Conceptualization and design of an Asset Performance Management solution within a Manufacturing Execution System

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To my sister, parents and grandparents

Abstract

Industry 4.0 revolution brings a whole set of opportunities and challenges for companies and Asset Performance Management (APM) is part of the change. The industry is shifting for intelligent and autonomous systems with the use of sensors and new technologies, enabling real-time data collection to be processed with advanced analytics, which in turn can boost APM strategies. Older methods and techniques should then be discarded if companies want to keep up with this evolution and get the full benefit out of this paradigm shift. Predictive maintenance, fuelled by the Industrial Internet of Things (IIoT) and all this new era of technological sophistication, emerges as a more effective strategy to detect likely failures and anticipate asset breakdowns, which saves time and money while increasing operational performance. Therefore, Manufacturing Execution Systems (MES) providers should innovate and extend the set of functionalities to offer their customers the solutions they need.

The main goals of this study are developing an APM solution to be integrated in an MES that enables real time production monitoring and includes an alarms' view to give notice when certain parameters and Key Performance Indicators (KPIs) do not comply with specified thresholds. Moreover, this solution aims to facilitate a predictive maintenance strategy as well as provide useful information to run inspections and other asset related actions.

In the scope of predictive maintenance, distinct survival analysis methods were applied to predict the Remaining Useful Life (RUL) of assets and assess the effect of categorical and numerical covariates on the time-to-failure of machines, using sensor telemetry and historical asset data as an input for these models. This application serves the purpose of highlighting the potential of the use of advanced analytics in APM systems.

As future research, it would be interesting to test the conceptualized APM solution in a real-life scenario in order to assess the impact it brings in terms of improvements on the operational and financial performance. Moreover, in what concerns the prediction of the RUL, real historical asset data should be used in further investigation on this topic, instead of a dummy dataset, so that the relevance of survival models for this purpose can be confirmed.

Resumo

A revolução da Indústria 4.0 traz todo um conjunto de oportunidades e desafios para as empresas e a Gestão do Desempenho dos Ativos (APM) faz parte da mudança. A indústria está a mover-se no sentido da adoção de sistemas inteligentes e autónomos com o uso de sensores e novas tecnologias, permitindo que a recolha de dados em tempo real seja processada com técnicas analíticas avançadas, o que, por sua vez, pode impulsionar as estratégias de APM. Métodos e técnicas mais antigos devem ser descartados se as empresas quiserem acompanhar essa evolução e obter todos os benefícios desta mudança de paradigma. A manutenção preditiva, alimentada pela Internet Industrial das Coisas (IIoT) e toda esta nova era de sofisticação tecnológica, surge como uma estratégia mais eficaz para detetar falhas prováveis e antecipar avarias de ativos, o que economiza tempo e dinheiro, aumentando o desempenho operacional. Desta forma, os fornecedores de Sistemas de Execução da Produção (MES) devem inovar e alargar o seu conjunto de funcionalidades para oferecer aos clientes as soluções que estes precisam.

Os principais objetivos deste estudo são desenvolver uma solução de APM a ser integrada num MES que permita a monitorização da produção em tempo real e inclua uma vista de alarmes para avisar quando certos parâmetros e Indicadores-Chave de Desempenho (KPIs) não cumprem com os limites especificados. Além disso, esta solução visa facilitar uma estratégia de manutenção preditiva, bem como fornecer informações úteis para a execução de inspeções e outras ações relacionadas com os ativos.

No âmbito da manutenção preditiva, métodos de análise de sobrevivência distintos foram aplicados para prever a Vida Útil Restante (RUL) dos ativos e avaliar o efeito de *covariates* categóricas e numéricas no tempo que decorre até à falha das máquinas, usando dados de sensores e dados históricos dos ativos como dados de entrada para esses modelos. Esta aplicação tem a finalidade de destacar o potencial do uso de técnicas analíticas avançadas em sistemas APM.

Como pesquisa futura, seria interessante testar a solução APM conceptualizada num cenário real com vista a avaliar o impacto que traz em termos de melhorias no desempenho operacional e financeiro. Além disso, no que diz respeito à previsão da RUL, dados históricos reais de ativos deveriam ser usados em investigação futura, em vez de um conjunto de dados fictício, para que a relevância de modelos de análise de sobrevivência para este propósito possa ser confirmada.

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Contents

Acronyms

AFT	Accelerated Failure Time
APM	Asset Performance Management
BI	Business Intelligence
CA	Criticality Analysis
CMF	Critical Manufacturing
DSN	Digital Supply Network
EAM	Enterprise Asset Management
ERP	Enterprise Resource Planning
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
IIoT	Industrial Internet of Things
KPI	Key Performance Indicator
MAE	Mean Absolute Error
MES	Manufacturing Execution System
MOM	Manufacturing Operations Management
OEE	Overall Equipment Effectiveness
PLM	Product Lifecycle Management
PH	Proportional Hazards
RUL	Remaining Useful Life

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1 Introduction

In today's dynamic and competitive business scenario that requires companies to be productive, effective and efficient, improving the performance and reliability of the assets is mandatory. Considering that assets' maintenance and operational costs represent between 60% and 80% of their life-cycle cost, Asset Performance Management (APM) becomes critical in reducing assets' downtime and achieve their operational maximum availability and readiness, as well as keeping assets at the minimum cost and inventory (Parida 2016). Moreover, almost 20% of the world's assets are close to the end of their useful life, so it is key to carefully make decisions on their maintenance, operations and replacement (Wan 2017).

In this sense, anticipating a system breakdown through the detection of primary failure signs is essential to proactively perform maintenance and enhance assets' availability, reliability, efficiency, safety and quality (Selcuk 2017). A predictive maintenance program is essential to provide the necessary data to allow scheduling and planning plant stoppages for specific repairs and for other activities to be executed. This type of maintenance also avoids the unnecessary need to perform repairs that would usually be comprised in the maintenance outages. Thus, managing predictive maintenance contributes to enhance the global operational performance of plants and optimize the production (Mobley 2002).

In addition to defining the maintenance strategy and collecting, analysing the data and assessing its quality for APM, Key Performance Indicators (KPIs) as well as performance measures have taken a crucial role in deciding the necessary data to be measured and the reason for its measuring (Parida 2016).

In this way, through the combination of the above-mentioned elements, this project finds the basis for its development with the exploration of these topics and its application to a real-life industrial scenario.

1.1 Context and motivation

Critical Manufacturing (CMF) is one of the leading Manufacturing Execution System (MES) providers in the market, delivering advanced software solutions for manufacturing enterprises. CMF MES is specifically oriented for complex and discrete manufacturing, providing useful insights on the overall production operations. This project was carried out at the Business Intelligence Department of CMF within the scope of this master's dissertation.

Monitoring assets' health condition is increasingly important in this new industrial context and technological revolution to optimize assets' performance as well as to accomplish stakeholders' requirements and fulfil legal compliance. In this sense, this critical role and forthcoming relevance of APM for the prosperity of a business makes it an emergent topic that deserves exploration. Therefore, this project arose from the need revealed by CMF to study and create an APM solution to be integrated into their MES.

1.2 Approach and Goals

Regarding the approach followed to develop this project, in a first phase, there was a research of the relevant KPIs for the Manufacturing Operations Management (MOM) level. Then, an extensive literature review on APM was carried out in order to understand the current state-of-the-art on this topic, followed by an investigation of available APM tools in the market. Afterwards, an APM solution was conceptualized and designed based on previous research and, finally, it was performed a study of analytical methods to estimate predictive maintenance indicators, resorting to the R software for the computational experiments of survival analysis models.

Thus, this dissertation aims at designing an APM solution to be implemented within an MES. This solution must include certain features such as dashboards to help with the monitoring of real-time production as well as a set of alarms which are triggered when certain parameters or KPIs cross the defined thresholds. Moreover, it aims at executing important calculations from the data collected and estimating predictive maintenance indicators, resorting for that to the evolution of historical assets data and condition monitoring sensors. Furthermore, it should provide valuable information to aid in the execution of asset related actions, such as inspections.

1.3 Dissertation Outline

Following the above sections, the remaining project is structured in the following way. In Chapter 2 a literature review is conducted, which explores the topics of Industry 4.0, Industrial Internet of Things (IIoT), MES and KPIs, namely the ones used in MOM. Furthermore, it is presented an overview of Asset Performance Management and the way companies can implement APM tools effectively. In this same chapter, the topics of types of maintenance, Failure Mode, Effects and Criticality Analysis (FMECA), and survival analysis are approached. Chapter 3 presents the conceptualization of an APM solution and the explanation of its functionalities. In turn, Chapter 4 demonstrates how to use survival analysis models in the predictive maintenance scope, namely for the prediction of the Remaining Useful Life (RUL) of machines and the estimation of the impact of covariates on the survival time of the assets. Finally, Chapter 5 draws some conclusions on the work developed as well as limitations and some guidelines for future research.

2 Literature review

This chapter presents and provides a deeper understanding of the several concepts that surround APM systems to further enable the execution of the desired goals. It starts by addressing the current revolutionary paradigm of Industry 4.0, being important to approach in this context the Industrial Internet of Things topic to explain the technological development. Afterwards, it is described what is a Manufacturing Execution System and its importance to manufacturing success. This is followed by an explanation of the Key Performance Indicators used in Manufacturing Operations Management based on ISO 22400. Furthermore, it is essential to present the state-of-the-art concerning Asset Performance Management, going through the importance of this subject and finding out more about its implementation. Lastly, maintenance related topics such as the types of maintenance, FMECA and the use of Survival Analysis for Predictive Maintenance are addressed to expose the fundamental concepts involved in asset management.

2.1 The Industry 4.0 paradigm

Fourth industrial revolution, the so-called Industry 4.0, is one of the recent tendencies in the industrial automation sphere. Current industrial companies are more complex than in the past regarding the specific needs on automation, control, logistics and the difficulties engineers find in handling system diversity (Mabkhot et al. 2018). In this context, the International Society of Automation defined the automation pyramid levels in the ISA-95, alleging that companies should focus on diverse stages such as Business Planning & Logistics, Manufacturing Operations Management, which are the top levels, and the control stages that comprise Batch, Discrete and Continuous control operations (ISA-95 2005).

While the top levels focus on accounting and financial issues, resource planning and marketing, the bottom levels are more directed to maintenance and quality operations, resource allocation, data collection, scheduling and inventory management. Monitoring techniques and tools are key in these last levels in the sense that they must allow to check certain criteria at system runtime without interrupting running processes (ISA-95 2005).

Nowadays, organizations search for the proper adaptation of Industry 4.0 because more and more they have to set a proper and efficient data flow management, which is based on getting and assessing data taken out from the interaction between smart and distributed systems. In turn, this data collection and processing relies on the setup of self-control systems that allow to take measures in advance before system operation is damaged (Salkin et al. 2018).

The use of information and communication technologies allows to collect great quantities of data that support the needs for control, logistics and automation, being the processing of that data useful to system performance measurement, which in turn is applicable to any level of the ISA-95 automation pyramid (Ferrer et al. 2018). In this domain of industrial automation and Industry 4.0, the data gathered and switched between and along the systems can be processed at runtime and allows the calculation of KPIs that will enable the system performance evaluation (Zhang, Postelnicu, and Lastra 2012).

It is on the MOM level that KPIs are calculated, which requires an information flow from the bottom to the top levels of the pyramid, being sensors essential to deliver manufacturing system insights. This information assists on the calculation of KPIs, which after being calculated are sent to an upper level, namely business planning and logistics for later use and decision-making (Ferrer et al. 2018).

Industry 4.0 covers a great variety of concepts, from developments in automation, miniaturization and digitalization to networking (Lasi et al. 2014). It is focused on setting communicative and smart systems embracing machine-to-machine communication and interaction between humans and machines. Besides, it integrates active networks of value creation in the sense of incorporating physical and software systems along with economic areas and industry types (Lidong Wang and Wang 2016). This fourth industrial transformation entails building the proper organizational structure, planning strategically the work force, taking part on the technological standardization and nurturing partnerships (Salkin et al. 2018).

New and changed processes constitute the basis of Industry 4.0 in manufacturing enterprises. Under this revolution, the data collected from customers, suppliers and the own organization is previously assessed before being connected to real production, resorting more and more to new technologies like smart robots, sensors or 3D printing. This interconnectivity between systems and great coordination result in an entirely integrated supply chain making manufacturing processes precisely adjusted aiming at the settlement of value-added networks. Other results from Industry 4.0 are related to more flexibility, freedom and personalization given to the manufacturing process on which custom-made products are adjusted to each customer needs and created at low marginal cost (Berger Strategy Consultants et al. 2014).

The implementation of Industry 4.0 is based on fundamentals such as standardization, innovation and research, reference architecture and secure network systems. This implementation is only possible when suitable structures supported by machineries, workplaces, sensors and systems related to information technology are provided and communicate with each other within a company and with other communication systems (Salkin et al. 2018).

2.2 Industrial Internet of Things

The extensive Industrial Internet use enables scattered devices to connect and to be involved in an aggregate system. Progress in IIoT empowered the connection between cloud structures, wireless sensor systems, flexible robots and embedded systems, being all included in the distributed systems scope (Borgia 2014).

Since autonomy and decision making in real time for production and service processes are determinant, it is key that the whole system comprises data analytics and diverse coordination devices. To ensure gathering production and service system data in real time, processing devices, sensors network, autonomous and function-based instruments should be merged together (Rüßmann et al. 2015). Smart networks and smart objects are the basis for the Industrial Internet of Things, being IIoT main goal offering connectivity in any place, in any time for anyone and anything through machines and computers that enable the sensing and view of the applications of the real world (Vermesan et al. 2011).

The manufacturing intelligence development boosts the manufacturing productivity and quality improvement and helps in finding out the production complications and flaw mapping root causes as well as enhances the machine performance monitoring and decreases machine downtime and failure (Salkin et al. 2018). Actually, in recent years, there has been a trend that asset-intensive companies have taken advantage of the IIoT in order to enhance a key part of their business, which is the assets' reliability and as a result APM solutions become increasingly important for these firms. Besides, the evolution of IIoT technology along with the reduction of the cost of sensors made it easier to make more data-driven and more informed decisions regarding maintenance activities (Daecher et al. 2019).

2.3 Manufacturing Execution Systems

Manufacturing Execution Systems need to fit into the new paradigm change on which products are tailor-made to satisfy customer requests. A whole new environment powered by technology and innovative software sets new challenges. These systems are essential to keep up with the agility, performance and quality demanded by Industry 4.0 and the globalized manufacturing business (Almada-Lobo 2016).

MES offers a data management system and a user interface, providing valuable data and keeping track of the process progresses through the application of a standardized working manner. Therefore, it is essential to include MES processes into the ongoing cycle of improvement, so that the old-fashioned methods are transformed and better results are ensured (Cottyn et al. 2011).

