosis model, 100 full shaft turns of each scenario (*Hc,* F_1 and F_2) are used (300 total), where 70% are employed for training and 30% are employed for testing. This process was repeated five times with five different training-test set distributions, randomly selected and fixed. Regarding the neural network, the architecture used is shown in **Fig. 5.2.11**. A configuration of one hidden layer with 10 neurons is selected, 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.

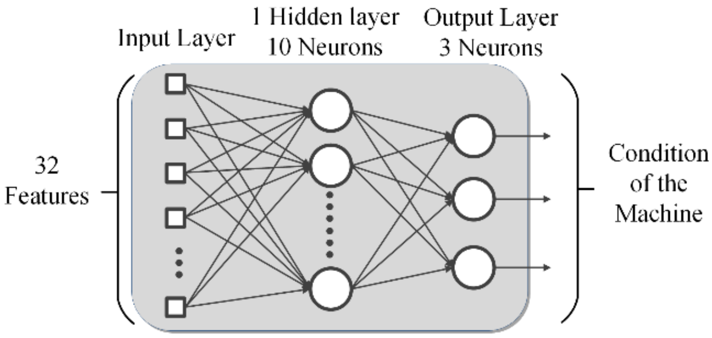

Fig. 5.2.11 Probability density function of regions 1 and 5. The feature space is divided in 3 zones that delimit the degree of novelty according the novelty score.

The resulting confusion matrix of the test measurements is shown in **Table 5.2.1**. A global classification rate of 99% is achieved. It is important to notice that the misclassifications are mostly present between the two faults, which is understandable since F_2 is a combination of a fault from both cams, and a different fault.

Table 5.2.1. Performance of the Diagnosis Stage using the ANN model. The classification accuracy and the standard deviation is presented for each scenario and for the global performance.

	Hc	**F_1**	**F_2**	**Global**
Training Accuracy	-	-	-	0.99(±0.01)
Test Accuracy	1.00 (±0.00)	0.98(±0.01)	0.96(±0.01)	0.98(±0.01)

Since the methodology is intended to be performed in a continuous monitoring approach where 30 full shaft turns are analyzed each batch, the diagnosis module is also tested using less samples for training, in this case, only 30 full shaft turns for training and 30 full shaft turns for testing are used five times with five different training-test set distributions, randomly selected and fixed, obtaining a global test accuracy of 0.97(±0.01), which implies that 30 full shaft turns supply enough robustness to characterize the scenarios under study.

Conclusions

A methodology for a FDI system under an incremental framework with a multi-modal scheme for novelty detection applied to monitor the condition of a camshaft-based machine is proposed in this section. The proposed approach successfully detected the two novel scenarios considered, F_1 and F_2. The methodology includes a batch type analysis with a repository database which allows the classical incorporation of the novel scenarios into the available models for knowledge upgrade. Three different experimental conditions have been considered, representing a significant set of scenarios, including the healthy operation, a single fault condition, F_1, and a combination of two faults condition, F_2. Under all these experimental conditions, the proposed methodology shows proper diagnosis results. During the novelty analysis of the combination of two faults condition, two of the four considered novelty detection models misidentified the scenario as *known*. This is a clear example of the challenge of the novelty detection framework. When dealing with *unknown* fault conditions, it is critical to use multiple feature analysis approaches, as proposed by the present novelty detection models structure, since the less the number of considered features is, the higher the risk of misidentification. It must be noted also that the user supervision is necessary after the detection of a novel scenario in order to confirm and track the corresponding root-cause. Thus, the proposed methodology is constrained to 2-dimensional representations, where the underlying physical phenomena of the machine condition can be visualized. Indeed, the role of the supervisor is crucial in industrial machinery monitoring; since novel scenarios detected must be properly labeled.

A characterization of the uncertain zones in the feature space of the novelty detection analysis is also included in this methodology to reduce the number of false alarms and to provide more information regarding the condition of the machine to the user. The intrinsic variability of the measurements in industrial applications often cause an increment of false alarms, by labeling this variations as uncertain and performing a fault diagnosis to those uncertain measurements, the user is provided with more information to draw a conclusion regarding the anomaly presented.

The proposed methodology shows almost 99% of diagnosis accuracy, which represents a high performance ratio. Note that this is the first time that this methodology and the corresponding analysis are made in electromechanical system diagnosis. The results obtained in this work suggest that this methodology may be also useful for any other rotating mechanical component faults.

5.2.2 Incremental learning when a repository database is not available

In comparison to the previous approach that leads to the formulation of a methodology where any classical model can be applied due to the availability of a repository database, in this approach, the limitations that involves the absence a database in a FDI system are analyzed.

As mentioned in the presentation of the state of the art, there are several strategies proposed for novelty detection and fault diagnosis that can incorporate new information without requiring a complete re-training of the models structure, including adaptive or incremental models, ensemble strategies and evolving models.

Regarding novelty detection, two strategies are considered mainly in the literature: incremental models and ensemble of one-class classifiers. Incremental models are mainly applied within big data analytics, where a great deal of continuous data is available. The performance of such approach over electromechanical systems may be limited, considering the low inertia of multiple wear based faults and the necessity of multi-fault patterns recognition. In general terms, the use of an ensemble of one-class classifiers provides more design flexibility in comparison of the incremental based models. That is, dealing with an ensemble-based approach, a new model can be created when a new data set is detected; therefore, there is no loss of previous knowledge because it is retained within the set of models. In this sense, the discard of knowledge is user-dependent, by selecting the specific model to remove. Moreover, any novelty detection technique can be used to be part of an ensemble-based scheme.

Regarding fault diagnosis, the same both discussed strategies are also applicable with their respective modifications. Indeed, there is considerable literature on incremental learning and ensemble-based classifiers, and most of the characteristics discussed in the novelty detection side applies also for fault diagnosis. It is important to note that, in general, such methods work under a supervised or semi-supervised environment, where the labeling process of a new data set as well as the model tuning is carried out manually and off-line. However, as it has been aforementioned, dealing with fault diagnosis purposes, the evolving strategy is being considered as a superior adaptive approach in multiple studies, as stated by Z. Gao *et al.* in 2015 [62]. Indeed, the fault diagnosis stage requires the consideration of a more complex data boundary structure. Unlike novelty detection problem, where a binary scenario is considered, the fault diagnosis applied to electromechanical system requires the consideration of a multi-fault scenario. In this sense, the conclusions of some studies suggest that the computational complexity of an ensemble-based approach for diagnosis can lead to unfordable structures after different adaptions to new data sets. Evolving strategies, however, allow the possibility of modify the structure of a unique model in function of the different boundaries to be considered. Indeed, this evolving strategy avoids the risk of a complex ensemble-based fault diagnosis structure, in which the relations among the multiple models must be defined manually depending on their labels.

Therefore, dealing with the adaptive CBM implementation applied to an electromechanical system, the ensemble-based approach for novelty detection and the evolving approach for fault diagnosis, represent the most suitable solutions. Thus, a methodology for a FDI system under an incremental framework by means of an ensemble-based approach for novelty detection and an evolving classifier is presented in this section. **Fig. 5.2.12** shows a scheme of the proposed methodology, which includes different stages regarding the activity performed: an initial training stage, an online monitoring stage and a re-training stage. The methodology proposed also consider separate stages of feature reduction for novelty detection and fault diagnosis, therefore the advantages of separated stages for novelty detection and fault diagnosis is maintained.

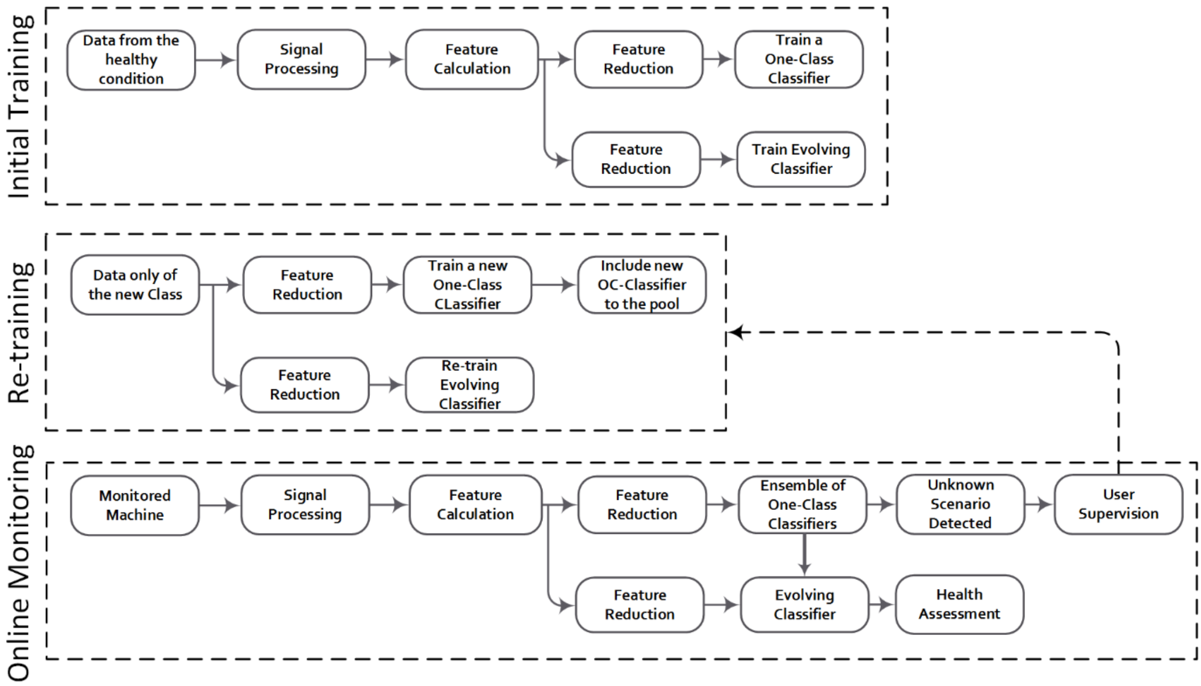

Fig. 5.2.12 Proposed scheme for a FDI system working under an incremental learning framework when an repository database is not available.

