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A joint framework for condition-based maintenance integrating Prognostics and Imperfect maintenance effects

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Alla mia famiglia

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Abstract

Every system at a certain point of its life-cycle requires maintenance, with the overall aim of restoring its functionalities. However, such intervention is not always perfect, but could bring the system to an intermediate condition between as-good-as-new and as-bad-as-old: this generalization of the concept of maintenance is called imperfect maintenance. The present thesis aims to bring further insight to this topic applied in a condition-based maintenance context, which benefited from the developments of sensors technology and data processing of last years. With this goal in mind, the work proposes a literature review of the state of the art of the subject. From such analysis emerged first of all that the publications tend to perform an optimization of the maintenance policies making assumptions about the degradation of the system and the effects of the imperfect maintenance instead of trying to estimate them. Secondly, most papers lack of a real application, focusing more on numerical assessments without detailing the nature of the asset and the types of maintenance performed. These gaps found in literature are used to set the objective of the work: the development of a framework for a condition-based maintenance model which aims to identify and quantify the degradation pattern and the imperfect maintenance effects in order to improve the asset prognosis and the recommendation of types of maintenance intervention. Such operative framework aims to guide the user in the implementation of a condition-based maintenance model where the imperfection of the repairs is given by their capability of restoring only one of the failure modes which cause the degradation, leaving untouched the others. The main peculiarity of the model consists in the adoption of machine learning techniques using condition monitoring and historical event data to characterize the degradation of the asset together with the maintenance effects; this information is utilised in a real time logic with the aim of improving the present actions. The framework is then assessed starting from a dataset made available by the Industry 4.0 Lab at Politecnico di Milano; this part constitutes a practical example of the CBM model too.

Chapter 0

Executive Summary

0.1 Research motivation

Every system at a certain point of its life-cycle requires maintenance, with the aim of restoring it to a state in which it can perform its function. Maintenance can therefore be seen as an essential solution to avoid failures, increase the asset availability, extend its lifetime and allow to operate it in safety. However, often in practice due to several reasons such intervention does not restore the system completely but brings it to a state between as-good-as-new and as-bad-as-old; this kind of repair is called imperfect maintenance and can be seen as a generalization of the maintenance concept itself.
Imperfect maintenance began to be object of study during the 1970s, gaining popularity with the years and undergoing the influence of the technological context. During the last decades it was in fact seen an increased interest toward models based on a condition-based maintenance policy, based on the actual conditions of the system, rather than time-based maintenance models scheduling interventions at predetermined intervals. Such phenomenon was then enhanced by the advent of the Fourth Industrial Revolution during last years, which brought a great development to sensors technology and techniques capable of processing and elaborating large amounts of data, tending to move the condition-based maintenance towards enhanced prognostic capabilities. In such scenario still in evolution imperfect maintenance can therefore find new investigation lines, with the overall aim of being able of better characterizing complex assets and improve their maintenance management.

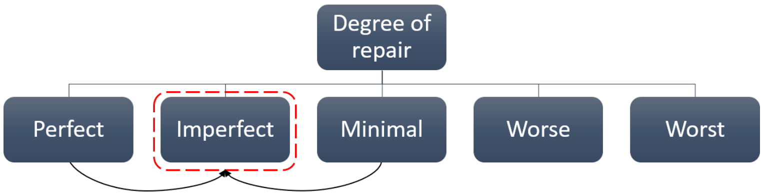

Figure 1: The different degrees of repair/maintenance. Classification according to Pham et al. [1]

0.2 Methodology

Made the previous considerations, this thesis aims to provide further investigation to the concept of imperfect maintenance applied to a condition-based maintenance policy. In addition, the study is conducted in a context where no run-to-failure data about the system are available, since this choice allows to be closer to reality and to the exigencies of modern industry. To achieve this goal, first of all is presented a literature review about the topic, with the aim of individuating possible research areas. Then, basing on the results obtained, the practical part of the work consists in the formulation of an operative framework illustrating an innovative approach in the application of imperfect maintenance to a system continuously monitored through sensors. Finally, the model developed is assessed through a simulated experimental campaign built on a reference dataset made available by the Industry 4.0 Laboratory of the School of Management of Politecnico di Milano.

0.3 Literature review

The scope of the literature review is to build a wide yet profound knowledge about imperfect maintenance and describe its state of the art in the context object of study. To do so, a keywords based research was established with the aid of Web Of Science and Scopus databases; the initial results were then progressively filtered, leaving 47 selected papers to be classified according to specific drivers.

The actual classification was made with the aid of six tables, describing different aspects of the state of the art about the topic. The first table gives a general overview about the papers, reporting their industrial field, the application they deal with and their main content. The second one focuses on the models used to describe the degradation and the inspection policies applied. The third table shows the maintenance policies in use, specifying also what are the types of intervention included and if the model aims to estimate the remaining useful life of the asset. The fourth describes the imperfect maintenance itself in terms of its effects on the system. Finally, the fifth and the sixth tables show, respectively, the optimization targets of the models and what are the related variables.

What in general emerged from the analysis is a tendency of the publications to perform an optimization of the maintenance policy rather than using the data acquired to characterize the system in terms of degradation and imperfect maintenance effects, updating then the related parameters as new information arrives; these aspects are in fact usually assumed at priori. This is particularly true for systems monitored continuously through sensors and for which the target is to predict their future conditions. In addition, there emerged a generalised lack of real applications for the models developed and an absence of details regarding the nature of the assets and the types of maintenance performed.

0.4 Research objective

Taking into consideration the findings of the literature review and with the target of contributing in an innovative ways to such research area, the following research objective is formulated:

"The development of a framework for a condition-based maintenance model which aims to identify and quantify the degradation pattern and the imperfect maintenance effects in order to improve the asset prognosis and the recommendation of types of maintenance intervention."

To achieve this goal, an operative framework is formulated and then presented. It has the objective of giving guidance in the implementation of the CBM model proposed; for this reason, its purpose is to be as general as possible. After that, the framework is assessed starting from a reference dataset of the Industry 4.0 Lab and using that data to design a simulated experimental campaign. This part is focused on a specific situation, with specific modelling choices, and acts as a practical example of the CBM model too.

0.5 Operative framework presentation

The operative framework developed consists in a CBM model in which the concept of imperfect maintenance is associated to the one of failure mode:

the repairs are imperfect since they restore the degradation corresponding to one of its failure modes. The main innovation, in addition to some improvements in the estimation of the remaining useful life, lies in the ability of characterizing the effects of the imperfect maintenance actions in order to expand the prognostic capabilities of the model: thus, the traditional RUL prediction is accompanied by the estimation (prediction) of the type of intervention to be executed at the next repair.

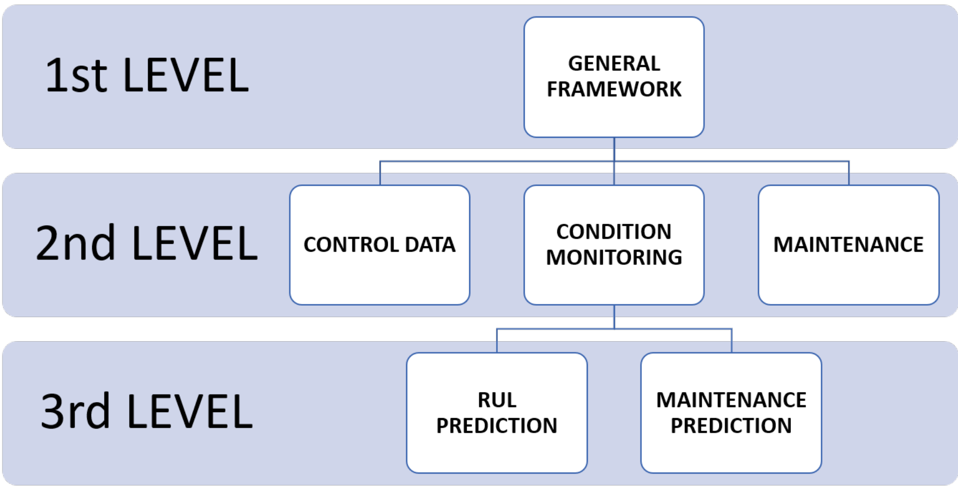

Figure 2: The three levels of detail of the operative framework

The framework is represented in a hierarchical model form organised on three levels, so that each part of the CBM model is progressively explained and implemented in detail. Figure 2 gives a graphical representation of such organization.

The first level of detail consists in the **general framework** itself (ref. Figure 3), which is a macro representation of the relationships between the other main blocks. It in fact describes the cyclic succession of condition monitoring and maintenance on the asset which usually characterizes its life-cycle; these two phases are supported by the control data. In addition, the condition monitoring phase is supported by the information elaborated at the moment of maintenance, with the aim of improving the present actions.

The **control data**, on the second level, are the ones necessary to execute correctly the different parts of the CBM model. In particular, they can be divided into degradation control data, which allow to monitor the health

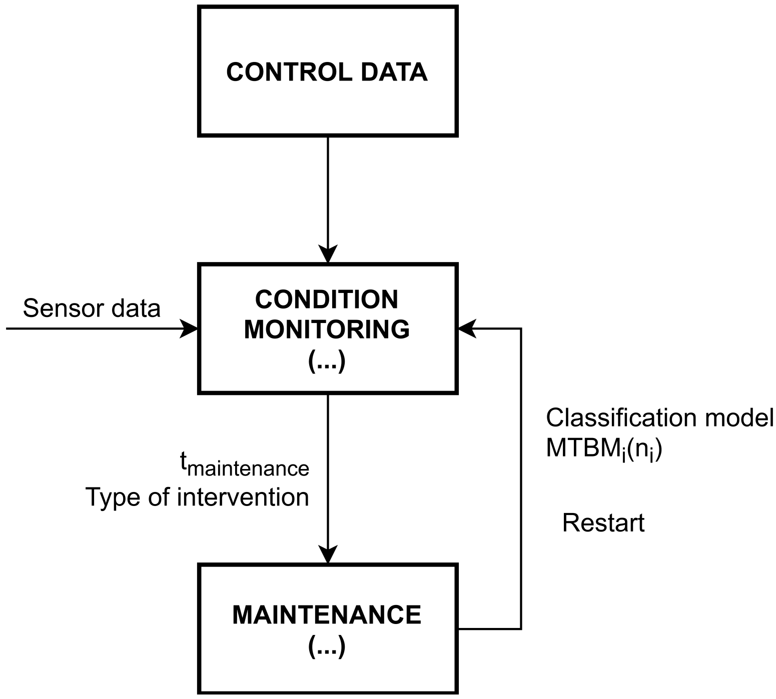

Figure 3: General framework of the CBM model

state of the asset; logistic data, needed to schedule and organize the maintenance; models inputs, which are specific data required by the different models part of the framework.

The **condition monitoring** is the phase in which the degradation of the asset is supervised, in order to schedule maintenance at the right time and avoid failures. Here sensor data are collected in real time and elaborated to acquire information about the present conditions of the asset, with the target of determining the future ones. This part is further specified in the third level of detail by creating two other blocks: the RUL prediction and the maintenance prediction.
The **RUL prediction** step aims, as the name suggests, to estimate the remaining useful life of the asset. In particular, an improvement is made to this process, i.e. the continuous choice of the degradation model basing on the sensor data. It is in fact implemented a feature which allows to choose every time new data are acquired the degradation function most adapted to represent the deterioration pattern, continuously updating at the same time the curve coefficients and the RUL estimation.
In the **maintenance prediction**, which represents another innovation point

of this work, is decided which is the type of repair to be executed at next maintenance. This involves the estimation of the failure mode responsible of the deterioration and a consequent decision-making phase based on the past experiences recorded. These steps are achieved mainly using two machine learning approaches: a classification model of the failure modes, which records how they evolve maintenance after maintenance, allowing to make predictions about them; the regression of the repair intervals, creating the mean time between maintenance functions $MTBM_i(n_i)$ (where i is the failure mode index) which indicate when each failure mode is going to reappear after being maintained basing on how many times the same one was observed (n_i). They both represent, in different ways, an expression of the effects of the types of imperfect maintenance, whose behaviour is thus captured and used to improve the prognostic step.

The **maintenance** is the part in which not only is executed the actual repair on the asset, but also the data gained during the condition monitoring are elaborated a posteriori. In particular, the main innovation here is the updating of both the classification model and the mean time between maintenance (MTBM) functions: thus it is obtained a continuous update of the effects of the imperfect maintenance types, whose aim is to increase the knowledge of the phenomena occurring in order to do better in the future.

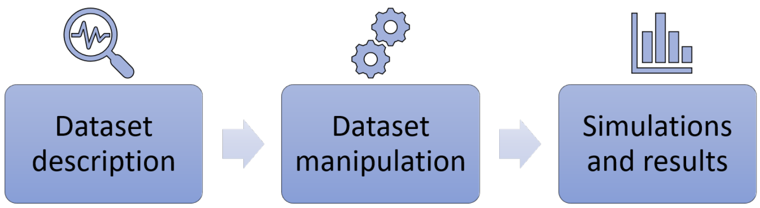

Figure 4: The three assessment steps executed

0.6 Framework assessment

The assessment of the framework is obtained through three main steps (ref. Figure 4): the analysis and description of the original dataset of reference, which reports the vibrations along the spindle axis of the drilling machine of the laboratory, and the extraction of information from it; the manipulation of such dataset in order to generate another one coherent with the previous information and suitable for the testing purposes; the execution of the actual simulations and the presentation of their results.

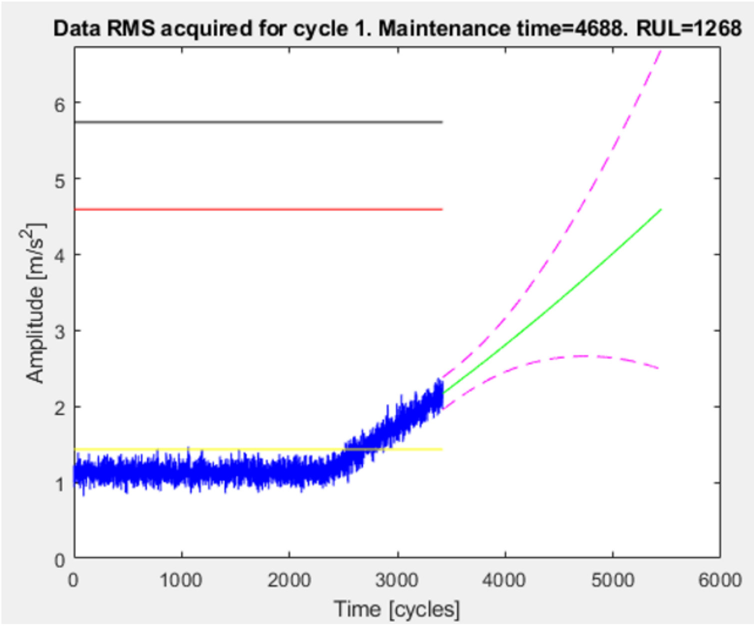

Figure 5: Example of fitting of a linear degradation pattern

Three innovative features of the framework were object of testing: the choice of the degradation function for the remaining useful life estimation, the failure modes classification model and the regression of the mean time between maintenance (MTBM) data.

The first feature was tested using different failure modes modelled to have distinct different patterns: in Figure 5 is for example reported a linear one. Here, the model showed to be effectively capable of selecting the best function in order to represent the type of degradation seen. This results in a more reliable and self-adaptable estimation of the remaining useful life, with a consequent improvement in the maintenance scheduling process.

For what concerns the failure modes classification model, it was discussed by means of the behaviour of its validation accuracy training after training (ref. Figure 6) and in terms of its actual prediction capabilities. In particular, there emerged that 30-50 observations were necessary to reach a good accuracy, which however is a feasible number if the monitoring is done across many assets of the same type; secondly, the classification model was correct in circa the 85% of the cases. For this reason, such innovative feature results to be a potentially useful tool to expand the prognostics on the asset, allow-

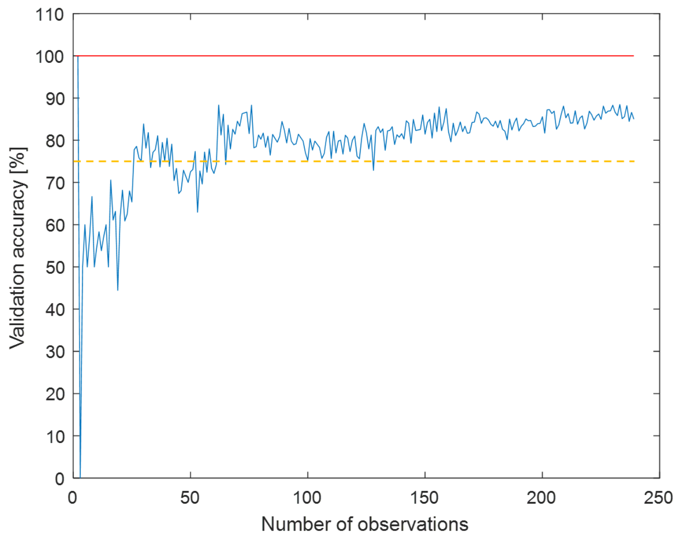

Figure 6: Validation accuracy of the classification model based on the number of observations used for its training

ing the user to know not only when to execute maintenance, but also the dominant cause of degradation; this additional information could enhance the decision-making phase about the type of intervention and improve the maintenance organization process.

Finally, the results of the regression of the mean times between maintenance data were discussed with the aid of selected images, like for example Figure 7; they demonstrated the feature capability of capturing the general trend, together with its variability, of the maintenance intervals for the failure modes. Thence, this innovation results to be another potentially useful tool, capable of understanding when the imperfect maintenance actions lose efficacy, making the user to opt for a more complete repair, and allowing to have a first estimation of the time taken by the failure modes to cause critical levels of degradation, with further improvements in the asset prognosis and the maintenance decision-making.

0.7 Future works

The work presented has possible investigation lines which could be expanded in future studies. In particular, the main ones individuated are:

- **Collaborative maintenance**: the framework for the CBM model

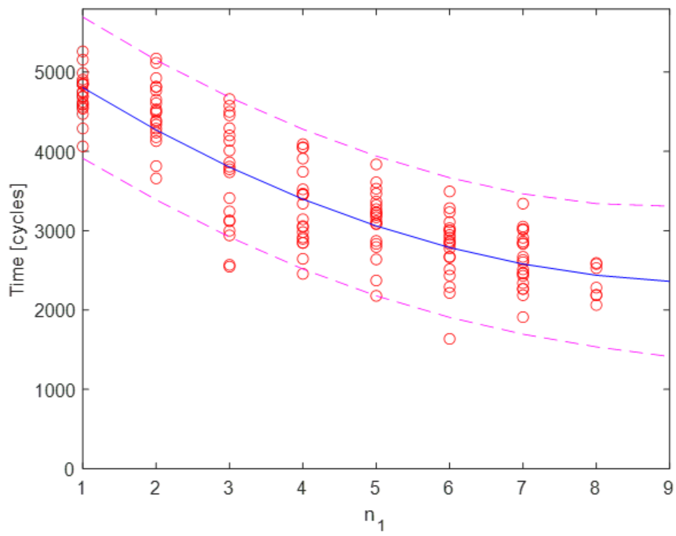

Figure 7: Example of Mean Time Between Maintenance curve

presented has the feature of performing a dynamic characterization of the asset as event and condition monitoring data are acquired. It could be interesting to integrate such learning process with the concepts of Social Internet of industrial assets and collaborative prognostics. This would require to face challenges like the storage of data in a shared database, their retrieval and their usage between different machines.

- **Multiple maintenance lead times**: the present work approaches the maintenance scheduling more from a prognostic perspective, bringing to the assumption of the same lead time for all kinds of intervention. However, such hypothesis is true only in some situations. Therefore, relaxing such constraint would make possible a generalization of the framework and the integration in it of the logistic aspect of maintenance.

- **Maintenance optimization**: the literature review showed a strong presence of publications aiming for an optimization of the maintenance policy. Following this route, the findings of this work could be used to explore new aspects of the optimization approach, which would benefit from an enhanced prognostic on the asset.

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Chapter 1

Research objective

1.1 Research motivation

Every system at a certain point of its life-cycle requires maintenance, with the aim of restoring it to a state in which it can perform its function. Maintenance can therefore be seen as an essential solution to avoid failures, increase the asset availability, extend its lifetime and allow to operate it in safety. For this reason, different studies have been conducted during the years about the topic, optimizing the maintenance strategy in order to increase the system performances at the lowest cost. In particular, a branch of these works which was born in 1970s and has increased in popularity with time regards the concept of imperfect maintenance, which can be defined as a kind of repair which brings the system to an intermediate condition between as-good-as-new and as-bad-as-old. In fact, traditionally maintenance is modelled as a type of intervention able to restore completely the asset. However, such an approach finds scarce application in reality due to several factors which can affect the result like human errors, materials quality, lack of spare parts and time, etc. This is particularly true for complex systems, where the interventions tend to focus more on the substitution or repair of single components rather than restoring completely the asset. For this reason, imperfect maintenance can be seen as a generalization of the maintenance action, whose study allows to approach more closely real life applications.

As previously said, the concept of imperfect maintenance has increased in popularity with time, undergoing the influence of the technological context. During the last decades it was in fact seen an increased interest toward models based on a condition-based maintenance policy, which aims at scheduling repairs basing on the actual conditions of the system instead of at predetermined intervals, allowing savings in terms of time and costs and more effective interventions. Such phenomenon was then enhanced by the advent of the Fourth Industrial Revolution during last years, which brought a great development to sensors technology and techniques capable of processing and elaborating large amounts of data. This provoked an evolution of the traditional condition-based maintenance, which became more prognostic and focused on assessing the future conditions of the asset. In such scenario still in evolution imperfect maintenance can therefore find new investigation lines, with the overall aim of being able of better characterizing complex assets and improve their maintenance management.

1.2 Objective

Made the previous considerations, this thesis aims to provide further investigation to the concept of imperfect maintenance applied to a condition-based maintenance policy. In addition, the study is conducted in a context where no run-to-failure data about the system are available: such datasets in real cases are in fact difficulty retrievable and their acquisition usually requires onerous experimental campaigns which in the last years have been often substituted by simulation approaches. This choice therefore has the target to bring the research closer to reality and to the modern industry exigences.
To achieve the target of this work, first of all is presented a literature review about imperfect maintenance in the described context, with the aim of illustrating the actual state of the art about the topic and individuate possible areas of study. Basing on the results obtained, the following research objective is formulated: the development of a framework for a condition-based maintenance model which aims to identify and quantify the degradation pattern and the imperfect maintenance effects in order to improve the asset prognosis and the recommendation of types of maintenance intervention.
This target is then achieved through the practical part of the work, which consists in the formulation of such an operative framework, illustrating an innovative approach in the application of imperfect maintenance to a system continuously monitored through sensors. Finally, the CBM model developed is assessed through a simulated experimental campaign based on a reference dataset made available by the Industry 4.0 Laboratory of the School of Management of Politecnico di Milano.

1.3 Structure of the text

The thesis is organised in seven chapters. After the current introduction, the pillar concepts about Industry 4.0 and maintenance are briefly described in Chapter 2, in order to contextualise the work and give some basic information about its topics. Then, Chapter 3 presents the literature review conducted, reporting at the end the gaps found. These last ones are used to formulate in Chapter 4 the research objective and expose the methodology followed in Chapter 5 and Chapter 6 to, respectively, present the framework and perform its assessment. Finally, Chapter 7 reports the conclusions of the work, summarizing its contributions and discussing some further research areas available.

Chapter 2

Pillar concepts

The current industrial context is characterized by a period of great technological disruption, usually known with the term of Industry 4.0. Such transformation is based on the possibility of collecting and analysing data across different machines, resulting in an increased efficiency, flexibility, quality and speed of processes at reduced costs. This revolution is therefore changing various aspects of the industry, having influences on the global economy, the structure of the supply chains and people, intended both as customers and workforce [2].

One of the manufacturing aspects which is strongly influenced by Industry 4.0 is the maintenance field [3]. The main target of maintenance consists in ensuring the availability of the asset, palliating situations like costly and unscheduled downtime and unexpected breakdown, which represent major threats to the production efficiency. Traditionally, the maintenance approach was kindly static, based on fixing the equipment at failure or preventively with the aid of past experiences to estimate its expected lifetime, with the main risk of substituting good parts and incurring in failure due to an unforeseen faster degradation. However, with the advent of Industry 4.0 and the consequent availability of massive data from processes and systems, new maintenance opportunities arise. In particular, it gives the possibility to operators to monitor the actual conditions of the asset and from that compute predictions about the future status, thus anticipating failures and providing benefits in terms of production, logistics, safety and quality [4].

Made such premises, the current chapter aims to illustrate some basic concepts useful for the comprehension of this thesis work. In particular, Section 2.1 reports a brief description of Industry 4.0, introducing its main aspects in order to give a vision of the current technological context; Section 2.2 gives an overview on the base theory about maintenance and introduces the concept of imperfect maintenance, main topic of this work

2.1 Industry 4.0

2.1.1 Introduction

Industry 4.0 is often named as Fourth Industrial Revolution. The term industrial revolution indicates a period of great technological disruption, which provokes important and irreversible changes not only to the industrial fields but to the entire society too. To characterize properly Industry 4.0 is therefore first of all necessary to retrace the path which brought to it, starting from its predecessors.

The First Industrial Revolution happened in Britain by the end of 18th century (1760-1840). Its main characteristic was the introduction of steam-powered engines and water as a source of power. These changes were brought first to agriculture and then to the textile industry, which benefited enormously from the aid of machines in the production in substitution to manual power [5][6].
The Second Industrial Revolution took place between the 1870 and 1914 and was characterised by the introduction of mass production, represented as icon by the assembly line. This drastic change was possible mainly thanks to the electrification of factories, together with the introduction in the facilities of preexisting systems like the telegraph and railroads [5][6].
During the second post-war period (1950-1970) entered the scenes the Third Industrial Revolution, often named as Digital Revolution or Information Age. This one resulted from the huge development of computers and information technology, which brought to a shift from analog and mechanical systems to digital ones [5].
Finally, the Fourth Industrial Revolution, or Industry 4.0, began to take place in the early 2010s and is still in progress. It represents a major improvement in the automation technology, in which machines are able to operate independently and/or in collaboration with humans, being able of collecting and analyzing data to create advises upon them. This change is making and will make possible a new flexible customer-oriented industrial field, in which mass production is taken to a new level [5]. In the following sections the characteristics and components of Industry 4.0 are explained in greater detail.

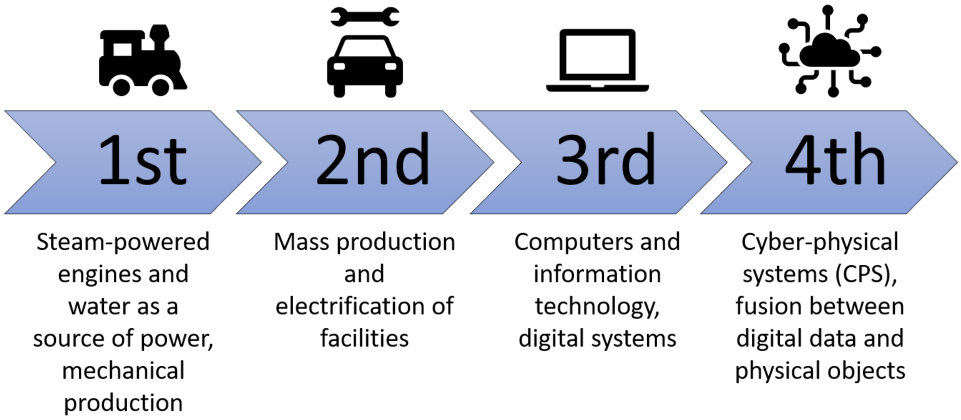

Figure 2.1: Overview of industrial revolutions. Based on [5]

2.1.2 Definition and components of Industry 4.0

As already seen in the introductory paragraph, the Fourth Industrial Revolution enables industry, and manufacturing sector in particular, to become digitized by potentially providing sensing devices to all components, assets and products, thus creating a fusion between digital data and physical objects which is going to transform radically all industrial fields.
Tay et al. [7] worked out a literature review about the various definitions of Industry 4.0 in the last years, from 2013 to 2017. The authors summarized the results of their research as:

Industry 4.0 describes a future scenario of industrial production that is characterized by new levels of controlling, organizing and transforming the entire value chain with the life cycle of products,resulting in higher productivity and flexibility through three types of effective integration which are horizontal, vertical and end-to-end engineering integration. [7]

As it is possible to see from the previous definition, the authors identify three major components of Industry 4.0 [7]:

- Horizontal integration: it means that corporations in the supply chain should both collaborate and compete with others with similar characteristics, in order to increase the efficiency of the production system. Therefore, this integration regards the connection between company's components like manufacturing and materials, economics and finance and information and knowledge.

- Vertical integration: it represents the idea to achieve hierarchical subsystems, both informational and physical, at the production line in order to create an easily configurable and flexible production system. The focus in this case lies in the integration of sensors and actuators signals with the various levels of automation in the factory or industry, thus creating intelligent machines capable of setup automatically to the different types of products and process data in a transparent way. Vertical integration can be represented through the so-called automation pyramid (shown in Figure 2.2), i.e. a pictorial example of the different levels of automation previously cited, going from the field to the management level.

- End-to-end engineering integration: the last component regards the integration of all product-centric activities like customer requirements analysis and expression, product design and development, production activities, dismissing and recycling. This allows both the re-usability of each stage for the same product model and a greater customization.

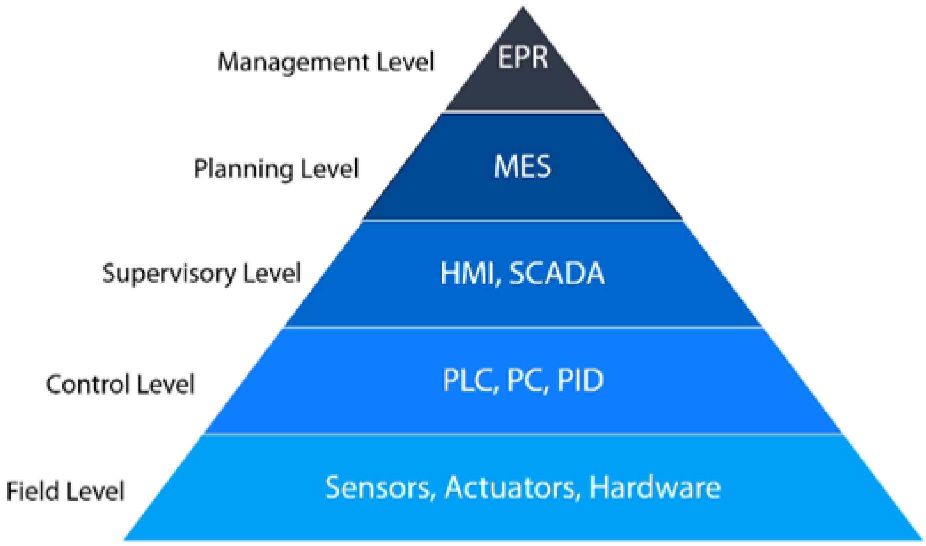

Figure 2.2: The automation pyramid, representation of vertical integration in a factory, is composed by 5 levels (from bottom to top): field, control, supervisory, planning and management. Figure from [8]

2.1.3 Characteristics

According to Tay et al. [7], there are 9 main characteristics of Industry 4.0:

- **Cyber-Physical System (CPS)**: derived from the great developments in communication and computation of the last year, a CPS is a system in which the physical object is connected to its virtual model through the use of sensors, allowing them to collect, process, communicate data and initiate actions. CPSs are also the basis to create the Internet of Things (IoT). According to Napoleone et al. [9], the higher level characteristics of Cyber-Physical Systems are: complexity/heterogeneity, being composed by numerous systems of different nature; interoperability, since constituted by components able to connect, communicate and operate with each other; service orientation, i.e the capability of providing timely service to manufacturing tasks keeping a high accessibility between the different entities; modularity, consisting in the capability for a CPS to be modularized, flexibly changed, and reconfigured in response to changing customer needs and product characteristics; virtualization and real time capability, meaning that sensor data are acquired in real time and used to link the physical system to virtual and simulation models; high computational capability; cooperation and collaboration, intended as the ability of assigning the entities of a factory to the different tasks in order to optimize the performances; dynamic reconfigurability, which can be seen as the capability of changing structures, functionalities and boundaries in order to adapt to the market and the industrial context.

- **Internet of Things (IoT)**: IoT consists in an advanced connectivity between systems, services and products, thus increasing the flow of information across the production process and allowing data analysis and decisions making to be held in a decentralized way, improving response times [10].

- **Internet of Services (IoS)**: based on the Internet of Things, the Internet of Services delivers the idea of companies providing a large amount of services through the internet, answering to the various needs of the customers in a flexible way. Moreover, web services which up to now are delivered separately, in a future perspective will be combined into an unique and more valuable network, giving benefits to the various actors of the market [11].

- **Big Data and Analytics**: as already seen, the presence of sensors and the interconnection between systems generate a huge amount of data, which cannot be treated with traditional methods. Therefore, over the last few years have been developing analytic techniques to handle these information, establishing the topic of the Big Data, name given to the technology able to quickly and efficiently manage constantly growing databases. Commonly, Big Data are described through four dimensions, the so-called 4V: volume, describing their amount; variety, meaning the different sources they can come from; velocity, which is their speed of generation and analysis; value, indicating the importance of the information brought [12].

- **Augmented Reality (AR)**: it consists in the enrichment of the human perception ability through the use of additional information, usually delivered by digital devices. Regarding industrial production, AR can be used as a supportive tool for maintenance, allowing to predict and adjust the frequency of interventions, reduce errors and save time and money for this kind of activities [13].

