



Elaboration d'un système de maintenance prédictive basé sur l'analyse des données de production et l'expertise humaine : application à un procédé d'extrusion soufflage.

Vincent Ciano

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ÉCOLE DOCTORALE SCIENCES DES MÉTIERS DE L'INGÉNIEUR
Laboratoire de Conception, Fabrication et Commande (LCFC) –
Campus de Metz

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**Elaboration d'un système de maintenance prédictive
basé sur l'analyse des données et l'expertise
humaine : application à un procédé d'extrusion
soufflage**

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Development of a predictive
maintenance system based on data
analysis and expert knowledge:
application to a blow-molding process

Abstract

Maintenance activities have evolved over the recent years, through the digitalization of the field and the application of tools and concepts from Industry 4.0. By connecting and communicating with the production system, companies are now able to create knowledge about its current and future health state, allowing more and more efficient control over the equipment. This approach is called Predictive Maintenance (PdM), and its goal is to reduce unplanned downtimes and organize efficiently maintenance actions before failures and stoppages appear. However, to reach such performance, it is still quite challenging for the industrial actor to implement an Intelligent Maintenance System (IMS) that will help with the data management. Many requirements and limitations from the industrial context add complexity to this system. It needs to be able to connect to multiple sources, collect data of different nature (physical data, process data, and more), propose different analyses and alerting channels while being user-friendly. This statement is especially true for the automotive sector, which is facing new challenges and increased competition nowadays. Customer satisfaction depends on products and parts quality, as well as possible customizations. To reach these objectives, productivity is key, meaning machines availability needs to be maxed and not impacted by unplanned breakdowns. These cost a lot of money and time and can possibly generate quality issues on parts produced during the deteriorating phase of the production system.

In this research work, initiated by Plastic Omnium (Clean Energy Systems division), in collaboration with Ecole Nationale Supérieure d'Arts et Métiers (EN-SAM) and Laboratoire Conception Fabrication Commande (LCFC) located in Metz, we propose a methodology to implement a Predictive Maintenance system in the industrial context. This methodology is tested and applied on concrete use cases, and the results are used to improve and propose a final solution. This solution is an Intelligent Maintenance System built on this methodology, Industry 4.0 tools and open-source software. We employ and put the emphasis on

the term flexible for this solution, as it is one of the major features required by this system to work in different contexts and be adaptable to the needs and limitations previously discussed about.

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Glossary

AFNOR Association Française de NORmalisation: French Standardization Association. [25](#)

API An Application Programming Interface is a software designed to make communication possible between two different applications. The API provides various interactions, for instance sending a request to login, sending a query to fetch data, or even sending data in the system. [23](#)

Artificial Neural Network ANNs are computing systems that take the human brain as inspiration. The system is usually composed of an input, hidden and output layer, and each layer is composed of nodes. These nodes (or artificial neurons) are connected to each other, therefore they can have multiple inputs and outputs. Each node has weights and thresholds that trigger the signal transmission to others. The training of ANN consists in adjusting these weights by minimizing the error between a known output and assumptions made by the model ([McCulloch and Pitts 1943](#)). [41](#)

Autoregressive An Autoregressive model is designed to forecast any time series variable, based on its previous values: the forecasted value is a linear combination of past values ([Yule 1927](#)). [39](#)

Autoregressive Integrated Moving Average ARIMA is the generalized form of the ARMA model, introducing the Integrated part. The model considers the difference between each value of a time series, instead of its raw data. By doing so, it allows transforming non-stationary time series into stationary ones, which improves the results given by application of AR and MA ([Box et al. 2015](#)). [39](#)

Autoregressive Moving Average ARMA is the combination of an AR model, and a Moving Average (MA) model. The MA allows to consider the trends that can appear in time series, to improve the forecasting. If only AR is used in the case of time series having repeating events, these could be seen as errors or noise by the model and therefore produce poor results

(Box et al. 2015). 39

Bayesian Autoregressive A Bayesian Autoregressive model is an AR model, with a different assumption on the variable used. In the AR context, the variable is considered as a fixed value with no prior knowledge, whereas BAR treats variables as random and having prior probabilities. This introduction of "priors" can produce better forecasts than AR in cases where datasets are smaller, increasing the difficulty to calculate the many parameters of the model and giving less reliable results (Litterman 1980). 39

Bayesian Network A Bayesian Network is a graphical representation of a probabilistic model. It includes several parameters with their dependencies, making it able to understand the influence of each factor on a given event. It is often used to predict such events using the probability that a known cause will occur and lead to the monitored event (Pearl 1985). 34

CES Clean Energy Systems, a Plastic Omnium division that manufactures fuel tanks and depolluting systems. 2

CIFRE Convention Industrielle de Formation par la REcherche - PhD done in partnership with a laboratory, a university and a company. It is therefore conducted mostly in an industrial context, with support from academics. 5

CPSs A CPS is a system where physical equipment and computer-based software are interacting together, to create efficient and autonomous systems capable of taking decisions on their own. 3

CPU A Central Processing Unit is a complex circuit board able to execute actions based on the instructions given by its internal program. 20

DASIP Data Acquisition System for Industrial Processes - Supervision system developed by Plastic Omnium, that acts as a SCADA system (Supervisory Control And Data Acquisition). It is used for monitoring the machines through critical parameters of the manufacturing process. 57

Data Lake Central data storage allowing data analyses on large volumes, to aggregate data from different sources, create visualizations or train algorithms. Often described as an internal Cloud Computing system. 56

Deep Neural Network DNNs are complex ANNs, composed of multiple hidden layers between input and output. They are able to model non-linear relationships in the dataset, and are widely used due to their automatic pattern recognition. This feature allows them to outperform many other models (Bengio et al. 2009). 42

Discrete Bayes Filter Discrete Bayes Filter, or Recursive Bayesian estimation, is a statistical model used to estimate the value of a parameter, based on its previous values. It is applied recursively on new incoming data, to get the most probable current state of the system. [40](#)

ERP An ERP (Enterprise Resource Planning) can be defined as a management software that stores different type of data coming from various departments or businesses of a company, for instance purchasing and maintenance. [59](#)

FMEA Failure Modes and Effects Analysis consists in identifying the possible failure mechanisms that can appear in the system, by decomposing it as much as possible to get the most detailed analysis. The effect of these failures is also studied. [28](#)

FMECA Failure Modes, Effects and Criticality Analysis adds the criticality analysis to the FMEA, it is calculated from the probability that such a failure will appear, and its severity. [34](#)

Generative Adversarial Network GANs are machine learning techniques used to generate data with similar characteristics, based on an original training dataset. Two models are used to achieve this result: the first one is learning the patterns within the dataset and generates new data, the second one classifies incoming data as either original or fake (generated by the first model). The training is complete when the first model can "fool" the second one about half the time, meaning that the generated data is close enough to the original one ([Goodfellow et al. 2020](#)). [42](#)

HAZOP Hazard and Operability analysis is a review of a process in order to evaluate the various issues that can happen and create a risk to the users and/or the machines. [34](#)

Hidden Markov Model A system modelled using HMM is assumed to have an observable part, and a hidden part. The hidden variable (often called "state") influences and controls directly the known variable (often called "observation"), and such system is called a Markov process. The goal of HMM is to determine the hidden parameters using probabilities and observations of the known parameters. It is very efficient in determining the underlying the probability that a state (or set of states) lead to an observation ([Baum and Petrie 1966](#)). [39](#)

ICT Information and Communications Technology relates to all components making computing and interactions with digital information possible. Such

components can be hardware, software, telecommunications, internet, and computing architectures presented in section 2.1.2. 4

Intelligent Maintenance System An IMS is a computing system that analyzes data coming from any production system, to provide a predictive maintenance solution to detect incoming failures. 82

IoT The Internet of Things is the interconnection between devices through internet. 3

Long Short-Term Memory LSTM is part of the Recurrent Neural Network (RNN) models, meaning that the output of some nodes can affect their own input. LSTM includes feedback connections, allowing it to handle events that affect the data in the long-term; which is not possible with other RNN models (Hochreiter and Schmidhuber 1997). 42

Multi-Layer Perceptron MLP refers to a feedforward (output does not affect the input) ANN composed of perceptrons. A perceptron is a supervised machine learning technique that aims at classifying data. Consequently, MLPs are able to solve complex issues where the relationship between input and output is non-linear (Rosenblatt 1958). 41

Natural Language Processing NLP is a branch of machine learning algorithm that processes natural languages to understand automatically their content, as a human would. Many applications derive from NLP, such as sentiment analysis (to determine the intention behind the words), automatic language detection and translation. 71

OEM An Original Equipment Manufacturer in the automotive industry is a company producing the original parts of a vehicle that are assembled by the car manufacturer. Such parts can be exhaust systems, brake cylinders, or fuel systems for instance. 6

Open Platform Communications OPC refers to an industrial communication protocol, mostly used to exchange data between PLCs and other devices or applications (source: <https://opcfoundation.org/about/what-is-opc/>). 46

PES Plant Execution System - It is the MES (Manufacturing Execution System) used by Plastic Omnium, which ensures traceability of the produced parts, as well as monitoring the different events related to the production machines within the plant. 57

PFMEA Process Failure Modes and Effects Analysis is the application of FMEA to the manufacturing processes. 35

- PHM** Prognostics and Health Management - In literature, prognostics and health management (PHM) systems have been studied by many researchers from many different engineering fields to increase system reliability, availability, safety and to reduce the maintenance cost of engineering assets (source: <https://www.phmsociety.org/>). 12
- PLC** A Programmable Logic Controller is an industrial computing device able to operate in difficult conditions. It is used to control and operate manufacturing systems. Common PLC manufacturers are Siemens, Schneider Electric, Allen Bradley, Mitsubishi Electric. 23
- Principal Component Analysis** PCA is a mathematical method that reduces the dimension of large datasets. The main idea is to only keep variables responsible for the variations in the dataset, meaning that the algorithm will try to find uncorrelated parameters with the highest variance. These parameters are then used as new principal components, allowing to project the rest of the data on them. Usually only the 2-3 first components are kept, the choice can be made knowing the percentage of "information" (variability) held by each component ([Hotelling 1933](#)). 39
- Prognostics** Prognostics focuses on estimating the time at which a component or machine will no longer perform the function it was designed for (this time or duration is also called RUL: Remaining Useful Life, or TTF: Time To Failure). 30
- Raspberry Pi** A Raspberry Pi is a nano-computer widely used in IoT applications (<https://www.raspberrypi.com/>). 46
- RUL** Remaining Useful Life - Remaining time before failure of the monitored component or machine. 29
- Scopus** Scopus is an abstract and citation database created by the academic publishing company Elsevier. It allows searching for references in a very large amount of publications, and also creating advanced analyses on the various data linked to the published books, journals and articles. 3
- Support Vector Machine** SVM is a supervised machine learning technique used for classification of data. It requires labelled data, and attempts to compute a hyperplane that maximizes the distance between the different classes observed in the dataset, in order to then predict in which class the new incoming data will belong ([Boser et al. \(1992\)](#), [Cortes and Vapnik \(1995\)](#)). 40
- Support Vector Regression** SVR is a method based on SVM, for regression purposes. In this algorithm, the idea is to determine the regression plane which contains the maximum number of points from the training set. This

hyperplane is often seen as a tube, composed of the best fit line and two lines placed above and below. The distance between the best fit line and other line is the error (ϵ) (Drucker et al. 1996). 40

Time series Time series is a flow of data collected with a fixed time rate. Each value has its corresponding time of collect, it is often called a timestamp: time is a variable in a time series database. They are mostly used to monitor events, because the time variable is used to show the evolution of data over time. 58

Unified Architecture OPC UA is the latest release of the OPC protocol, extending it to many other platforms, and including improved interoperability and features linked to cybersecurity (source: <https://opcfoundation.org/about/opc-technologies/opc-ua/>). 46

Chapter 1

General introduction

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One of the key activities for a company is the continuous improvement of its manufacturing system's performance. This statement is especially true when it comes to global companies operating in multiple countries, because they need to remain competitive and propose the most attractive products to its customers while reducing operational costs. To reach this goal, companies are working towards global amelioration of quality for the manufactured products, and maintainability of the manufacturing systems.

Over the recent years, Industry 4.0 has been one of the most proficient research domains for the industrial actors, with the promises to bring new technologies and concepts to achieve the previous goal. Industry 4.0 refers to the interconnection between the physical world and the virtual world for a manufacturing system and thus, how information, data and knowledge are dealt with. As data has become one of the most valuable resources for companies in recent years, it is therefore critical that the management of all the collected data is done in the

most efficient way.

For Plastic Omnium Clean Energy Systems (*CES*), which produces fuel tanks and depolluting systems for the automotive industry, the topic of industrial performance greatly matters. Because those parts are regulated and tagged as security parts (they involve the security of the end-user), the manufacturing quality is a critical issue. The consequences of non-quality and non-production can be disastrous for various aspects of the company: economics, legal, societal, environmental. In addition to this, the automotive sector is one of the most competitive industries, which also reinforces the need for performance. Having explored lean practices for a long time, the company now believes that the next step for improving quality and productivity is through Industry 4.0, to have the most efficient control possible over its manufacturing system.

The topic of interest for this research work is related to industrial maintenance, and more specifically about developing an efficient methodology to enable the industrial actors to switch from a "classical" curative-preventive maintenance system to a more proactive one: Predictive Maintenance (PdM). As industrial equipment will eventually fail, from ageing or unexpected events, the goal of this work is to bring more insight regarding the machines' behavior. This is mostly done through data-driven approaches, by collecting physical or process data related to the equipment, studying its evolution, and proposing alerts to the users on potential incoming failures. Strong with this new knowledge, maintenance can then be planned more efficiently, and have less impact on the initial production schedule.

Predictive Maintenance has been extensively studied over the past 25 years, and is still a topic of great interest. One of the main reasons, which will be developed throughout this thesis, is that even though methodologies exist to implement such system, these are continuously evolving. In addition to this, the tools used in the industrial context to apply them are also changing and improving rapidly. These tools are linked to data collection and processing, but also for communication and visualization. Consequently, as of today, it is still quite complex to have a standard methodology that can be applied as such across the various industries, which can also have their own specificity.

One of the key concepts emerging from this work is the necessity to propose a methodology as standard as possible to define the PdM system, with flexible tools to carry out its implementation in the industrial context. This flexibility is related to several aspects of the implementation, such as the use of multi-

ple communication protocols to collect data, or scalability of the data storage solution.

1.1 Scientific context: predictive maintenance

The maintenance field has evolved over the recent years, moving from corrective actions (when failures already happened) to a predictive approach. With the advances in data processing, information coming from the production system now allow the assessment of its current and future health state. Because machines and processes are becoming more and more complex to deliver new features to products, maintenance is impacted and requires more advanced skills and knowledge to deal with potential issues (Gouriveau et al. 2016). It is therefore a necessity today, for any company seeking performance, to strive toward predictive maintenance.

Predictive maintenance is currently the most active topic in the maintenance field, as it is highly linked with Industry 4.0 and the availability of data within companies. We can see in Figure 1.1 the evolution over time of the number of publications linked to the three main categories of maintenance: corrective, preventive and predictive, from 1995 to 2021. We will review more in detail these different maintenance policies in the next section. To obtain this graph, we did simple queries within *Scopus* ("corrective AND maintenance" for instance), to determine how many papers were published over the years on each maintenance policy. To try and be more accurate, we excluded each time the other two policies from the title and abstract, as in most cases the three categories will be discussed in the papers. We can observe that since 2016, predictive maintenance has received a lot of attention from researchers, making it one of the most studied topics in the Industry 4.0 paradigm.

This increase of interest for this topic is easily understandable with the context of *CPSs*¹. The opportunities for predictions based on data analysis are numerous thanks to *IoT*² and CPS, and therefore the maintenance activity is a great candidate to extract value from those analyses and improve its performance (Yan et al. 2017).

To understand further why maintenance has been in the spotlight recently, we need to go back in time and see that historically, the maintenance activities

¹CPS: Cyber-Physical System

²IoT: Internet of Things

1.1. SCIENTIFIC CONTEXT: PREDICTIVE MAINTENANCE

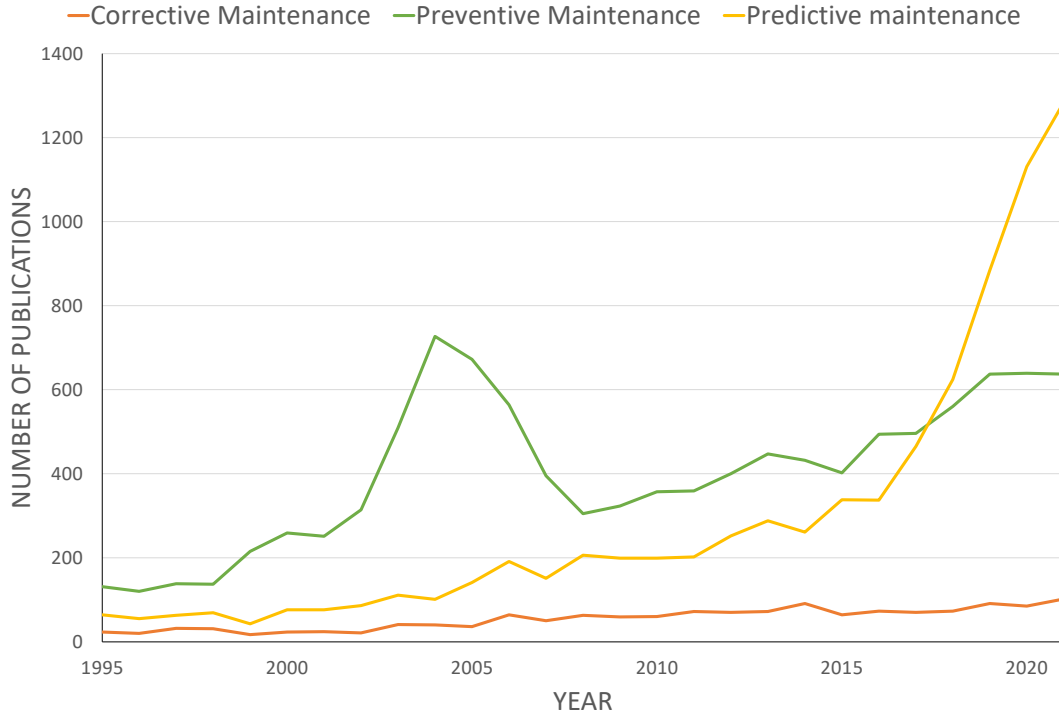


Figure 1.1: Number of publications per maintenance policy (1995-2021)

were tagged as "necessary evil" or that they were a "cost-centre", meaning that they only generated costs and no profits ([Al-Najjar \(2007\)](#), [Chesworth \(2018\)](#)). Twenty years ago, [Mobley \(2002\)](#) addressed this issue by explaining that these statements were already old-fashioned back then, mostly due to the development of *ICT*³. Its application in the industrial context for maintenance improvement purposes helps removing unnecessary costs and reducing occurrences of catastrophic breakdowns.

However, as mentioned by [Fusko et al. \(2018\)](#), many industrial companies are still not ready for that digital transformation of maintenance, as it requires advanced CPSs and ICTs, with skills that are not yet well developed within the organizations. This digital transformation not only brings new tools, but also changes completely the way maintenance topics are being worked on, compared to how it was handled previously. In addition, as mentioned in Introduction, methodologies and tools supporting the development and implementation of such solutions are changing and evolving rapidly, increasing the difficulties inherent to that transformation.

³ICT: Information and Communications Technology

As this thesis is *CIFRE*, the works are positioned in the automotive industrial context. The main objective is to address the topic of the implementation of predictive maintenance in the complex and global context of Plastic Omnium's production. The thesis work was conducted within the *Digital Manufacturing* team, in charge of the topics related to Industry 4.0. Consequently, in the next section, the industrial application is described.

1.2 Industrial context: automotive industry

In this section, we introduce shortly some key aspects of the automotive industry, as Plastic Omnium is one of its major actors. These aspects help understanding the motivations behind this research work. In a second part, we present the main process involved in the production at Plastic Omnium Clean Energy Systems. This will help understanding some key characteristics of the work presented in Chapters 3 and 4.

1.2.1 Industry 4.0 to solve some key challenges of the automotive industry

From the industrial point of view, the automotive industry activities always led to significant changes in the global industrial scope. Starting at the beginning of the 20th century, Ford was one of the major actors who led the industry towards "mass-production". The creation of a moving assembly line, bringing the product (Model T) to different locations using a conveyor belt made possible the manufacturing of millions of cars, faster and cheaper than any other competitor (Hounshell 1985).