Furthermore, MES scope also encompasses design, supply and business mechanisms of manufacturing companies, being able to accomplish customers growing requirements for real-time and faster replies through decentralized manufacturing control. This real time information provided by MES makes it possible to accomplish one of the Industry 4.0 design principles, which is transparency of information, because this critical manufacturing data contributes to this visibility and traceability. MES is thus a key element in this new context of smart factories to assist machines and manufacturers in doing their tasks more efficiently and in the production complexities management with its extended set of functionalities (Mantravadi and Møller 2019).

MES has been evolving along time to integrate several point systems and offer diverse production functions to help in the execution of several manufacturing activities. Following the technology sophistication trends allowed MES to fulfil the breach between controlling systems like sensors and planning systems like Enterprise Resource Planning (ERP), so unlike the past, the production information does not need to be collected in loco in spreadsheets, which prevents the paperwork and largely enhances data consolidation, production processes support and software maintenance. Some of the benefits of MES are product quality improvement, manufacturing time minimization and predictive maintenance (Mantravadi and Møller 2019).

Organizations need to embrace strategic measures to harness the full potential of the resources and therefore enhance manufacturing and business outcomes by removing unnecessary manufacturing costs, minimizing cycle times and increasing the rate of production without lowering the quality. These strategic measures are empowered by the availability of real-time production information that helps to support business processes and identify opportunities to improve daily production operations and to evaluate the progress (Cottyn et al. 2011).

For this reason, companies implement, improve and develop their information technology solutions like the Product Lifecycle Management (PLM) software that drives and orientates the product throughout its lifecycle distinct levels and also the ERP software, which keeps relevant business data and provides assistance to the managerial procedures. Also, Business Intelligence (BI) helps to facilitate and improve decision making by giving thorough business insights. There are diverse software applications that examine real-time information and take precious information out of them so that industrial operations can be optimized. However, since software providers found difficult the integration of several point systems, they managed to join several execution management elements into one and integrated system solution, which is the Manufacturing Execution System (Cottyn et al. 2011).

2.4 Key Performance Indicators used in Manufacturing Operations Management

In today's competitive market, industries need tools and practices to measure performance to increase the efficiency of their processes. In performance measurement, the first action to take is collecting data from the manufacturing system and also the real-time monitoring. This is followed by the challenge of efficiently and generally applying these performance measurement practices on real life industry (Muhammad et al. 2018).

The anticipation of failures and errors allows to prevent delays or productivity disruptions (Ferrer et al. 2018). The interest in detecting industrial systems sections that need to be enhanced to boost the global production is motivated by the fierce competition that forces companies to continuously upgrade their performance at all organizational levels. Instead of outdated mass production strategy, companies are shifting to the implementation of lean production, which requires more flexible manufacturing and high effectiveness (Toledo 2009). Therefore, enterprises tend to move from reactive to predictive manufacturing in fields such as maintenance, production planning and scheduling, growing demands for high quality standards and production efficiency along with flexibility and reconfigurability (Ferrer et al. 2018).

As a result of the complexity of the manufacturing systems, considering the great quantity of raw data that must be gathered and managed in real-time, manufacturing enterprises heavily rely on the KPIs that are success drivers nowadays (Muhammad et al. 2018). Developments in data processing and information technology enable enterprises to generate a significant data pool from their business, being the challenge the evaluation of this data and the identification of the most important KPIs (Marek, Schuh, and Stich 2020).

ISO 22400 has been commonly recognized as a key industrial standard that gives a great support on MOM by outlining the most relevant and widely used manufacturing industry's measurement parameters (Zhu, Johnsson, Varisco, et al. 2018). According to ISO 22400, the critical success factors of a company can be quantified and strategically measured by KPIs, which helps in the evaluation of the manufacturing operations' success. Therefore, KPIs are very useful to understand and enhance manufacturing performance, either from the corporate standpoint to accomplish strategic objectives or from the lean manufacturing viewpoint of eliminating waste (ISO-22400 2017).

Also, KPIs are physical values used by organizations for the measurement, comparison and management of its performance (Ishaq Bhatti, Awan, and Razaq 2014). These indicators are key elements that determine the success of a company's ability in monitoring its business performance strength, easing the achievement of planned organizational goals (Khan Mohammed, Ahmad, and Harrison 2020). Therefore, KPIs help in supporting the decision-making by contributing to identify the existing gaps between the current performance and the desirable one, making possible to draw important improvement actions to achieve the goals (Zhu, Johnsson, Varisco, et al. 2018).

Besides, by using KPIs, several decision makers agents, such as supervisors, managers or operators, are offered a quick and enlightening picture of the current performance of the business, having the failures and bottlenecks highlighted to assess what is preventing the company to achieve its goals (Khan Mohammed, Ahmad, and Harrison 2020). KPIs are, thus, essential to understand the current performance level and based on this information, organizations can use measurable values to assess their internal and external processes, so the better the KPIs management, the better the overall organizational performance (Parmenter 2015).

Nevertheless, finding the most suitable and valuable KPIs that accomplish the desirable business goals is the greatest challenge for assessing the management of manufacturing operations, being essential the proper understanding and careful selection of the KPIs (Zhu, Johnsson, Mejvik, et al. 2018).

This KPIs selection is individually determined by each enterprise according to its own needs and priorities. Since they differ from one industry to another, it is challenging to select a general KPIs set that supports diverse manufacturing industry types (Marek, Schuh, and Stich 2020).

When selected accurately and implemented properly, KPIs are potentially and significantly helpful for manufacturers to measure and improve the overall business performance and to recognize bottlenecks. However, selecting the right KPIs is one of the biggest challenges that manufacturers face in the present industrialization age (Khan Mohammed, Ahmad, and Harrison 2020). Companies typically select their KPIs set based on the understanding of how processes are performed at diverse organizational levels and different methodologies to define KPIs may be applied. When defined by different companies, KPIs may vary though. They can be either personalised or standardized, depending on if they are defined and used by specific enterprises or defined by certain worldwide organizations and used by numerous enterprises, respectively. However, using personalised KPIs can potentially raise a conflict when migrating such parameters and metrics to different atmospheres owing to the use of distinctive terminology for defining the same concepts, being recommended the use of standardized KPIs (Ferrer et al. 2018).

Throughout ISO 22400, 34 KPIs are defined and designed to be wide-ranging enough to ensure their applicability (Zhu, Johnsson, Varisco, et al. 2018). This directive offers an overview of the concepts and terminology used to design a KPI in order to manage manufacturing operations. This list is useful for the manufacturing industry presenting for each KPI its particular definition, formula, description and scope (ISO-22400 2017).

KPIs on their own are not enough to accomplish the needed execution and management operations for a company because an organization needs to define a certain threshold for numerous indicators that triggers certain actions whenever the indicator value surpasses or goes below the threshold. Thus, defining action and warning limits becomes necessary as they assist on the detection of tendencies in equipment and process changes earlier than specific thresholds of the enterprise are breached. In this scope, industrial automation systems and control instruments provide useful information on resources, processes, materials and operators that offers critical insights through KPIs, which enhances the manufacturing assets productivity (ISO-22400 2017).

2.5 Asset Performance Management

2.5.1 Asset Performance Management Overview

Companies are increasingly giving more attention to Asset Performance Management in their search for long-term sustainability and profitability, being now considered part of business strategic thinking (Parida 2012). APM systems help the asset owners make better and more informed decisions in order to improve the assets availability, reduce the costs associated with overall asset maintenance and mitigate the risks associated with the handling of the assets. Moreover, APM systems are useful and innovative tools that aid managers in making efficient, effective and more intelligent decisions regarding the assets maintenance activities (Wan 2017).

Costs of assets like equipment and machinery, in terms of their maintenance and operations, represent a heavy burden for many industries. Since it is a great percentage of the overall cost, it is given critical importance to the continuous measurement, control, monitoring and assessment of asset performance, so that the economic viability and lengthy value creation are ensured. Also, the lack of performance evaluation makes it hard to manage and achieve the desired organizational goals, being the assets performance management key to preserve assets' safe regular operations and prevent malfunctions and downtime that harms the cost and quality of production and the plant's capacity (Van Der Lei, Herder, and Wijnia 2012).

Hence, planning and monitoring assets' total lifecycle is vital to optimize their value, taking into consideration all the costing factors underlying its overall operating life. The understanding and calculation of the cause and representativeness of these lifetime costs makes it possible to take successful actions and make good decisions on repairs and replacements. If bad decisions in asset maintenance and operations are made or ineffective actions taken, machinery and systems' breaks may potentially occur, which causes huge amounts of money to be spent (Parida 2012).

Thus, the strategic objectives of Asset Performance Management include maximizing reliability and equipment value, through the optimization of maintenance activities and equipment replacement decisions. Efficient APM systems are able to provide managers, engineers and operators with relevant and valuable data to help them with their day-to-day operations. Moreover, among the main capabilities and functionalities provided by APM tools, these include reliability-centered maintenance, predictive maintenance, risk management and financially optimized maintenance actions. Therefore, the main reasons that drive companies to invest in APM technologies rely on benefits that include the improvement of the operational assets' availability, reliability and safety, the reduction of unplanned repair work, the minimization of the costs associated with maintenance activities, and the reduction of the failure risks of critical assets (Wan 2017).

In order to achieve these goals, there are some processes that must be performed, including the collection of equipment data through sensors or external databases, the elaboration of predictive and interventions models, and the covering of both engineering and financial aspects. In addition, to effectively optimize maintenance related activities such as determining which operations should be performed on industrial resources and their scheduling, APM technologies must be able to capitalize on reliable data management, visualization techniques, risk mitigation tools and advanced analytics (Foust and Steenstrup 2020).

Data management and its usage are constantly challenged and changed by the continuous technological progress with the appearance of new technologies that have been of central importance in Asset Performance Management, such as Industrial Internet of Things, machine-learning, clouds, web-based software and image recognition. These technologies allow to connect computing instruments implanted in industrial machines, store the huge quantity of data created, run more quickly analytical models and streamline decision-making operations, being it all reinforced by an environment of cooperation allowed by web-based software. All of this allied to the domain experience and deep asset performance comprehension brings great industrial improvements (Borges et al. 2017).

Moreover, effective and well-organized data flow transversely to all company activities is required for APM to be fruitful. During several years, organizations had their departments operating in a fully independent way from each other, the so-called silos, which made data and information flow inefficient and with its potential value minimized or wasted (Borges et al. 2017). Nowadays, certain functions such as operations, maintenance and safety and compliance are still done in silos, which may lead to some conflicting objectives and ambitions. Thus, it is essential that a full understanding of the wide scope of asset management is established across the organization in order to achieve an effective collaboration between the distinct areas (Golightly 2018).

2.5.2 The way companies can implement APM tools effectively

The adoption of APM tools occurs at a varied pace across industries. Asset-centric businesses such as natural resources, utilities, transportation and manufacturing tend to make bigger investments on APM solutions because those industries rely more on the use of their assets to achieve their objectives. On the contrary, in service-intensive businesses such as financial services, retail and the public sector, asset management is not so significant and, thus, the investment in APM products is lower and less mature in this type of industries. Therefore, APM constitutes a must have tool in asset-centric industries due to the abilities it provides in helping in the decision-making processes of business-critical operations, while in industries that do not rely so much on assets, APM are nice to have tools in support to those businesses activities (Foust and Steenstrup 2020).

By merging information technology and operations technology, a mature APM solution enables the adoption of the most proper maintenance strategies according to the type of asset and its criticality. Regarding the maintenance strategies, reactive or preventive approaches are better suited for less critical assets, whereas continuous sensorization and monitoring is more appropriate for more critical assets, which require more than periodic inspections. When successfully implemented, several benefits can be obtained in many tasks, including asset strategy optimization, end-of-life calculations, equipment health monitoring, predictive management and management of alerts and compliance (Daecher et al. 2019).

Generally, enterprises find challenging setting priorities among the most critical systems and equipment components as it is needed to constantly weigh the production, environment and safety impacts, which implies to know what needs maintenance and when and how to perform planned and strategic maintenance (Borges et al. 2017). Therefore, before opting for a certain APM solution, companies must establish their priorities and their strategies regarding asset maintenance activities and identify their needs according to the variety of assets that they own. In this sense, there can be a combination of different asset maintenance strategies depending on the characteristics and specifications of the individual resources that they have (Foust and Steenstrup 2020).

Since most of the APM vendors do not provide all levels of APM maintenance strategies, companies might require multiple APM products, considering the requirements and specifications of their businesses and the characteristics of the assets they own, and the maintenance goals established. In this regard, a firm can have a specific product for a certain maintenance action on a certain class of assets and another product oriented for a different class of assets. Thus, they must select the APM products that better suit their necessities. Also, before implementing APM solutions, companies need to have an infrastructure that supports these tools. In this regard, it is important to note that APM tools are not execution systems and, consequently, they rely on Enterprise Asset Management (EAM) to perform its suggestions and provide feedback on the results. While APM products are devised to serve as a decision support tool, EAM products are devised for maintenance execution. Moreover, data quality is also a factor that affects the effectiveness of an APM system implementation. Therefore, organizations must have data quality assessment, mature EAM systems and effectively integrate both APM and EAM tools so that the implementation of APM systems is successful and valuable to the firm (Steenstrup and Foust 2017).

There are three key areas of business that, although their benefits may be commonly intermingled in practice, should be addressed in the scope of asset management: physical and mechanical; operational; safety, health and environmental. Regarding the physical and mechanical area, an APM solution must begin by understanding the variables that influence the performance and reliability of the physical mechanical assets in order to develop an effective mix of condition-based or reactive maintenance, according to each particular equipment. In this sense, there are five key steps, which include evaluating asset criticality, studying maintenance based on reliability, defining asset strategies, evaluating effects of operations on maintenance and continuous monitoring. These activities may result in improvements of workers safety, increases in equipment availability, reduction of unplanned downtime, and better Overall Equipment Effectiveness (OEE) and throughput (Daecher et al. 2019).

Concerning the operational aspect, organizations may utilize APM data to integrate decision-making across functions and consequently achieve optimizations in the supply of equipment and materials, as continuous monitoring may lead to more accurate root cause analysis of the process variables that cause reduced asset performance. In this sense, an opportunity arises to align the supply network in a more efficient way, optimize planning activities and reduce costs related to inventory and logistics. Finally, in what concerns the safety, health and environmental area, APM provides capabilities to mitigate risks, which leads to the reduction of insurance costs, enhancement of safety, and improved uptime (Laaper, Mussomeli, and Gish 2016).

Nevertheless, the market of APM solutions still lacks maturity and vendors products are very distinct. In the APM market, two different and overlapping submarkets can be identified: APM platform vendors and asset analysis solutions. While APM Platform Products constitute an integrated product set which provides wide and comprehensive capabilities, asset analysis products generally offer a subset of functionalities to support certain analytical approaches or certain groups of assets. In this regard, different vendor products provide distinct capabilities and functionalities. Also, there are vendors who develop their APM products focusing on the needs of a certain industry, which means that across different industries, there are customized products which are oriented to the needs of those specific industries (Foust and Steenstrup 2020).