- **Autonomous Robots**: with the future developments, robots will be able to interact between them autonomously and collaborate with human operators, thus providing an increase of efficiency in manufacturing operations at a lower cost [14].

- **Additive Manufacturing**: the implementation of smart production systems is achieved also through the utilization of smart manufacturing techniques, like additive manufacturing, which consists in creating objects by the deposition of subsequent layers of material. This system, in addition to suitable and new materials, requires also the integration of information technology along the product development stages [15].

- **Cloud Computing**: cloud storage consists in keeping data in online archives instead of the single devices, enhancing a great accessibility of the information at a lower cost. In addition, in recent times this technology has begun to be applied not only to single data, but to software too, enabling online computation [16].

- **Simulation**: the last characteristic of Industry 4.0 is the simulating approach. Simulation consists in running virtually a process or a system in order to predict its behaviour and outputs. Combined with the use of real time data and artificial intelligence able to adjust operations autonomously, it allows to optimize systems going from single machines up to entire factories, reducing costs, setup times and improving the production quality [17].

Figure 2.3 summarises the different elements analysed. As it is possible to see from the previous description, the different characteristics and compo-

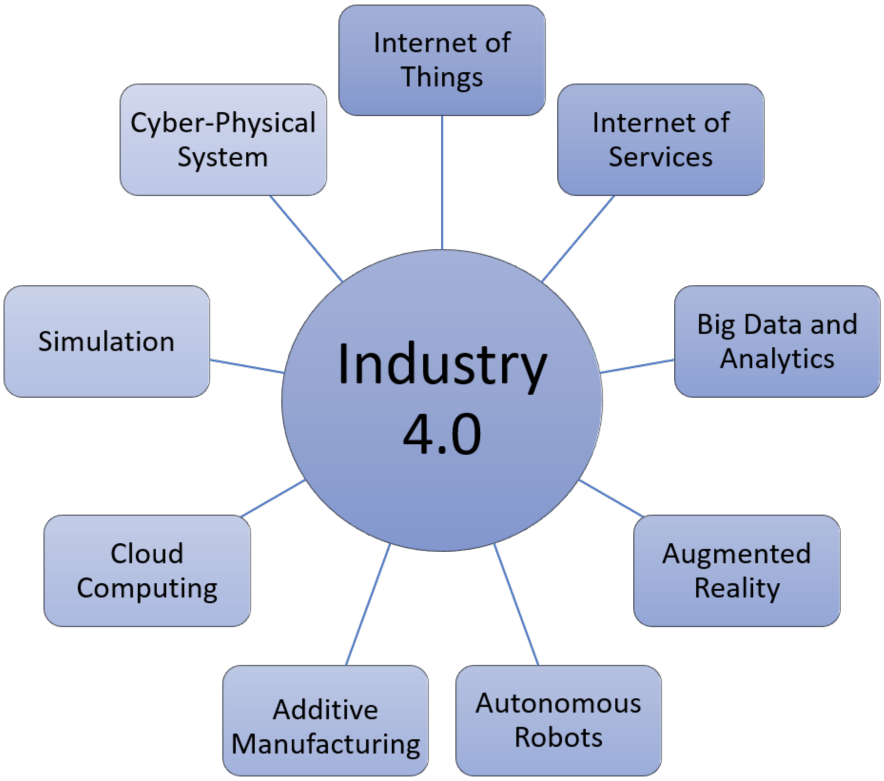

Figure 2.3: Characteristics of Industry 4.0 according to Tay et al. [7]

nents of Industry 4.0 are strongly linked between them, so that it is difficult to consider them as standalone elements. In addition, this industrial revolution is still a process in progress, making hard to distinguish among its components and leaving uncertainty about the future developments.

2.1.4 Maintenance in Industry 4.0

As previously introduced, one of the manufacturing aspects more influenced by Industry 4.0 is the maintenance field, changing the way in which interventions are organised and executed. In this paragraph thence are made some considerations about how the described characteristics of the Fourth Industrial Revolution are related to such changes, affecting the maintenance process.

According to companies like Bosch [18] there are three main changes in the maintenance process.

The first one is constituted by the introduction of real time condition monitoring. In fact, Cyber-Physical Systems allow to record and display sensor data in real time, making then the information available to all the connected devices and/or stored in the Cloud. This provides a higher accessibility of data, which now can be visioned not only by the dedicated operators but also by a variety of experts.
The second change regards the evaluation of the information gained, which can be performed through the Big Data technology, allowing thus an analysis based on the specific needs of the user and giving different operative options. For example, maintenance can be automatically scheduled when some machine parameters trigger defined limits or some rules can be set in order to make the operators receive immediate notification when an unscheduled stoppage happens. Thus, repairs are executed only when necessary and the downtime is reduced.
Finally, the third important change regards the way in which operators themselves are notified about the condition of the assets. In fact, once the need of a maintenance action has been identified, the right maintenance team can be forwarded about it directly through a digital ticket on their personal devices (e.g. smartphones and tablets); this is made possible by the concept of Internet of Services. The presence of such tickets not only allows to have immediately the necessary information for the task, but permits also to have all the interventions displayed on a unique interface, thus facilitating the organization and the logistics of the actions.

2.1.5 Benefits and challenges

To complete the brief vision on Industry 4.0 given in the current section it is useful to make some final considerations about how such process is going to revolutionise the manufacturing operations and some aspects of the society, illustrating the major benefits and some possible challenges which are then summarized in Figure 2.4. To be noticed that these last ones in particular involve complex themes, which in this work are only touched for contextualization purposes.

Advantages of Industry 4.0

It is possible to identify three main advantages that the Fourth Industrial Revolution can bring to companies and society [5]:

- **Optimization**: the optimization of the processes made possible by the creation of a smart factory constituted by hundreds of smart devices interconnected between them represents a key advantage of Industry 4.0. The implementation of robots and automated machines permits in fact an increase in efficiency and accuracy, boosting the production and reducing the errors usually associated to human operators. In addition, as already seen the real time monitoring of such equipment allows an increase of the availability and the organization capabilities thanks to the implementation of a more prognostic maintenance, improving at the same time the workplace safety [19]. The decrease of costs which derives from these changes can therefore generate a growth in the companies profits.

- **Customization**: the integration of all processes related to the product creation, together with the modularity of the systems involved allow a greater customization for the manufacturing industry. The concept of the Internet of Services is in fact going to reduce dramatically the gap between companies and customers, enabling a direct communication of these two entities and faster production and delivery lead times.

- **Pushing research**: the advent of Industry 4.0 has been provoking an exponential acceleration of the technological change and innovation during the last years [20]. This process is in turn pushing the research in the sectors touched, generating new opportunities in terms of education and training which reflect the skills needed by such an industry.

Challenges of Industry 4.0

Finally, below are briefly listed some of the challenges that this revolution is setting and may set in the future years [5]:

- **Security**: the online storage and computing of data allowed by the Cloud technology has the downside of creating IT security risks. In fact, cybersecurity breaches have been increasing during the years, compromising not only the networked manufacturing machines but in some cases the corporate business model too, generating losses of money and reputation [21]. Therefore, research in this ambit is essential.

- **Capital**: despite the operating benefits, the implementation of the technologies to create smart factories requires huge investment. For this reason, it is a choice to be evaluated carefully and which could exclude smaller manufacturing realities from competition.

- **Employment**: the automation of production and related devices is probably going to generate huge changes in the occupation of the workforce. If on one hand new opportunities and skills will be required, on the other different sectors of workers may risk to be alienated in this process.

- **Privacy**: during last years there has been an increased awareness regarding the theme of digital data privacy. However, this not involves only customers, but manufactures too, which need these data to understand the market. This topic is therefore probably going to affect the relationship between producer and end user.

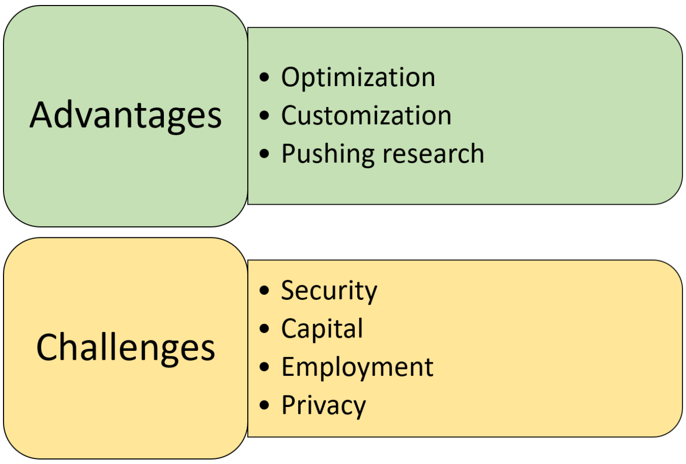

Figure 2.4: Main advantages and possible challenges related to Industry 4.0 according to Luenendonk [5]

2.2 Maintenance review

2.2.1 Fundamentals

According to the standard UNI EN 13306 [22], maintenance is defined as "the combination of all technical, administrative, and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform a required function". Therefore, it consists in all the activities, direct and indirect, required to conserve the original condition of an asset, while compensating for normal degradation, so that it can deliver its function as long as possible.

Historically, modern maintenance engineering began with the invention of the steam engine by James Watt (1736-1819) in 1769 in Great Britain, during the First Industrial Revolution, and from there it was developed in the years hand in hand with technological progress; during the last years, in particular, was developed the concept of e-maintenance, bringing to the integration of modern information and communication technologies as support of maintenance activities. As long as the assets became more and more complex, maintenance engineering became a stand-alone field of study, whose role consists in keeping the various equipment in its primary working condition and, at the same time, minimising the related costs. In particular, the integration of maintenance management in the entire company planning became vital in this context, potentially having a big impact on company competitiveness, on quality of life, on safety and on sustainability in general [23]. Therefore, the main objectives of maintenance engineering can be summarized, according to Pone et al. [24], as follows:

- Preservation of the assets during their useful life-cycle.
- Upkeep assets' availability at the required target level.
- Safety of the personnel.
- Environmental sustainability.
- Containment of maintenance related costs.
- Technical and economical control of the results.

In order to monitor the capability of the maintenance strategy to achieve these targets, it is important for a company to set up a performance measurement system, essential to align maintenance management with the organization's strategic objectives. For this reason, different performance indicators can be established with the aim of fulfilling this mansion, covering both technical, economical and organizational aspects. Among the others, the Overall Equipment Efficiency (OEE) is fundamental to monitor and assess the system's function [23]; its general expression is:

$$OEE(\%) = Availability \cdot Performance \cdot Quality \tag{2.1}$$

As it is possible to see from previous equation, the OEE is composed by three terms:

-Availability: it considers the impact of downtime loss (e.g. breakdowns) and it is defined as the percentage of the total time the asset is able to perform is function:

$$Availability(\%) = \frac{\sum T_{up}}{\sum T_{up} + \sum T_{down}} \tag{2.2}$$

-Performance: it takes into account the speed loss and it is defined as the percentage of production capacity (PC) which can be achieved in a given amount of time:

$$Performance(\%) = \frac{PC_{actual}}{PC_{ideal}} \tag{2.3}$$

-Quality: it considers the quality loss, i.e. the percentage of good production (so excluding scraps) on the total one:

$$Quality(\%) = \frac{Good\ pieces}{Total\ production} \tag{2.4}$$

The next sections are dedicated to the classification and description of the different maintenance strategies and policies, in order to complete the overview about the topic.

2.2.2 Classification

Maintenance activities are classified according to the policy adopted. A maintenance policy can be defined as a management method in order to achieve the objectives of the maintenance function, basing on types of maintenance interventions defined according to well known standards. According to Crespo Marquez [25], a first fundamental classification can be made distinguishing between corrective and preventive maintenance.

Corrective Maintenance

Corrective maintenance (CM) is "maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function" [22]. Different events can trigger the corrective maintenance action, like the detection of an issue through condition monitoring, a fault uncovered by an inspection or the sudden failure of the equipment. Corrective maintenance can be further classified, considering time dimension, as immediate or deferred:

- Immediate maintenance: corrective maintenance that is carried out without delay after a fault has been detected to avoid unacceptable consequences [22].

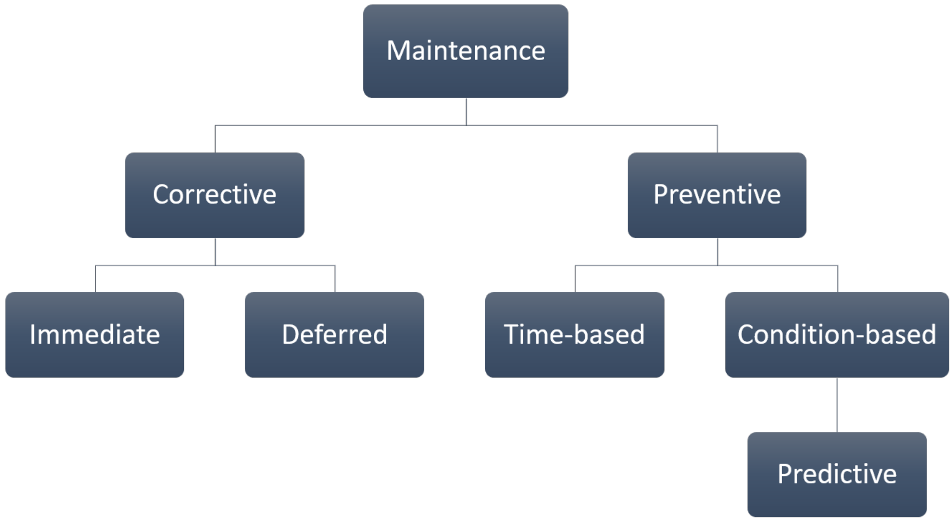

Figure 2.5: Maintenance classification. Classification according to Crespo Marquez [25] and based on EN 13306 [22]

- Deferred maintenance: corrective maintenance which is not immediately carried out after a fault detection but is delayed according to given maintenance rules [22].

This type of maintenance can be effective in situations in which a non-critical asset can be allowed to run-to-failure, in presence of redundancies (i.e. multiple components of the same type in parallel) and in general when the failure of the item can be recovered in an easy and inexpensive way without compromising safety. However, in most situations, due to the complexity of the assets and high costs, this is not the case, and corrective maintenance should be avoided in favour of a preventive maintenance policy.

Preventive Maintenance

Preventive maintenance (PM) is "maintenance carried out intended to assess and/or to mitigate degradation and reduce the probability of failure of an item" [22]; it can be performed at predetermined intervals or according to prescribed criteria, in order to reduce the probability of failure or the excessive degradation of the functioning equipment. Examples of preventive maintenance actions are adjustments, cleaning, lubrication, repairs and parts replacements.
The first benefit of a preventive maintenance policy is the reduced probability of incurring in unexpected failures, which translates in improvements

in terms of cost savings and safety with respect to corrective maintenance. Another great advantage is the possibility of decreasing downtime: in fact, with an appropriate PM schedule, managers can efficiently optimize the costs and time losses. However, it is important to avoid over-maintenance, since this practice can make the maintenance related costs more relevant that the actual savings. In addition, preventive maintenance has a number of other benefits, such as the extension of assets lifetime and the possibility of optimizing spare parts and resources allocation.

This policy can be further classified in time-based maintenance (TBM) and condition-based maintenance (CBM), depending on how it is organized [26]:

- **Time-based maintenance**: also called predetermined maintenance, it is defined as "preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation the maintenance" [22]; intervals can be at set-times (clock-based TBM) or at fixed age or usage of the components (age-based TBM). This policy is applicable if the failure behaviour of the equipment is predictable; usually this assumption is based on the knowledge of the hazard or failure rate trends, statistical functions which state the probability of failure at a given time.
  The greatest advantage of a time-based maintenance policy is that it is relatively easy to implement since it does not require condition monitoring but only the recording of the failure data; this also implies lower acquisition costs. In addition, once the failure rate distribution is computed, the obtained function can be theoretically used to obtain mathematically all the necessary properties and failure characteristics, necessary to execute the optimization. Finally, the output is a well-defined maintenance program, with a high predictability about the future activities and resources required.
  On the other hand, failure data can be sometimes very difficult to obtain, both due to all the issues related to the equipment failure already discussed for corrective maintenance policy, and due the fact that some complex assets and machines (e.g. aircraft engines) cannot be run to failure.

- **Condition-based maintenance**: it is "preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions" [22]. In general, the actual condition assessment of the equipment can be obtained in different ways, through inspections, non-destructive tests and/or condition monitoring. In

particular, in condition-based maintenance condition monitoring itself has a fundamental role: in fact, a signal (usually vibration, temperature, lubricating oil, contaminants or noise levels) is acquired, periodically or continuously, and used as a degradation indicator to determine the health state of the machine; when this indicator reaches a threshold level, sign that the component is out of normal working state, a set of maintenance actions are triggered.
The greatest advantage of condition-based maintenance over time-based maintenance is the capability of making decisions basing on the actual state of the machine, without making assumptions about its behaviour. In this way, it is possible to follow eventual changes in the degradation model of the component, better avoiding failures and over-maintenance. On the other hand, the main drawback of this approach is the quantity of data required and the costs of sensors and in general condition monitoring equipment, in addition to a more complex data processing. However, specially the cost issue is being solved with the introduction of less and less expensive monitoring equipment thanks to technology evolution.

2.2.3 Predictive Maintenance and Remaining Useful Life

Predictive maintenance is "condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item" [22]. Therefore, it is a type of preventive maintenance which can be considered as the evolution of condition-based maintenance. As its name suggests, in this case the PM actions are based on the forecast of the trend of one or more parameters clearly linked to the degradation process; fundamental in the process is the extrapolation of the remaining useful life (RUL) of the component, which can be defined as the length of time the system is likely to operate before it requires maintenance. It is therefore evident that predictive maintenance is a kind of CBM which highlights the prognostic capability feature. For this reason, it differs from traditional condition-based maintenance, more diagnostic, for the use of the acquired data of the monitored parameters in order to find temporal trends: the time in which the component is predicted to reach a threshold degradation value is in fact utilized to decide about the maintenance activities to be performed [25].

As it is possible to deduce from the previous paragraph, remaining useful life estimation is the last technical process as well as the ultimate goal of

predictive maintenance, fundamental for the decision-making. In this section an overview of the RUL estimation approaches is presented, including advantages and disadvantages of each method, in order to give a theoretical basis for the work of the current thesis.
According to Lei et al. [27], there are four basic approaches with the aim of estimating the remaining useful life: physics approaches, statistical approaches, AI approaches and hybrid approaches. In the next paragraphs there follows an overview of them.

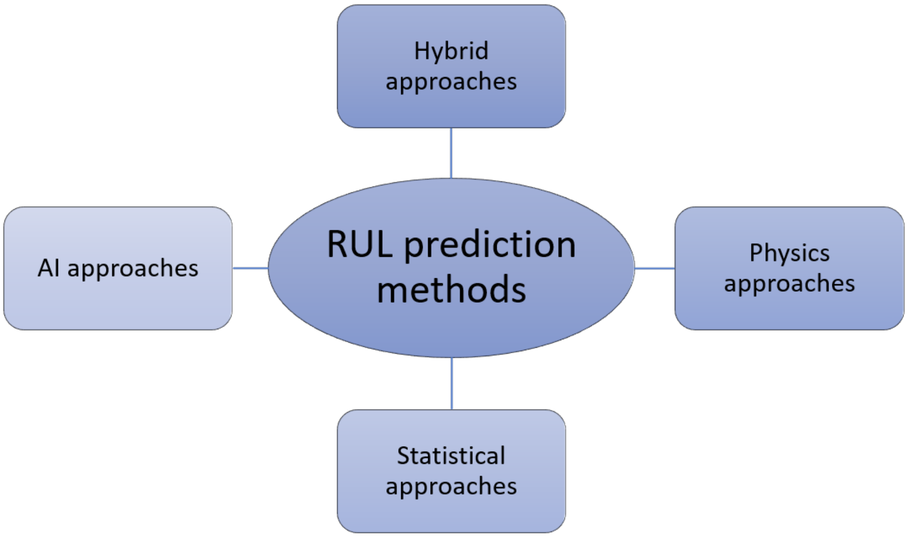

Figure 2.6: RUL prediction methods. Classification according to Lei et al. [27]

Physics model-based approaches

Physics model-based approaches describe the degradation process of the machine by mathematically modelling the failure mechanism or the damage propagation. Examples of such models are Paris law and its variants, aiming at describing the crack propagation subject to different stress conditions. Physics models can provide an accurate estimation of RUL, but only if the degradation phenomenon is well known, so as the material properties of the component; in any case it requires an intense and long study in order to have a complete understanding of it. In addition, for some complex assets it is almost impossible to reach such a phenomenon comprehension, which makes this approach restraint to a limited number of applications [27].

Statistical model-based approaches

Named also empirical-model based approaches, statistical models provide RUL estimation by fitting available observations into random coefficient models or stochastic processes under a probabilistic method: in this way, RUL prediction is generally presented as a conditional probability density function (PDF) based on data. The introduction of random variances in model parameters allow to describe the uncertainties which could rise due to the different variability sources of machine operations and data acquisition; thus, these models are effective in describing the variability of the degradation process and its subsequent influence on remaining useful life [27]. Over the years, different statistical models have been developed and applied for this scope; here are presented the main ones. Some of them will be then discussed in greater detail in Chapter 3.

- Auto-regressive (AR) models: they assume that the future state value of machine is a linear function of past observations and random errors. Despite their simplicity, the high dependency of these models on the trend information of historical observations may lead to inaccurate forecast.

- Random coefficient models: they describe the stochasticity of degradation processes by adding random coefficients into degradation models, usually assumed to follow normal distributions. The advantage of these models is the capability of providing a probability distribution function of RUL prediction including the variations of the random coefficient. On the other hand, the assumption of normal distribution is not always verified; in addition, they are unable to take into account the temporal variability in RUL prediction.

- Wiener process models: these models, belonging to one of the most used classes of stochastic processes, are generally composed by a drift term plus a diffusion term following Brownian motion. The benefits of using Wiener type models are the capability of describing the temporal variability of degradation processes and the possibility of modelling non-monotonic processes by introducing some random noise following a Brownian motion. However, the greatest drawback is that they rely on the Markovian property, i.e. the assumption that the future state of the system depends only on the current one and not on the history of the process, which is unlikely to be verified in reality. In addition, for this class of models is difficult to derive an analytical solution for the

RUL probability density function, reason for which numerical solutions are used to approximate it.

- Gamma process models: they assume that the increments of degradation processes at disjoint time intervals are independent random variables with a gamma distribution. As the Wiener process, Gamma models are able to consider the temporal variability of the degradation path, but they are as well restricted to the assumption of the Markovian properties. Moreover, noise is modelled following a Gamma distribution, which makes them effective in describing only monotonic processes.

- Inverse Gaussian (IG) process models: this class of models assume that the degradation process has independent increments following an inverse Gaussian distribution. Their biggest advantage is the capability of incorporating different kinds of random effects, giving them a high flexibility in describing different degradation processes. However, like Gamma process models, they are restricted by the Markovian property and can model only monotonic processes.

- Markov models: they assume that the degradation processes of machinery transform within a finite state space following the principle of the Markov property. This class of processes is used since generally it is possible to describe the health condition of a component as divided in several stages. However, basing on the Markovian property like the previous models, they are restrained only to a limited number of real applications. In addition, the estimation of the transition probabilities between states requires a large experimental campaign, which is generally expensive or complex to perform and does not ensure robustness against unpredictable behaviours of the machines.

- Proportional hazards (PH) models: in this type of models the hazard rate of a system is assumed to be composed of two multiplicative factors, i.e. a baseline hazard function and a covariate function; this allows to integrate the information from both the event data and the condition monitoring data, making the prediction more precise if these kinds of data are both available. However, usually it is difficult to acquire these two type of data simultaneously. In addition, the covariate functions need to be described using other statistical models, introducing all their related issues.

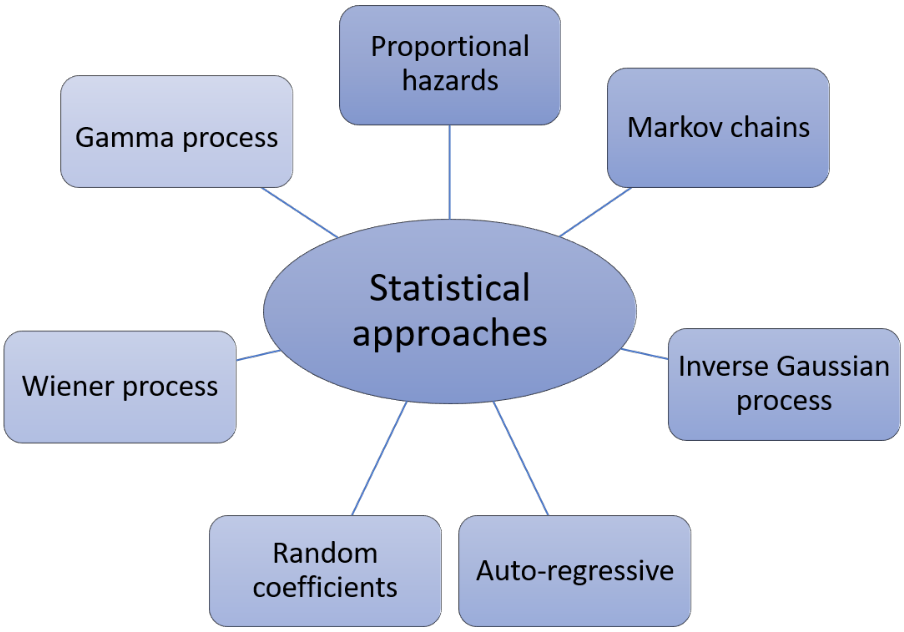

Figure 2.7: Statistical approaches. Classification according to Lei et al. [27]

AI approaches

Artificial Intelligence (AI) approaches aim to learn the degradation pattern of a machine using AI techniques from available observations. The popularity of these techniques has increased in recent years, since they are capable of dealing with prognostics issues of complex assets whose degradation pattern is difficult to be modelled by physical and statistical approaches. However, their common drawback consists in a low transparency and general low capability for the user of understanding the results: in fact, these approaches are typically black-box methods [27]. The most used ones are:

- Artificial Neural Networks (ANN): probably the most common used AI technique in the field of RUL prediction, ANNs mimic the working process of human brains, connecting lots of nodes in a complex layer structure. These models are able to learn very complex non-linear relationships by training the multi-layer networks, which makes them to have good performances in the RUL prediction of complex systems. However, in addition to the low transparency, their main drawback is the need of a large amount of good quality training data, which is difficult to obtain in real applications. Moreover, their generalization ability among different cases is usually restrained by the fact that their structures and parameters are typically initialized randomly or manually specified.

- Neural Fuzzy (NF) systems: they are fuzzy logic systems whose inference structures are determined by expertise and membership functions are optimized by ANNs. The combination of expert knowledge and artificial neural networks make this class competitive in RUL prediction. However, like ANNs, they still require a large amount of good quality training data.

- Support Vector Machines (SVM), Relevance Vector Machines (RVM): SVMs are a class of supervised models which aims to classify data by finding the optimal plane or hyperplane that separates the observations. RVMs are an evolution of SVMs, having the same functional form but providing a full predictive distribution, the lack of which is a limit to support vector machines. Both the techniques are more able to deal with the issues of small sample sizes than ANNs, making them suitable for predictions with only limited measurements available. On the other hand, their performance is strongly linked with the selection of the Kernel functions (i.e. functions which allow the mapping of non-linear observations into a higher dimensional space where they become separable), for which there is not still a standard method for selection. Finally, parameters estimation represents a challenge for these methods.

- Gaussian Process Regression (GPR): this AI technique implements Gaussian processes (i.e. cumulative damage processes of random variables with joint multivariate Gaussian distributions) for regression purposes. The greatest advantage of GPR with respect to other methods is the high adaptability, which makes it suitable for dealing with the RUL prediction issue of high-dimensional and small size datasets. On the other hand, it has generally a high computational weight.

Hybrid approaches

Since each of the three categories presented above have advantages and disadvantages, hybrid approaches aim to integrate the pros of them through their combined use. However, despite their potentialities, this type of approaches is still the least used due to the increased complexity.

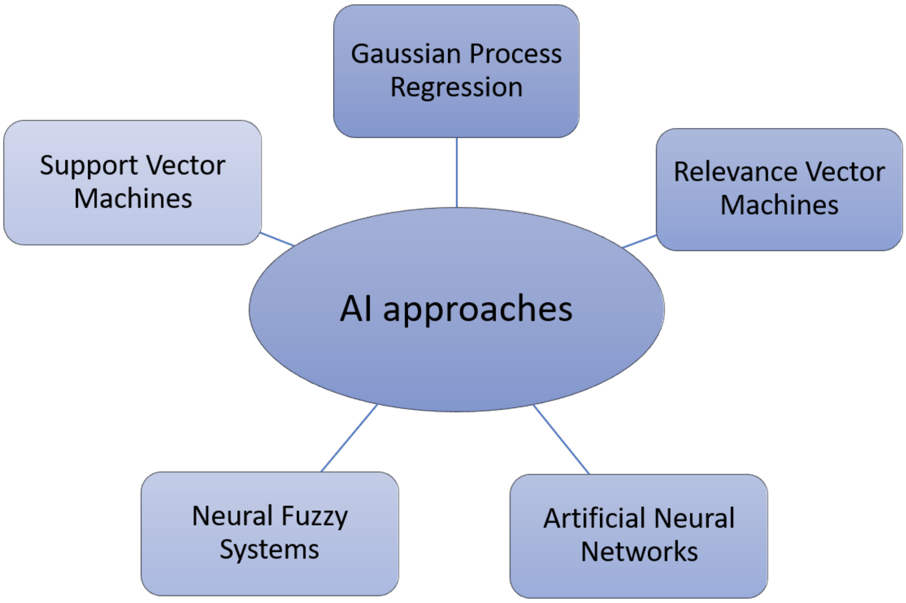

Figure 2.8: AI approaches. Classification according to Lei et al. [27]

2.2.4 Degree of repair and imperfect maintenance

Another way to classify maintenance actions is according to the degree to which the operating condition of an item is restored. From this point of view, according to Pham et al. [1] and as illustrated in Figure 2.9, the types of maintenance are:

- Perfect maintenance: a maintenance action which restores the system operating condition to as-good-as-new. Upon perfect maintenance, a system has the same failure and degradation characteristics as a brand new one. A typical example of this action is generally the replacement of a component.
- Minimal maintenance: a maintenance action which restores the system to the same conditions in terms of failure rate or degradation it had when it failed. An example consists in changing a single component of a complex system: the system overall degradation remains unchanged.
- Imperfect maintenance: a maintenance action which restores the system to an intermediate state between the as-good-as-new and the as-bad-as-old conditions. It is evident that imperfect maintenance is a general repair, comprehending as extreme cases the perfect and minimal maintenance options, as marked in Figure 2.9. Examples of this

type of actions are the lubricating, cleaning and fixing of a tool or an engine tune-up.

- Worse maintenance: a maintenance action which makes the system failure rate or degradation increase without causing failure. Thus, upon this action the operating condition becomes worse than before maintenance.

- Worst maintenance: a maintenance action which undeliberately brings the system to failure state. In general, causes of worse or worst repair can be the repair of a wrong part, the partial repair of a fault component, the damage of other parts during maintenance, the incorrect assessment of the condition of the unit monitored, performing the maintenance action off the schedule, the presence of hidden faults not detected during maintenance, human errors of various type and the replacement with wrong parts.

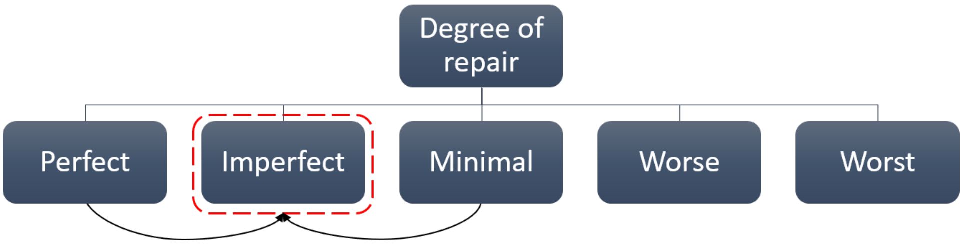

Figure 2.9: The different degrees of repair/maintenance. Classification according to Pham et al. [1]

Like the maintenance policy, also the degree of maintenance depends on the application and system costs as well as reliability and safety requirements. Mostly in the past, it has been assumed that the maintenance actions were limited to the extreme cases of perfect and minimal repairs. However, imperfect maintenance has increased in popularity in recent years, since it allows a generalization of the maintenance action and appears as more realistic. For this reason, next chapter presents a detailed discussion about imperfect maintenance and its applications.

Chapter 3

Literature review

The aim of the this chapter is to illustrate the literature review work executed for the current thesis, using the methodology explained in detail in Section 3.1. After having given a preliminary overview on the different imperfect maintenance applications in Section 3.2, Section 3.3 shows the classification of the most relevant works, explaining one by one the different drivers applied. Finally the results obtained are analysed in Section 3.4, highlighting the gaps emerged from the literature review.

3.1 Methodology

The procedure followed to search for, filter and analyse the state of the art of the literature about imperfect maintenance is shown in Figure 3.1. The research was conducted using two scientific databases: Web of Science and Scopus. In order to find relevant articles, a topic related research was established by using selected keywords; the choice of these last ones was therefore crucial for an exhaustive analysis.
Since the main purpose of the thesis is to investigate the application of imperfect maintenance, this topic was selected as pillar keyword, to be combined with others. Regarding the other topics to be coupled with "imperfect maintenance", the following ones were selected: "reliability", to have a wide view of the different contexts in which imperfect maintenance is applied, since it is a quite general yet fundamental term in maintenance engineering concerning the life of the equipment; "condition-based maintenance (CBM)", to search for models based on the actual conditions of the machine, since such application of imperfect maintenance is one of the specific targets of this study; "predictive maintenance" and "remaining useful life (RUL)", to give more emphasis to the prognostic aspect of the CBM policy, useful

to take decisions in advance; "condition monitoring" and "continuous monitoring", in order to consider the monitoring techniques of the equipment, both in terms of inspections and sensor driven.
Once selected the keywords to be used, a research was established by coupling "imperfect maintenance" at turn with one of the previous other keywords. The choice of this kind of binary search is twofold: on one hand, it allows to build a wide but yet profound knowledge about the topic, on the other it allows to find a greater number of articles, by not excluding a priori results.

