An Attribute Oriented Induction based methodology to aid in Predictive Maintenance: Anomaly Detection, Root Cause Analysis and Remaining Useful Life

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Declaration

Hereby I declare that this document is my original authorial work, which I have worked out on my own. All sources, references, and literature used or excerpted during elaboration of this work are properly cited and listed in complete reference to the due source.

Javier Fernández Anakabe
Arrasate, 2019

Bide honetan nire ondoan egon zareten guztiongatik. Ta bereziki zuregatik, Loriane.

Abstract

Predictive Maintenance is the maintenance methodology that provides the best performance to industrial organisations in terms of time, equipment effectiveness and economic savings. Thanks to the recent advances in technology, capturing process data from machines and sensors attached to them is no longer a challenging task, and can be used to perform complex analyses to help with maintenance requirements. On the other hand, knowledge of domain experts can be combined with information extracted from the machines' assets to provide a better understanding of the underlying phenomena. This thesis proposes a methodology to assess the different requirements in relation to Predictive Maintenance. These are (i) Anomaly Detection (AD), (ii) Root Cause Analysis (RCA) and (iii) estimation of Remaining Useful Life (RUL).

Multiple machine learning techniques and algorithms can be found in the literature to carry out the calculation of these requirements. In this thesis, the Attribute Oriented Induction (AOI) algorithm has been adopted and adapted to the Predictive Maintenance methodology needs. AOI has the capability of performing RCA, but also possibility to be used as an AD system. With the purpose of performing Predictive Maintenance, a variant, *Repetitive Weighted Attribute Oriented Induction* (*ReWAOI*), has been proposed. ReWAOI has the ability to combine information extracted from the machine with the knowledge of experts in the field to describe its behaviour, and derive the Predictive Maintenance requirements.

Through the use of ReWAOI, one-dimensional quantification function from multidimensional data can be obtained. This function is correlated with the evolution of the machine's wear over time, and thus, the estimation of AD and RUL has been accomplished. In addition, the ReWAOI helps in the description of failure root causes.

The proposed contributions of the thesis have been validated in different scenarios, both emulated but also real industrial case studies.

Resumen

El Mantenimiento Predictivo es la metodología de mantenimiento que mejor rendimiento aporta a las organizaciones industriales en cuestiones de tiempo, eficiencia del equipamiento, y rendimiento económico. Gracias a los recientes avances en tecnología, la captura de datos de proceso de máquinas y sensores ya no es un reto, y puede utilizarse para realizar complejos análisis que ayuden con el cumplimiento de los requerimientos de mantenimiento. Por otro lado, el conocimiento de expertos de dominio puede ser combinado con la información extraída de las máquinas para otorgar una mejor comprensión de los fenómenos ocurridos. Esta tesis propone una metodología que cumple con diferentes requerimientos establecidos para el Mantenimiento Predictivo. Estos son (i) la Detección de Anomalías (AD), el Análisis de la Causa-Raíz (RCA) y (iii) la estimación de la Vida Útil Remanente.

Pueden encontrarse múltiples técnicas y algoritmos de aprendizaje automático en la literatura para llevar a cabo el cálculo de estos requerimientos. En esta tesis, el algoritmo Attribute Oriented Induction (AOI) ha sido seleccionado y adaptado a las necesidades que establece el Mantenimiento Predictivo. AOI tiene la capacidad de estimar el RCA, pero puede usarse, también, para el cálculo de la AD. Con el propósito de aplicar Mantenimiento Predictivo, se ha propuesto una variante del algoritmo, denominada *Repetitive Weighted Attribute Oriented Induction* (*ReWAOI*). ReWAOI tiene la capacidad de combinar información extraída de la máquina y conocimiento de expertos de área para describir su comportamiento, y así, poder cumplir con los requerimientos del Mantenimiento Predictivo.

Mediante el uso de ReWAOI, se puede obtener una función de cuantificación unidimensional, a partir de datos multidimensionales. Esta función está correlacionada con la evolución de la máquina en el tiempo, y por lo tanto, la estimación de AD y RUL puede ser realizada. Además, ReWAOI facilita la descripción de las causas-raíz de los fallos producidos.

Las contribuciones propuestas en esta tesis han sido validadas en distintos escenarios, tanto en casos de uso industriales emulados como reales.

Laburpena

Enpresei errendimendu hoberena eskaintzen dien mantentze metodologia Mantentze Prediktiboa da, denbora, ekipamenduen eraginkortasun, eta ekonomia alorretan. Azken urteetan eman diren teknologia aurrerapenei esker, makina eta sensoreetatiko datuen eskuraketa jada ez da erronka, eta manentenimendurako errekerimenduak betetzen laguntzeko analisi konplexuak egiteko erabili daitezke. Bestalde, alorreko jakintsuen ezagutza makinetatik eskuratzen den informazioarekin bateratu daiteke, gertakarien gaineko ulermena hobea izan dadin. Tesi honetan metodologia berri bat proposatzen da, Mantentze Prediktiboarekin lotura duten errekerimenduak betearazten dituena. Ondorengoak dira: (i) Anomalien Detekzioa (AD), (ii) Erro-Kausaren Analisia (RCA), eta (iii) Gainontzeko Bizitza Erabilgarriaren (RUL) estimazioa.

Errekerimendu hauen kalkulua burutzeko, ikasketa automatikoko hainbat algoritmo aurkitu daitezke literaturan. Tesi honetan Attribute Oriented Induction (AOI) algoritmoa erabili eta egokitu da Mantentze Prediktiboaren beharretara. AOI-k RCA estimatzeko ahalmena dauka, baina AD kalkulatzeko erabilia izan daiteke baita ere. Mantentze Prediktiboa aplikatzeko helburuarekin, AOI-rentzat aldaera bat proposatu da: *Repetitive Weighted Attribute Oriented Induction* (*ReWAOI*). ReWAOI-k alorreko jakintsuen ezagutza eta makinetatik eskuratutako informazioa bateratzeko ahalmena dauka, makinen portaera deskribatu ahal izateko, eta horrela, Mantentze Prediktiboaren errekerimenduak betetzeko.

ReWAOI-ren erabileraren ondorioz, dimentsio bakarreko kuantifikazio funtzioa eskuratu daiteke hainbat dimentsiotako datuetatik. Funtzio hau denboran zehar makinak duen higadurarekin erlazionatuta dago, eta beraz, AD eta RUL-aren estimazioak burutu daitezke. Horretaz gain, ReWAOI-k hutsegiteen erro-kausaren deskribapenak eskaintzeko ahalmena dauka.

Tesian proposatutako kontribuzioak hainbat erabilpen kasutan balioztatu dira, batzuk emulatuak, eta beste batzuk industria alorreko kasu errealak izanik.

Eskertza

Tesi bat bakarkako lana dela esan dezaketen arren, hainbat dira helmugara iristea posible izatea eragin duten aktoreak. Batzuek tesian bertan erreperkusio zuzena izan dute, baina badaude beste batzuk ere, prozesu honetako ekosistematik kanpo egon arren, dena ondo atera dadin kolaboratu dutenak. Ez nuke inorekin ahaztu nahi.

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Chapter 1

Introduction

Maintenance in industrial sector became relevant in the last years. Product and service downtimes can suppose time and effort losses. Thus, systems for monitoring and predicting breakdowns have been implemented to help avoiding extra costs. In this thesis a novel methodology based on data mining techniques is proposed and developed to cover the stages of an effective maintenance strategy in the industrial sector. The Repetitive Weighted Attribute Oriented Induction (ReWAOI) has been defined for that purpose, and it has been applied in multiple use cases to validate the proposal with accurate results.

1.1 Introduction to Maintenance

From the early 90's until the first years of 21st century monitoring was the principal method to receive the information of the current state of an inspected element, mostly accompanied with a customised alert system. These kind of systems were based on defining some thresholds or critical values in order to generate an alert if the monitored asset overtook any of them. The goal was to generate a more representative way to let the operator or worker know whether an asset failed. So the initial purpose of the maintenance was to inform after a failure happened.

Then, a new idea of maintenance emerged, known as Preventive Maintenance, as a methodology that could avoid failures caused by excessive wear. This new maintenance trend sought to establish a priori conditions for which a substitution task would be executed. The action thresholds that were specified did not necessarily indicate that the machine suffered any failure, they were simply conditions to make a replacement. For this reason, in many occasions, the cost involved in the substitution task was not profitable, bearing in mind that the replaced machine could have continued working efficiently for a longer time.

Finally, a new concept called Predictive Maintenance came up in order to optimise the asset life-cycle, reducing unnecessary replacement costs, by better estimating failures of an asset. This methodology is based on extracting knowledge from asset's behavioural data in order to get more accurate, objective and representative results. In this way, maintenance is performed only when it is needed. There are many researches in this field in which this methodology is preferred to the others mentioned before. This is explained in more dept in chapter 2. Theoretical Background.

1.2 Motivation

Predictive Maintenance is the methodology that is growing among the most in the industrial sector [5]. The potential provided by recent advances in technology allows data to be extracted from different machines and processes, store it, and exploit its information to convert it into actionable knowledge. Thus, the tools to detect anomalies and predict failures based on the information collected are becoming mainstream in the sector.

Not only data collected from the machines provide useful information to perform predictions. There is another concept denoted Domain Knowledge. This information helps understanding data obtained from the monitoring of a machine, providing an overview of the scenario. These two information sources can be combined to form a solid database, to be analysed and make more accurate predictions.

For this reason, this thesis is based on the definition and development of a data mining algorithm which can combine both data collected from machines and knowledge obtained from experts. By using this algorithm, in combination with other data mining techniques, it may conclude on defining a working methodology which can obtain more accurate results for prediction.

1.3 Objectives and Hypotheses

The fundamental idea behind this research work lies in the design and implementation of a novel data-driven methodology that allows to fulfill the stages established by Predictive Maintenance [6]. These stages are (i) Anomaly Detection, (ii) Root Cause Analysis, and (iii) Remaining Useful Life, as mentioned by Z. A. Welts in the PhD Thesis of the author [6]. The thesis focuses on demonstrating the ability of the Attribute Oriented Induction (AOI) algorithm to help in that purpose. For this end, a set of objectives are defined, supported by several hypotheses, which are listed below.

1. To develop a system able to detect anomalies in the behaviour of an asset which includes Domain Knowledge.
   (a) The capacity of AOI algorithm to represent different groups according to the similarity and dissimilarity of the data, based on monitored control parameters referring to the behaviour of the inspecting element, will enable unexpected failure detection.
   (b) After having defined a collection of known states of the behaviour of a machine with the AOI algorithm, if an unknown state is registered, it may represent an anomaly.
   (c) In a sequential process of a machine, the order in which the states are registered is significant at the time of detecting anomalies.
2. To demonstrate that the anomaly detection system based on AOI is able to explain the abnormal behaviour of the asset under analysis, also known as Root Cause Analysis.
   (a) The hierarchical organisation that provides the algorithm AOI and a previously defined knowledge-base referring to the different possible states of the monitored parameters will enable the categorisation of the root cause of a detected anomaly or failure.
3. To accurately estimate the Remaining Useful Life of a monitored asset.
   (a) Based on the results obtained from the processing of AOI, Time Series based or Artificial Neural Network based models can predict future anomaly states.

(b) Models based on ARMA family or LSTM are able to generate accurate forecasts of the behaviour.

1.4 Main Contributions

The main contribution of this thesis is the definition, experimentation, and validation of a work methodology that meets the stages of Predictive Maintenance. For this aim, a Machine Learning algorithm that combines information extracted from both the machine and knowledge of domain experts of the area has been used. The novelty resides in the fact that this algorithm has not been used previously in a scenario like the one proposed, yielding to results that are easy to understand by the machine operators.

This algorithm is called Attribute Oriented Induction (AOI), and it is a bottom-up hierarchical clustering model based on applying generalisation hierarchies on the data collected from a machine or process. These generalisation hierarchies are provided by domain experts, thus achieving a model that takes into account the two mentioned information sources: (i) information collected from monitoring the process, and (ii) information offered by domain experts.

Moreover, an improved AOI algorithm has been proposed and validated, in order to optimise its execution and facilitate the process of the defined methodology. The most relevant additions are: on the one hand, the repetitive execution of the AOI feeding the algorithm with the outliers of the previous iteration, which allows reducing the number of final unclustered elements. And on the other hand, the establishment of weights to each of the generated clusters according to the generalised level they are and the number of instances they have, which allows to define a univariate quantification function for making predictions. The new algorithm is called *Repetitive Weighted Attribute Oriented Induction* (*ReWAOI*).

The experiments have been accomplished under a methodology that encompassed three different phases: Anomaly Detection (AD), so an unexpected failure or a behavioural trend that leads an asset to a possible failure can be detected in advance. Root Cause Analysis (RCA), so the reason behind the failure or imminent failure can be induced. And Remaining Useful Life (RUL), so an estimation of the time to failure can be performed, and maintenance operations can be scheduled in an optimum way. As a conclusion, promising results have been obtained for different use cases by applying the proposed methodology and algorithm in the area of application.

To estimate these different phases, multiple techniques have been used. For Anomaly Detection, Statistical Process Control (SPC) charts have been selected. These charts are useful to check whether a monitored operation is out of normality. Specifically, Exponentially Weighted Moving Average (EWMA) charts and the Western Electric Rules (WER) have been utilised. EWMA control charts are useful when small shifts on the data are wanted to be detected, helping to infer when a work behaviour of a machine is starting to go out of historically common conditions. WERs are valid to detect abnormal behavioural states in a work behaviour [7].

For the representation of Root Cause Analysis, the descriptive potential of the ReWAOI algorithm in combination with the Self-Organising Maps (SOM) have been used. SOM algorithm is based on a neural network architecture, thus it can generate clusters considering complex attribute relationships [8].

Finally, for the estimation of RUL, time series prediction methods have been defined. For this end the results obtained by the ReWAOI algorithm have been combined with Recurrent Neural Networks (RNN) algorithm, specifically Long-Short Term Memories (LSTM) [4]. Also Auto-Regressive Moving Average (ARMA) methods have been considered [9]. In cases in which the data to be modelled have a complex sequential structure, LSTMs are utilised, due to their capacity to manage predictions based on past data relationships [10].

1.5 General Results

Throughout the development of the thesis, different milestones and merits have been achieved that are discussed below. Some of the mentioned results are described in detail later in the thesis.

- **Participation in the European project MANTIS[1].** During the first phase of the thesis, the work has been developed in the context of the European project

[1] http://www.mantis-project.eu/

MANTIS (ECSEL 2014 Call), specifically in the work package related to Data Analytics. In this process, different deliverables have been written related to the calculation of the Remaining Useful Life and the Anomaly Detection that have served to advance the objectives of the research. All this is summarised in the MANTIS book publication [11].

Publications:

  – Larrinaga F., Fernandez J., Zugasti E., Garitano I., Zurutuza U., Anasagasti M., Mondragon M. *Implementation of a Reference Architecture for Cyber Physical Systems to support Condition Based Maintenance.* 2018. In 5th International Conference on Control, Decision and Information Technologies (CoDIT).

  – Larrinaga F., Fernandez-Anakabe J., Zugasti E., Garitano I., Zurutuza U., Olaizola J., Anasagasti M., Mondragon M. *A Big Data implementation of the MANTIS Reference Architecture for Predictive Maintenance.* 2019. In Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering.

  – Gregor Papa, Urko Zurutuza, Michele Albano, Erkki Jantunen. *The MANTIS Book. Chapter 5: Providing Proactiveness: Data Analysis Techniques Portfolios.* 2019.

- **Participation in the European project PROPHESY[2].** During the second phase of the development of the thesis, the work has been developed in the context of the European project PROPHESY (FOF-09 Call), specifically in the work package related to Data Analytics.

- **Implementation of the Repetitive Weighted Attribute Oriented Induction (ReWAOI) algorithm.** Various modifications and additions have been made to the original AOI algorithm in order to represent wear states of the monitored process. At the same time, a method to make the algorithm work without expert information has been implemented, using statistical processes to define generalisation hierarchies of the attributes. And finally, a way to minimise the number of outliers generated in the process of creating clusters has been included.

[2]https://prophesy.eu/

- **Implementation of a method to transform a multivariate dataset into a univariate one.** One of the implemented variants of the AOI algorithm has the capacity to represent the wear of a process over the time by means of a numerical function. This action is performed considering that the dataset has multiple descriptive attributes.

- **Design of a novel work methodology for the fulfillment of the stages of the Predictive Maintenance process.** A new methodology has been defined to accomplish a Predictive Maintenance process, using the different contributions and applications of proposed algorithms. For this end, the components Anomaly Detection, Root Cause Analysis, and Remaining Useful Life have been developed.

  Publications:

  – Fernandez-Anakabe J., Zugasti E., Zurutuza U. *An Attribute Oriented Induction based Methodology for Data Driven Predictive Maintenance.* 2019. Submitted to Journal of Intelligent Manufacturing, Springer. Preprint at arXiv:1912.00662.

  – Fernandez-Anakabe J., Zugasti E., Zurutuza U. *A novel data-driven methodology for the estimation of Root Cause Analysis by using the Attribute Oriented Induction algorithm.* 2019. Submitted to Applied Intelligence, Springer.

- **Development of a method to detect change points and anomalies.** Using Statistical Process Control charts and the outputs generated by the Repetitive Weighted Attribute Oriented Induction algorithm, the moment in which a behavioural state is out of control limits is estimated. This process is denoted in this thesis as Change Detection. Moreover, a mode to detect asset failure states has also been developed by means of the so-called Western Electric Rules [7].

- **Representation of the states of the behaviour.** Using the ReWAOI algorithm a univariate quantification function is constructed from the set of attribute values. Thanks to the capacity of the ReWAOI, a description of the attribute values of each point of the quantification function can be extracted. Thus, description of anomalies can be represented in the estimation of RCA.

- **Calculation of the remaining time until the next anomaly happens**. With the help of time series algorithms such as ARMA or neural networks such as LSTM, the future behaviour of the machine has been modelled, to estimate RUL. The function that is modelled is produced by the output generated by the ReWAOI algorithm.

1.6 Assumptions and Limitations

The methodology proposed in this thesis has several assumptions which limit its application.

On one hand, the datasets for Anomaly Detection must contain historical data on the correct operation of the machine. If the case study has only incorrect data or faulty data, the proposal of this thesis is not applicable to such scenario.

On the other hand, regarding the estimation of RCA, the goal is to analyse the states prior to an occurrence of a failure, and form clusters based on their similarities. Hence, different types of possible failures are explored. Based on the capacity of data representation of AOI, information of those states can be displayed, concerning the values of their respective hierarchy-trees defined by the domain experts.

If a new type of change state (a state prior to failure) is detected and is tried to be categorised as one of the previously registered change state types, the RCA model is not able to consider it as a new type, and will label it as a previously registered one. Thus, this methodology is valid in situations in which the failure states are known when the RCA model is trained, and new types of states do not appear.

Referring to the RUL estimation, it is only applied in cases in which a wear of an asset is registered. If the Change Detection system does not consider that an out of common behaviour is happening, the RUL is not estimated.

Moreover, for performing a predictive model to check when the next anomaly will occur, a valid quantification function is needed. A valid quantification function is considered when there is a wear evolution present in it. In cases in which no wear is perceptible in the quantification function, another strategy is followed. A set of recommendations is offered in order to know when to inspect the data and when the data is considered as correct and can be working with no problem.

Regarding the construction of hierarchy-trees for attributes, in cases in which there is a lack of domain experts, an alternative approach is suggested. However, this approach is valid only when the raw data of the attributes is numerical. Thus, the methodology proposed in this thesis is applicable in cases in which domain experts of the area are present, or when the data is numerical.

To apply the full methodology and estimate AD, RCA and RUL, correct and failure containing data must be present for training the predictive models. On one hand, correct data must be present to ensure the detection of states that go out of normal working conditions. And on the other hand, failure containing data is relevant to calculate the fault types and thus, estimate both RCA and RUL.

1.7 Organisation of the Work

The document is organised into nine chapters. In this first chapter, the most relevant aspects of the developed work are summarised. In chapter 2, the most relevant terms of the thesis are explained, putting special emphasis on their description and the state of the art. These are terms related to maintenance strategies, necessary to understand the context of the research. The third chapter describes the Attribute Oriented Induction algorithm, how it works, and the different applications and variants that it has had over the time. This section is considered as an essential pillar of the thesis, and consequently it has been paid special attention and placed in an independent section. These chapters refer to the first block of the document, in which the purpose is to put the reader in context.

The following chapters deal with aspects related to the development, the demonstration of hypotheses, and the achievement of objectives. Chapter 4 refers to the data-driven methodology developed to achieve the results. It explains the procedure designed for the correct fulfillment of the objectives. Chapter 5 describes the different case studies that have been used for experimentation. Specifically, four different case studies are described. In chapter 6, the results obtained for each of the case studies are discussed, that lead to the validation of the proposed hypotheses. Chapter 7 interprets the results obtained in the previous chapter, and expresses some general conclusions, as well as the future work related to this research.

Chapter 2

Theoretical Background

In this chapter the most relevant concepts that serve to lay the groundwork of the thesis are described. For each section, a brief description is provided, followed by a review of the related work in the scientific domain, and finished by a discussion that justifies the contributions proposed in the thesis work.

2.1 Maintenance Methodologies

According to R. Keith [12] three main categories of Maintenance are considered:

Definition 1. ***Preventive Maintenance*** *schedules maintenance tasks based on time periods.*

Definition 2. ***Corrective Maintenance*** *manages and schedules repairs after a failure has occurred.*

Definition 3. ***Predictive Maintenance*** *is focused on preventing unscheduled downtimes and premature damage on the equipment.*

The key of Preventive Maintenance, sometimes also named as Time-Based Maintenance (TBM) [13], is to execute maintenance activities like lubricating, calibrating, or inspecting elements following a previously established periodicity, in order to reduce failure states on the machine behaviour. These periods are usually determined by the experts' knowledge, manufacturer advices or data of historic breakdowns, but is unable to detect possible abnormal states out of the expectations. This way, this strategy indicates when a replacement of a component must be carried out, but does not analyse whether that component has suffered previous wear, or if on the contrary it is working correctly and does not need to be replaced yet.

A similar problematic could be considered with Corrective Maintenance. Until recent years, it has been one of the most commonly used maintenance strategies. Corrective Maintenance is a methodology that is based on executing a correction or maintenance action when a breakage occurs in the asset that is being monitored [14; 15]. In this way, maintenance efforts are minimised, allowing the asset to function until an error occurs or cannot provide more service. The disadvantage of this methodology is that it does not consider the asset suffering a degradation that, even if no error occurs, prevents it from working efficiently. Also, it does not consider that it can lead to production downtime which can severely impact in costs. Moreover, the maintenance is not scheduled thus costs soar once breakage happens.

Predictive Maintenance is based on capturing data from the asset to be monitored, and extracting relevant information. By using a data history that has been recording the behaviour of the asset, it is possible to model its wear and tear, and thus, prepare a maintenance action before a failure occurs. In this way, estimates of maintenance times and actions can be obtained more efficiently and accurately than by employing Corrective and Preventive Maintenance strategies.

However, these are not the only maintenance strategies. Mobley [12] introduces another strategy called Maintenance Improvement. It focuses on analysing why failures occur and it tries to establish context conditions which avoid those situations instead of generating a maintenance management schedule to control that.

While over the time the repair cost increases due to the level of degradation suffered by the machine, the cost of prevention decreases; the later the machine is replaced, the greater the profitability. Moreover too early a substitution can result in significant losses. It is important to determine the optimum point at which maintenance must be carried out, and this can be achieved through Predictive Maintenance. Figure 2.1 shows the cost relationship between these three maintenance methodologies.

Accordingly, it is important to preserve a consistency with ISO 13381 [16], which says that the prognosis is oriented to foresee how a component will evolve from its current degraded state until its failure and then until breakdown (performance level): to predict its Remaining Useful Life. The management philosophy to perform this maintenance process is called Condition-Based Maintenance (CBM) [13; 17].

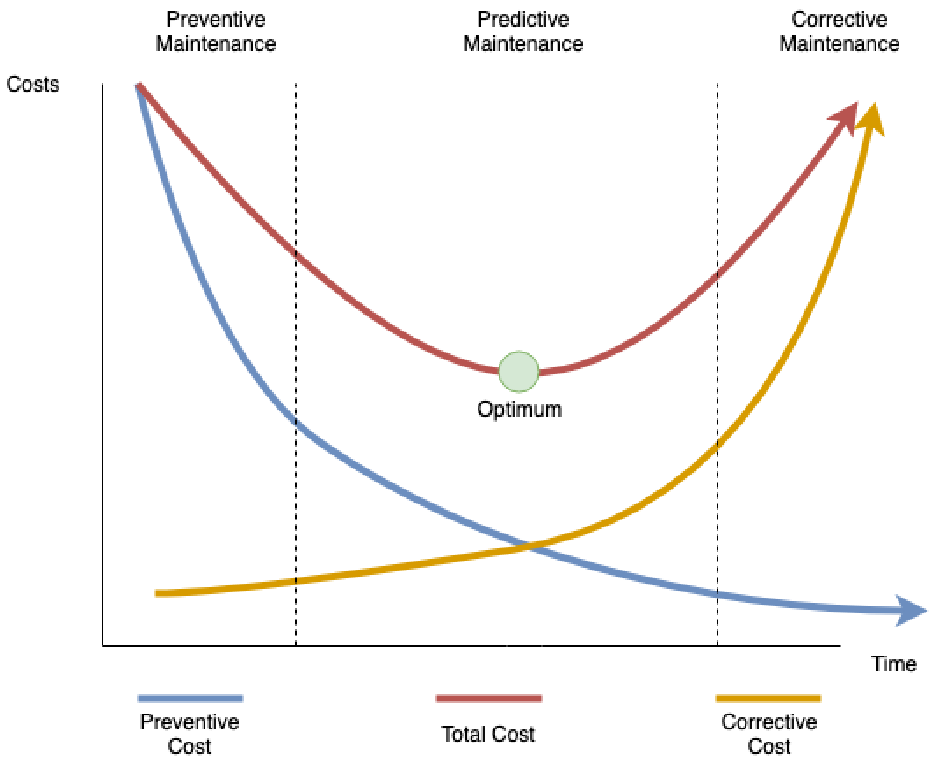


Figure 2.1: Cost relation between the different maintenance strategies [1].

Definition 4. *The objective of* ***CBM*** *is to minimise the total cost of inspection and repairs by collecting and interpreting intermittent or continuous data related to the operating condition of critical components of an asset (Knapp and Wang et. al., 1992).*

The principal idea of *CBM* is that signals are continuously being monitored using certain types of sensor or other appropriate indicators. Thus, the primary goal of CBM is to do a real-time assessment of equipment conditions in order to make maintenance decisions, therefore reducing unnecessary maintenance and associated costs [18].

At this point, we must observe the research literature regarding the current status on machine- and system-health prognosis and Anomaly Detection, to position the research on the actual context into the field.

As Accorsia et. al [19] state, the existing ICT solutions simplify the on-field collection of large amount of data, such as Radio Frequency Identification (RFID), Micro-Electro-Mechanical Systems (MEMS), Supervisory Control and Data acquisition (SCADA) systems, or Product Embedded Information Devices (PEID). But even so, they require models and tools able to create knowledge from the collected data, concretely Data

Mining and Machine Learning methodologies. It is also remarked the importance of domain experts on the data and machine-behaviour, in order to help selecting relevant data to face the analysis, and to discuss the results obtained by the generated knowledge model. We must remember that the goal of the Predictive Maintenance is not only getting results that show how, when and/or where can an asset fail, but extracting valuable information from them in order to produce knowledge that can help managing those situations. And that is only possible if domain experts are taken into account in the process. Another term that is closely related and meets with the previous explanation is Proactive Maintenance.

Regarding the methods applied in Predictive Maintenance of machinery in industry, there are several approaches related to signal processing techniques to extract valuable information about the health of a machine, oriented to manage a Condition-Based Monitoring. This thesis is oriented to demonstrate that the power of Attribute Oriented Induction algorithm to extract machine's behaviour-knowledge can be useful and effective in order to help managing Failure Detection and determining the Root Cause Analysis as well as estimating the Remaining Useful Life.

D. Goyal [20] affirms that nowadays every machine in industry emit vibration signals. As he says, vibration analysis has proved to be a measure for any cause of inaccuracy in manufacturing processes and components or any maintenance decisions related to the machine. Hence, it presents a study of different vibration-monitoring based methods, such as Statistical Time Series Models [21], Probability Distribution and Density Function [21], Fast Fourier Transform (FFT) [22], Short-Time Fourier Transform [23], Cohen's Class, Wavelet Transform (WT) [24], and so on [25]. Wang et. al. [24] focus on the analysis of vibration signals using Spectral Kurtosis algorithm, affirming its power on detecting abnormalities on machine-behaviours. But it concludes declaring that those methods are most commonly used in small and academic problems, supposing a big challenge applying them in big smart structures [26].

Heng, A. et. al. [27] expose the different methods for predicting failures in the field of rotating machinery. Even if the study is focused in a particular application, which is in rotating machinery, the classification of the different maintenance-based methodologies is interesting in order to reflect their possible area of application. Three main methods are distinguished: (i) event data based prediction, (ii) condition data based prediction, (iii) prediction based on both event and condition data. This classification is extended in section 2.4 Remaining Useful Life.