However, simply implementing APM solutions and digitizing existing processes may not lead to the enhancement of core operations and to the achievement of the desired financial performance. Instead, what represents perhaps the main transformative characteristic of APM tools is the way they can connect the different systems across the business, namely inventory management, ERP, safety and quality. However, a lot of firms still look at APM solutions as merely sophisticated maintenance tools, which results in siloed APM programs that do not capture the full potential and value of this technology. Therefore, companies need to look at APM tools through three lenses, which are maintenance, operations and safety, in order to be successful at integrating APM with other technologies in the digital supply network (DSN) of the enterprise and to have a meaningful impact in their businesses (Mussomeli et al. 2017).

2.6 Reliability Engineering

2.6.1 Types of Maintenance

Maintenance involves a set of actions performed to preserve or repair an item for it to be in a condition that allows the execution of its required functions. It is desirable that the organization designs and establishes a maintenance strategy as an integrated system that emphasises the importance of each equipment part. A correct and appropriate maintenance strategy enables the minimization of the trouble and difficulty of a big breakdown and should be adjusted to each equipment (Rani et al. 2015).

Concerning the types of maintenance, there are two main traditional strategies, which are the reactive or corrective maintenance and the preventive maintenance.

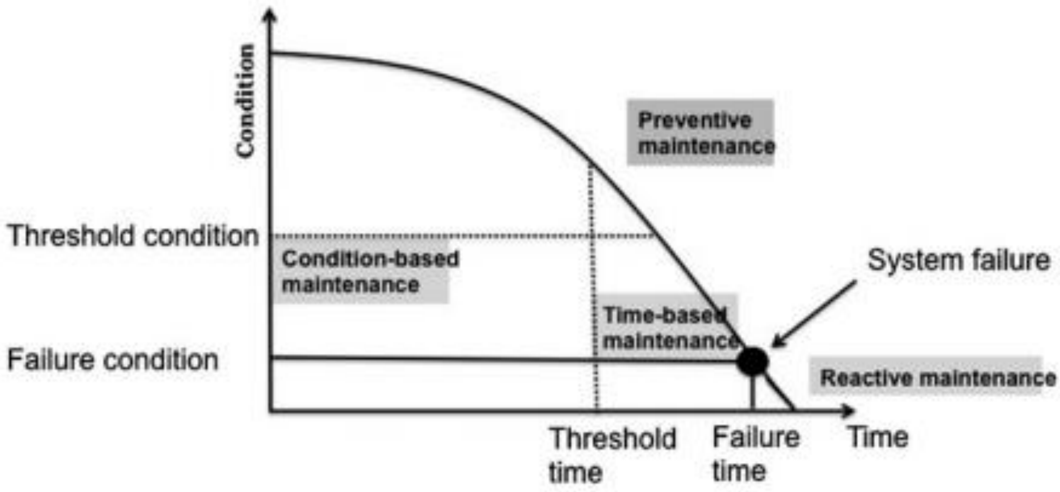


Figure 1 – Differences between the distinct types of maintenance (Kahraman and Çevik Onar 2015)

The reactive or corrective type is based on maintenance applied after the equipment failure, so only there, a repair or replacement are put in place. Depending on the asset's criticality, the maintenance is performed promptly or in a longer period of time, but due to the huge expenses incurred when the breakdowns are catastrophic and consequently emergency stoppages are actioned, the preventive maintenance has been introduced. Therefore, preventive maintenance is applied to prevent the asset failure, through repair or replacement of certain components before the equipment reaches a serious degradation condition that prevents its desired functioning. Preventive maintenance has been arranged into two groups depending on whether it is activated by the condition of the asset or its operating time. Condition-based maintenance considers the status of the asset by controlling its health without interrupting the normal equipment's operation. On the contrary, when time-based maintenance is applied, the asset is periodically subjected to maintenance activities, regardless of its condition. This leads to needless maintenance acts that, despite minimizing the totality of asset's failures, may not be the most optimizable solution (Kahraman and Çevik Onar 2015).

Besides these traditional strategies, predictive maintenance also came up, which is similar to condition-based maintenance in the sense that it is based on the asset's condition measurements. However, instead of using thresholds to determine when maintenance is required, predictive maintenance's aim is to forecast into the future the moment in time when maintenance needs to happen. These measurements can be carried out resorting to methods like infrared thermographs, vibration analysis and ultrasonic detection, for instance. Thus, this type of maintenance predicts asset's failure and allows to make the best decision of when to intervene and perform the asset's repair, enabling also a high availability. The criticality of the equipment, which considers its safety, operational and environmental impacts, should be considered for predictive maintenance, so FMECA should be applied to define the maintenance targets (Mobley 2002).

2.6.2 FMECA

Failure Mode, Effects and Criticality Analysis stems from Failure Mode and Effect Analysis (FMEA) and Criticality Analysis (CA). FMEA is used to identify likely failure modes, classify procedures to minimize the failures and evaluate the effects on the product process. It is preferably applied in the design of the product phase or in the process development, despite being beneficial its application on existing processes or products (Benbow et al. 2006).

Risk calculation on this method is based on three elements, which are the severity, occurrence and detection. These elements multiplied allow to get the calculation of the risk priority number

(RPN), so the higher this number, the higher the priority on taking action in a certain process. Moreover, it is also important to classify each failure in terms of its criticality effect as well as its occurrence probability, so critical analysis sorts the failure modes according to its relevance, which is measured by severity of failure and failure rate (Franceschini and Galetto 2001).

FMEA and FMECA are then methodologies intended to recognize possible modes of failure for a process or product earlier than the problems take place, allowing to evaluate the risk that these failures might carry. Hence, it is possible to establish priorities on problems to act on them as well as recognize and apply corrective measures to solve the most critical issues. Therefore, there are several benefits such as enhanced processes and products through a higher reliability, quality and safety, but also customer satisfaction improvement through reduction of operations without any addition of value and the minimization of development time and costs. Actually, when failure modes are identified earlier in the process, they are not so expensive to solve and these financial advantages also come up with increasing number of sales as a result of improved satisfaction of customers. Moreover, FMEA and FMECA allow to develop testing requirements, ideal maintenance plans and analysis of reliability growth (Lipol and Haq 2011).

2.6.3 Predictive Maintenance and the use of Survival Analysis

Regarding machine prognosis, it can be defined as the prediction of the state of an asset in the future, taking into account the system's past and current condition as well as its use in the future, with the purpose of assessing the machine's Remaining Useful Life (Ling Wang, Chu, and Mao 2009).

RUL is defined as the residual amount of time that an asset is likely to execute its functional capabilities before requiring repair or replacement. RUL can also be defined as the length of time between the current time and the time of failure of a machine or one of its components (Okoh et al. 2014). Therefore, RUL constitutes an essential predictive indicator which aids maintenance engineers planning operations more effectively, avoiding unplanned downtime and optimizing the scheduling of maintenance actions.

Regarding the estimation of RUL, there are several types of models which can be used, being Survival, Similarity and Degradation models three of the most common ones. The type of models one can choose to apply depends on the data available. Degradation models require the knowledge of a safety threshold of a condition indicator which must not be crossed to avoid failure, while Similarity models require run-to-failure data of similar machines which shows the full deterioration of an asset from a healthy condition until failure. Survival models are useful when there is data of the time it took for similar assets to fail, rather than full run-to-failure records (MathWorks 2018). In the context of this project, CMF MES can provide the data required for the use of Survival models, which makes them the most appropriate for the estimation of RUL in this particular situation.

Survival Analysis is a set of statistical methods whose focus is on estimating the expected time until a certain event of interest occurs. Although survival models can be used in a wide range of fields, they are typically applied to clinical studies to estimate patient time-to-death, sociology for event-history analysis and engineering for estimating machines time-to-failure, being the latter the use case described in the context of this dissertation (Kleinbaum and Klein 2012).

There are some essential concepts regarding survival analysis that must be understood in order to apply this type of models. First of all, in the context of predictive maintenance, the event corresponds to what we are trying to predict, which in this situation, is the failure of an asset. Another key concept concerning Survival Analysis is censorship. Censored observations occur when there is only partial information about survival time, in the sense that it is known that the subject of study does not experience the event of interest up until a certain time, but after that time of censoring there is no more information about that subject. In particular, these situations constitute right-censoring, which are the most common cases. Left-censoring can also occur in scenarios in which it is known that the event of interest happened before a certain time, but is not known exactly when it occurred. However, in the scope of this dissertation, left-censoring is not relevant as it is always recorded the specific time when a failure occurs. In the context of predictive maintenance, right-censored observations occur when a preventive maintenance action happens before the machine fails, and thus there is no information about the time it would take for the asset to fail if there was no maintenance in a preventive manner (Gogoberidze 2020).

The survival function S(t) is another fundamental object of interest in Survival Analysis. It gives us the probability that a machine survives longer than a certain time t. The survival function S(t) is defined as:

$$S(t) = P(T > t) \tag{2.1}$$

where T is a random variable denoting the survival time of an asset, with $T \geq 0$, and t is a certain time value of interest for T. It is assumed that S(0) = 1, since all machines are alive at time 0, and another relevant property of the survival function is that it is non-increasing, because the survival of a machine up until a later time requires that it has not experienced failure in a previous moment.

The lifetime distribution function F(t) corresponds to the complement of the survival function, giving us the probability that the event of interest has happened until time t, and is defined as:

$$F(t) = P(T \leq t) = 1 - S(t) \tag{2.2}$$

The event density function f(t), which gives us the rate of failure events per unit of time, corresponds to the first derivative of F(t), assuming that F(t) is differentiable:

$$f(t) = F'(t) = \frac{d}{dt}F(t) \tag{2.3}$$

Another key concept in Survival Analysis is the hazard function h(t), which gives us the failure rate at a certain time t for assets that have survived up until time t (Kleinbaum and Klein 2012).

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \tag{2.4}$$

There is a direct relationship between the survival function and the hazard function:

$$S(t) = \exp\left(-\int_0^t h(u)du\right) \tag{2.5}$$

$$h(t) = -\frac{S'(t)}{S(t)} \tag{2.6}$$

being $\int_0^t h(u)du$ the cumulative hazard function H(t), which can be interpreted as the expected number of failures a machine would have by time t, if the event was repeatable. Therefore, the survival function can be simply defined as:

$$S(t) = \exp\big(-H(t)\big) \tag{2.7}$$

3 Conceptualization of an APM solution

3.1 Contextualization

The paradigm shift caused by the appearance of Industry 4.0 and the Industrial Internet of Things requires that companies adapt accordingly. Hence, the evolution of technology allows for the establishment of more sophisticated tools like Asset Performance Management to help manufacturers achieve the next level in what concerns the optimization of their operations and the reduction of inefficiencies. In this way, CMF aims to provide to its customers the most modern MES and to be at the forefront of innovation, and thus this project was born with the objective to conceptualize an APM solution to be integrated into their MES.

Thus, throughout this chapter, it will be detailed the conceptualization and design of an APM solution, which was based on investigation and research of the fundamental concepts associated, on available tools in the market and on the most relevant KPIs within the MOM scope.

As pointed out in the Literature Review, APM tools must help engineers, operators and managers make better decisions in their day-to-day operations. Hence, in order to provide valuable data for decision-making, APM systems should take advantage of improved data management, advanced analytics and sophisticated visualization techniques that allow for a quick understanding of the state of production and assets condition. In this sense, the APM solution to be integrated into CMF MES was designed taking into account the required functionalities to achieve these goals. The desired functionalities must allow for an accurate real-time performance monitoring in a generic manufacturing plant, meaning that the APM solution created in the scope of this dissertation is not intended to address the needs of a specific industry, but instead it is intended for application in any type of manufacturing environment. Also, the APM solution must capitalize on CMF IoT Data Platform, which allows for the collection of relevant equipment data, real-time calculations and visualizations, as well as the processing of analytic algorithms.

Therefore, during the process of conceptualizing the APM tool, it was taken into account the specific goals of CMF for the APM tool, as well as investigation of fundamental capabilities that these programs must have and its objectives. Also, market research was performed in order to get a grasp on the state-of-the-art of available APM software.

Regarding the selection of the KPIs to be included in the designed APM solution, ISO 22400 was used as the primary source of information, since it constitutes the international standard for KPIs used in the scope of MOM. In ISO 22400, the KPIs are defined according to the context in which they are appropriated, namely for which type of manufacturing they are typically applicable to. Concerning the type of manufacturing, KPIs are divided into three groups, which are discrete manufacturing, batch manufacturing and continuous manufacturing. Since CMF MES is especially oriented for discrete manufacturing, the selected KPIs took this factor into consideration, and thus KPIs that are not applicable to discrete manufacturing were not considered.

The conceptualization of the APM solution will now be descripted, as well as its features and functionalities.

3.2 Home View

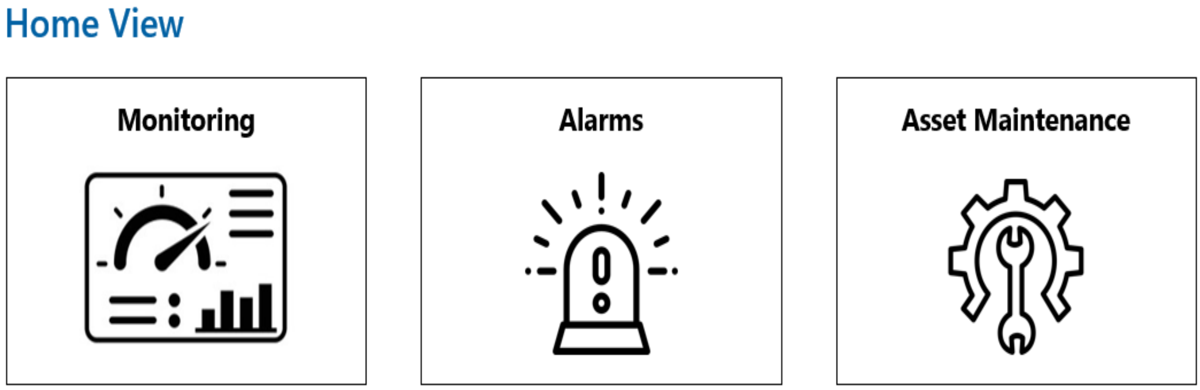


Figure 2 - Home view of the conceptualized APM solution

As previously stated, one of the goals for this APM solution was to allow for real time performance monitoring regarding the production activities. Therefore, one of the conceptualized views comprised in this application is the monitoring view, which allows for the monitoring of the most relevant production parameters and KPIs, and thus is essential for assessing if production targets are being achieved.

Another important objective for this application was to allow to determine abnormalities in the state of production. Hence, the alarms view was created to fulfil the need to find out about potential ongoing problems that need to be solved. It is important to note that there is an interaction between the monitoring view and the alarms view in the sense that the alarms view shows not only sensor telemetry parameters that are out of control, but also KPIs present in the monitoring view that do not comply with the predefined thresholds. Thus, both of these views provide valuable information to the production manager regarding the real time production status.