Taking into consideration that the initial knowledge consist only on the healthy condition, the models are initially trained with this scenario during the training stage. During the online monitoring stage, a batch-type analysis is proposed to evaluate the condition of the machine, where a certain number of measurements are temporary stored and then evaluated by the ensemble of one-class classifiers to identify the machine is working under known or novel conditions. The number of analyzed shaft turns is empirically selected to provide a robust decision regarding the condition of the machine; if only one measurement is analyzed each time then the rate of false alarm rate could be increased drastically due to outliers.

If the condition of the machine is determined to be known, then the measurements are analyzed by the evolving classifier to determinate the condition of the machine. If the condition of the machine is determined to be novel or unknown, a user supervision module is activated. If the user determinates that the novel condition correspond to a new fault condition that needs to be incorporated, the batch with the corresponding measurements of the new fault are used to re-train the fault diagnosis and novelty detection models. It is important to stress that these methods only need the measurements of the new scenario to include it to the base knowledge, but the training procedure varies depending on which model is used for the ensemble structure of one-class classifiers and also on which evolving mode is used for fault diagnosis. After the models are re-trained, the online monitoring stage starts again.

It is important to mention that the contributions presented in previous chapters, especially the multi modal scheme, can complement this methodology to increase the accuracy of the method.

Case Study: FDI system under an incremental learning framework applied to an EOL test machine

To validate the proposed scheme, the FDI methodology is applied to monitor the condition of an EOL friction test machine over the manufactured parts (steering system). Note that the machine applies its own algorithm to determine the condition of the steering system under test but the aim of the methodology is to monitor the proper function of the EOL test machine. A more in-depth description of the EOL test machine and the friction test e can be found in **Annex III**. The proposed methodology is shown in **Fig. 5.2.13**.

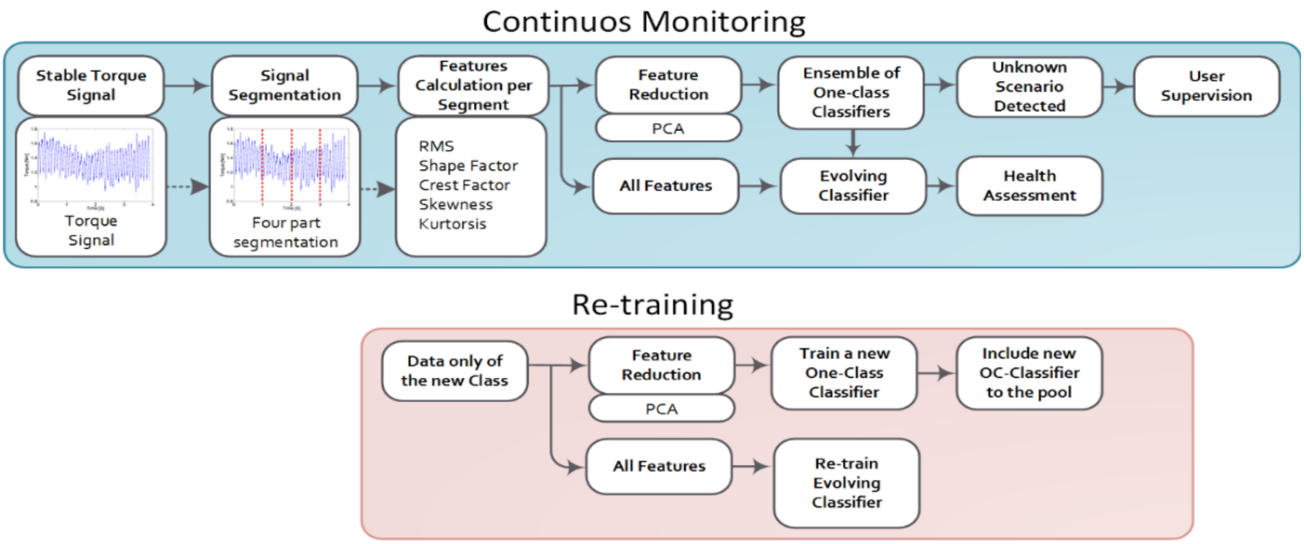

Fig. 5.2.13 Proposed methodology for the EOL test machine. The monitoring method is composed by a signal processing stage where statistical features are calculated and analyzed by a novelty detection and a multi-fault classification models to assess the condition of the machine.

The proposed method is composed by two stages: a continuous monitoring stage to assess the condition of the machine and a re-training stage to include new information to the novelty detection and fault detection models.

During the continuous monitoring stage, a torque signal analysis is performed, then the novelty detection and fault identification stages assess if the measurement analyzed of the machine correspond to a: healthy condition, faulty condition or novel condition.

If a novel condition is detected a user analyze the machine to find the cause of the anomaly. If the user confirms that the novel condition corresponds to a new fault, the re-training stage is triggered to incorporate the new fault to the novelty detection model and the fault identification model.

Continuous monitoring stage

First, a torque signal analysis is carried out during the stationary speed set point corresponding to a 360º 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 which consist of the Root mean square, the crest factor, the shape factor, the kurtosis and skewness. The formulas to obtain such features can be consulted in **Table 2.1.1** in Chapter 2. These features have been successfully employed in different studies for electromechanical systems fault detection [18]. Therefore, a total of 20 features are calculated from each torque signal measurement.

In order to exploit the potentiality of a separate novelty detection and fault identification 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. Indeed, from the novelty detection point of view, the data variance represents one of the most convenient characteristics to be considered. Thus, most of the data variance is enhanced and preserved by a reduced set of features called principal components.

The fault identification task is classically approached by previous feature reduction techniques in order to maximize the distances among available labeled classes. Unlike PCA, that preserves as much data variance as possible in a reduced set of features, the classification task requires supervised approaches. Nevertheless, one of the challenges considered in this work is the initial availability of only one class, the healthy condition, therefore such supervised approaches are not viable. Thus, in order to deal with such scenario, all the twenty estimated features are considered.

After the corresponding feature reduction, the novelty detection and fault identification models are initially trained using healthy measurements of the friction tests. As the monitoring of the machine progresses and new faults are identified, the models are eventually re-trained with new classes of detected faults.

To analyze a single torque signal measurement, the corresponding reduced set of features is first examined by the 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, therefore an alarm is activated to the user for supervision. 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 user determinates that the unknown condition correspond to a new fault in the machine or a new operation point the re-training stage is activated, otherwise, the alarm is considered to be a false alarm and the measurements are discarded.

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 an evolving classifier. The output of the model is a label that identifies the analyzed measurement as one of the considered classes.

In this application, instead of analyzing each EOL test individually, a batch-type analysis is performed, where 20 measurements (which corresponds to 20 EOL tests) are stored and then evaluated simultaneously by the methodology. The number of analyzed measurements corresponds, in this case, to the number of EOL tests performed for each shaft of the steering system. The number of tests is empirically selected to provide a robust decision of the friction test; if only one test is performed then the rate of false alarms could be increased drastically due to outliers. The condition of the machine is determined according to the majority of the labels.

In this work the OC-SVM with Gaussian kernel is used as a one-class classifier for the ensemble method. The preparation of each OC-SVM includes the selection of the parameters for configuration and the training of the model.

The ensemble method consist on training one novelty model for each class known and combine their outputs to detect if an analyzed measurements are *known* or *novel*. Each OC-SVM is trained with information of one known scenario (can be healthy and faulty sets). This means that the model defines a novelty threshold that encloses all the *known* scenarios, if a new measurement evaluated has a novelty score lower than the threshold defined, then, it is considered *novel*, on the contrary, if the novelty score is above the threshold, it is considered *known*. Each measurement is evaluated by all the OC-SVM trained, and if at least one of the model labels the measurement as *known* then the final label for that measurement is *known*, consequentially if none of the models label a measurement as *known*, then the final label is *novel.*

Regarding the fault identification stage, the evolving classifiers eClass0 and eClass1 are used. These classifiers are able to adapt dynamically to the new data with no need of any specific threshold to be specified. The FRB structure of both classifiers changes according to the data streams. In addition, in the case of eClass1, the parameters of the regression models are also constantly updated. The prototypes (existing data samples) to create the fuzzy rules are selected via the calculation of the potential, which is a Cauchy function of the sum of the distances between a certain data sample and all other data samples in the feature space. It is very important to remark that since the formulation of the potential is calculated in a recursive manner, instead of using the complete dataset, the current measurement uses only (n + 1) memorized quantities, where n is the number of features [77]. This aspect is essential in online applications.

To evaluate a new measurement, a firing level (degree of confidence) of the fuzzy rules is calculated and the output of the rules determinate the class of the evaluated measurements. For eClass0 the output label is directly associated to the activated rule, meanwhile, for the eClass1 an *eTS* model regress the feature vector to determinate the confidence value.

Re-training stage

The re-training stage is triggered when a novel scenario is detected and the user determinates that it correspond to a new fault or a new operating condition of the machine. The models used in the novelty detection stage and the fault identification stage have different re-training procedures to include a new class to their base knowledge.

Regarding the re-training of the novelty detection stage, a new OC-SVM model is trained including only information of the new class, this allows the monitoring system to include new information without needing access of the measurements initially used for training. Since the proposed approach for novelty detection considers a low number of features, three after the PCA, the model can perform an adequate novelty boundary for the new class with a limited number of samples and avoid the curse of dimensionality. The training of the model consists on selecting the configuration parameters and tuning them according the distribution of the data to select an appropriate novelty threshold.

Regarding the re-training of the evolving classifiers, both eClass0 and eClass1 have the capability of including automatically new measurements to their base knowledge to increase the robustness of classification of the known classes or to include new classes. In case a set of measurements with a new class is used for re-training, for both of the classifiers a new prototype is selected and a new rule is created for the new class; additionally, for eClass1, the parameters of the *eTS* models are updated. This is performed automatically as long as the true label of the measurements of the new class is provided.

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.*

The faulty conditions corresponds to different severities degree of Misalignment (MIS) and coupling wear (CW), more details of the EOL test machine and the considered faults can be found in Annex III. There is 80 measurements for each class, therefore, the dataset consist of a total of 640 measurements.

Performance metrics

Seven different scenarios for test are used to evaluate the capability of the methodology to detect and classify novel scenarios and the response of the models to the incorporation of new classes to the initially available information. The distribution of the classes for each scenario is presented in **Table 5.2.2**.