Once data is collected and ready to be analysed, they must be treated in order to generate a model which makes information become knowledge.

Collected data must be analysed in order to extract knowledge. Artificial Neural Networks [27; 28], Fuzzy Logic [27; 29], Expert Systems, and Bayesian Classifiers [25; 27] are commonly used data analysis techniques [20; 30; 31; 32; 33].

Khelf, I. [25] confirms the effectiveness of utilizing Naive Bayes Classifier and Support Vector Machines (SVM) in order to address a classification problem. It first extracts the most relevant features from vibration signals, but also includes other external variables such as temperature and angular speed of the machine. Caesarendra et. al. [34] also use SVM to train the classification model based on data captured from vibration signals. Abderrazak Bennane, S. Y. [35] proposes a new data-processing tool called Logical Analysis of Data (LAD) oriented to CBM applications. Collecting data from some indicators of a machine, such as temperature or vibration frequencies, the algorithm is able to generate a binary representation of the data in order to specify whether the behaviour is normal or not. Li, H. [36] also applies Support Vector Machines algorithm to analyse whether a network velocity violates regulations set by governmental safety agency or deteriorating rolling-stock conditions as determined by the railroad. In this case, multiple sensors collect information such as failure data, maintenance action data, inspection schedule data, train type data and weather data, to proceed with the anomaly detection process.

Most of the studies in the literature concerning to CBM on industrial machinery are based on vibration signal processing techniques. This fact is due to author's assumption that vibrational signals accurately predict a failure on the behaviour. But in many other scenarios, such as process maintenance, control parameters of the behaviour are monitored (temperature, speed, etc.) instead of vibrations. Thus, other Predictive Maintenance techniques must be considered. It must also be contemplated that vibration signals may not be captured in many machine monitoring processes due to context limitations.

Figure 2.2 shows the relationships between the distinct maintenance types found in the literature.

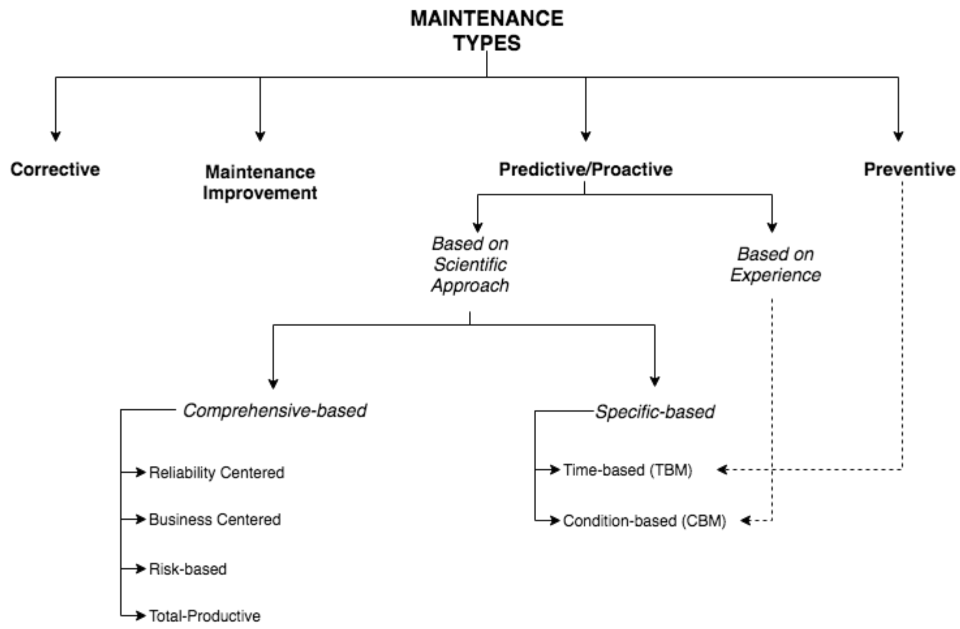


Figure 2.2: Distribution of the different maintenance types

After observing many of the recent studies about Maintenance in the industrial context, it is clear that the trend has evolved from simply *monitoring* to also *predicting*. The growth of the service demand, combined with the rapidly emerging technological advances caused a shift in thinking, from maintenance being a necessary evil, to becoming a critical driver of competitivity. While a few years ago extracting knowledge from the health of the assets was a useful tool, nowadays it is strictly needed in order to prevent considerable economical losses for the companies. Many different approaches are proposed in the literature, but it still lacks of a general and referential method to tackle the predictive maintenance process.

2.2 Anomaly Detection

Anomaly Detection techniques have been proposed since the 19th century, and related technology has been improving in time. It can be defined as the process of finding unusual behavioural states in a monitored asset that derivate from normality. First of all, however, the meaning of the term *anomaly* must be explained.

Definition 5. ***Anomalies*** *are patterns in data that do not conform to a well defined notion of normal behaviour.*

Anomalies might be induced in the data for a variety of reasons, such as malicious activity, credit card fraud, cyber-intrusion, terrorist activity, breakdown of a system, etc. Some experts define the Anomaly Detection as *novelty detection*, which aims at detecting previously unobserved (emergent, novel) patterns in the data as shown in the study of Chandola et. al. [2]. But taking into account their definitions, novelty detection is a process that is responsible for detecting states that have not been previously recorded, but unlike anomalies, they are considered normal later. So these are two concepts that should be distinguished. Another concept that also relates to the anomalies, but that is not considered as the same is the noise removal. The noise in those cases is not interesting to perform the analyses. In contrast, the anomalies reflect an infrequent behaviour of the asset being monitored [2].

Moreover, point and collective anomalies [37] must be distinguished. Point anomalies are those that one event alone outside of the established limits is sufficient to be considered as an anomaly. But it may be the case that a series of elements are within the limits of normality individually. If they are taken collectively they are not. These are the collective anomalies, in which a group of elements considering together can form an unusual state. An example is shown in Figure 2.3, in which the anomaly is registered between values 1000 and 1500 of the X axis. This Figure shows a periodic numerical function. Every data point in the function is inside an upper and lower boundaries (4.5 and -7 of the Y axis, respectively), but the sequence of points occurring between values 1000 and 1500 of the X axis is longer than the other periodical sequences.

There are still some challenges in the anomaly detection. A straightforward anomaly detection approach is to define a region representing normal behaviour and declare any observation in the data that does not belong to this normal region as an anomaly.

- The definition of a region in which all the elements are considered normal is complicate, and it is possible that some abnormal elements can be close to the boundaries of that normality region. Those abnormal states may be considered change states, not anomalies.

- In many scenarios the normal states can evolve, so abnormal states can become into normal ones with time.

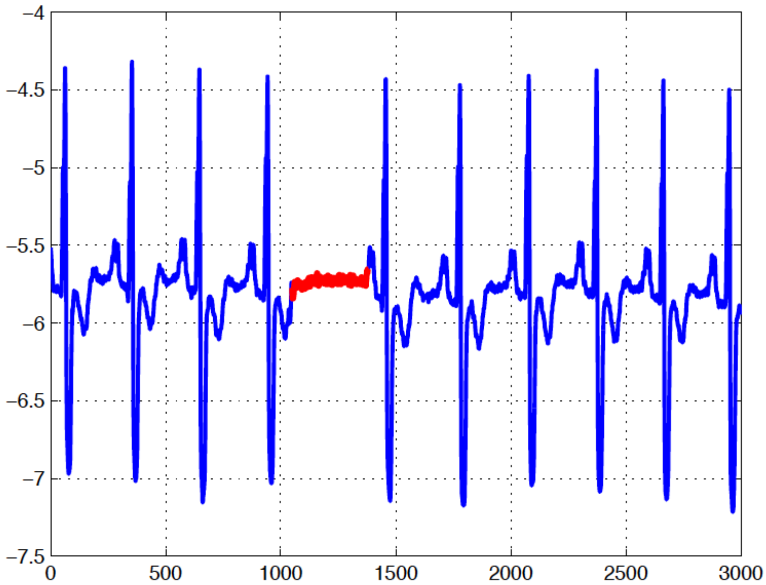


Figure 2.3: Example of collective anomaly corresponding to an Arterial Premature Contraction, extracted from the study of Chandola et. al. [2]

- Often the data contains noise that tends to be similar to the actual anomalies and hence it is difficult to distinguish and remove.

In addition, there must be taken into account the type of anomaly that is being detected since in a specific scenario there may be more than one type of anomaly.

Several methods based on Machine Learning are distinguished to detect anomalies. (i) Classification: where the data is labelled as normal or anomalous, and the idea is to try to train a model that can distinguish its label. (ii) Clustering: using this technique groupings of data are generated, and those that do not fit the parameters are considered as anomalies. Agrawal et. al. [38] distinguishes four main techniques for clustering anomaly detection. (i) K-Means, which defines k disjoint groups on the basis of the feature value of the objects to be grouped. (ii) K-Medoids, very similar to K-Means, but differing in the manner of defining the cluster centroids. K-Medoids establishes the centroid of the clusters using the most centric object in the cluster, rather than calculating the implicit mean that may not belong to the group, as K-Means does. (iii) The Expectation-Maximisation clustering (EM clustering) technique is similar to the

K-Means technique. However, in the case of EM clustering, it computes probabilities of cluster memberships based on one or more probability distributions [39]. And (iv) Outlier Detection Algorithms. Authors define the last one as "a technique to find patterns in data that do not conform to expected behaviour". They remark Distance based Approaches to detect anomalies. The greater the distance of the object to its neighbour, the higher the probability of being considered an anomaly.

Related to all this, and as previously mentioned, there are different applications for the detection of anomalies. Among others, (i) Intrusion Detection [40; 41; 42]: The main challenge is the large amount of data which they usually work with and the changing environment to learn from. Semi-supervised and unsupervised anomaly detection techniques are preferred in this domain. (ii) Fraud detection: the main idea is to maintain the user profile of each user and monitor them to detect any unusual behaviour [43]. (iii) Medical anomaly detection: the detection of anomalies is critical in this scenario, and a high level of accuracy is required. Most of the time there are data related to healthy patients, so the most used technique is semi-supervised anomaly detection [44]. (iv) Industrial damage detection: Industrial units suffer damages due to the natural wear caused by their use. These failures must be detected as soon as possible to avoid major damages and time and money losses for the company. The data collected in this sector are usually sensor data [45; 46; 47; 48]. In this thesis the Anomaly Detection is focused on this last application.

In a study performed by Ren, H. et. al. [49] a dynamic Markov Model is used in order to detect anomalies. An interesting segment of the paper explains a division of different categories to perform detection of anomalies: (i) distance-based anomaly detection; (ii) clustering-based anomaly detection; and (iii) prediction-based anomaly detection. The first one is oriented to detect anomalies taking into consideration the distance between data points or instances, the greater the distance, greater the probability of being an abnormal state. The second, directly or indirectly, uses a clustering approach to group the data. Those data points that cannot be easily clustered will be considered as abnormal. Prediction-based anomaly detection is oriented to utilise Machine Learning prediction algorithms to detect abnormal states, such as SVM, Markov Models, Bayesian Networks or ANN. Although Ren, H. et. al. distinguish three categories to perform anomaly detection, other authors such as Agrawal et. al. [38] distinguish only classification and clustering, and consider distance-based methods as techniques used for clustering.

Data collected from industrial sector tend to be unlabelled, not distinguishing correct behavioural data from anomaly or degradation containing data. For this reason, performing some exploratory analyses on the data to extract knowledge and categorise the different process behaviour states is considered, so clustering based techniques are considered relevant.

Patcha and Park [50] comment the importance of unsupervised learning in anomaly detection. They separate statistical-based methods, machine learning-based methods, and data mining-based methods. Statistical approaches are focused on inferring about the relationships between variables, which helps characterise the data. Machine learning centres on implementing models able to carry out predictions, based on previous occurrences of the data. And data mining is about extracting knowledge from data, applying transformations and providing a comprehension that is unable to obtain only by using the human eye. Statistical approaches and data mining are more human centered techniques that machine learning. In addition, I must mention that machine learning is a discipline that includes statistics among others, and data mining is a process where one of the steps is the generation of models (machine learning).

Moreover, in a study performed by Chandola et. al. [2] authors distinguish two ways of output for anomaly detection. (i) Scoring techniques: assign an anomaly value to each instance depending on the degree in which that element is considered as an anomaly; from here a ranking of anomalies is obtained. (ii) Assigning a label indicating if a state is an anomaly or not.

In this thesis, the goal is to detect anomalies in the data regarding to machines behaviour. The machine degradation level is wanted to be estimated to model the future trend or evolution of the wear and help detect the next failure or breakdown of the machine or asset. In addition, the objective is to label a single execution of a machine as correct or anomaly containing.

A highly related anomaly detection technique is the outlier detection field, as mentioned by Agrawal et. al. [38]. An outlier is an element that goes beyond the normality of a population. There are techniques to detect outliers, such as Statistical Process Control methods [7]. Shewhart, Cumulative Sum (CUSUM) or Exponential Moving Weighted Average (EWMA) are techniques utilised in this field. These are methods to find slight deviations in the behaviour of a function, which can help detecting uncommon states of the behaviour. On the one hand, the outliers are data points that are far from the mean or median in a distribution. On the other hand, anomalies are data points that do not conform to a well define notion of normal behaviour.

In this way, those work states that are not considered as anomalies, but go out of the normal conditions of the behaviour of a machine or asset should also be detected. These states may refer to data points that can lead to an anomaly in future moments of the behaviour. The Statistical Process Control charts such as EWMA or CUSUM are interesting techniques that can be applied to perform this analysis.

In a study performed by Kadri et. al. [51], a combination of time series models and Statistical Process Control charts is used for an early detection system applied to data collected from the paediatric emergency department of Lille. Specifically, EWMA control charts are used. Authors state that EWMA is successful when small changes in the process must be detected.

Moreover, a study carried out by Harrou et. al. [52], utilizes EWMA control charts to detect anomalies, combined with Partial Least Squares (PLS). Authors also say that EWMA is able to detect small faults in a process. This proposal is applied accurately in industrial sector.

Many studies consider the case of data not being labelled. In a study carried out by Xu [53], a novel sequential anomaly detection method based on temporal-difference learning is proposed. Author states that defining a normal region which considers every possible normal behaviour is difficult; and also says that finding labelled data is a challenging aspect in Anomaly Detection tasks.

Lejon et. al. [54] also comments that anomalies are events that are not included in the common behaviour of a process, and that there is often insufficient anomalous data to build reliable detector models. Authors remark three machine learning techniques to use for an anomaly detection approach in press-hardenings: ANN, SVM and ensemble classification.

Kotu and Deshpande [55] state the importance of unsupervised data mining algorithms to detect anomalies as well. At the time explaining the different techniques for Anomaly Detection, authors separate distance-based and clustering, as well as Ren, H. et. al. [49]. They explain distance-based methods as detection of points that are far from the neighbours, and clustering as detecting points which are not forming groups.

In this thesis, as mentioned previously, the study has focused on detecting anomalies in the industrial sector. Specifically, the objective is to detect anomalies in the work behaviour of the machines.

In this sector, not all the outliers mean a failure state. An outlier can signify an out of control state that may derivate into a failure in future states. Hence, to clarify the terminology, two distinct concepts are distinguished: (i) anomaly, and (ii) change state.
Definition 6. *A **change state** is a moment in the behaviour in which an uncommon work state is detected, without necessarily implying an error or an incorrect behaviour.*

It is only a deviation from the normal behaviour that can carry out the detection of a fault or anomaly.

The difference between a change state and an anomaly is that an anomaly is a moment in the behaviour that the work process registers a failure or a breakdown, and a change state is a moment in which a degradation is starting to be registered, but it does not necessarily imply a failure.

Thus, the first task is to find the change points that indicate that an anomaly can occur. For this end, the use of an unsupervised Machine Learning algorithm, named Attribute Oriented Induction (AOI), has been proposed, in combination with Statistical Process Control techniques. Subsequently, more information about this algorithm will be explained, as well as how it is intended to manage the AD approach.

2.3 Root Cause Analysis (RCA)

In the last years, fault detection systems have become a very important and active field in industry. With the help of the multiple technology improvements many companies got the possibility to install sensors in their machines or machine components, and thus, enabling the capability to monitor their health-status. This supposes an important improvement at the time to tackle the maintenance of the assets. They make possible the generation of alert systems that help to detect anomalies, and just optimise the actions for correcting and repairing.

Although these kind of systems helped on management of the product and process maintenance, they did not provide any interpretation of the detected behavioural abnormalities.

Definition 7. *The goal of* ***Root Cause Analysis (RCA)*** *is to describe the anomaly detection system, specifying the cause of the alert based on two factors: causality and explanation* [56].

Different descriptions collected from the literature review are represented in Table 2.1.

Reference	Definition
[57]	In maintenance decision making, Root Cause Analysis (RCA) refers to a class of problem solving methods which are aimed at identifying the focal root causes of recurrent equipment failures in technical assets.
[58]	RCA is targeting at identifying the causes of problems in processes for directing counteractive actions (Rooney & Heuvel, 2004).
[59]	RCA practice tries to solve problems by attempting to identify and correct the root causes of events, as opposed to simply addressing their symptoms.
[60]	RCA is the task of identifying root causes as well as the components they affect.

Table 2.1: RCA definitions provided in the literature.

To achieve this goal, it is necessary a definition of a knowledge-base referred to the area of study, denoted Domain Knowledge.

Definition 8. *The* ***Domain Knowledge*** *is the information provided by domain experts of the area to better contextualise the scenario of the analysis.*
Definition 9. *The* ***Knowledge-Base*** *is the combination of domain knowledge and knowledge achieved by the analyses of the data.*

This explicit knowledge is the factor that helps detecting the anomalies and determining their typology. In a paper developed by Venkatasubramanian, V. [61], a study of model-based anomaly detection and Root Cause Analysis is presented, and author remarks the importance of the domain knowledge, which is also referred as *a priori knowledge*. This and other related papers [56; 57; 60; 61; 62] insist on the necessity of an existing background information, explicitly defined, which represents the different anomaly and fault states in order to determine the causality of an error.

In a study performed by Kiran, M. [59] author exposes four distinct steps in RCA estimation process: (i) data collection, (ii) cause charting, (iii) root cause identification, and (iv) recommendation.

It is true that background information (domain knowledge) must exist, but there could be many situations in which an abnormal behaviour of the inspected element may occur and any conceptual reasoning for that situation is not registered. So an alert would be shown and there would be no explanations about it. Therefore, the goal of the background knowledge should be to represent a conceptual overview schema of the inspecting behaviour, and not directly the characteristics of each anomaly or failure (e.g. When "Temperature" variable is higher than value X, is considered as "High temperature", and component Y is prone to break). The result of an RCA analysis must not be understood as the direct and clear answer to failure reasons, but a clarification or explanation of the context in which a failure or anomaly has occurred, as a decision support for a domain expert.

To tackle the issue of how to extract the relation between an anomaly and its explanation, there are several studies in the literature which make use of data mining techniques. Inspecting the behaviour of a machine or process and detecting anomalies only with human intuition is a very challenging task. There are a huge amount of variables to take into account, and also so are calculations to perform. This is not a context to be efficiently monitored by human capacities. Thus, the use of computer-based knowledge representation and prediction systems becomes not only useful, but necessary, in order to reduce effort and generate more rapid and reliable results. Estrada, M. S. [56] accomplished a classification of algorithms and techniques to tackle RCA which includes, mainly, Machine Learning algorithms, such as: Bayesian Networks, SVM or ANN. But as the author comments, the majority of the most advanced classifiers, such as Neural Networks, only return a predicted root cause and it is difficult to obtain an explanation from them. For these techniques to provide some explanation, Explainable AI techniques should be used, as stated in a study performed by Arras et. al. [63]. In addition, they do not yield logical rules, and such approaches are difficult to combine with available domain knowledge. Authors refer to logical rules as complex structures of information obtained from the analyses by using machine learning tools. The techniques that are mentioned in the study are limited to obtain simple results, not based on descriptions that can be formed by IF-THEN rules. Thus, the importance of explaining why a failure has occurred is remarkable, and not only determine which the failure is.

Chemweno, P. [57] distinguishes three broad categories in which RCA can be divided: (i) qualitative, (ii) semi-quantitative and (iii) quantitative techniques. Qualitative techniques are oriented to represent causes based on descriptions and representations in diagrams such as Ishikawa cause-and-effect diagram or the '5-whys' analysis. These techniques are based on quality-management methodologies, together with other techniques such as Pareto's diagram or histogram representation. In quantitative-based approaches, on the other hand, the calculation is based on analysing the context and behavioural data. Authors in the most recent studies conclude that the potential of applying quantitative techniques in those cases in which relevant and exploitable data is collected is higher than the ones provided by qualitative techniques.

There are multiple studies referring to the estimation of RCA in the literature in which many of the algorithms belong to the classification carried out by Estrada et. al. [56], such as ANN, Fault Tree Analysis, or Bayesian Networks.

Alaeddini, A. and Dogan, I. [58] utilise Bayesian Networks for the estimation of RCA due to their power in knowledge representation. They use some context information of the asset under analysis as input data to train the model, and a specific information of the process at the time of an anomaly occurs. Bayesian Networks also have the capability of modelling conditional dependencies between variables, and that is what motivates Abele, L. [62] to use this Machine Learning algorithm to process RCA. The goal in that paper is to reduce the redundancy of alarms generated by a system. This allows to avoid alarm flooding and support the operator in his decision-making task by providing the root causes of alarms and their probabilities of occurrence.

A specific RCA estimation method is proposed by Groenewald and Aldrich [64] combining process causality maps and extreme Machine Learning algorithms. As a remarkable note in this study, authors state that there is not a specific algorithm to face RCA problem indistinctly of the use case. This is meaningful in order to understand the recent continuity of the studies respect to the calculation of RCA and its application in different scenarios.

In a study performed by Yunusa-Kaltungo, A. [65], author proposes an approach combining Fault Tree Analysis (FTA) and Reliability Block Diagram (RBD) in order to find root causes in chronic rotary kiln refractory brick failure. The most remarkable information of this research work is the importance of the domain knowledge and failure-event data in order to get accurate results.

In 2016, [57] Chemweno, P. proposed a novel method to estimate RCA, based on different data mining techniques to manage process-steps. The motivation of this study is that most commonly used algorithms in RCA such as Bayesian Networks and Fault Tree Analysis, depend mostly on the cause-effect associations defined by domain experts in the domain knowledge, delinked from failure associations embedded in the empirical failure events. Thus, in this study the author utilises four different clustering techniques, in order to group the different failures with similar characteristics in different representative groups. These clustering techniques are: (i) the hierarchical agglomerative technique, (ii) K-means, (iii) Fuzzy c-means, and (iv) the Self-Organising Maps. As a conclusion, author says that results obtained from the application of Fuzzy c-means and K-means needed more interpretative effort than hierarchical clustering or Self-Organising Maps clustering. This way, the idea is to ease and optimise the analysis resizing the failures defined in the knowledge-base according to their similarity/dissimilarity.

Julisch, K. carried out a remarkable paper for this thesis [60] in which RCA estimation is applied to the intrusion detection field. The study is focused on generating a more efficient way to discover the root of an intrusion alarm. The problematic in intrusion detection is that signatures to detect attacks are persistent, regardless the system is vulnerable or not to an attack, generating a huge number of redundant alarms that may distract the worker or operator. Accordingly, the author proposes a novel algorithm to cluster redundant alarms and optimise their analysis and inspection in order to estimate better the RCA. The most remarkable field of this study is that part of the algorithm they use for the clustering is based on the hierarchical clustering method Attribute Oriented Induction (AOI).

Finally, in this thesis, the proposal is to deal with RCA despite having defined initially the possible reasons which the failures are concerned to. Most papers comment the necessity of having defined an a priori knowledge in which the different failures are described in order to help label the detected anomalies. But it must be taken into consideration that new failures can happen apart from the previously registered ones.

As a conclusion for this section, the mention of domain knowledge in some of the papers reviewed in the literature remarks the importance of domain experts. Moreover, the assumption of there is not a specific algorithm to address the RCA estimation helps understanding that it is an ongoing research. Studies such as the one carried out by Chemweno, P. [57] utilise clustering based methods to estimate RCA. Due to the difficulty to collect labelled data in industry, clustering techniques such as Self-Organising Maps can be a valid choice to generate results in the RCA field. Finally, Julisch, K. [60] proposes the utilisation of the aforementioned AOI algorithm, which makes use of both domain expert knowledge and data collected from machines.

2.4 Remaining Useful Life (RUL)

One of the goals or main concepts in Predictive and Proactive Maintenance is to try to estimate for how long an asset or a service is able to continue functioning until a failure or anomaly occurs in its working behaviour. As told previously in section 2.1 Maintenance Methodologies, entities and organisations could not permit the loss of time and money due to an unexpected (and sometimes even expected) machine- or service-failure, so strategies and schedules to predict such stoppages have become necessary.

Definition 10. *The **Remaining Useful Life (RUL)** is the time remaining until a process cannot continue working properly or a failure is registered..*

Si, X.-S. [66] defined the concept as: *the useful life left in an asset at a particular time of operation.* He noted that the estimated time until the normal behaviour of an asset finishes is typically unknown. Information obtained from condition and health monitoring is relevant to help determine the RUL, and thus the concept is strongly related to Predictive Maintenance. On the other hand, Okoh, C. [67] proposed the following definition to describe RUL: *Remaining Useful Life (RUL) is the time remaining for a component to perform its functional capabilities before failure.* Even though many authors do not include the term failure in the description, they agree in defining the concept as the end of the correct-functional capacity of an asset. Different RUL definitions are shown in Table 2.2 [68].

Reference	Definition
[66]	The remaining useful life (RUL) of an asset or system is defined as the length from the current time to the end of the useful life.
[70]	Is the time left before observing a failure is called as remaining useful life.
[71]	Is the lifetime remaining between the present and the instance when the system can no longer perform its function.
[72]	Is the life time of the monitored system before failure occurs.

Table 2.2: RUL definitions provided in the literature.

There are multiple studies in the literature referring to the calculation of RUL. Ahmadzadeh, F. and Lundberg, J. [69] made a review of the different techniques to estimate RUL, and distinguished four different methodologies: (i) physical models construct technically comprehensive theoretical models to describe the physics of the system; (ii) experimentally based models, use probabilistic or stochastic models of the degradation phenomenon or the life cycle of components, by taking into account the data and the knowledge accumulated by experience; (iii) data-driven models are based on processing the historical data, without needing special product knowledge to be specified; and (iv) combination/hybrid prognostic methodologies, which are based on combining more than one of the previously mentioned models.

The most used Machine Learning algorithms to estimate RUL observed in the literature are ARIMA models [73; 74], Artificial Neural Networks (ANN) [67; 69; 70; 72; 75; 75; 76; 77], Support Vector Machines (SVM) [67; 69; 73; 78; 79], Bayesian approaches [67; 69; 73] and Hidden and Semi-hidden Markov Models (HMM, or SHMM) [67; 69].

Ahmadzadeh, F. [69] affirmed that the use of prognostics in calculation of RUL is crucial, and analysed the capacity of multiple algorithms to address this, utilising recent RUL estimation applications from the literature. The ANN, SVM and Bayesian Approaches are some examples from this comparative study into the field of data-driven approach, and ARMA family models if a Hybrid-model is considered, combined with any other Machine Learning algorithm such as Bayesian Networks or ANN.

In a paper of Okoh, C. [67] the purpose is to identify event prediction approaches in order to reduce uncertainties, and thus, help calculating the RUL in the context of manufactured products within the Industrial Product Service System (IPSS)[3]. Author describes briefly different methods commonly used in the literature, and highlights algorithms such as Hidden Markov Models, ARIMA, ANN and SVM.

Si, X.-S. [66] remarks the importance of RUL in CBM, considering it a key factor. An interesting assumption is given in this study. Author affirms that failure-event data is not really needed to estimate RUL, but a threshold and a model to describe the Condition Monitoring (CM) data are required to determine it. This is a significant field on which this research work is focused and that will be addressed later in the document.

As a conclusion to these observed comparative studies and revisions of the literature, a graphical representation of the different RUL estimation methodologies and the techniques commonly applied for each one has been generated, as shown in Figure 2.4.