Finally, an APM software must allow to assess the assets condition and to facilitate the decision-making concerning asset related activities, so an asset maintenance view was created for this purpose. Based on literature review and comparison of APM solutions in the market, the functionalities envisioned to be integrated in this asset maintenance view include the creation of models to assess survival estimation using historical information, risk management, failure modes, effects and criticality analysis and the visualization of essential maintenance KPIs. Therefore, the asset maintenance view is essentially used to aid reliability engineers manage the assets, essentially helping in the scheduling and planning of maintenance actions, as well as providing information about failure modes to help in inspections and corrective maintenance tasks.

During this chapter, the explanation of the three conceptualized views for the designed APM application will be further detailed, as well as the corresponding features included in each view.

3.3 Monitoring View

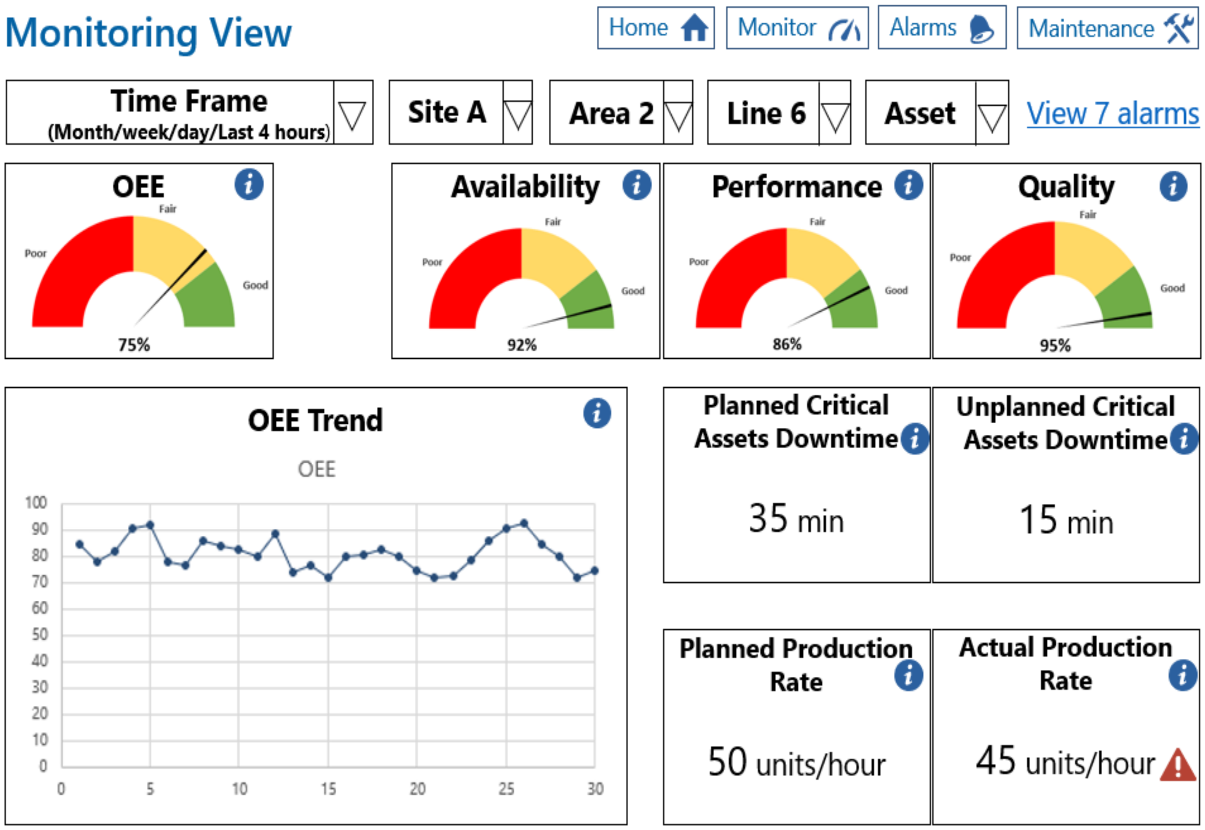


Figure 3 – Monitoring view of the conceptualized APM solution

In the monitoring view, filters can be used to narrow down the visualization according to the time frame or the entity for which one pretends to monitor the defined KPIs. The time frame filter allows to check the KPIs values for a certain period that the user wants to monitor. Regarding the zone of production that requires monitoring, the user can drill down by production site, area, line and asset. Now, the explanation of the selected KPIs to integrate this view will be executed, as well as its usefulness in the context of the monitoring of the state of the production.

According to ISO 22400, OEE is a major KPI as it provides improved manufacturing information, identifies production wastes and losses, and enhances the quality of the product through the optimization of processes. All these features make OEE a great source for improvements, through the comparison of the ideal and the actual performance. It is represented as a gauge chart, so that the user can quickly visually understand if its value is in a poor, fair or good state according to the goals of the company. The OEE Trend plot helps the production manager understand the evolution of the OEE KPI according to the timeframe selected in order to take action when undesirable trends happen or when established targets are not being accomplished. OEE can be broken down in three components, which are the availability, the work unit performance and the production quality.

$$OEE = Availability * Performance * Quality \tag{3.1}$$

Availability is an indicator that reflects the level of utilization and shows the production strength of the working unit capacity in relation to the capacity available, so this ratio demonstrates the proportion between the actual production time (APT) and the planned busy time (PBT) for a certain asset.

$$Availability = \frac{APT}{PBT} \tag{3.2}$$

where APT is the Actual Production Time, which is the actual time in which an asset is producing for an order, only including the value-adding functions, and PBT is the Planned Busy Time, which corresponds to the difference between the planned operation time and the planned downtime.

In turn, performance, also known as efficiency factor, exhibits the relation between the net operating time (NOT) and the operating time (OPT). Essentially, it allows to assess the speed of production in comparison with the ideal cycle time.

$$Performance = \frac{PRI * PQ}{APT} \tag{3.3}$$

where PRI is the Planned run time per item, which is the planned time destined for the production of one quantity unit, PQ is the Produced Quantity, which is the quantity of a production order that has been produced by a machine, and APT is the Actual Production Time, as previously explained.

Quality indicates the relation between the good quantity (GQ) and the produced quantity (PQ), so it constitutes a measure of the good finished products ratio.

$$Quality = \frac{GQ}{PQ} \tag{3.4}$$

where GQ is the good quantity, which corresponds to the produced quantity that is in accordance with the quality requirements, and PQ is the produced quantity.

Planned critical assets downtime and unplanned critical assets downtime are other particularly relevant KPIs that have been integrated in this view. Critical assets are defined by the production manager as those assets that are vital for the smooth running of production processes, such as certain machines that constitute bottlenecks. Thus, it is then fundamental to monitor the downtime of these assets due to their greater importance, in order to optimize the decision making regarding the planning of production.

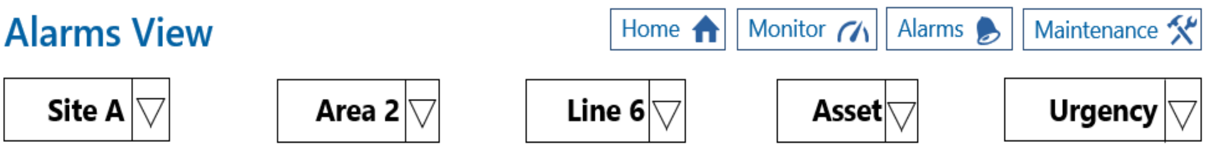
Finally, the planned production rate and actual production rate KPIs allow for the comparison between the desired production targets and the true production output.

$$Production\ Rate = \frac{PQ}{AOET} \tag{3.5}$$

where PQ is the produced quantity, and AOET is the Actual Order Execution Time, which is the time it takes for a production order to be completed, from its start time to its end time, which includes the actual busy time, the actual transport time and the actual queuing time.

The option “View X alarms” provides information regarding the number of current alarms according to the active filters and redirects to the alarms page with the current filters also applied.

3.4 Alarms View



Time	Urgency	Entity (site/area/ line/asset)	Parameter/ KPI	Most recent value	Threshold
2021/03/21 09:35	High	Machine X	Temperature	120 °C	100°C
2021/03/21 09:14	Medium	Line 6	Production Rate	45 un./h	50 un./h
2021/03/20 16:35	Low	Machine X	Vibration	62 Hz	60 Hz
2021/03/20 14:54	Medium	Machine Y	Temperature	95 °C	90°C
2021/03/20 11:35	Medium	Machine X	Torque	425 Nm	450 Nm
2021/03/19 15:02	High	Machine Z	Temperature	130 °C	105°C
2021/03/19 13:11	High	Machine Z	Vibration	80 Hz	60 Hz

Figure 4 – Alarms view of the conceptualized APM solution

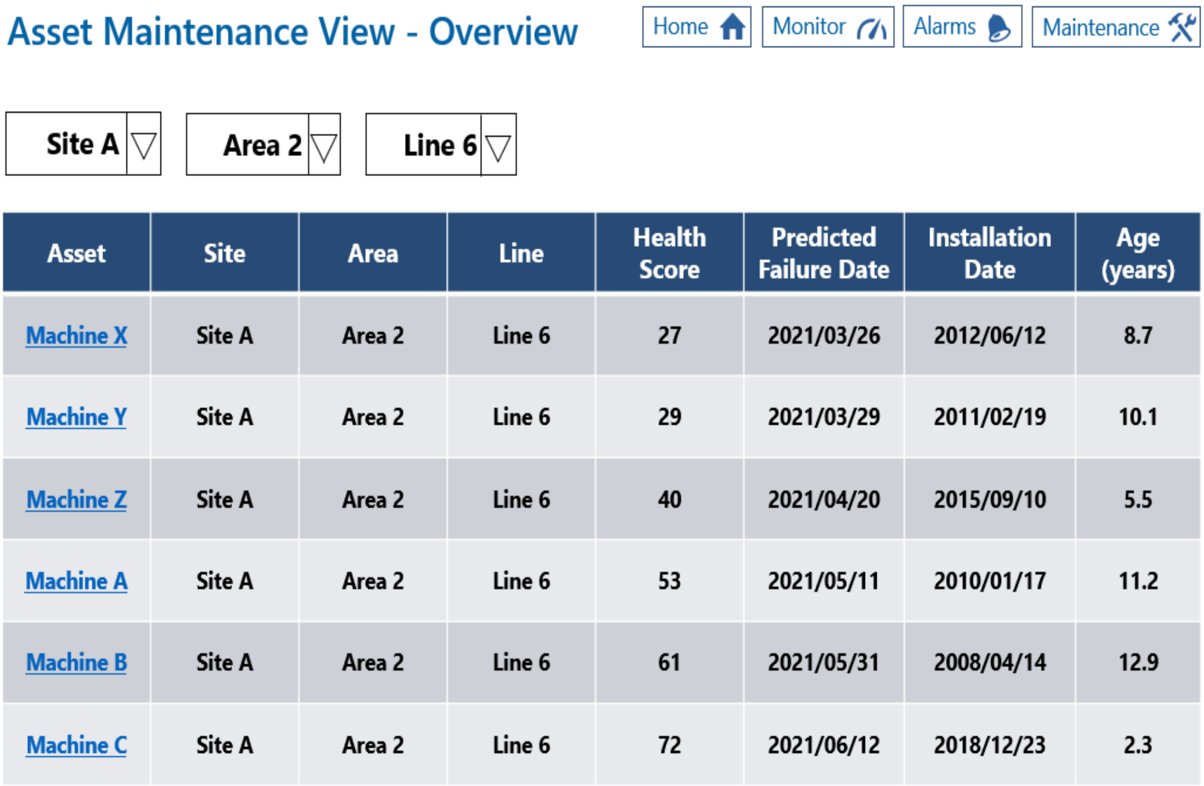
The alarms view can be accessed directly through the monitoring view as explained, or through the Home View. It provides information about the parameters or KPIs that are not in compliance with the usual and regular limits defined by the user.

As in the monitoring view, it is possible to filter down by site, area, line and asset. Also, the urgency filter enables to prioritize the alarms according to the degree of their importance.

The time corresponds to the moment when the alarm has been triggered, whereas the entity is related to the element being assessed. Apart from the KPIs explored in the monitoring view, it is also possible to set alarms for other parameters such as values from sensor telemetry that are out of control. While the threshold corresponds to the KPI or parameter value that must not be crossed, the most recent value corresponds to the last measurement obtained. Also, the production manager can click on a certain entity from a specific alarm and be redirected to the monitoring view of that particular entity in order to understand the impact of the parameters out of control on the monitoring KPIs. Finally, it is important to note that alarms that show a high degree of urgency concerning an abnormality in sensor telemetry values of machines, may indicate the need for maintenance activities.

3.5 Asset Maintenance View

3.5.1 Asset Maintenance Overview



Asset	Site	Area	Line	Health Score	Predicted Failure Date	Installation Date	Age (years)
Machine X	Site A	Area 2	Line 6	27	2021/03/26	2012/06/12	8.7
Machine Y	Site A	Area 2	Line 6	29	2021/03/29	2011/02/19	10.1
Machine Z	Site A	Area 2	Line 6	40	2021/04/20	2015/09/10	5.5
Machine A	Site A	Area 2	Line 6	53	2021/05/11	2010/01/17	11.2
Machine B	Site A	Area 2	Line 6	61	2021/05/31	2008/04/14	12.9
Machine C	Site A	Area 2	Line 6	72	2021/06/12	2018/12/23	2.3

Figure 5 – Asset maintenance overview of the conceptualized APM solution

In the asset maintenance view, it is possible to look into all the plant's machines and filter by site, area and line if the user wants to get an overview of the assets on a specific location. Therefore, in this overview it is provided general information about the assets, such as its identification and where it is located, but also other relevant indicators.

The Health Score is an indicator of condition, meaning that the higher its value, the better the health condition of a certain asset is. This indicator corresponds to the probability of survival of a given asset in a certain day and its calculation is made resorting to survival analysis techniques, which will be addressed later in this dissertation. Hence, the reliability engineer can sort the distinct assets by Health Score, quickly visualizing which assets are in a more critical condition and prioritizing the maintenance activities accordingly.

Also, the predicted failure date indicator helps in the scheduling of the required maintenance tasks by giving insights on the time of failure. Therefore, not only failures can be prevented, but also unnecessary preventive maintenance tasks can be avoided, resulting in lower maintenance costs. Finally, general asset information like installation date and age are provided in order to understand the degree of use of an asset.

On this overview, it is possible to select a specific asset, redirecting to that particular asset maintenance view on which it is possible to further analyse its condition with greater detail.