The 8 classes are grouped in three sets: *training set*, *known set* and *novelty set*. Each of the scenarios correspond to a progressing stage of the continuous monitoring approach, from an initial knowledge of only the Healty condition, (*Hc*) to a scenario where information of 7 classes is available.

These scenarios are intended to test the capabilities of the proposed methodology in the industrial framework where initially the healthy condition is initially available, and progressively new classes are detected and incorporated, in this case, one class to the training stage in each iteration.

The dimensionality reduction for novelty detection, the PCA, is performed in all seven scenarios using only measurements of the healthy condition (*Hc*). Since some of the contributions in this work are focused on providing an alternative of classical approaches that need storing a repository database of measurements of the monitored machine, a selection of more appropriate features whenever a new class is incorporated is out of scope in this work.

The proposed methodology is based on a sequential monitoring scheme, which implies that each sample is analyzed by the novelty detection model and then, if is labeled as *known*, analyzed by the fault identification model. If the tests are performed using this sequential monitoring scheme, the results obtained can mislead the analysis of the performance of the models due to an integration of error. For example, if all the measurements are labeled incorrectly by the novelty detection stage, the performance of the fault identification stage is not analyzed. Therefore, to avoid misleading interpretation of results, the tests are performed separately to the models. Thus, to analyze the performance of each stage, two sets of performance metrics are considered: one for the novelty detection stage and the other for the fault identification stage.

Regarding the results obtained from the novelty detection model, the following metrics are calculated:

- Test Set Performance: This metric refers to the number of correctly classified measurements of the *novelty set* and the *known set* divided by the total of test examples. This metric is used to obtain a novelty model global performance. Nevertheless, it is important to notice that it does not contemplate the accuracy of discriminating between the different classes composing the *known class* in the fault identification stage.

- Known Set Performance: This metric refers to the number of correctly classified measurements of the *known set* divided by the total of measurements belonging to the same set. This metric can be seen as the true negative rate (TNR).
- Novelty Set Performance: This metric refers to the number of correctly classified measurements of the *novelty set* divided by the total of measurements belonging to the same set. This metric can be seen as the true positive rate (TPR).

Regarding the results obtained from the fault identification stage, the following metrics are calculated:

- Training set Performance: This metric represents the capacity of the fault identification 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.
- Test Set Performance: This metric represents the measurements analyzed of the *known set* by the fault identification model that are correctly classified divided by the total number of measurements of the *known set.* It is important to notice that the *novelty set* is not contemplated in the fault identification stage because it is assumed that these samples were previously discarded by the novelty detection model. Including such class in the comparison between fault identification models induce an unnecessary constant error in the tests.

Table 5.2.2. Contents of the training and testing sets for each scenario

Scenario Name	Training Set	Testing Set	
		Known Set	Novelty Set
T_1	*Hc*	*Hc*	*CW1, CW2, CW3, MIS5, MIS6, MIS7, Nc*
T_2	*Hc, CW1*	*Hc, CW1*	*CW2, CW3, MIS5, MIS6, MIS7, Nc*
T_3	*Hc, CW1, CW2*	*Hc, CW1, CW2*	*CW3, MIS5, MIS6, MIS7, Nc*
T_4	*Hc, CW1, CW2, CW3*	*Hc, CW1, CW2, CW3*	*MIS5, MIS6, MIS7, Nc*
T_5	*Hc, CW1, CW2, CW3, MIS5*	*Hc, CW1, CW2, CW3, MIS5*	*MIS6, MIS7, Nc*
T_6	*Hc, CW1, CW2, CW3, MIS5, MIS6*	*Hc, CW1, CW2, CW3, MIS5, MIS6*	*MIS7, Nc*
T_7	*Hc, CW1, CW2, CW3, MIS5, MIS6, MIS7*	*Hc, CW1, CW2, CW3, MIS5, MIS6, MIS7*	*Nc*

Model estimation and parameter selection

A 70% of the available measurements per class are used for the *training set*. From the *training set*, a five-fold cross-validation is used in order to adjust each of the OC-SVMs parameters of the ensemble method. 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 models are trained and adjusted in each scenario, the test is performed using the remaining 30% of the measurements of each class of the *known set* and the *novelty set*. This process was repeated five times with five different training-test set distributions, randomly selected and fixed.

Results

In order to highlight the contribution and motivation of this work, the outline of the results will be presented as follows: first, the seven scenarios are tested by the novelty detection model proposed, then, the seven scenarios are tested again but using the 20 calculated features instead of the proposed PCA, after the novelty detection is tested, the proposed method for fault identification is tested and compared with a classical approach. The performance metrics are analyzed on each case to highlight the advantages and disadvantage of each model and each dimensionality reduction approach.

Different configurations regarding the dimensionality of the features are used to have an insight of the advantages of discarding irrelevant features. The number of selected features is reduced from an initial 20-dimensional space to a reduced 3-dimensional space, taking into consideration that the reduced set of features fulfill the respective restrictions from each dimensionality reduction approach.

The ensemble of novelty models are first tested with the seven scenarios proposed, the number of OC-SVM models trained correspond to the number of classes included on the training set of each scenario. It is important to mention that the scenarios tested are performed in consecutive order, therefore, the OC-SVM model trained with the Healthy class, *Hc*, is used on all the scenarios and not modified in a re-training. A re-training is performed when a new class is included, for example, from the scenario T_1 to the scenario T_2 to include a new class in a new OC-SVM, in this case the fault CW1.

For a better understanding of the test, the novelty score of the testing set of the scenario T1 is presented in **Fig. 5.2.14**. The horizontal line represents the novelty threshold, the samples on the upper side of the novelty threshold are labeled as *known* and the samples on the lower side are labeled as *novel*. Varying the novelty threshold, for example lowering the threshold value, can lead to a better detection of the *known class*, *Hc*, increasing the known set performance, but that variation also leads to labeling samples of the novelty class, *Nc*, as known, which lead to a lower outlier set performance. The vertical lines represent the division of classes among the measurements used of the testing set.

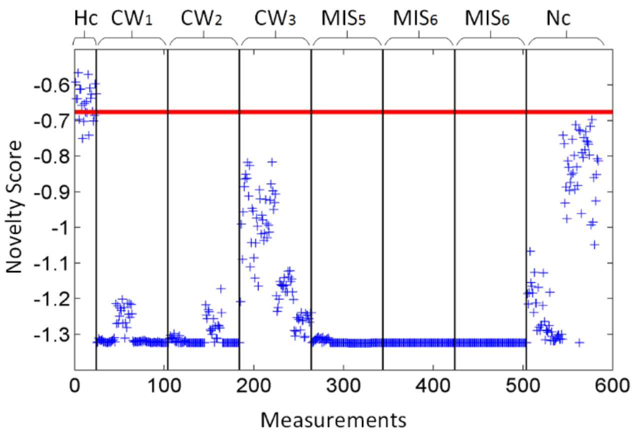

Fig. 5.2.14 Resulting Novelty Score of the T1. The red line is the novelty threshold, *Th*, which is set to -0.67. The black lines represent the division among the different classes during the test.

n this scenario only one class is included in the training set, therefore only one novelty score per measurement is obtained in the novelty detection stage, which implies that the labeling of measurements depends only of one model. To perform the test of the scenario T_2, where two classes are included in the training set, a new OC-SVM is trained for the *CW1* class and two novelty scores are obtained. The novelty scores of both OC-SVM is shown in **Fig. 5.2.15**.

As can be seen, all measurements from the test set are evaluated by the ensemble of models, therefore, all samples are labeled as *novel* or *known* by both OC-SVMs. As mentioned before, if at least one of the models label a measurement as *known*, then the final label of that measurement is *known*, consequentially if none of the models label a measurement as *known*, then the final label is *novel*. Since each of the OC-SVMs is trained to identify similar measurements of different classes, both output labels are equally important, therefore the only case when a sample is considered novel is when it does not belong to any distribution learned by the method. In this case, in a continuous monitoring approach, if a measurement is labeled as known the fault identification stage analyze such measurement to identify if the measurement belongs to a healthy case, *Hc*, or the fault case, *CW1*.

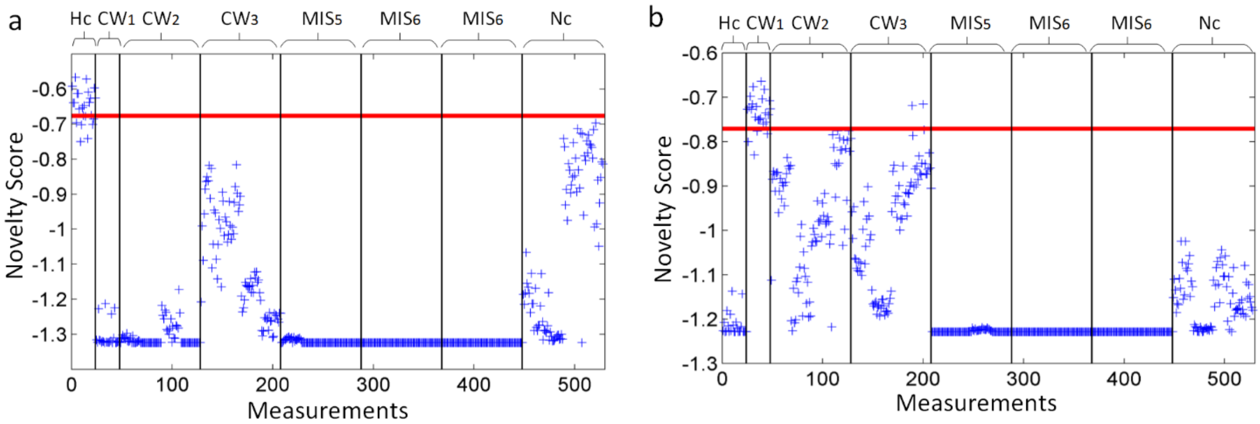

Fig. 5.2.15 Resulting Novelty Score of the T_2. The red line is the novelty threshold, *Th*, which is set to -0.67 for the first OC-SVM and -0.77 for second. The black lines represent the division among the different classes during the test. a) The novelty results of the OC-SVM trained using measurements of the *Hc* class. b) The novelty results of the OC-SVM trained using measurements of the CW_1 class.

Some authors propose to use the output of the ensemble of the OC-SVMs to perform the fault identification of the measurement; nevertheless, while in this scenario, T_2, such approach seems like a viable option, problems appear when classes with similar distributions are included. A solution for this problem is addressed in the methodology proposed in this work and discussed further ahead in this section.