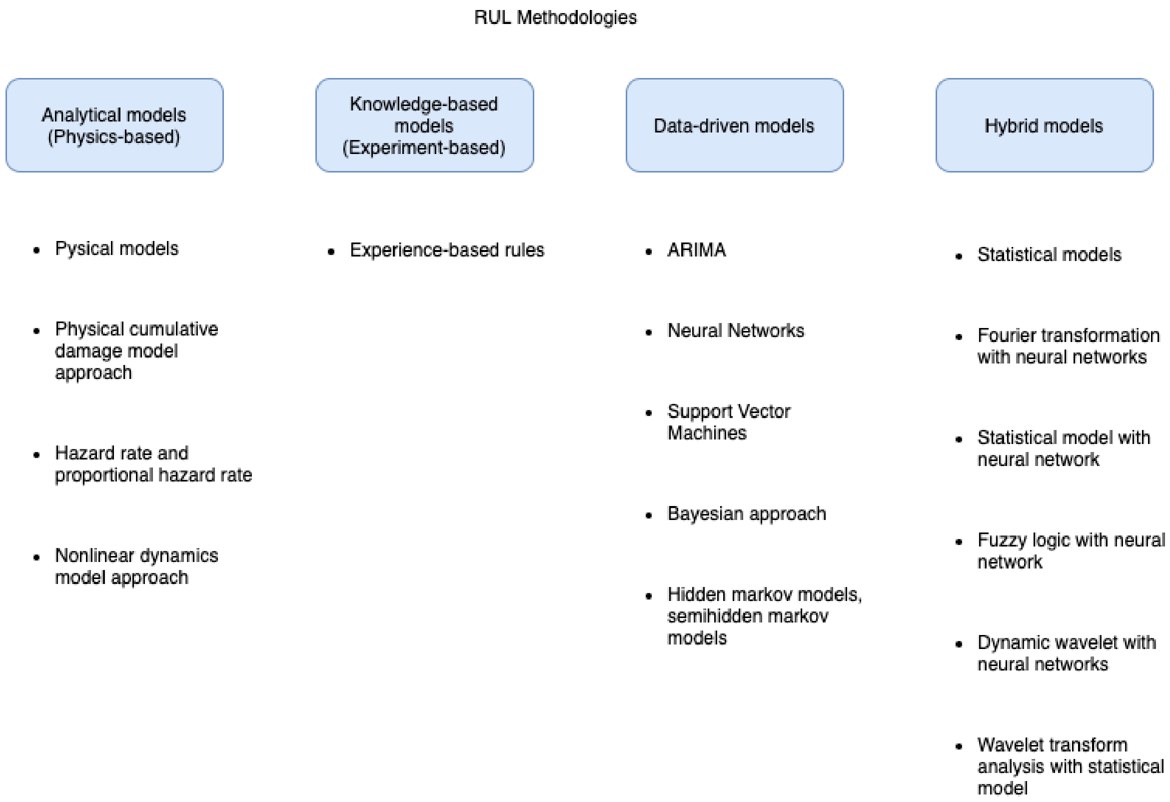


Figure 2.4: A global scheme of RUL methodologies organised by fields of study.

Inspecting particular use case studies in which many of the previously mentioned algo-

[3]More information about IPSS can be found in a study performed by Meier et. al. [80]

rithms are utilised to estimate RUL, there are many comments that can be remarked.

An ANN approach for RUL prediction using both failure and suspension historical data is proposed by Tian, Z. [76]. Author affirms that suspension historical data may help to generate a more precise RUL prediction, specially in cases which there are few failure data. The proposed approach is validated using real-world vibration monitoring data collected from pump bearings in the field, and the case study shows that the proposed approach can produce more accurate remaining life prediction results.

Tran, V. T. et. al. [78] propose a combination of Machine Learning tools to calculate the machine performance degradation. Authors divide the process in three different steps: (i) recognition of system behaviour utilising normal operating condition of the machine; (ii) estimate survival function of the system using Cox's hazard model; (iii) RUL forecast using SVM. It also suggests to use Time Series algorithms such as ARMA family models for it.

An ANN as a method to improve accurate RUL prediction of bearing failure is proposed by Mahamad, A. K. [77]. Author tries to demonstrate that the noise of a degradation signal from a target bearing can be minimised and the accuracy of the prognosis system can be improved by using time and Weibull hazard rates of Root Mean Square and kurtosis from present and previous points as input for ANN.

Rai and Upadhyay [70] also suggest an ANN based approach to calculate the RUL of bearings in any rotating machinery. They propose a nonlinear Autoregressive Neural Network with eXogenous Inputs (NARX-NN) combined with wavelet-filter technique. The results of the study show that the proposed algorithm provides better prediction results than the conventional Feed Forward Neural Networks.

Xia, M. et. al. [72] propose a method which calculates several RUL predictors based on the health stages of the degradation process of a rotating machinery instead of calculating a single RUL based on the entire degradation process in order to get a more accurate fitting.

A Support Vector Machine (SVM) based approach is presented by Kim, H.-E. et. al. [79] in order to estimate the RUL of machine bearings. A historical data of failure states is utilised in order to determine the degradation states of the machine, and then, tries to predict the estimation of those degradation states using SVM.

A data-driven fuzzy approach for the calculation of the remaining time until a moment in which system can no longer perform its function is presented in the study of Zio and Maio [71]. A collection of referent patterns of evolution of the behaviour is generated with data of different failure scenarios. Based on a Fuzzy similarity analysis, the evolution data are matched to the patterns in the library and their known residual life times are used for the estimation of RUL.

A novel approach combining Empirical Mode Decomposition (EMD) and ARIMA models is suggested in the field of estimating RUL of Li-ion batteries by Zhou, Y. and Huang, M. [81]. First, the parameters, global deterioration trend and capacity regeneration are obtained by utilising EMD, and then, ARIMA model is applied to predict their trend. Authors conclude that this approach provides more satisfying and accurate prediction results than Relevance Vector Machines (RVM)[4].

Another Time Series model based ARMA approach is proposed by Pham, H. T. et. al. [74] in combination with generalised autoregressive conditional heteroscedasticity (GARCH) to estimate and forecast the machine state based on vibration signal. In spite of being this proposal oriented to process vibration signal data, the goal of generating a trend or model of the future signal to estimate when will a failure or wear occur is the same.

Most of the recent works show a combination of multiple Machine Learning algorithms dividing RUL estimation process in two main steps: (i) valuable parameter estimation, and (ii) future trend and evolution calculation. As it is observed, ANN, SVM and Time Series based models are very present in the literature of the last years, so the suitability of the application for the RUL detection of these methods is represented.

This research is focused on data-driven approaches to help estimating RUL. Recent studies demonstrate that Machine Learning techniques have become increasingly powerful and useful when the goal is to predict events based on monitored behavioural data. Thus, a novel Machine Learning-based proposal using Attribute Oriented Induction (AOI) and a signal trend or evolution modelling technique is proposed and validated to generate RUL estimation.

After a through literature review have been performed, the extracted supposition is that

[4]Information about RVM: [82]

maybe the ideal algorithm for predicting RUL could be ANN. Both ANN and ARIMA models predicts values respect to prior values, but ANNs also take into account other aspects to perform the analyses.

2.5 Data Analysis techniques for AD, RCA and RUL

The Data Analysis techniques used in the thesis to carry out the experiments and fulfil the requirements of Predictive Maintenance methodology are explained in this section.

2.5.1 Exponentially Weighted Moving Average Control Charts

The Exponentially Weighted Moving Average (EWMA) is a type of control chart that is used to monitor the behaviour of a process and detect small deviations in it [3].

In the representation of the EWMA, weights are assigned to the individuals in geometrically decreasing order, making the most recent samples have a greater weight than the later samples.

This control chart has two control limits that establish the range in which the behaviour of the signal is considered normal: (i) the Upper Control Limit (UCL) and (ii) the Lower Control Limit (LCL). The Equations 2.1 and 2.2 show how these limits are calculated.

$$UCL = \mu_0 + L \cdot \frac{\sigma}{\sqrt{n}} \cdot \sqrt{\frac{\lambda}{(2-\lambda)} \cdot (1-(1-\lambda)^{2i})} \tag{2.1}$$

$$LCL = \mu_0 - L \cdot \frac{\sigma}{\sqrt{n}} \cdot \sqrt{\frac{\lambda}{(2-\lambda)} \cdot (1-(1-\lambda)^{2i})} \tag{2.2}$$

μ_0 and σ refers to the mean and standard deviation of the population. The variable i refers to the current data observation. Moreover, there are two coefficients that must be specified a priori: L and λ.

L is the multiple of the rational subgroup standard deviation that establishes the control limits. Its value is usually set between 2.7 and 3.0. λ is the weight given to the most recent rational subgroup mean. Assigning a value between 0.05 and 0.25 is recommended [3].

Once the control limits have been calculated, the function must be represented in the EWMA chart, and for this end, the transformation must be performed by means of the Equation 2.3.

$$z_i = \lambda \cdot x_i + (1 - \lambda) \cdot z_{i-1} \tag{2.3}$$

$$z_0 = \mu_0$$

, where μ_0 is the historical average of the correct data, and x_i is the current observation of the function to be represented in the EWMA control chart.

An example of an EWMA control chart is shown in Figure 2.5.

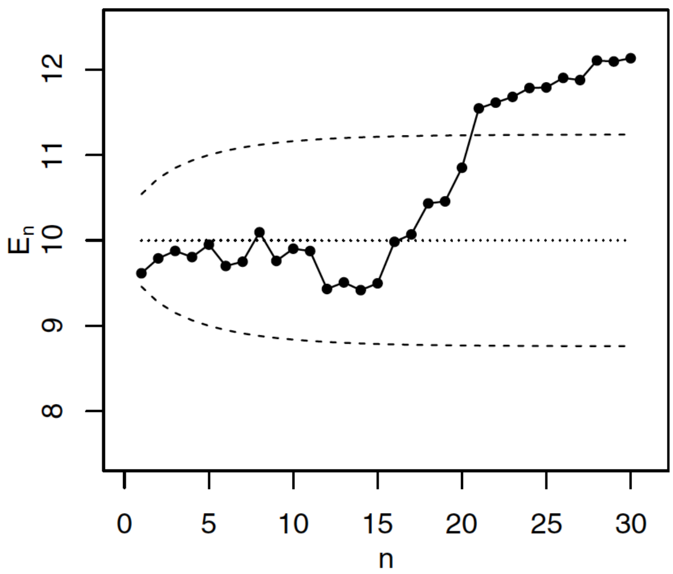


Figure 2.5: Example of an EWMA chart in which the UCL is overcome [3].

In this research work, the EWMA control charts have been used to detect when the behaviour of a machine is operating out of normality. In that way, these charts are used as flags that alert that an anomaly may occur soon.

2.5.2 Self-Organising Maps

The Self-Organising Map (SOM) method is a special class of artificial neural networks and is used extensively as a clustering and visualisation tool in exploratory data analysis [83].

Some of the areas where the SOM has been applied are: pattern recognition, data mining and processing, process control, robotics, telecommunications, medical applications, optimisation, and product management.

The main objective of the SOM is to convert high-dimensional input data into simpler ones, preserving the relationship of the data.

SOMs are trained through unsupervised learning schemes. That is, the input data is not labelled in such a way as to guide the learning process. Hence, the SOM is able to discover new patterns on the data.

Unlike most neural network models, SOMs directly connect the input layer with the output layer, with no need to use any hidden layer. The output layer represents a low dimensional representation of the data. Nodes in the output layer are arranged in form of a topological architecture. This structure is usually two-dimensional.

The weights of the neurons are fed with a value, and when a new input is presented to the neural network, the euclidean distance for all the weight vector is calculated. The neuron with the most similar weight vector with respect to the input is called Best Matching Unit (BMU).

In general, the SOM assigns weights to the relationships between the input data and each cluster on the map. The weights are assigned randomly at the beginning of the process [84]. The training is performed by comparing the input data set with the weight vectors calculating their Euclidean distance in order to find the BMU, as it is shown in the Figure 2.6.

As mentioned, the main feature of SOM is that it represents the structure of clusters in a two-dimensional space. It shows the distance between nodes based on a spectrum of colours that indicates it. An example of this is shown in Figure 2.7.

The Self-Organising Map algorithm is used in this research project to generate groups of

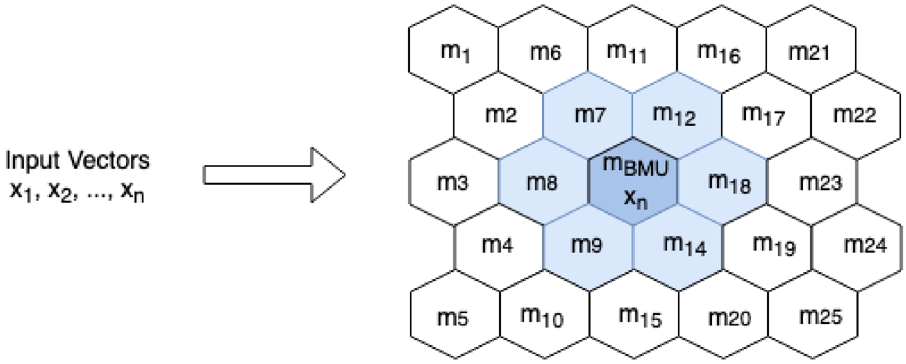


Figure 2.6: Elements in the Self-Organising Maps.

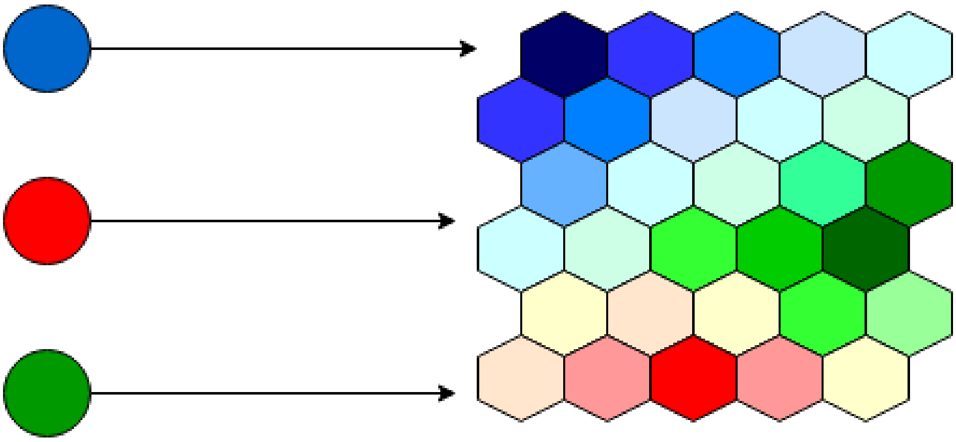


Figure 2.7: Example of a SOM map.

out-of-control states. In this way, taking into account the set of unusual states that are recorded in the monitored datasets, clusters that indicate the different possible anomalies that could happen are generated.

The decision to use the SOM algorithm instead of other clustering algorithms has been based on the fact that the SOM is constructed through neural networks. There may be use cases in which an element is characterised by many attributes, and in those cases the SOM is expected to achieve precise results when it tries to find similarities. In addition, in a study performed by Chemweno, P. [57], the results obtained after using the SOM are demonstrated to be accurate in a multivariate scenario.

In any case, the objective of this thesis has not been to find the best clustering algorithm for the process, but to use one that can provide precise results to validate the methodological proposal.

2.5.3 Long-Short Term Memory

Long-Short Term Memory (LSTM) are a type of Recurrent Neural Networks.

Unlike traditional Neural Networks, Recurrent Neural Networks (RNN) have persistence, so they are able to generate predictions at a specific time taking into account previous events. They have loops between their elements that cause them to have persistence, as shown in Figure 2.8.

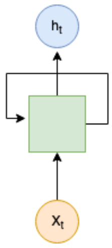


Figure 2.8: Representation of a recursive RNN block.

But this does not always work correctly. There are cases in which having more context information to be able to predict a future state is necessary. In the phrase "the temperature of the water in the Arctic is ..." it can be inferred that the next word must be "cold". But in the phrase "I lived in France. I speak fluent ..." the first part of the sentence is needed to know that the word that follows is "French". One of the appeals of Recurrent Neural Networks (RNN) is that they can connect previous information with previous tasks, but this works when the gap between the previous information and the current situation is small. In situations in which more context information is needed, the RNNs are unable to learn to connect the information. This problem is denoted as the problem of long-term dependency. The LSTMs do not have that problem. They are able to learn long-term dependencies, thanks to the structures shown in Figure 2.9.

“As shown in Figure 2.9, x_t is the input value and the h_t is the output. c_{i-1} is the previous cell state, a candidate to be transformed based on the other gates of the LSTM. The first x gate is the forget gate, which decides which information should be thrown away or kept. Then the + gate adds information that the neural network considered relevant. So, x are gates, elements which optionally let the information through, and are composed of a sigmoid neural net layer σ. $tanh$ is a tangent neural net layer.”

The problem of the Vanish Gradient must also be described. Each of the neural network

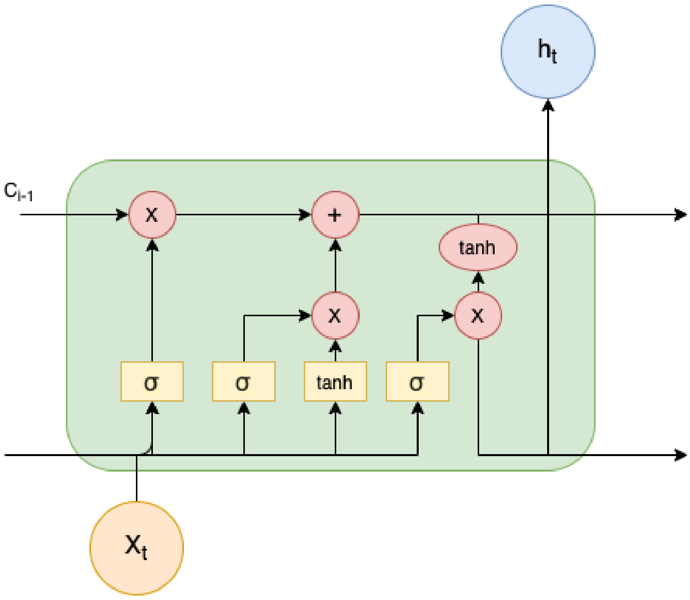


Figure 2.9: Representation of a LSTM block with its components [4].

weights receives an update proportional to the partial derivative of the error function with respect to the current weight in each training iteration. The problem is that, in some cases, the gradient can reach very small values, preventing the weight from changing its value. In the worst case, this may prevent the neural network from continuing its training.

A LSTM element is composed of a cell, an input gate, a forget gate, and an output gate. The cell remembers values over arbitrary time intervals, and the gates regulate the information that is remembered and the information that is not.

LSTMs are widely used in time series prediction problems, because they can retain previous events to predict later ones [4].

So, in this thesis, the LSTMs are utilised to model the future trend of the behaviour of the machine, and thus be able to predict when the anomaly may happen.

2.5.4 Auto-Regressive Moving Average time series models

Auto-Regressive Moving Average (ARMA) models are used to generate time series predictions. These models are basically a combination of Auto-Regressive (AR) and

Moving-Average (MA) models.

- AR (p) is a model that uses the dependent relationship between an observation and some number of lagged observations to make forecasts.
- MA (q) is a model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations to make forecasts.

So, the condition of a time series to be ARMA (p, q) is to be stationary and comply with Equation 2.4:

$$X_t = w_t + \sum_{i=1}^{p} \Phi_i X_{t-i} + \sum_{j=1}^{q} \Theta_j w_{t-j} \tag{2.4}$$

, where $\Phi \neq 0$ and $\sigma_w^2 > 0, w_t \sim wn(0, \sigma_w^2)$.

ϵ_t is white noise, while Φ_i and Θ_i are parameters related to AR and MA models respectively.

The component p is equivalent to the term AR, and q to the MA. In this way, if the component $p = 0$, then we will have an MA model. And instead, if the component $q = 0$, we will have an AR model.

To determine a prediction model correctly, two types of analysis are usually utilised: Auto-Correlation Plot (ACF), and Partial Auto-Correlation Plot (PACF). These statistical measures refers to how the elements of a time series are related to each others. These analyses help determining the value of the AR and MA components [9].

The ARMA time series models are used in order to predict the future behaviour of the machine, to detect when the anomalies may happen.

2.5.5 NullSpace

NullSpace is a method based on the null subspace (NullSpace) concept of the Hankel matrices. A Hankel matrix is a square matrix in which all its diagonals from right to left are parallel numerically. To find the NullSpace, a singular-value decomposition

(SVD) on the Hankel matrix is performed. In linear algebra, the SVD is a factorisation of a matrix, with many useful applications in signal processing and statistics, and it is defined as

$$H_{p,q} = U_H S_H V_H^t \tag{2.5}$$

where U_H is a unitary matrix, S_H is a rectangular diagonal matrix with nonnegative real numbers on the diagonal, and V_H^t (the conjugate transpose of V) is unitary matrix. The diagonal entries $S_{i,i}$ of S are known as the singular values of $H_{p,q}$. The columns of U_H and the columns of V_H are called the left-singular vectors and right-singular vectors of $H_{p,q}$, respectively. In this moment the NullSpace of the Hankel matrix (U_{h0}) has to be found. The NullSpace is a matrix that makes the next property to be true:

$$U_{h0}^t H_{p,q} = 0 \tag{2.6}$$

This null hypothesis is the base of the damage detection method. Basically, the healthy structure data will have similar null hypothesis. So, using a U_{h0} from a learning state of the structure and applying it to a healthy response, the value will be small, while applying it to a damaged response, the value will be higher [84].

NullSpace algorithm was used in damage detection scenarios in which accurate results were obtained [85]. Thus, it was considered in this thesis for a comparative study with ReWAOI.

2.6 Conclusions and Remarks

This thesis focuses on providing means for reliable Predictive Maintenance. This maintenance methodology has been proven to be the one that better optimise time and money costs, treated very closely with CBM. There are several ways to manage the Predictive Maintenance process in any of its phases: Anomaly Detection, Root Cause Analysis, and Remaining Useful Life. But it is still a field that does not have a unique solution and that is in constant evolution.

In the Anomaly Detection field, the importance of distinguishing anomalies from elements defined in this thesis as change points must be mentioned. When detecting a change point, an anomaly can be inferred. For that end, SPC methods such as EWMA are considered, as in the literature have been used to detect small deviations of the behaviour of a process with high accuracy.

In the estimation of RCA, the presence of domain experts of the area is relevant to achieve reliable results. There are studies in the literature in which the application of clustering methods such as Self-Organising Maps obtain precise results. Attribute Oriented Induction combine both domain expert knowledge and data collected from the different information sources, so it is a solid option to represent the outputs.

Moreover, for estimating the RUL, Machine Learning algorithms are considered due to their increasing power in the last years. Time series models such as ARMA, or neural network based predictive models such as LSTMs are selected for that purpose.

Finally, the aforementioned AOI algorithm is remarked due to its power to work with domain experts information to organise the data and obtain a reliable and comprehensive information representation. In chapter 3, the most relevant aspects of this algorithm are described as well as the novel variations added to manage the estimation of the different mentioned Predictive Maintenance requirements.

The importance that different authors give to the fact of having information from domain experts suggests that, perhaps, only with the data extracted from the machine is not enough to carry out a correct maintenance schedule. Obviously, there are solutions that enable generating predictions based on monitoring data, but to define the causality of the events, or to enable having a better visualisation of the context of a process, having experts knowledge is important. The aim of Predictive Maintenance is not to dispense with operators who perform maintenance, but to be a support in the decision making of the maintenance tasks of the experts themselves. In any case, Machine Learning tools are especially useful in these areas.

In relation to the Machine Learning algorithms that the studies suggest in the literature, the ANN should be highlighted. The scenarios in which Predictive Maintenance environments are developed usually have large amounts of historical data to be analysed. For this end, the ANN are especially useful. In this thesis, therefore, its use is also considered, especially to manage the RUL component as stated previously. And on the other hand, the AOI algorithm, which is particularly useful to combine context information and domain experts knowledge, as well as to represent the RCA.

Chapter 3

Attribute Oriented Induction

Attribute Oriented Induction (AOI) is the main algorithm used in this thesis to manage a data-driven Predictive Maintenance methodology. The power of the AOI algorithm to combine domain experts knowledge and data collected from the monitored processes make this algorithm relevant for the scenario of Predictive Maintenance. In addition, as data from industry tend to be unlabelled (correct and anomaly containing data is not distinguished) this unsupervised-based technique may carry out a data-exploration that can help understand better the data. Finally, the descriptive capacity it has converts it in an interesting approach to manage stages such as Root Cause Analysis.

For this aim, the traditional algorithm has been modified with three different functionalities: (i) minimise the number of unclustered elements; (ii) assign a weight to the generated clusters in order to represent the wear of the machine or asset; (iii) adapt for use in processing environments of large amounts of data through an implementation based on Apache Spark.

3.1 Brief description of the algorithm

Attribute Oriented Induction algorithm is considered a hierarchical clustering algorithm, first proposed by Jiawei Han, Yandong Cai, and Nick Cercone in 1992 as a method for knowledge discovery in databases [86; 87]. Specifically, it is considered a rule-based concept hierarchy algorithm. The representation of the knowledge is represented in structures denoted as concept-trees or hierarchy-trees [86]. These structures organise the knowledge in different generalisation levels with IF-THEN rules. The execution of the AOI algorithm follows an iterative process in which each variable, also referred as attribute in this document, characterises the data and has its own hierarchy-tree;

and all data of the given attribute is generalised one level in its hierarchy when certain conditions are met. This step is denoted as *concept-tree ascension* [87].

To ensure the correct functioning of the algorithm, establishing a domain background knowledge in which each attribute is specified different generalisation levels is necessary. If an attribute is numerical, multiple value-ranges that indicate which value of the upper hierarchy can be generalised to can be established for the initial data. Otherwise, if the attribute is discrete, instead of defining a value range, lists of discrete values can be defined in order to decide which value it generalises to, as shown in Figure 3.1.

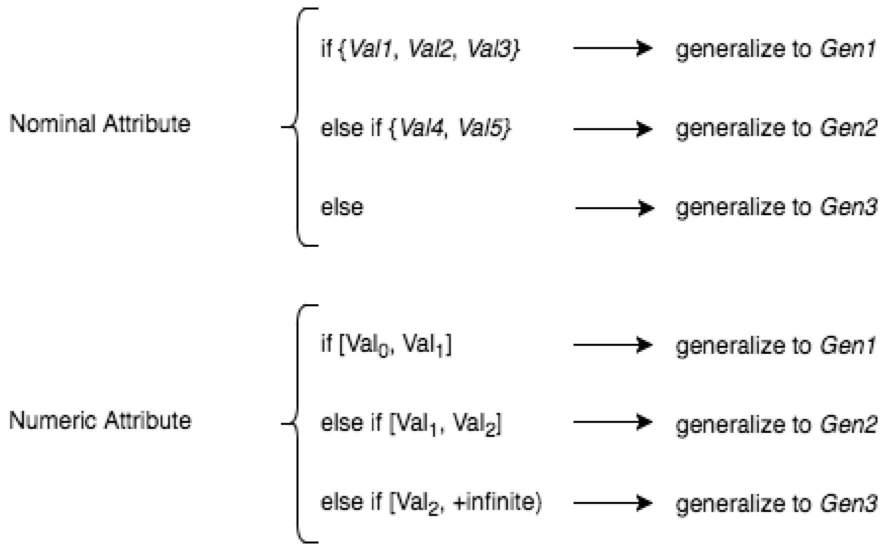


Figure 3.1: Example of the representation of generalisation-rules for nominal or numerical attributes.

An example of a concept-tree is shown in Figure 3.2. The background-knowledge should ideally be defined by domain experts of the area. The knowledge generated should be useful for the comprehension of the health-state of the machine, to help make decisions to facilitate the correct and efficient maintenance of the asset. For this reason the background-knowledge must be defined by domain-experts. The results extracted by the processing of the algorithm AOI will be in accordance with the definition of the background-knowledge.

Some relevant terms are explained next to provide a better understanding of how the AOI algorithm works.

- Concept-Tree: it is a structure containing the relationships between the raw data

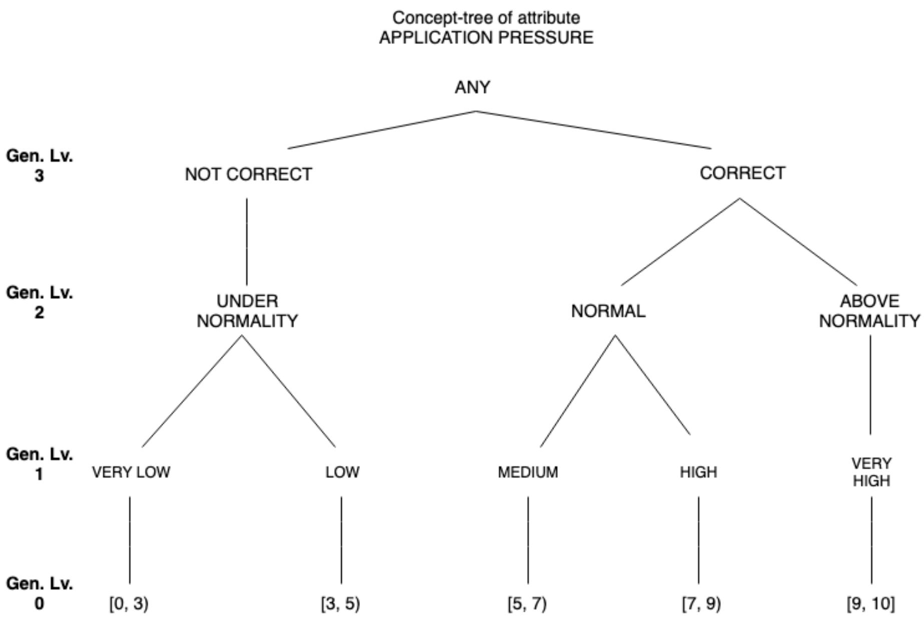


Figure 3.2: Example of a concept-tree or concept-hierarchy of a Predictive Maintenance attribute: Application Pressure.

and the knowledge provided by experts in a top-down hierarchy structure.

- Generalisation: it is the process of transforming the data into another which is more general or abstract.
- Generalisation value: it is the value representing to the concept after the generalisation is applied to the data.
- Generalisation level: it represents the set of generalisation values of the current level of the concept-tree.
- Generalised relationship: it is the combination of generalisation values of the attributes of a concrete instance.
- Instance: it is each of the data elements of the dataset.