Competition is probably the main factor of innovation in the automotive industry, as many car manufacturers exist all over the world. Since the globalization of the business, even though these companies are located in different places, they found themselves in direct competition to earn market shares everywhere they can. We can say that Ford's mass-production system does not exist anymore today, as companies are directing the competition towards mass-customization of cars, and proposing the most affordable products at the best quality possible (Holweg 2008). To do that, many new ways of manufacturing were developed, such as the Just-in-Time system from Toyota, enabling fast adaptation to market changes by using reconfigurable production lines, and automation (Shimokawa 1994). In this sense, the automotive industry was one of the first to automatize their manufacturing lines (Jovane et al. 2003).

1.2. INDUSTRIAL CONTEXT: AUTOMOTIVE INDUSTRY

To emphasize on the benefits provided by competition, we can see that car producers invest a lot in research and development. The European car producers reported 32 billion euro of R&D investment in 2011 (Vošta and Kocourek 2017), while nearly 60 billion was injected in 2020 (ACEA⁴ website), making European Union companies the world’s largest contributors to automotive R&D. The main idea behind is to bring new features, new technologies in the next generation of cars, to be ahead of other companies. Many strategies are employed, and a lot of different aspects are promoted by each manufacturer, whether it is linked to costs, size of the car, quality of materials used, new energies used for propulsion (electrical, hybrid fuel-electrical, hydrogen cars), or service-oriented features (Nazir and Shavarebi 2019).

As discussed previously, the current trend in automotive manufacturing is based on mass-customization. Most competitive companies are now using well-established processes such as the lean principles created by Toyota, to produce more and reduce wastes. As a result, they need to seek other ways to attract new customers, by proposing specific customizations to answer their demands (Alford et al. 2000). The complexity of this approach is that it requires new configurations of the manufacturing system, to be able to propose personalization on some aspects of the cars. As a result, the stakes are high for any company able to develop such system, and more and more we see that Industry 4.0 is the answer to address this complexity, as it brings new tools and methods facilitating this industry-wide transition (Kabasakal et al. 2017).

In the automotive industry, car manufacturers are not the only contributors, there are also *OEMs*⁵ that put a lot of efforts into all these changes (Kalogerakis et al. 2017). It is the case for Plastic Omnium, which is one of the major OEM for the automotive sector, and the industrial support for this research work. Complex processes are involved in the company’s production, and as discussed in Introduction, norms and regulations are drastic regarding these security parts, leading the company to aim for a zero-defect policy. To understand further the motivations behind this work, we will review in the next part the industrial process linked to the production of the fuel tank systems.

⁴ACEA: Association des Constructeurs Européens d’Automobiles / European Car Manufacturers Association

⁵OEM: Original Equipment Manufacturer

1.2.2 Industrial process: extrusion blow-moulding

The main industrial process involved in this thesis work is called extrusion blow-moulding. It is mostly used to produce hollow parts made of plastic and polymers, and these parts are used as containers for various applications (Dutta and Ryan 1982). For instance, plastic bottles of water are produced with extrusion blow-moulding of Polyethylene Terephthalate (PET or PETE), waste containers and plastic fuel tanks are made of High-Density Polyethylene (HDPE). The basic steps of this process are the following: first, a cylinder of melted material is coming out of the extrusion process, we call it a *parison*. Then this parison is trapped inside a mold to give the material its final shape. During this phase, the material is pushed against the mold inner shapes by blowing air inside the parison. Figure 1.2 shows these steps. We propose more details about Plastic Omnium, its products and the process in Appendices A, B and C.

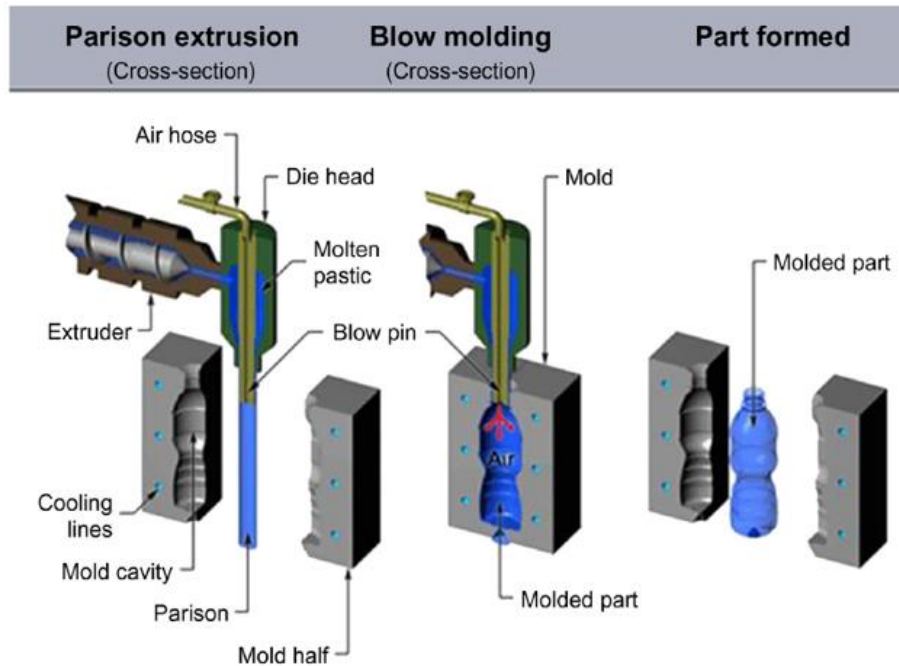


Figure 1.2: Extrusion Blow-Moulding process (Shrivastava 2018)

To understand the process and the equipment used we will describe in detail the extrusion and blow-moulding processes below.

Extrusion Extrusion is the process of forming the parison. As seen in Figure 1.3, the mechanical system is composed of a motor, a gearbox and a screw. The start of the process is to inject plastic pellets inside the feed hopper, the material

1.2. INDUSTRIAL CONTEXT: AUTOMOTIVE INDUSTRY

is then moved inside the screw. Here it will be heated, to melt down and to be carried easily throughout the screw. This heating is done by band heaters located all around the screw. The action of the screw on the material will bring some shear stress, which will produce some auto-heating. To reduce it, fans are located around the screw, to cool it down at some point after the start of the process, and respect the temperature required for the process. Finally, the melted material will arrive in the head, at the other end of the screw.

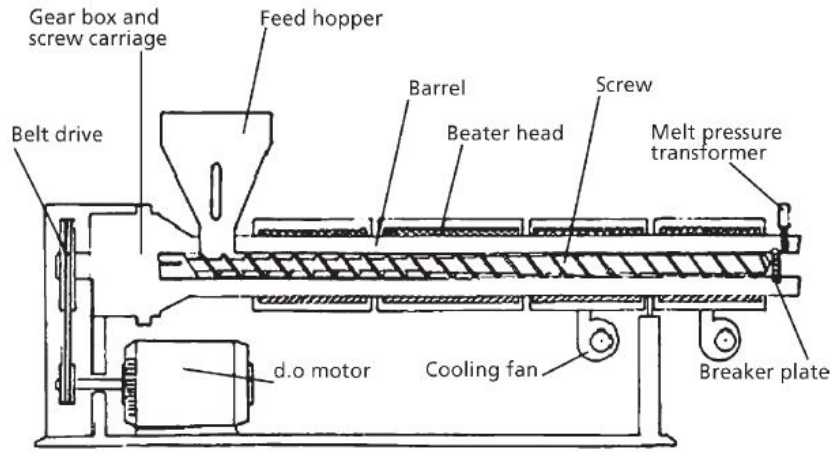


Figure 1.3: Extruder example (Lee 2006)

The final step of the extrusion process is to bring the material in the head and form the parison. We can see in figure 1.4 the inner shape. The moving die and programmed mandrel are used to give the shape of the parison, whether it needs to be round or oval. It will also influence the thickness of the parison and therefore the final shape of the product.

Blow-moulding Next, the parison is trapped inside the mold as seen in Figure 1.5. At this stage, the blow pin will inject air within the mold at high pressure, to push the material against the inner-mold shapes. Usually, the top part of the obtained product will be cut, in order to evacuate it afterwards. We can also observe that some material will be located around the blown part, and not useful for the end design. It is called the "flash" and is most of the time removed by an operator in a "deflashing" operation (the excess material is cut, then often reground for later use).

After this first process, extra operations are done on the tank, as shown in Appendix C. The applications cases proposed in this work and presented in Chapters 3 and 4, are linked with the full production process. The complexity of the process, the requirements regarding the quality of the products delivered

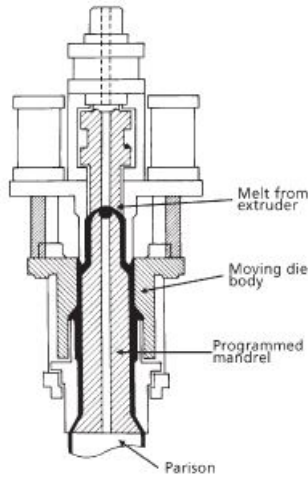


Figure 1.4: The head (Lee 2006)

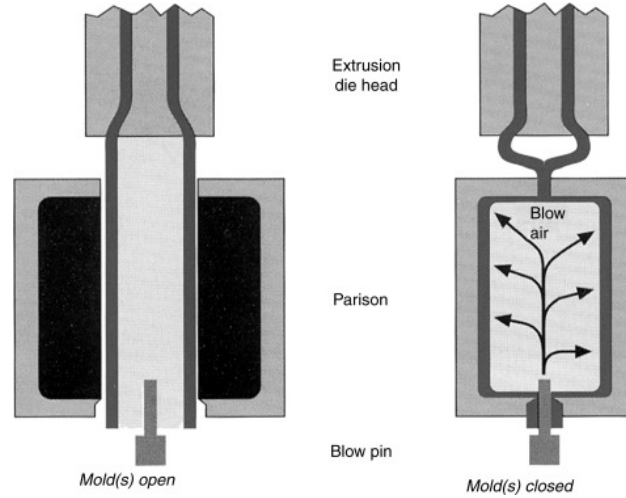


Figure 1.5: Blow-moulding process (Belcher 2017)

and the automotive industry context impose the production systems to be robust. Therefore, their availability greatly matters, and understanding their behavior to plan efficiently corrective actions in case of deviations is a major challenge, which can bring a lot of value to the company.

In the next section, the research objectives and the methodology employed throughout this research work are addressed.

1.3 Research objectives and methodology

To understand better the production systems, and more particularly their failure modes, there is a requirement to make the machines "smarter". As discussed previously, it is made possible with the Industry 4.0 paradigm and data which is more and more available in the industrial context (Sambrekar et al. 2018). The nature of this data can differ, and contributes to better understanding of the behavior of the production systems.

Predictive maintenance is one of these topics of interest for Plastic Omnium. Therefore, this thesis aims at looking for the best way to use the collected production data on the machines in order to propose a dynamic maintenance system. This system will help detecting machine failures before they happen, to plan the corrective actions accordingly. The main expected benefits are listed below.

1.3. RESEARCH OBJECTIVES AND METHODOLOGY

- Reduce corrective maintenance costs
- Reduce catastrophic breakdown events
- Improve availability of machines
- Create and improve knowledge about the production systems
- Decrease quality issues linked to machines degradation and failures

The Digital Manufacturing team has a standard way of working on the topics linked with Industry 4.0, as shown in Figure 1.6. As most of these works are transforming the way the company works, resistance to change can be a limitation for the success of the developments and implementations. As a result, the topics are always managed in two complementary ways:

- The Top-Down process, which ensures that the developments and deployments are standardized and proposed globally within the division
- The Bottom-Up process that enables new initiatives, and takes advantage of the experience from the local sight to develop new solutions

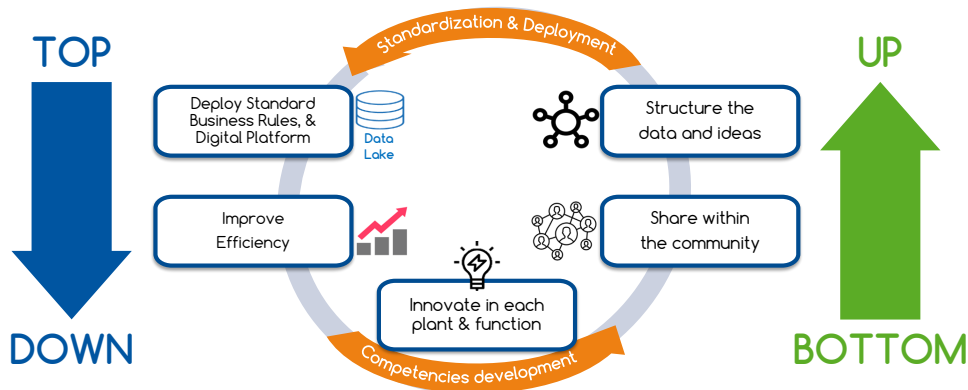


Figure 1.6: Work methodology for the Industry 4.0 topics

This circular process brings many opportunities, and reduces the chances that a topic will fail. The two key factors are the possibility of innovation from local resources, and the active feedback from local to global management makes certain that the requirements are fulfilled.

To anticipate failures on the production systems, a methodology will be proposed to implement a predictive maintenance architecture. This methodology will include both the requirements to solve the industrial and scientific issues linked to each topic. Finally, we want to develop a toolbox as the major contribution from the thesis work, to be used for dealing with predictive maintenance topics. It must be as general as possible in order to be flexible and adaptable to

the different use cases that can be treated in industries.

The main objective of the thesis is to answer the following research question:

How can industries implement predictive maintenance with the help of Industry 4.0?

To try and organize the work, we defined four industrial issues from the needs of Plastic Omnium. Each axis is linked to a scientific issue that needs to be overcome to answer the global research question.

1st industrial issue: Understand the failure modes of the production systems

- How to identify failure modes and assess their relevance for predictive maintenance?
- How to select relevant data to be used to monitor the system?

Scientific issue n°1: Formalization of the criticality of failure modes based on the understanding of their causes and effects.

2nd industrial issue: Develop a strategy for data collection

- What type of data needs to be collected?
- How to handle the data for predictive maintenance?

Scientific issue n°2: Structuring of the data management system to integrate multiple sources of data.

3rd industrial issue: Integrate data analyses to detect and predict the failures

- What are the available approaches to detect a failure?
- How to create indicators to anticipate the failure mechanisms?

Scientific issue n°3: Creation of health check on the production system based on processed data, to anticipate failures.

4th industrial issue: Define a decision-making system to share results from the analyses

- How to visualize the current and future state of the system?
- How to communicate the results from the detection/prediction system in an efficient manner?

Scientific issue n°4: Elaboration of relevant indicators to support operational and business-oriented decisions on predictive maintenance.

1.4 Structure of the thesis

Based on the scientific and industrial issues, the document is organized as follows.

A state of the art on predictive maintenance is conducted ([Chapter 2](#)). The *PHM*⁶ topic will be introduced and detailed. PHM and predictive maintenance are highly linked, and most of the time the PHM methodology is used as the base for the predictive maintenance system. A review of the current approaches for the implementation of this system will help understanding the challenges and limitations, and position this work by exploring the existing opportunities. This Chapter aims at giving a first answer to the four different scientific issues.

In the third chapter ([Chapter 3](#)), the methodology developed to implement predictive maintenance is detailed, and a framework is proposed to work on predictive maintenance. In this Chapter, we aim at providing a first set of solutions to the industrial issues, by developing a framework and applying it in our context. As this thesis was conducted in the industrial context, the development was done throughout a practical use case at Plastic Omnium. This first use case helps understanding better the constraints and requirements linked to the implementation of such system. Then, the application of this framework to other use cases is discussed, and the results are analyzed to highlight the limitations and opportunities to improve it.

Finally, the last chapter ([Chapter 4](#)) is dedicated to the development of an Intelligent Maintenance System based on the opportunities observed in the pre-

⁶PHM: Prognostics and Health Management

vious chapter. The goal of this last Chapter is to propose an answer to both our industrial and scientific issues. The developed solution was mainly designed for three purposes, to standardize the data management for predictive maintenance topics, to ease the deployment of solutions in a global context (for multiple plants), and to have a flexible system that can be used by various users with different profiles and skills. The methodology behind the application, as well as its practical implementation will be discussed, and a review is proposed based on industrial results from several use cases.

In the conclusion, the contributions from this work are summarized, and some future research perspectives are presented based on the results obtained and some limitations that were observed while conducting this research work.

Chapter 2

Maintenance activities in the Industry 4.0 era

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In this chapter, we review the literature to highlight the link between Industry 4.0 and maintenance activities. In a first part, we review the key topics of

Industry 4.0, to understand the influence it has on industrial maintenance. In a second part, we describe the different policies existing for industrial maintenance, and propose a classification of these architectures, as we observed that their definitions or the way they are organized vary in the literature. Then, we will focus on predictive maintenance, and the methods that currently exist to develop such system, as the ones proposed by PHM¹. Then, we study how these maintenance policies are applied in the automotive industry, to validate the interest of the development and deployment of predictive maintenance in this context. A synthesis of all the findings will help underlining the limitations from the literature, as well as pointing out the opportunities behind them to position this thesis work.

2.1 Industry 4.0 paradigm

In today's competitive market, manufacturers must use new strategies to propose products having the best quality, while reducing production costs. This approach imposes companies to implement more flexible manufacturing systems. For this objective, the traditional mass production system is moving toward customized mass production (Muhuri et al. 2019). Moreover, to organize this system properly, it is necessary to have up-to-date information from the machines and thus, connect all components of the manufacturing process together.

Figure 2.1 shows four revolutions that happened for industries over the past centuries. From the eighteenth century, with the introduction of the mechanical loom and the use of steam energy, to the twentieth century, with mass production and the automated production lines. In the 1970s, automation, computers, electronics, ICT² spread throughout industries worldwide. Finally, the fourth revolution is characterized by intelligent machines that communicate data with each other and its users.

This fourth revolution, also named Industry 4.0 (Kagermann et al. 2011), started in 2011 and brought a new vision for production systems, to solve the previously discussed challenges. More than automated production systems, autonomous and smart ones are required, able to learn and share information and knowledge by themselves. An interconnection between machines and company departments is also needed, to monitor, change, and predict the behavior of the manufacturing system. In the context of Industry 4.0, we call Cyber Physical

¹PHM: Prognostics and Health Management

²ICT: Information and Communications Technology

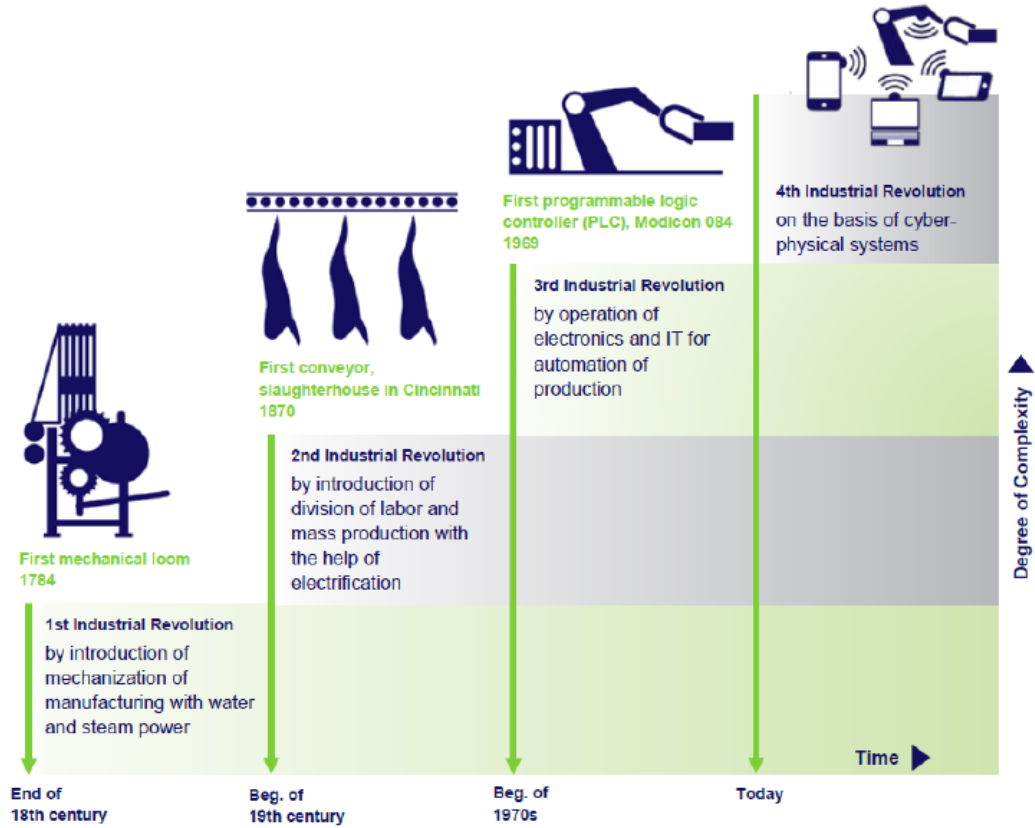


Figure 2.1: The four industrial revolutions (Gehrke et al. 2015)

System (CPS) or Cyber Physical Production System (CPPS) this structure of machine and human interactions and interconnections to create enhanced manufacturing processes (Bahrin et al. (2016), Bagheri et al. (2015)). From all this emerging data, value needs to be created so that the performance of the system and the quality of the final product are improved, in a way that allows both mass production and mass customization.