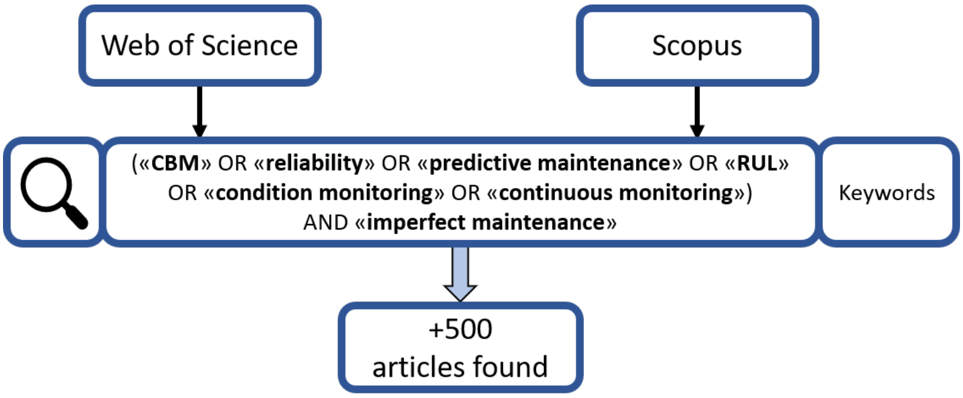

Figure 3.1: Scheme of database search

Following this procedure, and applying it to both Web of Science and Scopus databases, more than 500 articles were found. At this point, a first selection was made to choose the ones to effectively read and analyse. Thus, to select only the most relevant results, papers written out of the industrial maintenance field (e.g. belonging to medical field) were excluded, followed by the ones not talking about the topics selected or too aged to be more relevant than general overviews. In particular, regarding the articles age, there were excluded papers published before the year 2000 and those ones for which a more recent version of the same publication was available. Finally, it is important to underline that the exclusion criteria presented above were applied case by case, basing on the abstracts of the articles too.
As consequence of the filtering procedure applied, from more than 500 results found, a total of 154 articles was fully read and analysed, taking notes of the most relevant aspects of each of them. At this point, the next steps were the driver analysis (to identify variables driver of classification) and the actual classification, fundamental passages in order to systematically analyse the different aspects of the papers and find the gaps in literature. To proceed with this step, first of all another selection was necessary, with

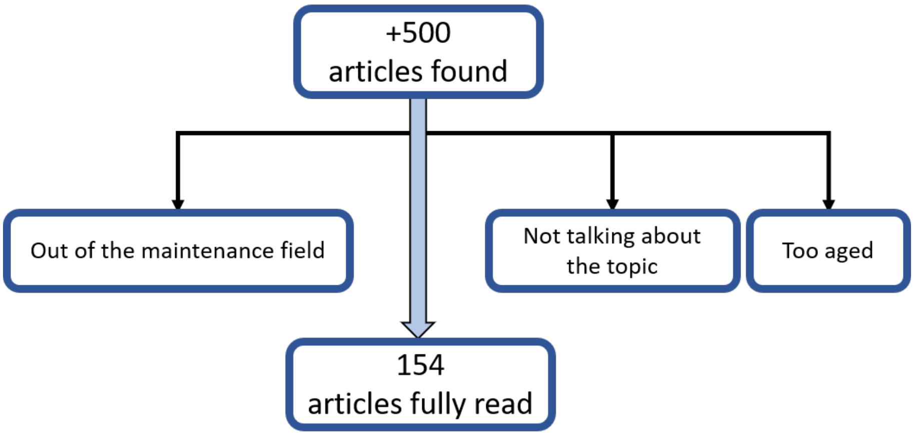

Figure 3.2: Selection for reading

the aim of taking only the most topic-related articles. The criteria for this further selection were found accordingly to the main target of the present thesis: investigate the application of imperfect maintenance in a context with CBM applied and with lack of run-to-failure data. Consequently, first of all the articles not effectively talking about imperfect maintenance but only mentioning it were excluded, since the application of this type of maintenance was only really marginal or almost absent in them. In addition, papers whose models were based on run-to-failure data were not considered: this criterion brought for example to the exclusion of the hazard rate based models. Moreover, only articles based on condition-based maintenance, completely or partially, were taken into consideration, eliminating in this way all the pure time-based maintenance models: however, to be noticed that combinations of CBM and TBM were allowed, as it is possible to see in Section 3.3. Finally, all papers consisting in literature overviews or very general frameworks were excluded, since, although useful, they did not bring any particular innovation to the already existing state of the art; however, some articles belonging to this class were used in one or more sections as an aid to explain some concepts.
The number of articles excluded by each of the criteria is shown in Figure 3.3. It is important to notice that each article is counted only once, according to the main reason of its exclusion: some of them could anyway be placed in more categories.
The previous analysis led to a reduction of the articles considered to a total of 47 papers, which were fully classified according to selected drivers, in order to find eventual gaps. This procedure is shown in detail in the dedicated sections.

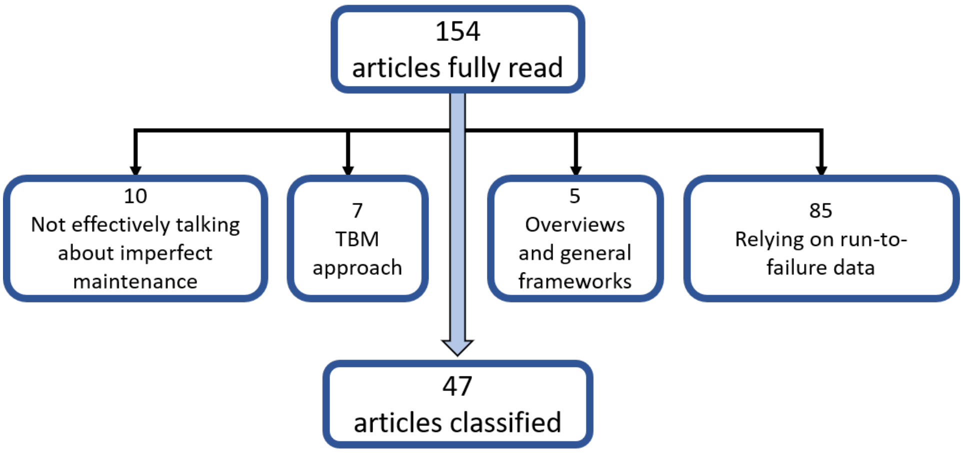

Figure 3.3: Selection for classification

3.2 Preliminary content analysis

Before entering in detail with the classification of the selected papers, it is useful to give a general overview about the context in which imperfect maintenance is applied, considering the different results emerged from the fully read articles.
Looking at the state of the art of literature, a first distinction can be made between papers talking about a single component system or in general considering the system as one entity, and others dealing with multi-component systems. While the first class do not need other distinctions at this level, regarding the multi-component systems it is possible to find for example selective maintenance models, whose aim consist in developing a strategy to select the components to maintain and at which level, balancing the resources available (typically money and/or time). From this point of view, remarkable is the work by Diallo et al. [28], who during the years have released numerous works about the topic, considering different assumptions from one to the other. Another typology of works related to multi-component systems is linked to the concept of opportunistic maintenance: it is "preventive maintenance or deferred corrective maintenance undertaken without scheduling at the same time as other maintenance actions or particular events to reduce costs, unavailability, etc..." [22]. In literature, linked to the concept of imperfect maintenance, is frequent the application of this particular strategy to wind turbine farms, where each intervention can be very expensive; an example is the work by Ma et al. [29]. An extension of multi-component systems is the fleet of systems, which is however much less frequent than the above two classes.

In addition, in literature it is possible to find models integrating imperfect maintenance not only in a standalone maintenance strategy, but considering also aspects like production and logistics (spare parts, holding and stock-out costs, etc...), as exemplified by the work by Bousdekis et al. [30], who developed a proactive model considering both imperfect maintenance and logistics using the sensor technology. Finally, there are also papers working in a leasing context, like the one developed by Wang et al. [31], where a warranty policy for leased equipment is treated by considering both customer usage and time as policy limits and integrating imperfect maintenance as a form of intervention.

Another overview of the state of the art about imperfect maintenance can be given talking about the way to describe the degradation of the system studied. In particular, the two most frequent approaches are the use of hazard rate models, which use run-to-failure data to estimate the probability of failure as time passes on, and the statistical degradation approaches, which model the degradation pattern analysing the behaviour of one or more features. Among the hazard rate approaches, it is worth to mention the proportional hazard rate model, which offers a combination of both historical run-to-failure data and real time data, in order to have a more precise assessment; this model is implemented for example by Yin et al. [32], considering the effects of imperfect maintenance as well. On the other hand, it is possible to further divide the statistical degradation approaches in continuous (e.g Gamma, Wiener, Inverse Gaussian, etc...) and discrete, modelling the degradation with a Markov chain. Sometimes, the degradation process described by these models is then integrated with the occurrence of random shocks, which increase the level of deterioration according to their magnitude.
Various examples of each of these last models are given in Section 3.3. Therefore, as it is possible to see, in literature both condition-based and time-based maintenance oriented approaches are developed, sometimes combining them in order to have a more complete description of the phenomenon and the related maintenance strategy.

Finally, looking at the totality of articles collected, the integration of imperfect maintenance is developed with different purposes. The majority of papers, in fact, have as main target the optimization of the maintenance policy basing on one or more objective functions. On the other hand, a relevant number of articles focuses on the parameters estimation, which is usually done using likelihood functions or Bayesian classification methods. Lastly, in literature are also present papers presenting general overviews about different topics, description of new developed models or giving an operational framework. Again, this last topic is better discussed in the classification section (i.e. Section 3.3), giving various examples of applications too.

3.3 Classification

As stated in the previous paragraphs, the method adopted led to the selection of 47 papers to be classified in detail. In order to achieve this target, the articles were listed using six classification tables: each of them aims to mark different types of content, so that a deep yet complete classification is given. For each table is reported the reference number of each paper and the corresponding publication year; regarding the last one, to be noticed that all the selected articles were published between 2012 and 2020, with a greater number in the more recent years (ref. Figure 3.4). Thus, this classification section allows to have effectively a presentation of the actual state of the art of the searched topic, fundamental to look for gaps in literature.
In the next paragraphs the different classification tables are explained in detail, with a particular attention to the description of the drivers used.

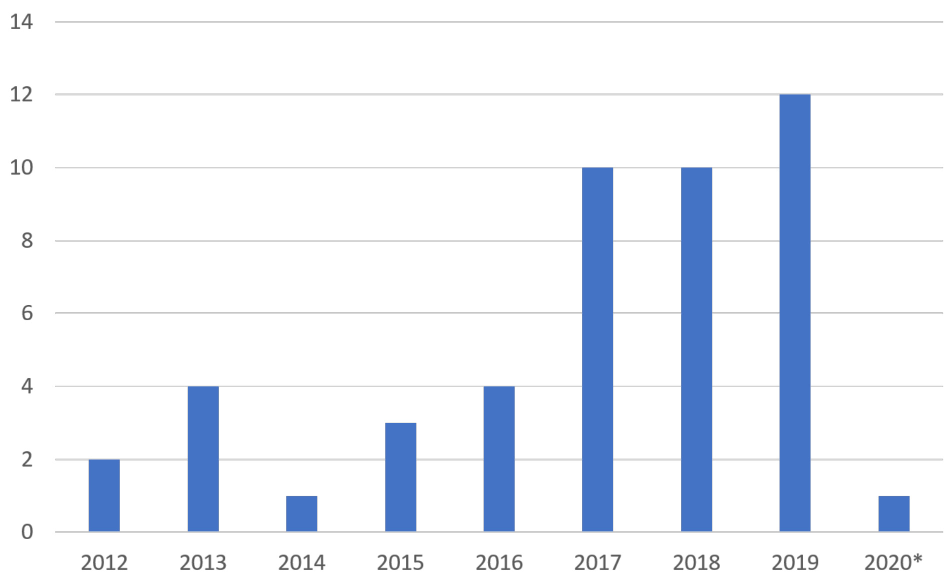

Figure 3.4: Number of selected papers per year.
∗considered till the end of February

Table	Section	Topic
3.2	3.3.2	Industrial field and application
	3.3.3	Paper main content
3.3	3.3.4	Deterioration process
	3.3.5	Inspection policy
3.4	3.3.6	Maintenance policy and RUL
3.5	3.3.7	Imperfect maintenance
3.6	3.3.8	Optimization target
3.7	3.3.9	Decision variables

Table 3.1: Summary of the topics touched by each classification table and related sections

3.3.1 Overview of the classification work

Prior to beginning with the actual presentation of the classification work, it is useful to give a general overview of it, explaining the contents of the different tables and subsections together with the main points of analysis. Thus the reader can be more easily oriented across the topics reported and focus on the ones of main interest. An index of the contents with the related tables and sections is shown in Table 3.1.

Table 3.2 presents an overview of the papers object of classification. It specifies first of all the industrial field articles refer to and their specific applications, which are then treated more in detail in Section 3.3.2.
Secondly, the table reports the main content of the papers, analysed then in Section 3.3.3. Such content is divided into three parts: the description of the model, the estimation of degradation and maintenance parameters and the optimization of the maintenance policy.

Table 3.3 aims to describe how the degradation is modelled and how is monitored. It specifies the deterioration processes used in the models (e.g Gamma, Wiener, Markov, etc.), which are then analysed in Section 3.3.4, reporting a brief description of them and explaining how they are applied in the papers.
Similarly, the table then reports the inspection policies applied, distinguishing it between periodic, non periodic and continuous (i.e. through sensors). As before, the three types are analysed in Section 3.3.5.

Table 3.4 and the related Section 3.3.6 present the maintenance policies adopted by the models. In particular, their description is structured by specifying first of all if they implement a pure CBM policy or a combination between CBM and TBM, noting then if they aim to estimate the remaining useful life. Secondly, there are reported the types of maintenance action included in the models developed, which can be perfect or imperfect and preventive or corrective.

Table 3.5 describes how imperfect maintenance is modelled in the classified papers, specifying its effects and their characteristics. The related explanation is reported in Section 3.3.7, dividing in the descriptions the effects applied to multi-state (e.g. Markov) and continuous (e.g. Gamma) deterioration models.

Finally, Table 3.6 and Table 3.7 indicate, respectively, the optimization targets and the decision variables considering the papers whose aim is to find an optimal solution to the maintenance strategy problem. These two aspects are then described in Section 3.3.8 and Section 3.3.9.

3.3.2 Industrial field and application

The first two classification drivers of Table 3.2 are useful to comprehend the industrial field papers refer to and their specific machinery application.

At a first glance, it is possible to notice that the imperfect maintenance models in the selected papers are applied to a wide range of industrial sectors. In particular, among the ones for which the industrial field is specified, a good number belong to the production sector: for example [33], [34] and [35] focus on a single stage production system, while Wu et al. [36] implement imperfect maintenance in a context with two production lines working simultaneously; finally, Chen et al. [37] develop a selective maintenance model for an engine cylinder head manufacturing system, entering in this way more in detail regarding the type of production performed.
Another sector with some applications is the extractive one, where by extractive industry is meant here both the raw materials mining with its subsequent processes until the steel industry and the oil extraction. In fact, for example Bousdekis et al. [30] develop a joint maintenance and logistics optimization model referring to a drilling oil machine; in [38] is presented a selective maintenance strategy for a coal transportation system; Wang et al. [39] propose a RUL estimation model applied to draught fans in steel mills, referring so to the steel making industry.

Table 3.2: General overview of classified papers

Ref.	Year	Industrial field	Application	Paper main content		
				Model description	**Parameters estimation**	**Optimization**
[40]	2020	Maritime	Gyroscope	X		X
[33]	2019	Production	Single-stage production system	X		X
[47]	2019	General	Micro Electro-Mechanical Systems	X		X
[30]	2019	Extractive	Drilling oil machine	X		X
[48]	2018	General	Control unit	X		
[49]	2017	-	-	X		X
[50]	2017	-	-	X		X
[51]	2015	-	-	X		X
[52]	2013	-	-	X		X
[53]	2013	-	-	X	X	X
[44]	2019	Infrastructure	Road pavement	X		X
[54]	2019	-	-	X		X
[55]	2019	-	-	X		X
[37]	2019	Production	Engine cylinder head manufacturing system	X	X	X
[45]	2019	Aeronautical	Aircraft gas turbine engine	X		X
[43]	2019	Energy	Electricity distribution devices	X	X	X

Table 3.2 continued from previous page

Ref.	Year	Industrial field	Application	Paper main content		
				Model description	Parameters estimation	Optimization
[56]	2018	General	Mechanical system	X	X	X
[57]	2018	-	-	X		X
[38]	2018	Extractive	Coal transportation system	X		X
[36]	2018	Production	Production lines	X		X
[42]	2017	Energy	Wind farm	X		X
[58]	2017	-	-	X	X	X
[59]	2017	-	-	X		X
[60]	2017	-	-	X		X
[61]	2016	-	-	X		X
[62]	2016	-	-	X		X
[63]	2016	-	-	X		
[64]	2016	-	-	X		X
[65]	2015	-	-	X		X
[66]	2013	-	-	X		X
[67]	2019	-	-	X		X
[41]	2019	Maritime	Gyroscope	X		X
[68]	2018	-	-	X	X	X

Table 3.2 continued from previous page

Ref.	**Year**	**Industrial field**	**Application**	**Paper main content**		
				Model description	**Parameters estimation**	**Optimization**
[69]	2019	-	-	X		X
[34]	2018	Production	Single-stage production system	X		X
[70]	2017	General	Actuator	X		X
[46]	2017	Automotive	Diesel engine	X		X
[71]	2017	-	-	X		X
[72]	2015	-	-	X		X
[73]	2014	-	-	X		
[35]	2012	Production	Single-stage production system	X		X
[74]	2012	-	-	X		X
[75]	2017	-	-	X		X
[76]	2013	-	-	X		X
[77]	2018	-	-	X	X	
[39]	2018	Extractive	Draught fans in steel mills	X	X	
[78]	2018	-	-	X		X

Among other sectors in which publications are present, it is possible to cite the maritime one, where both [40] and [41] develop a CBM model focusing on a gyroscope, a device used for measuring orientation and angular velocity and implemented in navigation systems for ships and submarines. Other types of applications belong to the energy sector, intended both as energy production, like in the work by Atashgar et al. [42] about an opportunistic maintenance strategy for a wind farm, and as energy distribution, like the publication by Zhao et al. [43], who optimize a maintenance strategy taking as case of study some electricity distribution devices. In the infrastructure or construction sector, Shi et al. [44] develop a multi-level preventive maintenance model referring to the degradation of a road pavement. Finally, there are some applications in both the aeronautical and automotive industries, respectively made by Wang et al. [45] on an aircraft gas turbine engine and by Liu et al. [46] on a diesel engine.

There are then some papers in which only the application is specified but not the industrial field: in this case, in fact, the models are developed taking as reference devices which can be used in a wide range of different sectors or very general entities. For example, [47] focuses on a micro electro-mechanical system (MEMS), [48] on a control unit, [70] on an actuator and, finally, [56] refers to a general mechanical system, without giving further information about its nature.

A general overview of the different sectors which the publications analysed refer to is shown in Figure 3.5, where to each sector is associated the number of papers in that field. Until now the description was focused on the articles which have sector or application of reference. However, from the histogram in Figure 3.5 as well from Table 3.2 emerges a very important data: for the greatest part of publications (28 out of 47) no application is specified, neither as a case of study nor as an example. The reason behind this fact is that many papers develop models with the main target of a numerical application only, useful to verify their correct working with given data but lacking of a practical feedback from reality.

Another consideration connected to the previous one regards the entity of the subjects of the models, intended as system level to distinguish between components, multi-component systems or fleets of systems. In fact, as for the industrial sector, also in this case for the greatest part of the articles no indication is given in this sense, with only few articles specifying that the object is a multi-component asset or a fleet and with the majority of

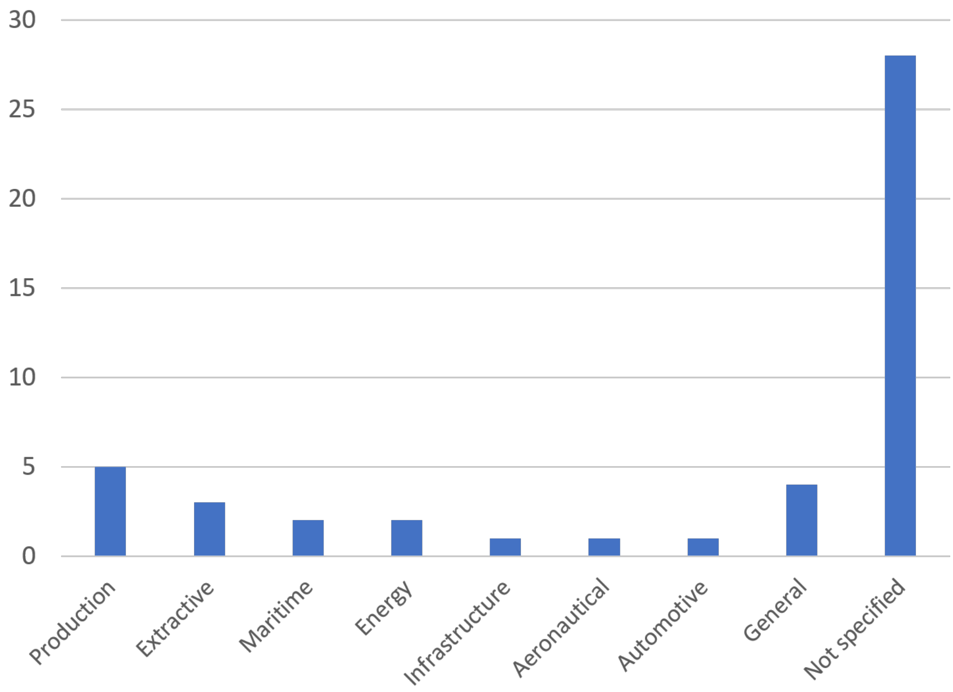

Figure 3.5: Industrial fields of analysed papers

them referring to it with the generic term of "system". Although such word is widely used also in the current thesis, in this precise context it acts like a cryptic term, making impossible to understand the real entity of the equipment the articles refer to. As mentioned at the beginning of the paragraph, this is linked to the previous consideration about the lack of real applications: the missing information about the system level enhances the hypothesis that a great part of the models are developed without any practical application in mind or, at least, considering it as a further step.
From this consideration the decision of non including the system level as a classification driver, since it would not have brought any additional relevant information.

3.3.3 Paper main content

To conclude with the general overview of the selected papers, another aspect which is worth taking a look at is the main content of the articles, as shown in Table 3.2. In order to perform this classification, the content was divided into three columns: model description, parameters estimation and optimization.

For model description is intended not only the actual description of the model, including its purpose, the assumptions and the explanation of it, but also the analysis of the results obtained, the explanation of the structural properties of the model and the measuring of its performances. Although all papers have this content, the column was included in order to distinguish between articles for which the description is only a section and others for which it is the main and only content. For example, in the work by Li et al. [48] the multi-state model developed is only described and then used to compare the results between different possible strategies; Castro et al. [63], after a description of the deteriorating system and its maintenance policy, find some important performance measures, like the expected uptime of the system or its reliability, and then run a simulation of the model to verify the results; another descriptive model is the one developed by Lu et al. [73], who create a health integrated model with the inclusion of imperfect maintenance and present the evolution of the state of the machine with time.

The pure descriptive models, as it is possible to see from Table 3.2, are very few (only 3 out of 47). In fact, usually the description is accompanied by an optimization of the variables introduced to describe the maintenance strategy. More details about the optimization target and the decision variables are given, respectively, in Tables 3.6 and 3.7 and in the dedicated paragraphs. In general, since the target function is usually in a complex form, the solution is found by using special algorithms like the genetic ones, developing some algorithms ad hoc, or by simulation methods like the Monte Carlo one, for example used in [40]. It is important to notice that an optimization method is performed in the greatest part of the papers.

Finally, another possibility for the main content of the articles is the estimation of the parameters. In a couple of publications this is the main scope of the paper after the model description: in both [77] and [39], after having derived the expression for the probability distribution function of the RUL, the parameters for the residual degradation after imperfect maintenance, for the degradation pattern and for the maintenance policy are estimated using likelihood functions. The work done by Letot and al. [58] on the other hand proposes the estimation of the degradation parameters but at the same time develops a system to choose dynamically if performing a maintenance action or not and if this one should be perfect or imperfect. In that sense, although it does not perform a real optimization together with the parameters estimation, it is still a model which acts on the decision variables selecting the best thing to do at each time.

Regarding all the other publications which have a part of parameters estimation, this last one is accompanied by an optimization and the model description. However, it is possible to notice that only a total of 9 articles among the 47 classified develop the estimation of the parameters given some historical data: in the other cases, the different parameters are already given as an input information for the problem, a situation which could be quite difficult to have in real applications, where at the beginning of an asset life cycle the degradation or maintenance parameters are usually unknown. This fact can be linked one more time to the scarce presence of real applications or, in general, of a method to effectively apply the models developed to real equipment.

Finally, about the parameter estimations a further consideration can be done about the estimation methodology: in fact, there are very few papers (only 3) which, once estimated the parameters, update them given new data from inspections. Among these three articles, in [77] the parameters regarding maintenance effects on degradation model are updated after every action; in [58], the updating is done on the deterioration pattern and until the acquisitions are enough to have a good estimate, but then the paper assumes to have already all the values known for the numerical example, making the estimation only a framework step; [53] is the only article which effectively uses the parameters updating in order to estimate better the RUL.

3.3.4 Deterioration process

Table 3.3 performs a classification based on the processes used to model the degradation pattern of the equipment and the inspection policies adopted. Regarding the deterioration process, its description was split into two columns: one reporting the degradation model adopted and the other specifying if the chosen process uses random coefficients, which means that the parameters of the model follow some specific distributions instead of being fixed.

Gamma process

As already stated in Chapter 2, Gamma process is a type of statistical model which assume that the increments of degradation at disjoint time intervals are independent random variables with a gamma distribution.
Given an interval of time h, the probability distribution function of a deterioration jump in such interval is [58]:

Table 3.3: Degradation patterns with related inspection policies

Ref.	**Year**	**Deterioration process**	**Random coefficients**	**Inspection policy**	**Non periodic type**
[40]	2020	Gamma	-	Periodic	-
[33]	2019	Gamma	-	Non periodic	Lot dependant
[47]	2019	Wiener + random shocks	-	Periodic	-
[30]	2019	Markovian	-	Continuous	-
[48]	2018	Markovian	-	Continuous	-
[49]	2017	Inverse Gaussian	-	Periodic	-
[50]	2017	Not specified	-	Periodic	-
[51]	2015	Gamma	-	Non periodic	RUL dependant
[52]	2013	Wiener	-	Non periodic	Mission dependant
[53]	2013	Wiener	-	Periodic	-
[44]	2019	Markovian	-	Periodic	-
[54]	2019	Gamma	-	Continuous	-
[55]	2019	Gamma	-	Periodic	-
[37]	2019	Markovian	-	Not specified	-
[45]	2019	Not specified multi-state	-	Not specified	-
[43]	2019	Gamma	-	Non periodic	Geometrically decreasing
[56]	2018	Wiener	-	Continuous	-

Table 3.3 continued from previous page

Ref.	Year	Deterioration process	Random coefficients	Inspection policy	Non periodic type
[57]	2018	Gamma	-	Periodic	-
[38]	2018	Markovian	-	Non periodic	Mission dependant
[36]	2018	Markovian	-	Not specified	-
[42]	2017	Not specified multi-state	-	Periodic	-
[58]	2017	Gamma	-	Non periodic	RUL dependant
[59]	2017	Gamma	-	Periodic	-
[60]	2017	Not specified multi-state	-	Not specified	-
[61]	2016	Wiener + random shocks	-	Non periodic	Mission dependant
[62]	2016	Gamma	-	Periodic	-
[63]	2016	Gamma	-	Continuous	-
[64]	2016	Gamma	-	Continuous	-
[65]	2015	Linear + random shocks	Yes	Periodic	-
[66]	2013	Gamma	-	Continuous	-
[67]	2019	Inverse Gaussian	-	Periodic	-
[41]	2019	Gamma	-	Periodic	-
[68]	2018	Random Fuzzy Accelerated Degradation	Yes	Periodic	-
[69]	2019	Markovian	-	Non periodic	Decision dependant

Table 3.3 continued from previous page

Ref.	Year	Deterioration process	Random coefficients	Inspection policy	Non periodic type
[34]	2018	Gamma	-	Continuous	-
[70]	2017	Gamma	-	Continuous	-
[46]	2017	Wiener	-	Periodic	-
[71]	2017	Markovian	-	Periodic	-
[72]	2015	Exponential	Yes	Periodic	-
[73]	2014	Integrated Health Function	No	Continuous	-
[35]	2012	Gamma	-	Periodic	-
[74]	2012	Gamma	-	Periodic	-
[75]	2017	Exponential	Yes	Periodic	-
[76]	2013	Markovian	-	Continuous + Non periodic	Decision dependant
[77]	2018	Diffusion process	Yes	Periodic	-
[39]	2018	Wiener	-	Continuous	-
[78]	2018	Wiener + random shocks	-	Periodic	-

$$f(x) = \frac{\beta^{m(h)}}{\Gamma(m(h))} x^{m(h)-1} e^{-\beta x} \tag{3.1}$$

Where $m(h)$ is the shape parameter, controlling the rate of arrival of the jumps, and β is the scale parameter, defining the jump size; Γ is the gamma function, defined as:

$$\Gamma(m(h)) = \int_0^\infty x^{m(h)-1} e^{-x} dx \tag{3.2}$$

From Figure 3.6 it is possible to see that it is the most used model in the selected literature, with 18 papers out of 47 implementing it. The reason behind its popularity lies in the fact that it is strictly monotone increasing, property which is well suitable to represent physical degradation mechanisms as wear, creep, or crack growth; moreover, being a discontinuous process, it can be seen as the accumulation of small shocks over time, as observed in [51]. Linked with this last concept is the consideration that this process presents a time dependency, meaning that the longer the time elapsed the higher the degradation jumps; for this reason, as stated in [58], it should be used only in applications where the deterioration jumps are proportional to the elapsed time. Finally, Khatab et al. [57] notice that its mathematical modelling is quite straightforward, making it easier than other processes to be implemented and analysed.
Among the articles using this model, Shen et al. [54] add the peculiarity of having different Gamma processes to simulate different degrading environments; in [57], in the context of a selective maintenance model, the authors make each component follow its own deterioration path; both [59] and [62] modify its expression adding the influence of random effects, useful to simulate the heterogeneity in degradation between different units.

Wiener process

Wiener process is another type of statistic model, generally composed by a drift term plus a diffusion term following Brownian motion. Its general expression for the overall degradation at a time t is [53]:

$$X(t) = X_0 + \mu t^\alpha + \sigma W(t) \tag{3.3}$$

Where X_0 is the initial degradation of the system, μ is the slope of the non-linear (when $\alpha \neq 1$) or linear (when $\alpha = 1$) drift, σ is the diffusion coefficient and $W(t)$ a standard Brownian motion, i.e. $W(t) \sim N(0, t)$.
As well as the Gamma process, the Wiener one is widely used in literature,

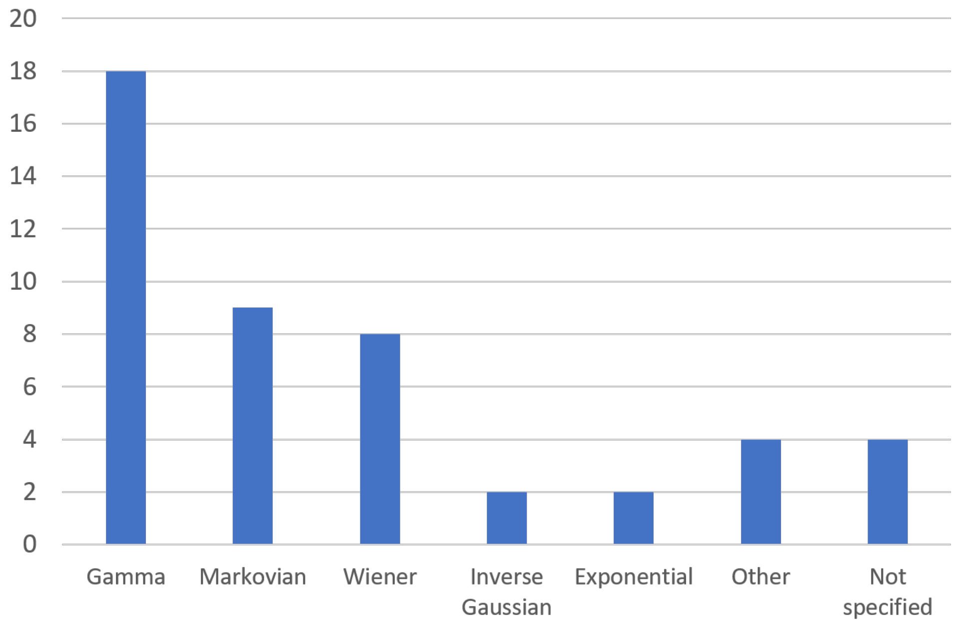

Figure 3.6: Deterioration processes used in the analysed papers

as shown in Figure 3.6. Similarly to the Gamma, in fact, it has a quite good mathematical tractability and a flexible modelling structure. As stated by Do Van et al. [53], who implement it in their paper, it is mostly suitable for all applications where the deterioration level increases linearly or non-linearly in time with random noise, which is likely to occur when acquiring a signal through sensors. In addition, it is a non-monotone process, although its mean increment (represented by μ) is monotonically increasing; however, it is possible to have an approximation of a monotonic behaviour by setting the drift parameter much higher than the diffusion one, as done in [47].
In some publications ([47], [61] and [78]) the Wiener process is used in concomitance with the presence of random shocks whose arrival times follow a Poisson distribution, in order to simulate sudden degradation increments due to the external and operating conditions. Finally, in the work by Wei et al. [47], where the deterioration process is divided into two overall states (i.e. normal and weakened) a two phase Wiener process is implemented, with larger drift and diffusion parameters for the weakened state such that the system deteriorates faster when it has a high degradation level.