3.5.2 Asset Maintenance View of a specific view

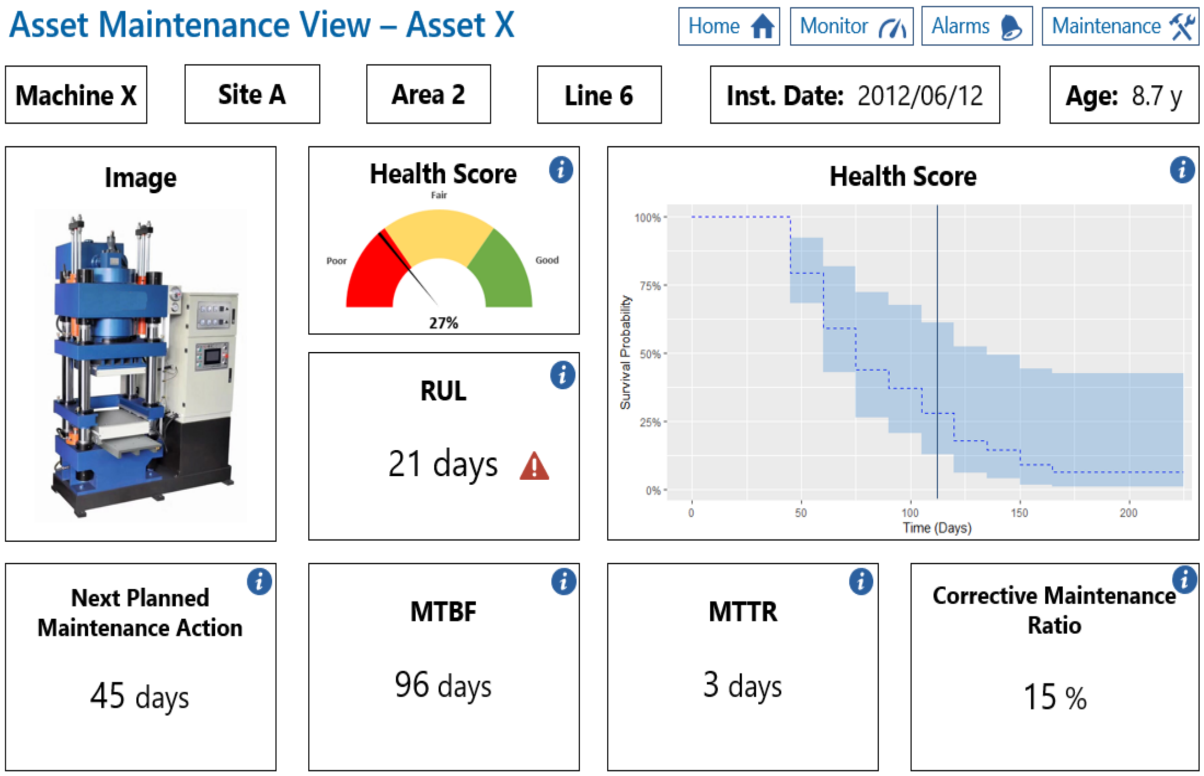


Figure 6 – Asset maintenance view of a specific asset in the conceptualized APM solution

At the top of this view, the identification of the asset and its general information are presented. The asset image is also represented, so that the user is able to quickly identify it visually. There are several KPIs here illustrated that provide key details of the asset condition.

Regarding the Health Score, it corresponds to the probability of survival on the current day, as previously explained. It is represented as a gauge chart, so that the reliability engineer quickly visualizes if its value is in a poor, fair or good state, and then take measures accordingly. By analysing the Health Score plot, one can see the predicted evolution of the Health Score indicator, which constitutes valuable and essential information to determine when to perform maintenance, so that a potential failure is avoided. This plot corresponds to the survival function, which will be introduced in the next chapter. The shaded area corresponds to the 95% confidence interval for the probability of survival on a given day and the vertical line in the plot represents the current day.

The RUL indicator is the Remaining Useful Life of the asset, which corresponds to the difference between the predicted failure date and the current day. The methods for the determination of the RUL indicator will be approached in the next chapter. By comparing the RUL indicator with the next planned maintenance action indicator, one can determine if adjustments to the maintenance scheduling need to be made. Therefore, when RUL is lower than the next planned maintenance action indicator, a failure is likely to happen, so the reliability engineer must take action and make changes in the planning of that asset maintenance activity so that unplanned interruptions are avoided and the damages associated can be minimized.

There are other maintenance KPIs essential to explore, such as the Mean Time Between Failure (MTBF), the Mean Time to Repair (MTTR) and the Corrective Maintenance Ratio.

MTBF is a metric of expected system reliability measured in a statistical way based on the already known failure rates of the several work unit elements and representing the expected time between failure.

$$MTBF = \frac{\sum_{i=1}^{i=FE} TBFi}{FE + 1} \tag{3.6}$$

where TBF is the Time Between Failures, which corresponds to the actual unit busy time between two consecutive failures of a machine, including the setup time, the production time and the repair time related to the processed orders, and FE is the Failure Event Count, which corresponds to the number of times that a machine has a failure over a certain period of time.

MTTR is the mean time an item needs to re-establish an element that failed in a work unit, being measured as the average of all repair events time for a work unit, representing the expected time to repair.

$$MTTR = \frac{\sum_{i=1}^{i=FE} TTRi}{FE + 1} \tag{3.7}$$

where TTR is the Time to Repair, which is the actual time that a machine is not available because of a failure event, and FE is the Failure Event Count, as previously detailed.

The Corrective Maintenance Ratio expresses the corrective actions extent considering all maintenance tasks executed in a work unit. Thus, it exhibits the time spent in corrective activities in relation to the whole maintenance time, which is the sum of corrective and planned maintenance time. This ratio should be the lowest possible as it means that in proportion to the total maintenance actions, there are few corrective maintenance actions because the reliability engineer is able to perform maintenance before the failure takes place. Hence, this KPI reflects the need for improving the system reliability.

$$Corrective\ Maintenance\ Ratio = \frac{CMT}{CMT + PMT} \tag{3.8}$$

where CMT is the Corrective Maintenance Time, which corresponds to the time spent performing a corrective maintenance action on a machine, and PMT is the Preventive Maintenance Time, which corresponds to the time spent performing a preventive maintenance action on a machine.

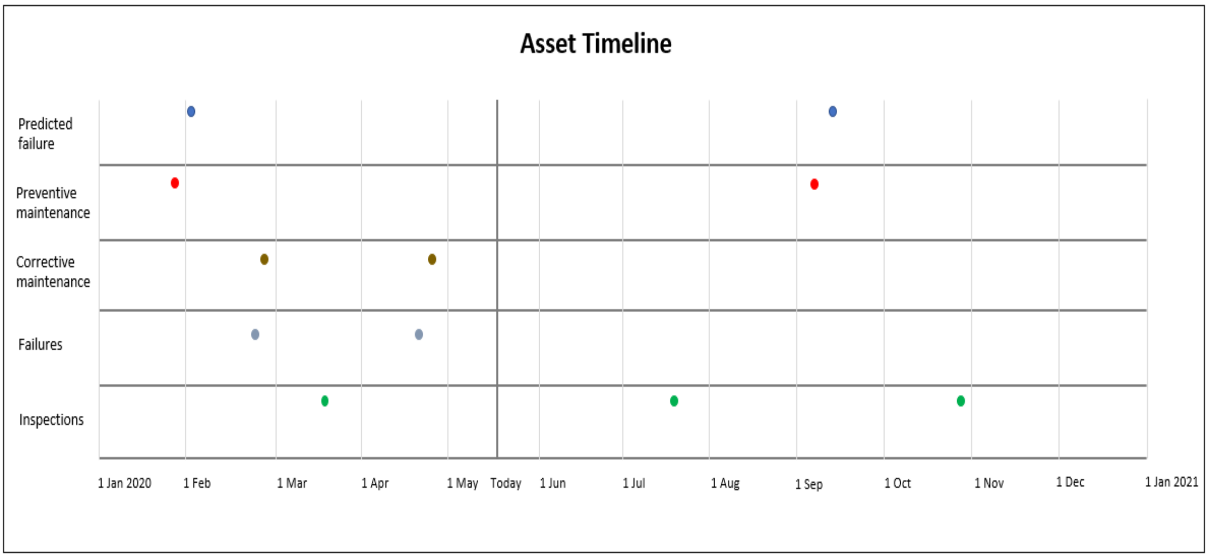


Figure 7 – Asset timeline in the asset maintenance view of a specific asset

Also in the asset maintenance view of a specific asset, the Asset Timeline chart provides very useful information of past and future asset related activities. By analysing this chart, the maintenance manager can see the dates of predicted failures, preventive maintenance activities, corrective maintenance activities, failures and inspections. Not only it is useful to understand the types of activities that were performed on this asset in the past, but also to quickly visualise future planned actions and predicted failures, and make adjustments if necessary.

Maintenance History

Date	Description of the Maintenance action	Type of Maintenance	Failure Mode Prevented/Corrected	Status
2021/03/23	Rest machine	Preventive	Overheating	In progress
2020/08/16	Change oil	Corrective	Motor bearings seize	Finished

Figure 8 – Maintenance history in the asset maintenance view of a specific asset

Furthermore, in the asset maintenance view of a specific asset, the Maintenance History is also exhibited. The Maintenance History acts as a complement to the Asset Timeline chart, since it gives detailed information about the maintenance activities previously performed on the asset. Not only it includes the date of the task performed, but also a description of the maintenance action executed and the type of maintenance it corresponds to. Moreover, information regarding the failure mode prevented or corrected with that maintenance activity is provided, as well as the status of the maintenance action, which states if it has already been finished or if it is still ongoing. This information helps the reliability engineer understand which failure modes tend to occur more frequently, and therefore he can pay closer attention to certain parameters of the machine, managing its required maintenance tasks accordingly.

Failure Mode, Effects and Criticality Analysis

Failure Mode ID	Failure Mode Description	Effects	Causes	Probability Score	Severity Score	Detection Score	RPN	Recommended Actions
1	Motor bearings seize	Motor bearings wear abnormally	Lack of lubrification	6	4	3	90	Change oil
2	Overheating	Motor bearings wear abnormally	Lack of rest	3	5	5	75	Rest machine

Figure 9 – FMECA tool in the asset maintenance view of a specific asset

Finally, FMECA is also a valuable tool to show in the asset maintenance view of a specific asset, namely for analysing in an organized way the potential failure modes associated with a certain asset. In this way, the risk related to these failure modes can be assessed in terms of importance, aiding reliability engineers in the adoption of an appropriate strategy in the management of the asset.

In this view, there is the identification of the failure as well as its description. The effects correspond to the consequences that a certain failure mode may generate, and the causes correspond to what leads to the generation of that failure mode, which constitutes helpful information in understanding the aspects that surround a failure and the factors that require more attention.

In order to calculate the Risk Priority Number (RPN), there has to be a multiplication of the probability, severity and detection score. The probability score gives information about the frequency of that failure mode, the severity score is defined by the user according to extent of the impact it causes, and the detection score concerns the capacity for detecting that failure. Having these scores specified, the RPN is calculated and gives information regarding the priority for designing measures to reduce the RPN, either by improving prevention, reducing the severity with safety measures or enhancing detection with more sophisticated inspection procedures. Therefore, the higher the RPN, the higher the need for taking action. At last, the recommended actions advise what procedures to apply to correct a failure mode and minimize its associated risk.

3.6 Selection of analytic methods to estimate the Health Score and the RUL indicator in the designed APM tool

Before proceeding to the next chapter in which the use of Survival Analysis methods for Predictive Maintenance is detailed, it is important to understand why these types of models were chosen in the context of this project.

Regarding the APM tool to be integrated into CMF MES, the established goal for the study of predictive analytic methodologies to be applied in a predictive maintenance context was to research and find out about models that could be used to predict the time-to-failure in a generic machine. This means that the types of models chosen should not depend on domain knowledge nor on the characteristic of specific types of machines, but instead should be applicable for any kind of manufacturing asset.

In what concerns the estimation of the RUL of machines, there are several types of models that can be used. As stated in the Literature Review, the most common methods are Similarity Models, Degradation Models and Survival Models.

Similarity Models are the most useful when that there is run-to-failure data of assets that behave in a similar way to the specific asset for which one is trying to predict the RUL. Therefore, these models make use of a condition indicator which evolves from a healthy state until a decayed state in which there is the occurrence of a failure, showing the complete degradation than happens during this process.

Degradation Models are appropriated in the cases in which there are prescribed threshold values for a condition indicator. Hence, in these models, the RUL is estimated through the prediction of the evolution of the defined condition indicator, determining the moment when it is expected to cross the safety threshold. Degradation models are distinct from similarity models in the sense that there is not the availability of failure data from similar assets, but there is domain knowledge regarding a threshold that must not be crossed.

Survival Models are indicated for the cases in which there is not full run-to-failure data, but there is data concerning the life span of similar assets, meaning that information of the duration it took for similar machines to experience failure events is available. Also, apart from failure data, survival models can also make use of covariates data when available.

Therefore, it is concluded that the decision to choose a certain type of model when trying to estimate the RUL of machines depends on the data that is available for use and on the existence or not of domain knowledge regarding certain thresholds that must not be crossed. In Figure 10, a summary of the data required for the application of the three types of models approached for predictive maintenance is presented.

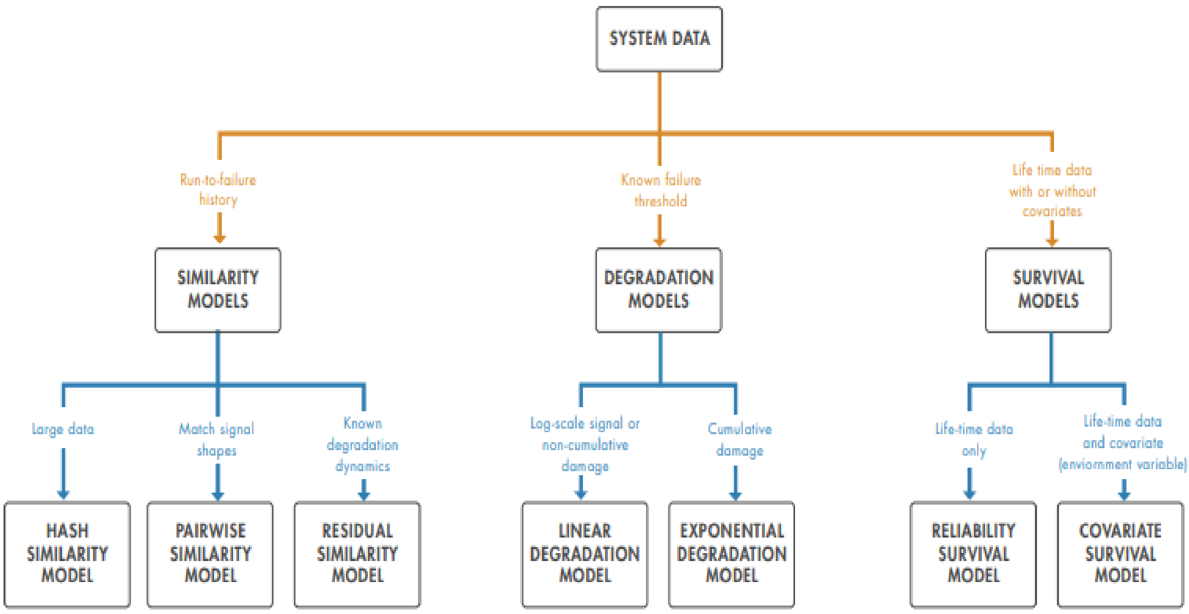


Figure 10 – Data requirements for the distinct predictive maintenance models (MathWorks 2018)

Concerning the goals for this project regarding the prediction of the RUL indicator, it is important to note that data extracted from condition monitoring sensors is not always available in CMF MES, and thus it is not always possible to define condition indicators that require this type of data. Consequently, Similarity Models are not appropriated for use since they need a database of complete run-to-failure information from similar assets, thus requiring sensor telemetry data for the definition of the condition indicator. Degradation Models also need to access data from condition monitoring sensors to define a condition indicator, which makes them inappropriate for this situation. Also, they require domain knowledge regarding the safety threshold value, which is another reason why they do not meet the goals for this project, because the objective is to apply predictive models to generic machines without relying on specific asset related knowledge. Lastly, the Survival Models are useful in the context of this project because CMF MES can always provide lifetime data, meaning that the history of failures and the history of maintenance actions involving a certain asset is stored and available to be used as an input to these models. Additionally, Survival Models allow for the incorporation of covariate data, in which sensor telemetry data is included. Therefore, these models are very flexible in the sense that they can incorporate other variables in the prediction process, but they do not depend on them. Thus, in situations in which this type of data is not available, Survival Analysis methods can still be used due to the fact that they allow for estimations of the RUL indicator using only lifetime data.