In the next part, we will discuss the various components of Industry 4.0, which contribute to the transformation of manufacturing in its entirety. These elements participate in the overall improvement of the performance of the production systems.

2.1.1 Key concepts for industrial performance

Industry 4.0 does not only deal with connection, it also has to overcome some global challenges (Wang et al. 2016). The way of producing goods is changing, as well as all the activities that touch directly or indirectly this production. As a re-

2.1. INDUSTRY 4.0 PARADIGM

sult, processes, services, society, environment, and economy are impacted.

All these changes can lead to wastes, overproduction, pollution, accidents; Industry 4.0 is bringing new tools and methodologies to deal with that (Lee et al. 2014). These various components can be found in Figure 2.2, and a definition is proposed below for each point.

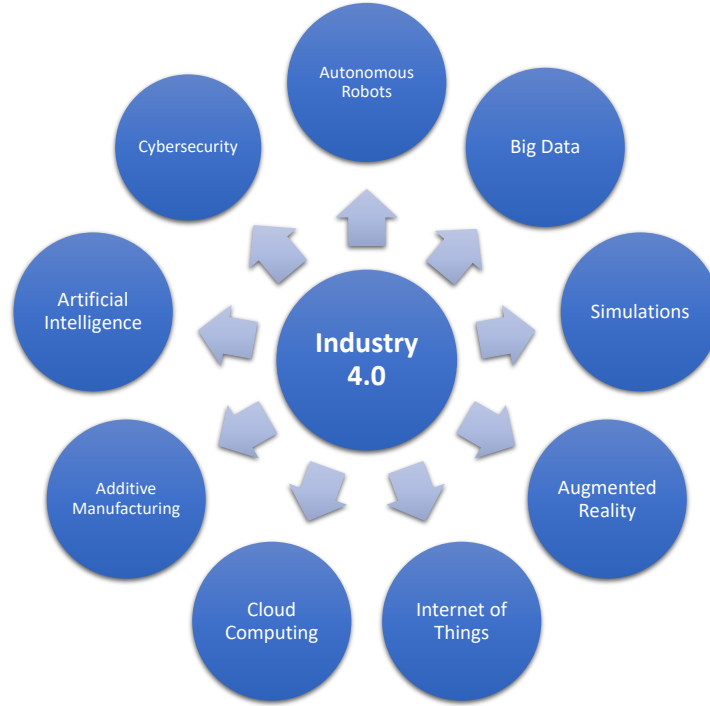


Figure 2.2: Key components of Industry 4.0

- Robots are essential for improving manufacturing processes. Connected and collaborative robots (cobots) make interactions possible between each other and users, to build more efficient production systems
- Big Data refers to advanced analytic techniques used to find value in the increasing volume and complexity of data
- With the amount of available data and computing power, more efficient simulations can be created. These allow to better optimize products and production systems, reduce costs and wastes from prototyping as it can be done virtually with different setups and an infinite amount of times
- Augmented reality gives the possibility to add virtual objects to the real world. Users can then interact with them through head-mounted displays, haptic sensors or by using their smartphones' cameras. It gives the opportunity to physically touch the virtual world

- The interconnection between devices through internet is called Internet of Things (IoT) or also Industrial Internet of Things (IIoT) in the industrial context, and it is one of the major components of Industry 4.0. Among other features, it gives the possibility for these devices to send and receive huge amounts of data, which allows creating value from it, as well as developing and using other features from Industry 4.0
- Cloud computing uses remote servers to store and process data. Instead of having the data locally, users can interact with it through internet. It enables several features such as long-time storage and backup or using specific software to analyze the data
- Additive manufacturing, also called 3D printing, refers to a process in which objects are created by adding materials layer by layer. This technology can be used to produce finished products as well as individual components that can then be incorporated into the design of other products
- Artificial Intelligence (AI) is a field of computer science dedicated to creating algorithms capable of performing tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, or translation between languages
- Cybersecurity is the collection of technologies, practices, and procedures designed to protect networks, devices, programs, and data from attack, damage, or unauthorized access

This list of features is not comprehensive, but it brings a general overview of the various possibilities offered by Industry 4.0 (Vaidya et al. 2018). We can see that data is at the center of all these applications, either to use or create it. From this observation, we will discuss next the topics of data management in the Industry 4.0 context, as well as the major contribution brought by the Internet of Things.

2.1.2 Internet of Things and data management

Data in the Industry 4.0 context refers to a digital piece of information that can be stored, processed, shared in many ways. The process to convert physical or analog information to digital is called Digitization, whereas Digitalization is linked with the digital transformation of "traditional" processes or businesses by using digital tools or techniques (Brennen and Kreiss 2016). It is important to understand the difference between these two terms, as they are often used in the wrong context when discussing about the digital aspect of Industry 4.0.

2.1. INDUSTRY 4.0 PARADIGM

In this context of digitalization, the amount of data generated is increasing rapidly every year, and it is predicted in Figure 2.3 that the global size of the digital world will reach 175 Zettabytes by 2025 (Reinsel et al. 2018). To try and understand this number, one Zettabyte corresponds to one billion (10^9) Terabytes, or one trillion (10^{12}) Gigabytes. According to Reinsel (2021), half of this data will be coming from IoT devices in 2025.

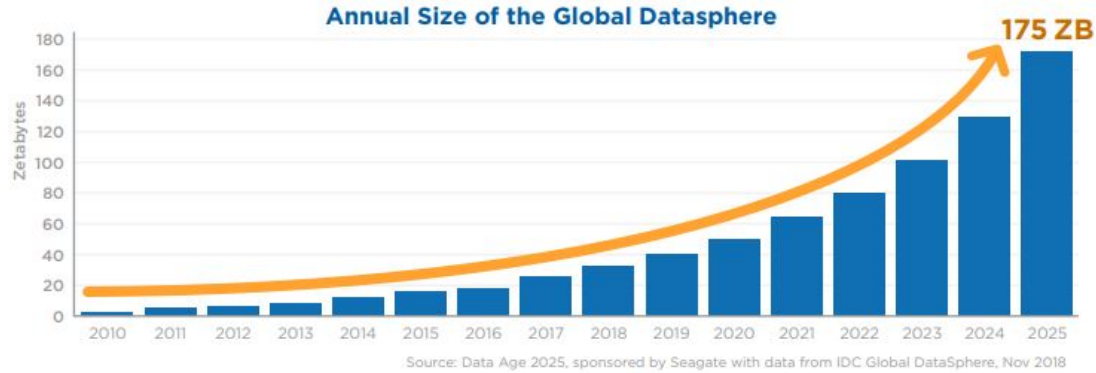


Figure 2.3: Evolution of the size of the Digital Universe (Reinsel et al. 2018)

IoT devices are often defined as physical objects capable of sensing features from the real world. As they are also connected to the Internet, they can send to and receive data from other devices (Abu-Elkheir et al. 2013). They also integrate a CPU^3 that can be programmed to act depending on the data it processes. In this way, most of the IoT devices used in the private and industrial context are tagged as "smart", because they can sense the state of the physical asset and take actions accordingly (Diène et al. 2020).

The number of these devices is increasing rapidly, as shown in Figure 2.4. Three fourths of the total connections are expected to be from IoT devices in 2025, as they are being used more and more in various fields, whether it is for healthcare, industry, financial activities, or private use (Lueth 2020). The number of non-IoT devices (phones, PCs, laptops, tablets ...) will remain quite steady in the next few years. It can easily be explained because owners of these devices mostly possess one of each type, and their usage is punctual. In comparison, the use of IoT devices in the previously presented cases can require several of them, and they are most of the time sending data continuously, increasing at the same time the volume of data generated and stored globally (Vongsingthong and Smanchat 2015).

³CPU: Central Processing Unit

Total number of device connections (incl. Non-IoT)

20.0Bn in 2019— expected to grow 13% to 41.2Bn in 2025

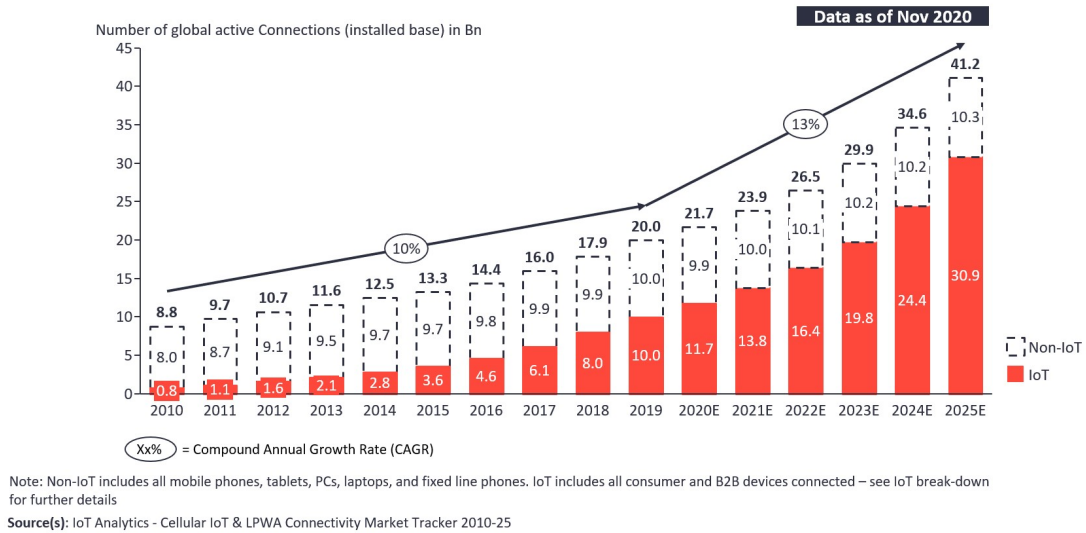


Figure 2.4: Number of connected devices 2010-2025 (Lueth 2020)

After understanding the importance of the Internet of Things, the place it is taking today and the contributions it will bring tomorrow to the global data space, comes the question of how to organize these devices and the data they generate. To manage efficiently the connection and interconnection of the IoT devices, several architectures have been developed. Each can be independent or complementary, depending on which context they are used. These solutions are often compared by considering the distance between the management system, and the source of the data. Below will be presented the three main architectures, called respectively edge computing, fog computing and cloud computing.

Edge computing Edge computing is the data management system closest to the data source. It is named as such because it is located at the edge of the network used to address the data. The main benefit is having low latency regarding the connection and the data collect, as well as sending back instructions or actions into the source (Varghese et al. 2016). In this context we are talking about close to real-time interactions, allowing the system to be very reactive in case of sudden changes (Khan et al. 2019). We use the term online processing in this case. The main drawback of this architecture is the difficulty regarding the scalability of the system. It is most of the time designed for one or several assets and it can be challenging to upgrade it to handle more than its original purpose. For instance, computational power can be limited, as well as the number of connections it can manage. Edge devices are most of the time industrial PCs, optimized to resist in

difficult conditions. As an example, they are designed to be fanless to prevent any issues coming from dusty environments. These devices can also be directly the sensors themselves, the smart sensors or IoT devices discussed previously.

Fog computing Fog computing can be seen as being on top of the edge computing architecture. The major difference between fog and edge computing is that fog computing is using some of the features from the cloud computing architecture presented below. It uses server called fog nodes, which are still close to the data sources, and will most of the time address multiple edge devices. It is often described as a geographical distributed architecture (Atlam et al. 2018). This system is scalable depending on the requirements of each use case; however, the latency will be higher than for edge computing. A common use for fog computing is to provide a more global analysis of the data collected through the edge devices, by aggregating them and combining multiple types of data. One key feature from fog computing is to serve as an intermediate node for cloud computing, to reduce latency and storage issues (Bonomi et al. 2012).

Cloud computing Cloud computing is the architecture which is the farthest from the data source. It is often proposed as a service (IBM, Amazon, Google, Microsoft, OVH for example) for all sorts of companies, from startups and SMEs⁴, to large and global enterprises. The data is therefore stored inside massive data centers and made available remotely through a web browser for example (Kim 2009), for any user that has the necessary credentials. The main benefits from cloud computing are the long storage times, the high scalability of the architecture, making available advanced analyses and processing on the data. In the industrial context, we could say that edge computing will address one or several production machines for instance, fog computing can handle one or several plants at regional level, and edge computing is designed to deal with data coming from all plants, at a global level. However, latency is the highest due to the distance, making it impossible to consider real time processing of the data. The data processing is qualified as offline in the case of cloud computing, as it can process huge amounts of data, taking longer time. There is also often the question of privacy and security with cloud computing, as sensitive data can be hosted externally (Qian et al. 2009).

Table 2.1 summarizes the features, the benefits and the limitations of each solution, to understand better where to use them.

⁴SME: small and medium-sized enterprises

⁵API: Application Programming Interface

⁶PLC: Programmable Logic Controller

Table 2.1: Main features from each data management architecture

	Cloud computing	Fog computing	Edge computing
Architecture	<ul style="list-style-type: none"> The physical assets are located in a remote data center Each part of the data center is dedicated to a specific task: data collect, storage, analysis The data is accessed through the Internet, or using an <i>APF</i>⁵ 	<ul style="list-style-type: none"> The system is composed of fog nodes, which can be servers, computers, storage units. It is decentralized because at the edge of the network, but not necessarily physically close to the data source Fog computing can make the link between cloud computing and edge computing, by acting as a gateway to send data in both ways 	<ul style="list-style-type: none"> Edge devices are physically close to the data sources. They can sometimes be the data source themselves, in the case of IoT devices which are equipped of sensors The information collected and processed can be pushed rapidly back to the data source, to act on the physical asset based on the different events observed
Main features Benefits	<ul style="list-style-type: none"> High computing power Highly scalable Long-time storage High interoperability Advanced data processing 	<ul style="list-style-type: none"> Close to the edge Sensitive data stored within the internal network High interoperability Scalability possible to address more devices Close to real-time interactions 	<ul style="list-style-type: none"> Cheap solution per edge device Low latency, real-time interactions Take quick actions Possibility to interact directly with <i>PLC</i>⁶
Limitations Drawbacks	<ul style="list-style-type: none"> High latency and response time Power consumption, cooling system Privacy issues for sensitive data Potential bandwidth issues while sending data over Internet 	<ul style="list-style-type: none"> Possible latency issues depending on the distance between the data source and fog node Using multiple node to send data to the cloud can create weak points in the architecture, or more opportunity for failure 	<ul style="list-style-type: none"> Difficulties regarding scalability, each edge device has limited resources and they need to operate storage, collect, processing and communication of the data Interoperability is limited due to the design of the edge devices Sending data directly to the cloud can be challenging
Extra features Comments	<ul style="list-style-type: none"> No maintenance required by customer 	<ul style="list-style-type: none"> Possibility to install fog nodes internally, externally, or in a hybrid manner 	<ul style="list-style-type: none"> The interactions with PLCs allow the development of powerful applications able to perform actions and make changes on the production system

As previously discussed, data is at the center of Industry 4.0 and all the activities shown in Figure 2.2. The Internet of Things is the top contributor for data collection in this context and is helping this digital transformation of the industry (Sniderman et al. 2016). We have seen that more and more data is being generated, especially in the different industries, and that consequently, an

efficient management system is required to extract value from this raw material. Different architectures exist, and they can be used independently or in a complementary way, based on the requirements and business model of the use case or the company itself. In the next part, we explore the different industrial maintenance policies existing today, to understand the influence Industry 4.0 had on them.

2.2 Definition of maintenance activities

Maintenance activities are often placed under the reliability engineering field. Reliability refers to the capability of a system to work under specified conditions during a certain period ([Dhillon 2002](#)). Consequently, the lower the reliability gets for an equipment, the more it will require maintenance actions to operate back in the correct state. Figure 2.5 shows a widely used representation of the failure rate for a given equipment over time. The function plotted is named "hazard function" and is of great interest in the reliability analysis context. The example shown in the figure is called "bathtub curve", due to its shape. The left part represents the early life of the equipment, and we can observe that the failure rate will decrease over time, until it reaches the center part. This decrease is explained by early changes in design to correct "infant mortality" failures. The center part follows the "normal" life of the equipment, where random failures can appear, but the rate is constant as it is assumed that all random failure events have the same probability of occurrence. Finally, we observe on the right side an increase of the failure rate, due to aging of the equipment and natural degradation from wear of its components.

Even though the use of this curve is debated among researchers, as stated by [Klutke et al. \(2003\)](#), the assumption of the three parts regarding the failure rate of a given equipment during its lifetime is relevant for production systems. From this curve, we can begin to picture that maintenance activities are required throughout the whole life cycle of any industrial equipment. Consequently, in this section we review and detail the existing maintenance policies from literature.

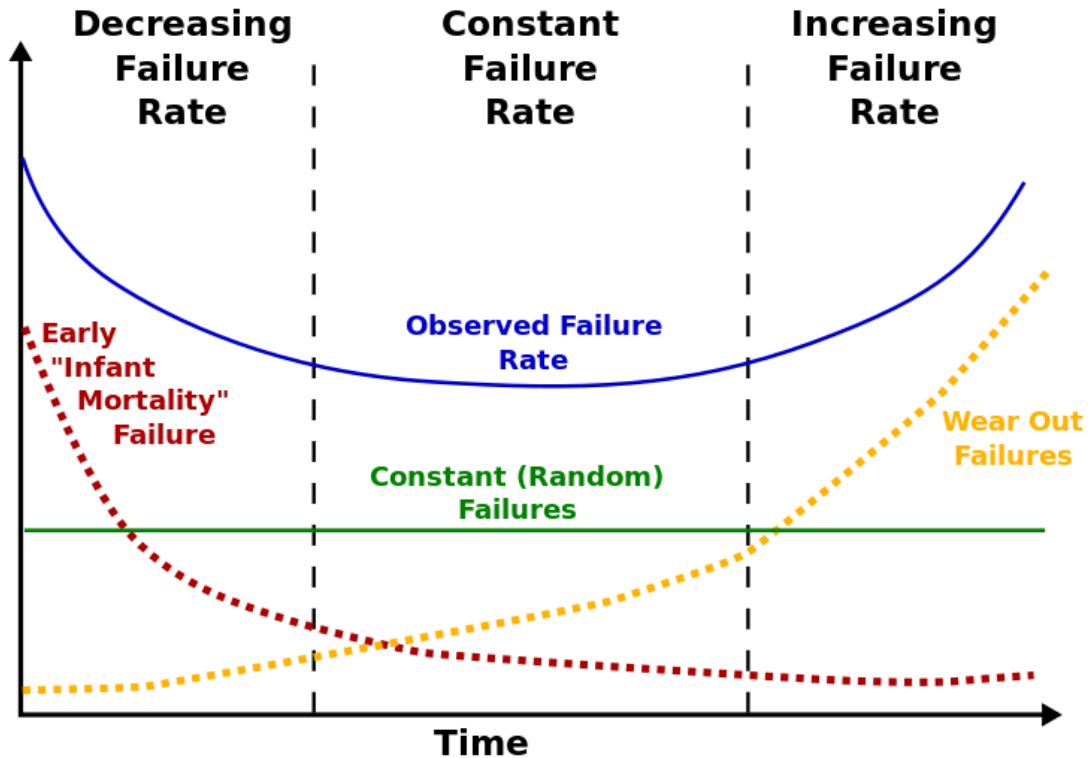


Figure 2.5: Bathtub curve used in reliability engineering

According to European standards and [AFNOR⁷](#), maintenance can be defined as such:

Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function. (NF EN 13306 2001)

The efficiency of those different actions will strongly depend on the maintenance strategy adopted by the industrial entity. Figure 2.6 shows the different types of maintenance policies that exist, and implemented across all industries.