3.2 Related work

AOI was applied in many scenarios, such as spatial patterns, medical science, intrusion detection, strategy making, and financial prediction [60; 88; 89]. In addition there are multiple variations and improvements of the original AOI algorithm which have been published in the literature over the years.

In 1995, Hoi-Yee Hwang and Wai-Chee Fu propose a change to improve the efficiency of the original algorithm defined by Han, Cai and Cercone [90]. They affirm that the computation cost of the algorithm becomes from $O(nlogn)$ to $O(n)$ complexity by defining a path id and eliminating backtracking. The generalisation-status of the attributes in a current moment of the AOI process is represented by a vector of type x_a, y_b, z_c, ..., w_d where x, y, z, ..., w are the attributes and a, b, c, ..., d are the levels of the generalisation of each attribute.

In 2000, Cheung, D. W. et. al. focused on the development of a rule-based concept hierarchy to support a more general concept generalisation. In the traditional AOI algorithm, a generalisation of an attribute depends only on the value of the element to be generalised and the generalisation conditions defined in the background knowledge [87]. Author explains that there are cases in which a generalisation may rely on the combination of more than one attribute, so he proposes a variation to cover those cases. In addition, the expected complexity of the execution of the algorithm is $O(n)$. Later in 2010, Nguyen Duc Thanh et. al. suggested an improvement over the same proposal of rule-based Attribute Oriented Induction using Generalisation Dependency Graph (GDG) [91]. In 2016, a more precise explanation of AOI characteristic-rule algorithm was exposed with a step-by-step execution example [92].

Other improvements not only focused on the computational complexity were also proposed. Chung-Chian Hsu et. al. suggested in 2004 the use of what they denoted as *major values*, and process continuous numerical-attribute data in order to help constructing concept hierarchies more objectively [93]. A major value makes reference to the value that encompasses most of the subset of values in a current generalisation.

For example, as shown in Figure 3.3, let's suppose there is a set of circular figures of different colours, and almost the totality of them are blue, except for a few ones which are red and green. If all circular figures including both blue, red and green are generalised to

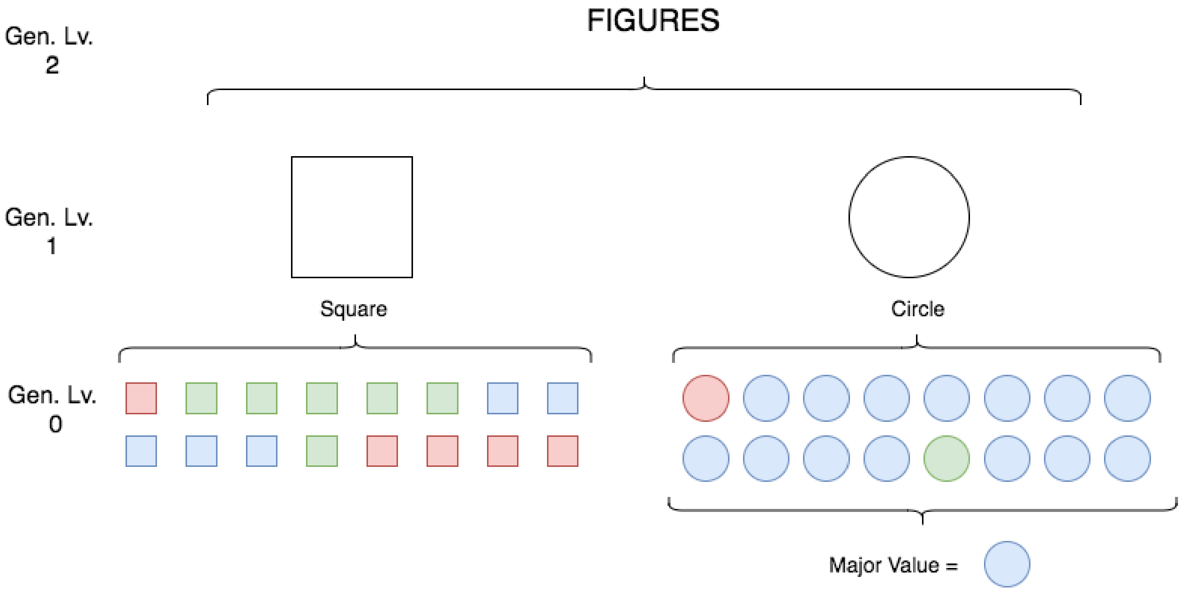


Figure 3.3: Example of major values generalisation.

the concept "circular figures" there is a perspective-information loss of the blue figure proportion respect to the others. To help dealing with that issue, authors suggest defining a threshold in order to determine when a value can be considered as a major value, and then, show it in the results. In addition, authors consider the management of numerical values also important. They observed a problem when defining different continuous subsets of values in order to help with their discretisation-criteria (e.g. [0, 10] generalise to 'LOW'; (10, 20] generalise to 'MEDIUM'; etc.). They argue that the nature of that specification is too subjective when considering the limit-values of the subsets, and the final results may be affected. It is clear that the representation of the generalisation-rules is subjective in most of the cases, but authors in this study suggest an improvement at the time of defining the limit-values of the subsets, by calculating the average and the deviation of the values in order to avoid any subjectivity excess. Conclusions extracted from this paper can help to achieve more objective results with the application of AOI, and also to make the conclusions of the results more consistent with the consideration of the major values.

In 2010, two main approaches appear by the hand of Spits Warnars, both oriented to manage AOI with SQL statements. On the one hand, he proposed a novel Attribute Oriented Induction algorithm with Star Schema [94]. It detects a problem in conventional AOI algorithm in the sense that it only provides a snapshot of the generalised knowledge, and not a global vision. Hence, he tried to solve it using some "group by" operators in SQL select statement. On the other hand, he affirmed that AOI algorithm works quicker, easier, and faster by using a simple SQL statement, due to the possibility of combining some of the traditional AOI processing steps that it brings [95].

Many other examples of different AOI applications can be found in the literature. A study performed by Huang et. al. [96] defined a modified AOI algorithm by implementing the concept climbing and generalisation process with Boolean Algebra and modified Karnaugh Map. The modified AOI algorithm was applied to generate clusters regarding to the readers of a library with similar characteristics, and also the connection between the readers and the book collections. Another study, developed by Tanutama [97], shows the development of a simple method of mapping the business activity, reflected by network data. The conclusion was that the method could provide the management and a general overview of the usage of its infrastructure, and lead to an efficient, effective and secure ICT infrastructure.

As observed in the literature, in most cases in which the AOI algorithm has been used, the processed data type has been numerical, as it occurs with the most significant clustering algorithms. In a study of Devaraj and Punithavalli, [98] it is proposed a novel approach to manage mixed data types on clustering, by the use of AOI. Another suggestion on the traditional AOI algorithm was published by Chen et. al. [99]. The resulting generalised-relation obtained after the processing of AOI is different depending on the initially specified thresholds. It only let the system to describe a specific view of the generalised-knowledge, not a general view of the knowledge. This paper proposes a global AOI (GAOI) approach, which generates multiple-level and cross-level generalised knowledge at one time.

As in the study of Wu et. al. [88] is explained, many existing AOI approaches are only focused on mining positive generalised knowledge from databases. Positive generalised knowledge is referred in this study as a previously known and defined knowledge. Author defends that the knowledge not previously specified, the non-expected one, referred as negative generalised knowledge, is the most meaningful and relevant for the induction process. Therefore, a novel approach of AOI called Global Negative AOI (GNAOI) is proposed, which can generate comprehensive and multiple-level negative generalised knowledge at the same time. This helps to induce more comprehensive negative generalised knowledge from relational databases.

Another variation of the AOI algorithm is proposed by Muyeba et. al. [100], which defines a hybrid interestingness heuristic algorithm, called clusterAOI. As authors say, this generates a more interesting generalised final table than the one offered by the traditional algorithm. Authors suggest attribute features such as concept hierarchies and distinct domain attribute values to dynamically recalculate new attribute thresholds for each of the less significant attributes to avoid overgeneralisation. The study affirms that the dynamic threshold adjustment, aggregation and evaluation of interestingness within each generalisation iteration ultimately generates a higher quality final table than what the traditional AOI does.

In 2012, Spits Warnars published an article in which he criticised AOI algorithm for not being able to discover new emerging patterns from data, but only to produce high-level characteristic summary. Thus, he proposed an approach combining both AOI and High-Level Emerging Patterns (HEP) in an algorithm named HEP-AOI. [101] He used the potential of HEP to discriminate between two datasets by comparing growth rates, after AOI algorithm have defined knowledge-rules when it was processed. Mostly this approach was oriented to find patterns between generated knowledge-rules of two datasets, not improving the efficiency of the AOI algorithm. Later on, in 2014, Warnars published a paper extending the approach for the combination of AOI and HEP, and showing with some experiments that it is feasible to find frequent patterns between the logic rules generated by the AOI algorithm [102]. In 2015, Warnars explained the capacity of AOI in mining patterns, emphasising its advantages when working with unlabelled data and generating knowledge [103].

As commented previously, AOI is a descriptive Data Mining method which creates clusters generalising data based on a predefined criteria. This could bring a problem, which is known as Overgeneralisation. In 2013, a proposal to solve that issue was suggested using entropy to enhance the generalisation process, feature selection, and stop condition [104] (Al-Mamory et. al.). Applying this method, feature selection for generalisation process depends on feature entropy measurement; algorithm runtime is less than the traditional; and it only needs one threshold number instead of the two needed by the traditional.

As a conclusion of the literature review of AOI, it is remarked that this algorithm has not been used before in a maintenance scenario in the industrial sector. This fact provides a novel context in which apply the proposal.

In addition, there are variations of the AOI algorithm proposed in the literature. Many of them are related to optimise the computational complexity of the traditional algorithm. The elimination of backtracking by representing the generalisation levels using vectors has been considered for this thesis. The aim of this research is not optimising the traditional AOI algorithm, but providing a valid approach to manage Predictive Maintenance in industrial sector.

In this way, the traditional AOI algorithm was selected for implementation due to its power on data representation and description. Moreover, its capacity of generation of clusters based on the similarity of the data using also domain experts knowledge makes this algorithm coherent with the suggestions found in the literature for the different stages of Predictive Maintenance. The clusters that the algorithm is able to generate are related to the different work states that the execution of a machine can have, and it can provide an exploratory analysis at the time of inspecting unlabelled data.

Moreover, the usage of major values to build representative clusters has also been taken into account. As mentioned in section 3.4 Repetitive Weighted Attribute Oriented Induction, later in this chapter, one of the variations proposed in this thesis is the construction of a univariate quantification function based on the generated clusters. This is obtained considering the values that form each cluster, so the groups with higher number of values are more representative.

Negative generalised knowledge can also be mentioned from the inspected literature. The goal of each clustering method is to explore the data and extract new knowledge. In this thesis, new knowledge about the wear of a monitored machine or asset can be extracted from the data by the generation of the quantification function.

The proposed solution aims to be useful to manage a data-driven Predictive Maintenance methodology, and to estimate accurately the AD, RCA and RUL stages.

3.3 Working pipeline of the traditional AOI algorithm

Data selection and preprocessing is one of the most important steps to obtain benefits from AOI. The power of AOI resides on defining thresholds and generalisation hierarchies for the features of the data. This is why the application of the AOI must be managed in close collaboration with domain experts. The goal is to establish the most precise generalisation criteria, and thus obtain the most reliable representation of the data after the generalisation is performed.

There are some parameters that must be set before starting the cluster generation process:

- **Minimum Cluster Size**: The minimum number of tuples (instances) needed to form a cluster.
- **Attribute Generalisation Threshold**: The maximum number of instances allowed in a generalisation level. If the number of different values of an attribute generalisation level is greater than the specified threshold, a generalisation must be applied on that attribute.
- **Tuple Generalisation Threshold**: The maximum number of distinct tuples allowed in a generalised relationship. If the number of different tuples in a generalised relationship is higher than the threshold, a generalisation must be applied in one of the attributes. There could be different criteria to select the attribute to be generalised.
- **Generalisation Hierarchies and Rules (for each attribute)**: Definition of different generalisation levels for each attribute with their respective elements; and the conditions to determine which value of the next generalisation level can an element be generalised to.
- **Attribute Generalisation Weights**: Each attribute must have specified a weight according to its relevance on the clustering process. Those weights must be specified by the domain experts in order to guarantee the coherence of the weighting proposal. This step is important to ensure the correct working of the AOI clustering process. In case two attributes have the same possibilities to be generalised to the next level, the attribute with the highest weight is the one selected.

Once the preprocessing parameters are set, there are several steps or strategies that must be followed to work with the traditional AOI algorithm, which are listed below:

1. **Generalisation of the smallest decomposable attributes**: The most het-

erogeneous attribute (with the highest number of different values) is the one that must be generalised to reduce the diversity of the dataset and help minimise the complexity, in accordance with the Least Commitment Principle [105].

2. **Attribute removal**: If there is an attribute with more distinct values than the Generalisation Threshold, and there is not a higher generalisation level for it, the attribute must be removed.

3. **Concept tree ascension**: If a higher level generalisation exists in the generalisation hierarchy for an attribute, all the values of the current generalisation level of that attribute must be replaced by the next level values.

4. **Vote propagation**: When an attribute is generalised, some tuples (instances) become identical. Each tuple, at the beginning of the AOI process, contains a vote value equal to 1. This vote value refers to the number of equal tuples that are present in the dataset. When an attribute is generalised and some tuples become identical, the votes from the tuples on the previous generalised relationship must be added to the new generalisation.

5. **Threshold control for each attribute**: If there is an attribute with more distinct values than the Attribute Generalisation Threshold, then the attribute must be generalised to the next level of the hierarchy.

6. **Threshold control for generalised relationships**: If there is a generalised relationship with a higher number of different tuples than the Tuple Generalisation Threshold, further generalisation of an attribute must be performed. In this approach, the attribute that will be selected to be generalised is that with the highest number of different values. In case of more than one attribute with the same number of different values exist, the one with the highest weight will be chosen.

The pseudo-algorithm of the AOI is shown in the Algorithm 1.

The AOI algorithm overcomes two major obstacles. On one hand, it characterises the origin of an anomaly or error. This is the foundation of Root Cause Analysis, since it extracts knowledge and gives meaning to raw data. On the other hand, AOI is able to summarise vast amounts of data into a small number of groups.

Algorithm 1 Pseudo-code of AOI algorithm

procedure PROCEEDAOI
  possible_to_generalise ← True
  non_clusterized_instances_exist ← True
  outlier_count ← dataset.size()
  while (possible_generalise & non_clusterized_exist) **do**
    curr_dtset ← clusterize(curr_dtset, outliers) ▷ Generates clusters + cluster-order and -appearance Knowledge-base
    generalisable_attributes ← getGeneralisableAttributes(current_dataset)
    if *len*(generalisable_attr) = 0 **then**
      possible_generalise ← *False*
    if *outlier_count* = 0 **then**
      possible_generalise ← *False*
    else
      curr_dtset ← *genAttr*(*curr_dtset*, *generalis_attr*) −

The AOI algorithm follows a cyclic methodology. It first generalises the most changing attribute (the attribute with the highest number of different values). Next, it generalises the second most changing attribute. It continues the generalisation process until it meets a stopping criteria, like the absence of sufficient similar elements to form a cluster. Finally, it provides a collection of data groups or clusters. Moreover, every step, the data processing workload is reduced.

Although AOI algorithm was used in different contexts or applications, none of them were real-time processes, nor their purpose was the evaluation of AD, RCA or RUL. Thus, one of the objectives of this thesis is to validate its usage to reduce the required computation load and extract knowledge from raw data.

Table 3.1 shows a visual representation of the generalisation process. It first selects the variable with the higher number of distinct values (39 in the example) to then generalise following the criteria established by the background knowledge (e.g. [0, 3]: X, (3, 100]: Y). Table 3.2 shows the resulting state after the generalisation-step was performed.

The process continues iteratively, forming clusters until no more generalisation can be applied or there are not more elements in the dataset. Table 3.3 shows the next step of the iteration, after having generalised the Var N attribute with the next generalisation criteria: [0,25): LOW, [25, 35): MEDIUM, [35, 50): HIGH.

After this execution, one cluster is generated ([1, Y, C, HIGH]). The tuples forming groups are saved in the knowledge-base as representative clusters, and they are not considered for future concept-tree ascension steps at the time of checking the data to form clusters. The process continues until meeting the stopping criteria mentioned before.

Table 3.1: Results before Generalisation step

	Var 1	Var 2	...	Var N
Tuple 1	0	0.50	A	21
Tuple 2	1	0.90	A	24
Tuple 3	1	1.80	A	30
Tuple 4	1	2.40	B	38
Tuple 5	1	4.20	C	42
Tuple 6	1	4.80	C	43
Tuple 39	1	3.21	F	39
# Dist. Val.	2	**39**	6	30

Table 3.2: Results after Generalisation step

	Var 1	Var 2	...	Var N
Tuple 1	0	X	A	21
Tuple 2	1	X	A	24
Tuple 3	1	X	A	30
Tuple 4	1	X	B	38
Tuple 5	1	Y	C	42
Tuple 6	1	Y	C	43
Tuple 39	1	Y	F	39
# Dist. Val.	2	2	6	30

Table 3.3: Results after second Generalisation step

	Var 1	Var 2	...	Var N
Tuple 1	0	X	A	LOW
Tuple 2	1	X	A	LOW
Tuple 3	1	X	A	MEDIUM
Tuple 4	1	X	B	HIGH
Tuple 5	1	Y	C	HIGH
Tuple 6	1	Y	C	HIGH
Tuple 39	1	Y	F	HIGH
# Dist. Val.	2	2	6	3

3.4 Repetitive Weighted Attribute Oriented Induction

In this thesis, some variants have been added to the previously explained traditional AOI algorithm.

First, a loop in the execution of the algorithm is included. One of the parameters that must be specified prior to the execution of AOI is the minimum number of instances that will generate a cluster. Depending on which value is specified, there may be instances that do not belong to any cluster at the end of the clustering execution.

To carry out the proposal for managing the different Predictive Maintenance stages [6], the maximum number of elements must be clustered. The goal with this approach is to have a consistent Knowledge Base in which each element of the dataset refers to a cluster. Thus, defining an iterative execution process, the unclustered elements of the previous iteration may be clustered in the current one, minimising the number of total unclustered instances.

As an example of this variant, let's suppose it is set a value for the minimum cluster size of ten. The algorithm runs with that value and at the end there are X elements that are not clustered. In that case, the AOI algorithm would again be executed with a minimum cluster size value of nine with the rest of elements (or X in the case of $X < 9$). The process continues until the value is two. In this way, the number of unclustered elements is minimised.

Those elements that at the end of the process are not clustered (the minimum cluster size value is equal to 1), would not be considered as significant states of the behaviour of the machine, due to their non repetitive characteristic, and the calculations would only be performed considering the generated clusters.

The second variant that has been included is the addition of a weight to each cluster. This is a decision that has been taken in order to perform the calculation of AD and RUL. As previously mentioned, each cluster is composed by a number of instances. In addition, each of the clusters belongs to a specific generalised relationship. In this sense, a cluster that belongs to a generalised relationship in which the levels of generalisation are low refers to more representative states than those with greater generalisation levels.

For example, suppose there is a cluster in which none of the attributes has been generalised. In this case, the similarities at the time of generating the cluster have been made on raw data. Therefore, it is considered that this cluster refers to a usual and concrete state of the behaviour of the machine. While if there is a cluster that has some attributes that have been generalised to a higher level, the representation of the state is no longer as accurate, it is more abstract. In addition, not only the generalisation level of attributes establishes the weight of a cluster, but also the number of elements in the group. The more instances are in the cluster, the higher is the weight. The process of assigning a weight to clusters is explained in chapter 4. Methodology.

The repetitive behaviour of the execution, and the weighing of the generated clusters, provide the capacity of generating a quantification function value that helps analysing the wear of a monitored machine or asset. The modified AOI algorithm is called: Repetitive Weighted Attribute Oriented Induction (ReWAOI).

Finally, the implementation of the algorithm has been based on the Apache Spark execution framework. Apache Spark is a unified analytics engine for large-scale data processing[5]. The reason for carrying out the implementation in this way and with the tools provided by Spark, is that the algorithm can be extended to case studies in which large amounts of data must be processed quickly. In Predictive Maintenance scenarios, large amounts of data may need to be managed, so ReWAOI provides a solution to these types of environments.

Regarding the differences between the traditional and the proposed algorithm, and the contributions that the ReWAOI provides for accomplishing the stages of Predictive Maintenance, a comparison between the two algorithms is explained next.

The traditional AOI algorithm has the capacity of combining both domain knowledge and data collected from a monitored process, but it only works with a static value of the minimum cluster size parameter. The ReWAOI iterates the execution varying the minimum cluster size to obtain as many clusters as possible and for generating a knowledge-base that can better represent the different work-states of the monitored process.

Moreover, the ReWAOI assigns a weight to each cluster, providing the capacity to define a quantification function that is used for modelling the degradation of a machine

[5]Apache Spark information source: https://spark.apache.org

or machine-component. The lack of weights associated to each cluster in the traditional algorithm makes the AOI not able to monitor the wear of an asset; it only serves for partially identifying the states of the behaviour of a monitored process.

Finally, based on the implementation of the ReWAOI with the Apache Spark execution framework, scenarios in which big amounts of data can be better and faster processed, considering it a possible need in industrial scenarios.

Therefore, the traditional AOI algorithm has been extended with three different functionalities: (i) minimise the number of unclustered elements; (ii) assign a weight to the generated clusters in order to represent the wear of the machine or asset; and (iii) adapt for use in processing environments of large amounts of data through an implementation based on Apache Spark.

3.5 Conclusions and Remarks

The ReWAOI algorithm has been defined in this thesis to manage a data-driven Predictive Maintenance methodology for several reasons.

First, the traditional AOI algorithm has not been used previously in a maintenance scenario in industry, as checked in the literature review. This provides a novel characteristic to the usage of the algorithm in such context.

As previously mentioned in chapter 2. Theoretical Background, the presence of domain experts in maintenance is important. The power of AOI algorithm resides on combining both domain knowledge and information extracted from a monitored asset. Therefore, the obtained results can be more representative for experts, who are the ones that analyse the outputs to perform maintenance actions.

The addition of a repetitive behaviour in the execution of the algorithm, and the weighing of clusters provide the algorithm the capacity of extracting knowledge about the wear of a monitored machine or asset.

In addition, the ReWAOI has the capacity to represent the information that can be useful when estimating the Root Cause Analysis, as it historically has been used as a representation of information in databases.

Finally, the implementation of the algorithm based on the Apache Spark framework can help managing scenarios in which large amounts of data are required to be analysed.

Chapter 4

Methodology

The methodology proposed in this thesis aims to meet the stages of Predictive Maintenance, bringing forward the ReWAOI data mining algorithm as its key component. As previously mentioned, this is a novel approach, since the algorithm has not been used before for this purpose.

For this end, it is necessary to fulfil the stages specified in this thesis for this maintenance methodology: Anomaly Detection, Root Cause Analysis, and Remaining Useful Life. In turn, we have defined, previous to Anomaly Detection, an initial phase in this thesis called Change Detection, which is the flag that indicates if an anomaly may happen in the future.

The data analysis process is divided into two different phases: (i) the Training Phase, and (ii) the Testing Phase. The Training Phase is responsible of generating the necessary models to carry out the tasks required by Predictive Maintenance. However, the Testing Phase applies these models to obtain the results.

The proposal of the methodology is described in more detail below, beginning with the Training Phase, and continuing with the Testing Phase. This methodology is applied in scenarios in which the data refer to a set of simulations or operating processes of the machine or asset, in order to learn from them and generate knowledge. The terminology used in this thesis for these operating processes is called *simulation* or *work execution*.

4.1 System model

This section describes the different requirements for applying the methodology in terms of data model and its application. The purpose is to provide an abstraction level able to explain how the methodology can be applied and in which scenarios is suitable. This is an extension of Section 1.6: Assumptions and Limitations, and it focuses on defining the characteristics of the data and the possible application scenarios of the thesis.

A general overview is provided in this section, and for the different subsections of the explanation of the methodology, the data model requirements are explained in more detail.

4.1.1 Data model

To apply this methodology data must be organised in different blocks representing the behaviour of single executions of the monitored machine. Let's imagine we are monitoring a clutch-brake machine. A single clutch or a single brake operation of the machine refers to a single work execution. In this way, collected data is divided according to it, and the analyses are performed considering these structures. In this thesis, the terms used to refer to these data blocks are: *simulation* or *work execution*. Each simulation is formed by a set of N time units, and each time unit has a representative value for the different attributes or features that characterise the dataset.

Attributes of the dataset with no variation in their values are not considered. The ReWAOI algorithm is based on defining hierarchy-trees that organise the data in different generalisation values and levels. In cases where there is no variation of data values for an attribute, generalisation values are redundant, and hierarchy-trees cannot be constructed.

Regarding the characteristics of the data, correct behavioural and anomaly containing data is needed to apply the defined methodology. With correct behavioural data the limits of correctness of the behaviour for a machine process are defined. This is relevant at the time of constructing a system able to detect deviations from the normal behaviour. Moreover, anomaly containing data is also important to build a model able to precisely predict the moment of an anomaly in a monitored work execution.

- We have a set of K simulations with N timestamps and M attributes.
- This set of siumlations would be expressed as: $S \in \mathbf{M}_{NxMxK}(\mathbb{R})$

4.1.2 Application model

Data coming from industrial sector tend to be unlabelled, so it is uncommon for data to be categorised as correct or anomaly containing from the beginning. Thus, domain experts are relevant in this process. In every case study in which the methodology is being applied, the data must be understood and work executions containing anomalies must be differentiated from those that do not. However, there can be scenarios where domain experts are not present or even if they are, they have no expertise on certain features of the data.

In this way, domain experts knowledge should ideally be used to define two aspects that are relevant for applying the methodology: (i) the construction of hierarchy-trees for the attributes of the dataset, and (ii) help understanding the data and distinguishing correct from anomaly containing simulations.

Hence, there are two different scenarios to consider in this thesis: (i) case studies where domain experts are present, and (ii) case studies where there is lack of domain experts. For the first case, the hierarchy-trees of the attributes should ideally be defined by the experts of the area. However, for the context in which no domain experts are present, an alternative approach to define the hierarchy-trees is defined. In both approaches, data needs to be numerical, as explained in section 1.6: Assumptions and Limitations. This alternative proposal for constructing the concept-trees is explained in more detail in Section 4.1.1 ReWAOI Training and Auxiliary Parameter Calculation.

4.2 Training Phase

The Training Phase is the responsible of generating the necessary models to carry out the stages of Predictive Maintenance. Hence, this phase is divided into two blocks: (i) ReWAOI Training and Auxiliary Parameter Calculation, and (ii) Predictive Models Construction.

4.2.1 ReWAOI Training and Auxiliary Parameter Calculation

Data model

For generating the clusters two different scenarios are considered: (i) domain experts distinguish correct behavioural data from degradation or failure containing data; and (ii) data cannot be divided into correct and anomaly containing data. In the first scenario, only correct behavioural data is selected for the generation of clusters of ReWAOI. These clusters refer to working states of correct behaviour of the machine. For the second case, as no distinction between correct and degradation data is present, the ReWAOI is fed with both correct and anomaly containing data.

Application model

In the training phase, data must initially be preprocessed and cleaned for the application of the ReWAOI algorithm. Each dataset (each case study) has its own criteria for preprocessing the data according to the limitations it has. After the preprocessing is performed, the parameterisation of the ReWAOI is carried out and the clusters are generated.

In addition, a subset of correct behavioural data must be selected for the calculation of the EWMA control limits, and another subset containing anomaly containing data must be used for the selection of the WER that best fits with the real moment of the anomaly.

Description of the pipeline

The objective of this first block is to generate the necessary auxiliary models to manage the tasks of Change Detection, Anomaly Detection, Root Cause Analysis and Remaining Useful Life.

The flowchart is shown in Figure 4.1.

One of the most important steps in any Data Analysis scenario is to inspect the data. On one hand, the validity of the data must be ensured, since the results greatly depend

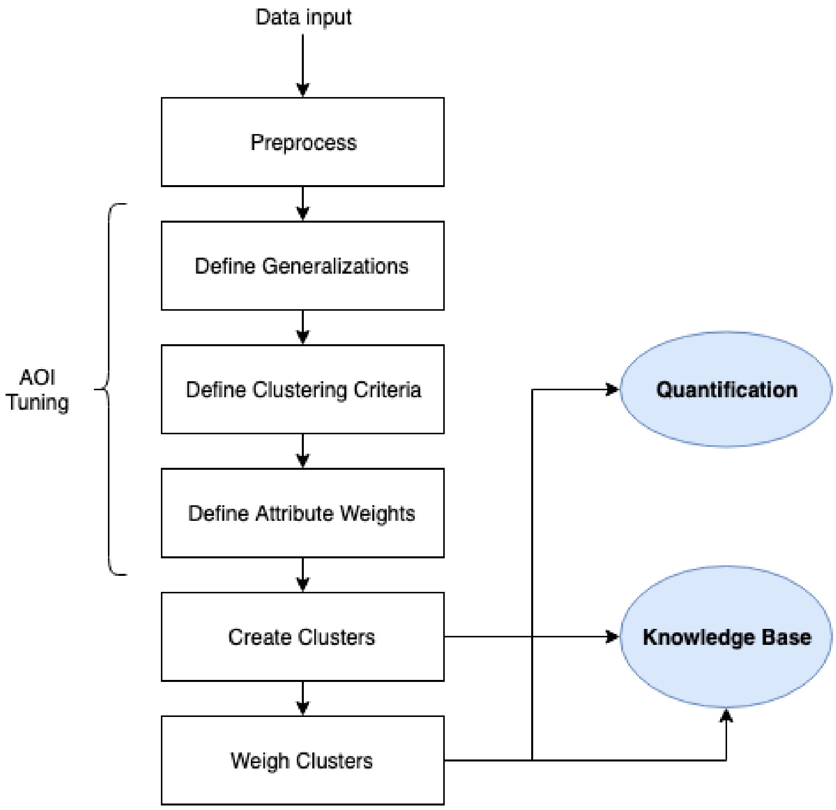


Figure 4.1: First block of the training methodology.

on that. On the other hand, this data must be understood, to be able to apply the most appropriate transformations according to its characteristics.