4 An application of predictive maintenance in the context of APM

In the context of predictive maintenance, the estimation of the RUL of the assets is a top priority. By accurately predicting when an asset will experience failure, maintenance actions can be performed just before it happens, which allows for the optimization of operations efficiency by reducing the unavailability of machines caused by the need of fixing unplanned breakdowns. Hence, this chapter will focus on the application of different models for the estimation of the RUL indicator as well as the Health Score indicator defined in the previous chapter.

As stated before, Survival Analysis methods will be used for this purpose, because CMF MES is able to provide the necessary data for the application of these models, which is life-time data. Furthermore, these techniques can also incorporate covariate data when available. Covariates are explanatory variables or characteristics of the objects of study that may affect the time-to-event.

In order understand the usefulness of Survival Analysis methods for predicting the RUL of assets, a design of experiments was created involving eight different models, each with different characteristics or assumptions, as it will be further detailed throughout this chapter. All computational experiments done in the scope of this dissertation were performed resorting to the R software and its available open-source packages.

4.1 Data used for the application of Survival Models

Due to the lack of real data for this project, the computational experiments performed were based on a dummy dataset, which is a dataset that contains the same type of content and layout of real machine historical data. The used dataset is available for download at (Boylu Uz 2016).

The dataset comprises data of 100 similar manufacturing machines and the asset data used includes a history of maintenance actions, failure dates, sensor telemetry and general information about the machines such as the age and the model. Regarding the variables of the used dataset, those are the following:

- ID: identification of a run-to-failure or run-to-maintenance observation.
- MachineID: identification of the machine to which the observation concerns.
- Model: categorical covariate with 4 levels (Model1, Model2, Model3 and Model4) indicating the model of the machine.
- Age: numerical covariate indicating the age of the machine.
- Volt, Rotate, Pressure and Vibration: continuous numerical time-varying covariates extracted from condition monitoring sensors.
- Days-To-Event: time-to-failure for uncensored observations or time-to-maintenance for censored observations.

- Tstart and Tstop: interval of time concerning a new measurement of the time-varying telemetry data.

- Status: binary variable indicating if it is a censored or uncensored observation. Censored observations (Status = 0) occur when maintenance happens in a preventive way, meaning that the machine did not experience failure at or before that moment in time. Uncensored observations (Status = 1) occur when there is a failure at end of the observation period, and thus the machine requires corrective maintenance.

In Figure 11, an extract of the dataset used, that contains the variables previously mentioned, can be analysed. The dataset contains historical data and sensor telemetry values of 100 machines, each one having several observations.

ID	Date	MachineID	Model	Age	volt	rotate	pressure	vibration	Days-To-Event	tstart	tstop	Status
1	06/01/2015	1	model3	18	183,4275797	437,6282276	94,0061046	37,98500513		0	1	0
1	07/01/2015	1	model3	18	180,7833309	421,6760657	83,67332445	39,450313		1	2	0
1	08/01/2015	1	model3	18	175,7740298	410,6896406	111,7051031	36,8614976		2	3	0
1	09/01/2015	1	model3	18	143,5065618	438,7059292	94,27311897	47,92907674		3	4	0
1	10/01/2015	1	model3	18	167,7566965	448,3186675	110,5810236	40,99239707		4	5	0
1	11/01/2015	1	model3	18	169,1896561	443,5933881	87,4375975	38,79039262		5	6	0
1	12/01/2015	1	model3	18	162,3555251	486,4533957	111,269645	47,55425898		6	7	0
1	13/01/2015	1	model3	18	147,3940606	485,8815563	88,76344424	38,23808313		7	8	0
1	14/01/2015	1	model3	18	159,3774323	446,9741778	108,65942	37,14400236		8	9	0
1	15/01/2015	1	model3	18	194,5339917	398,4669059	92,55211219	27,10551236		9	10	0
1	16/01/2015	1	model3	18	191,5721308	431,5254133	106,6961923	37,07039304		10	11	0
1	17/01/2015	1	model3	18	193,5024814	438,3858589	101,1178831	34,33796264		11	12	0
1	18/01/2015	1	model3	18	175,3175549	444,8826238	102,6627628	43,19364541		12	13	0
1	19/01/2015	1	model3	18	165,9022734	459,3680491	102,0976636	37,60063289		13	14	0
1	20/01/2015	1	model3	18	157,7745102	442,8167483	105,1606918	42,13512722	15	14	15	0
2	21/01/2015	1	model3	18	155,5682146	447,2731595	98,27257947	39,98913156		0	1	0
2	22/01/2015	1	model3	18	170,178877	463,217153	108,2262698	36,84738996		1	2	0
2	23/01/2015	1	model3	18	184,9416502	401,6064557	88,80395096	41,31176992		2	3	0
2	24/01/2015	1	model3	18	166,9334176	462,3337873	100,2112135	41,10522323		3	4	0
2	25/01/2015	1	model3	18	164,7751261	409,4257347	106,1297108	42,16455132		4	5	0
2	26/01/2015	1	model3	18	176,8235315	499,1230683	99,7524032	31,3029183		5	6	0

Figure 11 – Portion of the dataset used as an input to the survival analysis models

In Figure 12, there is the representation of how this survival problem was modelled according to the available dataset. Each interval starts with the execution of a maintenance operation that restores the asset condition to perfect health and ends in a failure, in the case of uncensored observations, or in a preventive maintenance action, in case of censored observations. Each machine (identified by MachineID) may contain several observations (identified by ID). Regarding preventive maintenance actions, they do not have a specified periodicity, and thus can happen at any given point in time, as well as the failures. Also, regarding the time-to-event, it is measured in days.

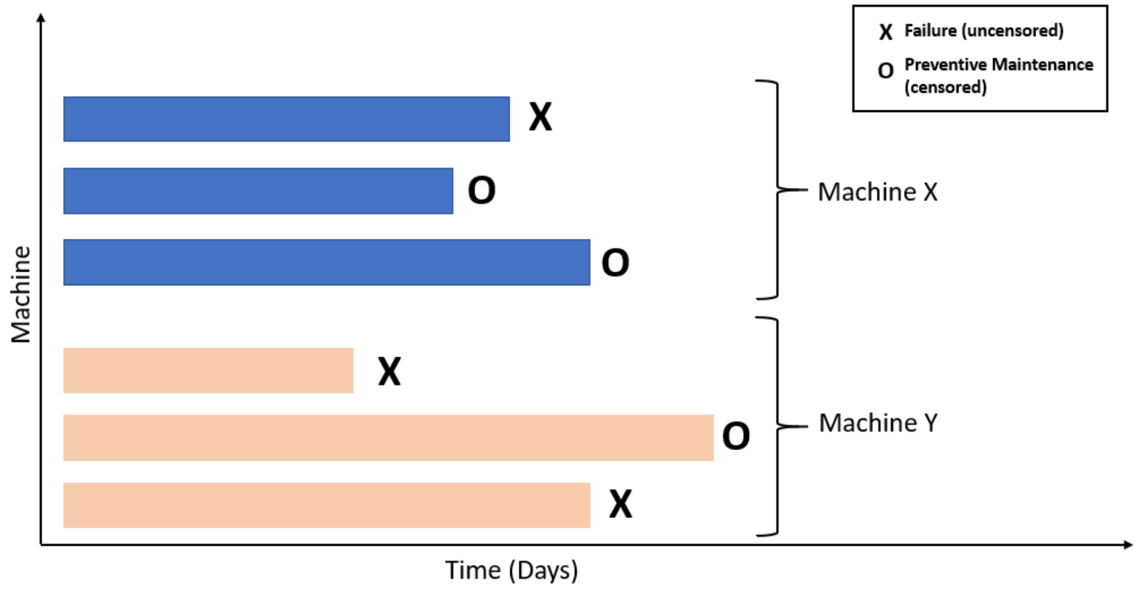


Figure 12 – Representation of distinct survival observations on distinct machines

When dealing with Survival Analysis, it is important to understand how the covariates are encoded in R. While continuous data types are intuitively encoded as continuous covariates, categorical covariates need special encoding. In this sense, categorical covariates with N levels lead to the creation of N – 1 covariates. In this case, since there are 4 models for the machines, 3 categorical covariates are created (Model2, Model3, Model4). Each model is represented by setting its value to 1 and the others to 0. In the case of Model 1, which acts as the reference, it is represented by setting all 3 categorical covariates created to 0. In what concerns continuous covariates, it constitutes good practice to use mean centering due to the fact that they may not have a meaningful value of 0 and it also allows for easier interpretation. Mean centering means that for a specific continuous covariate, its mean from all the observations in the training dataset is subtracted from each of its values, being the new covariate's mean equal to zero. Thus, one can interpret the new transformed continuous covariate values as the difference from the mean. Regarding the data used in the context of these experiments, the asset age and the sensor telemetry covariates were mean centered, and thus these new transformed covariates were used as an input to the models.

The different survival models approached in this study have distinct specific assumptions which will be further detailed when analysing each specific method. However, there is one assumption which concerns all models. It is assumed that every maintenance action performed in machines, either in a preventive way in the case of censoring or in a corrective way in the case of failure, fully restores the asset to a perfect condition, which means that every distinct observation (identified by the ID variable) can be treated independently.

4.2 Types of Survival Models approached

The aim of the distinct survival methods studied in this project is to compute an appropriate estimation of the survival function, which can then be used for the computation of the RUL. In Survival Analysis, there are three types of options for the modelling of the survival function, which are non-parametric, semi-parametric and parametric methods.

Non-parametric methods enable to infer survival functions from the existing data in an empirical way, without assuming a parametrized closed distribution, being the Kaplan-Meier method the most common non-parametric technique.

Semi-parametric models permit the inference of the effect of the covariates on the time-to-event without the need for making assumptions regarding the baseline hazard function, meaning that it does not have a parametric closed form, which allows for a time-varying baseline risk, like in the Kaplan-Meier model. However, there is a multiplicative component concerning the effects of the covariates on the time-to-failure that is parametrized, which is the reason why these are called semi-parametric models. Both in non-parametric and semi-parametric methods, the survival function is a step function, not allowing for extrapolations after the last observed time-to-failure.

Parametric methods are those which assume that the survival function follows a certain parametric distribution. Hence, in parametric methods the survival function is smooth. When there is not a lot of data available and the parametric distribution chosen is a good fit for the data, parametric models are very useful. Furthermore, they allow for extrapolations and interpolations.

In Table 1, it is presented a comparison between the different types of methods concerning survival analysis.

Table 1 – Summary of the characteristics of the distinct types of survival models

	Non-parametric methods	Semi-parametric methods	Parametric methods
Distribution assumptions	Empirical survival function without the assumption of parametric distributions.	No assumption of a parametric distribution for the baseline hazard. However, the relative risk can be parametrized.	Survival function is assumed to follow a certain parametric distribution.
Covariates	Can only incorporate few categorical covariates.	Can incorporate both categorical and numerical covariates.	Can incorporate both categorical and numerical covariates.
Survival function type	Step Function.	Step function.	Smooth Function.

4.3 Experiments design

In the scope of this dissertation, eight distinct survival models were used in order to make predictions for the time-to-failure of the machines. The original dataset, which comprises data of 100 machines, was divided in a training dataset containing data of 80 machines, and in a testing dataset including data of 20 machines.

Before proceeding to the description of each of the eight models approached, it is important to understand the difference between Proportional Hazards (PH) models and Accelerated Failure Time (AFT) models. While PH methods make the assumption that the hazard ratios are constant over time, AFT methods make the assumption that the covariates have an accelerating or deceleration effect on the survival time by a constant factor.

In what concerns the estimated predictions from the different models used, the expected value of the RUL at a certain time t was obtained by calculating the area under the survival curve after time t (mean residual life). In the case of non-parametric and semi-parametric methods, which do not allow for extrapolations, the mean residual life at time t is obtained by calculating the area under the survival function between time t and the last observed time for a failure. In the case of parametric methods, the survival curve follows a certain closed distribution, which makes it possible to make extrapolations. Therefore, the mean residual life at time t in parametric techniques is obtained by integration of the survival function between time t and a time where $S(t) \approx 0$.

4.3.1 Kaplan-Meier method

The first survival analysis technique approached in this project was the Kaplan-Meier (KM) estimate, which is the most common non-parametric method. It estimates a step function of the survival probability, in which every event at a certain time *t* changes the survival probability. Therefore, it has the advantage of being a very flexible method and, with the increase in the number of observations, the model becomes more robust as the survival function approaches a smooth estimator. However, the KM method can only deal with few categorical covariates with few levels, which constitutes a big disadvantage. As an example, regarding this particular experiment, which includes the categorical covariate Model with 4 levels (Model1, Model2, Model3 and Model4), the application of the KM method would result in 4 distinct survival functions, each according to the specific machine model. Hence, the data used to produce each survival function corresponds only to the data regarding that specific categorical covariate value, which requires that there is a significant number of observations for each machine model for the method to be robust. Therefore, it is easy to conclude why non-parametric models make it hard to incorporate categorical covariates.

With the purpose to assess if the different machine models impact the time-to-event, a log-rank test was performed. A log-rank test is a hypothesis test that can be used on KM models to make a comparison between survival estimates of different samples.

Log-rank test:

H_0: survival in the 4 groups (Model1, Model2, Model3, Model4) is the same.

H_1: survival in the 4 groups (Model1, Model2, Model3, Model4) is not the same.

Since it was obtained a p-value of 0.8, there was not statistic evidence to reject the null hypothesis, and thus there is no evidence that the machine model categorical covariate has a significant effect on the time-to-failure of the assets, which is why, in this case, it does not make sense to create a KM method that includes the machine model covariate. Therefore, this first experiment was a KM model with no covariates incorporated, which means that, after training the model with the training dataset, all the predictions made in the test dataset have exactly the same time-to-failure because the specific value of the covariates of each observation are not considered for each prediction. In Figure 13, the survival function that resulted from the application of the KM method is represented, with the shaded area representing the standard 95% confidence interval.