Three principal categories of maintenance policies are defined: corrective, preventive and predictive. Some sub-categories exist, and are described below.

⁷AFNOR: French Standardization Association

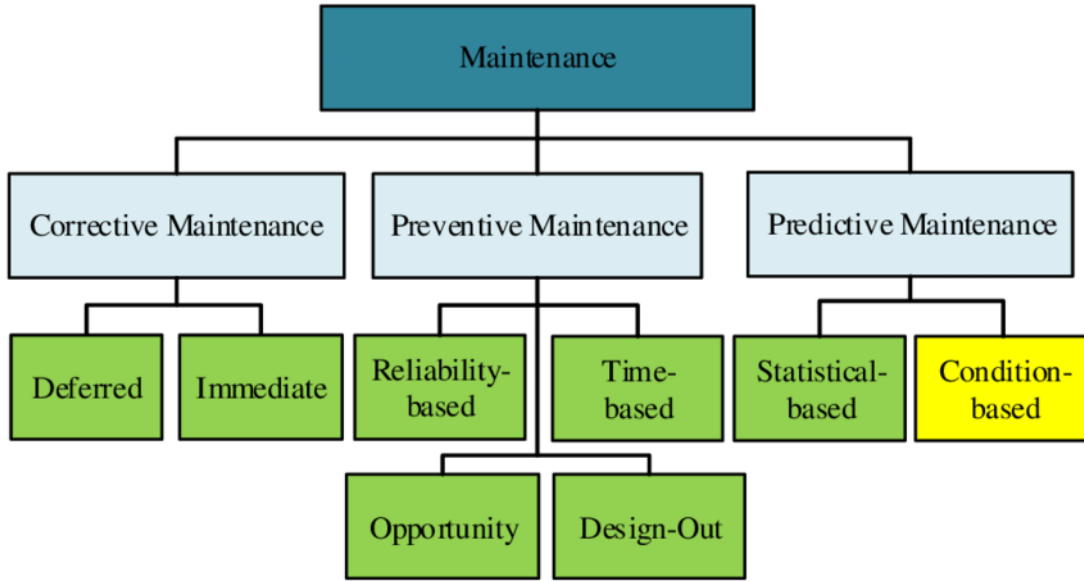


Figure 2.6: Maintenance policies (Wang et al. 2015)

- Corrective maintenance: this strategy deals with machine failures after they appear
 - Deferred: corrective actions are postponed, for different reasons (not a priority action, no replacement parts, expert required) (Lind and Muyingo 2012)
 - Immediate: corrective actions are carried out directly after the failure happens (Lind and Muyingo 2012)
- Preventive maintenance: this second strategy is based on finding the optimal time to take corrective actions, four types of preventive maintenance exist, using different inputs to make decisions on maintenance actions:
 - Reliability-based: prioritizes maintenance actions according to the impact of failures on productivity (Vishnu and Regikumar 2016)
 - Time-based: maintenance actions are performed at a fixed frequency, it is not taking into account the current state of the machine (Horner et al. 1997)
 - Opportunity-based: uses planned or unplanned downtimes of machines to take corrective actions, to reduce production losses and improve machine reliability (Shafiee and Sørensen 2019)
 - Design-out: modification of the design of an equipment in order to remove any root cause of a failure (Mostafa et al. 2015)

- Predictive maintenance: its goal is to predict failures before they happen. It is done by monitoring continuously the assets to detect issues. Those detections are made possible by creating Health Indicators (HI) that will show the asset's degradation over time ([Bashiri et al. \(2011\)](#), [Legát et al. \(2017\)](#), [Wang et al. \(2007\)](#)). Two main categories are currently studied:
 - Statistical-based: uses mathematical techniques on data coming from the machines and its sensors, to estimate the time of appearance of the next failure. It allows an efficient planning of corrective actions during the time between the detection and the estimated time of the issue
 - Condition-based: thresholds are set on specific parameters to detect when a failure event is starting. It is often based on expert's knowledge, and experience from previous failures

Although the main maintenance policies are identified above, researchers still struggle to come up with a single hierarchy for these different activities. Three other representations are highlighted by [Gackowiec \(2019\)](#). To try and classify these policies, some groupings are introduced, and from one definition to another, some maintenance policies are observed in different categories. As a summary of these definitions, we observe that maintenance policies are either reactive or proactive, corrective or preventive, planned or unplanned. Reactive, corrective or unplanned maintenance happens after a failure has appeared on the equipment, while proactive, preventive or planned maintenance relates to all activities that take place before the appearance of any failure.

Consequently, we propose a hierarchy in Figure 2.7, based on the works from [Sambrekar et al. \(2018\)](#), [Mostafa et al. \(2015\)](#), [Gackowiec \(2019\)](#), and the observations done during this thesis work in various industrial contexts. The main goal is to have a clear understanding of each existing maintenance policy, and their position regarding equipment's failure management.

The main feature of this architecture is the grouping of maintenance policies under three categories. Reactive and corrective maintenance are put together, as they are most of the time defined as the same activity. They are dealing with maintenance actions after the failure has happened on the equipment. All policies taking actions before the occurrence of a failure are put behind the proactive maintenance category. Finally, the design-out maintenance is separated as this policy deals with changes in the design of the system to reduce maintenance actions. Therefore, a certain amount of time of usage is required to understand the root causes of the most impacting breakdown, and to identify the changes

2.2. DEFINITION OF MAINTENANCE ACTIVITIES

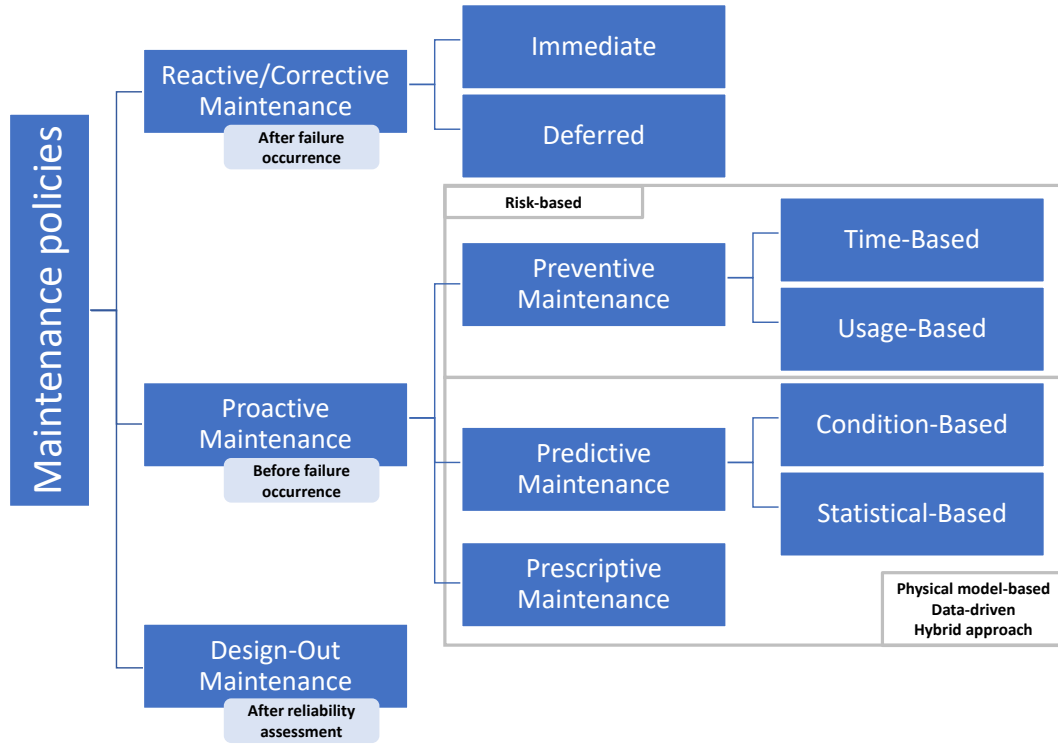


Figure 2.7: Hierarchical overview of maintenance policies (adapted from Sambrekar et al. (2018), Mostafa et al. (2015) and Gackowiec (2019))

needed to be done (Muganyi et al. 2018).

Secondly, preventive maintenance is declined into two sub-categories. Preventive maintenance is designed based on *FMEA*⁸ results, and a large number of companies use the time-based method, meaning that the maintenance actions are performed periodically and based on a calculated amount of time between each action (Cicek et al. 2010). Another method exists, based on the usage of the equipment. Here the scheduling of the maintenance actions will rely on periodic fixed number of cycles performed by the asset. Usage-based preventive maintenance is supposed to be more efficient, as it is taking into account the use and therefore the degradation coming from it. In the case of equipment running sporadically, the time-based method is less efficient and will generate unnecessary costs. We qualified the preventive maintenance category as risk-based, because as discussed above, the rules created are using the estimation of the risk linked to the appearance of any failure mode (Khan and Haddara 2003).

⁸FMEA: Failure Modes and Effects Analysis

The third noticeable addition to the architecture is the introduction of prescriptive maintenance. Prescriptive maintenance is defined as the next step of predictive maintenance. It integrates history of failures, understanding of root causes, and corrective maintenance actions associated to a specific detection of anomaly from the system (Khoshafian and Rostetter 2015). As a result, in addition to proposing an estimation of the remaining time before a failure happens (*RUL*⁹), it also generates an action plan to the maintenance teams in order to do some verification, and specific tasks to try and increase this amount of time left (Sahli et al. 2021).

Finally, we grouped predictive and prescriptive maintenance together under a category that can be qualified as data-oriented. All the rules and decisions defined in these policies are linked to the analysis of data coming from the monitored system, whether it is process or sensors data. Three main architectures are identified here (Wang 2016), which change the way rules are created. The first category is using physical models to characterize the system, making it possible to have a precise monitoring of its behavior, and detecting early changes. The second category is purely based on data analysis, and it uses statistical methods or machine learning algorithms to predict the future behavior of the system. Some approaches use both in a hybrid manner, to get the advantages from the two solutions and to reduce their respective drawbacks and limitations. These features will be discussed in Section 2.3.3.

From this analysis of the literature on Industry 4.0 and industrial maintenance policies, we have seen that the digital transformation of industry also greatly impacted maintenance activities. Many works have been conducted and are still being carried out on the digitalization of maintenance, leading to the implementation of the predictive maintenance policy in all industries. As this topic is the core of the thesis work, we will next review the existing methodologies that help switching from a classical maintenance system to predictive maintenance. One of the goals will be to understand the role of data in this activity, and how it is used in industry, to perform this change.

⁹RUL: Remaining Useful Life

2.3 Methodologies for the implementation of predictive maintenance

We have seen that many research works focused on this topic over the past few years, to bring a new dimension to maintaining production equipment. The main features of predictive maintenance are the use of real-time data, and the remote monitoring of assets to propose high-end analyses, to detect equipment failures before they impact the production system (Rødseth et al. 2017). The most active research community is the PHM Society, which proposes a framework for implementing health monitoring in order to estimate the RUL of a given system. Standard methodologies are issued, from data collection and sensors selection, to the *prognostics* and decision systems regarding maintenance interventions (Lebold et al. 2003). Consequently, PHM is not only used to design predictive maintenance, it is a general methodology to maintain efficiently any type of engineering system. However, most predictive maintenance systems are built on the PHM methodology. Therefore in the next section, we introduce PHM and its framework, to try and understand how it can be applied for predictive maintenance.

2.3.1 PHM framework overview

We will first investigate the PHM methodology in order to understand the different activities that are part of the framework, and used to design such a monitoring system. Figure 2.8 explains the different features of this approach.

As shown in the figure, the framework is composed of three categories: "Observe", "Analyze" and "Act". The first steps within the "Observe" activity deal with the input data from the system. Mainly how to select, collect, store, and process the data, to create a standard structure. The second part "Analyze" is related to the different analyses made on the collected data. First, data is studied to understand the current status of the system. This allows to monitor the evolution of the system's behavior, and detect changes that can announce an incoming issue. Once this analysis is performed, it is possible to create indicators to detect these previous changes early, the main goal being to avoid these future issues when they happen again. Finally, the system must communicate these results efficiently to the end-users visually, and propose some actions to reduce the risks that a failure will impact the monitored system.

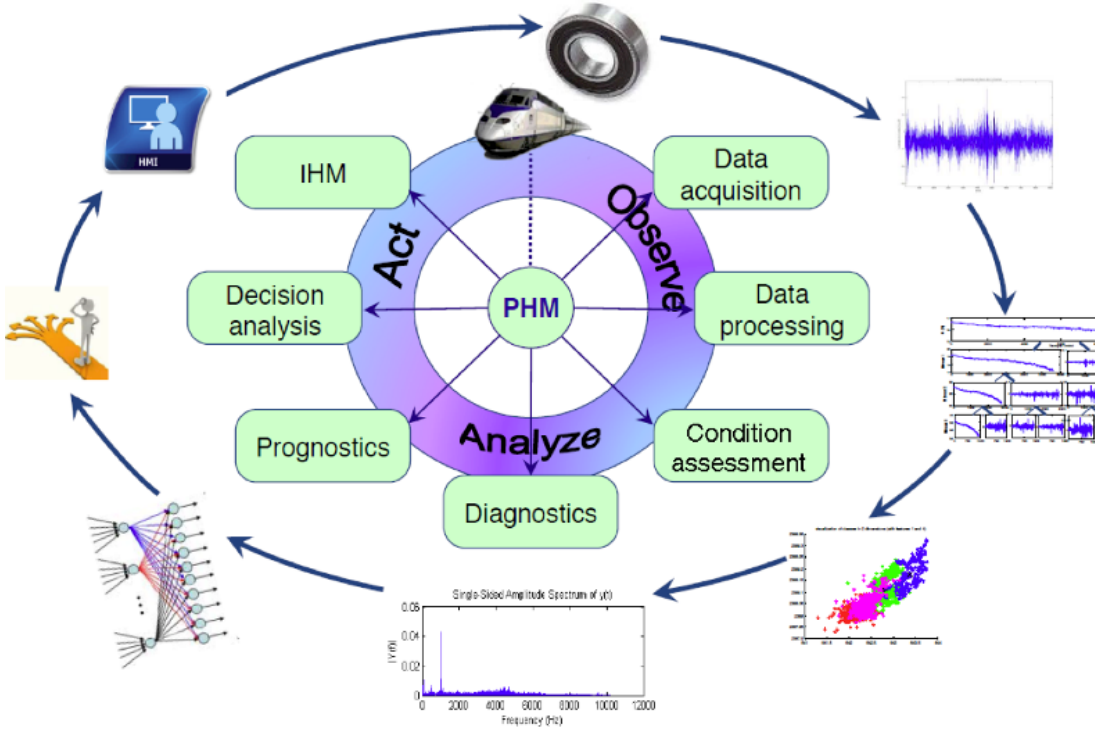


Figure 2.8: PHM cycle (Gouriveau et al. 2016)

The standard PHM process is represented in Figure 2.9, and below is proposed a summary of its different activities:

- The first step is to understand the potential use cases that would benefit from such a system, meaning that avoiding this kind of failure could save money and time
- Once the choice is made, an analysis on the required data is carried out to study the failure, as well as the data management system to put in place (collect, processing, storage, visualization)
- Measurement techniques must be studied to collect the necessary data in the most efficient way
- The diagnostics and prognostics phases are related to the analysis on failure data to better understand it, to detect it and predict it in the future
- Finally, the system is tested according to the initial goals, and end-users must be trained to use such a tool

Regarding the data management system, the organization "Machinery Information Management Open Standards Alliance" (MIMOSA) proposed a commu-

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

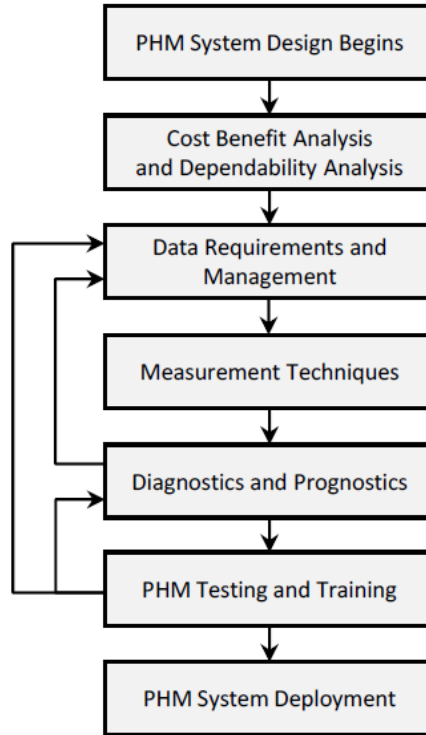


Figure 2.9: PHM system design (Vogl et al. 2014a)

nication framework for dealing with data in a PHM system. It has been first developed by Lebold et al. (2003), and the architecture is shown in Figure 2.10. The Open System Architecture for Condition Based Maintenance (OSA-CBM) deals with all the data aspects of a PHM system, and its goal is to propose an interoperability between the communication devices. This architecture is composed of several blocks that help deploying the PHM framework previously discussed, as well as technical recommendations on hardware systems and communication protocols. Löhr and Buderath (2014) focused on implementing such system and improving its efficiency.

For the measurement techniques, some standards are issued to have a first hint of which data would be interesting and how it could be collected. The National Institute of Standards and Technology (NIST) issued some standards related to PHM and details every step of the methodology and the standards already in place on some specific aspects of the process. Some measurements techniques are shown in Figure 2.11. This list is not exhaustive compared to the possible use cases, but it gives some leads on which sensors and data to use in order to study the potential failures.

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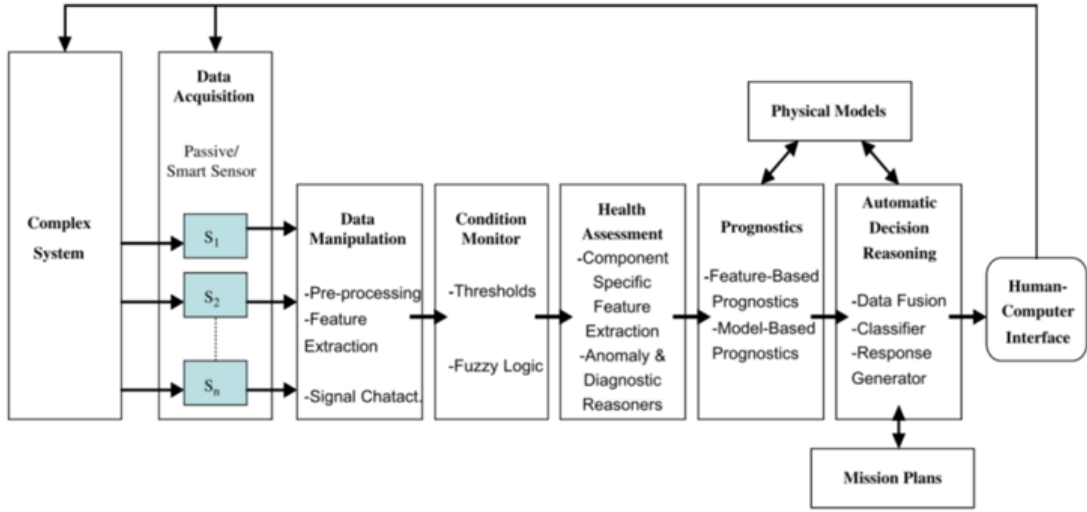


Figure 2.10: OSA-CBM architecture for PHM (Lebold et al. 2003)

Other standards are issued by IEEE (2017) on electronic systems, but the global methodology can also be reused on other topics. Figure 2.12 and 2.13 show both functional and operational aspects of this system. These architectures help defining and implementing practically the final PHM system. In the next sections, we will review in detail the different activities of the methodology, starting with the data selection process.

2.3.2 Data selection process for efficient monitoring of the system

The first and most important step of the PHM approach is the data selection, to study the system's failures. It is the basis on which all the system will stand. If the selected data cannot measure or explain the deviations and failure modes of the industrial process or equipment, a lot of time will be wasted. Many papers studied below propose to use FMEA¹⁰, to get a first idea of which parameters will be useful to detect failures. FMEA is a dysfunctional analysis that provides information on failures such as root causes, observed degradation and how to detect them (McDermott et al. 2009). Consequently, it is an important input for finding the correct parameters to monitor in order to understand and detect failures.