Next, the tuning process of the ReWAOI algorithm begins. With the help of the domain experts knowledge, generalisations for the attributes should ideally be established and the hierarchy-trees constructed. In the case that there are no domain experts who provide knowledge, or the context information of the dataset is limited, the processing by means of the ReWAOI algorithm does not have the same value.

Thus, having a lack of expert knowledge to construct the hierarchy-trees and establish weights for the attributes is possible. In that case, an alternative approach must be found, in order to obtain reliable results. Only for the case in which the values of the attributes of the dataset are numerical, an alternative is defined.

This option enables to apply the same methodology. When defining the attributes generalisations, raw values can be divided into blocks of percentiles. In this way, the values belonging to the blocks defined by the percentiles form the next level of generalisation. It is a manner of representing generalisation hierarchies through a statistical base. The only factor that is arbitrary is the choice of the number of blocks to be formed, as well as the number of generalisation levels.

The same happens with the definition of the weights for the attributes. Without domain experts that indicate the relevance of the attributes that characterise the data, the criterion for establishing the weights is arbitrary.

In this thesis datasets with no domain experts knowledge have been used, and the results using the alternative system were accurate. This is shown in more detail in chapter 6. Results.

Once the ReWAOI algorithm is tuned, the process of generating the clusters begins, assigning each one a weight according to the characteristics they have. The final set of generated clusters is denoted as Knowledge Base.

To calculate the weight of the clusters, it is first necessary to compute the weight of the Generalised Relationship. Depending on the level of generalisation of attributes in a Generalised Relationship, the weight varies. The more attributes that are generalised and the higher their level of generalisation, the lower the weight will be.

With the help of these weights the quantification function for a concrete simulation or work execution is estimated. For each element or tuple of a simulation, the knowledge-base that contains the set of generated clusters is checked. Then, the most representative cluster in relation to the attribute values and their possible generalisations of the inspecting tuple is selected, and its respective weight is assigned for the tuple. Hence, the tuple obtains a numerical value. Performing this action for all the elements of the simulation, a numerical function called quantification is obtained.

The quantification function indicates the degree of reliability which a state can be considered to be frequent in behaviour. In other words, the more repetitive is a concrete state in the behaviour of the set of inspecting simulations, the more representative will be the concept and the higher will be the weight. If the generalisation level is high, it indicates that the description of the state is more abstract, and therefore, the value of the cluster is lower. Let's take Figure 3.2 as an example. It shows a hierarchy-tree referring to an attribute named "Application Pressure". Suppose we have a cluster formed with a value for Application Pressure of 3.0, and another cluster formed with a value of "Very Low". The first mentioned cluster is more specific, so the descriptive potential and the representativeness is higher. Thus, the value of the cluster is higher regarding to that attribute.

The partial weight of a cluster for a specific Generalised Relationship is set out in Equation 4.1.

$$GeneralisedRelationWeight(i) = \frac{\sum_{j=0}^{numattributes} \frac{1}{2^{genlevel(j)}}}{numattributes} \tag{4.1}$$

The *numattributes* variable refers to the number of attributes of the dataset, and $genlevel(j)$ indicates the generalisation level of attribute j. As explained in Figure 3.2, each attribute has its own hierarchy-tree, with distinct levels in which the values of the attribute are represented. The hierarchy-trees should be ideally constructed by the domain experts of the area, and the criteria to establish the different generalisation levels and generalisation values is up to them. In this sense, it is possible for an attribute's hierarchy-tree to have more generalisation levels than the hierarchy-tree of another attribute. In this thesis, the proposal only checks how many times the generalisations are applied on the data. The more generalisations are applied, more ambiguous is the term because more transformations have suffered.

Table 4.1 shows an example of the values of the clusters after executing the ReWAOI and assigning them the weight of the Generalised Relationship. The first and the second columns refer to the id of the cluster and the weight of the Generalised Relationship which the cluster belongs to. The third column indicates the number of instances that belong to a given cluster. This variable is important when assigning the final weight to the clusters. The more instances that form a group, the greater the weight in the quantification function. The fourth column indicates the number of elements existing before the cluster is formed. The last variable indicates the difference in weight that exists between the current Generalised Relationship and the previous one.

In Table 4.1 the partial weight of the clusters is shown considering only the Generalised Relationship which they belong to. Equation 4.2 shows the method to calculate the final weight of the clusters. On one hand, the weight of the Generalised Relationship is computed, as shown in Equation 4.1, and on the other, calculating the value between

Table 4.1: Variables of interest to compute the cluster weights.

Cluster	Gen. Rel. Weight	Elements	Population	Difference
Cluster 1	0.8	100	500	0.2
Cluster 2	0.7	20	400	0.1
Cluster 3	0.55	10	380	0.15
...	...	...	...	...
Cluster N	0.1	40	40	0.05

that weight and the weight of the previous Generalised Relationship that will be assigned is necessary. Hence, if the value of a Generalised Relationship is 0.5, and the value of the preceding Generalised Relationship is 0.6, the clusters of that Generalised Relationship will have a value between 0.5 and 0.6 depending on how many elements it is composed of.

$$Clusterweight(x, i) = GenRelationWeight(i) + \frac{instances(x))}{outliers(i)} \cdot diffweight(i) \quad (4.2)$$

Each Generalised Relationship can contain multiple clusters. Therefore, in this equation, the weight for the x-th cluster on the i-th Generalised Relationship is represented. $GenRelationWeight(i)$ refers to the weight of the i-th Generalised Relationship. $instances(x)$ indicates the instances that comprise the x-th cluster; $outliers(i)$ makes reference to the number of outliers of the Generalised Relationship i; and $diffweight(i)$ is the difference of the weight between the i-th Generalised Relationship and the previous one.

Finally, the set of clusters and their respective weights create the Knowledge Base.

There are two cases in which this methodology can be applied: (i) the data is not initially labelled as correct and incorrect, and (ii) correct and incorrect simulations are distinguished. In the first case, the ReWAOI generates clusters referring to correct and incorrect states. Then, the quantification function must be analysed to inspect the moment in which the failure may be occurring. In the second case, the ReWAOI only generates clusters with the correct behavioural data. In this way, only clusters referring to correct considered states are obtained.

After establishing the weights for the clusters, the quantification function can be calculated for each simulation. The quantification process consists of defining a numerical function that is correlated with the level of machine wear. To do this, the generalisation possibilities for each element of each simulation must first be analysed. Once the possible generalisations are detected, a check is made to determine if there is a cluster that corresponds to that generalisation, and if it exists, the corresponding cluster weight is assigned. This process is explained further in section 4.2 Testing Phase.

Once the quantification criteria and the Knowledge Base are defined, two more outputs must be generated to manage the Change Detection and Anomaly Detection tasks: (i) EWMA control limits, and (ii) the Western Electric Rule which best fits. These outputs are shown in Figure 4.2.

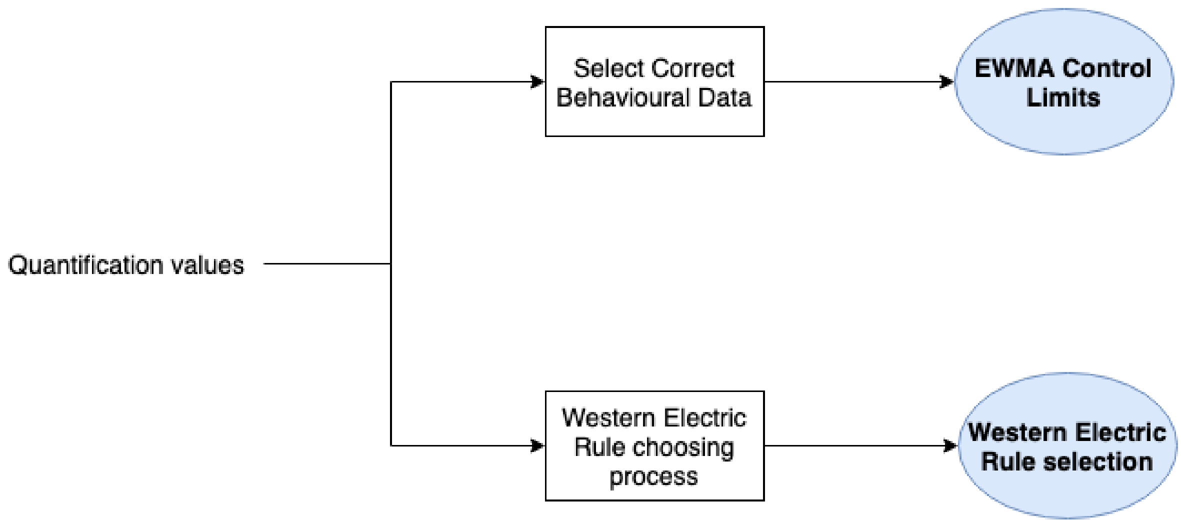


Figure 4.2: Part II of the Training Phase of the Predictive Maintenance workflow with the ReWAOI algorithm.

Calculation of EWMA control limits

As mentioned in chapter 2. Theoretical Background, detecting an anomaly or a change point is not the same. The goal, therefore, is to first detect when a state goes beyond what is established as normal. In this way, we can know if the process is close to detect a failure or anomaly.

To carry out the Change Detection, Statistical Process Control (SPC) charts are utilised. These charts are useful when there is an interest in detecting certain variability in a specific process. In this case, the so-called EWMA (Exponentially Weighted Moving Average) control chart was selected, which is used when small process shifts are of interest [7].

To calculate the control limits of the EWMA control chart, selecting data that refers to the correct operation of the machine is necessary. In this way, an area in which the EWMA chart is able to detect whether a state goes out of normality is defined.

The control limits are established based on the historical data that is considered to be working correctly with no degradation or errors. In that sense, domain experts should be present in the context of the analyses to determine which values refer to data with no degradation.

Thus, the domain knowledge that must be present in the scenario of the analysis regarding the application of the methodology is related to: (i) the construction of the hierarchy-trees, and (ii) the decision of which data is considered as correct and which not.

Selection of Western Electric Rule that best fits

Once a change in the behaviour of the process is detected, predicting how many work cycles remain until the error or breakdown occurs is necessary. Thus, establishing a criterion to decide when a state is considered an anomaly is crucial.

For this, the so-called Western Electric Rules (WER) are used. They are decision rules within the SPC area that are used to detect out-of-control conditions in control charts.

There are 4 WERs:

(i) One point above Upper Control Limit or below Lower Control Limit.

(ii) Two points above/below +2/-2 times standard deviation from the centre line.

(iii) Three out of four points above/below +1/-1 time standard deviation from the centre line.

(iv) Eight points in a row above/below the centre line of the chart.

Depending on which WER is used, the condition to be able to detect an anomaly changes.

The aim, therefore, is to analyse the predictive capacity of each WER in each of the case studies. For this end, the point at which each WER indicates that there is an anomaly is compared with the real point of the anomaly in the dataset. This is motivated by finding a way to be able to detect the anomaly methodically.

In this way, the first block of the Training Phase aims to generate 4 outputs that allow managing AD and RUL tasks. First, (i) form the clusters and (ii) establish their weights to be able to represent the quantification function of each simulation. Then, (iii) calculate the control limits to represent the EWMA control chart, which enables to detect changes in the behaviour of the machine. And finally, (iv) select the WER that best suits the estimation of the remaining cycles until the failure happens.

4.2.2 Predictive Model Construction

Application model

A set of anomaly containing simulations must be selected in this step. Those simulations should be preprocessed first, and the quantification function is extracted to generate the necessary models to perform the estimation of the AD, RCA and RUL. There must be at least one simulation concerning to each failure type present in the dataset. If this aspect is unknown for experts, or no experts are present in the scenario, the set of anomaly containing simulations should be as big as possible to consider the maximum number of failure types possible. With the help of these anomaly containing simulations, and using the EWMA control chart, the change points of the simulations are detected, and the Self-Organising Map and the respective LSTM models are generated.

Description of the pipeline

The objective of this second block is to generate the models to carry out the Root Cause Analysis and Remaining Useful Life estimations. In Figure 4.3 the process of the second block of the Training Phase is described in a flowchart.

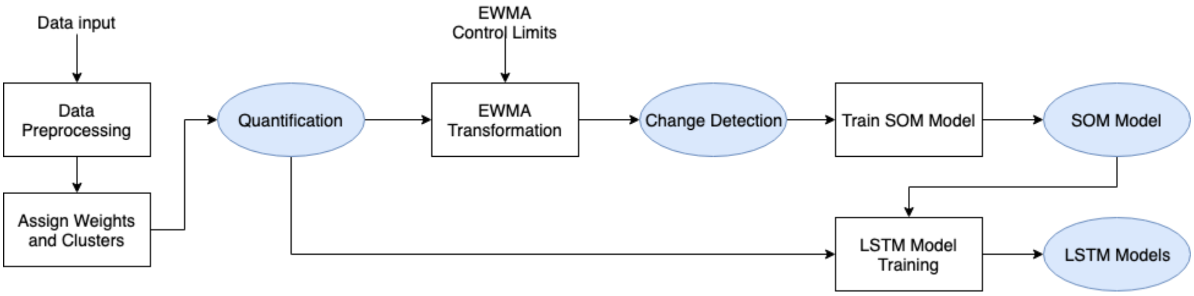


Figure 4.3: Part III of the Train Methodology of the Predictive Maintenance workflow with the ReWAOI algorithm.

As well as in the first block, the training data must first be preprocessed. Next, the Knowledge Base is inspected to assign weights to the elements of the training data. To do this, the following procedure is followed: Each element of the train simulations is analysed individually, and checked if it can match with any cluster of the Knowledge Base. If a match is produced, the weight related to that cluster is assigned to the inspecting element, and if not, that element is generalised to the following Generalised Relationship of lower weight. The process is iterative until the element can no longer be generalised. In case of not finding any matching cluster, the assigned value is zero. This process can be checked in Figure 4.4.

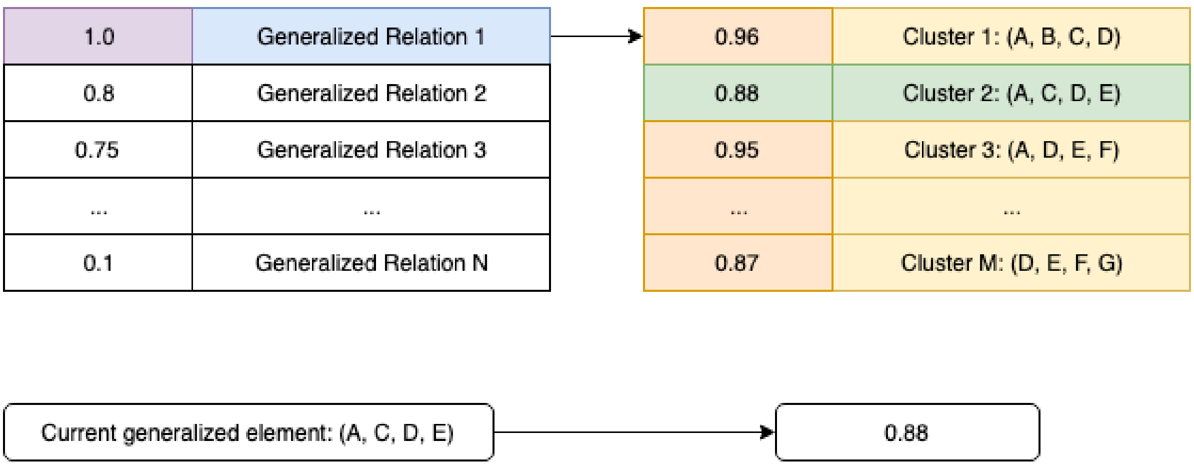


Figure 4.4: Process of assignation of weight to an element according to the clusters of the Knowledge Base.

Once the training data is quantified, each simulation is transformed into an EWMA chart. In that way, each simulation is represented in a manner in which the system is able to detect when a state goes outside the control limits.

For each simulation of the training dataset the change points are selected. These selected change points are the elements referring to the first time in which the simulation exceeds the normality threshold. Hence, a set of change points is generated to perform the management of the RCA. Thus, failure containing data is needed. It is important to work with failure containing data in this step to be able to detect faulty states in other inspected simulations.

To do this, the Self-Organising Map (SOM) algorithm is used. The goal is to construct a map which identifies the number of clusters that are formed considering the group of change points. The description of the attribute values of each change point is inspected by the SOM, and the clusters are generated according to the similarities of the descriptions. In this way, detecting the different types of existing states is the objective, taking into account that a specific type of state can lead to the occurrence of a specific anomaly. Thus, the typology and description of the possible failure before it happens can be obtained. The more failure containing simulations to work with, the more reliable and solid will be the analyses. The ideal scenario is to have at least one (or more) anomaly containing simulation referring to each failure type present in the data, for the failure distinction process to be the most precise possible. Therefore, a SOM model is trained for the estimation of RCA.

Once the SOM model is generated, the goal is to construct a different RUL prediction model for each group of simulations. For this end, a different Long-Short Term Memory (LSTM) model is calculated for each group. In this way, modelling the future behaviour of the function is the objective, in order to know when it can fail (register an anomaly).

To carry out the calculations, the quantification function of the simulations is used. The LSTM model learns from the simulations and tries to generate the prediction of future states, starting from the moment in which the change point is registered. Hence, the process tries to detect the change point and generates the prediction thereafter, using the appropriate LSTM model associated with each cluster detected by the SOM. This can be shown in Figure 4.5

Thus, in the training process, auxiliary models for the calculation of Anomaly Detection, Root Cause Analysis and Remaining Useful Life are calculated.

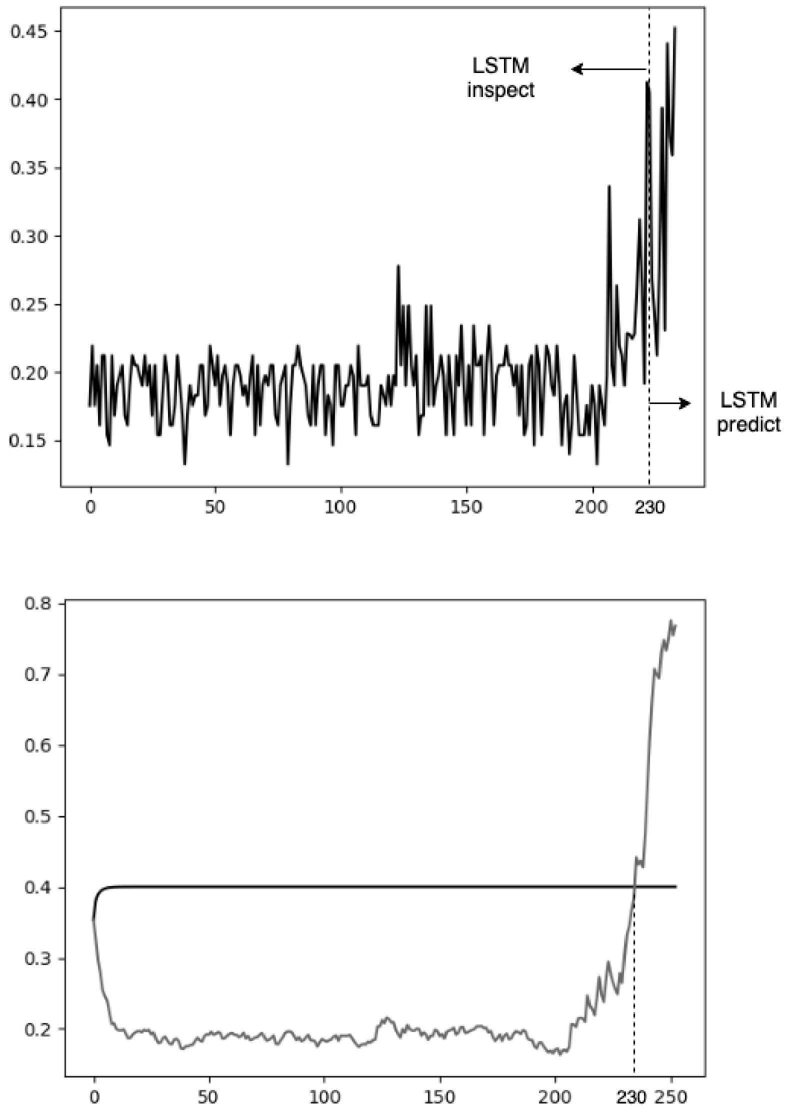


Figure 4.5: Representative image of how the Change Detection and LSTM model work together.

4.3 Testing Phase

In the Testing Phase, the objective is to apply the models generated in the Training Phase, to assess their ability to detect changes in behaviour, describe those changes, and predict when the machine is going to fail. The workflow defined to carry out this phase is shown in Figure 4.6.

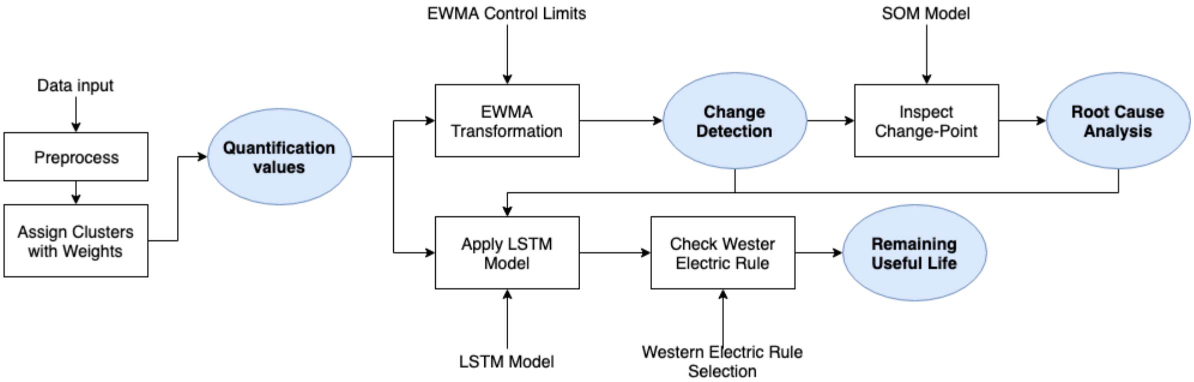


Figure 4.6: Test Methodology of the Predictive Maintenance workflow with the ReWAOI algorithm.

The first step, after preprocessing the test data, is to generate the quantification function of each of the simulations. For this end, the process explained in the second block of the Training Phase is followed: a check is performed to find a cluster in the Knowledge Base that matches with the inspected element. If it exists, its corresponding weight is established, and if not, it is generalised to a higher level and the check is performed again.

Once the quantification function can be represented for a simulation, the Predictive Maintenance stage estimation process is carried out.

4.3.1 Change Detection

The first step in the defined work methodology is to detect when a process is occurring out of normal conditions. For this aim, the EWMA control chart is used. Having the control thresholds calculated in the Training Phase, it is necessary to transform the quantification function appropriately in order to analyse it with the EWMA chart.

As previously explained, states going beyond the normality thresholds are considered as change states or change points.

In those simulations in which change points are not detected, the RUL is not estimated. If there are no moments in the behaviour that are behaving out of control limits, it is considered that the machine is working correctly and that it is not expected to fail.

4.3.2 Root Cause Analysis

Once the change point of a specific simulation is detected, the SOM model generated in the Training Phase is utilised to check which cluster it refers to. Hence, the goal is to know what type of failure that simulation may belong to, and thus be able to apply the corresponding RUL prediction model.

Moreover, thanks to the potential of the ReWAOI algorithm, extracting the description of the states of all the attributes related to the change point from the quantification function is possible. Thus, a more specific view of the context of the event is provided to the domain experts of the area. It helps to better classify the types of failure.

4.3.3 Anomaly Detection and Remaining Useful Life

Once the process is detected to be working out of the control limits, the next step is to analyse when the error or anomaly may occur.

To do this, the quantification function of the current simulation is used. In addition, the moment in which the change point occurs in the process must also be taken into account, as well as the typology of the change point, detected by the RCA system. Depending on the cluster to which the change point belongs, an specific LSTM predictive model is used.

The selected LSTM model observes the trend of the elements prior to the moment in which the change point has been registered. Then, the model predicts the behaviour of the quantification function. In addition, the moment in which the selected WER meets the anomaly detection condition is observed. Finally, the number of time units remaining for occurring the failure is calculated.

4.4 Conclusion and Remarks

The proposed methodology considers the estimation of the stages specified in this thesis for Predictive Maintenance, based on a data-driven approach, and combining the data collected from the machines and the knowledge of domain experts. In this way, achieving more reliable solutions is expected.

For this aim, the concept of quantification is relevant. Thanks to the ReWAOI algorithm, it is possible to convert a multivariate dataset into a univariate one that allows to be modelled with greater simplicity. The stages of Predictive Maintenance are calculated by means of that quantification function.

Another remarkable aspect is that in the process of Anomaly Detection a new component is introduced: Change Detection. In this thesis, the Anomaly Detection is defined as the estimation of the moment in which the anomaly or failure occurs. However, the Change Detection indicates the moment in which the behaviour begins to be different and can lead to an anomaly happening. By introducing this new concept, the goal is to detect the typology of a possible future failure before it happens, and to have an indicator to start predicting when it may fail. If the behaviour of a simulation is within the normality thresholds, the machine or asset is considered to be working in normal conditions and no failure is prone to happen.

In the Testing Phase the Anomaly Detection is estimated at the moment of analysing the RUL. It must be noted that the Anomaly Detection is performed by the help of the WER. The WER is applied when the RUL is inspected, as a method to know when the LSTM prediction must be stopped. That is the reason why the Anomaly Detection process is closely related with the RUL. However, it can also be estimated out of the methodology proposal. If checking whether a simulation is anomalous is necessary, Anomaly Detection can also be performed. The existence of any change point in the simulation is first inspected, and if it exists, the respective WER is applied to detect if there is an anomaly.

Finally, it must be noted that despite the LSTM is the selected technique to be applied when estimating the RUL, the ARMA family models can also be considered. In one of the use cases, as mentioned in chapter 6. Results, ARMA based models are utilised.

CHAPTER 5

Case Studies

5.1 (Clutch-Brake) Press-Machine

5.1.1 General description

One of the case studies used in this thesis to validate the research proposal is concerned with analysis of a clutch-brake system and its components in press machines to (i) detect the most important failure sources, and (ii) perform Predictive Maintenance in those press machines[6].

A clutch-brake contains two friction discs, which are the elements to transmit power to the system. One of the friction discs is attached to the static part of the machine. The second friction disc is always rotating at the machines nominal speed (non-stop friction disc). When the clutch-brake piston makes contact with the first friction disc surface, the clutch-brake and the whole system after it are stopped immediately (0 rpm). However, if the clutch-brake piston makes contact with the second friction disc surface the whole power transmission system after the clutch-brake will start rotating at nominal speed. Friction discs' material get wear while they are used, as in conventional bicycle brakes. The next parameters are identified as key to check the friction disc wear status.

- Friction disc position: position of the rotatory friction disc and output shaft.
- Springs force: springs are responsible to push the clutch-brake piston towards the stopped friction disc or towards the rotating friction disc.

[6] As Larrinaga F. et. al. says [106], Goizper Group is one of the market leaders of power transmission components for metal forming machine tools like clutches, brakes or cams.

- Friction disc wear: this is the attribute that must be calculated, in order to predict when it will run out of material.

Figure 5.1: Press-Machine case study test bench.

The overall objective seek by Goizper Group is to early detect internal wear of a clutch-brake. For that aim, the moving parts of the clutch-brake need to be sensorised. By continuously monitoring the system conditions, proper operation of the clutch-brake can be ensured. Moreover, the most critical operating variables can be registered in the platform in order to analyse the working process and prevent misuses.

5.1.2 Data explanation and preprocessing

The data extracted from the sensors of the clutch-brake to complete the analysis were all numerical.

In order to carry out the calculations, a few additions were performed on the collected data, and two more features were added to the structure:

(i) An identification-point feature was set to the data structure. Data is collected in a given sampling frequency. Each batch is composed by a thousand points, referring to a single clutching or braking process. Thus, each data point represents the identification of the point number into the batch, from 1 to 1000. The order of appearance of the states is of great interest in this case study. This means that under normal conditions, the clutch or brake process of different simulations should have the same duration. Therefore, two states that are equivalent at the same time should be equal. In case of being different it could mean that there are anomalies.