Inverse Gaussian process

Another statistic model used is the inverse Gaussian, which assume that the degradation process have independent increments following an inverse

Gaussian distribution. The probability density function of the degradation path at time t is given by the following expression:

$$f(x) = \sqrt{\frac{\lambda\Lambda^2 t}{2\pi x^3}}\, exp\left[-\frac{\lambda\Lambda^2 t(x-\mu\Lambda t)^2}{2(\mu\Lambda t)^2 x}\right] \tag{3.4}$$

Where $\mu\Lambda(t)$ is the shape parameter and $\lambda\Lambda(t)^2$ is the scale parameter [49]. Although less popular than the previous models (it appears only in [49] and [67] in Table 3.3), it is a monotone process which, as stated in [67], has some good properties: an appreciable fitting effect when dealing with historical data; a clarity in the physical meaning comparable to Gamma process; the possibility of incorporating parameters randomization methods. In particular, regarding this last possibility, it is implemented in the work by Wu et al. [67], with the introduction of a stochastic shape parameter following a normal distribution and whose variance decreases with time, simulating so the effect of an improvement of the parameters estimation given the greater amount of acquired data.

Markov process

In the Markov processes it is assumed that the degradation pattern of machinery transforms within a finite state space following the principle of the Markov property, i.e. the probability of next state transition depends only on the current state and not on the process history. As it is possible to see, the greatest difference with respect to the previous models is the discretization in states of the deterioration process. Figure 3.7 shows a typical Markov state transition diagram, where λ_{ij} and u_{ij} represent, respectively, the degradation ad repair intensities from state i to state j.

In general, the Markov model can be discrete, if at every time step the possibility of transition between states is described by a probability matrix (e.g. in [48]), or continuous, for which a transition rate matrix determines the average number of jumps from a state to another per unit of time, like for example in [37] and [38]. As it is possible to see in Figure 3.6, the Markov process is quite popular for describing a degradation pattern. According to Li et al. [48] its wide usage is due to the fact that the number of failures in a arbitrary time interval can be described according to a Poisson process and the times for state transitions (both for degradation and repair) are assumed to obey to an exponential distribution, which makes the problem mathematically very tractable. In addition, it is easy to implement in this type of process the economic dimension, by associating to each state a cost, which is influenced by the type of action performed too: in this case, the

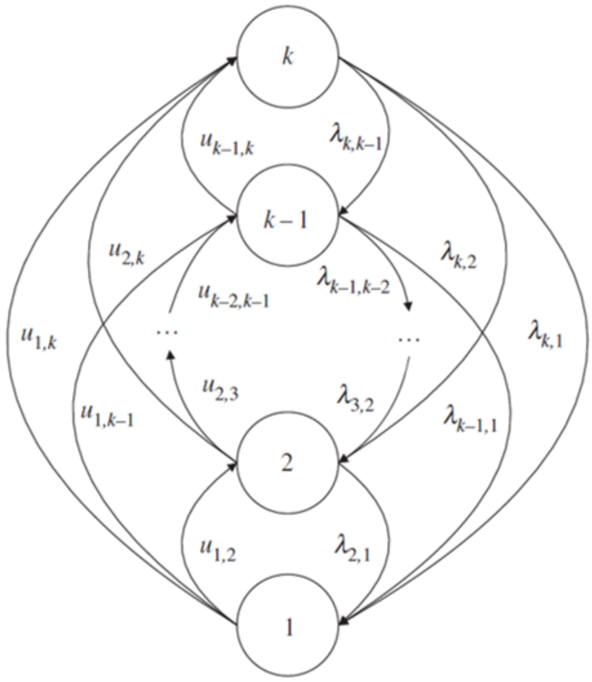

Figure 3.7: Example of a Markov state transition diagram. Figure from [48]

result is a Markov decision process (MDP), which allows, with appropriate algorithms, to find the best action to take given the current state; examples of such implementation are [30] and [44], which have also the peculiarity of transition probabilities that change with time, making the policy an action-time pair one.
Some papers in the selected literature use the so-called Semi-Markov models, like [36] and [71]: the difference with respect to the original Markov process is the relaxing of the hypothesis of exponential sojourn times, which in this case can follow any distribution. In this way, it is possible a greater process generalization, at the expenses of a more complex mathematical model.
Finally, another variant is represented by the work by Fan et al. [69], in which it is not possible to know exactly the state the process is in, making it a Partially Observable Markov decision process (POMDP); however, this kind of problem can be solved with an appropriate states reformulation, which makes it similar to a standard MDP.

Exponential process

Continuous degradation can be represented also by exponential processes. Among the selected papers, it appears only in two of them ([72] and [75]), which have the peculiarity of implementing this form with random coefficients. According to these papers, the cumulative degradation of equipment at time t_i is represented by the following expression:

$$X(t_i) = \Phi + \theta e^{\beta t_i + \epsilon(t_i)} \quad i = 1, 2, ...; \quad 0 \leq t_1 \leq t_2 \leq ... \tag{3.5}$$

Where Φ is the initial degradation, θ and β are parameters mutually independent and represent characteristics common to all individual systems in the population and $\epsilon(t_i)$ is the error term representing the degradation characteristics unique to an individual system. In particular, $\log \theta$ has a normal distribution and the error term follows a Markov process. This last property about error terms implies that any two increments in log degradation are independent from each other and so are the increments in original degradation values [75].

Other processes

Here are presented those processes which appear only once in the classified literature and consequently are less popular than the previous ones.
Rafiee et al. [65] adopt a linear degradation model with random coefficients and with the occurrence of random shocks which, as already seen in the previous paragraphs, increase suddenly the deterioration level by a quantity according to their magnitude.
Another example of standalone model is present in the paper by Ma et al. [68], where a Random Fuzzy Accelerated Degradation (RFAD) process is used. According to the authors, this model considers the time-stress-dependant structure, the random uncertainties caused by random effects in time dimension and unit-to-unit variations, and the epistemic uncertainty caused by the small sample problem simultaneously.
Lu et al. [73] describe the degradation in their work by using a so-called integrated health function, which combine the information about age and operational and environmental conditions to assess the state of the machine.
To conclude, Hu et al. [77] utilize a diffusion process (so belonging to the same family of the Wiener model) in which it is comprehended the influence of imperfect maintenance in the degradation expression and characterized by random coefficients.

Not specified processes

Finally, there are some papers in which the deterioration process is not specified, although in this case it happens only for 4 papers out of the 47 classified. Among these ones, three of them ([45], [42] and [60]) are multi-state models in which it is not stated the assumption of the Markovian property, while in [50] there is a continuous degradation model of unknown nature.

3.3.5 Inspection policy

In order to verify the degradation level of an asset it is necessary to make inspections on it. According to the classification performed in Table 3.3 and as shown in Figure 3.8, there are three main types of inspection policies used in the selected papers: periodic, non periodic and continuous. The first two are performed at discrete times and usually involve manual operations; the last one, as the name says, happens continuously in time and is usually performed by sensors. There are then some papers in which the inspection policy is not specified, although it is a minor part of the totality (only 4 out of 47).

Periodic inspections

In this type of policy, which is the most frequently used in literature (23 out of 47 papers), the asset is examined at predefined times according to a periodic schedule. An advantage of this policy is its ease in planning and organizing inspection activities, to be added to the cost savings in sensors technology. On the other hand, like the scheduled maintenance, it reduces flexibility and can lead to a lost in information if the inspection period is too long or, at the contrary, in an excess of activities if it is too short, with consequent higher costs. Often, as it is possible to see in the paragraphs about the classification of the decision variables (ref. Section 3.3.9), the inspection period is an important optimization parameter.

Non periodic inspections

Under this category there were grouped all inspection policies in which the observations are made at discrete times but not following a periodic schedule: in this case, activities can be organized according to specific inspection time laws, depending on some events or by management decision. In order to be more precise about the nature of this policy in the various cases, a further column in Table 3.3 was added, giving details about the non periodic type. In particular, in the work by Zhao et al. [43] inspections are programmed at intervals which follow a geometrically decreasing law, since it is necessary to observe more frequently the equipment when its age increases. In the paper

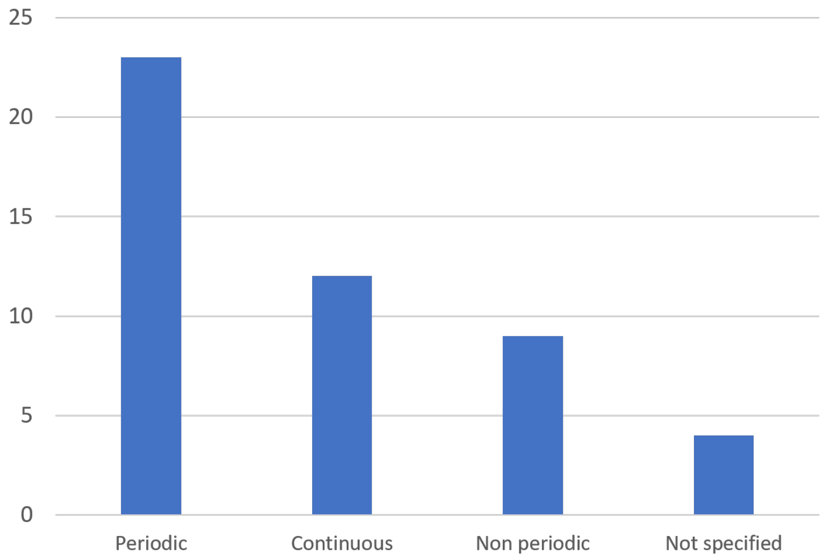

Figure 3.8: Overview of the inspection policies used in the classified papers

by Wang et al. [33], in which the subject is a production system, inspections are programmed according to the lot size. Similarly, in other articles ([52], [38] and [61]), the asset is inspected at the end of missions with a determined or stochastic duration. In [51] and [58], the remaining useful life of the system is computed and the information is used to program efficiently the inspection time, doing the activities only when necessary. Finally, in some publications like [69] and [76] the moment in which observe the asset is a decision to be taken by the management before any action according to some criteria.

Continuous monitoring

In regime of continuous monitoring, the system is inspected continuously through a flow of data coming from sensors. As it is possible to see from Figure 3.8, in comparison with the discrete time inspections this type of policy is less used but still quite represented with 12 papers out of 47 implementing it. Its main advantage is the capability of giving a continuous assessment of the asset, which can be very useful in order to decide which actions to take and when. On the other hand, for years the main disadvantage of implementing sensors was their cost, although in recent times this has become less and less relevant due to technological progress. Another issue this method can have is the amount of data to analyse, for which industrial analytic and Big Data techniques may be necessary.

Among the papers which implement it, the work by Le et al. [76] presents the peculiarity of combining continuous monitoring with a non-periodic policy: in fact, it is assumed in the publication that the sensors are only able to give a partial assessment of machinery condition, which therefore must be inspected manually; whether to perform the inspection and its time constitute a decision variable of the paper.

3.3.6 Maintenance policy

In Table 3.4 the selected papers are classified basing on the maintenance policy adopted. In order to achieve a complete classification of this aspect, three columns have been created, specifying respectively the type of policy, the presence of RUL estimation and the maintenance actions which is possible to do.

Type of maintenance policy and RUL estimation

Regarding the type of policy, it is appropriate to remember that one of the classification criteria is to include only papers which adopt a condition-based maintenance (CBM) policy. However, at this stage it is necessary to distinguish between publications which have a pure CBM policy and others that integrate it with a time-based maintenance (TBM) one. In this case both approaches are quite widely used in literature.
With a pure CBM policy is intended a maintenance strategy in which every action is triggered by the condition of the machine, whose assessment is done by the methods explained in the previous paragraphs. On the other hand, sometimes the moments for specific actions like the preventive replacement of the system with a new one are planned a priori according to some time-related criteria, leading to a combination between condition and time-based maintenance policies; usually this is done for safety reasons. For example, some models allow a maximum number of imperfect maintenance actions before replacing the machine, like the one by Wei et al. [47], in which partial repair is allowed only once, or like in [49], for which the number of actions before replacement is a decision variable. In [52] the limit is represented by a maximum number of operating missions after which it is necessary to substitute the system. In the work by Ponchet et al. [74] instead there is a predefined time limit for the renewal cycle (i.e. the maintenance cycle between two consecutive replacements) duration.
Particular is finally the publication by Mercier et al. [55] which develop two models, one purely CBM and the other combining CBM and TBM with a

Table 3.4: Maintenance policy

Ref.	Year	Maintenance policy	RUL	Type of actions	Ref.	Year	Maintenance policy	RUL	Type of actions
[40]	2020	CBM	No	IPM, PR, CR	[61]	2016	CBM	No	IPM, PR, CR
[33]	2019	CBM	No	IPM, PR, CR	[62]	2016	CBM	No	IPM, PR, CR
[47]	2019	CBM+TBM	No	IPM, PR, CR	[63]	2016	CBM	No	IPM, PR, CR
[30]	2019	CBM	No	IPM, PR	[64]	2016	CBM	No	IPM, PR, ICM, CR
[48]	2018	CBM	No	IPM, PR, ICM, CR	[65]	2015	CBM	No	IPM, PR, CR
[49]	2017	CBM+TBM	No	IPM, PR, CR	[66]	2013	CBM	No	IPM, PR, CR
[50]	2017	CBM+TBM	No	IPM, PR, ICM	[67]	2019	CBM+TBM	No	IPM, PR, CR
[51]	2015	CBM+TBM	Yes	IPM, PR, CR	[41]	2019	CBM	No	IPM, CR
[52]	2013	CBM+TBM	Yes	IPM, PR, CR	[68]	2018	CBM+TBM	No	IPM, PR, CR
[53]	2013	CBM	Yes	IPM, PR, CR	[69]	2019	CBM+TBM	No	IPM, PR, CR
[44]	2019	CBM	No	IPM, PR, CR	[34]	2018	CBM+TBM	No	IPM, PR, CR
[54]	2019	CBM	No	ICM, CR	[70]	2017	CBM	No	IPM, CR
[55]	2019	CBM/CBM+TBM	No	IPM, PR, CR	[46]	2017	CBM	No	IPM, PR, CR
[37]	2019	CBM	No	IPM, PR, ICM, CR	[71]	2017	CBM	No	IPM, PR, CR
[45]	2019	CBM	No	IPM, PR, ICM, CR	[72]	2015	CBM	No	IPM, CR
[43]	2019	CBM+TBM	No	IPM, PR, CR	[73]	2014	CBM	No	IPM, PR, CR
[56]	2018	CBM	No	ICM	[35]	2012	CBM+TBM	No	IPM, PR, CR

Table 3.4 continued from previous page

Ref.	Year	Maintenance policy	RUL	Type of actions	Ref.	Year	Maintenance policy	RUL	Type of actions
[57]	2018	CBM	No	IPM, PR, ICM, CR	[74]	2012	CBM+TBM	No	IPM, PR, CR
[38]	2018	CBM	No	IPM, PR, ICM, CR	[75]	2017	CBM	No	IPM, CR
[36]	2018	CBM	No	IPM, ICM	[76]	2013	CBM	No	IPM, PR, CR
[42]	2017	CBM	No	IPM, PR, ICM, CR	[77]	2018	CBM+TBM	Yes	IPM, PR, CR
[58]	2017	CBM	Yes	IPM, PR, CR	[39]	2018	CBM	Yes	IPM, CR
[59]	2017	CBM	No	IPM, PR, CR	[78]	2018	CBM	Yes	IPM, CR
[60]	2017	CBM	No	IPM, PR, ICM, CR					

IPM = Imperfect Preventive Maintenance; PR = Preventive Replacement;
ICM = Imperfect Corrective Maintenance; CR = Corrective Replacement;

maximum number of imperfect actions, in order to compare them.

The column right to the type maintenance policy in Table 3.4 specifies the presence of remaining useful life estimation. In this case, it is interesting to notice that only a small part of the papers analysed (7 out of 47) integrate the RUL prevision in their work: this is usually done in order to program better maintenance and inspection activities, in order to take an action only when really necessary.

Type of actions

Finally, the last column of Table 3.4 lists the types of action allowed by the model. There are four types: imperfect preventive maintenance (IPM), preventive replacement (PR), imperfect corrective maintenance (ICM) and corrective replacement (CR). As it is possible to see, the actions are divided in preventive and corrective ones which, in turn, can be imperfect or perfect (i.e. a replacement). To be noticed that the replacement action is always assumed to be perfect by definition, concluding a maintenance cycle.
Looking at Table 3.4, only 8 papers implement all the actions in their models; in fact the most frequent combination is IPM, PR and CR: this means that only preventive maintenance can be imperfect and if the machine fails it is replaced with a new one. In the work by Bousdekis et al. [30] only preventive actions are allowed; this is probably because failure of the equipment is considered very rare and so the corrective actions are not normally contemplated. On the opposite, in [54] and [56] only corrective maintenance is implemented, perfectly or imperfectly, since a run-to-failure strategy is considered. Another example is [36], in which only imperfect maintenance is allowed, both preventive and corrective. Finally, some papers consider only imperfect preventive actions while the asset is running, to replace it perfectly at the moment of failure.

3.3.7 Imperfect maintenance

Table 3.5 is dedicated to the description of imperfect maintenance in the selected literature. In order to analyse the various aspects of this type of intervention, the table is organized in four columns: the first describes what is the effect of imperfect maintenance, the second specifies if this effect is deterministic or stochastic, the third gives details about the stochasticity of the effect, when it is present, and, finally the last column reports some particular aspects of the imperfect maintenance model. To be noticed that in the rows in which multiple effects are present these ones can be preceded by a number: this is done in order to link each effect with its specifications in the other column when these ones are different. For example, this method is used in the row corresponding to paper [51], since the two different effects belong to different distributions: on the other hand, it is not done for example for article [53], because both the effects have the same characteristics.

In order to understand the various effects of imperfect maintenance modelled in literature, first of all it is necessary to make a distinction between the multi-state degradation models (e.g. Markov) and the continuous ones, like the Gamma or the Wiener processes. The choice for this division is to be found in the mechanics which describe both the degradation and the maintenance action effects. In fact, while in multi-state models these processes are translated into passages between discrete states, in the other ones the degradation is represented by a continuous function and it is more appropriate to talk about deterioration levels, with the repair action removing in most cases a percentage of the degradation accumulated over time. As it will be possible to see from the next paragraphs, there are also some cases in which imperfect maintenance acts in a similar way for both types of models: it happens primarily when the effect of repair is to bring the deterioration to a precise previous state or level. However, this is a particular case which does not make the division less effective in describing the general differences in the respective mechanics.

Multi-state models

Starting with the multi-state models, in this case the maintenance action overall effect is a transition to a better deterioration state, which can be deterministic, if it is possible to know in advance which state the system will reach after maintenance, or stochastic, if the outcome is uncertain. Usually, in this last case the transition is ruled by a probability matrix, which links the current state to the possible better ones.

Particular cases are constituted by the work by Atashgar et al. [42] in which maintenance brings the system to a given state: the difference between the standard situation of a better state transition is that the arrival state is always the same, independently on the starting point or the decision of the user. Another peculiar case in represented by [71], where the asset is brought only to the previous deterioration state: this event is stochastic since there is the possibility that the intervention has no effect, leaving the system to the current state, or can provoke failure in the worst case. Finally, in [36]

Table 3.5: Imperfect maintenance description

Ref.	Year	Imperfect Maintenance			
		Effect	**Deterministic/ stochastic**	**Stochastic distribution**	**Particular rules**
[40]	2020	Degradation reduction, degradation rate increase, degradation variance increase	Stochastic	Not specified	New degradation level worse than after previous repair
[33]	2019	Degradation reduction	Deterministic	-	-
[47]	2019	Redution to a given level	Deterministic	-	IPM only once
[30]	2019	Transition to a better state	Stochastic	Probability matrix	Selection of IPM level, IPM level dependant on resources
[48]	2018	Transition to a better state	Stochastic	Probability matrix	Selection of IPM level
[49]	2017	Degradation reduction	Stochastic	Exponential decreasing	Maximum number of IPM
[50]	2017	Redution to a given level	Stochastic	Not specified	Maximum number of IPM/ICM, effect decreasing with number of actions
[51]	2015	1)Degradation reduction 2)Degradation rate increase	Stochastic	1)Truncated normal 2)Exponential	Maximum number of IPM
[52]	2013	1)Degradation reduction 2)Maintenance duration increase	Stochastic	1)Exponential based geometric decreasing 2)Not specified	Maximum number of missions

Table 3.5 continued from previous page

Ref.	Year	Imperfect Maintenance			
		Effect	**Deterministic/ stochastic**	**Stochastic distribution**	**Particular rules**
[53]	2013	Degradation reduction, virtual age reduction	Stochastic	Beta	Maximum number of IPM, effect dependant on resources and decreasing with age and number of actions
[44]	2019	1)Transition to a better state 2)Degradation rate reduction for a limited time	1)Stochastic 2)Deterministic	Probability matrix	Selection of IPM level
[54]	2019	Degradation reduction	Deterministic	-	Maximum number of ICM, effect decreasing with number of actions
[55]	2019	Degradation reduction or virtual age reduction	Deterministic	-	Maximum number of IPM or none
[37]	2019	Transition to a better state	Stochastic	Probability matrix	Selection of IPM level, IPM level resource dependant
[45]	2019	Transition to a better state	Deterministic	-	Effect dependant on resources and decreasing with age
[43]	2019	1)Degradation reduction 2)Degradation rate increase	Stochastic	1)Beta 2)Not specified	Maximum number of IPM
[56]	2018	Degradation reduction	Stochastic	Truncated normal	Effect dependant on resources
[57]	2018	Degradation reduction	Deterministic	-	Effect dependant on resources

Table 3.5 continued from previous page

Ref.	Year	Imperfect Maintenance			
		Effect	**Deterministic/ stochastic**	**Stochastic distribution**	**Particular rules**
[38]	2018	Transition to a better state	Deterministic	-	Selection of IPM level, IPM level dependant on resources
[36]	2018	Transition to best state, degradation rate increase	Deterministic	-	-
[42]	2017	Transition to a given state	Deterministic	-	-
[58]	2017	Degradation reduction	Stochastic	Not specified	Effect decreasing with number of actions
[59]	2017	Complete restoration	Stochastic	(p,q) model	Possibility of no effect
[60]	2017	Transition to a better state	Deterministic	-	Selection of IPM level, IPM level dependant on resources
[61]	2016	Degradation reduction	Deterministic	-	Effect decreasing with number of actions
[62]	2016	Complete restoration	Stochastic	(p,q) model	Possibility of no effect
[63]	2016	Degradation reduction	Deterministic	-	-
[64]	2016	Degradation reduction	Deterministic	-	Selection of IPM level, IPM level dependant on resources
[65]	2015	Redution to a given level	Deterministic	-	IPM only once
[66]	2013	Virtual age reduction	Deterministic	-	-

Table 3.5 continued from previous page

Ref.	Year	Imperfect Maintenance			
		Effect	**Deterministic/ stochastic**	**Stochastic distribution**	**Particular rules**
[67]	2019	Degradation reduction, degradation rate change	Stochastic	Not specified	Maximum number of IPM
[41]	2019	Degradation reduction	Stochastic	Not specified	New degradation level worse than after previous repair
[68]	2018	Degradation reduction	Deterministic	-	Maximum number of IPM, effect decreasing with number of actions
[69]	2019	Transition to a better state	Stochastic	Probability matrix	Maximum number of IPM, effect decreasing with number of actions
[34]	2018	1)Reduction to a given level 2)Degradation rate increase	Stochastic	1) Beta 2)Geometric process	Maximum number of IPM
[70]	2017	1)Reduction to a given level 2)Degradation rate increase	Stochastic	1) Truncated normal 2)Normal	Minimum interval between IPMs, effect dependant on resources
[46]	2017	Reduction to a given level or degradation reduction	Deterministic	-	-
[71]	2017	Transition to previous state	Stochastic	Not specified	Possibility of no effect or of failure
[72]	2015	Redution to a given level	Deterministic	-	Effect dependant on resources
[73]	2014	Degradation reduction	Deterministic	-	-

Table 3.5 continued from previous page

Ref.	Year	Imperfect Maintenance			
		Effect	**Deterministic/ stochastic**	**Stochastic distribution**	**Particular rules**
[35]	2012	Degradation reduction	Stochastic	Uniform or truncated normal	Maximum number of IPM, effect dependant on resources
[74]	2012	Degradation reduction	Deterministic	-	Maximum renewal cycle duration, effect dependant on resources
[75]	2017	Degradation reduction	Deterministic	-	Effect dependant on resources
[76]	2013	Transition to a better state	Stochastic	Probability matrix	Effect dependant on resources
[77]	2018	1)Reduction to a given level 2)Degradation rate increase	Stochastic	1) Normal 2)Not specified	Maximum number of IPM
[39]	2018	Degradation reduction	Stochastic	Poisson	-
[78]	2018	Degradation reduction	Deterministic	-	-

maintenance action brings always the system to the best state: in this case, in fact, the imperfection is given by an accelerated degradation rate after the intervention; it is possible to notice that the increment in the deterioration speed is present in [44] too, where it is deterministic, unlike the transition to a better state which is stochastic and ruled by a probability matrix.

Considering now the particular rules for the multi-state models, a frequent one is the selection of the Imperfect Preventive Maintenance (IPM) level, which is the effort given to the action. Such situation can happen, for example, when it is possible to choose between different maintenance actions (like lubricating, tightening screws, cleaning, etc...): the type of intervention chosen will have a different influence on the resulting effect of maintenance, like in [30]. In other cases, like in [48], it is possible to choose between minor repair, bringing the system only to the previous degradation state, and major repair, restoring the asset to a range of better states according to a probability matrix.
Similar to the previous one, another quite frequent rule is the dependency of the maintenance effect on the resources allocated; for resources is in general intended time and money. In particular, when the effect is indicated to be deterministic, it means that the allocation of resources determine the outcome of the intervention with certainty; on the opposite, in presence of a stochastic effect, the resources allocation only increases the probability of some results. An example of this rule is [76]. When it is present a selection of the maintenance level, usually each action has a specific cost: this is indicated in Table 3.5 with "IPM level dependant on resources", like in [30] and [37], in order to differentiate it from the other situation.
Finally, in some works the effect of maintenance decreases with time. For example, in the one by Wang et al. [45] the actions are less effective as the age of the asset increase; in a similar way, in [69] the effect decreases with the number of imperfect maintenance actions. This last article present also the peculiarity of having a maximum number of IPM interventions before replacement which, as already discussed in the previous paragraphs, makes the policy a combination between CBM and TBM.

Continuous degradation models

Regarding the continuous degradation models, in literature the capability of restoration of the imperfect maintenance action can be classified into three main effects:

- **Degradation reduction**: in this case, the maintenance action re-

moves a portion of the degradation accumulated until that time. In general, this effect is the most used.
Let the degradation in time be represented by the function $X(t)$. According to the degradation reduction effect, the new deterioration level after the intervention is $X'(t) = \alpha X(t)$, where $0 < \alpha < 1$ is called restoration factor, describing the percentage of residual degradation. It is possible to see that the new deterioration level is proportional to the condition before maintenance: the more the machine is deteriorated, the higher the residual degradation after the action, if the same restoration factor is used.
Again, the effect can be deterministic or stochastic: the former, when the restoration factor is fixed or known nonetheless, like in [33]; the latter, when it belongs to a certain distribution, as done in [49]. Regarding the type of distribution, several are implemented, as it is possible to see in Table 3.5 in the dedicated column.

- **Virtual age reduction**: this kind of effect acts, instead of on the degradation itself, on the age of the machine, bringing it back to the condition it was at a given time.
Considering again the degradation function introduced before, let β be the age restoration factor. Therefore, the new deterioration level after the intervention is $X'(t) = X(\beta t)$, with $0 < \beta < 1$ having a similar function to the previously considered degradation factor. The same considerations as before hold for the proportionality between the new age of the machine and the one before the intervention, as well as for the stochasticity of the age reduction factor. However, the main difference is that this time the maintenance action brings the machine to exactly the same state it was at that age: this means that the restoration, in this case, depends on the pattern followed by the deterioration process and not only on its overall amount at the moment of maintenance.
This effect is used, for example, in [66]; on the other hand, Do Van et al. [53] implement in their imperfect maintenance model both the virtual age and degradation reduction effects, introducing two factors.

- **Reduction to a given level**: in this case, the maintenance action brings the asset to a given deterioration level, independently on the state the machine was before the intervention. It means that the degradation function is transformed in the following way: $X'(t) = H$, where H is the given level the maintenance action brings always the system to.

> The stochasticity of this effect is therefore linked to the new deterioration level, which can be known in advance and fixed (deterministic) or belonging to a random distribution (stochastic). Examples of reduction of the degradation to a given level are constituted by [47] and [50].

Appearing in only two papers ([59] and [62]), another effect that the maintenance action can have is the complete restoration: in this case, the imperfection lies in the fact that such regeneration is not certain, but the intervention can also leave the asset in its original condition with a given probability, having so no effect at all.
Moreover, it is quite frequent that imperfect maintenance has one or more additional effects contemporaneously with the previous ones. For example, many papers model a change in the deterioration rate, which is usually an increase of it, like in [51], but that can also be a random change, as done in [67]. In the work by Huynh et al. [40] in addition to the degradation reduction and the increase of deterioration speed is implemented also the increase of degradation variance. Another peculiar effect is the one modelled by Guo et al. [52], for which the time taken by every maintenance action increases with the number of interventions.

Finally, many continuous degradation models are implemented with various particular rules. Some of them are the same ones of the multi-state models: many papers give a maximum limit to the number of imperfect maintenance action or, in general to the time before replacement, forming a combination between CBM and TBM (e.g [67]); quite often, the maintenance effect depends on the resources allocated, like in [56]; in some articles, the effect decreases with the number of actions and with the age of the asset, like in [53]; in [64] it is possible to select the maintenance level, exactly as for some of the multi-state models.
Finally, there are some peculiar rules which happen very rarely. In [40] and [41], for example, the new degradation level after repair is always worse than the one after the previous maintenance. In the work by Chen et al. [70] there is a minimum interval between two imperfect maintenance actions to respect; if this is not possible, a replacement occurs.

To conclude, it is clear now that imperfect maintenance is modelled in literature in many different ways, with multiple effects that can depend on the degradation process. However, the drawback of this approach is the quantity of assumptions necessary before actually running the model. In fact, as already seen, only a small number of papers try to estimate the maintenance parameters and even less update these coefficients as the asset is observed. The greatest part of publications, instead, start with given values, which can be found from historical data, if an application is present, or simply used for numerical examples, probably considering their estimation as a further step once the target application is known. This makes the models less flexible to be used on different assets and in presence of different behaviours of the maintenance actions, with a consequent loss of applicability.

3.3.8 Optimization targets

Table 3.6 presents an overview of the optimization targets used by the classified literature, when of course an optimization is performed. However, it is necessary to remember from the main content section that the greatest part of papers perform an optimization.

Maintenance cost

The optimization of the maintenance cost is in absolute the most used target. Very often, for maintenance cost is intended the cost per time unit: this is obtained, according to the renewal theory, by dividing the total maintenance cost (considering imperfect maintenance, preventive replacement, corrective actions, inspection cost, downtime, etc...) in a renewal cycle by the length of the cycle itself, which is the time elapsed between two replacements. Examples of paper which consider the maintenance cost rate are [40] and [47]. In other cases, it is considered the total cost spent until the moment considered, like in [46]. In the work by Van et al. [35], then, the maintenance cost is computed per piece produced. In general, this target can be standalone or part of a joint optimization, as shown with the next objectives.

Production cost

In this case the target is to minimise the cost of the production. The production cost optimization is present in only two papers ([33] and [34]). In both publications, a joint optimization is performed: Wang et al. [33] consider simultaneously production and maintenance cost to find an optimal production planning and maintenance policy; Cheng et al. [34] add to these two optimization target the minimisation of logistics cost for a production-inventory system.