¹⁰FMEA: Failure Modes and Effects Analysis

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

Machine type: Electric motor	Symptom or parameter change												
Examples of faults	Current	Voltage	Resistance	Partial discharge	Power	Torque	Speed	Vibration	Temperature	Coast down time	Axial flux	Oil debris	Cooling gas
Rotor windings	•				•	•	•	•	•		•		•
Stator windings	•							•	•		•		•
Eccentric rotor	•							•			•		
Brush(es) fault	•	•			•	•			•				
Bearing damage	•					•		•	•	•		•	
Insulation deterioration	•	•	•	•									•
Loss of input power phase	•	•						•			•		
Unbalance								•					
Misalignment								•					
• Indicates symptom may occur or parameter may change if fault occurs.													

Figure 2.11: Monitoring techniques (Vogl et al. 2014b)

Laloix et al. (2018) proposed a structured methodology to define health indicators of a machining center, based on joint FMEA and *HAZOP*¹¹ methods. HAZOP is more flow-oriented and defines the deviations that can happen within a system. The complementary aspects of FMEA and HAZOP allow to identify efficiently the relevant parameters to be used, to create these health indicators.

Other research works proposed frameworks using FMEA in a different manner. Srivastava and Mondal (2015) used a modified *FMECA*¹² (Mod-FMECA) to quantify the outputs of failure modes, to detect and target deviations from the current process status: then maintenance teams can plan actions to correct the issue. The quantification of the output is based on machine performance. Brahim et al. (2019) transformed FMECA by including a *Bayesian Network* (BN), to incorporate the diagnostics and prognostics of failures using probabilistic models between each failure modes. The BN can be used with back chaining, to perform the diagnosis and identify the causes when a failure occurs, but also with front chaining, to estimate the probability that a failure will happen according to the

¹¹HAZOP: Hazard and Operability analysis

¹²FMECA: Failure Modes, Effects and Criticality Analysis

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

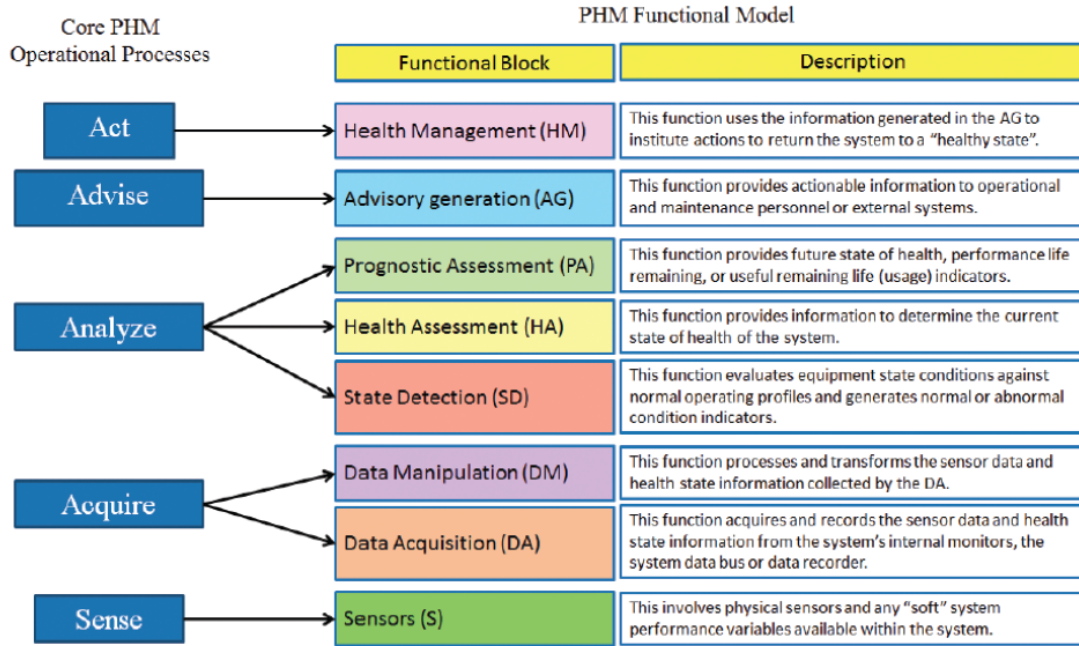


Figure 2.12: PHM functional model (IEEE 2017)

actual status of the machine.

Li et al. (2017) worked on machine centers in the context of Industry 4.0, with the objective to propose a framework for predictive maintenance, with vibration, ultrasonic and acoustic sensors. The importance of selecting the correct parameters and related sensors is underlined, however the choice methodology is not detailed. In the proposed industrial use case, sensors were already implemented. Stanula et al. (2018) presented an approach for selecting data sources when using machine learning algorithms in industry. The concept of Cross Industry Standard Process for Data Mining (CRISP-DM) is introduced, which is a methodology to work on data mining projects for industrial applications. Figure 2.14 shows an improved version of CRISP-DM with technical considerations from the point of view of the engineer. The first input of the system is the *PFMEA*¹³, which gives information on the relevance of data to be used when working on specific failure modes.

Analysis of failure modes on a given equipment is important, to assess the risks linked with known possible issues on the system. It also gives relevant information on the causes and effects of these failures, which allow to identify parameters and data to be used for the predictive maintenance activity.

¹³PFMEA: Process Failure Modes and Effects Analysis

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

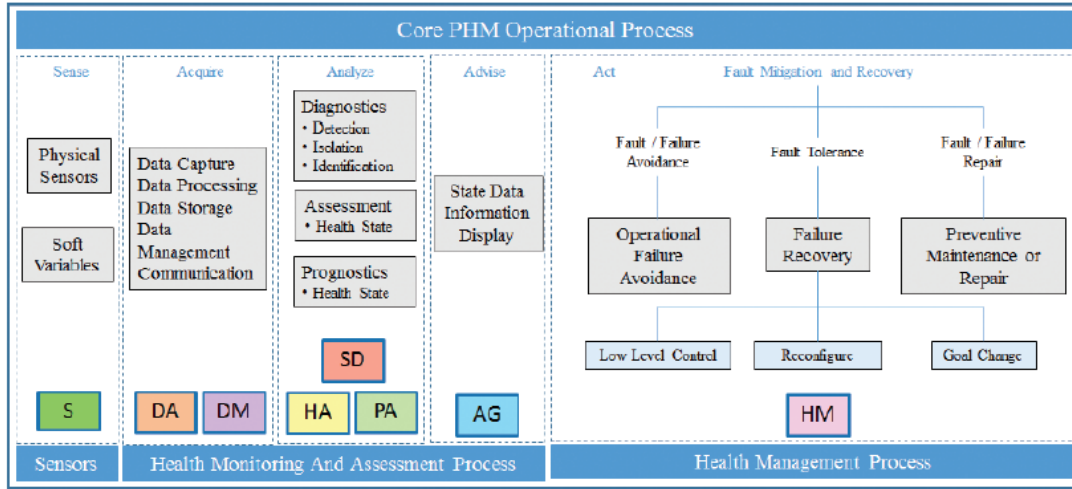


Figure 2.13: PHM operational process (IEEE 2017)

Functional and dysfunctional analyses are not the only ways to deal with data selection, other methods work directly on data to find relevant parameters that will help with the detection and prediction of failure modes. Dai and Gao (2013) reviewed the different approaches for Fault Detection and Diagnosis (FDD). They are classified into three groups: model-based that relies on physical models to understand and detect the failures, signal-based that consists in analyzing outputs from sensors measurements to work on failures, and knowledge-based, which involves machine learning techniques on historical database to extract knowledge of failures. As mentioned in this research work, all these approaches are data-driven, and most of the times, an efficient system will combine the three categories.

Fernandes et al. (2019a) worked on different data sources in the metallurgic industry to collect features, correlations and knowledge in order to implement a predictive maintenance system. Data mining and machine learning techniques were applied on this dataset, to discover new links between data, which allowed the creation of rules for predictive maintenance. The authors mentioned that some rules were already known from experts' knowledge, but some were newly discovered from the analyses, showing the interest of the approach.

One of the challenges of this topic is to evaluate the correct way to select the data, by applying the two approaches on concrete use cases. The difficulty might be to find an indicator to evaluate the relevance of the chosen parameters. One possible approach could be a joint step using both methods and selecting the parameters based on a correlation value on the results of the two processes.

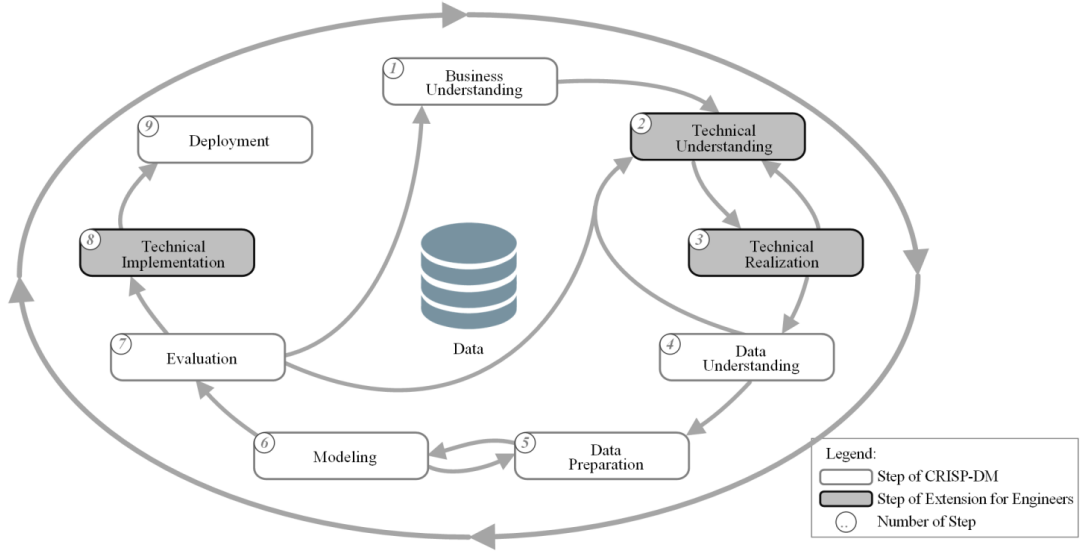


Fig. 3: The DMME process.

Figure 2.14: CRISP-DM for engineers (Huber et al. 2019)

The data selection phase is important, but the data management system to collect and analyze this data also matters. In most reviewed papers, the data management system is not detailed, or is only valid for working on a specific use case during the experimentation phase. One of the observations from the literature is that there is a need to consider the data management system for the deployment in production and not only for testing and validating a model or an approach. It is a complete system that needs to operate in the given industrial context, in several plants, considering different data sources, and that interacts with plant's management, maintenance teams and operators. A validated approach on a specific machine or use case in a laboratory context might not be easily deployed in the industrial context, which has a lot of constraints, mostly regarding cybersecurity and costs.

After reviewing the existing approaches for an efficient data selection for the predictive maintenance framework, we will next study the available techniques to assess the current and future health state of the monitored system.

2.3.3 Health assessment

The next step of the framework is the health assessment of the system. Health assessment is often separated into two phases, diagnostics, and prognostics. The difference is shown in Figure 2.15: diagnostics will study the causes of a recorded failure, while prognostics will estimate the remaining time before the failure

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

happens, when detecting a previously observed pattern in the system's behavior.

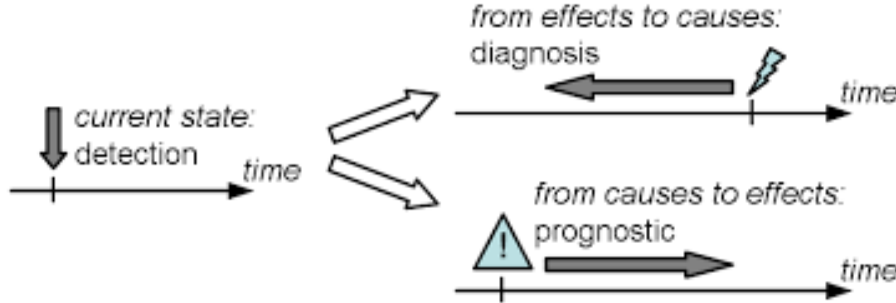


Figure 2.15: Diagnosis and prognostic (Jouin et al. 2013)

The first studies were oriented on physics-based models, meaning that the research focused on understanding the physics phenomena at stake in the degradation process. In the recent years, with Industry 4.0 and the ease to perform advanced calculations on data, a new approach arose: the data-driven analysis. This method works directly on the collected data to detect changes and thus, a potential degradation of the system. This trend is reported by [Lei et al. \(2018\)](#) and shown in Figure 2.16. These approaches represented 80% of the produced literature over the past few years, separated into two parts: statistical-based approaches and AI (Artificial Intelligence) methods. The rest is physics-based and hybrid studies, which are much more complex to implement, but quite efficient in describing failure processes.

We will not address all the available techniques used in prognostics, only some approaches that could be of interest for our applications. Review papers such as the ones proposed by [Dragomir et al. \(2009\)](#), [Si et al. \(2011\)](#) and [Lei et al. \(2018\)](#) help understanding the main contributions of the different topics, with industrial applications involved, as well as challenges that remain in the field. Such challenges concern all the steps of the PHM framework: for instance data collection, the choice of model or technique to be used on data, and uncertainties of the designed systems. These review papers tend to agree on the efficiency of implementing data-driven approaches in the Industry 4.0 paradigm, with data being easily available, and because data analyses do not necessarily require "a priori" knowledge about the failures. We will discuss next the two main methods, which are statistical-based and AI-based. Most of the techniques discussed below will be presented in the [Glossary](#), with key references given.

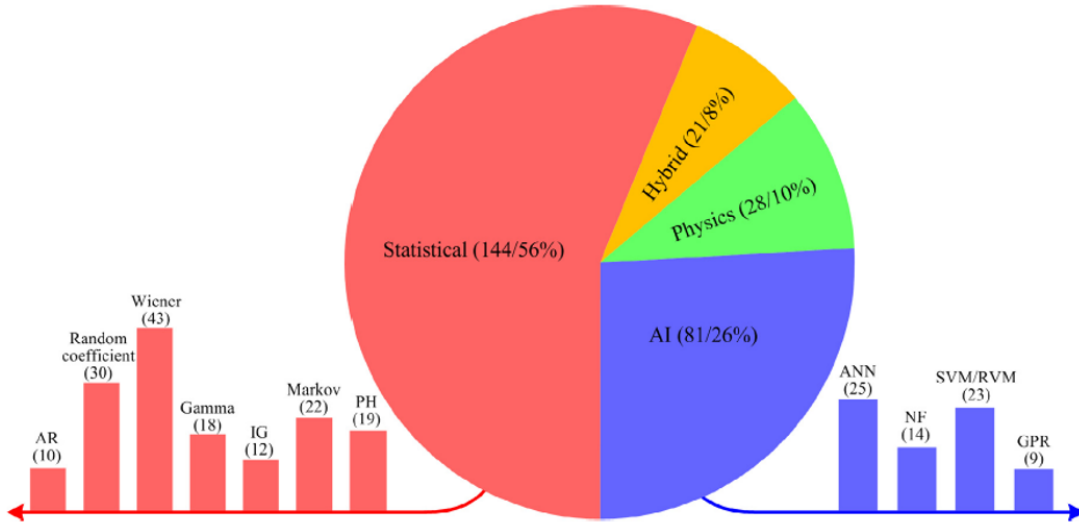


Figure 2.16: Health assessment approaches (Lei et al. 2018)

2.3.3.1 Statistical approaches

Statistical models are employed on monitored data to estimate their future state. Therefore, they are based on observations from the data, and RUL is often estimated as a probability that the monitored parameters will end up in a faulty state. These methods deal with uncertainties and allow modelling RUL without necessarily having historical failure data. One important term to define first is the *Autoregressive* (AR) model, as some variants are proposed in the next paragraphs.

Zhao et al. (2010) used *Principal Component Analysis* (PCA) on process data to get indexes that feed a *Bayesian Autoregressive* (BAR) model to estimate failure times. A comparison between prognostics based on *Autoregressive Moving Average* (ARMA) modeling and *Hidden Markov Model* (HMM) is proposed by Marjanović et al. (2011), to detect changes in a steam separator system. Results show slightly better performance for HMM, to estimate the time of the degradation of the system efficiency. However, the method employed does not work on RUL, it is a fault detection system. Fernandes et al. (2019b) proposed the use of *Autoregressive Integrated Moving Average* (ARIMA) on vibration data, to predict the interval of future values. Then incoming data is compared to the predicted interval, to detect anomalies and alert when a high number is observed.

One hybrid approach has been developed by Baptista et al. (2018). Prediction results from ARMA model are used in PCA, to get features about raw data that

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are not correlated. This makes it able to be used as input of machine learning models to predict future time of failure of the system. A comparison is made between several models, and shows better results when using *Support Vector Machine* (SVM) as a regression model (*Support Vector Regression* (SVR)) to estimate failure time. Ruiz-Sarmiento et al. (2020) worked on a complete system to estimate the degradation state in the metallurgic industry, in order to propose a maintenance scheduling. Expert knowledge and sensor data are fused into a *Discrete Bayes Filter* (DBF) to determine the next state of the system from previous data. The prediction is made by estimating the future state of the system after several cycles, providing some inputs to the users about possible degradation. A comparison with classical regression models from Machine Learning is proposed, to validate the proposed method.

Some examples of RUL estimation from statistical models are proposed below. Figure 2.17 estimates RUL from probability that the system will have a failure after a number of cycles.

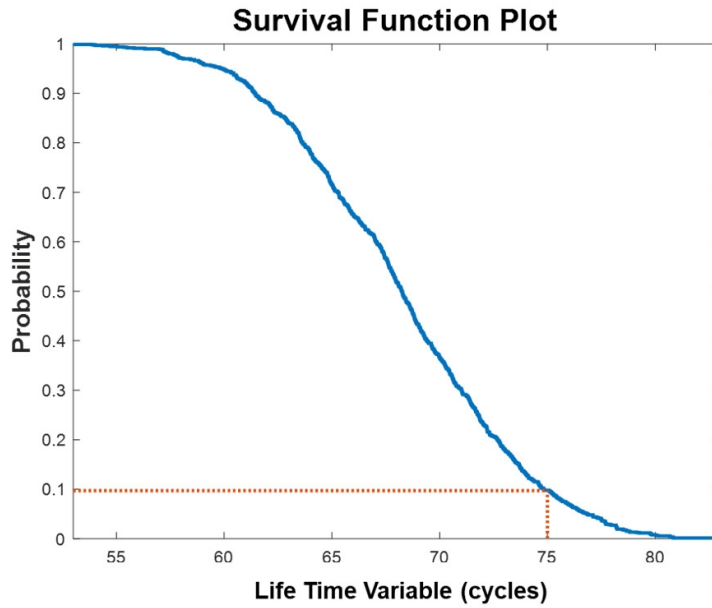


Figure 2.17: Survival modelling for RUL (Baru 2018)

Figure 2.18 works on failure data to estimate the current values according to previous observations. It allows estimating RUL based on previous failure events. This method is not necessarily easy to implement, because in the industrial context, failure events are scarce.

Figure 2.19 shows an approach based on a prediction of future value for a

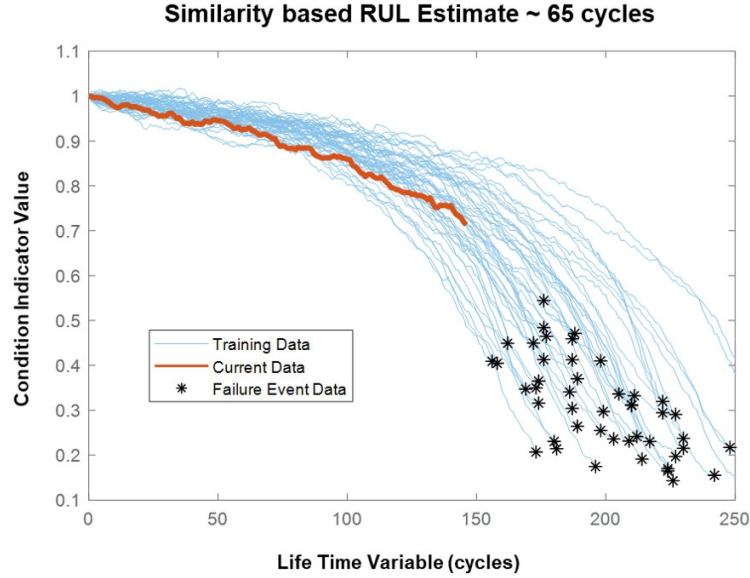


Figure 2.18: Similarity modelling for RUL (Baru 2018)

parameter or a calculated indicator, that allows estimating RUL with probability that the predicted value will cross a failure threshold. This method implies that the failure threshold needs to be known.