The results of the proposed novelty detection approach in the seven scenarios are shown in **Table 5.2.3**.

Table 5.2.3. Performance of the proposed novelty detection scheme

	Novelty Detection PCA - 3 Features						
	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
Test Set Performance	0.959(±0.004)	0.955(±0.008)	0.894(±0.002)	0.890(±0.014)	0.876(±0.019)	0.836(±0.027)	0.810(±0.031)
Known Set Performance	0.969(±0.005)	0.962(±0.002)	0.917(±0.007)	0.916(±0.009)	0.928(±0.017)	0.903(±0.028)	0.840(±0.068)
Outlier Set Performance	0.842(±0.046)	0.842(±0.064)	0.767(±0.053)	0.804(±0.044)	0.772(±0.029)	0.763(±0.033)	0.765(±0.023)

A high test set performance, around 96%, is obtained on the T_1 and T_2 scenarios, nevertheless, the performance gradually decrease to a final 81% as new classes are incorporated to the base knowledge. This decrease of performance is expected, in each scenario new information is incorporated to the model, therefore more variability and cases are considered normal to the model and this limits the capacity of the model to detect anomalies.

To verify if the dimensionality reduction stage improves the performance of the model, the seven scenarios are also tested using the 20 calculated features, the results are shown in **Table 5.2.4**.

As can be seen that, regarding the T_1 to T_3 scenarios, a performance around 96% is obtained in both approaches, nevertheless starting from the T_4 scenario, the performance of the model using the 20 features start decreasing at a higher rate in comparison to the PCA proposed approach. The decrease of performance is caused by the misclassification of the known set, labeling them as *novel*, which implies that reducing the features allows a more adequate tuning of the novelty detection boundary to achieve a more robust detection of the known classes.

Table 5.2.4. Performance of the novelty detection considering 20 features calculated

	Novelty Detection 20 Features						
	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
Test Set Performance	0.971(±0.004)	0.949(±0.014)	0.908(±0.014)	0.834(±0.011)	0.813(± 0.01)	0.748(±0.006)	0.656(±0.006)
Known Set Performance	0.981(±0.003)	0.957(± 0.01)	0.920(±0.015)	0.815(±0.012)	0.793(±0.012)	0.691(±0.015)	0.395(±0.029)
Outlier Set Performance	0.850(±0.054)	0.863(±0.047)	0.861(±0.034)	0.896(±0.024)	0.855(±0.029)	0.811(±0.013)	0.780(±0.008)

To test the fault identification stage a separate analysis is performed where only the scenario T_7 is used. Testing the fault identification method in a scenario where the class discrimination is evident would lead to an excellent performance of every model and does not contribute in highlighting the limitations and advantages of each model and features used for comparison. Therefore, the scenario which presents a more adequate challenge regarding number of classes for discrimination is used. The result of the fault identification stage using evolving classifiers and a supervised classical approach used in many condition monitoring systems, the multi-layer Neural Network (NN), is shown in **Table 5.2.5**. 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.

Table 5.2.5. Results of the T_7 scenario for the fault identification stage. The evolving classifiers are compared to a classical approach in both feature selection approaches.

	Fault Identification					
	20 Features			**PCA**		
	eClass0	**eClass1**	**NN**	**eClass0**	**eClass1**	**NN**
Training Set Performance	0.872(±0.024)	0.736(±0.024)	0.942(±0.015)	0.586(±0.052)	0.364(±0.038)	0.636(±0.022)
Test Set Performance	0.839(±0.016)	0.726(±0.032)	0.874(±0.014)	0.547(±0.044)	0.369(±0.035)	0.601(±0.023)

A comparison between using the 20 calculated features and a dimensionality reduction by PCA is also performed. Better results are obtained with all three models using the 20 features than the PCA approach. Meanwhile the PCA represents a better option to detect outliers in the novelty detection stage, for the fault identification stage the use of 20 features represent a better option to discern between classes. The misclassification is caused by an overlapping of classes in the feature space, this can be highlighted by the training set performance and the consistent low performance in all three models. If the novelty detection task and the fault identification task are performed in the same stage, the selection of a different feature selection for each stage would lower the performance of the methodology.

Regarding the test set performance of the three models using the 20 calculated features as input, the Neural Network approach present a slightly better performance, around 3%, than the evolving classifier eClass0 and a 15% increased performance than the eClass1, nevertheless, the advantage of the evolving methods in terms of incursion of different classes and low computational cost of training and testing, represent a better option for the fault identification stage for online applications.

Conclusions

A methodology for continuous learning of condition monitoring applied to an end-of-line test machine of the automotive sector by analyzing the torque signal has been proposed and validated. The methodology assess the condition of the machine under monitoring without altering the undergoing operation.

Taking into consideration that the methodology presented work under the assumption that only the healthy condition is initially available, the main contributions presented are focused on the proposition of an ensemble of novelty detection models and an evolving classifier to perform incremental learning when a database storing the measurements of the machine is not available.

The methodology proposed is compared in each stage with different feature reduction approaches to perform a proper selection of features for each model taking in consideration the challenges of an industrial framework. A set of several tests with the corresponding performance metrics are proposed for the evaluation of both stages, novelty detection and fault identification. By monitoring separately the accuracy of the models, it is possible to identify the advantages and limitations of the methodology and compare different models for each stage.

Regarding the novelty detection stage, the ensemble method of OC-SVMs successfully discerned among the known set and the outlier set of the seven performed tests. Using the PCA to select a reduced number of features in comparison of using the 20 features lead to a better performance, especially at the last test, where an increment of 44% of accuracy on the known set is achieved.

Regarding the fault identification stage, among the evolving classifiers, the eClass0 obtained better results than the eClass1, where an increment of 11% of accuracy on the test set is achieved using the 20 features and an increment of 17% on the test set is achieved using the PCA. Since each class is composed by four different models of steering systems, four different distributions are expected among the data; therefore the eClass0 is more suitable in this case to enclosure a multi-modal distribution of the data with the Gaussian enclosure of the prototypes than the regression performed by the eClass1. Regarding the Neural Network classifier comparison, the eClass0 obtained a slightly lower accuracy; nevertheless Neural Network the intensive offline training of the

Neural Network is not suitable for online applications where a repository database of measurements is not available.

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

5.3 Conclusions and discussion

In this chapter, the limitations and challenges regarding the incorporation of an incremental learning framework to FDI systems are analyzed.

The capacity to continuously store the measurements of the monitored machine represents an important factor regarding what novelty detection and fault diagnosis models can be used. If a repository database is available, traditional novelty detection and fault diagnosis models can be used since a complete re-training of the models structure with the data combining the initial and new scenarios can be performed. In this sense methodology to implement a FDI system under an incremental learning framework when a repository database is available is presented and applied to a camshaft-based machine.

Taking into consideration that the initial knowledge consist only on the healthy condition, the models are initially trained with this scenario during the training stage and follows a sequential approach to determinate the condition of the machine. First, the analyzed measurement is examined by a novelty detection model. Then, the measurement can be cataloged as novel or known. 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 fault diagnosis model. The output of the model is a label that identifies the analyzed measurement as one of the considered classes. If the measurement is catalogued as novel, the machine is considered to be working under unknown conditions. This can be triggered by different cases, including outliers, the presence of a new fault or by a new operation condition of the machine. If a new fault is detected and confirmed by the user, a complete re-training is performed in a classical approach combining the initial and new scenarios to the training set. After the models are re-trained, the online monitoring stage starts again.

Beside the considerations included to the methodology to work under an incremental framework, some key aspects were also included in this case study to improve the robustness of the method.

The first one consist on the incursion of a batch-type analysis to evaluate the condition of the machine. This implies that a certain number of measurements are stored and then evaluated by the novelty detection model to identify the machine is working under known or novel conditions. The number of measurements is empirically selected to provide a robust decision regarding the condition of the machine; if only one measurement is analyzed each time then the rate of false alarm rate could be increased drastically due to outliers.

The second one is the characterization of the uncertain zones in the feature space of the novelty detection analysis to reduce the number of false alarms and to provide more information regarding the condition of the machine to the user. The intrinsic variability of the measurements in industrial applications often cause an increment of false alarms, by labeling this variations as uncertain and performing a fault diagnosis to those uncertain measurements, the user is provided with more information to draw a conclusion regarding the anomaly presented.

On the other hand, if a repository database is not available to continuously store the monitored measurements, models that can performed a re-training to include the new scenario without the measurements of the initial scenarios are necessary. This lead to a study and analysis for the selection of the most adequate strategies for novelty detection and fault diagnosis that could cope with this limitation, and it was concluded that the ensemble-based approach for novelty detection and the evolving approach for fault diagnosis, represent the most suitable solutions. In this sense a methodology to implement a FDI system under an incremental learning framework when a repository database is available isn't presented and applied to an EOL test machine.

The main difference of this methodology, besides the models used, resides on the re-training stage. The ensemble of one-class classifiers and the evolving classifiers can incorporate new scenarios to their base knowledge using only measurements corresponding to the new scenario.

Some conclusions can be drawn from the case study presented of both methodologies. The main advantage of the first methodology consist on the possibility to use classical models for novelty detection and fault diagnosis. This permit the use of specialized models depending on the limitations presented in the application domain, meanwhile the second methodology restrict the number of models that can be applied. It is important to mention that the contributions presented in past chapters, for example the multi modal scheme, can complement the methodologies presented to increase the accuracy of the method, as seen in the first case study.

6.

General conclusions and future work

The main contributions of this thesis research, as well as the conclusions and future work are presented in this chapter.

CONTENTS:

6. Conclusions and future work

6.1 Conclusions

This chapter presents the conclusions in relation with the stated hypothesis, and the obtained results during the development of the thesis work. In this regard, the exposed conclusions of this thesis are divided in the sequential research stages: Novelty detection, Fault detection and identification systems, and Incremental learning framework. In order to complete the conclusions, the global impact in regard with the analysis off all the contributions of the thesis is also considered.