Table 3.6: Overview of optimization targets

Ref.	Year	Optimization target					
		Maintenance cost	Production cost	Logistics cost	Profit/Net value	Reliability	Availability
[40]	2020	X					
[33]	2019	X	X				
[47]	2019	X					
[30]	2019	X		X			
[48]	2018						
[49]	2017						X
[50]	2017	X					
[51]	2015	X					
[52]	2013	X					
[53]	2013	X					
[44]	2019	X					
[54]	2019	X					
[55]	2019				X		
[37]	2019					X	
[45]	2019	X					
[43]	2019	X					
[56]	2018	X					

Table 3.6 continued from previous page

Ref.	Year	Optimization target					
		Maintenance cost	Production cost	Logistics cost	Profit/Net value	Reliability	Availability
[57]	2018	X					
[38]	2018					X	
[36]	2018						X
[42]	2017	X					
[58]	2017	X					
[59]	2017	X			X		X
[60]	2017					X	
[61]	2016	X					
[62]	2016	X					X
[63]	2016						
[64]	2016	X					
[65]	2015	X					
[66]	2013	X					
[67]	2019	X					
[41]	2019	X					
[68]	2018	X					
[69]	2019	X					

Table 3.6 continued from previous page

Ref.	Year	Optimization target					
		Maintenance cost	Production cost	Logistics cost	Profit/Net value	Reliability	Availability
[34]	2018	X	X	X			
[70]	2017						X
[46]	2017	X					
[71]	2017	X					X
[72]	2015	X					
[73]	2014						
[35]	2012	X					
[74]	2012	X					
[75]	2017				X		
[76]	2013	X					
[77]	2018						
[39]	2018						
[78]	2018	X					

Logistics cost

As introduced in the previous point, some papers integrate the logistics cost in the optimization targets. For logistics are intended all the activities which act as support for the production system, like product inventory and spare parts; for simplicity under this category is considered the shortage cost too, since strictly linked to the previous functions. As for the production cost, the minimisation of the logistics cost is performed simultaneously with the maintenance one. The two papers which implement it are [30] and, as already seen, [34].

Profit/Net value

Instead of minimising the cost, some publications decide to maximise the profit of the system or the net value of the maintenance strategy. For example, Xiang et al. [59] develop an imperfect maintenance model for a leased equipment and perform a single-objective optimization trying different targets; one of the tested target is the maximisation of the profit from the leasing contract. In [75], on the other hand, is computed the net value of the maintenance strategy, with the aim of optimising it. Finally, Mercier et al. [55] assume that the system provides a reward which decreases with the deterioration level and provide to maximise this reward function finding an optimal maintenance policy.

Reliability

Another used target is the maximisation of the reliability of the system. Just to recall the meaning of this term, for reliability is intended the "ability of an item to perform a required function under given conditions for a given time interval" [22]; usually it is expressed as a probability. In the selected literature, this target is always standalone. In particular, it appears in three papers ([37] [38] and [60]) in concomitance with missions to be completed successfully by the system.

Availability

The availability is the "ability of an item to be in a state to perform as and when required, under given conditions, assuming that the necessary external resources are provided" [22]; it can also be seen as the fraction of time the equipment is able to operate. The maximisation of availability is a target quite used in the selected literature, usually as standalone objective, like in

Table 3.7: Overview of the decision variables used in the classified papers

Ref.	Year	Decision variables							
		Inspection time	Maintenance degradation threshold	Type of action/ maintenance effect	Max. failure probability	Renewal cycle duration	Time/state to maintenance	Production and logistics	Resources allocation
[40]	2020	X	X						
[33]	2019			X	X			X	
[47]	2019	X	X						
[30]	2019			X			X	X	
[48]	2018								
[49]	2017		X			X			
[50]	2017	X	X			X			
[51]	2015		X		X	X			
[52]	2013		X						
[53]	2013	X			X	X			
[44]	2019			X			X		
[54]	2019					X			
[55]	2019		X			X	X		
[37]	2019			X					X
[45]	2019			X					X

Table 3.7 continued from previous page

Ref.	**Year**	**Decision variables**							
		Inspection time	**Maintenance degradation threshold**	**Type of action/ maintenance effect**	**Max. failure probability**	**Renewal cycle duration**	**Time/state to maintenance**	**Production and logistics**	**Resources allocation**
[43]	2019	X	X						
[56]	2018			X					
[57]	2018			X					X
[38]	2018			X					X
[36]	2018						X	X	
[42]	2017	X	X					X	
[58]	2017			X			X		
[59]	2017		X						
[60]	2017			X					X
[61]	2016		X						
[62]	2016	X	X					X	
[63]	2016								
[64]	2016			X					X
[65]	2015	X							
[66]	2013		X						
[67]	2019	X	X						

Table 3.7 continued from previous page

Ref.	Year	Decision variables							
		Inspection time	Maintenance degradation threshold	Type of action/ maintenance effect	Max. failure probability	Renewal cycle duration	Time/state to maintenance	Production and logistics	Resources allocation
[41]	2019	X	X						
[68]	2018			X					
[69]	2019			X			X		
[34]	2018		X			X			
[70]	2017								X
[46]	2017			X			X		
[71]	2017	X							
[72]	2015	X		X					
[73]	2014								
[35]	2012	X	X						
[74]	2012	X	X						
[75]	2017	X		X					
[76]	2013	X		X			X		
[77]	2018								
[39]	2018								
[78]	2018	X							

[49], but also as part of a multi-objective optimization, as done in [62]. In general, it is applied to various types of contexts.

3.3.9 Decision variables

The last classification driver regards the decision variables object of optimization, when this one is present. Since the amount and variety of these parameters is quite large, they were grouped in categories, as shown in Table 3.7; usually papers use more than one of these variables in their optimization models. In the next paragraphs, each category is explained in detail, citing the different examples.

Inspection time

Under inspection time are grouped all the decision variables which influence the inspections schedule, when continuous monitoring is not implemented. In most cases, it is applied when periodic inspections are adopted, with the aim of finding the optimal period to them; examples are, among the others, [62] and [65]. In the work by Zhao et al. [43], where there is a non periodic inspection schedule with geometrically decreasing intervals, the target is to find the related law's parameters. Finally, another particular example is the paper by Le et al. [76], in which making an inspection is a decision to take associated to the state of the machine in the context of a Markov decision process.

Maintenance degradation threshold

With maintenance degradation threshold are intended all the decision variables that consist in a deterioration level over which an action is implemented; it is easy to notice that this type of variables is applicable only for continuous degradation models. Typically, the parameter to determine is the optimal imperfect preventive maintenance threshold, i.e. the deterioration level which triggers an IPM action, like for example in [49] and [50]. There are also cases in which a level for the preventive replacement is decided, as in [40] and [47]. Among the other decision variables of this type, Zhao et al. [43] introduce a threshold after the intervention to decide which action will be the next: if the degradation level after an IPM is below this threshold, the next intervention will be an IPM too; otherwise, it will be a replacement. Atashgar et al. [42], in their multi-component system, find an opportunistic maintenance threshold for each of the elements of the asset, to determine on which other components execute maintenance if one of them already requires it. Wu et al. [67] develop a dynamic maintenance threshold, i.e. an IPM threshold which is function of time: in this case, the parameters of this function are the decision variables.

Type of action/maintenance

In this case the decision variable consists in the choice of the action or maintenance type to do at a given time. In some models, this decision is made time by time at given instants, like in [33] and [58], and the type of action chosen is the one which guarantees in that moment the lower expected cost: this decision is thence dynamic. For most multi-state models, however, usually this variable traduces in an optimal action-state pair, i.e. the best action to do in a given state in determined conditions, which is found by solving the related Markov decision process (e.g. [30] and [44]). In selected maintenance problems, like in [37] and [45], usually the decision variable is the level of maintenance to execute on each component, ranging from no action to a perfect replacement. In other publications, the optimal decision regards the residual degradation after the maintenance action: it can be a target level for continuous degradation models ([46]) or a target state for multi-state models ([42]). Zhao et al. [56] have as their decision variable the effort of the maintenance action, which is a variable part of the overall effect to be optimised.

Maximum failure probability

Not representing an actual category, but placed standalone due to its differences in comparison with the other ones, this decision variable is the maximum failure probability which is tolerated with respect of an interval of time, according to the degradation pattern trend. In the work by Wang et al. [33], for example, the failure probability is referred to the production time to complete a batch, while in other papers, like in [51] and [53], it is referred to a generic mission time.

Renewal cycle duration

As already seen in the section dedicated to the maintenance policy, some of the models analysed implement a combination between condition and time-based maintenance, giving a limit to the duration of the renewal cycle. For some of these papers, the optimal cycle length represents a decision variable: the target is to find the optimal number of imperfect maintenance actions to minimise (maximise) the objective function, like for example in [49] and [51].

To be noticed that this is not the only type of event which can end a cycle: other examples are a predetermined time for replacement or a maximum number of mission. However, in these cases they are given data and not variables to be optimised.

Time/state to maintenance

Under this category are grouped all the decision variables which influence the time or state to make a maintenance action. For multi-state models, like in [30] and [44], usually the optimal state for doing a determined intervention is given by a Markov decision process, as already explained. In other cases, for continuous degradation models, the optimal time to maintenance is decided dynamically at predetermined times, in other to choose the instant which minimises the expected cost, as done in [58] and [46]. In the work by Mercier et al. [55] the decision variable is the imperfect maintenance period: in this case, although maintenance is scheduled, the policy is still a CBM one since this value is optimized with respect to the expected conditions of the asset. Similar in this way is the article by Zhao et al. [43] which optimise the inspection law parameters, as stated in the previous paragraphs: however it is necessary to cite it into this category too since in this case inspection and maintenance happens at the same time. Finally, Wu et al. [36] determine the optimal maximum continuous production time after which the line has to be stopped to execute maintenance: to be noticed that this variable was not inserted into the renewal cycle duration category since maintenance in this case is not necessarily a replacement.

Production and logistics

For production and logistics are intended all those decision variables which are related to the production, its support activities and their management. For example, in [33] is determined the optimal production plan; in the work by Bousdekis et al. [30] the variable is the number of spare parts to order; in [36] a production capacity threshold is optimised, under which a maintenance action is needed; in [42] the decision regards the number of maintenance facilities; finally, Xiang et al. [62] optimise the burn-in time of the machine, which was inserted under this category for its asset management characteristic.

Resources allocation

The last category is related to the allocation of limited resources among different components or maintenance actions. Typically, this decision variable is implemented in selective maintenance problems due to its nature, allowing to find the optimal quantity of resources (money and time) to allocate in multi-component systems (like in [45]) but also for a fleet of machines, as in [37]. Peculiar is the work by Chen et al. [70], in which the resources are allocated among sequential maintenance actions acting on the same system, with a given budget.

3.3.10 Summary of the classification work

This section analysed the state of the art of imperfect maintenance applied to a context with a condition-based maintenance (CBM) policy implemented, at least partially, and with no availability of run-to-failure data. In particular, the selected literature was classified according to appropriate drivers and the results were reported in six different tables, in order to divide the information basing on the subject.

Table 3.2 reported a general overview of the selected papers. First of all, the articles were classified according to the industrial field they belong to and the particular application, whenever it was present. On one hand, this driver highlighted the presence of imperfect maintenance in a wide range of industrial sectors, on the other it also showed a generalized lack of industrial references and applications, with a great part of the papers implementing models verified only by numerical examples. This fact has to be added to a very diffused absence of details about the systems treated.
The overview was then completed by classifying the papers according to their main content. In particular, this one was divided into three categories: model description, parameters estimation and optimization. From this analysis emerged a strong prevalence of optimization models and, at the contrary, a small number of papers performing an estimation of the parameters, with only a couple of them providing an update of these coefficients as new data are acquired.

Table 3.3 provided a classification in terms of degradation pattern and inspection policy. Regarding the first, it was divided into the description of the deterioration process adopted, which showed various models used with the predominance of Gamma and Markov ones, and into the presence or not of random coefficients: in this case, few models utilized such feature.

Secondly, the inspection policy was first of all classified according to three types: periodic, non periodic and continuous. While the first two classes execute inspections at discrete time instants, the last one aims to monitor continuously the asset through the use of sensors. The classification showed a predominance of the first two categories, although in this case all of them are quite used. Moreover, the non periodic policy was further characterized by defining the mathematical laws or events which determine when to check the machine.

Table 3.4 aimed to give further details about the maintenance policy. In particular, it was specified if the one implemented is a pure CBM policy or a hybrid between condition and time-based maintenance. Secondly, it was detailed the presence of a remaining useful life (RUL) prediction, driver which highlighted a small number of this type of models. Then, further detailing was given by specifying the types of actions that each article takes into consideration, which in general can be preventive or corrective and perfect or imperfect.

Table 3.5 provided an overview of the different ways in which imperfect maintenance is formulated and applied. For this purpose, the greatest attention was paid in detailing the types of effect of the maintenance action on the assets, specifying after that if those consequences are deterministic or stochastic and, in the last case, what is the distribution they belong to. Finally, the last column gave some additional information about imperfect maintenance reporting particular rules used in the various models, if any. From the analysis emerged a large quantity of assumptions made a priori about the results of imperfect maintenance; only in few cases, as already seen, these hypotheses are accompanied by the related parameters estimation.

Table 3.6 reported a classification of the optimization targets present in those papers which aim to find an optimal policy or at least to take optimal decisions to improve the current one. Different targets were presented, of which the minimisation of the maintenance cost demonstrated to be the most used one.

Finally, Table 3.7, referring to the same type of papers of the previous paragraph, gave an overview of the different decision variables object of optimization. Once again, this highlighted in particular how much the optimization approach is used and the large number of forms it assumes, both in terms of targets and variables.

3.4 Literature gaps

Concluded the classification part of the current thesis, the current section aims to elaborate and formalize the main gaps found in the analysis; these ones will be then used to formulate the research objective developed in the thesis.

The first information which emerged is the lack of details given to the systems studied in the models. In fact, presenting an overview of the industrial fields and specific applications on which the papers operate, it was possible to notice that in the greatest part of them this data was not specified, at least with no precision. In addition, in few articles were given details about the nature of the system, leaving unknown in most of the works if the object of study was a single component, a multi-component asset or a fleet of machines. These two factors, combined to the fact that often papers give only numerical examples to validate their models, make the word "system" a cryptic concept, on which are executed generic maintenance actions. Therefore, the previous sentences can be summarized as a generalised lack of models built around a real asset or fleet of machines, giving furthermore precise details about the nature of maintenance actions and the components object of intervention.

Another point which is necessary to underline regards the parameters estimation. As already marked in the dedicated section of the chapter, there is only a limited number of models which provide an estimation of the coefficients describing the degradation pattern (i.e. the parameters of the function chosen to describe it) and/or the imperfect maintenance effect. In addition, the papers which update the parameters as new data are acquired are even less. Regarding these last ones, then it is possible to notice that first only one paper computes the remaining useful life in order to decide when to carry out the next intervention; secondly, no article updates both maintenance and deterioration (in this work used as synonym of degradation) parameters, but only one of them; finally, all these publications work under a periodic inspection policy, without implementing continuous monitoring. Summing up, from this analysis emerges a lack of models which, working in a continuous monitoring environment, provide a continually updated estimation of the parameters of both deterioration pattern and imperfect maintenance effects, in order to determine the remaining useful life of the asset and decide about future actions.

Regarding the degradation pattern, in Section 3.3 several models were presented, as they were adopted by the articles. However, looking at the different papers, it is possible to notice that the type of model selected to represent the deterioration of the asset is always an initial assumption of the author rather than a decision made after the analysis of data. Consequently, this fact underlines the lack of a model which, using the data acquired from the asset, aims to estimate which is the most appropriate function to represent the degradation pattern.

Finally, a further consideration regards the imperfect maintenance effects. As already stated, usually papers make a large variety of assumptions about the results of maintenance action; then, as seen before, in some cases the parameters used to represent these effects are estimated using historical data. This approach, useful in a context in which a certain knowledge of the asset is already present, risks to be ineffective when it is necessary to test and work with a new machine. Therefore, it is possible to mark a lack of models which identify and quantify the effects of imperfect maintenance only once the related data are acquired, starting from no previous knowledge about how the asset behaviour will evolve after these interventions.

In conclusion, the gaps found in literature can be summarized as:

- *GAP 1*: Lack of models focusing on a real asset or fleet of machines and giving detailed information about its nature, level and the type of maintenance actions executed.
- *GAP 2*: Lack of models which use the data from the asset, acquired in regime of continuous monitoring, to estimate and continually update the parameters of both degradation pattern and imperfect maintenance, in order to determine the remaining useful life of the machine.
- *GAP 3*: Lack of models which, using the data acquired from the asset, aim to estimate which is the most appropriate function to represent the degradation pattern.
- *GAP 4*: Lack of models which, aim to identify and quantify the effects of imperfect maintenance actions through the acquired data, starting from no previous knowledge of these effects.

In the next chapter, the gaps highlighted will be used to formulate the research objective of the thesis.

Chapter 4

Practical research design

Formalized the gaps emerged from the literature review (ref. Chapter 3), the current chapter aims to formulate the research objective of the thesis and illustrate the methodology adopted to fulfill it.

4.1 Research objective

As already stated in the previous chapters, the overall target of the present thesis is to study the application of imperfect maintenance in a context with a CBM policy applied and no availability of run-to-failure data. For this reason, subject-related literature was selected and classified in order to find the above presented gaps. In the light of what discovered, since this work aims to bring innovation in this field of scientific studies, the following research objective is formulated:

"The development of a framework for a condition-based maintenance model which aims to identify and quantify the degradation pattern and the imperfect maintenance effects in order to improve the asset prognosis and the recommendation of types of maintenance intervention."

In particular, the present thesis aims to dedicate mostly to GAP 2, GAP 3 and GAP 4.

4.2 Methodology

In order to achieve the research objective, the work is organised into two parts: the presentation of the operative framework elaborated and its assessment.

4.2.1 Operative framework presentation

The first step consists in the development of an operative framework in order to illustrate the functioning of the model worked out in this thesis. In particular, this one consists in a CBM model in which the concept of imperfect maintenance is associated to the one of failure mode: the repairs are imperfect since they restore the degradation corresponding to one of its failure modes. The main innovation, in addition to some improvements in the estimation of the remaining useful life, lies in the ability of characterizing the effects of the imperfect maintenance actions in order to expand the prognostic capabilities of the model: thus, the traditional RUL prediction is accompanied by the estimation (prediction) of the type of intervention to be executed at the next repair.
Therefore, the objective of this framework is to give guidance in the implementation of such a model. For this reason, its purpose is to be as general as possible, making it usable in more industrial applications and allowing the user possibility of choice about some aspects, depending on the specific problem setting.

The framework is represented in a hierarchical model form organised on three levels, so that each part of the CBM model is progressively explained and implemented in detail. Figure 4.1 gives a graphical representation of such organization, specifying the hierarchical relationships between the blocks component, at the different hierarchy levels, of the framework.

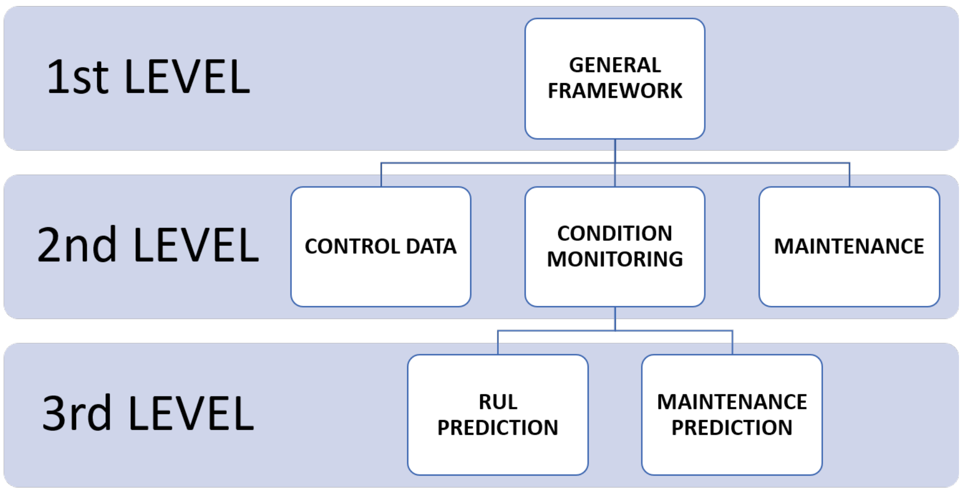

Figure 4.1: The three levels of detail of the operative framework

The first level of detail consists in the **general framework** itself, which is a macro representation of the relationships between the other main blocks. It in fact describes the cyclic succession of condition monitoring and maintenance on the asset which usually characterizes its life-cycle; these two phases are supported by the control data, containing the information for their correct execution.

The second level explains the main blocks constituting the general framework. These ones are, as previously introduced: control data, condition monitoring and maintenance.
The **control data** are the ones necessary to execute correctly the different parts of the CBM model. In particular, they can be divided into degradation control data, which allow to monitor the health state of the asset; logistic data, needed to schedule and organize the maintenance; models inputs, which are specific data required by the different models part of the framework.
The **condition monitoring** is the phase in which the degradation of the asset is supervised, in order to schedule maintenance at the right time and avoid failures. Here sensor data are collected in real time and elaborated to acquire information about the present conditions of the asset, with the target of determining the future ones. This part therefore contains the prognostic steps of the remaining useful life estimation and the prediction of the type of repair, which aim to assist the maintenance scheduling process.
The **maintenance** is the part in which not only is executed the actual repair on the asset, but also the data gained during the condition monitoring are elaborated a posteriori. This allows to improve the future actions learning from the past experiences.

Finally, the third level of detail consists in a further specification of some parts of the condition monitoring block: the RUL prediction and the maintenance prediction.
The **RUL prediction** step aims, as the name suggests, to estimate the remaining useful life of the asset. Here is described the main improvement made to this process, which is the continuous choice of the degradation function basing on the sensor data acquired.
In the **maintenance prediction** is decided which is the type of repair to be executed at next maintenance. This involves the estimation of the failure mode responsible of the deterioration and a consequent decision-making phase based on the past experiences recorded.

The operative framework of the model is exposed in detail in Chapter 5. In particular, the explanation is organised in terms of sections and subsections in order to reflect the hierarchical relationships represented in Figure 4.1. Furthermore, most of the blocks composing the framework are presented in a flow-chart form, in order to highlight the functioning of the processes involved together with the related flow of information.

4.2.2 Framework assessment

The second step consists in the assessment of the framework for the CBM model presented. This is performed starting from a dataset regarding the vibrations along the spindle axis of a drilling machine, made available by the Industry 4.0 Lab at Politecnico di Milano. Such dataset in fact constitutes the basis for the simulated experimental campaign designed: here degradation histories are created in order to verify the correct functioning of the different features of the CBM model implemented, with particular attention to the learning and predictive capabilities, remaining at the same time coherent with the original dataset. The results are then analysed with the aid of charts and graphics.

The assessment of the framework is exposed in Chapter 6. As it is possible to deduce, this part is focused on a specific situation, with specific choices regarding some model aspects, which are indicated and motivated when necessary. In addition, it acts also as a practical example of the framework implemented, permitting to show the execution of its main features.

Chapter 5

Operative framework presentation

As anticipated in Section 4.2, the current chapter aims to present the model framework elaborated to answer the gaps emerged from the literature analysis. After having delineated the problem in Section 5.1, formulating the main assumptions, the thesis continues by presenting the actual operative framework developed in Section 5.2, describing the different parts and models composing it in detail.

5.1 Problem setting and assumptions

The main purpose of this work is to develop a framework for a condition-based maintenance model capable of determining prognostics on the asset in order to schedule the future repairs efficiently. This is assumed to work in a context where the machine is continuously monitored by sensors, making necessary to collect and process a large amount of data, and where there are different failure modes which can evolve in time, making the degradation of the asset increase; to these ones are then associated different types of maintenance. In particular, these types are imperfect since they are assumed to restore the degradation caused only by the corresponding failure mode, leaving the others unvaried. Since it is hypothesised, to answer to the literature gaps, that no information is available regarding not only the failure of the asset, but also about the degradation behaviour and the effects of the imperfect maintenance actions, it is necessary to learn how the different failure modes evolve and what happens when a maintenance intervention is implemented. The information gained in this way can be then used to improve the prognostic phase, suggesting which failure mode is occurring and which type of maintenance (perfect or imperfect) is necessary to apply.

Summarizing what written in the previous paragraph, the basic assumptions of the model are:

1. The system is continuously monitored through sensors.
2. Maintenance actions are scheduled according to a CBM policy.
3. Absence of data regarding failure events and the degradation evolution of each of the failure modes of the machine considered.
4. The maintenance actions are constituted by imperfect ones of various types, each acting on a single failure mode, plus a perfect maintenance, able to restore the machine to an as-good-as-new condition.
5. The different types of imperfect maintenance (and so the related failure modes) are known a priori, but there is no information (i.e. quantification) about their effects.
6. Imperfect maintenance effects depend on the number of interventions of the same type already done from last perfect maintenance.
7. Each failure mode develops independently from the others.
8. Inspections executed during maintenance are perfect, i.e. they are always able to determine the main failure mode responsible of the degradation of the asset.
9. The maintenance lead time is the same for all types of intervention.

Regarding the previous assumptions, it is necessary to explain better some of them.
First of all, the 6. states that maintenance effects, whatever they are, depend on the number of interventions of the same type. As it is possible to see from Section 3.3, this hypothesis is common among the analysed papers: it explicates the idea that executing only partial maintenance its effect becomes lower and lower, until a perfect one is necessary. In this work such behaviour is incorporated as well, since it gives more generality to the model.
Then, the 7. states that each failure mode, in its evolution, does not influence the other ones. This assumption derives from a similar one which is done, for example, in [47], [61], [65] and [78], where there are different causes which, independently from each other, increase the degradation level of the system, thus leading to the occurrence of subsequent failure modes.

Notations	
$t_{maintenance}$	Time at which the maintenance is scheduled
t_c	Current time
$LT_{maintenance}$	Maintenance lead time
ρ	Safety coefficient used on the maintenance lead time
D_{up}	Feature threshold between healthy and unhealthy state
D_{fault}	Feature value at which the system is expected to fail
D_{limit}	Safety feature threshold used to compute the remaining useful life
η	Safety coefficient used on D_{fault}
N_{FM}	Number of failure modes of the system
FM_i	i-th failure mode ($i = 1, \dots, N_{FM}$)
IPM_i	Imperfect preventive maintenance of type i
n_i	Number of observations of failure mode of type i since last perfect maintenance
$MTBM_i(n_i)$	Mean time between maintenance related to failure mode and imperfect maintenance of type i
m	Number of condition monitoring cycles since last perfect maintenance
N_{fun}	Number of degradation functions taken into consideration
$f_j(t)$	j-th degradation function ($j = 1, \dots, N_{fun}$)
N_{reg}	Number of functions taken into consideration for the MTBM regression
$g_l(n)$	l-th maintenance interval function ($l = 1, \dots, N_{reg}$)
λ	Validation accuracy threshold for the failure modes classification model
RUL	Remaining useful life

Finally the 9., according to which the lead time is always the same, deserves a special mention, since it is probably the strongest one. In fact, this can be true only when the maintenance actions are similar to each other, like in the case of minor ones, while in general different types of intervention require different forewarning time, depending on the resources needed. However, this choice is done since the main purpose of the thesis is to focus more on the degradation of the asset which brings to a specific maintenance than the intervention itself. This further generalization about the maintenance lead time represents a possible future work.

Set the problem with the related assumptions, it is now possible to begin with the actual presentation of the operative framework developed. As already stated, this one is presented in a hierarchical model form organised on more levels; thus, the presentation will start from the general framework and progressively will enter more and more in detail, expanding the related blocks.

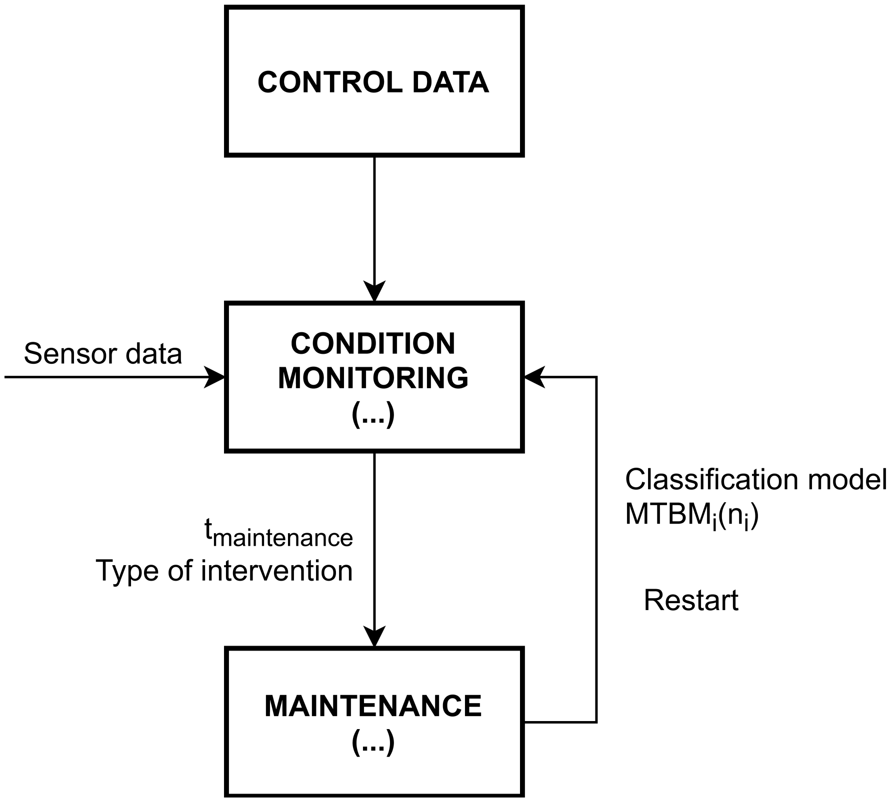

Figure 5.1: General framework of the CBM model

5.2 General framework

The general framework (first level of the operative framework) is shown in Figure 5.1. As it is possible to see, it is constituted by three main parts: the control data, the condition monitoring of the system and the maintenance. The control data contain all the required information to set the monitoring system and evaluate correctly the conditions of the asset. They are explained more in detail in Section 5.2.1. The condition monitoring (ref. Section 5.2.2), as already seen, aims at supervising the health of the machine and detect the presence of degradation, which can be caused by the insurgence of one or more failure modes. The inputs of this part are the already cited control data and the sensor data. When the deterioration of the asset is foreseen to reach a critical value, a preventive maintenance is scheduled. Therefore, the outputs of the condition monitoring block are both the time at which the maintenance has to be executed ($t_{maintenance}$), according to the remaining useful life estimation, and the type of intervention needed, which can be perfect or imperfect. In particular, the capability of evaluat-

ing the type of maintenance represents one of the main innovation points of this work, expanding the predictive step of a condition-based maintenance policy. As it is better described in the dedicated section, this information derives mainly from a classification of the different failure modes (here called FM_i) based on their degradation behaviour.
Once the scheduled time arrives, the maintenance (ref. Section 5.2.3) is executed to restore the degradation caused by the main failure mode developed, if it is imperfect, or to bring the asset to an as-good-as-new condition, in case the intervention is perfect. The main outputs of the maintenance block are the classification model of the failure modes, which is trained at every intervention basing on the new degradation data acquired, and the mean time between maintenance ($MTBM_i(n_i)$) curves for the main failure mode just observed. This second outcome is a function which expresses how much time is predicted to pass before a given failure mode FM_i shows up again from its last related maintenance and requires another intervention. Such behaviour is obtained from historical recordings, whose data are updated at every maintenance and associated to the number of times the same failure mode is observed since last perfect intervention (n_i); this is done according to the assumption that the imperfect maintenance effects depend on the number of actions executed. As it is possible to see from Figure 5.1, the classification model and the $MTBM_i(n_i)$ functions are sent back as inputs to the condition monitoring block, where they are used to predict the failure mode and decide the type of intervention to do every time. In this way, it is implemented a machine learning system which uses both condition monitoring and historical event data; these information are then accessed in real time, with the overall target of improving the present actions.
Finally, the last output of the maintenance block is the restart command to the machine and the acquisition system, so that the cycle can be repeated.

5.2.1 Control data

As already introduced, the control data represent the information needed to execute correctly the condition monitoring of the system, schedule maintenance interventions and run the minor models part of the overall model framework.

Degradation control data

To monitor the degradation of the asset it is first of all necessary to set properly the acquisition system. With the great development of sensor technology during last years, in fact, a large variety of signals became available to be

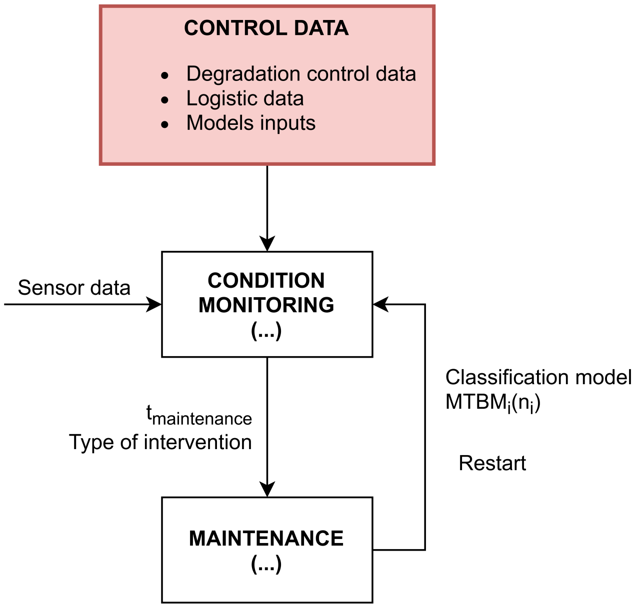

Figure 5.2: General framework: control data

monitored, the most common ones including vibrations, acoustic emissions, oil analysis, temperature, pressure, moisture, humidity, environment data, etc. The correct choice of the signal to monitor is hugely dependent on the specific application and represents a fundamental step in order to assess correctly the health condition and, consequently, having a precise prediction of its future evolution. Decided the data to be acquired, it necessary to select and extract features from them, i.e. possible indicators of the health state of the machine. Different descriptive statistics are available for this purpose, the most common ones being mean, peak-to-peak, standard deviation, crest factor, root mean square (rms), skewness and kurtosis.