Many methods and models exist with statistical approaches, one challenge for predictive maintenance is to understand which are the most efficient to use depending on the use case involved. To do so, a classification must be done to know the output of each method, to match the industrial objective and the expected result of the statistical approach. Requirements on the type of data to be used also need to be known.

2.3.3.2 Machine learning approaches

Machine learning approaches for predictive maintenance aim at discovering patterns within the collected data to understand how the system behaves, and how it will evolve. Most of the time, these models can be described as "black boxes" because the system will learn by itself, and the learning mechanism that leads to a result is not necessarily easily understandable by human. Below is presented some of the works that could be of interest for our industrial application.

Einabadi et al. (2019) used a *Multi-Layer Perceptron* (MLP) which is a type of *Artificial Neural Network* (ANN) for predicting RUL of machined parts in automotive industry. The prediction allows the scheduling of maintenance for the

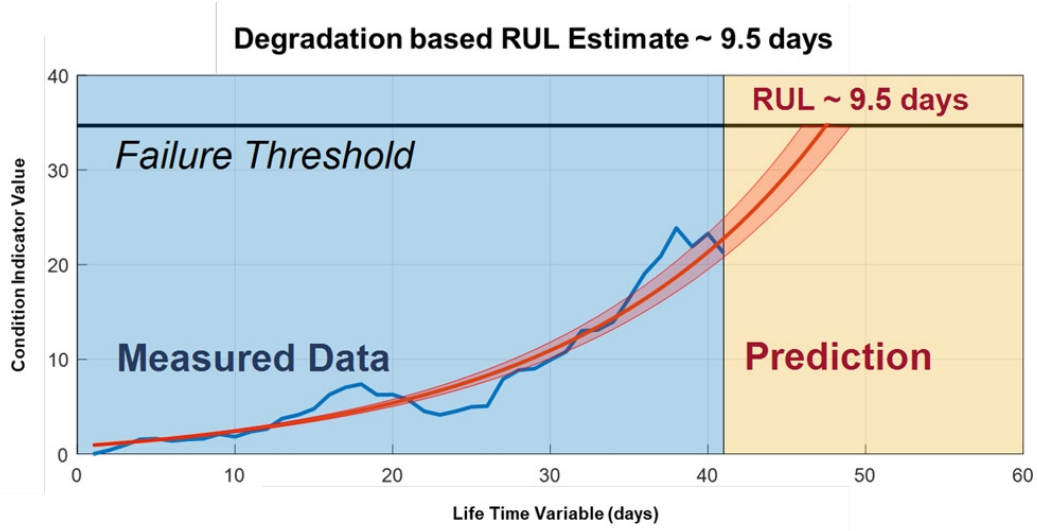


Figure 2.19: Degradation modelling for RUL (Baru 2018)

faulty parts, and the schedule is updated when new sensor data enters the system. Li et al. (2017) proposed a predictive maintenance framework for machine center, to illustrate the different steps of PHM and how they interact between one another. The framework goes from data collection to the decision system from RUL prediction. An industrial use case is studied with the use of ANN to predict RUL of a machine center. Liu and Zio (2016) discussed a prediction algorithm based on SVM to predict peak values of a pump in the nuclear industry context. Predicting the peak values can be useful in the case where failures are due to the increase of the maximum value of a monitored parameter.

A dynamic predictive maintenance framework is proposed by Nguyen and Medjaher (2019), using *Long Short-Term Memory* (LSTM) network to estimate the probability that the system will fail within the different time frames of the maintenance planning. As a result, the designed system is optimized for applications with a strict maintenance schedule, such as aircrafts for instance, where maintenance interventions can only happen outside of flight time intervals. Lee et al. (2017) have been working on *Generative Adversarial Network* (GAN) to reduce the imbalance between faulty and good condition data within the datasets in order to train a *Deep Neural Network* (DNN) for failure classification. The idea behind the GAN is to generate extra data so that the trained model has enough "good" and "bad" data to efficiently detect machine failures.

The main difference between statistical and AI approaches can be seen in Figure 2.20. The data analysis part of the statistical methodology is separated

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

into different phases, when there is only one step regrouping everything for the AI methodology. Another noticeable difference is that the health indexes for the statistical approach are often created manually, whereas it is done automatically in the AI approach. This can lead to making the design of the system easier, but the interpretation of the results more difficult. However, the automatic aspect has the advantage of potentially finding more efficient data correlation that would not have been possible when doing the data preparation manually.

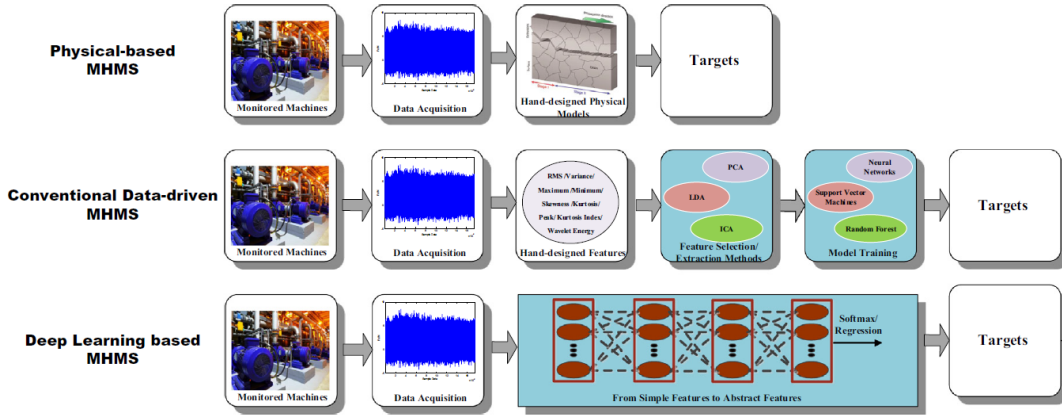


Figure 2.20: Machine health monitoring approaches (Zhao et al. 2019)

After reviewing the available techniques that can be applied on data to detect and predict failure modes, we will next review how the results from the analyses can be shared to users. A relevant communication is important, as the users need to have a clear understanding of the output from the analyses, to act and plan corrective actions accordingly.

2.3.4 Decision-making system

To design an effective decision system, the interconnection of all the information systems within a company greatly matters and makes it able to gather and aggregate a lot of information to feed the decision rules. As discussed in the introduction, the tools linked to data handling are changing rapidly, consequently there exist many ways of communicating and sharing results. Similarly, a lot of methods have been developed to support decision-making for users of these solutions.

Faiz and Edirisinghe (2009) defined a Decision Support System (DSS) as a computer-based tool helping decision-making by using incoming data and information. These tools can go from simple visualization or reporting of data, to complex systems using statistical or machine learning algorithms.

2.3. METHODOLOGIES FOR THE IMPLEMENTATION OF PREDICTIVE MAINTENANCE

[Bousdekis et al. \(2019\)](#) organized the surveyed literature on decision-making systems for predictive maintenance under five topics.

- Maintenance scheduling, which refers to algorithms used to plan and recommend efficient maintenance actions
- Degradation-based algorithms, proposing decisions regarding maintenance actions to be performed according to the current and future health state of the equipment
- Joint optimization, which aims at finding the correct balance between equipment availability and maintenance interventions, according to business requirements
- Multi-component approaches, considering dependencies among components to optimize their maintainability, as well as multi-state methods that define several stages of health level for a given equipment and tailored decisions for each of them
- Costs and risks optimization algorithms supporting decision-making by evaluating the financial impact of various repair scenarios, or from the occurrence of a specific failure

[Li et al. \(2017\)](#) proposed a framework for predictive maintenance, composed of different modules. The decision support module is defined as a system that shares results from data analyses, and proposes corrective actions accordingly. The key features of this module are visualizations of the predictions and KPIs¹⁴ linked to the state of the monitored equipment, and recommendations regarding maintenance interventions.

[Mourtzis and Vlachou \(2018\)](#) presented a cloud-based environment capable of dynamically adapt maintenance scheduling, based on all the data collected in the plant through a sensor network. One of the main observations is the necessity of having interoperability within the system, meaning the possibility to communicate data and information among different layers of the information system of any company.

The decision-making aspect of the predictive maintenance system is a challenging part of the architecture. It needs to consider many parameters and can be greatly influenced by the choices made regarding the design of the ICT¹⁵. In this sense, [Bousdekis et al. \(2019\)](#) pointed out that the designed decision systems are often valid for the specific architecture mentioned in the reviewed papers, or

¹⁴KPI: Key Performance Indicator

¹⁵ICT: Information and Communications Technology

to solve issues linked to the studied industrial cases. Interoperability is key as this system will have to communicate with various entities and share data and information of different nature, using various communication protocols. With this topic also comes the question regarding the interpretability of the results proposed by the algorithms. [Bousdekis et al. \(2019\)](#) discussed the possibility of using more automated solutions to build these decision rules, however there is always a risk that the reasons behind a rule might not be understandable by humans. The main reason is the way correlations are found, using mathematical models that can be difficult to interpret. There is often a trade-off regarding the "prescription level" between experts' knowledge-based rules and rules created by data-driven techniques.

After understanding the key concepts of the predictive maintenance architecture, we review in the next section its main challenges and the difficulties observed in industry regarding its development and deployment. After this, it will be interesting for our research work to understand how predictive maintenance is used within the automotive industry, to highlight some key topics to consider and develop in the presented approach of the next chapters.

2.4 Applications of predictive maintenance

One of the recurrent themes of this research work is the challenging aspect of the development and deployment of the predictive maintenance solutions among the industrial practitioners. In this section, we investigate these difficulties mentioned in the literature, as well as how these research works are being carried out in the automotive industry context.

2.4.1 Challenges and adoption level

Many papers reviewed below have been presenting approaches to develop intelligent maintenance systems across different industrial fields with success, but the main statement from these papers is the same: it is still quite challenging for the industrial actors to implement an efficient predictive maintenance system. These challenges are of different natures, but all coming from the complexity of such systems, because they deal with a lot of engineering fields. As an example, the deployment of a predictive maintenance solution on a specific machine will involve knowledge on the process, mechanical understanding of the system and related to the failure modes, knowledge on data collect, storage, analysis, and the place of the user must be taken into consideration: interactions, visualizations,

alerting.

To illustrate this statement, the existing standards and methodologies for PHM implementation help understanding the full scope of such a system because the different functional blocks are clearly identified; however, its deployment in a real context can be demanding. As mentioned by [Sheppard and DeBruycker \(2018\)](#), the PHM topic is a rather new engineering discipline, and the various fields touched by PHM, such as data management, are constantly technically evolving, making it difficult to come up with a general standard. Moreover, even if the end solution must comply with different industrial contexts, specific local needs and requirements will impact the design of the final system deployed. These local features might impact the end solution and require some extra developments relevant only in this context.

To tackle these challenges, [Garcia et al. \(2019\)](#) proposed a methodology to design a predictive maintenance system, by describing the needs and requirements from the industrial actors. The goal is to have guidelines for implementation of predictive maintenance systems without being focused on a specific industry. Similarly, a framework is proposed by [Schmidt et al. \(2017\)](#), to manage the data through the different information systems available in the industrial context. The methodology and solution presented in this research work use bricks coming from these requirements, as well as parts of the PHM methodology.

A full system is described by [Mourtzis and Vlachou \(2018\)](#). A cost-efficient solution for the shop floor is proposed, using [Raspberry Pi](#) devices and micro controllers, and also proposing state of the art communication between a cloud platform where the analyses are made, and the previous devices through [Open Platform Communications Unified Architecture](#) (OPC UA) protocol. [Ayvaz and Alpay \(2021\)](#) and [Bourezza and Mousrij \(2020\)](#) proposed a system based on machine learning analysis applied on data coming from IoT systems. A solution is proposed by [Cachada et al. \(2018\)](#), based on the PHM principles, with various modules to manage the data such as the integration of augmented reality, to improve the decision-making system.

Three challenges of the current developments are shown and answered through a technical solution by [Christou et al. \(2020\)](#), mainly the scattered data across different information systems, the difficulties to have multivariate analyses and the lack of possibilities to act directly on the production system according to predictions made. From these observed challenges, it is necessary to propose a solution that integrates several blocks to answer the common needs regarding

predictive maintenance, while giving the opportunity to customize it according to specificities that can be encountered in the different industries.

An increasing number of papers are also studying the financial impact of the development and deployment of predictive maintenance solutions. As we have seen previously, it requires multiple investments, related to the ICT, but also regarding sensors and software solutions to process the data. Consequently, companies must be aware of these costs, and compare them with the expected benefits (Tiddens et al. (2020), Arora et al. (2021)). This is even more true for SMEs¹⁶, where any new project needs to have identifiable return on investment, which can be difficult to justify when starting the predictive maintenance journey (Krupitzer et al. 2020). Moreover, in addition to the investments in software and hardware, skilled people also need to work on these topics, creating major changes in any company's organizational structure (Khan et al. 2022).

Finally, one of the key elements that appear in the previous papers and in Isaksson et al. (2018) is the benefit to use open standards, and open-source software, because it allows a high flexibility for the development of all these applications. It also answers partially the issues regarding costs mentioned previously. This flexibility is required in the industrial context because there are specific needs and requirements. Therefore, and it is illustrated by the papers, specific developments are made to implement the most efficient systems (Achouch et al. 2022), making it difficult to implement such solutions in different contexts. This also constitutes a major challenge because it is quite difficult to develop non-domain-centric applications. Consequently, as discussed in introduction and in this paragraph, the flexible aspect of the predictive maintenance system must originate from the tools used to apply the methodology behind it.

2.4.2 Predictive maintenance in automotive industry

The PHM Society website proposes articles tagged as automotive industry topics, but most of them are dealing with embedded components within a vehicle, and not the production systems used in automotive industry, which is the topic of this thesis work.

Brown et al. (2009) proposed a diagnostics-prognostics solution to estimate in real-time the RUL of an Electro-Mechanical Actuator (EMA). When the RUL is estimated, and depending on the remaining time the vehicle needs to operate, a reconfigurable system is designed so that the EMA remains in suitable condition

¹⁶SME: small and medium-sized enterprises

2.4. APPLICATIONS OF PREDICTIVE MAINTENANCE

for the rest of the vehicle mission. In the presented use case, it is done by reducing the input current of the motor, and by doing such, the RUL is increased, while the efficiency of the system is decreased.

A prognostics system based on the Cox Proportional-Hazards Model is proposed by [Sankavaram et al. \(2016\)](#). This model is mainly used in medical research but is applied here using failure data and real-time data coming from the monitored systems. It is applied on two automotive systems, to validate the approach and estimation of RUL. [Kleyner et al. \(2017\)](#) used RUL prediction to estimate when a component will fail, thus reducing the need for cycle testing the robustness of a component. It is tested on Power Electronic Controller and Engine Controller Unit, both systems are used inside cars. The goal is to reduce the number of tests done on these parts, and therefore the costs of testing. However, as mentioned by [Kleyner et al. \(2017\)](#), this method needs to be developed and accepted by the community, because the prognostics need to be accurate enough to be trusted by the industrial actors. This last statement is often true for topics related to replacing part or totally some manual checking by automatic systems. These actions are most of the time required by customers, and therefore any modification needs to be thoroughly reviewed and validated.

Other works exist but tagged as predictive maintenance, as such, most of the time the papers focus on specific parts of the PHM methodology, for instance the data collection and the analyses, or the study of prognostics models on datasets that are available online.

[Einabadi et al. \(2019\)](#) proposed a methodology for maintenance scheduling according to RUL prediction on machined parts in automotive industry. The use of machine learning models, more particularly Neural Networks, allow an efficient estimation of RUL from machine data input (vibrations, temperature, energy consumption). A Bayesian Network (BN) designed from FMECA is proposed by [Brahim et al. \(2019\)](#). The resulting is a BN that can be used for the diagnostics-prognostics steps of the PHM framework, because the system can link back to the cause when a failure happens, and an estimation of a failure event can be made knowing all the probabilities of the tree of failures.

[Voisin et al. \(2010\)](#) proposed one of the first platforms for predictive maintenance in the automotive context (Fiat, Volvo), based on MIMOSA and OSA-CBM standards (improved with several modules). Predictive maintenance was applied by [Sanz et al. \(2021\)](#) in the automotive sector context, in a painting shop of the Volkswagen Group (SEAT plant - Spain). A framework is described, built

on Industry 4.0 tools and Industrial Cloud using Amazon Web Services. Within this framework, several activities are described, from data collect and storage, to providing prognostics results on four industrial cases.

[Fernandes et al. \(2021\)](#) proposed to use Business Process Model and Notation (BPMN) as a way to model the processes linked to predictive maintenance, in the industrial context (Renault Cacia plant - Portugal). It allowed to precisely describe the action plan, as well as the different systems responsible for each activity. In addition, it can be used as training material to involve more actors in such project. [Dremel et al. \(2017\)](#) discussed the journey of Audi AG towards digital transformation. One of the key topics is related to data collect when vehicles are being used, to propose advanced descriptive and predictive analytic. As such, predictive maintenance is considered as a service to be provided to car users, to improve maintenance actions required on cars.

2.5 Synthesis of the literature review

Through this state-of-the-art review, we observed that the PHM methodology is validated to design the various predictive maintenance frameworks proposed in the reviewed papers. The different steps of PHM presented in section [2.3.1](#) are standardized and are most of the time the basis of most of studied articles, even if it is not always mentioned.

Regarding the data and features selection, two approaches are investigated in section [2.3.2](#), based on experts' knowledge and functional analyses, or directly on data by using data-driven techniques to extract knowledge. One area of investigation will be to find the most effective approach, which will most likely depend on the type of failure use case studied. Concerning the diagnostics and prognostics aspect of the PHM methodology (section [2.3.3](#), two main approaches were described, one based on statistical models, and the other one on Artificial Intelligence. Both approaches are efficient in predicting RUL in the reviewed papers, however it strongly depends on the available data and the final objective of the designed system. A benchmark of the different techniques seems necessary when designing a complete predictive maintenance system, as one model might be more efficient in a certain context compared to another one. Finally, we briefly discussed the decision-making aspect of the predictive maintenance system in section [2.3.4](#). This topic is probably the most challenging one within the architecture, as it deals with several issues. Many possibilities exist to propose recommendations as an output of the system, and these can be influenced by the

2.5. SYNTHESIS OF THE LITERATURE REVIEW

initial design of the ICT solutions.

From all these observations, we reviewed the known challenges linked to the practical implementation of predictive maintenance in section 2.4.1, as well as the initiatives within the automotive sector in section 2.4.2. These two topics highlighted some key themes to be considered when developing such solution. The difficulties found in the literature are of different nature, as this topic is multi-disciplinary. Mainly, we observed that the process of developing and deploying predictive maintenance requires new skills not commonly found yet in companies, investments can also play a role in these issues as the first-time costs can be high. The financial issue is especially true for SMEs, and more and more papers are looking to develop cost-efficient solutions. To do so, we discussed the possibility to use open-source software that are more and more used in industry.

For the application of predictive maintenance in the automotive industry, we observed that major automotive companies are working closely on this topic. We discussed in section 1.2.1 the challenges of the automotive sector, but also of its innovative aspect that often impacted the whole industrial world. Predictive maintenance is one of the topics of high interests for car manufacturers and automotive suppliers, and the literature also shown many papers dealing with predictive maintenance of vehicles themselves (Arena et al. 2021). A summary table is proposed in Figure 2.21, to highlight the expected contributions of this research work.

Finally, one of the observations made on the studied papers shows that many deal operationally with a partial aspect of the PHM framework (in the industrial context) or propose a conceptual framework for predictive maintenance. However, considering the requirements and limitations of the industrial world when implementing a full diagnostics-prognostics system that will collect, analyze, and alert users is the core of the challenges discussed previously, and maybe less studied. Such considerations greatly matter, as the economic aspect might infer with results found when experimenting with software and hardware that are not suited for the industrial context. However, in the past years, more research works presented approaches for the development and implementation of a full predictive maintenance system in various industrial contexts. This also shows that the predictive maintenance topic is getting more and more mature, reinforced by the global digitalization of industry and the availability of tools able to shape operationally the theoretical features of this system.