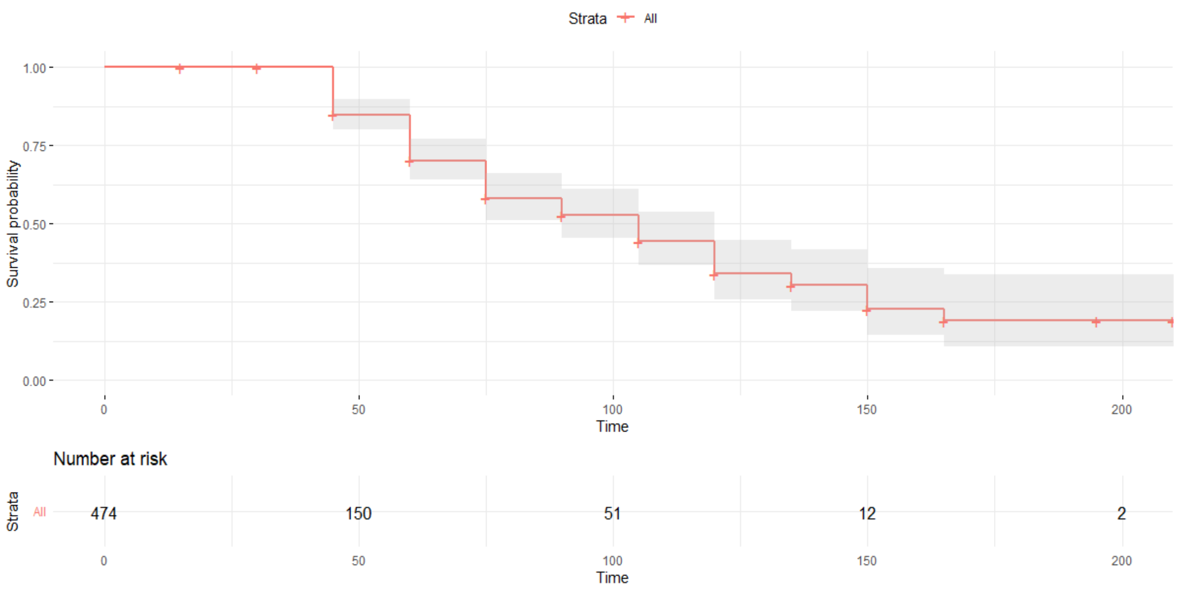


Figure 13 – Kaplan-Meier survival function

4.3.2 Cox Proportional Hazards models

The Cox Proportional Hazards model is the most used semi-parametric technique and it allows for the estimation of the effects of the covariates on the hazard rate. There is a decomposition of the hazard in a non-parametric baseline hazard, which concerns all of the assets under observation, and a parametrized relative risk, which is specific to the individual covariates values of each observation. In this method, there is a linear relationship between the log-hazard and the covariates. The hazard function is defined as follows:

$$h(t) = h_0(t)e^{\beta_1 X_1 + \cdots + \beta_p X_p} \tag{4.1}$$

where $h(t)$ is the hazard function at time *t*, $h_0(t)$ corresponds to the baseline hazard at time *t*, the X_i variables correspond to the distinct covariates and the betas are the covariates coefficients. The baseline hazard can be obtained by setting all covariates to zero and is a function of time, while the partial hazard $e^{\beta_1 X_1 + \cdots + \beta_p X_p}$ is independent of time, and thus its impact on the hazard is constant over time. This constitutes the basis for survival models with the Proportional Hazards assumption, which declares that the hazard ratio between two certain machines is constant over time:

$$HR(i, i') = \frac{h_i(t) = h_0(t)e^{\beta_1 X_1 + \cdots + \beta_p X_p}}{h_{i'}(t) = h_0(t)e^{\beta_1 X'_1 + \cdots + \beta_p X'_p}} = e^{\beta_1 (X_1 - X'_1) + \cdots + \beta_p (X_p - X'_p)} \tag{4.2}$$

Therefore, the big advantage of the Cox PH model in comparison with the KM method, is that it allows for different observations to have distinct survival curves within the same fitted model, due to the incorporation of the effects of the covariates on the time-to-failure. However, regarding the survival curve that results from Cox PH models, it is still a step function, which constitutes a disadvantage when using this method for a prediction use case, since it only allows for predictions with time-to-failure values that were observed in the training dataset, due to the fact that it does not allow for interpolations or extrapolations.

In the scope of this dissertation, three different Cox PH models were used to make predictions of the RUL of assets. The most classic use of Cox PH models considers that the covariates are time-fixed, which means that the specific covariates values for a certain observation do not change over the time of that observation run. Concerning the dataset used for this design of experiments, there are two covariates that are inherently time-fixed, which is the case of the machine model and the machine age covariates. Regarding the four sensor telemetry covariates, there is a new measurement every single day, which means that for a certain observation which lasts *N* days, there are *N* different measurements of these covariates values. Therefore, in order to incorporate these sensor telemetry covariates in a Cox PH model with time-fixed covariates, feature engineering techniques need to be performed on these specific covariates. Hence, in the experiments with time-fixed covariates carried out in the scope of this dissertation, the mean of the sensor telemetry covariates values served as an input to models with time-fixed covariates.

Apart from the Cox PH model with time-fixed covariates, there is also an extended Cox PH model which is able to handle time-varying covariates (also called time-dependent covariates). Contrary to the time-fixed covariates, time-varying covariates are those that change their values throughout the period of observation. In this situation, the sensor telemetry covariates are the ones that are time-dependent, since they change their values every day, as previously explained. Two experiments using the extended Cox PH model with time-varying covariates were performed, which differed in the assumption of the values of the time-varying covariates after a certain time *t*. In order to make predictions on observations of the testing dataset using Cox PH models with time-dependent covariates, there is the need to know the values of the covariates over the full period of study, which starts at $t = 0$ and ends at the last observed time for a failure in the training dataset, which is $t = 225$ days in the case of the data used for these experiments. Therefore, when the calculation of the remaining useful life happens at a certain time *t*, the covariates values of the period (t, 225] are unknown and assumptions need to be made.

In one of the Cox PH models with time-dependent covariates, the last measurements known of the sensor telemetry covariates, which happened at time *t*, were assumed to continue constant throughout the rest of the observation period. In the other Cox PH model with time-dependent covariates, the mean of the sensor telemetry covariates values of the period (0, t] was assumed for the rest of the observation period. In Figure 14, it can be seen an example of a survival curve for an individual prediction case that results from the application of a Cox PH model.

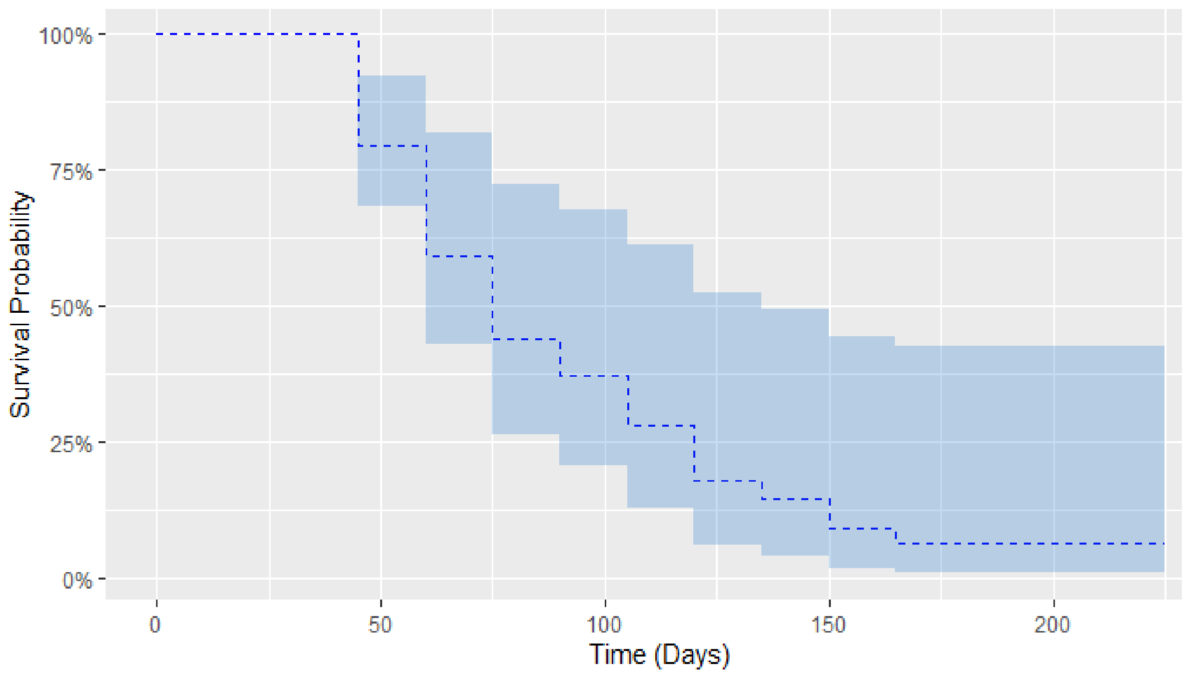


Figure 14 – Cox PH survival function for a specific prediction

Effects of the covariates on the survival time

Apart from being applied to a prediction use case, Cox PH models are also appropriate for the inference of the effects of the covariates on the time-to-failure. The reason why semi-parametric models are usually chosen for an inference use case is because they do not need to make strong assumptions on the probabilities distribution for the survival function, which makes them appropriate for an accurate estimation of the impact of the covariates on the time-to-failure. Therefore, in this section it will be shown how to interpret the output of the classic Cox PH model with time-fixed covariates in order to demonstrate the usefulness of these models for estimating how the covariates influence the time-to-failure of machines. The output results are presented in Table 2.

Table 2 – Results of the inference of the effects of covariates on the time-to-failure using Cox PH model

covariate	coef	exp(coef)	exp(coef) lower 95%	exp(coef) upper 95%
model2	-0.019	0.981	0.488	1.972
model3	-0.234	0.791	0.463	1.352
model4	-0.137	0.872	0.490	1.553
age	-0.001	0.999	0.965	1.035
volt	0.265	1.303	1.161	1.463
rotate	0.033	1.034	0.999	1.071
pressure	-0.065	0.937	0.805	1.091
vibration	-0.335	0.716	0.508	1.008

First of all, it is important to note that the machine model is encoded as a categorical covariate, in which the baseline level of this covariate is model1. This means that the estimated coefficients for model2, model3 and model4 serve as a comparison with model1. In order to interpret the effect of the machine model on the time-to-failure, one needs to apply the exponential function to the coefficients of the model covariates, which is represented in Table 2 as exp(coef). As it can be seen in Table 2, model2, model3 and model4 have exp(coef) values lower than 1, which means that the hazard rate is lower than model1. As an example, model3 has an exp(coef) value of 0.791, meaning that machines of mode3 have a hazard rate that is 20.9% (1-0.791) lower than the hazard rate of machines of model1, and therefore are 20.9% less likely to fail at any given moment in time according to the Proportional Hazards assumption. Regarding the categorical covariate model, machines of model1 have the highest risk of failure and machines of model3 have the lowest risk of failure, meaning that maintenance operations on machines of model1 should be prioritized.

In what concerns the numerical covariates, they were mean centered as previously explained. Hence, the interpretation of the effects of these covariates concerns the difference of the values around their means. As with categorical covariates, the effects of the numerical covariates on the time-to-failure are given by the exponential of their coefficients. The exp(coef) concerns the effect on the hazard ratio of increasing by one unit that particular numerical covariate. Therefore, as an example, one unit increase in the volt covariate in comparison to its mean represents an increase on the risk of failure of 30.3% (1.303-1). In the case of vibration, since the exp(coef) value is lower than 1, a unit increase in the vibration covariate represents a decrease on the risk of failure of 28.4% (1-0.716).

4.3.3 Parametric Models

Parametric survival models make the assumption that the survival function follows a certain parametric distribution. In situations where, through previous research, it is known that the distribution of the survival time has a known parametric form, these models are very useful because they are able to tackle the objectives of the analysis better. One of the main benefits of parametric survival models is that the survival function is now smooth, which allows for interpolation and extrapolation, providing greater flexibility in the output predictions. Also, in cases when there is not a lot of data available and the choice of the parametric distribution is appropriate, it provides greater intuition for how the survival time behaves. The main disadvantage is that they require additional assumptions that may not be appropriate, meaning that if the chosen parametric distribution is not a good fit for the data, the output results will be poor.

Parametric models may be either Proportional Hazards models or Accelerated Failure Time models, which are the most common. Since the proportional hazards assumption was already previously explained, it is now important to understand the meaning of the Accelerated Failure Time assumption. Contrary to PH models, which assume that the effect of a covariate is obtained through the multiplication of the hazard by a certain constant, AFT models make the assumption that covariates have an effect of acceleration or deceleration on the survival time. The relationship between the survival function $S(t)$ and the survival function of a baseline object $S_0(t)$ is defined as follows:

$$S(t) = S_0\left(te^{\beta_1 X_1 + \cdots + \beta_p X_p}\right) \tag{4.3}$$

Therefore, the reason these are called Accelerated Failure Time models is because of the existence of an accelerator factor, which corresponds to the exponential function of the linear combinations of the covariates and is multiplied by the survival time *t*. This type of models can be very useful in the context of predictive maintenance, since frequently there are covariates which may cause an acceleration or deceleration effect in the failure time, such as machine age.

Regarding this particular design of experiments, four distinct parametric models were applied to predict the RUL of machines. All the covariates were incorporated in these parametric models as time-fixed covariates and each model differs in the parametric distribution utilized and in the AFT or PH assumption. The parametric models tested in this design of experiments were the following: exponential PH model, Weibull AFT model, Log-Logistic AFT model and Log-Normal AFT model. By plotting each of four parametric models against the Kaplan-Meier estimates, it is possible to visually check the goodness of fit of each model to the training data. In the following plots, one can visually infer that the Weibull, Log-Logistic and Log-normal AFT models seem to be a better fit to the data than the Exponential PH model.