Set properly the acquisition system, the two most important data to control the health condition of the asset are two feature thresholds, one indicating the beginning of degradation (D_{up}) and the other representing the value at which the system is expected to fail (D_{fault}).
Regarding the D_{up} threshold, it derives from the division of the degradation process in more health stages. According to Lei et al. [27], in fact, numerous systems tend to have a degradation process composed by two health stages, respectively called healthy and unhealthy (or abnormal) stage. During the first one, the signal maintains an approximately steady behaviour with some fluctuations and therefore it is unnecessary to predict the remaining useful life; in the unhealthy stage, on the contrary, the feature level

begins to increase, marking the starting of the actual degradation and the need of computing the RUL to avoid failure. The D_{up} value can be estimated through tests, monitoring the asset in normal working conditions; a practical example of such methodology is given in Section 6.3.1.
Regarding then the failure threshold (D_{fault}), it is a very important value for the RUL prediction and typically can be retrieved by analysing the historical data and identifying the faults. Even though in this work is assumed a lack of availability of run-to-failure data, as noticed by Vega Ortega [79] it is possible to determine approximately this limit by taking as reference similar assets for which this data are available. The uncertainty on the exact limit given by this approach can then be managed by introducing a safety coefficient ($\eta \in [0, 1]$) on D_{fault}, thus lowering the reference value for the remaining useful life estimation.

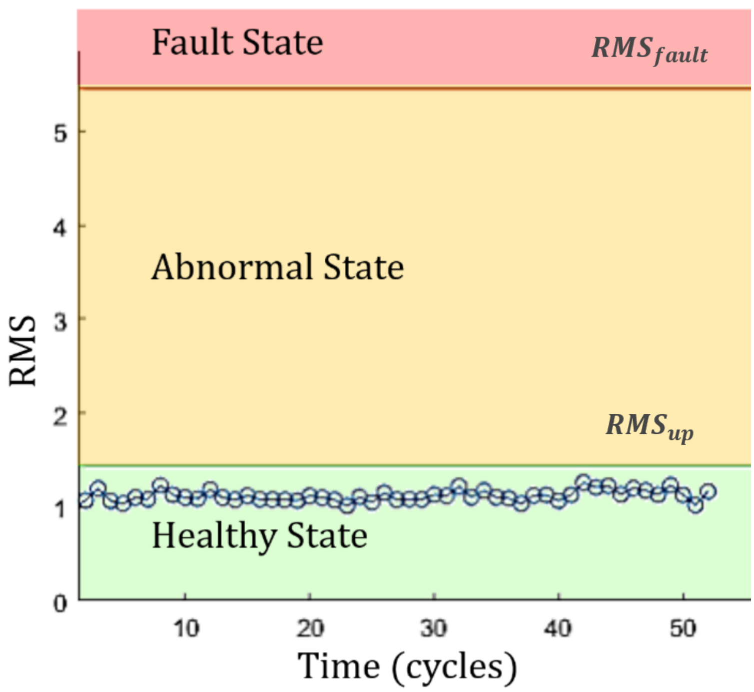

Figure 5.3: The two degradation thresholds expressed in terms of RMS. RMS_{up} indicates the passage between healthy and unhealthy or abnormal state, while RMS_{fault} the feature value over which the system is expected to fail. Figure from [79]

Logistic data

The most important logistic data for the condition monitoring is the maintenance lead time ($LT_{maintenance}$), which is the lapse of time required between the initiation of the maintenance scheduling process and its effective execution; this value can then be accompanied by a safety coefficient $\rho \geq 1$. A maintenance intervention, in fact, in order to be organized and executed efficiently needs to be scheduled with a sufficient forewarning. This time should be assessed depending on the company's organization and maintenance capability. In particular, according to Crespo Marquez [25], it is influenced by factors like the identification and assignment of resources (personnel, external materials and communication), the acquisition of spare parts, the availability of the equipment required and eventual procedures to be followed. As previously stated, for modelling choice the maintenance lead time in this work is assumed to be the same for all the types of intervention.

CONTROL DATA		
Degradation control data (referred to feature level)	**Logistic data** (referred to maintenance scheduling)	**Models inputs** (specific settings)
• Unhealthy state threshold: D_{up} • Fault state threshold: D_{fault} • Fault state safety coefficient: η	• Maintenance lead time: $LT_{maintenance}$ • Lead time safety coefficient: ρ	• Failure mode/imperfect maintenance: $FM_i \Leftrightarrow IPM_i$ • Degradation function: $f_j(t)$ • Maintenance interval function: $g_l(n)$ • Validation accuracy threshold: λ

Figure 5.4: Summary of the control data

Models inputs

Finally, to operate correctly the models in the framework are needed some other input data. First of all, it is necessary to give as input which are the failure modes that it is expected to observe (here called FM_i for $i = 1, \ldots, N_{FM}$, where N_{FM} is their number). This information, by assumption, is known in advanced; in addition, it comprehends also the imperfect preventive maintenance types (IPM_i), which are associated to the failure modes themselves.

Another important model input is constituted by the degradation functions which, as the name suggests, are all the functions taken into consideration

to fit the degradation data of the asset and then predict the remaining useful life. As already seen in Section 3.3, several degradation models can be used for this task; the target, as later explained, consists in finding the best one to describe the degradation behaviour depending on the failure mode responsible of it. These functions are indicated as $f_j(t)$ for $j = 1, \ldots, N_{fun}$, where N_{fun} is their number.
In a similar way, it is possible to define as inputs the maintenance interval functions, i.e. the ones taken into consideration to fit the mean time between maintenance (MTBM) data regarding the different failure modes, so that the effects of the maintenance actions, expressed as the time for each FM to develop, can be adequately captured and represented in order to improve the decision making. In this case, they are indicated as $g_l(n)$ for $l = 1, \ldots, N_{reg}$, where N_{reg} is once again their number. In general, they should be selected to have an overall decreasing behaviour, since it is expected from the literature that an imperfect maintenance loses efficacy with the number of actions, making the failure modes reappear more often.
Finally, it should be defined in advance the validation accuracy threshold $\lambda \in [0, 1]$ of the failure modes classification model; this is a percentage value of accuracy over which it is worth to make a prediction. As it is possible to see in the maintenance prediction framework further on (ref. Section 5.2.2), where its utility is explained in detail together with the classification model itself, such value should be set basing on the cost of a wrong failure mode prediction.

5.2.2 Condition monitoring

The second part of the general framework is the condition monitoring, which is illustrated in Figure 5.6. As already mentioned, this block receives, among the other inputs, the so called control data to give as outputs, at the end, the time at which executing maintenance and the type of intervention.

Starting the explanation of the diagram from top to bottom, at the beginning the system is simply monitored (monitor system block), receiving as input the sensor data already processed. In particular, every time N data are acquired, the program compares these ones with the D_{up} threshold: until all these N data are not greater than that limit value it means that the asset is in the healthy stage and the procedure is just repeated for the subsequent set of data, without any further action. In fact, as already stated, during this phase it has little sense to compute the remaining useful life, since the feature level is almost constant. In addition, verifying this condition tak-

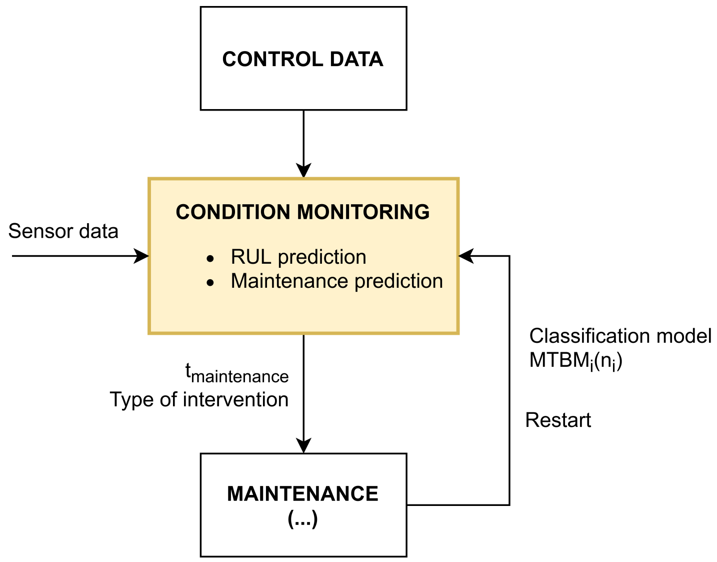

Figure 5.5: General framework: condition monitoring

ing the last N data instead of simply the last one is a necessary measure to avoid false alarms, which can occur if there is a sudden variation of the signal without an actual degradation, making only few points to grow up exceeding the limit.

At a certain point, with the increasing of the working time of the system, the previous condition becomes satisfied and the asset enters the abnormal or unhealthy state, showing signs of degradation. When this occurs, it is necessary to start with the RUL prediction, in order to foresee how much time the machine can be still operated before maintenance. This is once again an iterative process, at every iteration of which new sensor data are given as input; the difference from the previous situation is that now these data are saved and used to compute the remaining useful life of the system, being them degradation data. The block about the RUL prediction is expanded and explained in greater detail later on, with a dedicated framework. The iterative process continues until $RUL \in [LT_{maintenance}, \rho \cdot LT_{maintenance}]$: it means that the iterations stop when the remaining useful life becomes lower than the maintenance lead time increased by its safety coefficient; in addition, it states also that the RUL must be greater than the necessary lead time itself in order to schedule correctly the intervention. When the condition is satisfied, first of all is determined, using the remaining useful life, the time in which to perform maintenance ($t_{maintenance}$), which constitutes one of the two outputs of the condition monitoring block. Secondly, it is saved

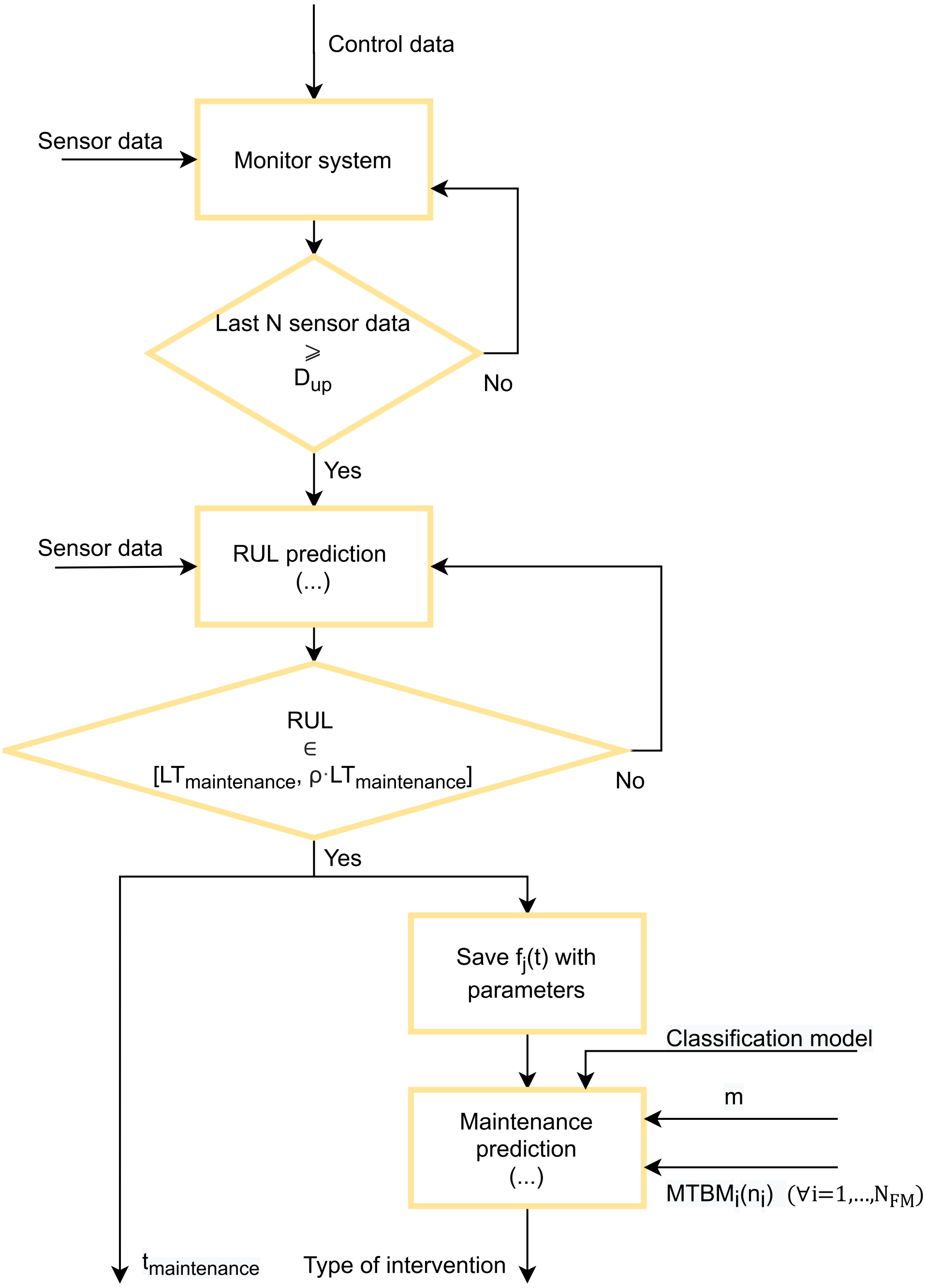

Figure 5.6: Condition monitoring framework

the degradation function, with its parameters, which best fit the deterioration pattern seen until that moment. Such degradation model constitutes an output of the RUL prediction block: for this reason, how a precise function is chosen among the others is explained in the dedicated section.
Saved the degradation function with its parameters, they are sent as input to the maintenance prediction block, whose scope consists in deciding the type of intervention to be performed at the given time $t_{maintenance}$. The other inputs of this step, which is expanded later as well, are: the classification model able to distinguish among the different failure modes; the number of condition monitoring cycles executed since last perfect maintenance (m); the mean time between maintenance functions ($MTBM_i(n_i)$) for each failure mode.

RUL prediction

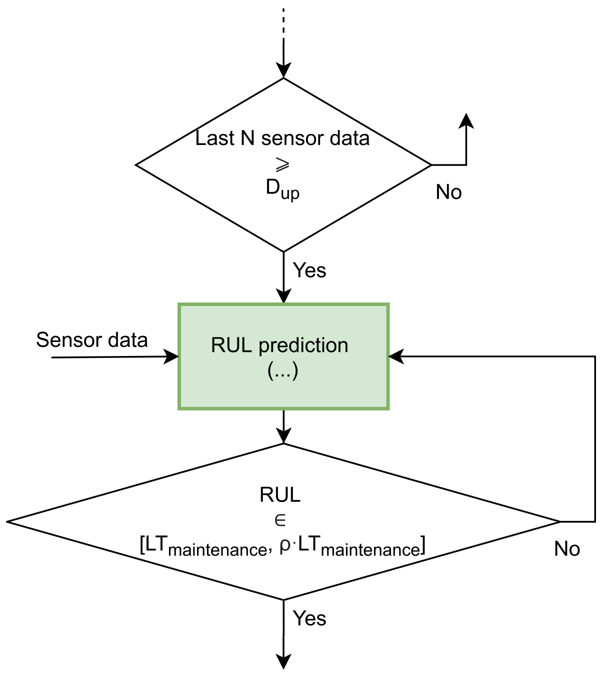

Figure 5.7: Detail of the condition monitoring framework: the RUL prediction

As seen in the previous section, the remaining useful life estimation starts when the asset enters the unhealthy stage. In Figure 5.8 is represented the RUL prediction framework.

The main input of the process are the sensor data, which, differently from

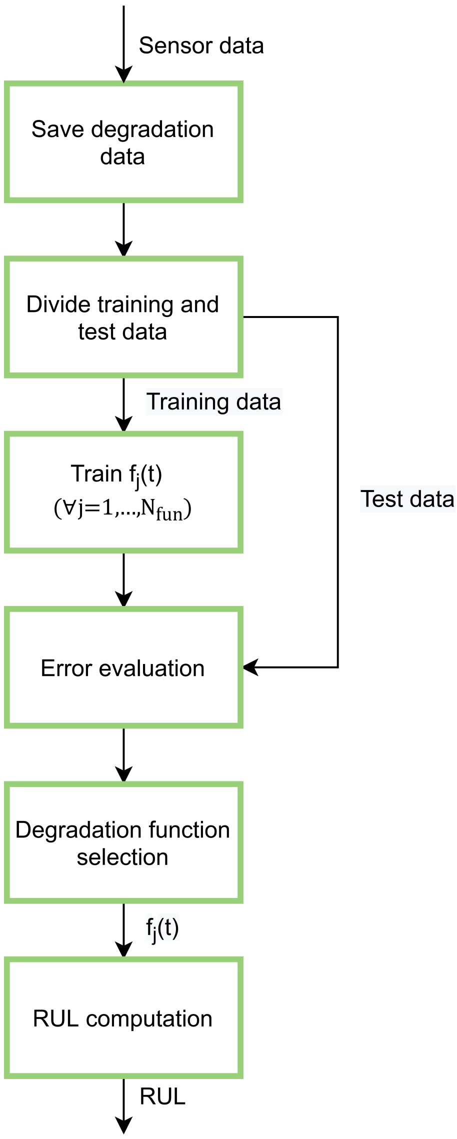

Figure 5.8: RUL prediction framework

the monitoring during the healthy stage, are this time saved being them degradation data. At this point, they are divided into two subsets: training data which, as the name suggests, are used to train and compute the parameters of the different degradation functions $f_j(t)$ for $j = 1, ..., N_{fun}$ taken into consideration; test data, which serve to perform an assessment and choose among the trained models.
This is a practice used in machine learning in order to avoid the over-fitting phenomenon, i.e. the building of a model too much based on training data and with scarce predictive capabilities. In addition, such division can be performed in more ways: if the target consists in assessing the predicting capabilities, like in this case, a good method could be labelling the first 70-80% of collected data as training, and the remaining 20-30% as test data. Thus it is possible to simulate how a degradation function is able to predict future data out of its training interval.
Therefore, once all the degradation functions are trained, the error is computed basing on the test data. Different statistics can be used for the error evaluation: residual sum of squares (RSS), mean squared error (MSE) and root mean squared error (RMSE) are all examples of error indicators based on the residuals.

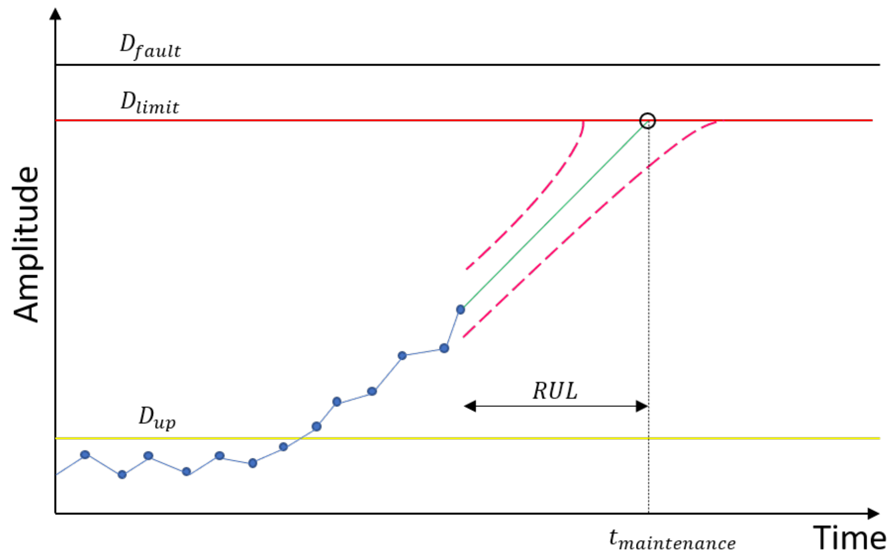

Figure 5.9: Example of RUL prediction. The estimation, referred to D_{limit}, is accompanied by confidence intervals based on the degradation function parameters.

Chosen the specific model $f_j(t)$ having the smallest error, this one can be retrained, using this time all the data available, in order to refine the parameters estimation. Finally, the model computed is used to predict the remaining useful life, which is the interval between the current time and the instant at which the degradation should reach the limit for maintenance. Instead of selecting this limit as the value at which the asset should fail (D_{fault}), it is safer to set it to a lower one, $D_{limit} = \eta D_{fault}$, where η is a safety coefficient. This is done in order to both mitigate the uncertainty regarding the real value of the failure threshold and deal with unexpected future degradation behaviours. In formula:

$$RUL = t_{maintenance} - t_c \tag{5.1}$$

Where $t_{maintenance}$ is the time in which the fitted degradation model $f_j(t)$ is expected to reach the threshold value D_{limit} and t_c is the current time at the moment of the prediction.
The RUL is usually reported accompanied with a probability density function and confidence bounds, which derive from the variation that the estimated parameters could have basing on the degradation history and can be used as a further safety measure.

The remaining useful life prediction procedure is repeated every time new data from sensors arrive. Thus, it is implemented a system which, instead of selecting the degradation model at priori, makes this choice on the basis of the data available, modifying it if the degradation behaviour changes (for example if another failure mode becomes relevant) and providing a continuous update of the related parameters.

Maintenance prediction

The last block to be detailed in the condition monitoring framework is the one related to the maintenance prediction. The main target of this step consists in defining the type of intervention to perform at next maintenance, enabling a strengthen of the prognostic action. The development of this process is represented in Figure 5.11.
The related framework is divided into two main parts: the classification and the decision-making. Starting with the first, its main input consists in the classification model trained at the time of maintenance using the degradation patterns observed until that moment, with the overall aim of predicting the main failure mode that is happening. In general, the classification is a machine learning technique whose goal is to learn a mapping from inputs, called predictors, to outputs, called responses or classes. Several methods

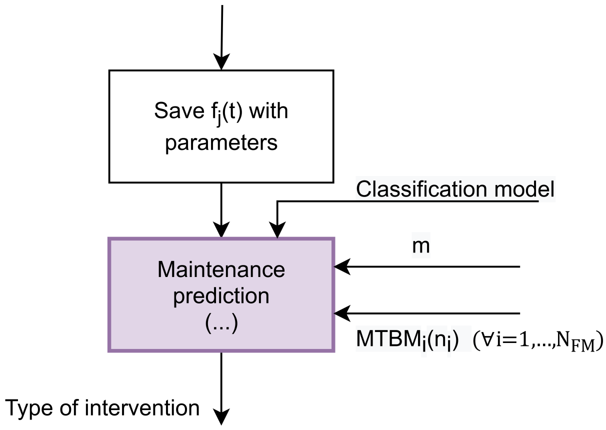

Figure 5.10: Detail of the condition monitoring framework: the maintenance prediction

can be used for this purpose: k-nearest neighbour (KNN), decision trees, support vector machines (SVM), etc. Regardless of the algorithm used, the main target is to utilize the trained model to make predictions on new input data. In this case, the response to be obtained is constituted by the main failure mode which is causing the degradation. To make such prediction the following types of data are used:

- **Shape of degradation function**: the first predictor is the specific degradation model $f_j(t)$ which is able to best represent the feature pattern seen. The function is selected during the RUL prediction framework, according to the procedure already illustrated. The form of the degradation model gives itself an important clue about the failure modes, due to the assumption that each of them evolves always in a similar way. Such hypothesis derives from the literature analysis (ref. Section 3.3), where it is possible to notice that all the articles found about imperfect maintenance use the same function to represent the degradation for all the maintenance cycles, from the first to the last; in some cases the function parameters are updated, but not its base form. This holds also for those papers ([47], [61], [65] and [78]) in which the degradation is determined by more causes: each source contributes to the growth of the deterioration level independently from the others and according to its own law, which remains unvaried with time. However, this input alone is not enough for two reasons: on one hand, there could be more failure modes with the same type of degradation pattern, making the association not biunivocal; on the other, while a failure mode is evolving there could be the insurgence of another one:

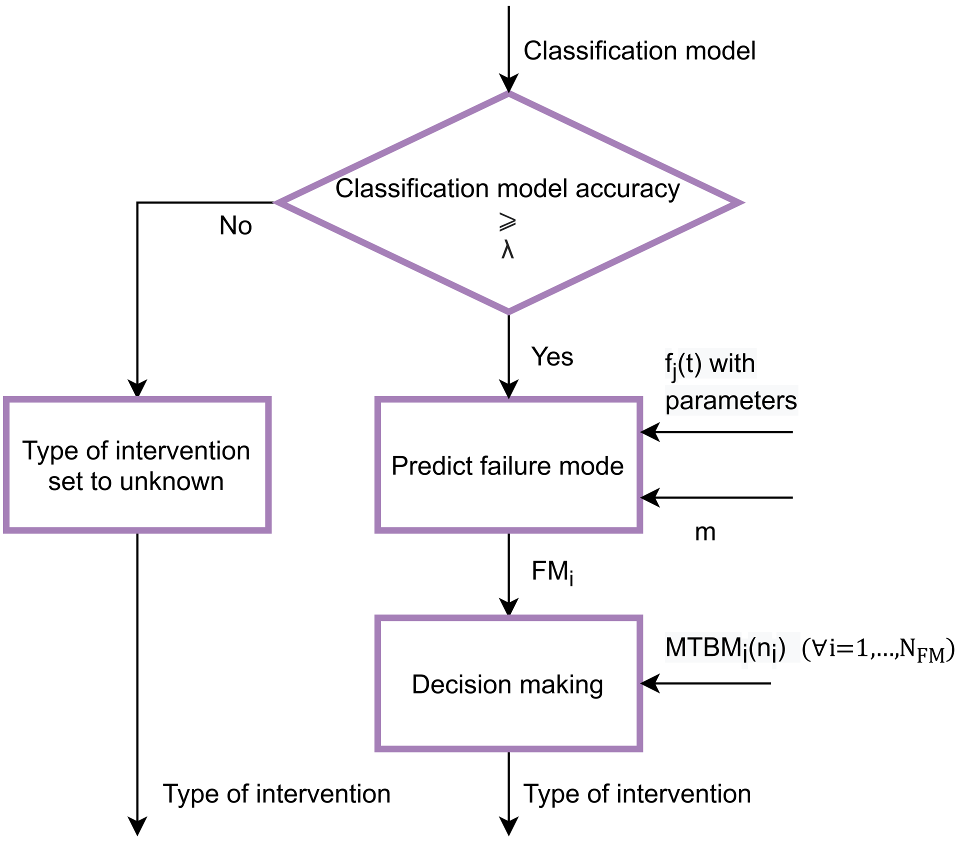

Figure 5.11: Maintenance prediction framework

the overlapping of the two effects on the degradation could therefore change the deterioration pattern that the main failure mode normally would have and so the related degradation function fitted.

- **Set of degradation function parameters**: the second predictor is constituted by the degradation model parameters, which are computed as well during the RUL prediction. These coefficients provide in fact a complete description of the deterioration pattern, including information like its rate and thus allowing to distinguish between failure modes characterised by the same baseline degradation function. In addition, such set of parameters allow to record the evolution of the failure modes intervention after intervention: this is equivalent to record the effects of the various types of imperfect maintenance, which thus are updated continuously together with the classification model.

- **Number of condition monitoring cycle**: the last predictor used is the number of condition monitoring cycles, i.e. the number of times the system has been run between two repairs since last perfect maintenance. This input allows to introduce a temporal dimension to characterize the degradation pattern. In fact, the degradation parameters during the first cycles after the perfect maintenance could be different from the ones after several interventions, given the influence of maintenance on the deterioration behaviour. This is particularly useful in those cases where failure modes with the same degradation function have similar parameters in different phases of the asset life-cycle.

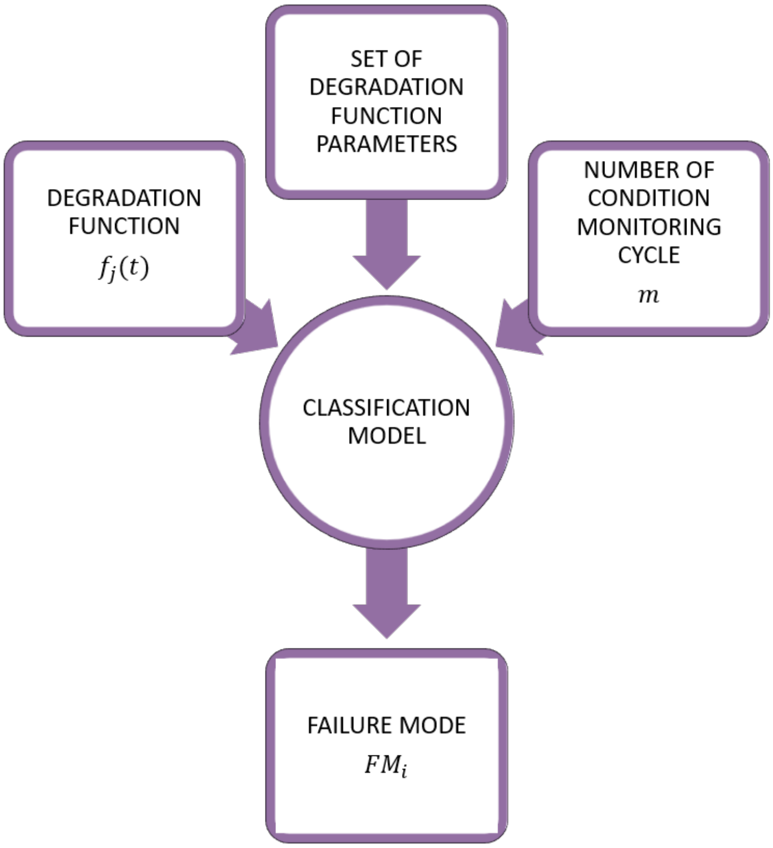

Figure 5.12: Inputs and outputs of the failure modes classification model

Every time the RUL approaches the maintenance lead time, these predictors are used to estimate the main failure mode which is provoking the degradation. However, such process is executed only if the classification model accuracy is greater than a given threshold λ, being this last one a percentage number which should be optimised basing on the error cost due to a wrong prediction. The validation accuracy of the classification model represents an estimation of its performance on new data compared to the training data and it is a statistic given as output at the moment of training. The point behind this approach is that it has sense to make a prediction about the type of intervention only if there is a high enough probability to make it right; otherwise it is better to discover the causes of degradation only at the moment of maintenance through inspection, reason why the type of intervention is set to unknown in case the condition is not satisfied.

Assuming now that the validation accuracy is greater than the set threshold and the classification model is used to predict the main failure mode FM_i which is evolving, the second part of the maintenance prediction framework is the so called decision-making. In this phase it is decided, given the failure mode estimation, the kind of maintenance to be performed next, if it should be imperfect of a specific type or perfect. For this purpose, in addition to the previous prediction, another type of input is used: the mean time between maintenance $MTBM_i(n_i)$ curves for all failure modes which have these data already available.
These curves, as already introduced, express the elapse of time which is expected to pass before a specific type of imperfect maintenance is required again. In other terms, they represent a kind of periodicity for the different failure modes, which however depends on the number of times the same failure mode was observed since last perfect maintenance (n_i). Therefore, the $MTBM_i(n_i)$ functions provide a high level information about the imperfect maintenance effects, expressing it in a time dimension: after many interventions, in fact, it could be realistically expected from the literature that a failure mode occurs more often and quickly due to the reduced efficacy of the imperfect repairs. Consequently, the utility of this type of input is twofold: on one hand it could help to decide after how many interventions it has no more sense to execute an imperfect maintenance; on the other, it provides an indication of when the different failure modes are going to occur, allowing once again to decide which type of maintenance is better to choose.

Completed the choice about the type of intervention, whether it is possible, the system is run until the scheduled time $t_{maintenance}$ arrives, when the maintenance is effectively executed, concluding the condition monitoring phase.

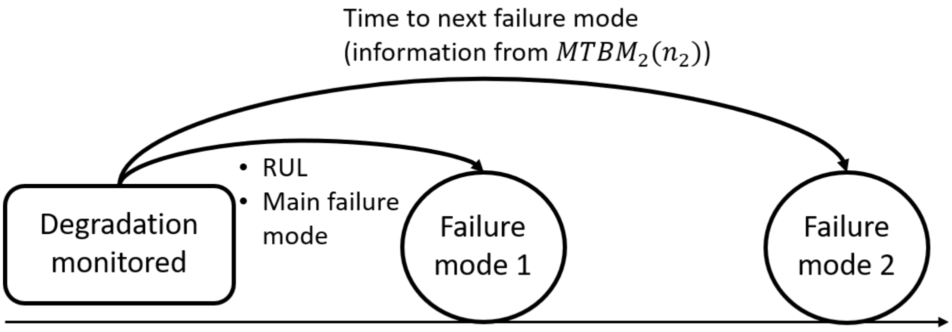

Figure 5.13: The MTBM functions allow to have a first estimation of the time at which another failure mode, in addition to the one currently monitored, is likely to emerge

5.2.3 Maintenance

The maintenance framework is represented in Figure 5.15.

When the scheduled time arrives, the first operation to be performed is the inspection of the asset. According to the model assumptions, the inspections are perfect, i.e. they are always able to individuate the main failure mode responsible of the degradation. Therefore the target of this procedure consists in fully investigating the asset in case the type of intervention is set to unknown or verifying that the failure mode prediction done in the previous part is correct. Obtained such information, the maintenance is effectively executed, refining the decision about the type of intervention in case it is necessary.

The output of the inspection block is the specific actual main failure mode FM_i in evolution and responsible of the degradation, being it already predicted or not. This information is used for two different processes, in addition to the actual repair: the training of the classification model and the mean time between maintenance data regression.
Beginning with the first, the predictors previously used (the specific $f_j(t)$ with its parameters and m) can be now labelled with certainty under a precise failure mode FM_i. Therefore, these data are added to the ones of the same type already recorded during the past repairs and used to train once again the classification model; this last one can then be sent as output together with its validation accuracy. Thus a continuous training of the model is performed, making possible to increase, maintenance after maintenance, the knowledge of the asset and improve the prediction capability.