(ii) The real duration of the braking or clutching process was added to the data structure. Although the collected data-batches were composed of 1000 points each, the real duration of the clutching or braking process was not 1000. Actually, the beginning and the end of the signal was related to the machine in a resting mode, so, a preprocessing step was performed in order to delete those elements. We only took the working signal part into consideration for the analysis. This is shown in Figure 5.2

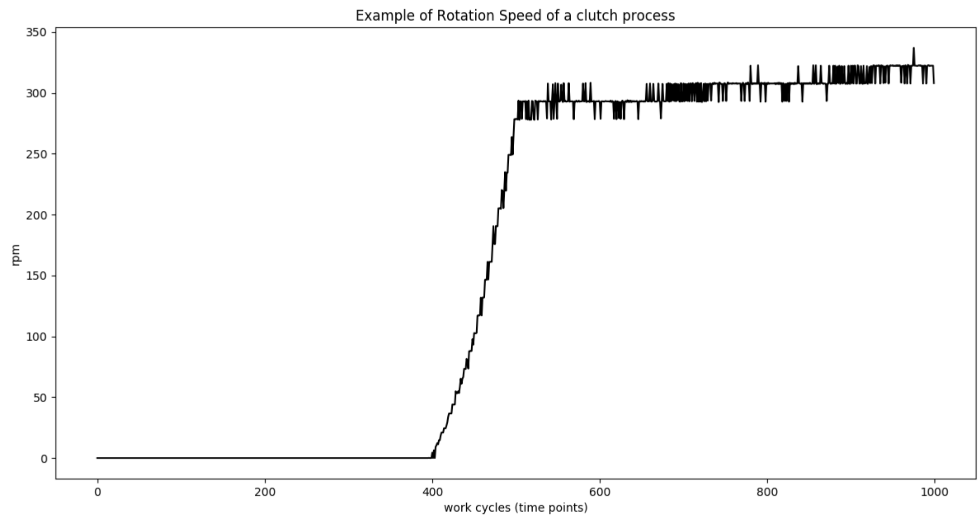


Figure 5.2: Example of Rotation Speed signal of Press-Machine case study for a clutch simulation.

The final structure of the data is shown in Table 5.1. The coloured cells are related to the new feature additions.

Then, the used attributes are briefly explained.

- Point: Each data-element number (order) of the clutch or brake cycle.
- Duration: The number of points composing the clutch or brake cycle.
- Trigger: Signal representing if the electrovalve is activated or not.
- Application Pressure: Pressure applied to the machine to perform a clutch or brake process.

- Shaft Speed: Speed of the crankshaft.
- Line Pressure: Constant pressure value applied to the machine to perform some clutch and brake characteristics.
- Position: Angular position (degrees) of the rotating part of the crankshaft.
- Flywheel Speed: Speed of the flywheel.

Table 5.1: Final data structure of the Goizper case study.

Point	Duration	Trigger	Application Pressure	Shaft Speed	Line Pressure	Position	Flywheel Speed

3916 work executions were registered during the data collection process, divided in different months of behaviour of the machine. Each work execution was preprocessed for only considering the relevant part of the signal for the analysis. Those data points regarding to the machine in a resting mode were deleted, as stated before.

5.1.3 Limitations and provided solutions

Data used in the case study could not be collected continuously. In fact, the data was stored on very sparse days, so it was difficult to represent a continuity that eased the calculation of time series models.

Therefore, when processing attributes, the decision was grouping the data by day within each month. In this way, the goal was to analyse the wear of the machine on a day-to-day basis. Thus, as the wear was reflected in a long time (duration of years), this decision allowed the results to be significant, and simpler to carry out.

5.2 Turbofan dataset (I)

5.2.1 General description

This dataset is provided by the Prognostics CoE at NASA Ames [107]. This dataset is made up of multiple simulations of the wear in a turbine engine. There are two groups of data: (i) training data with 100 different simulations, starting at a random point in the wear process, and ending after the failure has occurred, and (ii) test data with 100 different simulations, starting at a random point in the wear process and ending before the failure occurs. It should be noted that each start moment of each simulation can be different, and it is not specified in any of them. In the case of the test dataset, the number of work cycles before the failure occurs is also not registered. The type of failure that is recorded in all cases is of the same type, as well as the operating conditions in which the simulations were registered.

Each element, both in the training and testing dataset, has 24 attributes. Three of the attributes are related to Operational Settings, and the rest are sensor measurements connected to the state of the machine. No additional information is provided in the description of the dataset to help describe the attributes.

The aim in the present research is to model the wear of the simulations of the test dataset to see how many work cycles remain until the failure occurs.

5.2.2 Data description and preprocessing

As mentioned before, there are three attributes related to Operational Settings. These have not been taken into account when doing the analysis, due to they refer to the different operational conditions of the machine, and for this case study, the operational condition is of the same type. Thus, each dataset contains twenty one attributes that serve to describe the operation and behaviour of each simulation.

In addition, there are sensor data that do not vary in time, so they do not provide sensitive information about the behaviour of the simulation. For that reason, these attributes were removed and only those that varied over the time (variance higher than 0) were considered. In that way, the number of useful variables was reduced from twenty four to fourteen.

All the variables were numerical, and they were anonymised, so no relevant information about the characteristics of the variables were offered. The only information present in the context of the data was that they were vibration data.

5.2.3 Limitations and provided solutions

The main limitation found with this dataset is the non-existance of domain experts. The absence of the experts means that the available data lacked of context information to define the generalisation-hierarchies. As mentioned in chapter 3. Attribute Oriented Induction, the ReWAOI algorithm requires domain knowledge incorporated as concept-trees in order to generate generalisations as representative as possible. On the other hand, no information is offered regarding the meaning of the features which would help define the generalisation-hierarchies.

To overcome the limitation, an alternative was proposed to generate the generalisation hierarchies for each attribute. As data is numerical, the way the generalisation hierarchies were defined was generating partitions in blocks, with the aim of doing those partitions to be the less arbitrary possible. Thus, the spectrum of values of each attribute was divided into ten blocks, according to the values that represented their percentiles. In this way, generalisation hierarchies based on statistical distributions were defined. Thus, we assess whether that way of dividing the data to generate the generalisation hierarchies was appropriate.

Another difficulty encountered in this dataset was the fact that each simulation begins at a random point before the failure occurred. This implies that the same labelling criteria cannot be used as in the case study of the clutch-brake. In this case, point identifiers were not set to the data points and at the time of generating the clusters with the ReWAOI algorithm, the moment in which a specific state occurs was not discriminated.

5.3 Turbofan dataset (II)

5.3.1 General description

This dataset is also provided by the Prognostics CoE at NASA Ames [107]. Some of its characteristics are the same as the ones explained in Turbofan dataset (I): there are 100 different simulations with twenty four different attributes, but in this case, instead of having a unique type of failure, there are two possible failure types. The operating condition is the same for all the simulations.

5.3.2 Data description and preprocessing

As well as in Turbofan (I) case study, there are three features related to Operational Settings. These variables was not considered due to the equal characteristics of the operational conditions of the simulations. Thus, twenty variables were considered to be valid for description of the working context. At the end of the preprocessing, the number of attributes with variance higher than 0 were reduced from twenty four to fifteen.

5.3.3 Limitations and provided solutions

The limitations and provided solutions are the same mentioned in the Turbofan (I) case study.

5.4 Cold-Forming machine dataset

5.4.1 General description

The monitored machine for this case study is a cold-forming machine.

The collected data is divided into multiple strokes or executions of the machine. Each execution have x different values that can be distinct with the other executions. This is due to the duration of the process is recorded in a non automated way and the start and end moments of the strokes is not necessarily the same in all the executions.

This data have multiple attributes, containing two distinct signals each: (i) the angle, a variable that indicates the time series property of the attribute and the angle of the central crankshaft; and (ii) the value corresponding to each time series data point. The value containing attributes are concerning to force measurements.

Data registered from four different months is available for this case study, and the number of executions collected for each month is not the same.

5.4.2 Data description and preprocessing

Among the attributes of the dataset there are variables that have zero values, so they do not provide useful information about the execution. These attributes were removed in order to consider only those that can serve to build a solid Knowledge Base. Thus, the final number of attributes selected for performing the analyses are six, each containing two related variables, as mentioned previously. There is one variable concerning to the indication of the overall tool force; one variable for the guide plate signal; and four more variables regarding to different tool modules. All the variables are numerical.

Moreover, data was transformed in order the executions to be comparable with each other. As the number of elements of each stroke is not necessarily the same, the data was preprocessed with a low pass filter. Hence, the final data contains 275 elements for each execution. The initial length of the signals were different to each other, and for carrying out the analyses it was more interesting to work with work executions containing the same number of time units.

5.4.3 Limitations and provided solutions

The only limitation was the initial distinct number of values of each execution. This issue produced the executions not being comparable with each other, so a preprocessing step was performed to adjust the number of samples of each stroke.

5.5 Conclusions and Remarks

The case studies analysed in this thesis are shown in a chronological order. In this way we show the evolution of the methodology definition process, as well as the experiments that were carried out, and that served to validate the hypotheses.

The first case study, in section 5.1 (Clutch-Brake) Press-Machine, refers to the first approach in which the Anomaly Detection and the Remaining Useful Life were carried out. This first approximation shows the initial idea of the quantification function, which in subsequent experiments improved.

The second and third case studies are based on the same data repository, but they are not the same dataset. The case study 5.2 Turbofan dataset (I) aims to refine the proposal of Anomaly Detection and Remaining Useful Life of the first case study. This refinement was produced due to the application of more consistent techniques of estimating both AD and RUL. In addition, the final proposal of the methodology defined for this thesis is explained in more detail. In turn, the case study Turbofan (II) shows the methodology for the calculation of Root Cause Analysis.

Finally, the aim with the 5.4 Cold-Forming machine dataset case study is to apply the full defined methodology to calculate, if possible, the AD, RCA and RUL.

In this way, the intention is to explain chronologically the evolution of the proposals when estimating the stages defined in the thesis for Predictive Maintenance: AD, RCA, and RUL.

Chapter 6

Results

The results obtained in each of the case studies are explained below. These case studies are represented in the order in which they were defined during the development of the thesis. The goal is to explain how the results were achieved and in which scenario.

6.1 Press-Machine (Clutch-Brake Machine) Case Study

The Press-Machine case study is the first in which the ReWAOI algorithm was applied for the calculation of the Anomaly Detection and the Remaining Useful Life.

This case study served to make a first approximation of the methodology that was defined later. Thus, although the followed process did not completely fulfil the steps of the methodology defined in the previous chapter, it was used to validate the application of the ReWAOI algorithm for the defined purposes.

This case study was composed by a set of clutch datasets, collected from the monitoring of the clutch-brake machine.

First of all, the ReWAOI algorithm was executed, after the domain experts established the parameters. Thus, in this case, the experts defined the weights for the attributes, as well as the generalisation-trees.

To build the set of clusters through the ReWAOI algorithm, approximately 80% of the data was selected. The objective was to select that data that the domain experts considered as correct, or that had no wear. In this way, the wear containing data was split for the validation process.

As mentioned in chapter 5. Case Studies, in the transition from a simulation of a clutch or brake to another, it is not common to register noticeable wear. Thus, the decision was to calculate the median of each simulation and build a quantification function that represents the wear of the simulations in time. The median was calculated to have a value that represents a trend in the simulation dataset. Then, to perform the analyses in a day-to-day basis, the average of the representative value of each quantification was calculated per day. In this case, it was chosen to prioritise the central population value of the current simulation.

6.1.1 Anomaly Detection

To understand how the Anomaly Detection was calculated, another term defined for this case study must be explained: the *Normality Threshold*.

When the median of each clutch action is calculated, the minimum value of the quantification function is also extracted. In this case, a low quantification value would refer to an unusual state of the machine or asset, and that could lead to a failure. Thus, analysing the minimum values can lead to find the limit values of correctness of the machine or asset.

Therefore, the minimum value of all simulations equivalent to the correct operating group of the machine set the Normality Threshold. If the value of the quantification in a wear simulation exceeded the limit defined by the Normality Threshold, an anomaly was considered.

An example of a wear simulation is shown in Figure 6.1 in which points that exceed the Normality Threshold were found.

Anomaly containing data was not labelled in the dataset. Thus, validating the Anomaly Detection system became difficult. That is why the presence of domain experts was important. They validated that the detected anomalies could be real anomalies, based on their expertise and intuition. Therefore, the validation of the process was carried out according to the criteria of the domain experts. They affirmed that in the moment the system detected an abnormal point the presence of possible failures was usual in their machines.

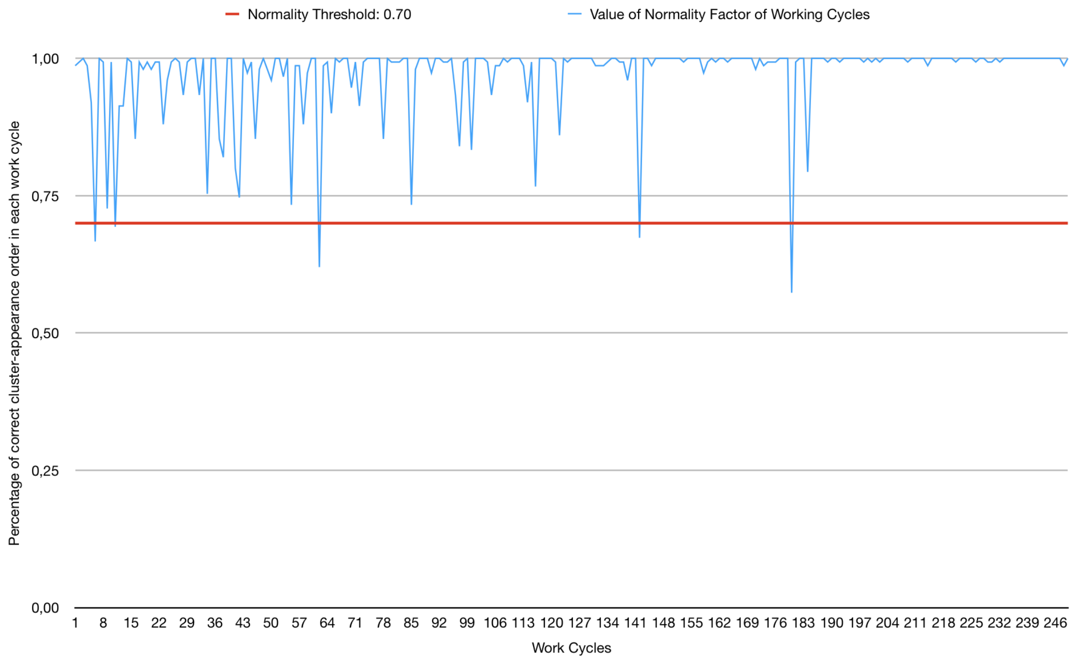


Figure 6.1: Example of Anomaly Detection in a Goizper clutch process.

6.1.2 Remaining Useful Life

An Auto Regressive time series model was used to calculate the Remaining Useful Life in this case study. Moreover, the result of the quantification obtained from the Knowledge Base generated by the ReWAOI algorithm was also utilised.

Figure 6.1 shows an example of quantification of a clutch simulation that registered errors after some wear. There are points that exceed the Normality Threshold (anomalies), but there is not a decreasing trend in the function. That is the scenario in which the Press-Machine case study is contextualised: although anomalies can be found at specific points of the function, the wear of the machine is not appreciated from one simulation to another. A long series of clutch processes are necessary for wear to occur.

Therefore, a value that summarises the content of each simulation was calculated, and the series of simulations over the time were analysed. To represent the summarising value of each simulation, the median was used, as stated before. In this way, the new quantification function was defined.

The value of the new quantification function decreased over the time, observing a greater number of unusual values. This was an indication of wear and that the states that appear in subsequent simulations were not common.

For training the AR model, the data of the quantification function regarding the moments in which the domain experts considered that the machine had begun to register a wear were selected.

In Figure 6.2 the prediction performed by the AR time series model is shown.

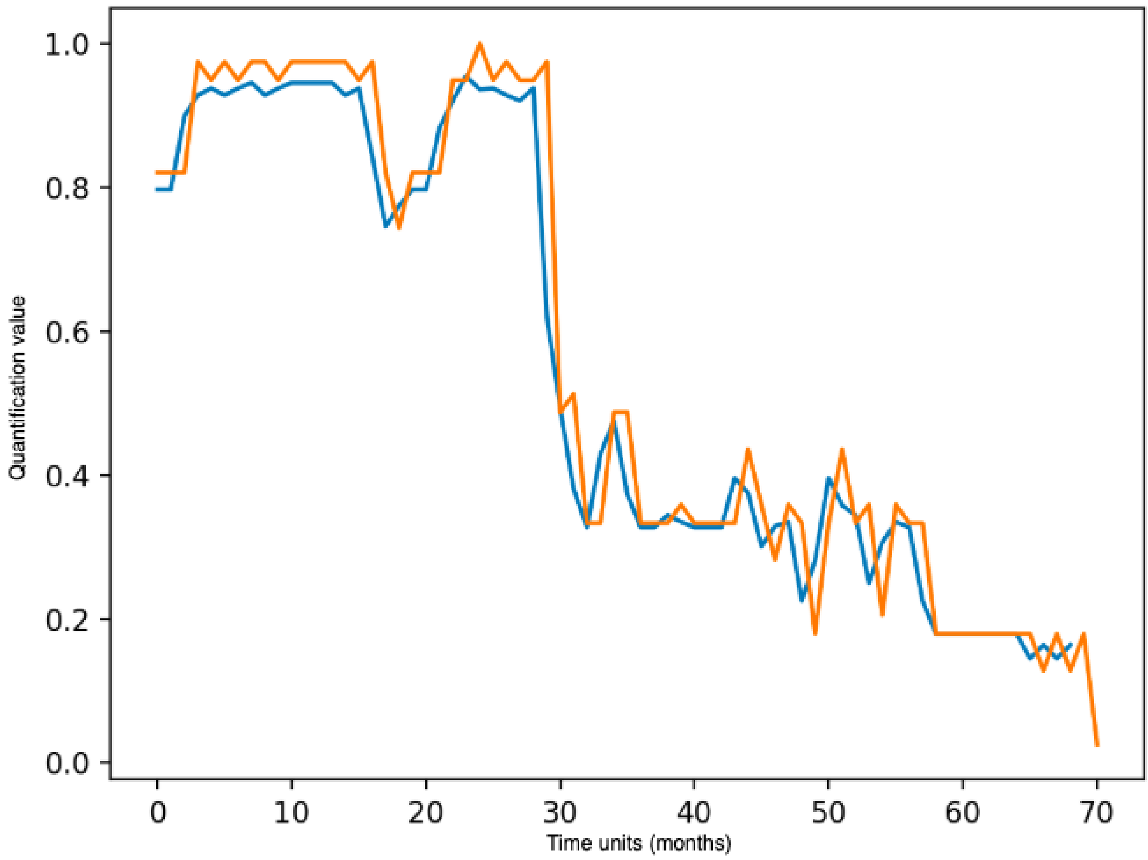


Figure 6.2: Remaining Useful Life prediction performed by an AR model in the Press-Machine case study.

The function represented in blue indicates the original wear function, while the orange line represents the prediction made by means of the AR model. The root mean squared error was 0.4782.

Accurate results were obtained by using the defined AR model, making the system helpful for domain experts after its observation and validation.

6.2 Turbofan (I) Case Study

In this case study, the components of Anomaly Detection and Remaining Useful Life were calculated, following the methodology explained in chapter 4. Methodology.

As mentioned in chapter 5. Case Studies, for the Turbofan (I) dataset, after preprocessing the data, fourteen attributes of interest were selected, containing one hundred different simulations to perform the tests.

Next, the results obtained after applying the proposed methodology are explained.

6.2.1 Knowledge Base generation with ReWAOI

First of all, in this case study there were not domain experts, so the strategy to define generalisations was different. Since all attribute values were numerical, the range of the values of each attribute was divided into percentile blocks; specifically in ten percentile blocks. The goal was to define a number of blocks that was not very extensive so that the operation of the algorithm neither was slowed down, nor too low for diversity. The number of generalisation levels was set to four, with the hierarchy-tree of each attribute as shown in Figure 6.3.

The ReWAOI algorithm was trained with 80% of the training data available, leaving the remaining 20% for validation. After generating the clusters, the idea for validation was to check whether the generated Knowledge Base was consistent. For this end, the number of states of the validation dataset that did not match with the clusters of the Knowledge Base was observed. The number of mismatched states was zero, so it shew that the generated Knowledge Base was consistent to carry out the analyses.

6.2.2 Quantification and auxiliary model calculation

Then, how the auxiliary models were calculated and which were the obtained results are explained.

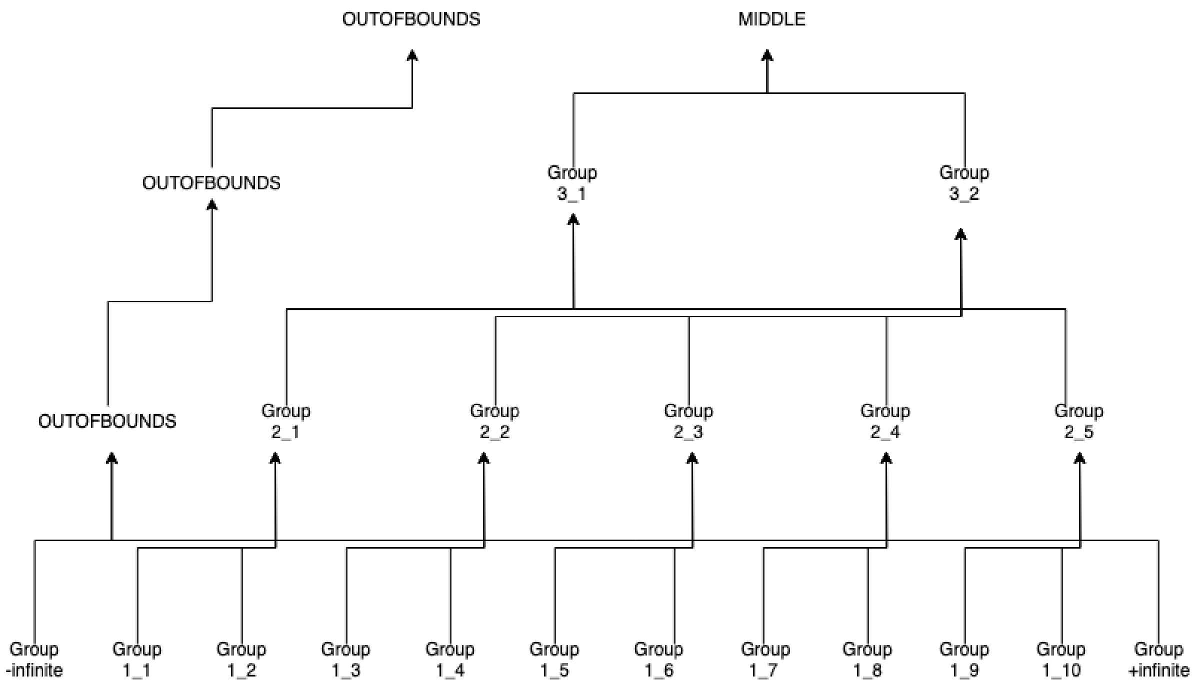


Figure 6.3: Hierarchy-Tree for the attributes in the Turbofan (I) dataset.

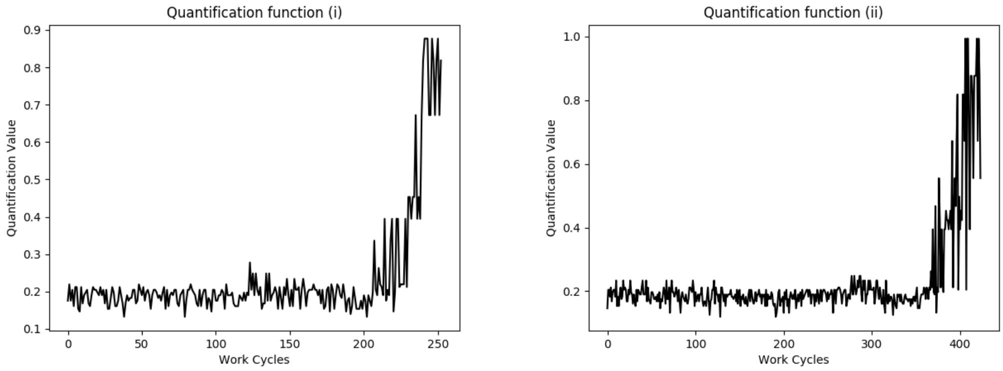
Quantification function

To generate the quantification function, 80% of the data was selected. This was motivated by separating a set of data for the validation of the models for the next phase.

Some examples of the quantification function for different simulations are shown in Figure 6.4.

As it can be observed, the quantification functions have a similar form: they start by adopting low and stable values, and end up having an ascending peak at the end.

The weight calculation algorithm of the clusters considers the frequency of occurrence of habitual states in the different simulations. As mentioned in chapter 5. Case Studies, this case study had only one type of failure. Hence, the upward trend at the end of the simulations is due to the moment of the error is approaching, and the states registered when occurring that error are very similar in all the simulations. Therefore, the representation of the quantification indicates that when the trend is rising the error may be occurring.



(a) Quantification function (i) (b) Quantification function (ii)

Figure 6.4: Examples of quantification function for different simulations of the training set.

EWMA chart calculation

After the inspection of the trend of the quantification functions, the thresholds of the EWMA control chart were calculated. As discussed in chapter 2. Theoretical Background, selecting correct operation data is necessary. For this aim, the data prior to the moment in which the quantification function started to increase was selected as correct behavioural data. As no domain experts were present in the case study, this assumption was performed.

Western Electric Rule selection

Once the EWMA control chart thresholds were calculated, the system was able to detect when a state started to go out of normal conditions. As explained in chapter 4. Methodology, then the goal is to find a method to detect when the anomaly will occur. WERs are the chosen method for this end.

The WER that is closer to the real anomaly moment of the simulations was inspected. 70% of the data was selected for training, and 30% for validation.

The results obtained are shown in the Table 6.1. These results are represented in relation to the error in units of time when detecting the anomaly.

WER 4 obtained the best result. The prediction error respect to the real anomaly

Table 6.1: Representation of the mean error between the real RUL and the estimated RUL with the different WER conditions.

WER	Mean Absolute Error	Mean Squared Error
WER 1	56.0	8518.48
WER 2	33.25	4125.35
WER 3	17.55	1084.13
WER 4	6.26	72.74

moment is the smallest for that WER. One possible reason may be that the system needed some time for the error to occur, after the change point was detected, and WER 4 considers that situation.

Therefore, that WER was selected to apply in the test phase to estimate Anomaly Detection and Remaining Useful Life.

LSTM model calculation

Thanks to the capacity of LSTM neural networks, the future trend of the quantification function could be modelled in this case study.

Thus, a neural network with three layers of hundred neurons was defined. The prediction through the LSTM model was made by inspecting the forty previous elements. The objective after the application of this neural network architecture was to achieve a model that would validate the methodology, allowing the quantification function to be modelled with a low error rate.

The Root Mean Squared Error (RMSE) when training the LSTM model was: 0.034361. The results obtained with the help of this neural network model are shown in the RUL calculation section.

6.2.3 RUL calculation

To carry out the calculation of the RUL, 30% of the simulations that were previously set aside for testing were used.

For each test simulation, a transformation into an EWMA chart was first applied. In this way, the goal was to discover at what point a simulation exceeded the thresholds. An example in which a simulation was transformed and represented in the EWMA control chart is shown in Figure 6.5.

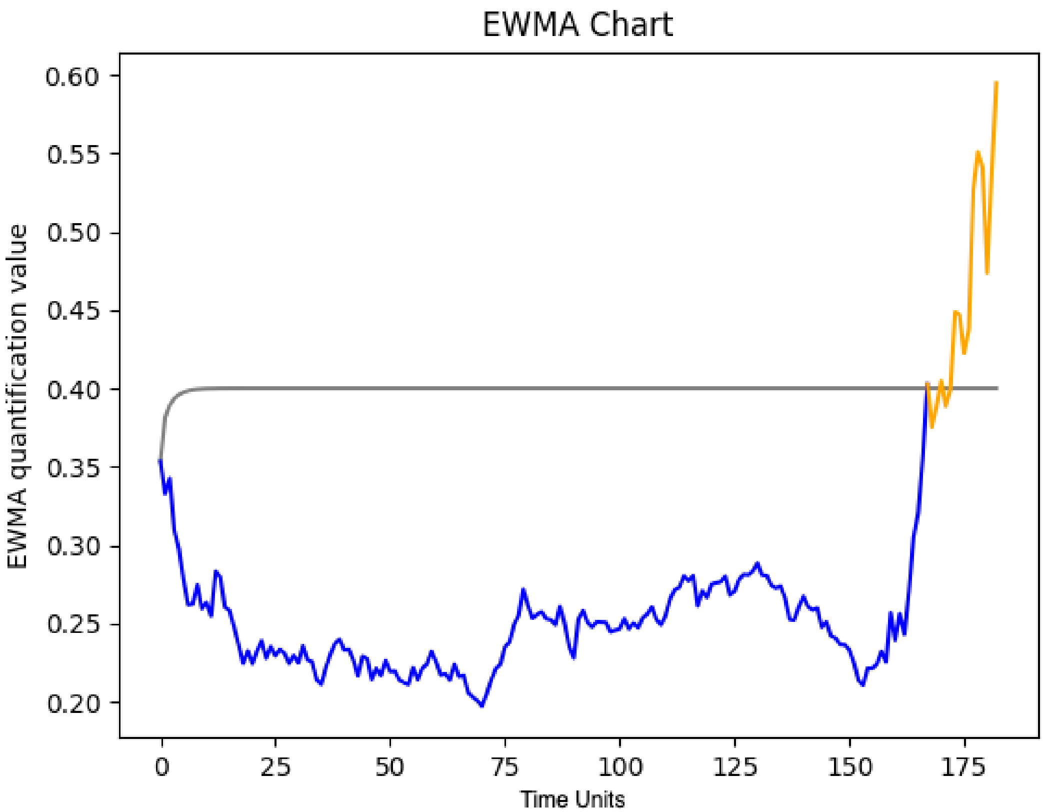


Figure 6.5: Example of representation of a simulation in an EWMA control chart.