In regard with novelty detection, the application to electromechanical systems represented a challenging task in terms of the complexity involved in the data processing and the feature calculation and reduction stages. In other application domains, the selection of variables employed to characterize a process are evident and in most cases the limitations to apply novelty detection resides mostly in the capacity of the model to characterize a given signal. This fact leads the state of the art to be focused on improving the performance of the model without taking into account the previous processing stages. In electromechanical systems, the faults in a machine are not that evident reflected in changes of the monitored variables, there is an enormous effort in the signal processing, feature calculation and reduction topics focused solely in highlighting faults on a monitored machine, therefore, a direct implementation of a novelty detection methodology is not viable in this application domain. Indeed, the performance of the novelty detection models is heavily influenced by the signal processing and features calculated used to characterize the monitored component. Thus, as presented in the hypothesis, by improving the feature calculation and feature reduction stages the performance of the novelty models would increase. In this sense, two schemes were proposed to increase the robustness and reliability of the novelty detection models in electromechanical systems, a multi-modal scheme and the reformulation of features each time a new scenario is incorporated to the base knowledge.

The proposed muti-modal scheme and the reformulation scheme of features intend to increase the resolution of what the novelty models need to characterize, therefore, a more detailed novelty detection boundary can be performed by the models, which lead to an increased performance of the novelty detection models.

Regarding the multi-modal scheme, it is important to mention that it can be successfully applied to a monitored machine if each novelty model trained monitors a different part of the machine or a different signal or segment of the signal. A multi-modal scheme over a set of features that are not complementary in the characterization of the machine could overfit the models instead of providing resolution.

Regarding the reformulation of features, the consideration of a faulty scenario in the novelty model may contradict the principle of anomaly detection, where the objective is to detect healthy behaviors from the rest. Nevertheless, the aim of an adaptive condition monitoring system should be to learn from all the identified conditions to subsequently detect them if they are presented again by a fault detection module.

Both proposed schemes can be complementary since both increase the novelty detection accuracy by different approaches. Each scheme was proposed by considering certain limitations. The multi-modal scheme was proposed to cope with applications that have a limited number of measurements available and a high number of calculated features to characterize a complex distribution. By dividing the distribution onto different models, the resolution provided by the high number of features is maintained without overfitting a single model, leading to an increased accuracy. The feature reformulation scheme was proposed to cope with applications that have an increasingly complex distribution, in this case the number of samples are not considered as a limitation. When new information is constantly included to the novelty detection model, it is expected that the complexity of the characterization of the monitored machine would increase, therefore the capacity of the models to characterize the machine would decrease. By constantly searching for a more appropriate set of features each time a new scenario is incorporated, it is possible to reduce the complexity of the characterization of the machine by gaining resolution of the recently incorporated scenario, therefore, increasing the performance of the novelty models.

In this thesis, a limited number of measurements to characterize a certain scenario is assumed as a premise in the development of each methodology, nevertheless, if the number of measurements is not a limitation, it could be possible to use other novelty detection models with enhances capabilities to converge in a solution even with a high number of analyzed features without compromising the performance of the model. Nevertheless, the increased performance achieved by this models would not be greater than the performance than can be obtained by the multi-modal scheme.

In regard with the fault detection and identification system, a sequential scheme with separate feature reduction stages for novelty detection and fault diagnosis has been proposed. The limitations and advantages of such approach are analyzed and compared to a classical approach and a simple sequential approach with only one feature reduction stage in a case study where proposed methodologies showed significant improvement over the other methodologies. The proposed FDI system with separated stages for novelty detection and fault diagnosis has a sequential approach to determinate the condition of the machine. First, the analyzed measurement is 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 fault diagnosis model. The output of the model is a label that identifies the analyzed measurement as one of the considered classes.

The experimental study has been performed using the linear discriminant analysis for fault diagnosis and the principal component analysis for novelty detection proved the importance of including separated feature reduction stages of the proposed methodology, improving the overall accuracy in comparison to the other two methodologies.

The novelty detection stage exhibits similar results by the three methodologies using the PCA, however, the fault diagnosis stage exhibits increased performance by using the LDA. Both classical approaches limit the selection of these techniques to one, conditioning the performance of each stage by the selection of the feature reduction algorithm. In this regard, the proposed approach allowing different dimensionality reduction techniques for novelty detection and fault diagnosis, leads to a better overall performance compared to both classical methodologies, It is important to notice that the methodologies were also tested without a feature reduction stage, which implies that the models are trained with all the calculated features leading to a very poor performance in comparison to any methodology with a feature reduction stage. This proves not only the initial hypothesis of this thesis regarding the importance of the feature reduction stage, but also proves that the challenges of each application domain requires different solutions in comparison to other methodologies where the number of features introduced to the models were not a limitation or were not considered as a possible problem.

As proposed, a separate implementation of the novelty detection and fault diagnosis tasks allows an optimal selection of features for each task that will improve the performance of both tasks. In addition, in a methodology that considers a separate implementation of the novelty detection task and the fault diagnosis task, the overall performance can be increased by initially performing a reliable novelty detection task that subsequently increase the performance of the fault diagnosis stage in a sequential implementation. This has been proved by the methodology proposed and validated in the case study. Moreover, the study performed leads to an additional conclusion, the use of incoherent feature reduction approaches for each of the tasks could decrease the performance of the novelty detection model and the fault classifier. This has been observed by using the PCA for fault diagnosis, that lead to a lower results than a coherent technique like the LDA which is aligned with the objective of the fault diagnosis task, which is to discriminate among the known scenarios. This alignment of objectives is the key factor to implement a reliable and robust fault detection and identification system, a simple separation of tasks doesn’t imply a high performance.

In regard with the incremental learning framework, two methodologies are proposed to include new scenarios to the sequential fault detection and identification system previously presented. As a premise, in an incremental learning framework applied to electromechanical systems it is desired to keep the information previously incorporated instead of discard it. This is a key factor to determinate the appropriate models to work under an incremental learning framework if a repository database is available or not.

If the measurements during the monitoring of the machine are being constantly stored and are accessible for re-training, domain-based and non-parametric statistical-based algorithms for novelty detection represent the most adequate choice in terms of flexibility to incorporate new scenarios without analyzing the underlying distribution of the data corresponding to the new scenario. Indeed, the incorporation of new scenarios to the base knowledge during the monitoring in a semi-automatic approach, implies that the distribution of the data is not thoroughly analyzed, therefore, the models used for novelty detection and fault diagnosis should be able to adapt to any distribution given, which limits the selection to those models that can cope with complex distributions.

If the measurements during the monitoring of the machine are not being constantly stored and only a small amount of measurements representative of the new scenario are accessible for re-training, an ensemble of domain-based algorithms for novelty detection and evolving classifiers for diagnosis represent the most adequate choice by providing an optimal trade-off between computational burden and accuracy. Even if a methodology is proposed to work under these circumstances, the absence of a repository database limits not only the models that can be used for both task, but also the characterization of the data to the initial formulation and prevents the reformulation of the features.

To include a new scenario, the addition of a specific model for that scenario for novelty detection and the addition of a representative prototype with a new fuzzy rule of the new scenario for fault diagnosis, represents the simplest solution with a competitive performance for the incursion of new classes to the base knowledge.

As a step beyond the analysis of the different proposals, most of the contributions on this thesis have been integrated in a specific study: the multi-modal scheme and the characterization of the uncertain zones are incorporated to a sequential fault detection and identification system under an incremental learning framework to monitor faults over an industrial camshaft-based machine.

Regarding the uncertain zones, on the initial studies performed on this thesis about novelty detection in electromechanical systems, an uncertain zone was identified, which was caused by the intrinsic variability of the measurements analyzed. This variability is higher in an industrial environment than on controlled environments, which leads to a higher rate of false alarms in comparison to applications in laboratory test benches. The characterization of this uncertain zone, is complementary to the both schemes for novelty detection presented, leading to a robust implementation by reducing the low alarm rate caused by the variability of the monitored signals. Indeed, the uncertain characterization performed on the multi-modal scheme FDI system under an incremental learning framework, lead to a reduction of the false alarm, therefore, increasing the performance of the novelty detection task. Nevertheless, the optimal delimitation of the limits of the uncertain zone represent a challenge, while widening the uncertain zone leads to a poor assessment of the machine condition, a relatively small uncertain zone would not have the sufficient impact on the performance of the machine. In this sense, in the proposed work the uncertainty of the measurements is obtained in base of the probability density function. Measurements with a low value are considered novel, while measurements among one third and two thirds of the maximum probability are considered uncertain, everything above two thirds of probability are considered normal. This characterization, while simple, presented good results on the case study.

In respect to the reformulation approach, it could be applied in addition to the multi-modal scheme if the computational complexity is not a limitation, since it would require a re-training of each novelty model employed in the multi-modal a scheme each time a reformulation is performed. It is important to notice, that the FDI system with separated stages allows that these two schemes could be applied toward the novelty detection task.

It is important to stress that the application of all of these contributions could present some limitations if a repository database is not available. In this sense, the reformulation of features cannot be performed. Also, if the multi-modal scheme is applied under an ensemble of one-class classifiers for novelty detection, the storage of information increase in great scale due to the elevated number of models used and the information each one requires to store. Therefore, to achieve the high reliable and robustness degrees that the methodologies of this thesis aim to achieve, it is highly recommended to dispose of a repository database to store the monitored measurements.

6.2 Future work

Certain improvements over the proposed methodologies can be considered, especially under the incremental learning framework. Incorporating new cases to the novelty detection and fault diagnosis models in a semi-supervised approach could lead to a saturation of overlapping information in the feature space. For example, if two scenarios with similar characteristics are incorporated to the models, it is possible that the fault diagnosis would not be able to discern among them, even if there both represent complete different behaviors of the machine. Certain metrics should be constantly monitored when a scenario is incorporated, this could include the training performance of the fault diagnosis model, since it provides information of how capable is the model to discern among the known scenarios. Establishing certain restrictions in the semi-automatic incursion of new scenarios leads to a more efficient condition based monitoring system. Regarding the condition based monitoring scheme, it can still be expanded to provide more useful information the user. In addition of detecting multiple faults or unexpected events, the degradation of the monitored component could represent viable information that leads to proper maintenance strategies.

Future work in relation with the proposed thesis consist on facilitating the implementation of the proposed methodologies in a digital platform for their practical integration in the industry. This implies optimizing the digitalization of the methodologies proposed for their implementation to digital platforms. On this thesis, the methodologies were tested in Matlab platform, therefore, the limitations usually presented in a digital implementation were not considered. This could lead to a series of improvements to the methodologies that could facilitate the implementation of the algorithms without compromising the performance.