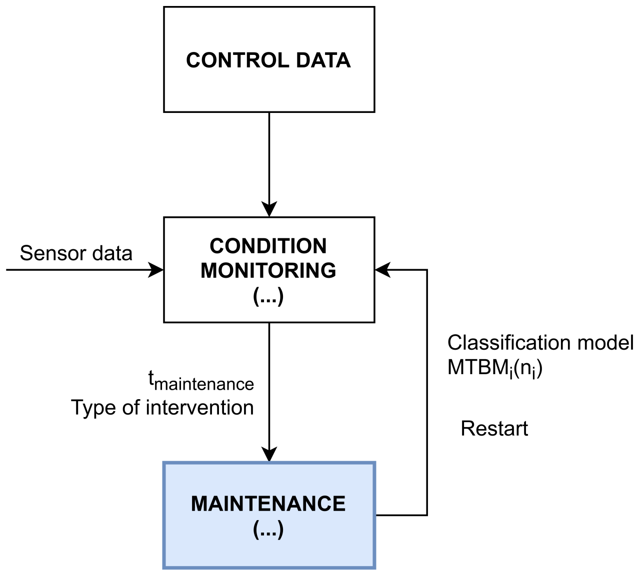

Figure 5.14: General framework: maintenance

Regarding the second process, at the moment of maintenance is recorded the operating time since the main failure mode individuated FM_i was last time repaired and this information is associated to the number of times the same one was observed (i.e. n_i). Such data are then added to a database containing similar recorded information (called $MTBM_i$ data) related to that failure mode, so that they can be fitted. The regression is done according to a procedure similar to the one used for the degradation function fitting (ref. Section 5.2.2), reason why the block is not further expanded. In particular, a number N_{reg} of maintenance interval functions $g_l(n)$ is taken into consideration and trained on the data available; then the one with the smallest error is selected to represent the mean time between maintenance behaviour $MTBM_i(n_i)$ for the specific failure mode FM_i and sent back to the condition monitoring framework, together with the other similar functions available. Being the procedure repeated at every maintenance, observation after observation it is possible to refine the knowledge about the time taken by each failure mode to cause the degradation of the asset, which is once again an expression of the imperfect maintenance effects. An example of such curves is given in Section 6.3.3, during the assessment of the model. The benefits of this process then consist in an improvement of the decision-making phase, using historical event data to perform better in the present.

Finally, when the maintenance operations are finished and the two processes

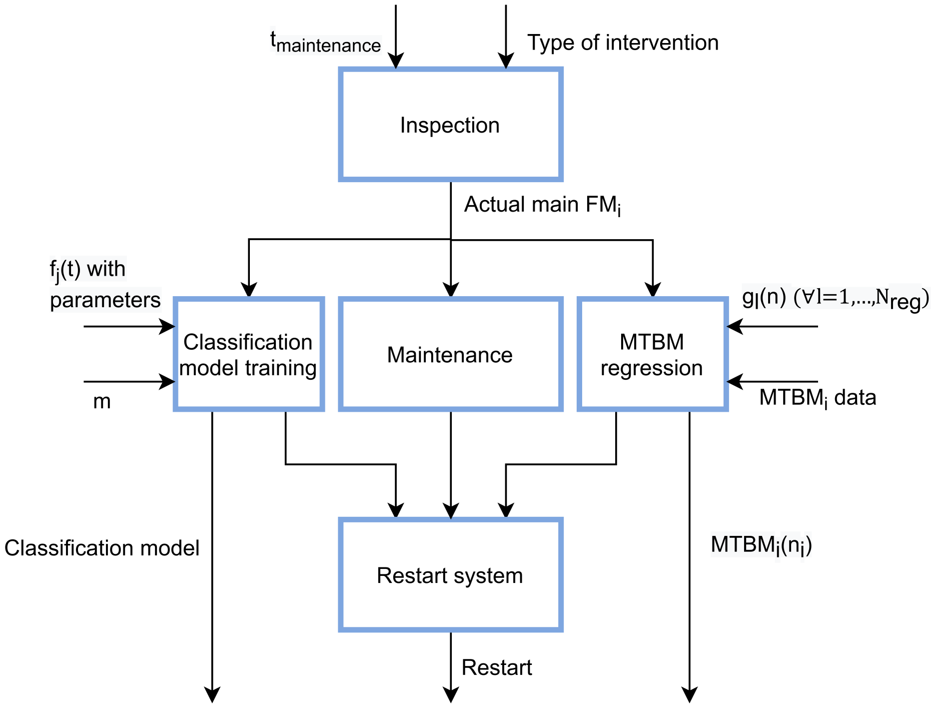

Figure 5.15: Maintenance framework

described above are terminated it is possible to give the restart command to the machine. In this way, the last block of the framework ends and the cycle can begin once again.

5.3 Conclusions

The chapter illustrated the framework for the CBM model elaborated in this work. After the setting of the problem, which presented the main assumptions done and other general comments, the actual framework was detailed. In particular, the explanation was conducted by dividing the general scheme into three main parts: the control data, the condition monitoring and the maintenance.

The control data are the information needed for the CBM model implementation and execution. They were further categorized in degradation control data, which are the information needed to monitor correctly the asset; logistic data, comprehending for example the lead time for maintenance, essential information to schedule the repairs; models inputs, which constitute the other data needed to run properly the parts and models constituting the framework.

The condition monitoring has the main target to control the degradation of the machinery and schedule the maintenance when necessary. The first innovation point here lies in the remaining useful life prediction: it was in fact added a feature which allows to choose every time new data are acquired the degradation function most adapted to represent the deterioration pattern, continuously updating at the same time the curve coefficients and the RUL estimation; this provides an answer to GAP 3.
The second innovation point of this part is then the maintenance prediction, which has the target to determine the type of intervention to be performed. This is achieved mainly using two machine learning approaches: a classification model of the failure modes, which records how they evolve maintenance after maintenance, allowing to make predictions about them; the regression of the repair intervals, creating the mean time between maintenance functions $MTBM_i(n_i)$ for $i = 1, ..., N_{FM}$ which indicate when each failure mode is going to reappear after being maintained. They both represent, in different ways, an expression of the effects of the types of imperfect maintenance, whose behaviour is thus captured, answering thence GAP 4, and used to improve the prognostic step.

Finally, the maintenance is the part in which the repair is performed and the data acquired during the last condition monitoring cycle are processed. In particular, the main innovation here is the updating of both the classification model and the mean time between maintenance (MTBM) functions: thus it is obtained a continuous update of the effects of the imperfect maintenance types, whose aim is to increase the knowledge of the phenomena occurring in order to do better in the future. Such update, together with the one of the degradation parameters in the RUL prediction, represents an answer to GAP 2.

Ended the presentation of the framework, Chapter 6 deals with the assessment of the overall CBM model illustrated. This is done by starting from a real asset and, using a reference dataset, designing a simulated experimental campaign in order to test the main innovative parts and models composing the framework. In addition, such part gives also a practical example of the different aspects presented, allowing a further clarification of their functioning and of their targets.

Chapter 6

Framework assessment

Concluded the presentation of the framework for the CBM model in Chapter 5, the current chapter aims to illustrate how the assessment of the same is performed. After a brief explanation of the methodology followed in Section 6.1, in Section 6.2 the context of the Industry 4.0 Lab at Politecnico di Milano is described together with the specific application used as real case of study. Then, Section 6.3 illustrates the actual assessment. In particular, this one is articulated in Section 6.3.1, which provides a description of the experimental dataset made available by the laboratory; in Section 6.3.2, with the explanation about how the same is used to model the degradation histories for the simulated experimental campaign; in Section 6.3.3, which reports the actual simulations together with the description of their settings, the analysis of the results and the related conclusions.

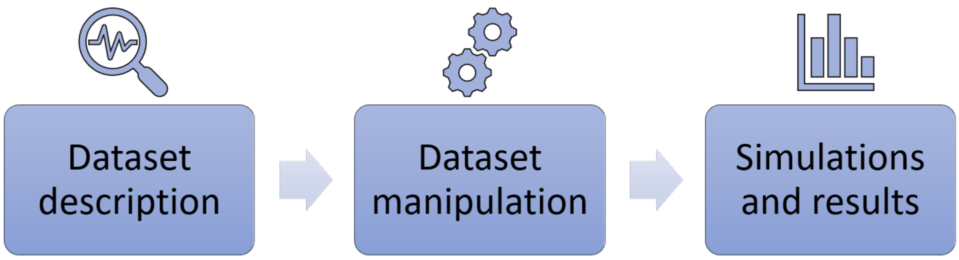

Figure 6.1: The three assessment steps executed

6.1 Assessment methodology

In this section is illustrated the methodology followed to perform the assessment of the framework for the CBM model. It consists in three main steps (ref. Figure 6.1): the analysis and description of the original dataset, the manipulation of such dataset to achieve the testing purposes and, finally, the execution of the actual experiments.

As already noticed, the starting point for the framework assessment consists in an experimental dataset made available by the Industry 4.0 Lab at Politecnico di Milano. Such dataset describes the vibration signal, acquired through accelerometers, along the three working axes of a drilling machine. Therefore, first of all are reported the settings used to acquire the data together with the processing of these last ones, which is done utilizing the root mean square (RMS) as health indicator. After that, since the dataset is representative of the vibrations recorded in standard working condition without sign of degradation, i.e. during the healthy state, it is shown the procedure which, starting from such data, allows to compute the threshold value D_{up}. Similarly, it is reported how the related indicator D_{fault} can be estimated in absence of run-to-failure data. As already noticed in Section 5.2.1, these values represent, respectively, the threshold which separates the healthy from the abnormal state and the feature level at which failure is expected, and are control data of the model developed.

The second step is the manipulation of the dataset, i.e. the generation of a similar one for testing purposes. In order to be coherent with the original ones, the generated data are created respecting its characteristics in terms of mean and variance. Moreover, to allow the execution of the simulated experimental campaigns, they are modelled so that the degradation history shows the presence of more failure modes. In particular, the deterioration pattern seen has different characteristics basing on its cause and it is created in order to be influenced by the imperfect maintenance performed, according to the assumptions presented in Section 5.1. These choices allow in fact to test the main features of the model, i.e. the improvements done to the RUL prediction and the machine learning techniques applied to characterize the imperfect maintenance effects.

Finally, the third step consists in the actual simulations and the analysis of the related results. Here are reported first of all the various settings and the specific modelling choices adopted; an example is constituted by the selection of the degradation and regression functions. After that, the actual simulated experimental campaign is run, with the scope of testing primarily the following features: the degradation function choice in the RUL prediction, the classification of the failure modes and the regression of the mean time between maintenance (MTBM) data. The results are then reported with the aid of graphics and pictures. These ones are analysed both from the technical point of view, verifying the right functioning of the above cited innovative features, and from a managerial one, making considerations about how the model itself can improve the maintenance management processes.

6.2 Experimental context

Before entering in detail with the previously cited assessment steps, the current section aims to describe the experimental context in which the original dataset of reference is generated, motivating also the reasons of its choice for the model developed.

6.2.1 I.4.0 at Politecnico di Milano

The Industry 4.0 Laboratory of the School of Management of Politecnico di Milano, located in the Department of Management, Economics and Industrial Engineering, is an entity designed to carry out research and teaching activities in a real-like Industry 4.0 environment. The laboratory is equipped with industrial assets in order to represent the state of the art of the current equipment and technology, allowing to test research's results and develop customised solutions. In addition, such researches are conducted in collaboration with various industrial partners and centres, making the lab a pole of excellence and education for universities and companies [80].

There are three main assets which compose the Industry 4.0 Lab:

- Production line: it is a physical production line installed in the laboratory. It is equipped with industrial PLC, sensors, actuators and interfaces to assembly products in a real environment.
- Collaborative robots: such asset allows to perform assembly and disassembly operations in environment characterized by side by side working conditions between operators and industrial equipment.
- Automated Guided Vehicle (AGV): it is an autonomous vehicle used to transport materials between different workstations of a shop floor, without the need of an operator.

Regarding in particular the production line of the laboratory, it consists in an automated assembly line to simulate the manufacturing process of a

Figure 6.2: The Industry 4.0 Lab at Politecnico di Milano. Picture from [79]

fuzzy classic cell phone. The line is composed by various production modules connected through a transfer line and capable of executing each a different operation, which can be defined at the moment of the production order. In particular, such workstations are three assembly modules, a manufacturing module (the drilling station), a quality control module and a manual station in order to retrieve the workpiece [79].

As already introduced, the dataset taken as reference to model the degradation histories comes from the drilling module. Therefore, in the next paragraphs it is explained how such machine tool works and the reasons of choice of that specific dataset.

6.2.2 Drilling machine

The drilling is a manufacturing process which consists in creating a circular hole in a workpiece. This operation is executed by mean of a rotating cylindrical tool with two cutting edges on the frontal face, usually having a helicoidal form, called drill bit. This one penetrates the workpiece held still on the workbench, creating a hole of the same diameter. The machine tool used to perform such process is called drilling machine or drill.

Figure 6.3: The production line of the Industry 4.0 Lab at Politecnico di Milano. Picture from [80]

Regarding in particular the drilling unit in the drilling station of the laboratory, it has the main task of simulating the drilling of holes on the front cover of the cell phone produced in the assembly line. The manufacturing module is equipped with different movement sensors which allow to track the workpiece through the station, detecting when the carrier reaches the right position so that the drilling operation can correctly and automatically take place according to the instructions communicated. When this one ends, it is given signal to the carrier to bring the workpiece to the next module, while the drilling machine remains idle waiting for the successive part. Therefore, the normal operating conditions of such machinery are constituted by a succession of working cycles interposed by intervals in which the unit is in an idle state.

In order to monitor the conditions of the drilling machine, an accelerometer is attached to the drill spindle axis, allowing thus to record the vibration signals along the three working axes (X, Y and Z) of the machine tool. The acceleration provides in fact a good description of the state of the machinery in case of rotatory elements, like in the current case, since the vibrations can be easily monitored while the system is running and give evidence of anomalies with sufficient advance [27][79].

It is now possible to make some considerations about the choice of this specific application as case of study, from which the dataset taken as reference for the simulations is generated.

First of all, according to Perez [81] the level of vibrations on the spindle of a machine tool is a fundamental parameter in order to monitor the health conditions of the asset. In fact, the main function of the spindle is providing the rotating motion, and so the cutting speed, to the tool, allowing the material removal. Problems to this unit usually cause a lack of precision and accuracy during the operations, making the machinery unable to perform adequately its function [82]. In turn, one of the most common causes for the increase of the level of vibrations in the spindle unit is given by issues with its bearings [81]. These elements, in fact, have the fundamental role of reducing friction and transmitting loads, ensuring at the same time that the shaft maintains its correct position.
For this reason, the original laboratory dataset results to be particularly interesting for the assessment of a CBM model which aims to improve the maintenance of the asset, being it representative of the healthy conditions of critical components (the bearings) in a critical part of the machine (the spindle).

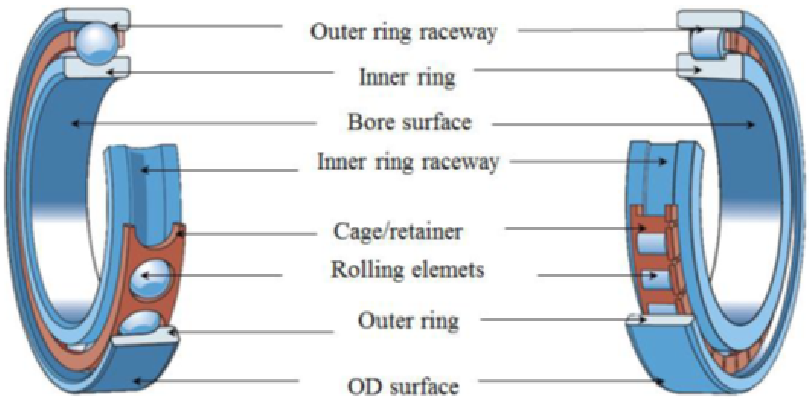

Figure 6.4: Scheme of a ball bearing. Figure from [81]

The second reason of choice regards the specific problems related to bearings. In fact, according to Urb Group [83] the malfunctioning of these elements can be caused, for example, by four common failure modes, to which correspond four preventive maintenance actions:

- Lack of lubrication: it could happen that the sliding surfaces of the bearing lack of lubricating fluid; in this case it is necessary to insert the right substance or repair the lubricating system itself.

- Contamination: it is caused by the presence of material particles from other components or brought by the lubricating fluid; it makes necessary to perform a cleaning, maybe with anti-corrosion additives.

- Misalignment of bearing components: it can be caused, for example, by an axial overload or by a temporary shaft deflection; this issue is corrected by a remounting and realignment operation.

- Fatigue: it is caused by the repeated cyclic stresses the component is subjected to; usually in this case the only solution is the substitution of the bearing itself.

Figure 6.5: Fault bearings due to lack of lubrication (top-left), contamination (top-right), misalignment (bottom-left) and fatigue related wear (bottom-right). Pictures from [83]

As noticed by Yang et al. [84], operations like the lubrication and the cleaning of the bearing can be considered as imperfect maintenance actions, since targeted minor repairs which does not restore completely its conditions. For analogy and for identical reasons, it is therefore possible to consider the remounting and realignment of the bearing elements in the same way. On the

other hand, the fatigue related wear of the component require its replacement, which is a classical example of perfect maintenance.
The application chosen presents thence a degradation which can be associated to more failure modes in turn preventively repaired by some imperfect maintenance actions. For this reason it results, together with the related dataset, suitable as reference for the assessment of the framework for the CBM model developed, which is based on these concepts.

6.3 Framework application

Described the experimental context from which the reference dataset takes origin and justified its choice, it is now possible to proceed with the actual steps of the assessment of the proposed framework: the original dataset description, its manipulation and the effective simulations.

6.3.1 Dataset description

As previously introduced, the dataset taken as reference to model the simulated experimental campaign and made available by the Industry 4.0 Lab contains the vibration data along the three working axes (X, Y and Z) of a drilling machine, acquired through an accelerometer mounted on the drill spindle axis. The data were sampled with an acquisition frequency of 200 Hz. Since, as already said in Section 6.2.2, the machine tool operates with a succession of working cycles each one with an average duration of 11 seconds, it means that for every workpiece are collected 2200 values of acceleration for each axis; in particular, the dataset is acquired through a production order of 100 units. In addition, these data refer to the healthy state of the drill, i.e. standard working conditions in absence of degradation.

In the next paragraphs is shown the method in order to extrapolate useful information from the dataset in absence of run-to-failure data, according to what done by Vega Ortega [79]. The numerical results reported are then used in Section 6.3.2 to generate new data for the simulations.

Extrapolation of information from the dataset

First of all it is necessary to process the acceleration data in order obtain an indicator about the conditions of the machine. One possible way of doing it is the root mean square (RMS), which is a statistic linked to the amount of energy dissipated through vibrations and used for rotatory components [27]. Its formula reads:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{6.1}$$

Where x_i are the single acceleration points and N is the number of values considered for the computation. This can be done so that a single RMS value is calculated after a working cycle of the machine ($N = 2200$), thus summarizing the data acquired between two idle times. The operation is performed for both X, Y and Z axes.

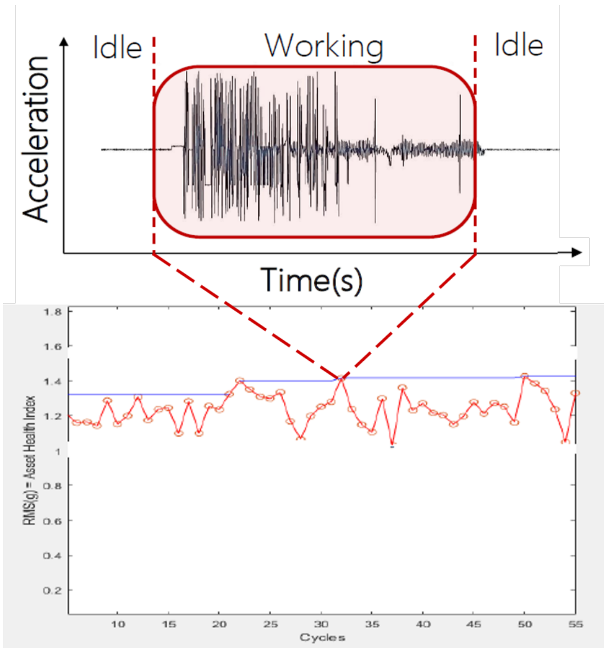

Figure 6.6: The vibration data acquired during a cycle can be summarized in one RMS point

After having computed the RMS values, the successive step is to link them to the actual conditions of the asset, in order to execute correctly the condition monitoring. In other words, it means determining the threshold limits D_{up} and D_{fault} which indicate, respectively, the passage from healthy to abnormal state and the expected failure of the system. Normally, this task could be executed by mean of a classification taking into consideration the "normal", the "abnormal" and the failure data. However, since according to the assumptions no run-to-failure data are available and the dataset represents only the healthy state, such method cannot be applied. Therefore, different procedures should be done.

For the estimation of the D_{up} threshold is necessary to perform a one-class classification method, which aims to differentiate the initial group of data (i.e. the healthy ones) from the others. It requires that the starting class follows a well-defined statistical distribution. For the dataset from the laboratory this assumption was already verified in [79], who demonstrated through a normality test that the RMS values along the three axes can be modelled according a normal distribution with the following characteristics:

$$RMS_x \sim N(\mu = 1.134,\ \sigma = 0.1004)\ m/s^2$$

$$RMS_y \sim N(\mu = 1.090,\ \sigma = 0.06446)\ m/s^2$$

$$RMS_z \sim N(\mu = 1.101,\ \sigma = 0.08749)\ m/s^2$$

At this point, the statistic theory states that a point can be considered outlier of a given normal distribution if this one has a value more distant than three standard deviations (σ) from the mean (μ). In fact, this criterion ensures that the healthy state data falls in this interval with a 99.87% of probability [85]. Applying the procedure to the previous results, it is obtained:

$$RMS_{up,x} = \mu_x + 3\sigma_x = 1.4352\ m/s^2$$

$$RMS_{up,y} = \mu_y + 3\sigma_y = 1.2834\ m/s^2$$

$$RMS_{up,z} = \mu_z + 3\sigma_z = 1.3635\ m/s^2$$

Those upper bounds thence indicate the maximum limit in which is possible to find healthy data.

For the estimation of the D_{fault} threshold, as previously noticed in Section 5.2.1, it is possible to use the data available from similar applications [85]. Such method was applied in [79], finding that for bearings the fault state can be considered as four times greater than the threshold between healthy and unhealthy stage. Therefore:

$$RMS_{fault,x} = 4RMS_x = 5.7408\ m/s^2$$

$$RMS_{fault,y} = 4RMS_{up,y} = 5.1336\ m/s^2$$

$$RMS_{fault,z} = 4RMS_{up,z} = 5.454\ m/s^2$$

This concludes the description of the laboratory dataset. In the next section is explained how, starting from these reference results, the simulation dataset is generated.

6.3.2 Dataset manipulation

The actual dataset used to perform the assessment of the CBM model should have two base characteristics: on one hand to be coherent with the original one from the laboratory, on the other to be suitable for testing the framework and its features.

To achieve the first target, the healthy state of the dataset is generated so that it has the same characteristics of the original one, i.e. a RMS value following a normal distribution with mean and variance according to the previous results. In addition, instead of creating the raw acceleration signal to be processed, the choice is to generate directly the RMS data: this allows to speed up the simulations saving computational power. Moreover, only one machine axis is taken into consideration for the sake of simplicity: the procedure can in fact be applied in a similar way to the other axes too. Thence, considering hereinafter only the X axis, in the healthy state for every time unit (i.e. working cycle) a point of the feature to be monitored D is generated according to the following distribution:

$$D_{healthy}(t) \sim N(\mu_x,\ \sigma_x) = N(1.134,\ 0.1004) \tag{6.2}$$

This represents the baseline signal, in absence of degradation, of the machine.

Characterized the healthy state, it is necessary to represent the deterioration of the system. In fact, in order to be able to perform the assessment of the CBM model, the degradation history should present more failure modes which make at a certain point the feature level (e.g. the vibrations) of the machinery rise. In particular, depending on the failure mode involved, the degradation pattern is expected to have different characteristics. Moreover, when the deterioration approaches a critical level (i.e. D_{fault}), an imperfect maintenance can be executed on the system: according to the assumptions in Section 5.1, it restores the degradation caused by only one failure mode, leaving untouched the others; on the other hand the same failure mode healed repair after repair is expected to come back again more and more rapidly, given the imperfection of the action. Finally, if a perfect maintenance is done all the failure modes are restored completely and the asset becomes as-good-as-new.

Made the previous considerations, each of the failure modes considered should be modelled in order to have a history characterized by the following steps:

1. After a time $T_{FM,i}$ from the last perfect repair, where i is the index indicating the specific failure mode, this one begins to make the degradation increase according to a pattern which depends on the specific failure mode itself.

2. When the degradation approaches critical levels, an imperfect maintenance is performed on that failure mode, restoring completely the deterioration caused by it.

3. After a time $T'_{FM,i} < T_{FM,i}$, i.e. after a smaller interval than before, the failure mode makes once again the degradation increase with a higher rate, until another imperfect maintenance is executed.

The steps are repeated in a similar way until the choice of a perfect maintenance action, which erases the memory of the system and makes the process to restart from the beginning, being the asset returned to an as-good-as-new condition.

For the current assessment, two failure modes are considered, with different patterns. The first one is modelled to have a linear pattern (ref. Equation 6.3), while the second an exponential one (ref. Equation 6.4):

$$D_{FM,1}(t) = (t - t_{repair,1} - T_{FM,1}) \cdot k_{FM,1} \tag{6.3}$$

$$D_{FM,2}(t) = e^{k_{FM,2}(t - t_{repair,2} - T_{FM,2})} - 1 \tag{6.4}$$

Where $D_{FM,i}(t)$ is the contribution to the degradation, set to be monotonically increasing and starting from zero, of failure mode i at the current time t, which is expressed in time units (i.e. cycles); $t_{repair,i}$ is the time at which the failure mode i was last time repaired through a perfect or imperfect action; $T_{FM,i}$, as already introduced, is the lapse of time before the failure mode i causes degradation; $k_{FM,i}$ represents the degradation rate of failure mode i, i.e. how quickly it makes the feature level increase.
In order to simulate the variability which can characterize the real-life deterioration histories and test better the machine learning techniques used, the values $T_{FM,i}$ and $k_{FM,i}$ for every failure mode are sorted from a random distribution, selected to be normal:

$$T_{FM,i} \sim N(\mu_{T,i},\ \sigma_{T,i}) \tag{6.5}$$

$$k_{FM,i} \sim N(\mu_{k,i},\ \sigma_{k,i}) \tag{6.6}$$

Therefore, a new value for both coefficients is determined after every repair; the values of mean and variance are then different between the two failure modes. Moreover, the mean of $T_{FM,i}$ is modelled to be linearly decreasing with n_i, i.e. with the number of observations of the same failure mode (ref. Section 5.1); on the contrary, the mean of $k_{FM,i}$ is programmed to be linearly increasing with n_i. This choice is done in order to simulate the influence of the imperfect maintenance actions, which make the failure mode reappear earlier and with a higher degradation rate. The numerical details about the coefficients are given in Section 6.3.3 with the other specific settings.

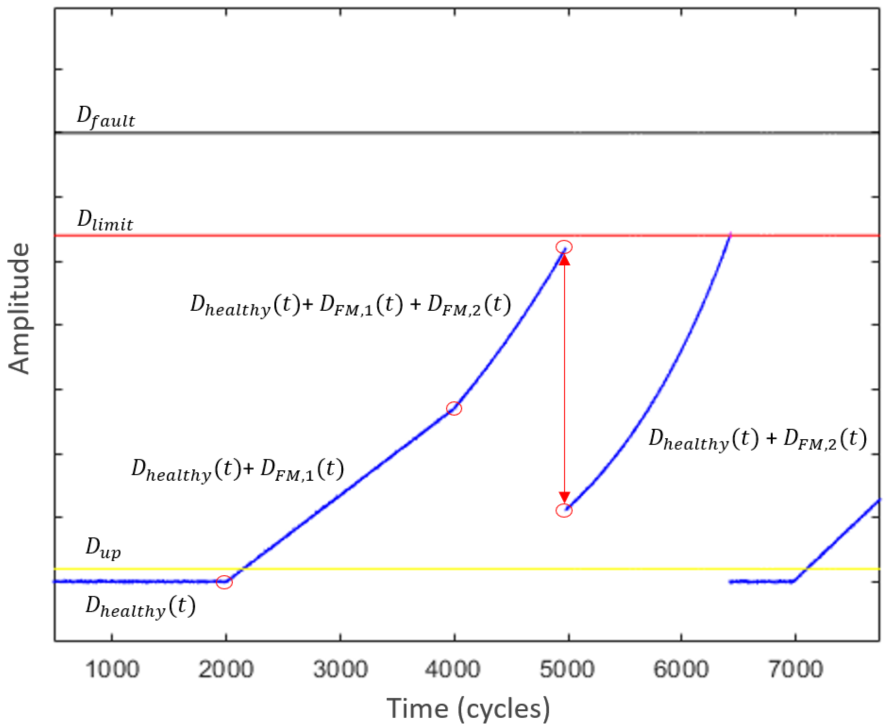

Figure 6.7: Example of degradation history involving two failure modes, FM_1 and FM_2. After a certain time, FM_1 appears (first red dot) causing degradation; after another lapse of time (second red dot) FM_2 appears too, and the resulting degradation is the sum of the two contributions; when the feature level becomes critical, an imperfect maintenance is executed (third and fourth red dots), removing the degradation caused by FM_1 but leaving unvaried the pattern of FM_2.

To conclude, the total feature level $D(t)$ results to be the sum of three contributions: the healthy state level $D_{healthy}(t)$ and the degradation caused by the two failure modes, $D_{FM,1}(t)$ and $D_{FM,2}(t)$. Therefore, the general law modelled, with respect of time t (which is counted from last perfect maintenance) and according to the effects superposition principle, is:

- **If $t - t_{repair,1} < T_{FM,1}$ AND $t - t_{repair,2} < T_{FM,2}$:**

$$\boxed{D(t) = D_{healthy}(t)} \tag{6.7}$$

- **If $t - t_{repair,1} \geq T_{FM,1}$ AND $t - t_{repair,2} < T_{FM,2}$:**

$$\boxed{D(t) = D_{healthy}(t) + D_{FM,1}(t)} \tag{6.8}$$

- **If $t - t_{repair,1} < T_{FM,1}$ AND $t - t_{repair,2} \geq T_{FM,2}$:**

$$\boxed{D(t) = D_{healthy}(t) + D_{FM,2}(t)} \tag{6.9}$$

- **If $t - t_{repair,1} \geq T_{FM,1}$ AND $t - t_{repair,2} \geq T_{FM,2}$:**

$$\boxed{D(t) = D_{healthy}(t) + D_{FM,1}(t) + D_{FM,2}(t)} \tag{6.10}$$

Briefly, what summarized in the previous equations and exemplified in Figure 6.7 is that the contribution of the failure modes starts only after $T_{FM,i}$ time units from the last repair. If this condition is not verified for any of the failure modes, the overall feature level remains the one of the healthy state; if it is verified for one of them, only its contribution is present, making the degradation pattern assume a certain shape; finally, if it is verified for both of them all the different contributions are summed up, implying that the pattern characteristics change basing on which failure mode is dominant.
Such modelling choices, as already introduced, are done in order to test effectively the innovative features of the model, with particular attention to the degradation function decision in the RUL estimation and the machine learning techniques for the characterization of the imperfect maintenance effects.

6.3.3 Simulations and results

Detailed how the degradation histories are modelled for the testing purposes, the current section aims to show the results of the actual simulated experimental campaign. First of all are reported the specific settings used, in terms of parameters values and modelling choices. They are then followed by the presentation and the analysis of the actual results obtained. As already stated, the focus of this assessment is primarily to test the innovative features of the overall CBM model: the correct choice of the degradation function for the RUL estimation; the classification of the failure modes to be used for their prediction; the regression of the maintenance intervals data to obtain the mean time between maintenance (MTBM) curves.

Simulation settings

Table 6.1 summarizes the values of all the parameters set in order to perform the simulations, according to the descriptions done in Chapter 5 and 6 and divided per type, i.e. the modelling aspect they are related to.

Regarding first of all the degradation pattern, as already said the healthy state is modelled according to the mean and the variance (μ_x and σ_x) observed for the RMS along the X axis of the drilling machine of the laboratory, as illustrated in Section 6.3.1. The same can be said for the two thresholds D_{up} and D_{fault}, which were computed starting from that data. In particular, to this last one is applied a safety coefficient $\eta = 0.8$ in order to better avoid failures.
Then are reported the means and the variances of the parameters $T_{FM,i}$ and $k_{FM,i}$ for the two different failure modes. In general, these parameters are selected to make the resulting graphics readable and ensure a reasonable simulation time. It is possible to see that the means, as previously introduced, depend linearly on the number of times n_i the same failure mode is observed from last perfect maintenance.
The parameters related to the maintenance scheduling are the maintenance lead time $LT_{maintenance}$ and its safety coefficient ρ. In this case too they are set to be reasonably scaled with the degradation pattern modelled.
Finally, it is reported the validation accuracy threshold for the failure modes classification model, selected to be a value reasonable for the related testing purposes and set equal to 0.75 (75%).