2.5. SYNTHESIS OF THE LITERATURE REVIEW

	Expert knowledge used	Data selection process detailed	Data storage detailed	Data management system detailed	Data-driven approach	Statistical model used	AI approaches used	Historical data used	Sensor data used	Process or shop floor data used	Real-time data used	Model benchmarking	Fault Detection system proposed	Prognostics proposed (RUL estimation)	Industrial use case	Industrial implementation of the system
[Brown et al. 2009]		✓			✓	✓					✓			✓		
[Zhao et al. 2010]					✓	✓				✓			✓			
[Marjanović et al. 2011]					✓	✓			✓				✓		✓	
[Srivastava and Mondal 2015]		✓						✓					✓		✓	
[Liu and Zio 2016]		✓			✓		✓	✓					✓		✓	
[Malhotra et al. 2016]		✓			✓	✓	✓	✓	✓			✓		✓	✓	
[Sankavaram et al. 2016]					✓	✓		✓								
[Kleyner et al. 2017]					✓	✓					✓			✓	✓	
[Lee et al. 2017]		✓			✓		✓	✓	✓		✓			✓	✓	
[Li et al. 2017]				✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
[Baptista et al. 2018]	✓				✓	✓		✓	✓			✓	✓			
[Laloix et al. 2018]		✓														
[Zhang et al. 2018]		✓			✓		✓	✓	✓			✓		✓	✓	
[Brahim et al. 2019]		✓			✓	✓			✓		✓		✓		✓	
[Einabadi et al. 2019]		✓			✓	✓	✓		✓				✓			
[Fernandes et al. 2019b]		✓			✓	✓	✓	✓	✓				✓		✓	
[Nguyen and Medjaher 2019]					✓		✓	✓	✓					✓		
[Zhou et al. 2019]		✓			✓		✓	✓	✓					✓	✓	
[Ruiz-Sarmiento et al. 2020]	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
[Wu et al. 2020]		✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
This thesis	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Figure 2.21: Summary table

2.5. SYNTHESIS OF THE LITERATURE REVIEW

Chapter 3

Proposition and application of a methodology to move from corrective to predictive maintenance

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This chapter is dedicated to describing our predictive maintenance framework, and how it was applied for our industrial application. First, we detail the framework that was developed from the results of the literature review and with the first industrial application chosen for predictive maintenance. In a second part, the data management architecture is discussed, as it is a major part of the predictive maintenance system. Then, we describe the application of this framework on a specific industrial use case. The different stages are explained, from the choice process for predictive maintenance to the results obtained from the application of the framework. Some specific use cases are then discussed, as they have low occurrences in our industrial application. However, their study in the predictive maintenance framework is relevant and pointed out some extra points to be considered for this work. Finally, we analyze the results and the limitations observed during the development of the system, which lead to highlighting some key opportunities to improve the framework and the operational methodology.

3.1 Framework for predictive maintenance

The literature review and the functional analysis proposed in Figure D.1 helped determining the key activities to consider when developing a predictive maintenance system. As a result, to deal with the challenges and opportunities discussed previously, a framework is proposed in Figure 3.1. It is based on the works from Lebold et al. (2003) and the method proposed in IEEE (2017). It takes into account experts' knowledge for machines parameters to be identified and monitored, as well as data-driven methods to be implemented in the condition monitoring and prognostics phases.

This framework was developed and tested jointly with the first industrial use case presented in Section 3.3, where it will be discussed more in details. For each feature of the system, major activities to develop were identified, as well

3.2. OPERATIONAL ASPECT OF THE FRAMEWORK

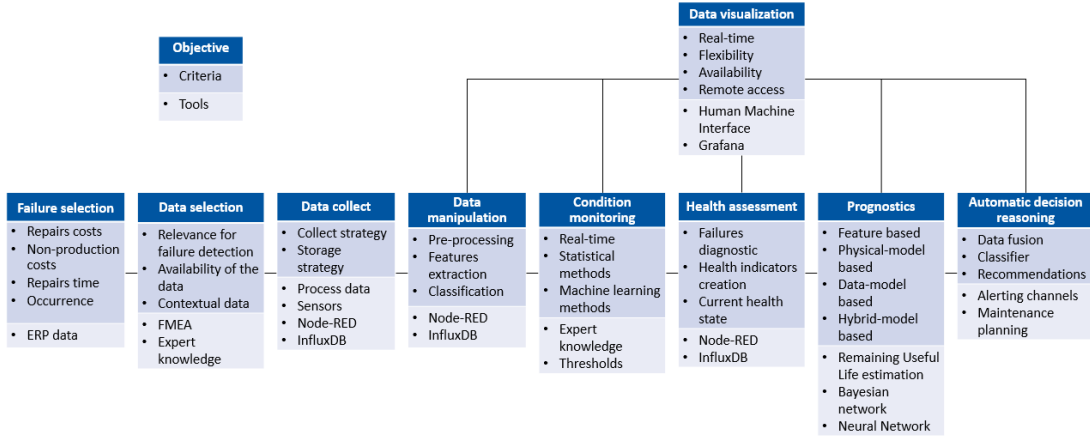


Figure 3.1: Framework for predictive maintenance

as the engineering or computing tools that are key contributors to achieve this development.

Below is proposed a summary of the concepts represented in the figure:

- The objectives that are the categories coming from the PHM framework
- The criteria, which are the inputs of each category, and help understanding the requirements and the possibilities
- The tools are the technical assets used to develop each category, they can be of different types: data, software, concepts

After detailing the key concepts of the framework proposed for the implementation of predictive maintenance, we will next discuss how it was applied for our industrial application. This will help detailing the different steps of the methodology and explain how it can be implemented in the industrial context.

3.2 Operational aspect of the framework

The operational methodology helps understanding the process behind the implementation of the system. It makes the link between the tools mentioned in the framework and the different activities related to the development and deployment of the predictive maintenance system.

3.2.1 Data management architecture

To understand how the framework will be used in the industrial context, it is first necessary to introduce the data management architecture that was set. The global architecture is shown in Figure 3.2.

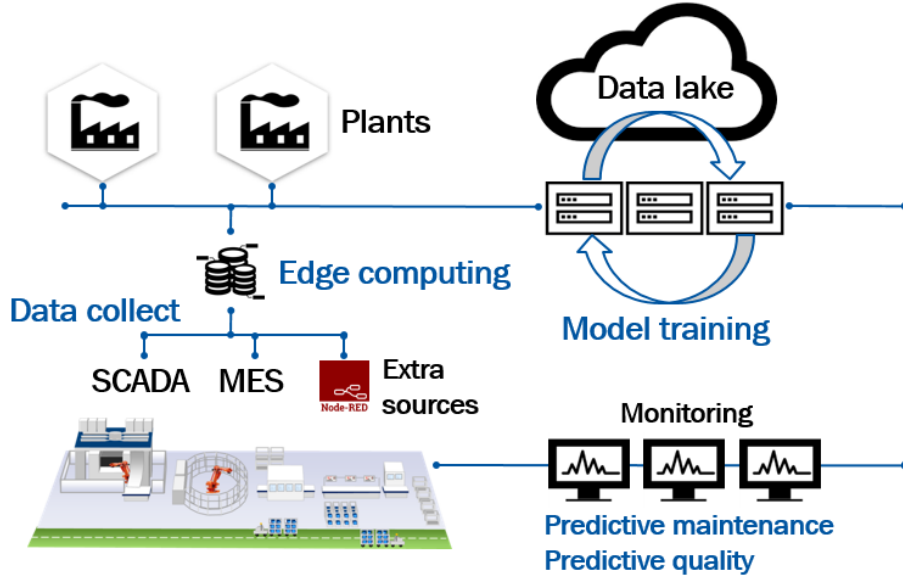


Figure 3.2: Architecture of the information system

The architecture has two levels: the plant's level that is dealing with data locally, by collecting, storing, and analyzing data from the plant's machines. The second level is global, at the company level. Here the data is collected from each plant, to create global applications such as dashboards or data analyses.

- The plant level is composed of the local SCADA (Supervisory Control And Data Acquisition) and MES (Manufacturing Execution System) systems. In addition, extra systems are deployed, such as the Edge Computing, which incorporates three open-source software: Node-RED, InfluxDB and Grafana. The main benefits of these tools are the high flexibility and the important number of features that are proposed and maintained by the community. This package allows collecting, storing, and making analyses on data, as well as creating visualization dashboards and alerting systems via various communication channels
- The company level, which is composed of a *Data Lake* that gathers data from all the plants. The goal is to work on aggregated data to train models of prediction, for both quality and maintenance services. Then, these trained models are reinjected at the plant's level, to monitor the production

systems locally

The main benefit from this architecture is to be able to analyze the collected data locally (i.e., within the plant) from the different data sources. Once this local analysis is carried out, interesting data can be moved at the global level, where more advanced data analyses are performed. The main benefit is the reduction of the use of the bandwidth, by not sending all raw data into the data lake, and thus it is possible to decrease its size. Indeed, the costs of implementation and maintenance get higher with the size of the data management system.

As stated by [Cara et al. \(2019\)](#), the SCADA system in place (*DASIP*¹) ensures the stability of the quality of the manufactured parts, by using a knowledge-based corrective approach. However, it was not designed for proposing a solution for real-time monitoring of health statuses of the production system. Nevertheless, the methodology employed to develop the tool is based on FMEA, and critical parameters are monitored to ensure a good process control, which is a strong basis for starting the implementation of a predictive maintenance approach. The MES (*PES*²) also provides some important context data that can be attached to data from the process and the machines. For instance, knowing the status of the machine, the name of the part produced, or the number of parts scrapped in a given period of time can help defining extra indicators. This new information can help classifying other data for example.

Consequently, our Edge Computing system was tested and implemented within plants, to make the link between different applications and collect data from various sources. This system is the basis on which was built the predictive maintenance system in our industrial application. The detailed architecture is shown in Figure 3.3. The standard install of this system is done on a Virtual Machine within the plant's server (similar to Fog Computing) but was named Edge Computing because the same system can be installed locally on an industrial computer. The server is physically located in the plant, on both the machines' network and the global network of the company. As such, it is accessible through the network, and from any location worldwide. This system allows making the convergence between IT and OT (Operational Technology), as it incorporates IT tools that interact with OT devices. As seen previously, IoT devices are also part of the enablers linked to such convergence.

¹DASIP: Data Acquisition System for Industrial Processes

²PES: Plant Execution System

3.2. OPERATIONAL ASPECT OF THE FRAMEWORK

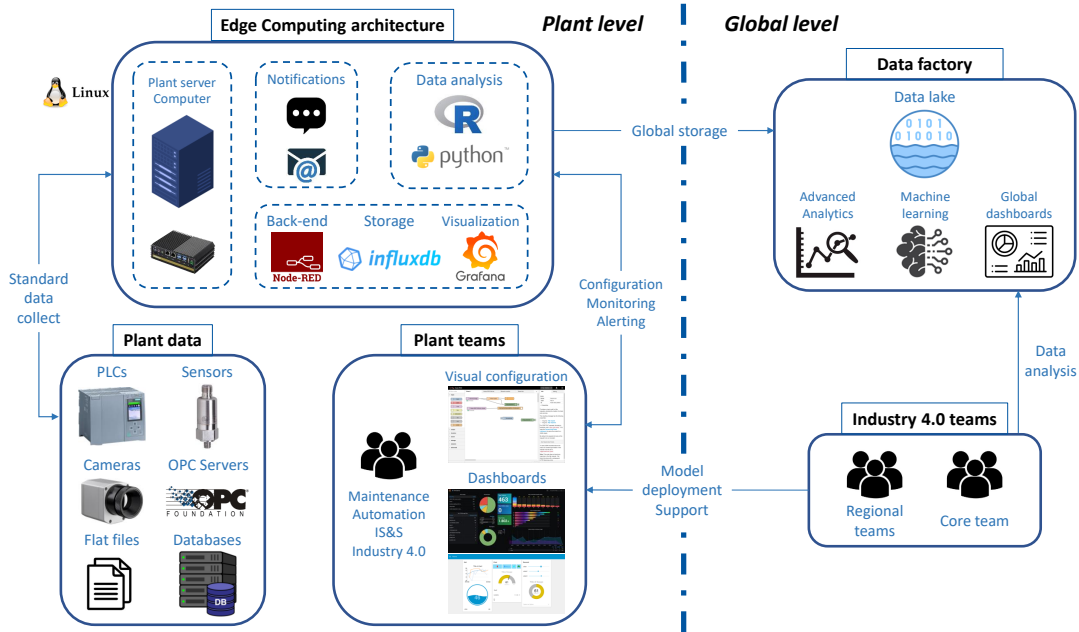


Figure 3.3: Architecture of the Edge Computing system

Node-RED (O’Leary and Conway-Jones 2013) is the center part of the system. It is a visual programming tool, where nodes that have different functions interconnect to create an application that is most of the time linked to IoT. Node-RED is using JavaScript (Crockford 2008) as its programming language, and because it is open-source, many nodes are created and then shared by companies or users. In most of our use cases, the application is connecting directly to the PLC of the machine through the network to collect its data. It has many benefits, because there is no need to modify the programs inside the PLC or stop the machine to install such monitoring system. The software collects the data and makes the connection to the database to store it. We also use it to make the analyses on data and the real-time detection of failures.

InfluxDB (Naqvi et al. 2017) is an open-source database. It is optimized for *time series* data collect. It allows creating very efficient monitoring of what is happening in real-time. It is possible to set data retention policies, meaning that data will be erased cyclically based on the chosen time window.

Finally, Grafana (Chakraborty and Kundan 2021) is the software that we use in order to create dashboards. It can connect to many databases, including InfluxDB. As it is also an open-source software, many new visualizations are proposed by the community, as well as the developers of the solution.

3.2.2 Presentation of the proposed approach

To investigate machines failures with a predictive approach, our first step consists in editing a Pareto of the most impacting breakdowns on the production system. Criteria used are the total breakdown time, occurrence and costs of both repairs and non-production time. It is done by analyzing the *ERP*³ that contains all the data from breakdown events: time to repair, costs, parts used to repair. Therefore, the methodology can be defined as cost-oriented because the final goal is to reduce the financial impacts of unplanned downtimes. It is important to involve the experts (maintenance, process, automation) during this first step, to validate the list of use cases and to collect the feedback from their experience.

Next, we need to get a first hint about the degradation processes involved in the selected failure(s), which can be determined from the FMEA. In our case, we are using PFMEA that is process oriented. Failures risks are listed, giving also a first idea of which parameters should be monitored to detect each issue. Experts' knowledge is a very important input, as mentioned by [Baglee and Jantunen \(2014\)](#), it is the first entry point for understanding failure mechanisms. Ideally, these inputs should help capitalizing on their experience, and lead to providing extra knowledge such as shown in Figure 2.11.

After that, the availability of the chosen data needs to be studied on the selected case(s). In this context, availability means that the information is made available digitally, and that the data management system is capable of connecting to the source of this data, and collect it using a specific communication protocol. We will see that in industry, PLCs are often the main source of data, as they contain all the instructions for the process, as well as sensors' data. If the data that must be collected by the monitoring system is not available, several possibilities exist as shown in Table 3.1.

A first strategy for data collection and analysis also comes with this study, in terms of frequency of collect, and data manipulations to extract interesting features. In addition, a classification of the data can be made upon various criteria. The idea is to add extra information to the collected data, this process is called *tagging*, and it brings many benefits. The main objective is to define specific contextual information attached to the data, for instance it can be linked to the name of the machine, the manufacturing process, the status of the system. Efficient tags can provide many insights around the data, and enable advanced

³Enterprise Resource Planning

3.2. OPERATIONAL ASPECT OF THE FRAMEWORK

Table 3.1: Solutions for data availability

Cause of unavailability	Solution
Data does not exist	Study the implementation of extra sensors to collect the necessary data Create the required data from raw data (feature engineering)
Machine not connected	Add network card to PLC to access data Use OPC server to access data Use an edge device connected to both the machine and company's network
Interoperability issue	Use a different communication protocol to address the data Export and read data through a flat-file structure

features linked to data visualization and analysis. For example, data classification makes possible the use of supervised machine learning techniques.

After this phase of data collection come different steps of data monitoring. Many methods exist to construct knowledge related to changes in data, in order to estimate the state of the monitored system (section 2.3.3). Some approaches are proposed in Table 3.2. The main goal is to develop a first system that will help detecting signals or patterns announcing a possible occurrence of the monitored failure.

The health assessment step from the framework is designed to investigate more in detail the anomalies found in data, and if possible, to create Health Indicators (HIs) that represent the evolution of the behavior of the system. As seen in the previous table, some approaches do not necessarily require failure data to implement a monitoring system. However, as the solution will eventually face the failure that it was designed to detect, this assessment step can help validating and improving the methods in place. As a result, depending on the choices made in the previous stage of the methodology, condition monitoring and health assessment can be done jointly.

In the prognostics phase, methods are applied to HIs to automatically detect changes in the data, and therefore a modification in the behavior of the system. The objective is to use these patterns previously discovered to estimate when

3.2. OPERATIONAL ASPECT OF THE FRAMEWORK

Table 3.2: Data-driven approaches to investigate failures

Approach	Detail	Main features
Thresholds	Use experts' knowledge to put limits on the data (example: ISO 10816-3 for vibration)	<ul style="list-style-type: none"> • Easy to implement from start • Not necessarily suited for complex failures
Run-to-failure	Record failure event and analyze its data	<ul style="list-style-type: none"> • Efficient to identify failure patterns • Not suited for failures with low occurrence
Anomaly detection	Using healthy data	<ul style="list-style-type: none"> • Easy to implement from start • Requires knowledge about healthy state • Difficulties linked to anomalies identification
	Using failure data	<ul style="list-style-type: none"> • Train model to detect anomalies automatically • Can require many events for efficient training • Not suited for failures with low occurrence

the system will reach a critical point. We have seen previously many methods able to provide such information, but the key aspect here is to consider the clear identification of the state of the system, to give valuable insight to the users. The result of prognostics can be a detection of a signal that previously led to a failure, or an estimation of the time left before the failure happens (RUL).

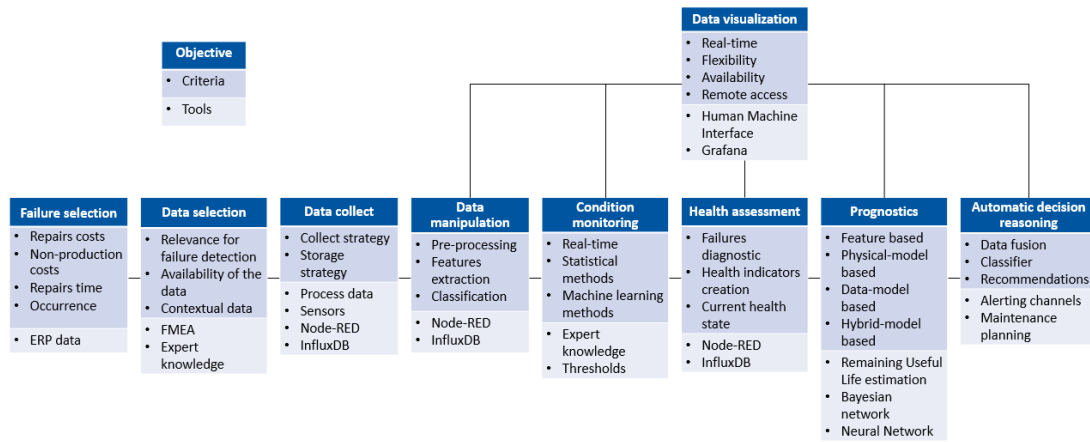
The last part of the process is focusing on the development of recommendations, based on the results from prognostics. The goal is to automatically propose information or actions to the end-users of the solution. Many outputs can be considered from this step, such as alerts, maintenance recommendations, automatic modifications of process parameters, maintenance planning. The use of one or several outputs depends on many factors that are evolving throughout the development of the solution, but their availability as features of the predictive maintenance system is a necessity to propose efficient solutions.

Finally, as observed in the framework, data visualization is placed on top of many activities. Visual observation of the data is one of the most important aspects of any data-driven system, especially for predictive maintenance where

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mainly time series data is used. As discussed previously, failure mechanisms are evolving with time, therefore it is important to have records of data following these trends. Data visualization often includes several "layers" that are designed for different users and linked with various type of data. As an example, data visualization for exploration by a data scientist will be very different compared to a visual dashboard designed to share results from prediction to maintenance operators.

We propose to put the figure of the framework a second time below, to ease the understanding of the text above.



In the next section, we discuss the application of this framework on a first industrial use case, after understanding the different steps of the implementation of predictive maintenance.

3.3 Application of the framework

The first application of the framework took place in the plant located in Compiègne (France). The proximity between the plant and the research & development center makes it attractive to test locally the solutions proposed by the Digital Manufacturing team. It is important to mention that the CES division is composed of nearly 40 plants (Figure A.1), and that consequently the developments made and tested in one plant will necessarily generate interest for other plants. The main reason behind this statement is that the machines and processes used within plants are the same, even if some machines designs may differ from one region to another. In the context of the company, we call regions the three major areas of operation: Asia, Europe, and Americas.