As can be seen, only the upper threshold was represented. The moment in which the anomaly occurred was when the function became ascending. Thus, the intention was to inspect when it exceeded that upper threshold. Once the moment in which the function exceeded the threshold was detected, the LSTM prediction model was applied to the quantification function. Hence, the prediction of future states started.

The model architecture was based on three layers of 100 neurons each, with adam activation function. After different trials, this architecture was demonstrated to provide accurate results with low error rate for the prediction.

Figure 6.6 shows an example in which an original quantification function is compared with a function modelled by means of the LSTM. The blue line represents the original function, while the orange one represents the prediction. The predicted function starts from the moment in which the change point was detected in the EWMA control chart.

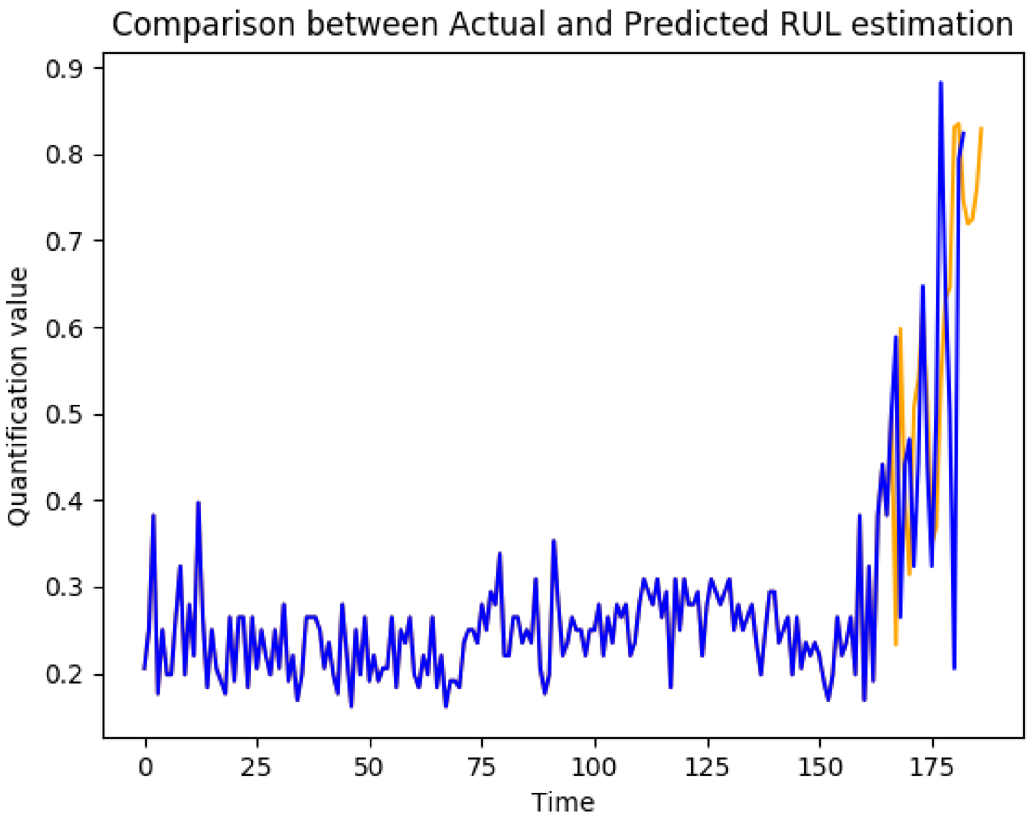


Figure 6.6: Example of representation of a real quantification function and the one predicted by the LSTM model.

In order to know when the LSTM model must stop predicting the quantification function, the WER criterion is established. In this way, it was checked whether it met the WER 4 condition for the estimation of the anomaly with the predicted values. An example of this application is shown in Figure 6.7.

The grey section of the quantification function represents the section in which the behaviour of the machine is considered normal, and does not exceed the threshold of the EWMA control chart. The blue section is the prediction performed by the LSTM model, after the change point was detected. And finally, the red section is the one that represents machine failure states. When a failure state was recorded, the LSTM prediction

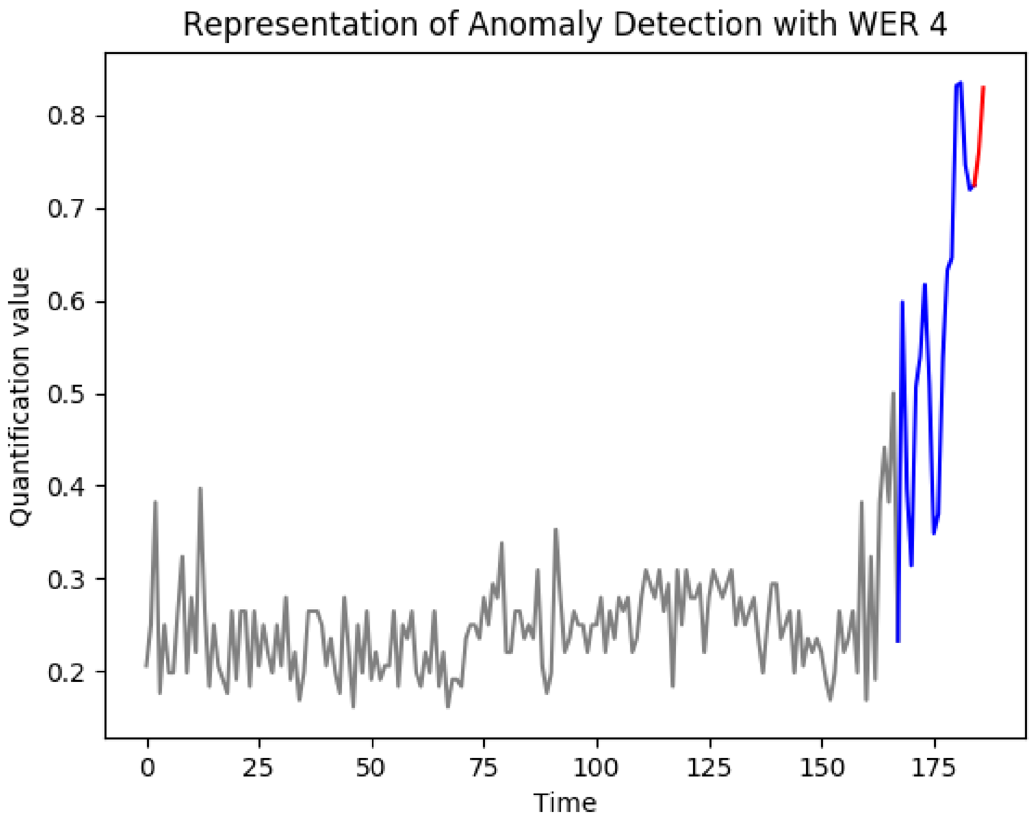


Figure 6.7: Example of prediction of the quantification function meeting the criteria established by the WER 4.

process stopped, and the RUL was calculated.

Finally, the quality of the implemented prediction system was measured. For this end, two main aspects were considered:

(i) Mean absolute error: The difference between the real RUL value and the predicted value from the moment a change point was detected. The result of the analysis was 39.02.

(ii) Detection of the change point before the occurrence of the anomaly: Detecting if the simulation is going out of the control limits before the failure occurs is critical to prevent breakdowns. The change point was detected before the failure in 100% of cases.

In some simulations the change point was detected very early (work cycle < 40). In these cases the prediction of the quantification function performed by the LSTM model was not as precise. If only those simulations in which the change point occurred after the first 40 work cycles were taken into account, the result of the mean absolute error improved (13.30).

6.3 Turbofan (II) Case Study

In this case study, the goal was to address the calculation of both the Change Detection and the Root Cause Analysis. For this end, the methodology proposed in chapter 4. Methodology was partially followed.

6.3.1 Knowledge Base generation with ReWAOI

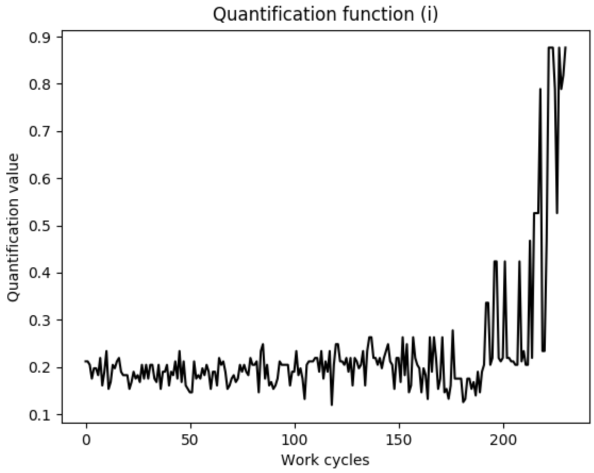
Although the dataset is different from the one used in the case study Turbofan (I), the results of the first block were similar. When generating the Knowledge Base, 80% of the simulations of the dataset were used. 100% of the data had states coinciding with the generated clusters.

6.3.2 Quantification and auxiliary model calculation

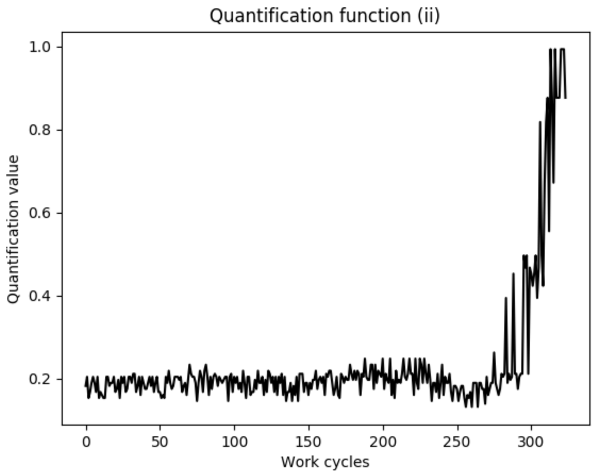
An example of quantification of a simulation is shown in Figure 6.8.

In this case study the quantification function of the simulations also followed the same trend as the simulations of the Turbofan (I) case study. During the first stage, the value of the quantification function is low, while in the end it increases. That was an indicator of the states being common in that section throughout the dataset. Considering that there were two types of failures, the increase in the quantification function may indicate that the states of the failures are similar.

Thus, the conclusion was that the data of the first part of the simulations could be considered as data of correct operation. Starting from that premise, and after inspecting the data, those first elements of 70% of the simulations were selected to calculate the EWMA thresholds. Moreover, 30% of the remaining data were separated for validation.



(a) Quantification function (i)



(b) Quantification function (ii)

Figure 6.8: Examples of quantification function for different simulations of the training set.

6.3.3 Change Detection

Once the auxiliary models were defined, the Change Detection was also calculated. For this aim, it was necessary to transform the current simulation to be able to represent it in the EWMA control chart. An example of a transformed simulation represented in an EWMA control chart is shown in Figure 6.9.

As mentioned for the case study Turbofan (I) and as indicated in the proposed method-

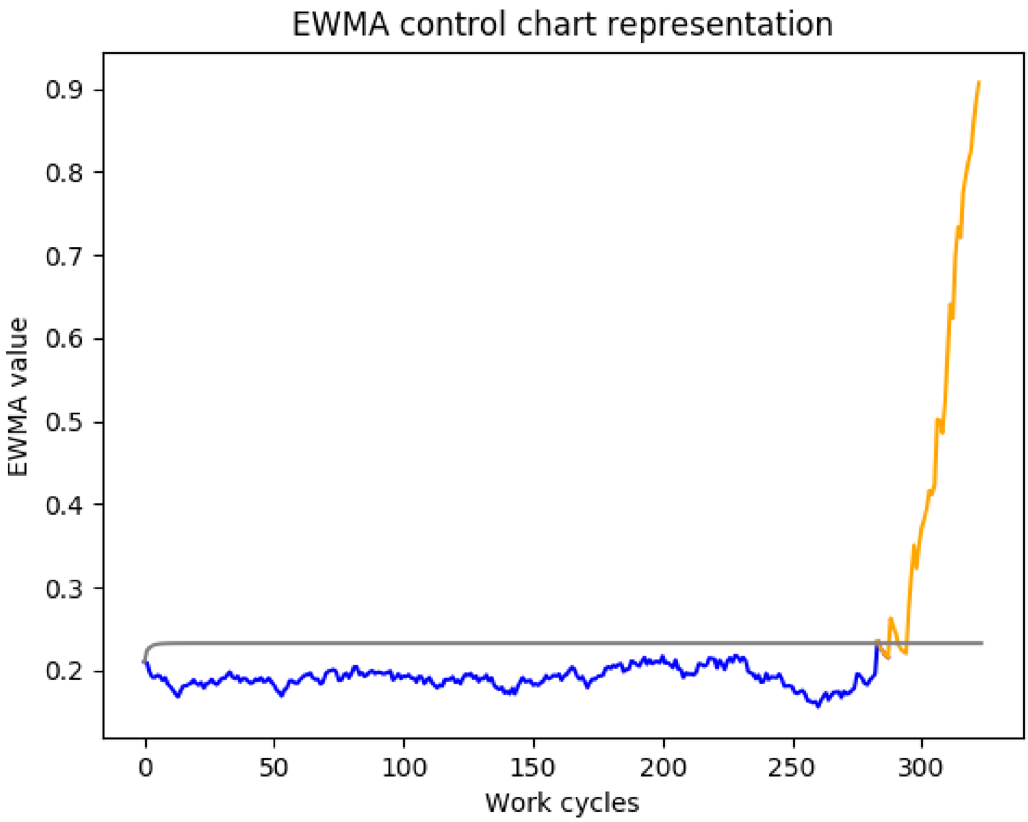


Figure 6.9: Example of representation of a simulation in a EWMA control chart.

ology, at the moment when an element exceeds the limits established in the EWMA control chart, a change in behaviour is detected. In this case, as well as in the case study Turbofan (I), only the upper limit was used for the same reason: the simulation trend was ascending and the error occurred when the quantification value rose.

6.3.4 Root Cause Analysis

For the estimation of the RCA, the detected change points in the Change Detection process were utilised. The change points of 70% of the simulations were analysed and the SOM clustering algorithm was applied.

Two different types of failure were present in this case study. The change points did not directly indicate the fault, but were states that happened before the failure occurred, and indicated that there were changes in the simulation behaviour that could lead to an anomaly happening. The assumption in this case was that analysing the change points two distinct types of failure could be observed.

The SOM algorithm inspected the similarities of the change points data to generate the distance map and represent the clusters. Figure 6.10 shows the map generated by the SOM.

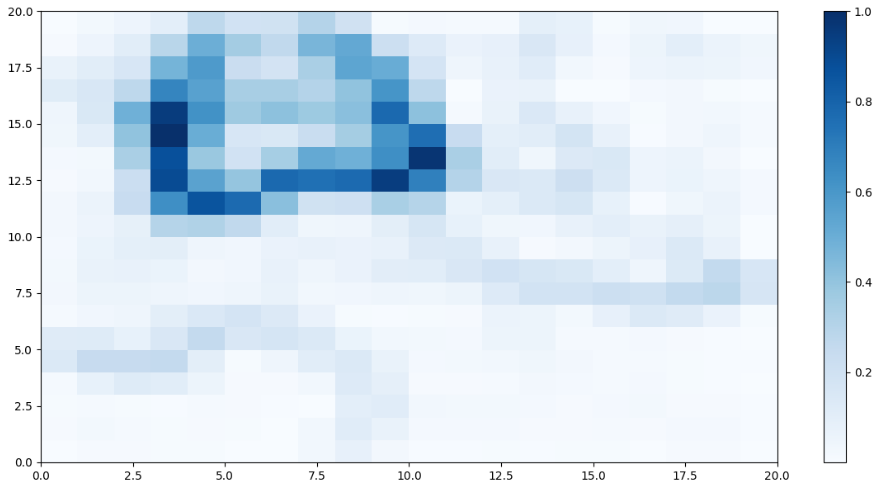


Figure 6.10: Representation of the Self-Organising Map clustering.

The matrix on which the SOM draws its result indicates the existence of two defined groups. Light coloured grids indicate that there is closeness between adjacent nodes, while darker coloured ones indicate that the distance is greater. In that way, a first group is made up of the interior in the form bounded by the dark-coloured grids, and the second group is formed by the outside.

The result is consistent with the description of the case study, which indicates the existence of two different types of failure. In this case, the change points were used as input to generate the SOM, so the conclusion is that there are two different scenarios that lead to a failure. Thus, two different failures are considered.

In this way, for a specific simulation, knowing the typology of the change point when it is detected, it can be known if it refers to one type of failure or another.

Apart from that, as mentioned in chapter 3. Attribute Oriented Induction, the ReWAOI algorithm has the ability to represent the collected information, so it is possible to describe the state of the machine at the change point.

6.4 Cold-Forming machine Case Study

The last case study is the Prophesy case study. The aim was to apply the full methodology workflow in order to estimate Anomaly Detection, Root Cause Analysis, and Remaining Useful Life. In the other analysed case studies in the thesis, the proposed methodology was applied partially, but it enabled to validate the proposals. This last case study was a manner to finish the validation, concluding that the full process was applicable to any Predictive Maintenance scenario.

At the beginning of the working pipeline, the dataset was preprocessed, as explained in chapter 5. Case Studies. The final structured dataset contained twelve different variables. In addition, data was organized in different executions (strokes). These executions were labelled as *correct* or *anomaly* data, but the source algorithm or technique that decided whether an execution was correct was unknown. These attribute names are: GP_M6_Angle, GP_M6_value, PH_M10_UC2_Angle, PH_M10_UC2_value, PH_M5_A_Angle, PH_M5_A_value, PH_M5_B_Angle, PH_M5_B_value, RAM_Angle, RAM_value, TOOL_H_Angle, TOOL_H_value

Then, the final dataset was divided into training data and testing data. The size of the full dataset consisted of almost twelve thousand strokes to be analysed. For training data a subset of correctly labelled executions was selected. That subset was about 75% of the data from the first three months, and about 30% of the full data (11500 strokes). In this case study the ReWAOI algorithm was fed with only correct labelled data in order the algorithm to find previously unregistered states.

6.4.1 Knowledge Base generation with ReWAOI

Equal to the Turbofan (I) and Turbofan (II) case studies, this one was lack of domain experts. As all the data was numerical, the method proposed in Turbofan (I) dataset to construct the concept-trees for each attribute was applied. Thus, four different generalisation levels were defined for each attribute with twelve initial leaf nodes in the lowest level, as represented in Figure 6.3.

The initial minimum cluster size for executing the repetitive iterative process of the ReWAOI algorithm was set to $\frac{n}{100}$ where n is the number of elements of the training dataset.

After the cluster generation process was completed, the quantification values for each stroke data were defined. In this case study, the generated clusters referred only to correct considered states of the machine.

6.4.2 Anomaly Detection

As mentioned in chapter 4. Methodology, the Anomaly Detection process can be performed independently from the other stages. In the defined methodology the AD and RUL estimations happen close together, but for this case study, one of the premises was to detect if a specific simulation was or not anomalous.

First of all, the EWMA control chart limits were calculated. Taking into consideration that EWMA control chart needs normal behavioural data to fit its control limits, data from the training dataset was utilised to perform the calculations.

In addition, the quantification function was also examined. Figure 6.11 shows a representation of the quantification function of a single execution. As can be observed, differently from Turbofan case studies, this time the scenario changed. High values of quantification do not refer to abnormal data representation, due to all values with which the clusters were generated were correct values. High values of quantification refer to very common states of correct behavioural data, and low values refer to unusual states of correct data. Thus, the lower the value of the quantification, the higher the possibility to be an uncommon state in the correctness of the behaviour. Due to this assumption, only the Lowest Control Limit (LCL) was considered in the EWMA control chart representation. If an EWMA representation of a quantification value exceeds the LCL, a change point is detected.

In order to decide which Western Electric Rule (WER) to use for Anomaly Detection in this case study, the next steps were followed.

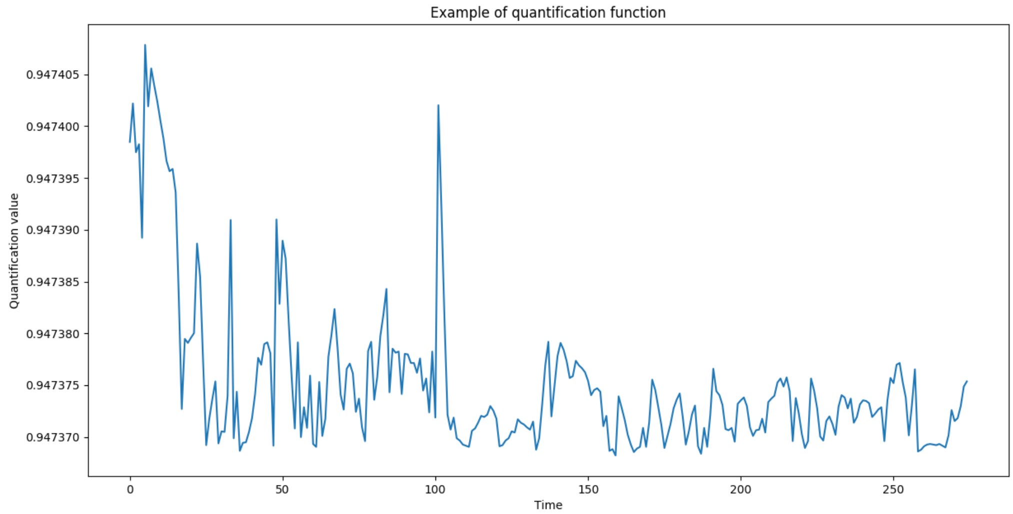
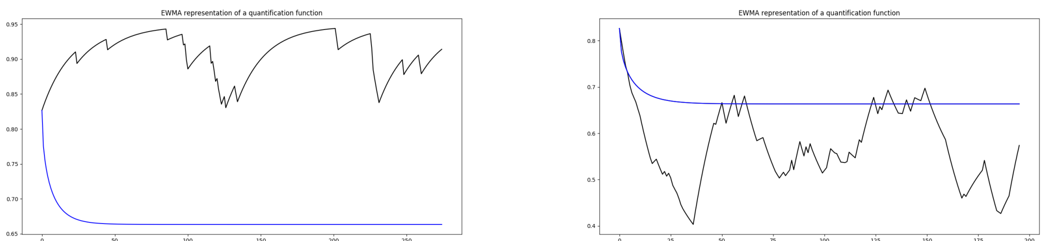


Figure 6.11: Example of a Cold-Forming machine case study quantification function of a single execution.

First of all, the same training dataset selected to perform the ReWAOI cluster generation was chosen. For each execution (stroke) of the dataset the EWMA control chart representation was applied. In some cases, the LCL threshold was not exceeded. Figure 6.12 shows two examples of EWMA control chart representation, one that exceeds and other that does not.



(a) EWMA representation (i)

(b) EWMA representation (ii)

Figure 6.12: Examples of EWMA representation. (i) Inside the control limit, and (ii) out of the control limit.

As mentioned in chapter 4. Methodology, only those cases in which the control limit is exceeded are considered to check whether it can be treated as an anomaly. Thus, the next step was to select the Western Electric Rule that minimises the number of predicted anomalies over the data classified as correct. Table 6.2 shows the results obtained after executing the four distinct WERs with the training data.

Table 6.2: Results of the execution of the different WERs over the data in which a change point has been detected.

WER	Number of datasets detected as anomalies
WER 1	0
WER 2	36
WER 3	25
WER 4	50

As can be seen, the WER 1 minimised the number of detected anomalies in the training dataset. Hence, this aspect demonstrates that WER 1 was a valid candidate to be used for Anomaly Detection. The next step was to calculate how much accurate was WER 1 at the time of classifying correctly both normal and abnormal considered executions. Thus, the training dataset was extended, considering both correct and incorrect executions, of about 60% of the full data.

Then, test data was selected in order to provide a test accuracy result. The accuracy for the test dataset was 0.99368. The confusion matrix is shown in Figure 6.3.

Table 6.3: Confusion matrix of the test result after applying the WER1 to classify the data.

<table>
<tr><td></td><td></td><td colspan="2">Predicted</td></tr>
<tr><td></td><td></td><td>+</td><td>-</td></tr>
<tr><td rowspan="2">Real</td><td>+</td><td>4396</td><td>6</td></tr>
<tr><td>-</td><td>22</td><td>4</td></tr>
</table>

As can be observed in the confusion matrix, the defined method predicted accurately the correct behavioural data respect to the data initially labelled as correct. However, it did not have an accurate capacity to predict the anomalies. There were twenty six faulty executions in the test dataset, ten were predicted, and four were matched.

Figure 6.13 shows a representation of the correct and incorrect labelled executions (strokes) estimated by the ReWAOI algorithm. Each circle point represents the median value of the quantification of a single execution. Green points are executions labelled as correct, and red points are executions labelled as anomalous.

As can be observed, most of the anomalous executions have a low median value, and none of them is higher than 0.65. There are also a few green points with a small value

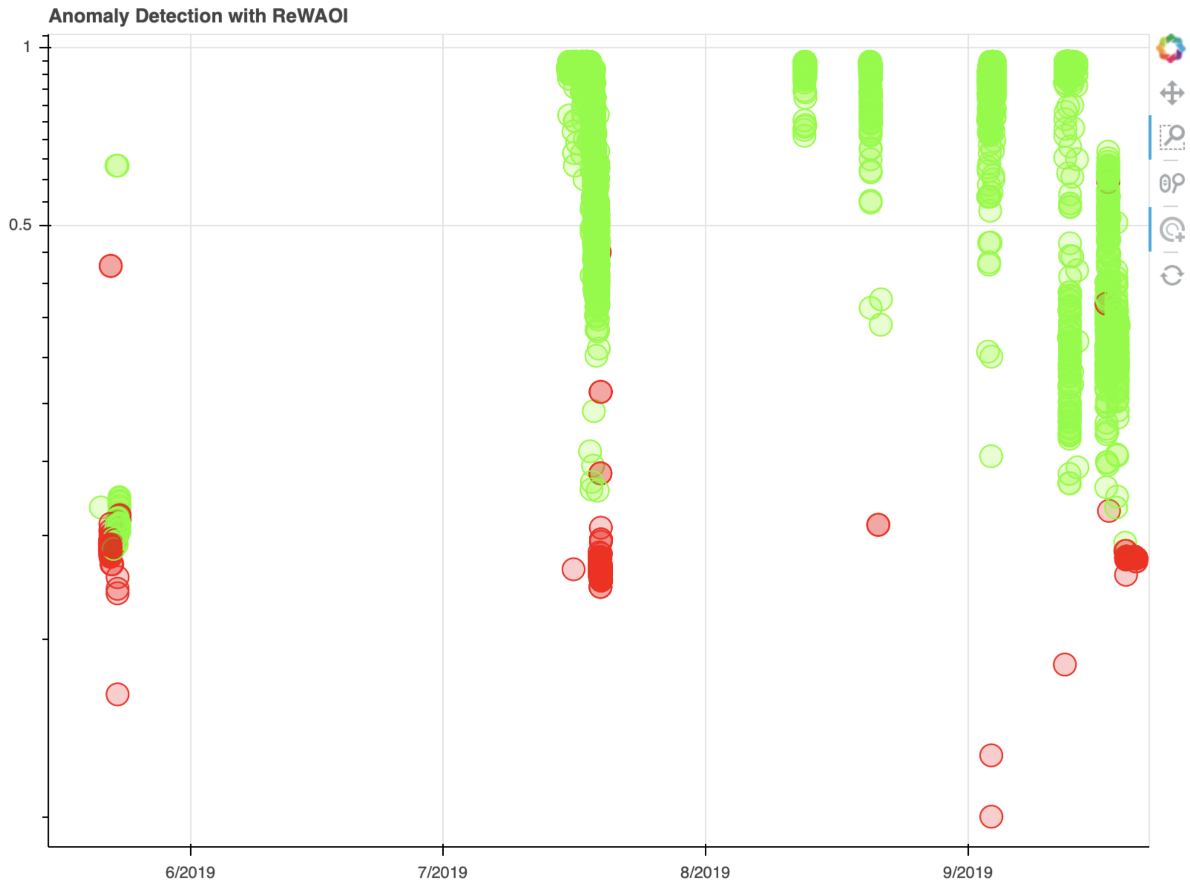


Figure 6.13: Anomaly Detection performed by ReWAOI algorithm. Green points refer to correct executions, and red points to anomalies.

of quantification, but almost the majority of the executions have higher values than the red ones. This aspect is discussed with more details in section 6.4.4 Remaining Useful Life estimation.