Also, over the past years, the estimation of the remaining useful life of a component or a machine surged as a trending research field in the community, due to the benefits that provide to the maintenance sector of the industry the determination of how long a component, system or machine would work under a healthy condition. A reliable remaining useful life estimation represents a difficult task due to the variability in which a component can deteriorate or break. In this sense, novelty detection strategies could be incorporated to these studies to estimate the reliability associated to the RUL estimation by other models.

7.

Thesis results dissemination

The direct contributions resulting from this Thesis work, in international journals as wells as in specialized conferences, are collected in this chapter. Additionally, the contributions in research projects related with the thesis topics are also briefly exposed.

CONTENTS:

7. Thesis results dissemination

7.1 Publications: Thesis contributions

Dissemination results directly related with the thesis contributions

Journals

J. A. Cariño-Corrales, J. J. Saucedo-Dorantes, D. Zurita-Millan, M. Delgado-Prieto, J. A. Ortega-Redondo, R. Alfredo Osornio-Rios, and R. De Jesus Romero-Troncoso, “Vibration-Based Adaptive Novelty Detection Method for Monitoring Faults in a Kinematic Chain,” *Shock Vib.*, vol. 2016, p. 12, 2016.

J. A. Carino, M. Delgado-Prieto, D. Zurita, M. Millan, J. A. O. Redondo, and R. Romero-Troncoso, “Enhanced Industrial Machinery Condition Monitoring Methodology Based on Novelty Detection and Multi-Modal Analysis,” *IEEE Access*, vol. 4, pp. 7594–7604, 2016.

J. A. Carino, M. Delgado-Prieto, D. Zurita, M. Millan, J. A. O. Redondo, and R. Romero-Troncoso, “Continuous Learning-Scheme Applied to the Condition Monitoring of a Camshaft-Based Machine,” *IEEE Transactions on Industrial Informatics.* **Major revision submitted, pending review.**

J. A. Carino; M. Delgado-Prieto; J. Iglesias.; A. Sanchis; D. Zurita; M. Millan; J. A. Ortega; R. J. Romero-Troncoso. “Fault detection and identification methodology under an incremental learning framework applied to industrial machinery” *IEEE Access*. **Under review.**

Conferences

J. A. Carino, D. Zurita, M. Delgado, J. A. Ortega, and R. J. Romero-Troncoso, “Hierarchical classification scheme based on identification, isolation and analysis of conflictive regions,” in *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*, 2014.

J. A. Carino, D. Zurita, M. Delgado, J. A. Ortega, and R. J. Romero-Troncoso, “Remaining useful life estimation of ball bearings by means of monotonic score calibration,” in *Proceedings of the IEEE International Conference on Industrial Technology*, vol. 2015–June, pp. 1752–1758, 2015.

J. A. Carino, D. Zurita, A. Picot, M. Delgado, J. A. Ortega, and R. J. Romero-Troncoso, “Novelty detection methodology based on multi-modal one-class support vector machine,” in *2015 IEEE 10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*, pp. 184–190, 2015.

D. Zurita-Millán, **J.A. Carino**, A. Picot, M. Delgado, J.A. Ortega. “Diagnosis Method based on Topology Codification and Neural Network applied to an Industrial Camshaft”. *2015 IEEE 10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*, pp. 124-130, 2015.

Picot, D. Zurita, **J. Cariño**, E. Fournier, J. Régnier, and J. A. Ortega, “Industrial machinery diagnosis by means of normalized time-frequency maps,” in *Proceedings - SDEMPED 2015: IEEE 10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives*, pp. 158–164, 2015.

Book Chapters

M. Delgado Prieto, **J. A. Cariño Corrales**, D. Zurita Millán, M. Millán Gonzalvez, J. A. Ortega Redondo and R. J. Romero Troncoso. Evaluation of Novelty Detection Methods for Condition Monitoring applied to an Electromechanical System.

7.2 Publications: Collaborations and other works

Dissemination related to collaborations in the topic

Journals

D. Zurita-Millán, M. Delgado-Prieto, J.J. Saucedo-Dorantes, **J. A. Cariño-Corrales**, R. A. Osornio-Rios, J. A. Ortega-Redondo, R.J. Romero-Troncoso. “Vibration Signal Forecasting on Rotating Machinery by means of Signal Decomposition and Neuro-fuzzy Modeling,” Shock Vib., vol. 2016, pp. 1–13, 2016.

D. Zurita, M. Delgado, **J. A. Carino**, J. A. Ortega, and G. Clerc, “Industrial Time Series Modelling by means of the Neo-Fuzzy Neuron,” *IEEE Access*, pp. 1–1, 2016.

D. Zurita, M. Delgado, **J. A. Carino**, J. A. Ortega, R.J. Romero-Troncoso, H. Razik, G. Clerc, “Ensemble Empirical Mode Decomposition and Neo-Fuzzy Neuron for Industrial Time Series Forecasting,” *IEEE Transactions on industrial informatics.* **Under review.**

D. Zurita, M. Delgado, **J. A. Carino**, J. A. Ortega, “Multimodal Forecasting Methodology applied to Industrial Process Monitoring,” *IEEE Transactions on industrial informatics.* **Under review.**

D. Zurita, M. Delgado, **J. A. Carino**, J. A. Ortega, H. Razik, G. Clerc, “Industrial Process Condition Forecasting by Neo-Fuzzy Neuron and Self-Organizing Maps,” *IEEE Access.* **Under review.**

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Annexes

The annexes of this thesis are related with the definition of the experimental test benches used for the development of the proposed thesis.

CONTENTS:

A.I Electro-Mechanical Test Bench

In order to test the methodologies presented in this thesis in a controlled environment, an electromechanical test bench is used. The laboratory test bench is shown in **Fig. AI. 1**. This test bench consists on a kinematic chain composed by a three phase 1492 *W* induction motor, WEG 00236ET3E145T-W22, which speed is controlled by a variable frequency drive-VFD, WEG CFW08, the operating speed is fixed to 60 Hz for all experiments. A 4:1 ratio gearbox, BALDOR GCF4X01AA, is used to couple the drive motor to a DC generator, BALDOR CDP3604. The DC motor is used as a non-controlled mechanical load that comprises around 20% of the nominal torque of the driving motor. The DAS is a proprietary low-cost design based on field programmable gate array technology. The output rotational speed is obtained by using a digital encoder; the motor start-up is controlled by a relay in order to automatize the test run. A 12-bit 4-channel serial-output sampling analog-to-digital converter, ADS7841, is used in the on-board data acquisition system (DAS).

Vibration signal from the perpendicular plane of the motor axis is acquired using a tri-axial accelerometer, LIS3L02AS4, mounted on a board with the signal conditioning and anti-aliasing filtering. Sampling frequency is set to 3 kHz for vibration acquisition. The data retrieved by the DAS is stored in a regular computer (PC).

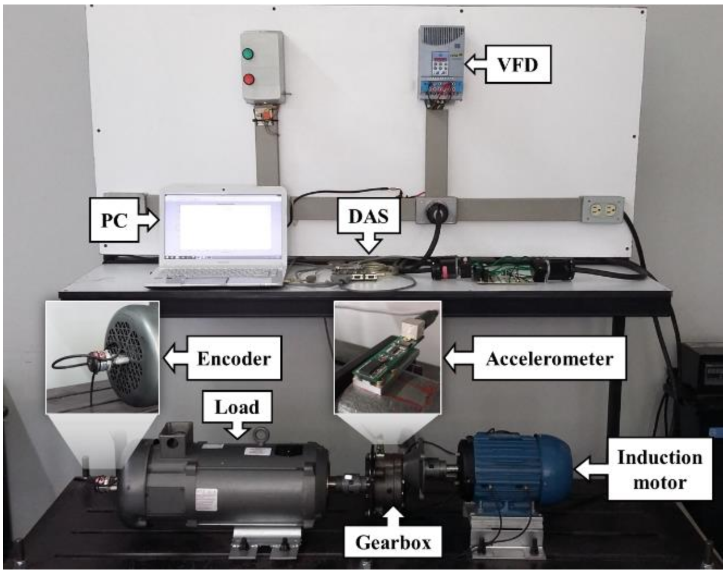

Fig. AI.1. Electromechanical test bench used for experimental validation of the methodologies.

Measurements from three scenarios are acquired from the test bench, the first one, *H*, is the kinematic chain working under healthy condition and the other two, F_1 and F_2, represent the kinematic chain working under faulty conditions. For F_1 the motor is working with a half broken bar, and for F_2 the motor is working with a fully-broken bar. The detail of the failures is shown in **Fig. AI.2**. The half broken bar failure is artificially produced by drilling a 6 mm hole with a depth of 3 mm that corresponds mostly to the 22% of the section of the rotor bar, and the full broken bar is produced by a through-hole with a diameter of 6 mm and a depth of 14 mm, which corresponds to the complete section of the rotor bar.

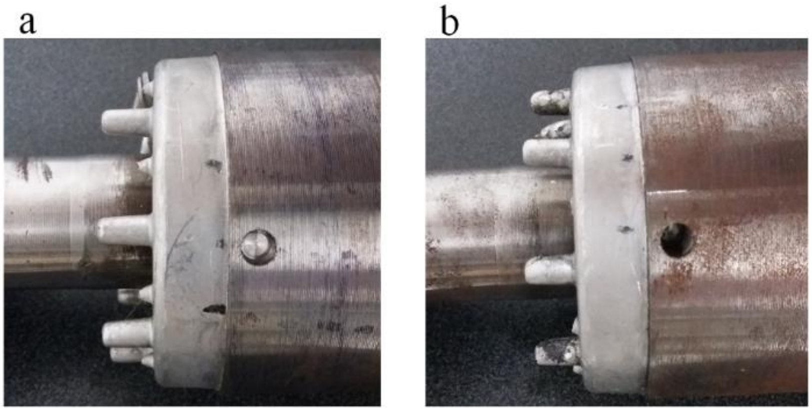

Fig. AI.2. Detail of the faults produced in the test bench. (a) Corresponds to the ½ broken rotor bar, and (b) to one broken rotor bar

A.II PRONOSTIA run to failure bearing degradation experiment

The PRONOSTIA test bench consist of accelerated bearings degradation tests. The test bench, as shown in **Fig. AII.1**, is composed by the speed variation, torque transmission and the load profile generation stages.