Reported the parameters values, it is necessary to describe the specific modelling decisions. A first one regards the choice of the degradation functions used to predict the remaining useful life. Two candidates are here selected for this scope:

- Exponential: $f_1(t) = ae^{bt}$

Type	Parameter	Value / Formula	Unit of measure
Degradation pattern	μ_x	1.134	m/s^2
	σ_x	0.1004	m/s^2
	$\mu_{T,1}$	$2000 - 100n_1$	*cycles*
	$\sigma_{T,1}$	300	*cycles*
	$\mu_{T,2}$	$4200 - 150n_2$	*cycles*
	$\sigma_{T,2}$	300	*cycles*
	$\mu_{k,1}$	$(n_1 + 4)/4800$	/
	$\sigma_{k,1}$	1/12000	/
	$\mu_{k,2}$	$(n_2 + 3)/6000$	/
	$\sigma_{k,2}$	1/12000	/
	RMS_{up}	1.4352	m/s^2
	RMS_{fault}	5.7408	m/s^2
	η	0.8	/
	N	10	/
Maintenance scheduling	$LT_{maintenance}$	300	*cycles*
	ρ	1.05	/
Classification model	λ	0.75	/

Table 6.1: Parameters used during the simulations

- Power: $f_2(t) = at^b + c$

Where $f_j(t)$ represents the degradation level at time t modelled with the degradation function j and a, b and c are coefficients to be determined fitting the data.
The reason behind the choice of these functions derives from multiple factors: firstly, they are simple functions already present and optimized in the Matlab Curve Fitting Toolbox library, thus allowing fast computational times for the degradation model selection with its coefficients, which is performed continuously as new data arrive. Then, regarding in particular the exponential function, which is a candidate together with the linear one, it is chosen since it describes well the degradation for rotating elements. A third

reason is that they can be derived from functions already used in literature: in fact, as it is possible to notice from Section 3.3, the exponential function derived directly from the exponential process (ref. Equation 3.5), while the power one can be seen as a simplified form, without the diffusion coefficient, of the Wiener process (ref. Equation 3.3). Finally, their form is coherent with the one of the degradation pattern modelled, allowing to verify their correct association to this one.

Secondly, another specific choice regards the maintenance interval functions, i.e. the ones used to fit the mean time between maintenance data for each failure mode. In this case, the candidate models are:

- Exponential: $g_1(n) = de^{ht}$
- Linear: $g_2(n) = dt + h$
- Quadratic: $g_3(n) = dt^2 + ht + p$

Where $g_l(n)$ is the expected lapse of time between two imperfect maintenance of the same type at the n degradation cycle for the failure mode monitored and d, h and p are coefficients to be determined performing the fitting of the maintenance times data. In this case, such functions are selected since they can have an overall decreasing behaviour, which is the one expected, and once again are already present in the Matlab.

Finally, another specific choice for the model is about the classification algorithm to be used for the failure modes prediction. As already stated in Section 5.1, different classification models exist to fulfill this task, like k-nearest neighbour (KNN), decision trees, support vector machines (SVM), etc. For this reason, first some simulations with the same settings described above were performed in order to obtain a set of predictors similar to the actual one. At this point, various classification models were trained using the Matlab Classification Learner Toolbox, and the results were analysed for the choice. Among the different algorithms tested (i.e. decision trees, logistic regression, naive Bayeses, SVMs, Ensembles), a Support Vector Machine (SVM) using the fine-gaussian method obtained the best results in terms of validation accuracy (98.3% using cross-validation on a sample of 240 observations generated with a reduced variability of parameters), having at the same time a reasonable prediction speed (circa 10000 objects/s). Thence, such model was selected for the actual simulated experimental campaign.

6.3.4 Results

The simulated experimental campaign, run on a PC mounting a processor Intel(R) Core(TM) i7-6700 CPU 3.40GHz (circa 5 hours of simulation), is designed to be composed by 20 perfect maintenance cycles. Each one, in turn, is constituted by 12 imperfect maintenance actions, for a total of 240 samples. This last choice is primarily made since it simplifies a lot the executions of the simulations; such setting is then justified by the fact that the main focus of the tests is an assessment of the innovative features of the CBM model. It is however important to notice that in the framework presented the end of a perfect maintenance cycle is dependent on the decision-making phase and based on the actual information available rather than selected a priori.

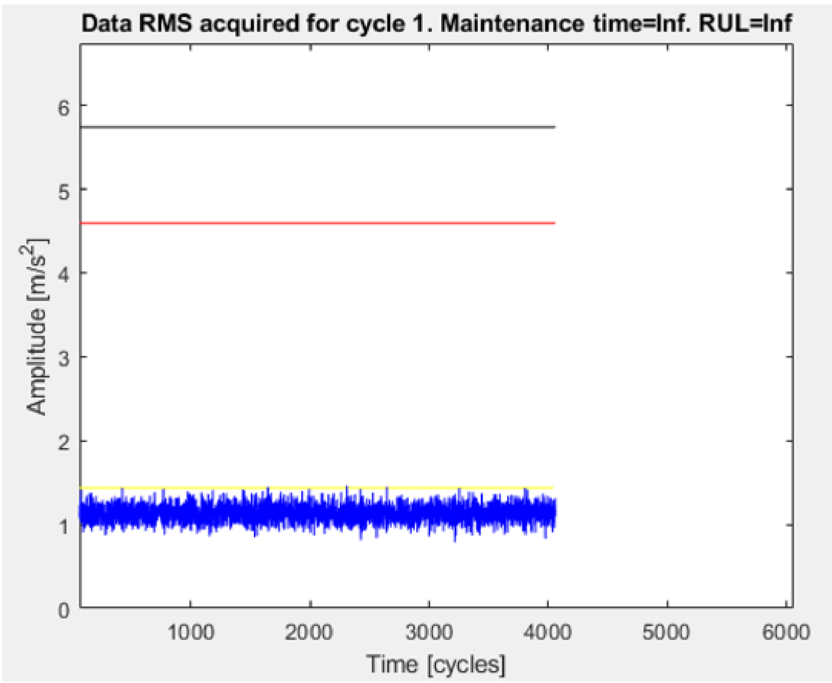

Figure 6.8: The healthy state modelled in the simulations

RUL prediction

The first aspect to verify regards the choice of the degradation function for the remaining useful life estimation, which in the framework is under the RUL prediction block (ref. Section 5.2).
First of all, Figure 6.8 represents the feature level in the healthy state during

the simulations. The blue line is constituted by the RMS points generated; the yellow line is the threshold D_{up}, after which the RUL is computed; the black line is the D_{fault} value, at which failure is expected; the red line is the safety value $D_{limit} = \eta D_{fault}$ used for the actual estimation of the remaining useful life. The figure shows also that the maintenance time and the RUL are reported as "Inf", i.e. infinite, meaning that they are not computed in this phase, on the contrary of what is possible to notice in the following pictures, where it is reported their time values in cycles (1 *cycle* ≈ 11 *second*).

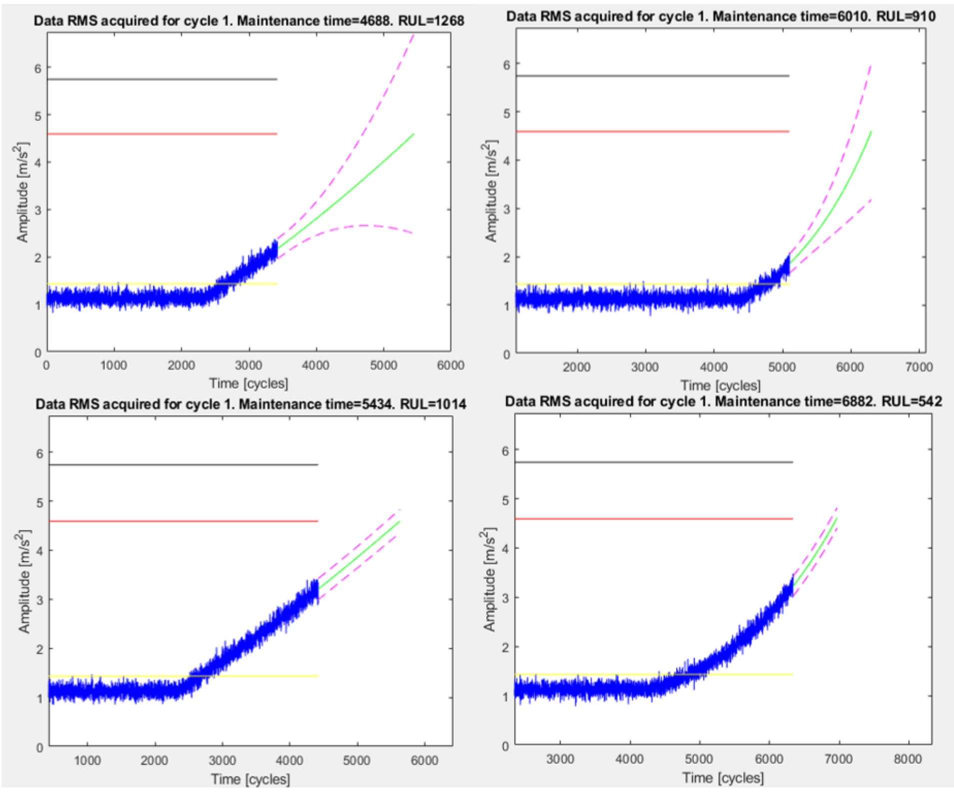

Figure 6.9: The two types of degradation pattern given by the linear (on the left) and the exponential (on the right) failure mode in two successive moment (top and bottom picture)

At a certain point, in fact, according to the values of $T_{FM,i}$, one or both the failure modes begin to make the monitored feature level rise and enter the unhealthy state. The left part of Figure 6.9 shows what happens when the failure mode modelled to have a linear behaviour appears. In particular, the prediction line used to compute the RUL and represented in green marks evidence of a linear pattern, meaning that the model was capable

of understanding the type of deterioration and consequently deciding the right degradation function to be used (i.e. the power with coefficient equal to 1). In addition, the figure shows the same degradation in two successive moments, the ones in the bottom having more data acquired than the other. From this comparison it is therefore possible to notice that the coefficient bounds of the prediction line, represented in magenta, tighten up with the passing of the working cycles and the increasing of data available, thus making the prediction more reliable.
In the right part of Figure 6.9 is reported the degradation pattern given by the failure mode having an exponential behaviour. In this case too the figure shows evidence of the right selection of the fitting function and of the tightening up of the prediction line confidence intervals as more data are acquired.

Seen the previous results, it is therefore possible to confirm the correct functioning of the degradation function selection implemented in the model. The consequence of this is a remaining useful life prediction method more robust and capable of adapt automatically basing on the effective degradation history seen, allowing thus an improvement and a greater reliability of the maintenance scheduling process.

Classification model

The second feature to be tested is the classification and relative prediction of the failure modes. The predictors used in such classification are, as already described: the degradation function ($f_i(t)$) with the set of parameters (a, b and c) which describe the deterioration pattern and the number of condition monitoring cycles (m) done from last perfect maintenance. The target of this feature is to learn how such predictors describe the failure modes, in order to give an estimation of these last ones (ref. Section 5.2). A mapping of two of these parameters (b and m), labelled with different colors basing on the failure mode, is shown in Figure 6.10 for exemplification purposes; similar pictures could anyway be generated for every combination of such predictors.

Every time a maintenance is executed, the classification model (SVM with fine-gaussian method) is retrained, in order to refine the mapping of the failure modes and with that the prediction capabilities. An important information regards the behaviour training after training of the validation accuracy of the classification model. In fact, such parameter is kept into account to decide if the classification algorithm is sufficiently accurate to be

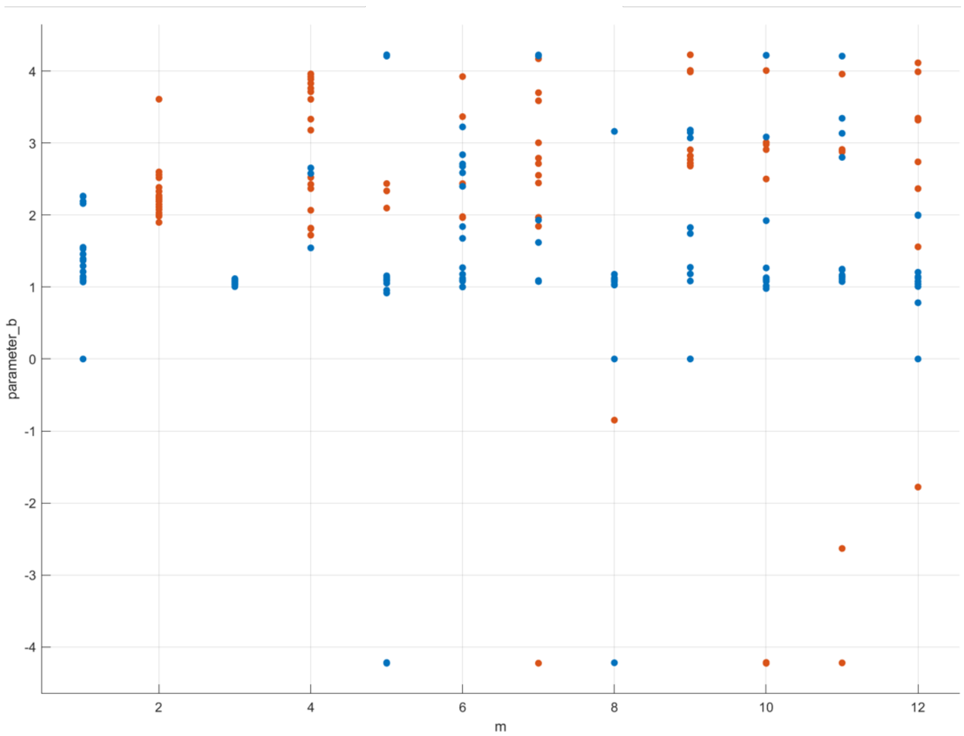

Figure 6.10: The value of the function parameter b against the one of the number of condition monitoring cycles m, labelled basing on the failure mode (in blue the linear, while in red the exponential one)

used for the failure mode predictions. In particular, as seen in the framework presentation, this condition is considered satisfied if the validation accuracy becomes greater than a predetermined threshold, set here to be $\lambda = 75\%$.

Figure 6.11 shows the validation accuracy behaviour as the number of observations used to train the classification model grows up. After a first very short phase (not taken into consideration for the comparison) in which there are large oscillation due to a training performed with very few data, the percentage of accuracy increases quite quickly until it approaches and surpasses the yellow line indicating the λ value; this happens between 30 and 50 observations. Successively, it continues to gradually increase approaching at the end the 90% of accuracy .
Thence, the information provided by the figure is that before the model becomes effectively capable of making predictions it is necessary to wait 30-50 repairs, since a new observation is acquired at every maintenance (ref. Section 5.2.3). This could be an issue for this feature of the framework, resulting in a lapse of time quite long for a single system monitored (various

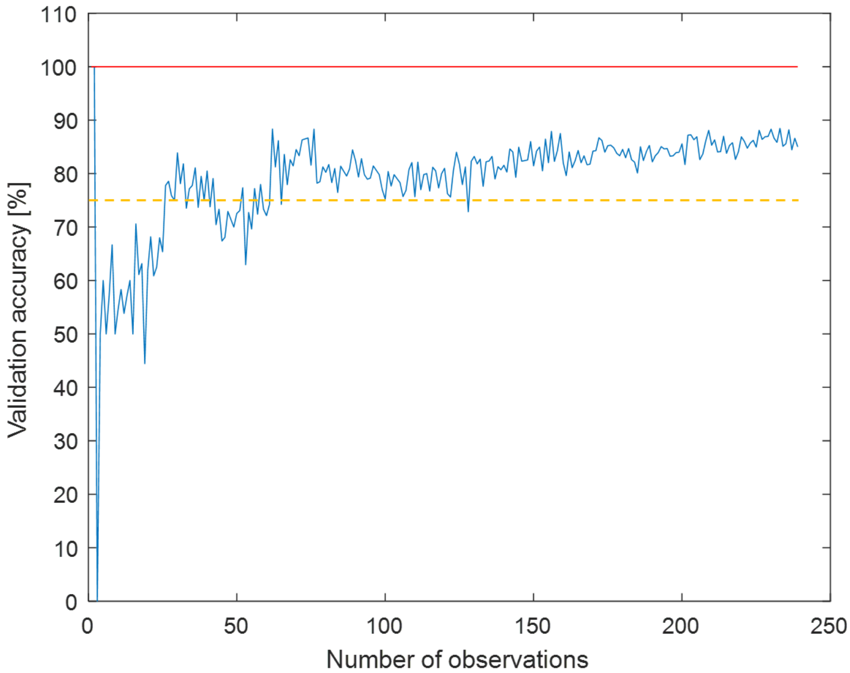

Figure 6.11: Validation accuracy of the classification model based on the number of observations used for its training

months), depending on the entity of the different failure modes.
Regarding the actual capability of foreseeing the failure modes, Figure 6.12 reports a graphic of the prediction accuracy versus the number of predictions done. The prediction accuracy is computed as the ratio between the number of predictions resulted correct and the total number done, which is slightly less than 200. The picture shows that, after a very first phase, the accuracy increases constantly in an asymptotic exponential way, meaning that at a certain point the model is capable of estimating correctly the failure modes for the greatest part. In fact, at the end the total percentage of failure modes rightly predicted is equal to circa 85%.

Basing on the previous considerations and evidences it is therefore possible to say that the classification model of the failure modes is effectively capable of learning a mapping of the characteristics of these ones, even with the presence of many elements of variability, in order to generate predictions about them while the machine is still working. Consequently, such feature can act as a useful tool to provide the user more prognostic information about the asset, enhancing the decision-making and allowing to improve the

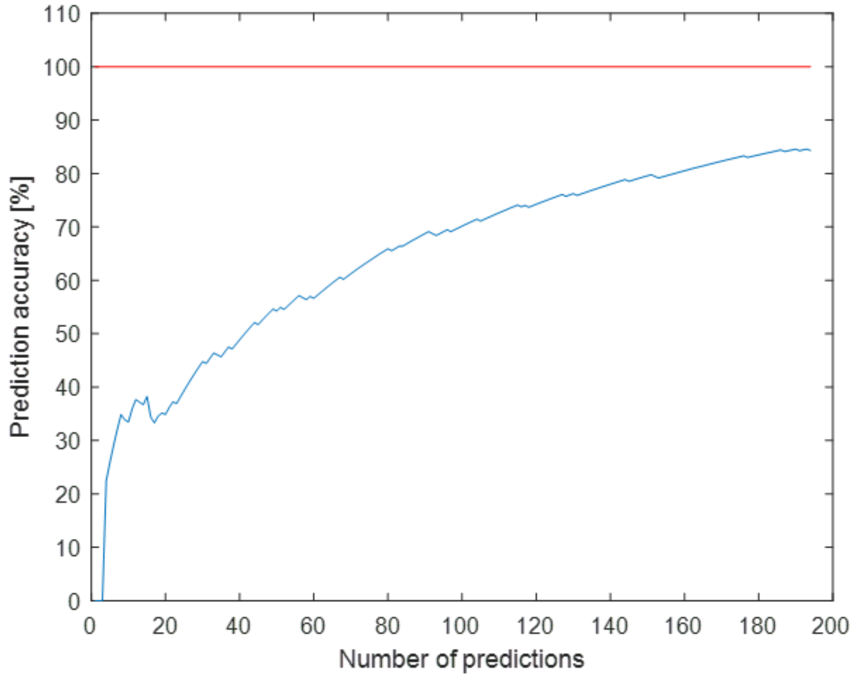

Figure 6.12: Prediction accuracy of the classification model based on the number of predictions performed

organization of the maintenance actions.

MTBM data regression

Finally, the last results to be analysed regard the regression of the mean time between maintenance data, i.e. the ones about the lapse of time between two repairs involving the same failure mode. The outcomes of the fitting done through the regression functions previously presented for, respectively, the linear and the exponential failure mode are reported in Figure 6.13 and Figure 6.14. The red dots indicate the maintenance event data object of fitting, plotted against the number of times the same failure mode is observed (i.e. causes degradation) since last perfect maintenance (n_i), while the blue curve is the actual fitting curve (the MTBM curve): in order to capture the variability of the maintenance times, this one is plotted together with its confidence bounds, represented in magenta.

What is possible to deduce from these figures is that the regression model is

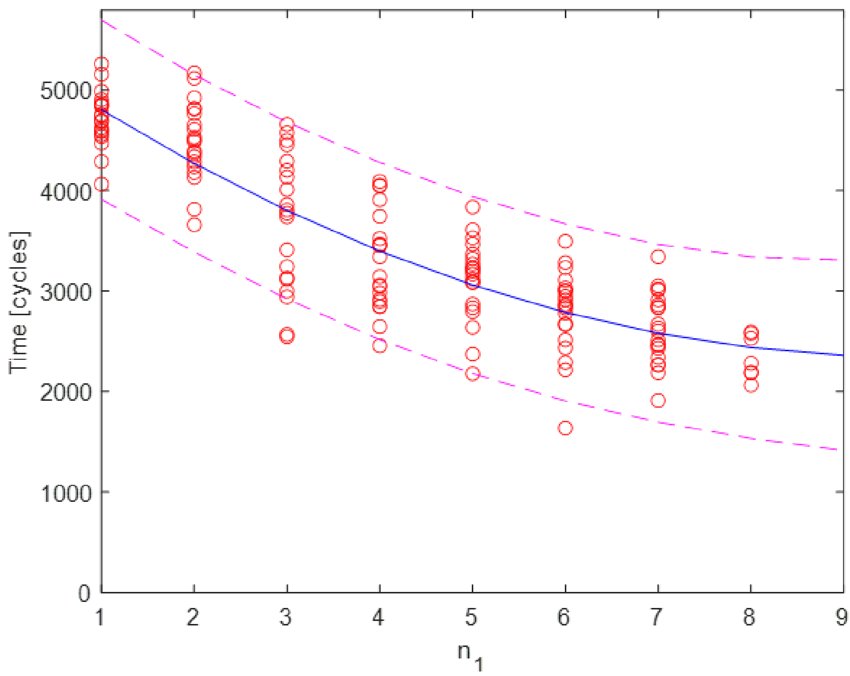

Figure 6.13: Mean Time Between Maintenance curve for the linear failure mode

effectively capable of recording a general trend of the expected time which is necessary to wait before a failure mode, after a repair, causes the degradation of the asset once again. For example, if a perfect maintenance is executed, probably the linear failure mode is going to be repaired after circa 5000 cycles, which is the fitting value for $n_1 = 1$; in fact, this is the first time the failure mode is observed since the perfect action. On the other hand, imperfect maintenance after imperfect maintenance the same failure mode is going to reappear quickly, making the related interval of time between two consecutive repairs decrease; for example, at the eighth time this one is observed ($n_1 = 1$), the expected interval is more or less halved. Similar examples can be done for the other failure mode too.

Therefore, the regression of the mean time between maintenance demonstrated to be effective in capturing the trend of these data, both in terms of mean and variability, by choosing the correct function and coefficients to perform such task. The information gained can then be used to estimate firstly how quickly the imperfect maintenance actions lose their efficacy and, secondly, to have a first estimation about how a certain type of intervention is going to be required again. Thus, it can act as a tool capable of using the

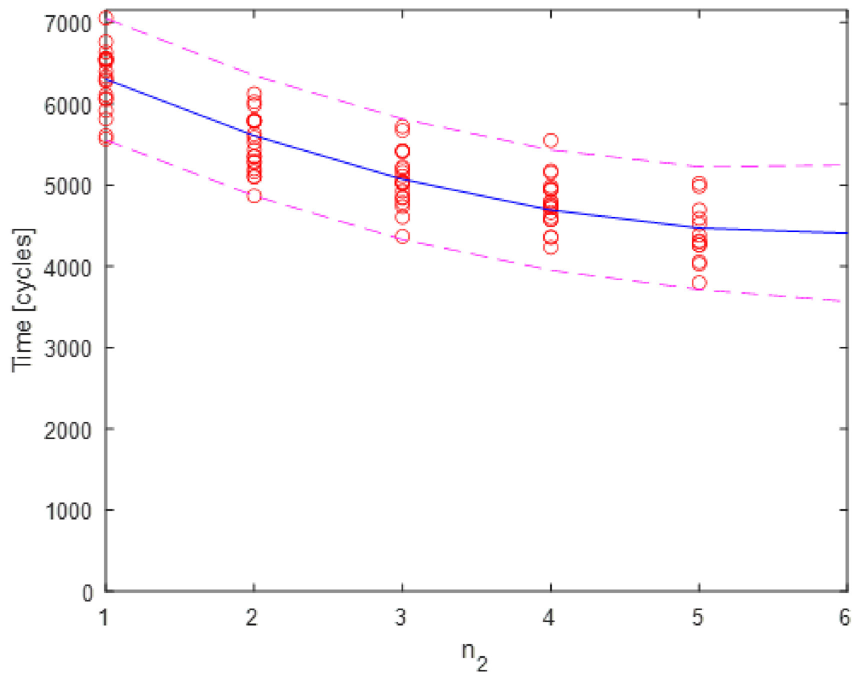

Figure 6.14: Mean Time Between Maintenance curve for the exponential failure mode

characterization of the maintenance effects to expand the prognostics on the asset and improve once again the decision-making phase.

Conclusions

The previous paragraphs explained the results of the simulated experimental campaign done in order to obtain an assessment of the framework proposed in Chapter 5. In particular, three innovative features of the CBM model were object of testing: the choice of the degradation function for the remaining useful life estimation, the failure modes classification model and the regression of the mean time between maintenance (MTBM) data.

Regarding the first, such feature was tested on two different failure modes modelled to have distinct different patterns: one linear and the other exponential. Here, the model showed to be effectively capable of selecting the best function in order to represent the type of degradation seen. This results in a more reliable and self-adaptable estimation of the remaining useful life, with a consequent improvement in the maintenance scheduling process.

For what concerns the failure modes classification model, it was discussed by reporting two different graphics. The first one (ref. Figure 6.11) was about the behaviour of the validation accuracy compared to the number of observations used for the training of the model; in fact this statistic is utilized to decide a priori if the model is sufficiently accurate to perform the predictions. What emerged is that, with the elements of variability included, there are necessary circa 30-50 observations to reach the accuracy required, which would result in a quite long time for a single system. However, maybe the learning curve for such process could be sped up by performing the same operation on different assets simultaneously, introducing the concept of the collaborative maintenance, which is then reported in Chapter 7 as a possible future work. The second figure (ref. Figure 6.12), regarded then the actual prediction accuracy and its behaviour against the number of predictions effectively done. It demonstrated that the classification model achieved good estimation capabilities, predicting correctly the 85% of the times. For this reason, such innovative feature results to be a potentially useful tool to expand the prognostics on the asset, allowing the user to know not only when to execute maintenance, but also the dominant cause of degradation; this additional information could enhance the decision-making phase about the type of intervention and improve the maintenance organization process.

Finally, there were reported two figures (ref. Figure 6.13 and Figure 6.14) showing, for each failure mode considered, the results of the regression of the mean times between maintenance data. The analysis of such pictures made possible to state that this feature of the model is effectively capable of capturing the general trend, together with its variability, of the evolving times for the failure modes. Thence, it results to be another potentially useful tool, capable of understanding when the imperfect maintenance actions lose efficacy, making the user to opt for a more complete repair, and allowing to have a first estimation of the time taken by the failure modes to cause critical levels of degradation. It is therefore possible to conclude that this innovative feature too could expand the prognostics capabilities and improve the decision-making about maintenance.

Chapter 7

Conclusions

This work had the target of investigating the concept of imperfect maintenance applied to a condition-based maintenance policy; in addition, the choice was to do it in a context where no run-to-failure data are available, in order to be closer to reality and to the modern industry exigences.
The first step of the research consisted in the literature review, which had the aim of building a wide yet profound knowledge about the topic and describe its state of the art. Such analysis was conducted by searching for scientific publications through selected keywords. Then, from the more than 500 articles found through this method, a progressive selection led to the choice of 47 scientific papers to be classified according to chosen drivers. In particular, these articles were all published between 2012 and 2020: thus they represented effectively the actual state of the art about the object of study.

What in general emerged from the analysis is a tendency of the publications to perform an optimization of the maintenance policy rather than using the data acquired to characterize the system in terms of degradation and imperfect maintenance effects, updating then the related parameters as new information arrives; these aspects are in fact usually assumed at priori. This was particularly true for systems monitored continuously through sensors and for which the target was to predict their future conditions. In addition, this is enhanced by the fact that the asset modelled is rarely specified or treated as generic. These considerations brought to formulate the following literature gaps:

- *GAP 1*: Lack of models focusing on a real asset or fleet of machines and giving detailed information about its nature, level and the type of maintenance actions executed.

- *GAP 2*: Lack of models which use the data from the asset, acquired in regime of continuous monitoring, to estimate and continually update the parameters of both degradation pattern and imperfect maintenance, in order to determine the remaining useful life of the machine.

- *GAP 3*: Lack of models which, using the data acquired from the asset, aim to estimate which is the most appropriate function to represent the degradation pattern.

- *GAP 4*: Lack of models which, aim to identify and quantify the effects of imperfect maintenance actions through the acquired data, starting from no previous knowledge of these effects.

The results of the literature review were used to set the direction of the second part of the work. In particular, in order to contribute to the available research areas individuated, and in particular to GAP 2, GAP 3 and GAP 4, the main objective of the thesis was formulated as follows:

"The development of a framework for a condition-based maintenance model which aims to identify and quantify the degradation pattern and the imperfect maintenance effects in order to improve the asset prognosis and the recommendation of types of maintenance intervention."

This goal was accomplished by formulating an operative framework which has the function of guiding the user in the implementation of the CBM model proposed. Its peculiarity consists in associating the concept of imperfect maintenance to the one of failure mode: the repairs are thence imperfect since they are able to restore only the damage caused by one failure mode instead of healing completely the asset. Its presentation was divided into three parts: the control data, containing the information to the correct setting; the condition monitoring, which has the target of controlling the degradation of the asset and scheduling maintenance basing on the remaining useful life prediction and the recommendation about the type of maintenance intervention; the actual maintenance.

The first innovation point consists in the remaining useful life estimation: instead of selecting the degradation function to be used a priori it was in fact developed a system to choose every time new data are acquired the model which best interprets the deterioration seen. This continuous update of function and related parameters allows thus to monitor more efficiently the asset, adapting to eventual changes and improving the RUL prediction in comparison with standard methods.

Secondly, another innovation lies in the maintenance decision-making phase: such process is in fact assisted by two machine learning techniques, respectively a classification and a regression algorithm, which have the target of using the information gained about the degradation process of the system to predict its future behaviour and help choosing the most adequate type of repair. In particular, the classification uses the degradation data acquired during condition monitoring to create a mapping of the different failure modes, while the regression method acquires the maintenance intervals data to estimate when the same failure mode is going to show itself again causing the deterioration of the system. These two algorithms are updated at every maintenance: thus it is achieved a dynamic characterization of the degradation behaviour of the asset and thence of the different effects of the imperfect maintenance actions, which are updated every time new information is gained.

Finally, the framework was assessed by starting from a reference dataset made available by the Industry 4.0 Lab at Politecnico di Milano and manipulating it in order to simulate a degradation process and execute a simulated experimental campaign. This one in particular focused on testing three aspects of the framework, i.e. the RUL prediction, the classification model for the failure modes and the regression of the mean time between maintenance (MTBM) data. The results were then analysed taking into consideration both the technical point of view, i.e. their correct functioning, and making considerations about how such innovative features could improve the maintenance management process. This practical part acted also as a practical example of the CBM model elaborated.

To conclude, this thesis work presented a framework for a condition-based maintenance model which includes machine learning techniques that combine condition monitoring and historical event data in order to characterize dynamically the system's behaviour and improve the present actions. Such framework therefore acts as a way to expand the prognostic part of a CBM policy, estimating not only the remaining useful life, whose prediction was anyway improved, but also forecasting the type of repair to execute, with the overall aim of improving the maintenance management in complex systems.

7.1 Future works

The work presented has possible investigation lines which could be expanded in future studies. In particular, the main ones individuated are:

- **Collaborative maintenance**: the framework for the CBM model presented has the feature of performing a dynamic characterization of the asset as event and condition monitoring data are acquired. However, this learning process could be improved and sped up if applied to numerous systems of the same type, which can then be linked through a common database. Such kind of integration, as already seen, is one of the main improvements given by Industry 4.0; this is leading to innovative approaches classified under the concept of Social Internet of industrial assets and a collaborative prognostics approach [86][87]. In particular, these concepts derive from the Internet of Things and deliver the idea of a social network composed by smart assets capable of sharing different kinds of information and using them in order to reach an awareness of their working context and take by consequence collaboration initiatives [87]. Therefore, it could be interesting to see how to apply in practice such an approach, keeping into account the expanded prognostic information proposed in this work and facing challenges like the storage of these data, their retrieval and their usage between different machines.

- **Multiple maintenance lead times**: as stated in Section 5.1, the present work approached to the maintenance scheduling more from a prognostic perspective, by considering the degradation of the asset, than from a logistic point of view. This brought to a simplification of the logistic dimension needed for the maintenance organization, which resulted primarily in the assumption of the same lead time for all kinds of intervention. However, such hypothesis is true only in some situations, in which the actions are similar in terms of resources, personnel required and methods adopted. Therefore, relaxing such constraint would make possible not only a generalization of the framework, but also the integration in it of the logistic aspect of maintenance, making it closer to reality even if at the cost of an increased complexity.

- **Maintenance optimization**: the literature review showed a strong presence of publications aiming for an optimization of the maintenance policy, so much that two classification tables out of six in Section 3.3 were dedicated to it. For this reason, this worked focused on other aspects of maintenance, more oriented to a characterization of the related parameters and effects. However, the findings of this work, and in particular the improvements in the RUL prediction and the recommendations about the type of intervention, could be used to explore new aspects of the optimization approach, which would benefit from an enhanced prognostic on the asset. In addition, the above mentioned future works could find a place in such a logic, by introducing in the problem other dimensions related to logistic and production (as already done in some papers) and by considering it in a context of cooperation between different machines, with the result of an optimization oriented not only to the single asset, but ideally to the entire factory.

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