As told before, the data came labelled a priori, but the method which that labelling was performed with is unknown. For this reason, an additional proposal was defined for this case study. This new proposal is led by the usage of a distinct data mining method for Anomaly Detection. This algorithm is called *NullSpace*.

Comparison with NullSpace algorithm

The objective behind this decision was to check the results obtained by a different Anomaly Detection method, and compare those with the results obtained by the ReWAOI and the initial labelling of the data. In addition, the aim was to confirm if the results obtained by the ReWAOI method were valid or not, and to adjust the trustworthiness of the initial labelling of the data.

Table 6.4 shows the results obtained for the accuracy metric comparing the three different labellings.

Table 6.4: Accuracy metrics of the different algorithm comparisons.

Compared algorithms	Accuracy	Matching / Total
Nullspace - ReWAOI	0.99639	4412.0/4428
NullSpace - A priori	0.99187	4392.0/4428
A priori - ReWAOI	0.99368	4400.0/4428

Also in Table 6.5 the confusion matrix of each comparison is represented in order to have a better view of the distribution of the predictions.

Table 6.5: Confusion matrices of the different comparisons.

		Predicted	
		+	-
Real	+	4407	5
	-	11	5
NullSpace - ReWAOI			

		Predicted	
		+	-
Real	+	4396	6
	-	22	4
A priori - ReWAOI			

		Predicted	
		+	-
Real	+	4389	13
	-	23	3
A priori - NullSpace			

As can be observed, the accuracy between the NullSpace and the ReWAOI algorithm is the highest one. This means that the predictions they generated were similar. Actually, the three calculated accuracy values are close to 1.0. If the confusion matrix of each of the comparisons is checked, some conclusions can be extracted.

The first conclusion is that both the comparison between the a priori labelled data and the NullSpace, and the a priori labelled data and the ReWAOI algorithm, matches precisely the correct data, but not the anomaly data. The specificity in both cases is low, but the precision of the ReWAOI in relation to the prediction of anomalous data is about 0.40-0.50. This means that the a priori labelling system detected more anomaly data than the NullSpace and the ReWAOI, but the ReWAOI has a higher precision when predicting anomaly data in comparison with the NullSpace. Moreover, when checking the confusion matrix of the NullSpace and ReWAOI comparison, specificity incremented, but it was still quite low, about 0.31.

The final conclusion extracted from this analysis is that both the NullSpace and ReWAOI results were very similar, quite more that the results obtained from comparing each of these two algorithms with the a priori labelling. In addition, it can be remarked that maybe the a priori labelling technique is not as precise when detecting anomaly elements, due to the high difference in prediction with the other two algorithms.

6.4.3 Root Cause Analysis

The RCA estimation was performed with the help of the SOM algorithm. As explained in chapter 4. Methodology, the detected change points were considered for generating similarity clusters. Hence, the different types of states that can lead to an anomaly were discovered.

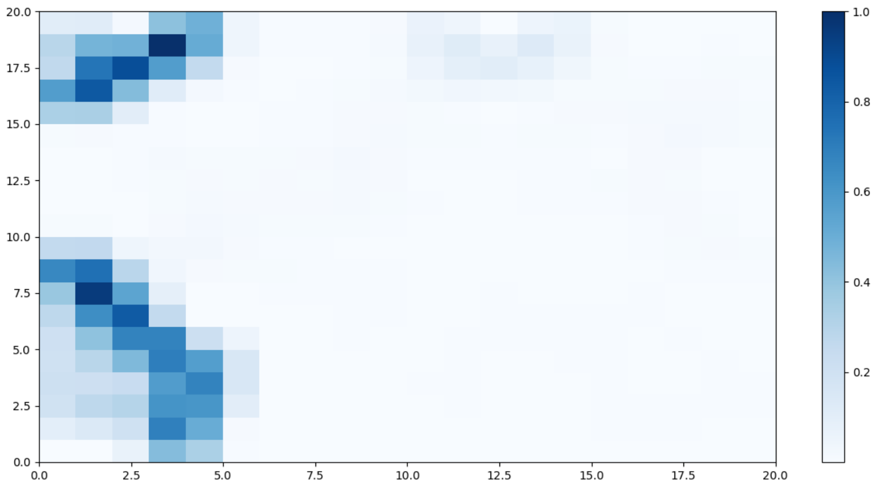


Figure 6.14: Result of the clustering process after applying the SOM.

As shown in Figure 6.14, the SOM algorithm differentiates three groups of change points, according to their similarity. In addition, due to the capacity of representing the description of the data based on the generalisation-hierarchies initially defined, the worker or domain expert can have a better idea of what is happening. That helps to manage the respective maintenance action properly.

6.4.4 Remaining Useful Life

As mentioned in section 1.6 Assumptions and Limitations, in chapter 1. Introduction, if the representation of a quantification function is not proper to perform a prediction model to check when the machine is going to fail, a set of recommendations is offered.

In this case study, as observed in Figure 6.13, the evolution over the time of the quantification function was not representative of its wear progression. Indeed, the failures registered in the dataset did not occur due to the wear of the machine, but due to unexpected external causes which were not contemplated in the analysed data.

Moreover, data was collected from the same machine, but in different moments of the process some changes were applied to that machine. Information about those changes was not available at the time of performing the estimations of the case study. Thus, it conclude in a non valid quantification trend over the time.

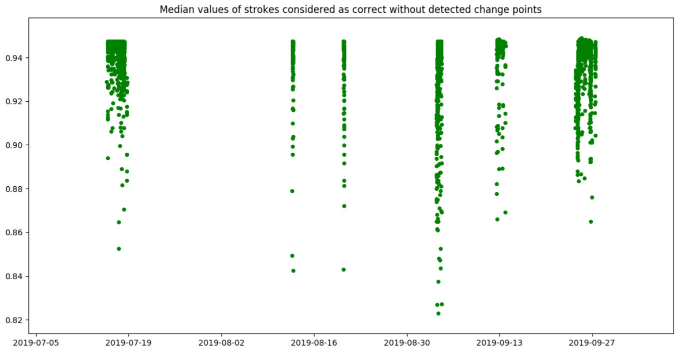
As no wear progress was noticeable in the quantification progression, a set of recommendations was proposed in this case study. Three groups of conditioned data were separated. Figure 6.15 represent those cases.

On one hand, Figure 6.15(a) shows the executions for which no change points were detected. These executions were considered as correct and their median value of the quantification function was higher than 0.82.

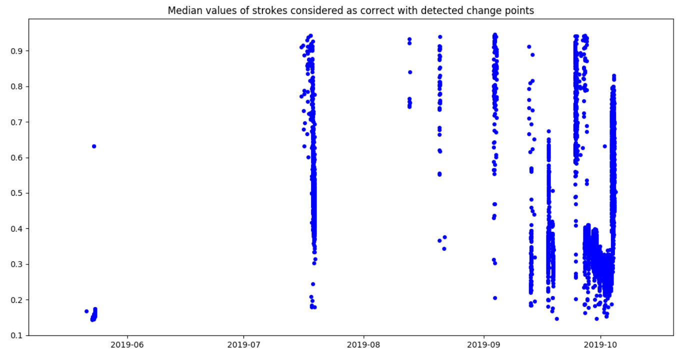
On the other hand, Figure 6.15(c) represents the set of executions that were considered as anomalies. In this case, the median value of these executions was lower than 0.63.

Finally, in Figure 6.15(b) the set of executions in which a change point was detected by the EWMA chart, but the WER did not consider to have an anomaly, is shown. In this case, the range of values in which the executions were located was wide.

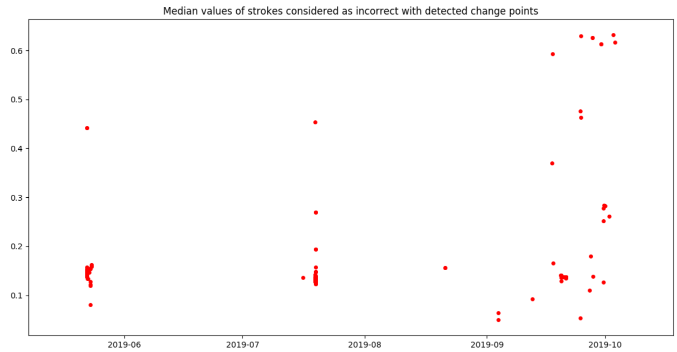
A few conclusions could be extracted from these Figures. First, it could be affirmed that if a stroke had a median of the quantification value higher than 0.82, the stroke could



(a) Correct data without change points



(b) Correct data with change points



(c) Incorrect data with change points

Figure 6.15: Median values of strokes divided into correct and anomalous executions.

be considered as correct. And second, if the median value of a quantification function was lower than that value, it should be analysed by the EWMA chart and WER.

6.5 Validation

The validation of the results of the different case studies was performed following the requirements defined in the system model defined in Chapter 4: Methodology. The different inputs and outputs for constructing the models were considered and the obtained conclusions were presented based on this.

The work methodology defined in Chapter 4: Methodology was applied in four case studies, validating different aspects of the contributions of the thesis in each one. The reason for validating the methodology and other contributions such as the capacity of the ReWAOI algorithm to obtain a quantification function that can represent the degradation trend of a monitored machine, is that the context of each case study did not enable to apply the full methodology.

To help with the validation process, domain experts were relevant in the cases in which they were present. Specifically in the Press Machine and the Cold-Forming machine case studies, the criteria of the domain experts was important due to the objective of the results obtained from the application of the methodology was to provide a decision support for the workers and experts of the area for applying the respective maintenance decisions. In the case of the estimation of Root Cause Analysis, two aspects were relevant to discuss with domain experts: (i) the description of the data provided by the ReWAOI, and (ii) the clustering process performed with the SOM to distinguish the different failure types. The descriptions should be valid for domain experts of the area because they are the ones that must interpret the results to apply a maintenance action.

Data used for the execution of the case studies was numerical in all the case studies, and the dataset was structured in work executions or simulations, as stated in the system model. In addition, anomaly containing and correct behavioural data was present in all the scenarios of this thesis. Thus, the accurate results obtained with the application of the methodology confirm that in cases in which the data is numerical, the proposed approaches are valid. Furthermore, scenarios in which domain experts of the area help define the hierarchy-tree for each attribute, as well as other scenarios in which the hierarchy-trees were constructed based on the percentile approach were analysed. Thus, this methodology can be applied in such contexts.

6.5.1 Clutch-Brake Press Machine case study

The results obtained after carrying out the experiments concerning the Press-Machine case study were validated based on domain experts knowledge. The main goal of this case study was to confirm that the usage of the ReWAOI approach for generating the quantification function was correct. The validation was carried out by estimating the Anomaly Detection (AD) and Remaining Useful Life (RUL) stages. The results obtained by the calculation of these stages were considered valid for the domain experts of the area, so the quantification function used to perform the calculations was validated too. Thus, the method defined to obtain the quantification function could be used in the rest of the case studies defined in this thesis, and was confirmed to be useful in scenarios that meet the requirements established in system model.

Moreover, another aspect of the ReWAOI algorithm was validated with the execution of the case study. The number of unclustered elements was minimised respect to the usage of the traditional AOI algorithm.

6.5.2 Turbofan (I) case study

The main objective of the Turbofan (I) case study was to estimate the Anomaly Detection and Remaining Useful Life stages using the previously validated ReWAOI approach. In this case, no domain experts were present in the case study, so the validation of the results had to be carried out in another way. For that aim, a set of anomaly containing simulations was used. At the time of obtaining the results, a subset of simulations was used to compare the predictions obtained by the usage of the LSTMs and WER-based approach. The error obtained in the comparison of the predictions and the real RUL value was low, so both stages were validated for scenarios in which degradation-containing data is present.

In addition, the change states that were used for alerting that an anomaly may occur in the future, were detected in all the cases before the occurrence of the anomaly. So the EWMA approach for detecting those small deviations in the data was also validated.

6.5.3 Turbofan (II) case study

In this case study, the goal was to estimate the Root Cause Analysis (RCA), and to group the different failure types according to the similarities of the change points detected for the simulations. As well as in the Turbofan (I) case study, no domain experts of the area were present in this case study, so the validation of the RCA was performed considering the information present in the description of the context. A Self-Organising Map model was trained using only the first change point of each simulation, and regarding the similarities of the attribute-values defined by the percentile-based hierarchy-tree construction approach, two clusters were encountered. This aspect met with the definition provided by the context of the problem, which affirmed that two failure types were present in the case study. Moreover, this aspect also served to validate the descriptions provided in the hierarchy-tree construction, being the percentile-based proposal a valid approach for estimating the RCA.

6.5.4 Cold-Forming Machine case study

In the initial step of the case study no domain expert of the area were present, so the hierarchy-tree construction was carried out using the percentile approach. Moreover, there was an a priori estimator that labelled the data as correct or anomaly containing, but no information about that estimator was provided by the owners. At the end of the process, the estimator owners validated the results provided by the ReWAOI algorithm and realised that those results were better than the ones obtained by using the a priori estimator. The conclusion extracted after performing the analyses was that there could be some simulations labelled as anomaly containing by the a priori estimator that actually were correct behavioural data.

Moreover, inspecting the quantification values of the simulations, the conclusion indicating that the anomalies registered for this case study was not due to a degradation but because of external conditions (different ways of measurement, material substitutions, etc.) was validated by domain experts. Thus, the ReWAOI was validated to be an approach that can obtain more reliable and trustworthy results for Anomaly Detection even in scenarios in which no degradation is present in the data.

The main validation aspect of this case study was the capacity of the ReWAOI to detect anomalies in scenarios in which no degradation data is present.

6.6 Conclusions and Remarks

After completing the four case studies in this thesis, different conclusions can be extracted.

First of all, and referring to the Press-Machine case study, it should be remarked that although the proposed methodology was not completely followed, the objective was met: validate the use of the Repetitive Weighted Attribute Oriented Induction algorithm. Hence, this case study enabled the definition of the remaining work methodology, with the guarantee that the algorithm proposed (ReWAOI) in this thesis could provide accurate and reliable results.

When assessing the results, the estimation of RUL is remarkable for studies 1 and 2. Although the choice of LSTMs seemed the best in the literature review, using a simple Auto Regressive (AR) time series model the system was able to model the quantification trend with little error margin. The reason for using a simple AR model in the Press-Machine case study was trying to simplify the calculations. The objective was to find a way to model a numerical function with autocorrelation between the data. The major effort of this case study focused on properly adapting hierarchy-trees and defining the allocation of weights to clusters to generate an adequate quantification function.

Related to the second and third case studies, their contextual characteristics are similar, but they were used to validate specific aspects of the methodology. An important aspect of these case studies is that no domain experts were available to help establishing the parameters of the inputs to define the ReWAOI algorithm. Thus, an alternative was defined. The goal was to enable the execution of the algorithm to be appropriate for accomplishing the objectives. As demonstrated in the results, this alternative is appropriate as long as the initial values of the machine variables are numerical. If there were nominal variables, another way of creating hierarchy-trees should be considered.

Within the Turbofan (I) case study an LSTM neural network architecture was defined to model the quantification function. The definition of this architecture was decided so that the results of the modelling were accurate, but as previously mentioned, the core of this case study was not based on defining an LSTM model as accurate as possible. As well as in the Press-Machine case study with the AR model, the goal was using a tool that would enable: (i) validating the conclusion drawn from the literature review; and (ii) help achieve results that validate the methodology proposal. In this sense, the LSTM model definition was demonstrated to be valid to model the quantification function accurately.

Moreover, the decision to use a system like the Western Electric Rules enabled having a way of generalising the criteria to choose when to stop the prediction process with a very small error margin.

In addition, it is interesting to comment the results obtained in the case study Turbofan (II), regarding the clustering process and RCA. Being a dataset that had little contextual information, as well as absence of domain experts, it is difficult to assess the capacity of the RCA model. But on the other hand, working with the ReWAOI algorithm in the same way as in the case study Turbofan (I) where there was only one type of error, the SOM model was able to detect two differentiated groups between the simulation change points. This fact refers to the presence of two types of error trends in the dataset, just as in the context information is specified. Thus, that was an important factor to validate the proposal.

Finally, on one hand the Cold-Forming machine case study needs a special mention related to RUL estimation. In this case study, the collected data come from the same machine, but many changes were performed on it over the time. Thus, the evolution of the wear of the machine is not perceptible, and a predictive model for estimating the time until the next failure cannot be performed. However, different conclusions about the inspected data were provided, in order the domain experts to know more about the conditions in which the machine is working. This case study is interesting to show that in many cases there can be a situation in which the evolution of the wear of the machine is not clearly represented.

On the other hand, Anomaly Detection and RCA estimations have been considered valid, reinforcing the proposed methodology and algorithms to use.

For AD, the validation of anomaly data prediction is relevant. Although the data came labelled, this criteria was not tested a priori, so this labelling cannot be considered at all. The specificity of anomaly data of the ReWAOI in comparison with the a priori method is low, and the conclusion that can be extracted from this is that the difference of the anomalous data in relation with the correct data could not be significant. If the ReWAOI is trained with only correct behavioural data and it is not able to detect as much abnormal data as the a priori method, could be due to some of the data that the a priori system considers anomalous are very similar to correct behavioural data. So, there could be many elements that are preferable not to be considered as anomalies. This is the reason why domain experts are crucial at the time of validating the results.

Moreover, as the precision when predicting anomaly data of the ReWAOI is higher than the precision of NullSpace respect to the a priori method, it can be concluded that ReWAOI works better in unbalance datasets that other Anomaly Detection methods.

Chapter 7

General Conclusions and Future Research

The main contribution of this thesis is the design and implementation of a methodology that meets the stages established in the Predictive Maintenance methodology. Tasks such as Anomaly Detection, Root Cause Analysis and Remaining Useful Life were addressed. These tasks were validated by means of four case studies in which the proposals were presented separately.

A study of the state of the art was first carried out that greatly helped in the realisation of the thesis. The goal in this thesis was the use of clustering based methods for the estimation of the stages defined for Predictive Maintenance. Data collected in industrial sector is typically unlabelled, so correct and failure states are not specified. In addition, knowledge of experts is relevant to help achieve more reliable results. Thus, the selected algorithm is the Attribute Oriented Induction, which is a hierarchical clustering algorithm which combines data collected with knowledge of domain experts. The inspection of the most relevant techniques for the AD, RCA and RUL, enabled to validate the adaptation of the initial proposal, and combine it with other techniques.

Moreover, an additional contribution was in the adaptation, creation and implementation of a variant of the AOI algorithm for the execution of the proposal: Repetitive Weighted Attribute Oriented Induction (ReWAOI). This variant enables the traditional AOI algorithm to run repetitively, feeding on the unclustered elements of the previous iteration, in order to fully fill the Knowledge Base. In addition, the algorithm establishes weights to each cluster depending on their frequency of appearance in the process of the machine, facilitating the identification of the most common states.

Once the ReWAOI algorithm was defined, the next step was to validate it in the Press-

Machine case study, in which the final methodology was not yet defined. The results of that case study were positive, which confirmed that the use of ReWAOI is successful.

Finally, a working methodology was defined to comply with the calculation of Change Detection, Anomaly Detection, Root Cause Analysis and Remaining Useful Life. This methodology was validated in three more case studies.

7.1 General Conclusions

The most relevant conclusions after the completion of the thesis are expressed below.

7.1.1 Case Studies

In this thesis we have worked with four case studies. Each case study was oriented to the validation of a specific aspect. In addition, they were explained in the same order in which they were developed in the thesis to better represent the evolution of the process.

Domain experts were present in the Press-Machine case study, and that was one of the most relevant aspects. This fact enabled working with ReWAOI in the way it was desired, and confirming that the algorithm is valid for such scenarios.

Subsequently, in the second, third and fourth case studies, there was already a defined and matured work methodology, and the idea was to apply it in order to confirm its validity. These three scenarios were more complicated to deal with, since there were no domain experts to establish the parameters of the ReWAOI. For that reason, an alternative method of creating generalisations was proposed, achieving accurate results. Hence, it was validated that the algorithm can work despite not having information from domain experts. The capacity of the ReWAOI to establish a weight to the process states according to their frequency of occurrence, despite the absence of domain experts, was demonstrated.

This fact does not have to contradict the statement that was concluded from the literature review. It would be necessary to demonstrate if better results could be achieved with the help of the domain experts.

Finally, in the case of the Cold-Forming machine case study, the full methodology was applied. The estimation of both Anomaly Detection, Root Cause Analysis, and the Remaining Useful Life were carried out, but in the case of the RUL, a set of recommendations was provided instead of the calculation of the remaining executions until a break. This leads to a clear conclusion. In those cases in which the anomalies happen due to other factors than the wear of the machine or asset, the RUL cannot be calculated as a remaining time until a failure occurrence.

In conclusion, the selected case studies were utilised to validate the proposals defined in the thesis.

7.1.2 Repetitive Weighted Attribute Oriented Induction

As mentioned, one of the main contributions of this thesis is the definition of the ReWAOI algorithm.

Thanks to its potential of assigning weights to the clusters that it generates, it is capable of converting a multivariate dataset into a univariate one. This aspect is important, since it eased the calculation of RUL through time series techniques and neural networks, but without omitting context information, since it can be extracted from the quantified value. As the signals referred by the case study variables are dependent on each other, calculating the RUL individually for each variable is not contemplated. Turning the representation of multiple attributes into a single function the analyses were eased.

Initially, the ability to represent the information of the AOI algorithm was expected to be helpful at the moment of displaying the results of the RCA calculation. But, bearing in mind that it combines the information both obtained from the machine and offered by the domain experts, the decision was to generate a way to quantify a function that is representative for the calculation of the wear of the behaviour. Therefore, this algorithm was the basis on which the thesis was built.

Moreover, the algorithm was implemented on the Apache Spark execution framework. This enables the ReWAOI to be scalable to Big Data scenarios where the necessity is to work with large amounts of data in an agile way. In this thesis there was not any similar scenario, all use cases had small amounts of data, but if necessary, it could be applied.

In conclusion, the algorithm implemented to address the solutions was successful, and enabled the system to obtain satisfactory results. The algorithm was validated to help achieving accurate results in the Predictive Maintenance scenario.

7.1.3 Change Detection

The EWMA control chart was the technique chosen to carry out the Change Detection. Its application is relevant in the proposed methodology since it is able to detect small changes in behaviour that can lead to an error or anomaly. In this way, the offering advantage is that it is capable of generating an alert or warning for the system before the error occurs, and thus be able to act in time to carry out the maintenance action.

In order to apply this technique having correct functioning data recorded in the data history is necessary. For this aim, the validation of domain experts is important, since depending on what is determined as "correct data" the result of the application of the EWMA control chart is different.

In reference to the case studies in which this technique was applied, the change points were detected before the error was identified. That is a very important factor, since as mentioned, the idea of Change Detection is to serve as a warning that the process may have started to work out of the normality. Subsequently, the detection of anomalies was developed with precision, so the moment of detection of the change point was considered correct.

Therefore, the choice of the EWMA control chart was successful for the detection of unusual states before the error occurs.

7.1.4 Anomaly Detection

In the calculation of Anomaly Detection, two aspects must be distinguished: (i) the use of the Normality Factor, and (ii) the use of the Western Electric Rules (WER).

In the Press-Machine case study the Normality Threshold technique was used. As a first approximation it may be appropriate since a threshold is established on the quantification function in relation to the minimum value of the data considered as correct.

Thus, if the threshold is exceeded, a rare state is identified, and it may be considered as anomaly. However, in this case study there is no way to validate the effectiveness of the system, since the anomalies are not previously registered. Only domain experts were able to state whether the detection of an anomaly was considered a true anomaly.

Moreover, the method defined by the WERs is a more generic way of detecting the anomaly. Depending on the scenario, the way of detecting an anomaly can vary, therefore, in the proposed methodology which of the 4 WERs fits best is inspected.

It can be concluded that the use of WERs gives a clearer sense to the detection of anomalies, and that it is an accurate method to be applied in the methodology.

7.1.5 Remaining Useful Life

For the calculation of the RUL, two different methods were used among the four case studies. Specifically, the calculation of the RUL was treated in the first two use cases, using an AR model in the first, and an LSTM in the second. In the case of the Cold-Forming machine case study the RUL was estimated as a set of recommendations due to the registered anomalies did not happen due to the wear.

LSTMs can work accurately for tasks in which future states of a numerical simulation must be predicted. Therefore, when defining the working methodology, the suggestion was to calculate an LSTM model. In the first case study, an ARMA time series model was calculated, obtaining precise results when predicting the evolution of the quantification function. The reason for not using a more complex model such as the LSTM is that the fundamental objective of that use case was to validate the use of the ReWAOI algorithm.

Moreover, in the second case study, a solution according to the proposed methodology was implemented. In this case, the use of neural network models for predicting the future trend of the quantification function was validated for providing accurate results. The results of using the LSTM model could be better by optimising the architecture of the implemented neural network. In this case due to both time constraints and the achievement of accurate results, it was decided not to focus more on that aspect, not being the core of this thesis.

The idea, after all, is to be able to model the behaviour of a numerical function over time in those cases in which the faults appear due to a wear of the machine or asset. In this thesis the use of LSTM models is suggested given the assumption that the evolution of the quantification function may be due to various factors, not only to the observation of previous values. But in some cases, models such as time series may help achieving accurate results in the same way.

7.1.6 Root Cause Analysis

After the inspection of the literature, the conclusion was that the RCA is an aspect that should be discussed with domain experts. It is difficult to provide a clear answer to the question of: *What is the reason for the failure?* Therefore, the objective in this thesis was to provide the maximum possible information to help the domain experts to take a decision. It must be borne in mind that the methodology proposed is intended to be a system to help decision-making, or in this case, to take maintenance actions.

Therefore, the RCA system of this thesis aimed to be able to detect if a change point is equivalent to one type of anomaly or another, as well as to provide a description of its states.

When the SOM model is generated, it is able to detect a specific number of change point types. However, if a new unregistered change point type is registered for a simulation, the SOM model would not be able to categorise that change point as a new type. It would be assigned to any of the existing clusters. In this thesis, that scenario is not considered, this methodology is thought to be used for categorising previously known and invariable failure types. But a different SOM implementation is available, named Growing SOM (GSOM) [108], that can be used for that purpose, as a future work.

The way to validate this type of calculation is also complicated, and in most cases, subjective. In the Turbofan (II) case study, domain experts were not present to validate the results, however these were consistent with the description. The system distinguished two groups of change points that could lead to the event of an anomaly, as explained in the description of the problem.

Therefore, it can be concluded that the RCA calculation system in this thesis is valid, and can be a support for domain experts.

7.2 Final remarks

The final conclusion that can be drawn from all this is that the Repetitive Weighted Attribute Oriented Induction algorithm proved to be valid to help achieving the objectives set at the beginning of the thesis. ReWAOI was the key that helped converting a multivariate dataset to a representation of the behaviour states in a single variable. In this way, the calculations were eased and applying the proposed methodology was possible.

Additionally, the methodology defined in the thesis, with the ReWAOI algorithm as its main element, was valid to comply with the stages of the Predictive Maintenance methodology. This statement is made because the obtained results were consistent and with a low error rate. Thus, through this methodology, the intention is to be considered as a suggestion to calculate the components of Predictive Maintenance, as well as a support system for maintenance decision making.

7.3 Future Work

After the completion of the thesis, some points to be addressed in the future were extracted.

First, applying the proposed methodology in environments where there are real data and domain experts is expected. The Press-Machine case study is a real case in which domain experts took part, but due to time constraints defined by the European project MANTIS, and the location of the case study in an early development moment of the thesis, the methodology was not fully applied.

Furthermore, the intention is to contrast the results that would be obtained in that scenario by defining the generalisations with the help of domain experts, and through the percentile system. Thus the effectiveness of the proposed method could be compared, and validated in another way.

Moreover, the intention is also to apply the ReWAOI algorithm in environments with large amounts of data to assess the efficiency of the Apache Spark implementation. The case studies in which the algorithm was applied did not have special requirements at the level of data volume in the realisation of this thesis. It is a factor which is wanted to be tested in order to confirm whether the implementation was adequate.

Regarding the RCA calculation, as mentioned in section 7.1.6 Root Cause Analysis, when a new type of change state is detected in a simulation, the SOM model would not be able to categorise it in a new group. Thus, application of GSOM approach is considered for future steps, in order to scale the 2-dimensional representation matrix. This approach was not studied in this thesis, but it is future line that is wanted to cover.

For the estimation of the RUL, the implementation of the architecture of the LSTM neural network could try to be improved in order to minimise the calculation error. As mentioned previously, it was not the core of this thesis, and the use of LSTMs was already validated, but it is wanted to inspect whether the proposed architecture has scope for improving.

It also remains to be analysed whether the implemented algorithm can be used in other contexts in which there are processes with a beginning and an end, outside the maintenance environment.

Finally, the intention is to work on a case study in which the whole methodology can be tested. Although the methodology was fully applied in the Cold-Forming machine use case, the RUL part was not estimated, and a set of recommendations was offered. A scenario in which multiple failure types are detected and the RUL for each of the failures is estimated is remaining.

Moreover, in this thesis, due to the characteristics that each case study had, the methodology was partially validated in the Turbofan and Press-Machine cases. The ideal scenario would be performing an experiment in which the ability to detect change points, the estimation of the RUL, the Anomaly Detection, and the RCA, could be performed together. Hence, the potential of the methodology proposed in this research work would be better confirmed.

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