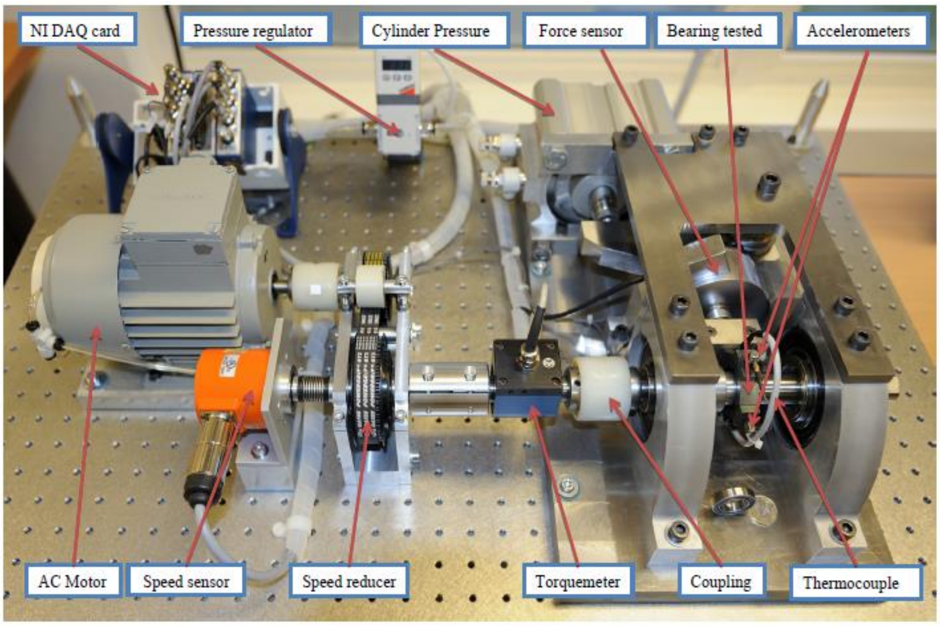

Fig. AII.1. Overview of PRONOSTIA experimental platform based on accelerated bearing degradation.

A cyclic radial load is applied on the external bearing under test in order to simulate its mechanical stress conditions. The experiment starts at a fixed speed condition, and stops when the measured vibration at the bearing under test is higher than 20g (1g=9.81 m/s^2). It should be noticed that, in order to speed up the degradation, the applied radial load exceeds the maximal load supported by the bearing. During the experiments any kind of failure (inner race, outer race, ball or cage) could occur. This fact allows better representation of a real industrial scenario.

Regarding the test bench instrumentation, two high frequency accelerometers (DYTRAN 3035B), are mounted on the bearing external race in order to measure the horizontal and the vertical accelerations. In addition, the monitoring system includes one PT100 to measure the bearing temperature, which is placed near the external ring of the bearing under test.

The signals are acquired by means of a NI DAQ card; the acceleration signals are acquired in successive windows with duration of 1/10 seconds, repeated every 10 seconds, with a sampling frequency of 25.6Hz. Similarly, the temperature signal is acquired every minute with a sampling frequency of 10Hz. One dataset from PRONOSTIA experiments under the same operating conditions have been selected. The characteristics of the selected datasets for this experimental validation can be seen in table I:

Characteristics of the dataset.

Seven experiments were extracted from the PRONOSTIA test bench. The duration of each experiment varies depending on the time that each tested bearing reached the predefined vibration threshold. The characteristics of the experiments performed on the test bench are show in **Table AII.1**.

Table AII. 1. Characteristics of the experiments perfomed in the PRONOSTIA test bench

Experiment	Duration	Conditions
Bearing 1_1	28000 sec	1800 rpm 4000 N
Bearing 1_1	28000 sec	
Bearing 1_4	14000 sec	
Bearing 1_5	24000 sec	
Bearing 1_6	24000 sec	
Bearing 1_7	22000 sec	

It's important to clarify that each acquisition of the bearing condition was measured every 10 seconds, so the number of acquisitions available for each set correspond to the duration of the experiment divided by 10.

A.III Camshaft-Based Machine

The industrial scale test bench used in this work tries to replicate some of the non-stationary behaviour present in the camshaft-based industrial machines such as a blister packaging machine [85]. The experimental platform is composed by a 1.5 kW induction machine, acting as a drive connected to a 20:1 rated gearbox. The motor, controlled from an inverter by means of a speed-loop based vector control scheme, has the following technical characteristics: 6 pair of poles at 1500 rpm of rated speed and a rated torque of 20 Nm, 230 V_{AC}. The gearbox is in turn, coupled to a 120 cm camshaft containing two cycloidal cams commanding different mechanisms.

The measurement equipment is focused on the acquisition of the stator current and shaft rotation position. One stator-phase current is measured by means of a Tektronix current probe model A622. It provides 100 mV/A output and it can measure ac/dc currents from 50 mA to 100 A-peak over a frequency range from dc to 100 kHz. The current probe was placed just on the power converter stator phase output. The shaft rotation position is measured by a XCC1510P Schneider encoder, 360 points of resolution, attached to the camshaft. Data acquisition is done with DAQ NI 6143, a multifunction board with 16 input channels, 16 bits of resolution, and 4000 samples of internal memory. Stator motor current is sampled at a rate of 20 kHz. The encoder channel signals are digitally acquired at the same sampling rate as the current. The experimental setup is shown in **Fig. AIII.1**. Regarding the features estimation, novelty detection and diagnosis calculation, the algorithms are carried out in a computer under Matlab.

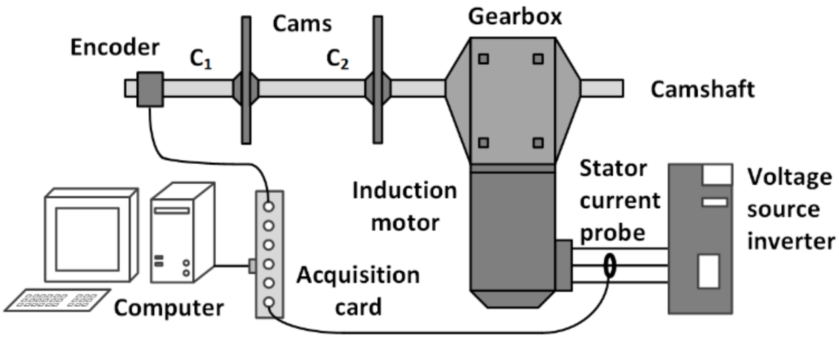

Fig. AIII.1. Scheme of the experimental setup formed by a drive motor, a gearbox, a two-cam camshaft, a stator current probe, an encoder and an acquisition card. C_1 and C_2 correspond to the disturbed cams in terms of required effort pattern.

Fault Scenarios Available

Three different experimental cases are available from the test bench: the healthy condition, *H*, and two faulty conditions by inducing effort disturbances. The first fault condition, F_1, involves the decrease of 25% of the effort pattern related with the first cam, C_1, through the adjustment of the thumbscrew related to the load grip by means of a dynamometric key. The second fault condition, F_2, includes a decrease of 25% of the effort pattern related to both of the cams, C_1 and C_2, also by the adjustment of the thumbscrew related to the load grip.

It must be taken into account that the induced fault scenarios correspond to common degradation patterns due to the continuous machine operation. Thus, although the effort disturbances induced by the fault conditions can be considered incipient deviations, it is expected to extract by the proposed methodology the corresponding affectation over the motor stator current

Signal Processing

It is well known that malfunctions caused by a misadjusted cam in a camshaft-based machine can be reflected in any part of the full shaft turn and, sometimes, the misadjusted cam can be tracked by analyzing the theoretical cam effort pattern [85]. Nevertheless, the information regarding the theoretical cam effort pattern is not always available or the association of the effort pattern to the corresponding part of the shaft turn is not always possible or accurate.

Due to these reasons, a signal processing approach capable of monitoring the changes of efforts in the full shaft turn and keep track of the position of the shaft is needed. Since the misadjusted cams cause an instant amplitude change in the current of the motor and in the spectral distribution, a time-frequency method is proposed to monitor the changes in the whole turn of the shaft and highlight the changes in the spectral distribution.In order to highlight the deviations during the operation of the machine, the calculation of a NTFM is employed.

The Short-Time Fourier Transform (STFT) is a local Fast Fourier transform applied on a sliding window. This way, it is possible to observe the evolution of the frequency content over time. The STFT of a signal *y* is noted *Y(m,f)*, being *m* the temporal index and *f* the spectral index. The magnitude squared of the STFT $|Y(m,f)|^2$, is called spectrogram and is expressed in dB as 20log(|*Y(m,f)*|).

The STFT analysis might be difficult since the modeling of the system is a complex task. Nevertheless, dealing with the presence of undesired patterns of operation in the machine, the objective is to be able to detect changes between the STFT corresponding to the healthy condition of the machine, and the STFT corresponding to the faulty one. In this regard, the normalization of the STFT is a suitable approach, this technique is a 2D extension of the statistic-based method. The main idea is to compute a statistical reference of the healthy STFT by computing the average spectrogram *M(m,f)* and the standard deviation *S(m,f)* of each time-frequency point. These are computed on a reference spectrogram, considering that the system is in a healthy state at the beginning. The normalized spectrogram, $Y_{CR}(m,f)$, called normalized time frequency map, is computed according to **Eq. AIII.1**.

$$Y_{CR}(m,f) = \frac{|Y(m,f) - M(m,f)|}{S(m,f)} \quad \textbf{Eq. AIII.1}$$

The normalized spectrogram $Y_{CR}(m,f)$ is considered to follow a standard normal distribution, *No(0,1),* and the normalization process can thus be assimilated to a student t-test. So, for each new STFT, the associated NTFM will have a value close to zero in case of similarity with the healthy STFT used as a reference, and a higher value in case of dissimilarities. The value is then proportional to the difference from the reference. Thus, the differences from the healthy condition are emphasized. Then, it is possible to estimate the quantity of such difference of a complete STFT or a specific region by adding the values of the complete NTFM or the considered region, respectively. More details can be found in [86].