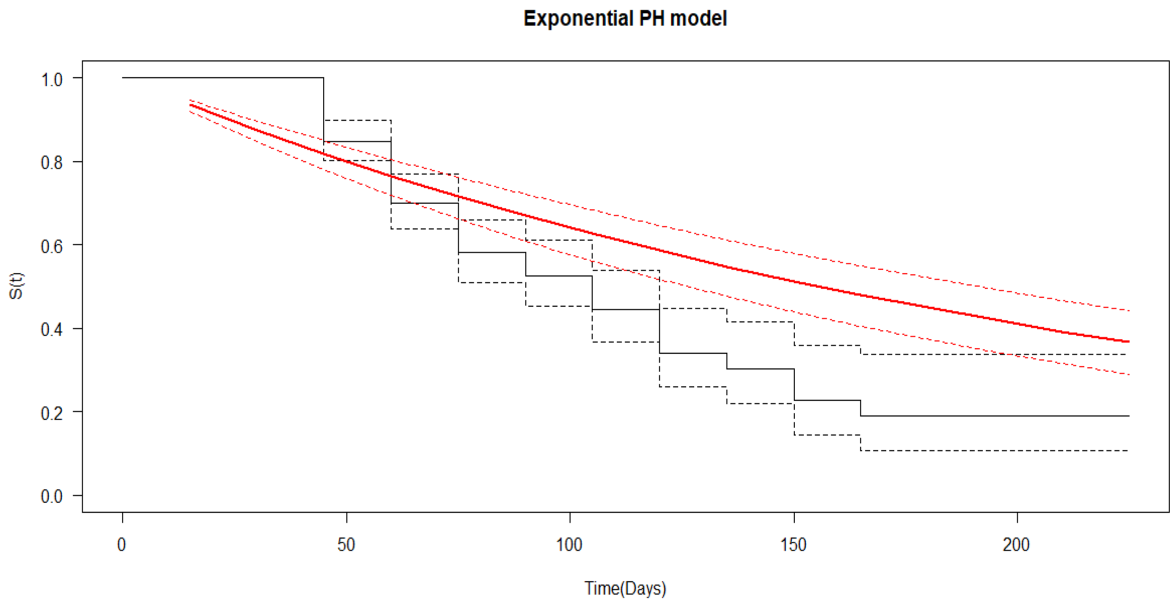


Figure 15 – Fit of the Exponential PH model to the data

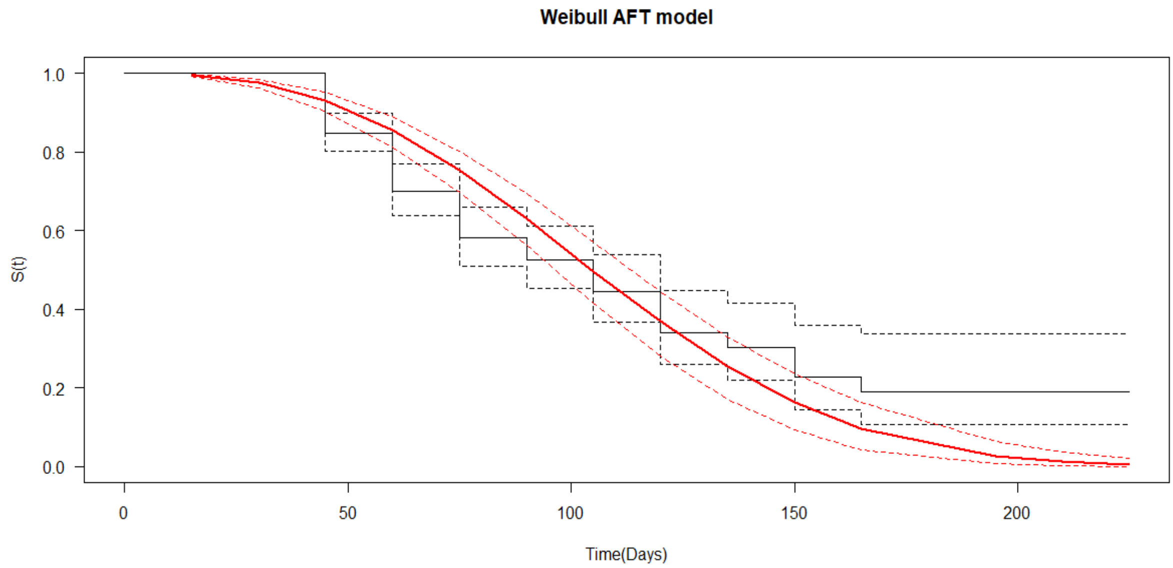


Figure 16 – Fit of the Weibull AFT model to the data

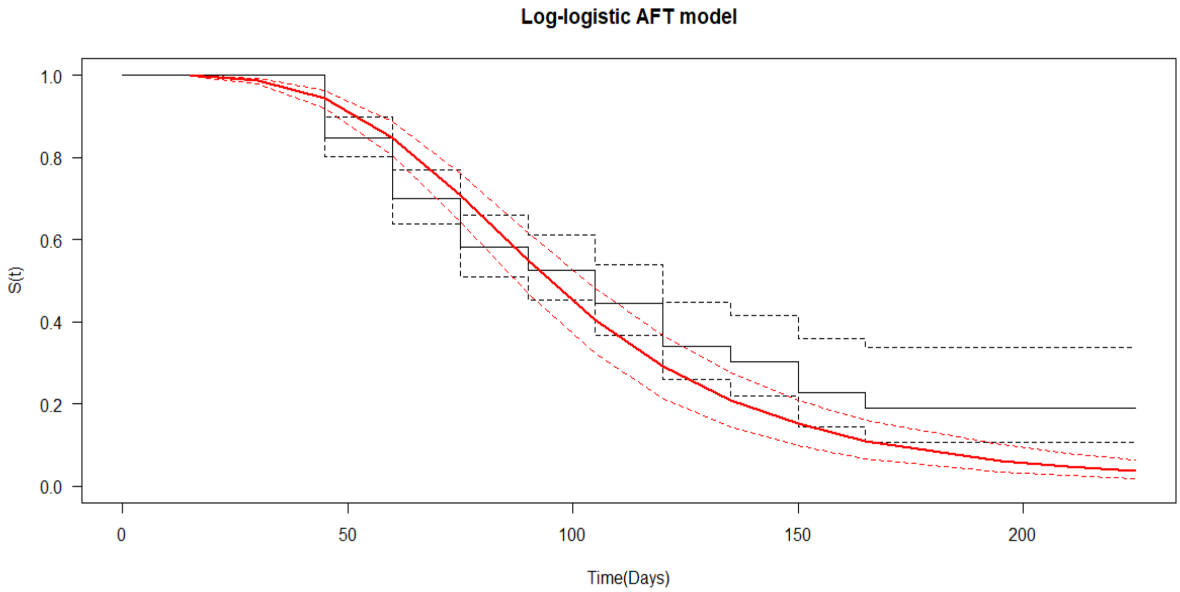


Figure 17 – Fit of the Log-logistic AFT model to the data

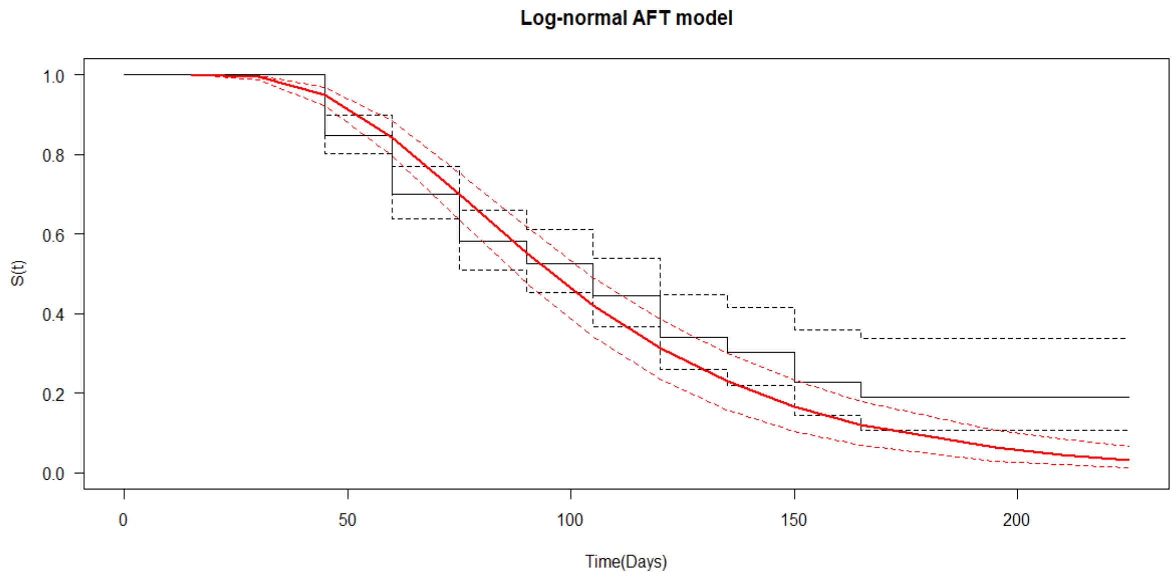


Figure 18 – Fit of the Log-normal AFT model to the data

4.4 Evaluation of the different models

In order to assess which of the eight different survival models had a better performance in the predictions of the RUL of machines, it is necessary to define an evaluation metric. Since the primary goal of predictive maintenance indicators is to determine the perfect moment to perform maintenance actions in order to avoid failures and reduce inefficiencies incurred when preventive maintenance happens unnecessarily too soon, the evaluation metric used in this design of experiments was the Mean Absolute Error (MAE). First of all, the Absolute Error of an observation corresponds to the absolute difference between the predicted time-to-failure and the true time-to-failure. It is not possible to compute the Absolute Error for censored observations due to the fact that preventive maintenance happened and, consequently, it is not possible to know what the true moment of failure would be if preventive maintenance had not occurred. Therefore, an Absolute Error was computed for every uncensored observation in the test dataset, being the MAE the average of the absolute errors computed.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n} \tag{4.4}$$

where y_i is the prediction value and x_i the true time-to-failure.

Two types of evaluation of the performance of the distinct survival models were performed. In a first set of experiments, the predictions of the different models were made knowing the covariates values during the full observation period in order to understand the performance of the different models when information for the full observation period is available. Then, in a second set of experiments, the predictions for the time-to-failure were made 7 days before the time of the event, which means that the information regarding the covariates values during the 7 days prior to the event was not used. This second set of experiments was carried out with the purpose of understanding the capacity of anticipation of the models, because in a real life scenario preventive maintenance actions need to be planned with some anticipation. The results for the first set of experiments are presented in Table 3.

Table 3 – Evaluation of the prediction of time-to-failure results for the first set of experiments

#	Model	Covariates	MAE (Days)
1	Kaplan-Meier	No Covariates	55.06
2	Cox PH	Time-Fixed	53.72
3	Cox PH with last values after *t*	Time-Varying	48.75
4	Cox PH with mean after *t*	Time-Varying	64.66
5	Exponential PH	Time-Fixed	160.00
6	Weibull AFT	Time-Fixed	44.94
7	Log-Logistic AFT	Time-Fixed	44.59
8	Log-Normal AFT	Time-Fixed	43.97

The model that had a better performance in this design of experiments was the Log-Normal AFT model, since it had the lowest Mean Absolute Error. However, by the analysis of the results, the Weibull AFT model and the Log-Logistic AFT model had very a similar performance. Therefore, it can be concluded that Parametric Accelerated Failure Time survival models are the most useful for a prediction use case.

The results for the second set of experiments are presented in Table 4:

Table 4 – Evaluation of the prediction of time-to-failure results for the second set of experiments

#	Model	Covariates	MAE (Days)
1	Kaplan-Meier	No Covariates	58.34
2	Cox PH	Time-Fixed	64.94
3	Cox PH with last values after *t*	Time-Varying	94.84
4	Cox PH with mean after *t*	Time-Varying	91.28
5	Exponential PH	Time-Fixed	192.97
6	Weibull AFT	Time-Fixed	53.88
7	Log-Logistic AFT	Time-Fixed	54.91
8	Log-Normal AFT	Time-Fixed	53.69

Through the analysis of the results of the second set of experiments, one can conclude that the Parametric Accelerated Failure Time survival models were the ones that had a better performance, as in the first set of experiments, being the Log-Normal AFT model the one with the lowest Mean Absolute Error. There was an average increase of 31% in the MAE metric in this second set of experiments, which was expected due to the fact that, in this situation, the values of the covariates in the last 7 days prior to the event were unknown, and therefore this information was not incorporated in the models, resulting in weaker predictions.

5 Conclusions, limitations and future research

The fast-changing business environment poses several challenges for companies as they need to constantly adapt to the rapid paradigm shifts and be able to innovate and adopt effective cost strategies. This scenario of fierce competitiveness increases the relevance of Asset Performance Management since assets represent a significant investment for enterprises and unplanned interruptions and breakdowns are severely costly. The next step to obtain hidden efficiencies in industrial firms involves digital transformation. In this sense, APM is a viable solution to generate significant returns by appropriately defining maintenance priorities and rational decisions on equipment replacement.

There is therefore an increasing need in companies to adopt an APM solution like the one developed in the scope of this project, which provides a set of functionalities, such as the monitoring of production in real-time with the visualization of relevant KPIs to assess production targets and to identify potential ongoing problems. Furthermore, it encompasses risk management techniques through the use of FMECA and predictive analytics methods with the purpose of estimating asset survival probability and the RUL. Through the utilization of these features, the planning and scheduling of asset related actions can be enhanced, leading to improvements in the operational and financial performance. Actually, MES developers and providers should go along with the Industry 4.0 technological revolution and sophistication to respond more quickly and assertively to market demands. In this sense, Asset Performance Management and predictive maintenance should be included in their agenda, so that they are able to present the newest techniques to satisfy customer needs.

In this dissertation, survival analysis methods have been used to calculate the RUL indicator and it has been concluded that these models are viable options to do such estimations, especially within the context of an MES, which is able to provide the required data for the application of these techniques. Regarding the distinct survival models approached in this dissertation, it has been concluded that parametric survival models are the ones that achieve a better performance for the prediction of the RUL use case. The main reason which makes parametric methods more effective is that they are more flexible by allowing to make interpolations and extrapolations on the predicted values due to the fact that the survival curve is smooth, unlike non-parametric or semi-parametric methods in which the survival function is a step function. Furthermore, semi-parametric and parametric methods are able to incorporate the effects of covariates on the time-to-failure, which constitutes an advantage in comparison to non-parametric methods. Regarding the impact of the covariates on the survival time, Cox PH models constitute a viable option for this inference use case, since in these techniques there is no need for the assumption that the survival time follows a certain parametric distribution. Thus, this constitutes a great advantage for an inference use case where the objective is to determine the effects of the covariates making as less assumptions as possible so that a higher accuracy is achieved.

The estimation of the RUL is particularly important from a maintenance perspective. By better understanding the failure behaviour of manufacturing equipment over time, there can be made more informed decisions in order to optimize the execution of maintenance actions. Furthermore, improved performance monitoring and maintenance planning results in efficient and cost-effective problem-solving, lower replacement costs and greater operational performance.

Regarding the limitations of this project, it was not possible to have access to real historical data of machines and sensor telemetry. Hence, the dataset used as an input to the distinct survival analysis methods approached in this dissertation was a dummy dataset. Since a dummy dataset is generated artificially instead of containing real life data, the obtained results may not be so good as one would expect.

Although it was possible to demonstrate how to use survival models for the prediction of the RUL of assets and the inference of the effects of the covariates on the time-to-failure, as future research it would be valuable if these methods were tested using real data as an input. Moreover, in future investigation, the conceptualized APM solution should be tested in a real-life context, and its impact in the operational and financial performance should be evaluated with the purpose of understanding the potential value of this tool and its implementation in manufacturing firms.

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