As aforementioned, the NTFM is obtained by means of the STFT of the acquired signal but normalized in regard to a reference, which is a STFT over the healthy condition during the calibration process. Each NTFM calculated from the current of the motor has a time window length corresponding to one full shaft turn.

The resulting frequency map presents an increment or decrement in those time-frequency regions in which the behavior of the analyzed signal differs from the reference; therefore, a NTFM calculated over a healthy condition presents values close to 0 and a NTFM calculated over a deviated operating condition exhibits values distant from 0 throughout the time-frequency representation. **Fig. AIII.2(a)** and **Fig. AIII.2(b)** show an example of the current of the motor working under a healthy condition and a faulty condition, respectively. The corresponding STFT of the currents are shown in **Fig. AIII.2(c)** and **Fig. AIII.2(d)**. The NTFM calculated over the STFTs are shown in **Fig. AIII.2(e)** and **Fig. AIII.2(f)**, where the healthy and faulty conditions show clear differences. It can be noted that, if both STFT are compared (Fig. AI.2c and AI.2d), the differences between the healthy and faulty condition are not obvious. Nevertheless, when the NTFM are computed, the difference is highlighted in different parts of the spectrum.

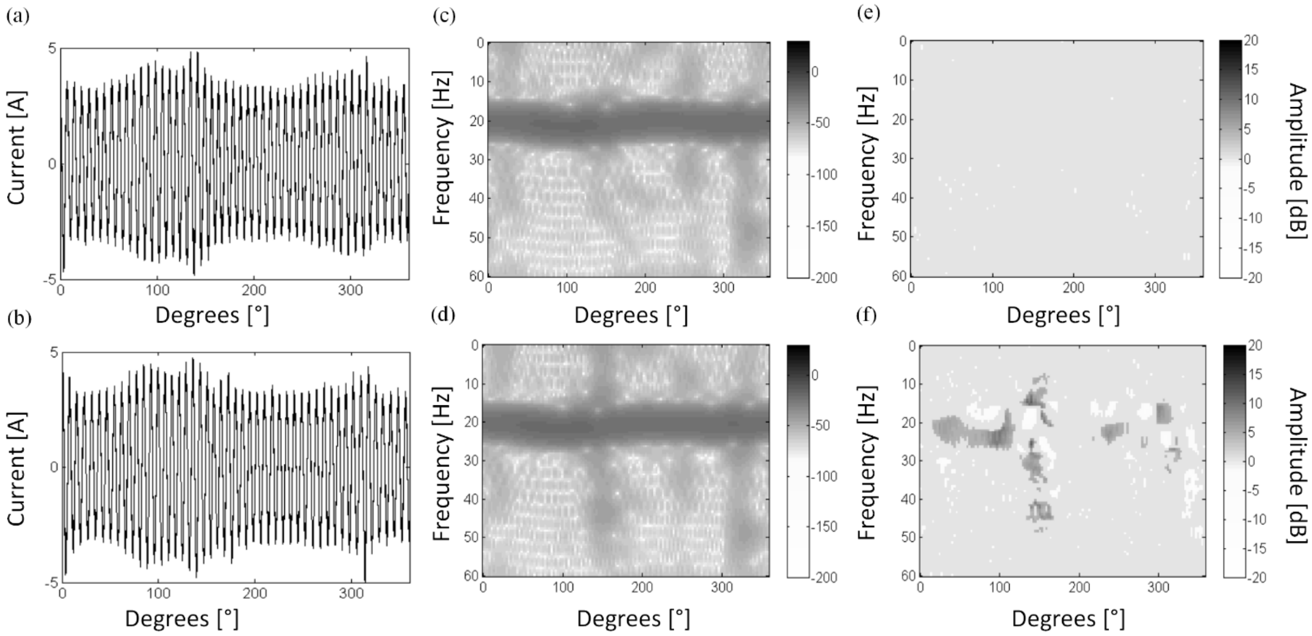

Fig. AIII.2. Calculation of the NTFMs parting from the STFTs of the stator current. a) Example of time-based stator current under healthy condition. b) Example of time-based stator current under faulty condition. c) Corresponding stator current STFT under healthy condition. d) Corresponding stator current STFT under faulty condition. e) Resulting stator current NTFM under healthy condition. e) Resulting stator current NTFM under faulty condition.

A.IV End-of-line test machine for steering systems

In order to test the methodologies presented on this thesis in an industrial environment, an EOL test machine that performs a friction test to steering systems is used. 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. AIV. 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.

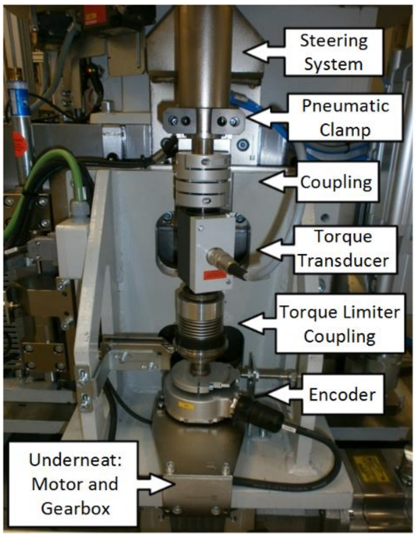

Fig. AIV.1. Machine that performs the end-of-line test composed by a servomotor, a gearbox, an encoder, a torque transducer and a pneumatic clamp to hold the intermediate shaft of the steering system.

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. AIV.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.

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. AIV.3.**

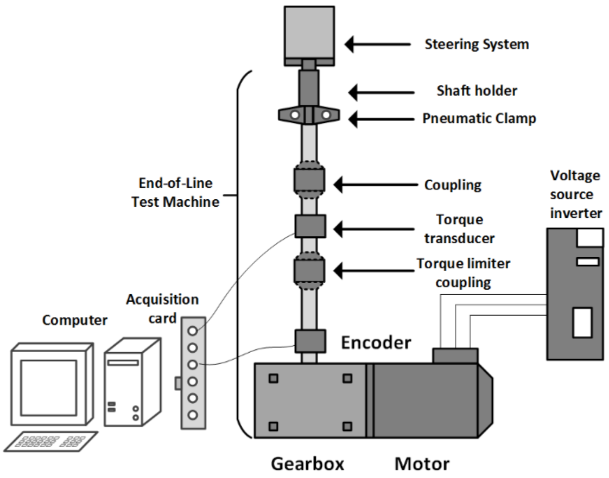

Fig. AIV.2. Schematic of the end-of-line machine under monitoring and the acquisition system.

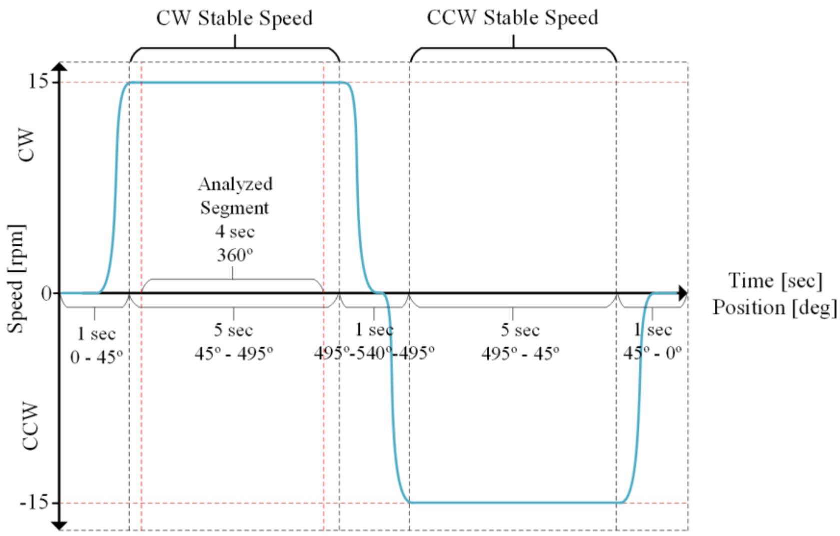

Fig. AIV.3. Speed profile applied by the EOL test machine.

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 shown in **Fig. AIV.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. AIV.4**.

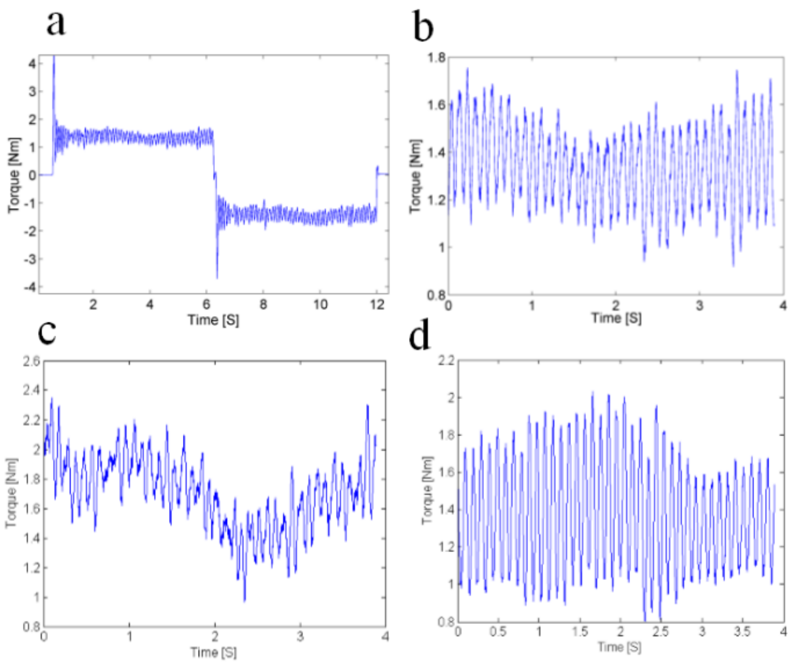

Fig. AIV.4. Torque signal measured during a test a) Complete torque measurement under machine healthy conditions b) Analyzed segment of a healthy machine measurement c)Analyzed segment of a machine misalignment fault d) Analyzed segment of a machine coupling wear fault

Scenarios available of the EOL test machine

Several 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*).

Characteristics of the dataset.

Eight classes regarding the condition of the machine are available:

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

For each class, 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 methodologies tested are affected by the variability of the torque response of the models. Nevertheless, it is desired to assess the capability of the methodologies to generalize between different models of steering system and correctly identify the machine condition.

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.