3.3.1 Use case identification

As discussed in [Chapter 1](#), the competitive nature of the industrial context requires the choice approach for dealing with failures to be pragmatic. Consequently, the proposed procedure is above all cost-oriented, meaning that each use case that will be worked on needs to generate a payback when implementing a predictive system. As discussed in the previous section, the first step of the process is to understand what the most impacting failures on the production systems are. The main goal is to answer the questions below:

- Does the failure have high occurrence?
 - If so, then failures that have a high ratio of breakdown time and repairs costs must be prioritized
 - Else, failures that have the most financial impact when they occur must be prioritized
- Is the failure impacting a majority of plants?
- Is the failure known by experts? Has it been studied before?
- Is data about the failure available?

In this local context, we are not considering the second question, as the study was first conducted within one plant. However, the analysis of the impact of this first use case globally is discussed later.

Figure 3.4 below describes this choice process.

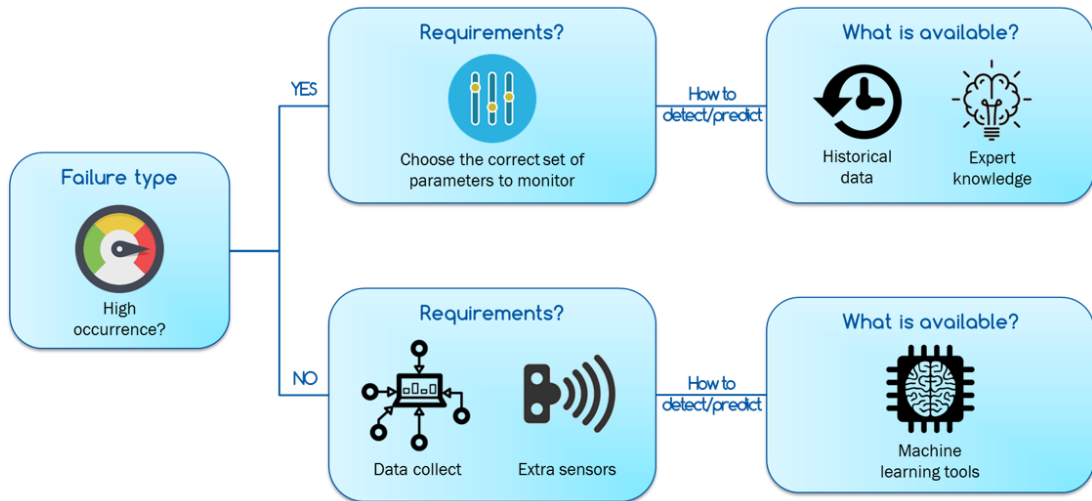


Figure 3.4: Operational choice process

3.3. APPLICATION OF THE FRAMEWORK

The first step of our experimentation was to study the breakdowns data from the plant, during the whole year of 2018. It has been done by extracting data from SAP⁴, which is the ERP system used by the company. ERP systems contain many data, in our case it also incorporates data from the maintenance department, such as the number and costs of maintenance interventions, but also various details about failures.

Some visualizations were created in order to understand better the extracted data, Figure 3.5 shows the Pareto created for the plant. As it may not be very visible here, this graph shows for each type of breakdown, its total time and cost of spare-parts for 2018. The analysis is made on all the machines of the plant, including utilities. A complete detail of the production process can be found in Appendix C. The failure that is ranked first here is related to the welding units located on the finishing centers of the plant, which represents approximately 15% of the total breakdowns in terms of costs and time for the plant.

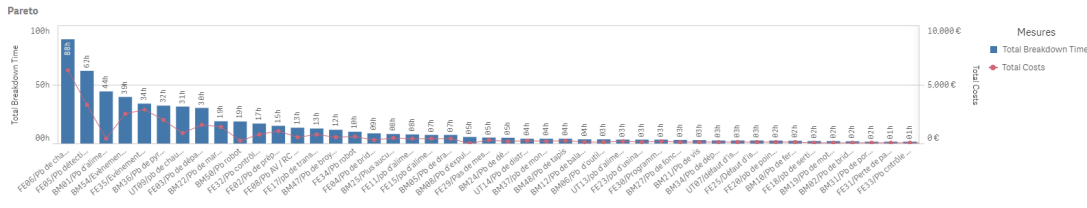


Figure 3.5: Breakdown Pareto of Compiègne plant 2018

The use case was validated with the local plant’s team, through a list of impacting breakdowns, and the choice to work on failures with high occurrence. It was also validated with other plants of the division, to be chosen as the first use case for predictive maintenance. The process is detailed in Figure 3.6.

3.3.2 Failure understanding

We combined experts’ knowledge about both process and failure, as well as data from the PFMEA⁵ done on the welding unit. An extract is shown in Figure 3.7. Two main components are at stake during the chosen process, the band heater that will heat the part to be welded on the tank, and the thermocouple that is used for the regulation of the temperature. A regular manual verification of the temperature is done by the maintenance team, to ensure that the thermocouple is providing accurate information to the system. A failure of the thermocouple

⁴SAP: Systems, Applications and Products in Data Processing

⁵PFMEA: Process Failure Modes and Effects Analysis

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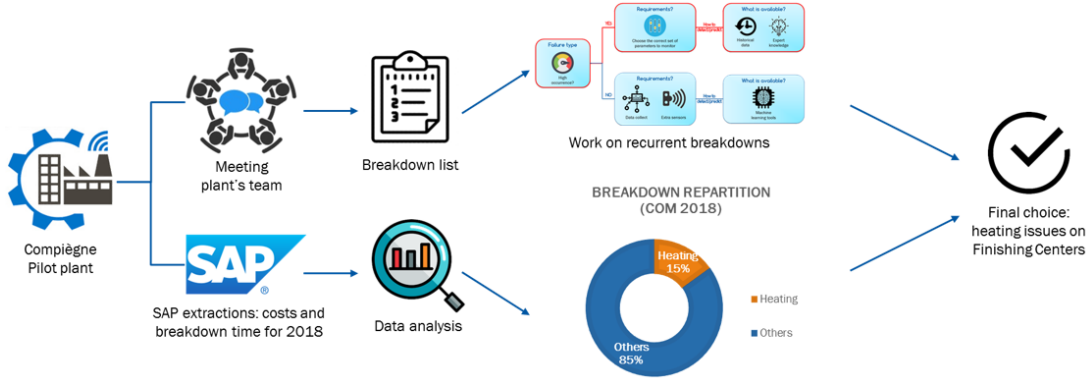


Figure 3.6: Choice process for the first use case

means that the regulation system will overheat, and damage both the band heater and the part heated (called mirror). A failure of the band heater will lead to a machine stop due to incapability to perform welding.

Process	Equipment	Process #	Equipment #	Process Operation / Requirement	Potential Failure	Mechanism(s) of Failure and related Potential Cause(s)	Potential Effect(s) of Failure	Current Process Controls Prevention	Current Process Controls Detection
Welding	Penetrating hot plate welding	110	40	Weld penetrating components	Component damaged	Wrong temperature	Internal - Scrap (7) External OEM Plant - Rework (6) End User - Fuel leak (10) or DEF leak (8) or Permeability not assured (10)	Preventive maintenance Machine set-up file	Visual inspection (8) Temperature process parameter alarm (CritiPar) (1)
Welding	Penetrating hot plate welding	110	40	Weld penetrating components	Component damaged	Wrong Pressure (at any of the 4 phases)	Internal - Scrap (7) External OEM Plant - Rework (6) End User - Fuel leak (10) or DEF leak (7) or Permeability not assured (10)	Preventive maintenance Machine set-up file	Visual inspection (8) Hot Plate Welding Pressures process parameter alarm (CritiPar with Block Program) (2)
Welding	Penetrating hot plate welding	110	40	Weld penetrating components	Component damaged	Wrong Time (at any of the 4 phases) (including withdrawal time)	Internal - Scrap (7) External OEM Plant - Rework (6) End User - Fuel leak (10) or DEF leak (8) or Permeability not assured (10)	Preventive maintenance Machine set-up file	Visual inspection (8) Hot Plate Welding Time process parameter alarm (CritiPar) (2)

Figure 3.7: Extract of PFMEA for the welding unit

In Table 3.3, we detailed the possible failures that can be observed on the two components, by taking into account the issues that can be caused by the process.

The internal rule within the PLC⁶ that is monitoring the temperature has several effects. It is verifying the temperature sent by the thermocouple during the welding operation, as it should be within a certain range around the temperature setpoint. If the observed temperature is outside of range for more than one second, then the weld is considered as poor, and the part is scrapped. If the temperature continues to evolve outside of the range, then the maintenance team will plan a corrective intervention to check the thermocouple.

⁶PLC: Programmable Logic Controller

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Table 3.3: Potential failures list on welding units

Component	Failure mode	Failure cause	Failure effect	Current control
Thermocouple	Damaged wire	Repetitive bending	Wrong temperature data	PLC internal rule*
		Cable cut during process	No temperature data	Zero threshold
	Sheath breach	Overheating from band heater	Wrong temperature	PLC internal rule
Band heater		Physical damage during process	Wrong/no temperature	PLC internal rule Zero threshold
		Damage during movement	Overheating Material lost	Visual control
	Damaged wire	Loose implementation		
		Cable wear Process movements	Wrong/no heating	Regulation loop
	Electrical issue	Ageing Repeated heating cycles Short circuit	No heating	Regulation loop

*Temperature data is checked with a threshold, during the welding operation

Several automated rules are programmed within the PLC, to ensure that the process runs smoothly, according to rules edited by experts. However, they are not necessarily efficient for maintenance activities, as they will alert after the issue is observed, or when the rule is triggered.

After this first step that allowed a better understanding of the failure, we will next discuss the data collection phase.

3.3.3 Data collection

The study of the failure modes, with the help of several experts, helped determining a first list of parameters to be monitored, as shown in Table 3.4.

Below, we provide more details regarding the collected data, as well as the data management strategy:

- The temperature data is provided by the thermocouple and used in the PLC program for various purposes. We collect it at the fastest rate allowed by the communication protocol
- The temperature setpoint is a parameter linked to the process, and represents the target temperature for the band heater, and the value that must be measured by the thermocouple. We collect this data only when it

3.3. APPLICATION OF THE FRAMEWORK

Table 3.4: Collected data

Parameter	Unit	Type	Detail	Collect frequency
Temperature	°C	Integer	Data used to regulate the heat	50ms
Temperature setpoint	°C	Integer	Necessary temperature for the welding operation	On event
PID load	%	Float	Percentage linked to chopped powering of band heater	50ms
Regulation switch	-	Boolean	Welding operation ON/OFF	50ms
Scrap information	-	Boolean	Information on scrap	On event

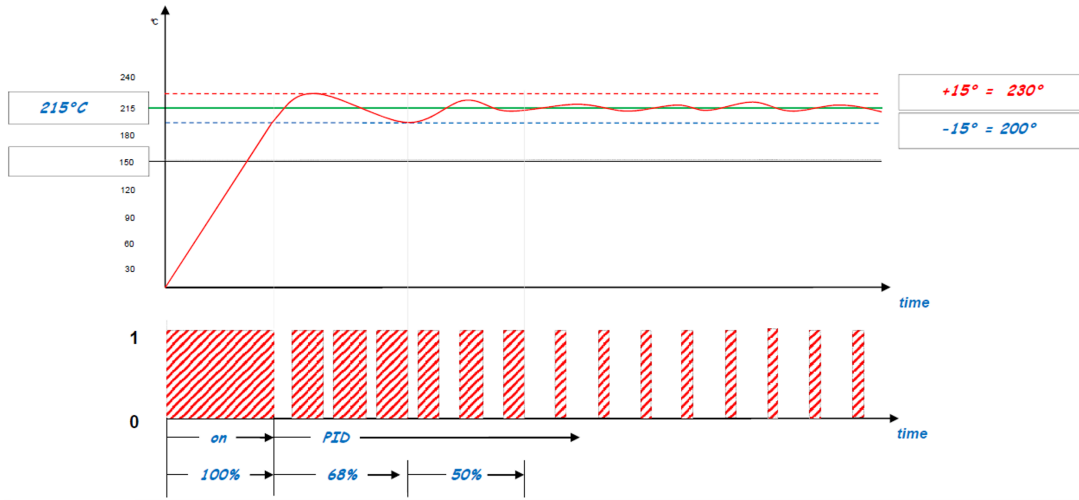
changes (change of production) or before it is erased due to the retention policy of the database

- The PID load corresponds to a percentage of time where the band heater will be powered by the regulation loop. A detail of how it works is proposed in Figure 3.8
- The regulation switch is providing the information that the welding operation is used or not during the process. As the machine can process multiple products, some operations may be offline, and therefore the data collect is not necessary
- The scrap information is given when the temperature crosses to internal PLC rule during the welding operation. Collecting this information can provide insight on repeated failures of the welding unit

Most finishing centers are different from one another, depending on the type of product they deal with. Indeed, the design of the product will also impact the design of the machine. They generally have around 10 welding operations, meaning that we collect about 50 parameters per machine to monitor this issue. All the data that we collect for this application comes directly from the PLC of the machine.

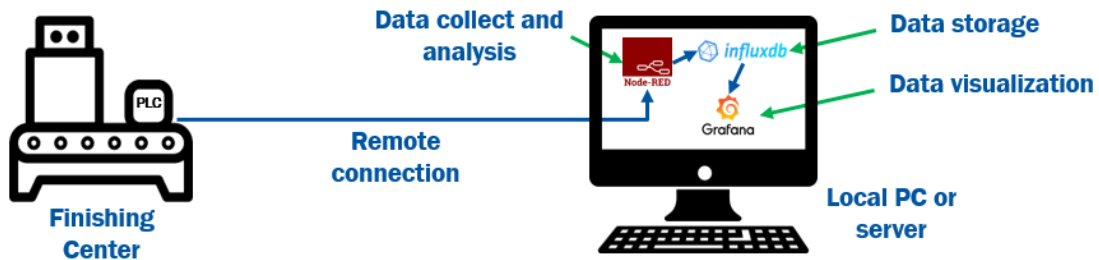
After defining the dataset that needs to be collected from the machines, we started to make some analyses on the data.

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3.3.4 Data exploration

Figure 3.9 illustrates how we access, collect, analyze and visualize the data from the machine, using the Edge Computing solution described previously.



One of the early observations on this use case is that despite the high occurrence nature of the failure, it can still be challenging to catch such event. Failure events can be spaced in time by several months, or a few hours. To deal with such uncertainty and be efficient we packaged this first application and deployed it on 15 machines in different plants around the world. The goal was to collect as much production data as possible, to get run-to-failure events.

In a time window of 3 months, we were able to observe and collect failure events. Cooperation with the local teams was essential, to get their observations and feedback, to help understanding the changes in data and link them with the physical world.

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Figure 3.10 shows the early detection made before failure of the thermocouple. Very high or low temperature peaks appeared, which last less than 300ms at the beginning of the deterioration process. These events are stored inside the database, and appear directly on the visualization graph, which enables a visual control (vertical red lines). As explained before, in the current process control of the machine, parts are scrapped when temperature values are too far from the target, during the welding phase. However, this rule is not considering the temperature data outside of the welding phase. Hence, early identification of the temperature peaks is the basis of the monitoring control that was developed to detect these issues.

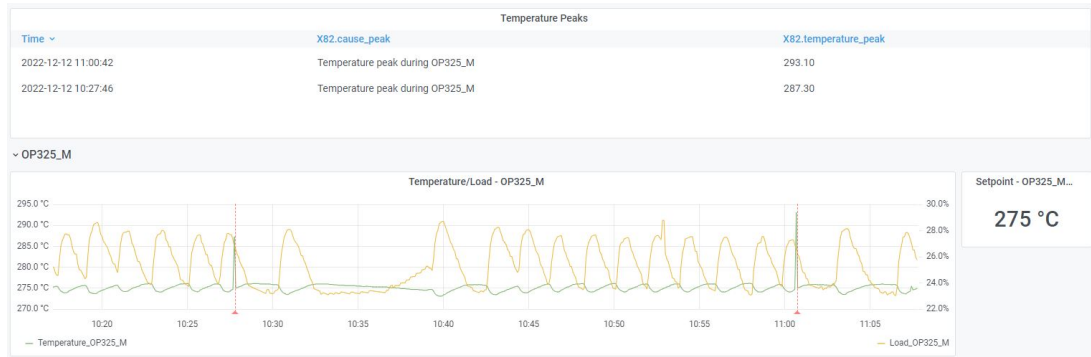


Figure 3.10: Temperature peaks detection

By looping back to the physical aspect of these events on the thermocouples that broke, we observed that temperature peaks appearances were linked to cable wear. As shown in Table 3.3, repeated movements are a cause for wire damages. In the early phase of the failure, the thermocouple will provide wrong temperature data on short periods (peaks observed) that correspond to micro-cuts in the temperature signal.

Thanks to this first detection, experiments were done by observing the evolution of the damages until the cable fully breaks. In this sense, the temperature peaks observed will last longer with time, and eventually generate scraps through the internal PLC rule. For this use case, the failure of the component has a huge impact on the quality of the produced parts. Therefore, solving the issue on the maintenance side also had benefits for the quality department.

In the next section, we detail the solution that was designed, in order to propose an efficient monitoring of this issue to the plant's team.

3.3.5 Proposed solution

The detection rule was designed to detect and count the temperature peaks. A threshold was defined for the number of peaks detected that can be accepted before alerting the maintenance team on the potential failure. That allows the maintenance team to organize corrective interventions prior to machine down-time. An example of failure detection is shown in Appendix E.

An alerting dashboard is made to monitor efficiently each machine, and determine the number of peaks that appeared on each welding operation during a fixed period of time, proposed in Figure 3.11. The system is able to send alerts via e-mails as in Figure 3.12 and SMS (through Node-RED) in order to warn the maintenance teams.



Figure 3.11: Alerting dashboard

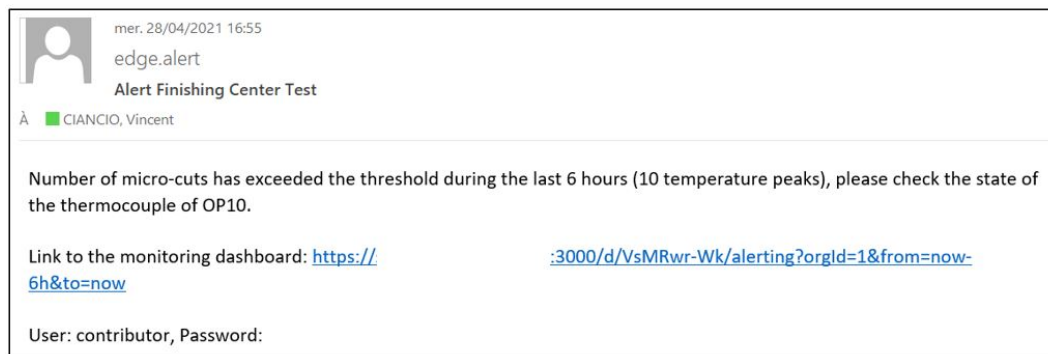


Figure 3.12: Example of email alerts sent

The main outcomes of the solution are the following:

- Monitoring and detection in real-time of the anomalies related to wiring issues
- Visual monitoring for the plant's team
- Early alerting for the maintenance team to plan corrective actions

- Reduction of the investigation time on the failures, as the alerting system provides information on which machine and which thermocouple is impacted

This first use case served as the basis of experimentation on the different parts of the framework for predictive maintenance, and to validate and improve the data management system. However, investigations made on the band heaters brought fewer results, but provided some valuable insights regarding maintenance data from the ERP system, as well as defining a process to deal with failures having low occurrences on the Blow Molding Machines. We will discuss these two topics in the next section.

3.4 Case of failures with low occurrences

A thorough analysis of maintenance data has been done at the global level of the 40 plants. The main objective was to apply the methodology previously tested locally, to determine globally the most impacting use cases and potential candidates for predictive maintenance. In parallel, failures linked to band heaters proved to be difficult to catch during production phases. To validate the interest of keeping the investigation, a test bench has been created to reproduce the failures. Finally, motivations behind the investigations done on the most impacting failure, to implement vibration and hydraulics analyses, are discussed.

3.4.1 Global maintenance data analysis

Investigation of maintenance data was conducted through several activities:

- Manual extraction of work orders⁷ data from all plants
- Collect local feedback from plants regarding pain points on maintenance activities
- Automatic analysis of work orders using *Natural Language Processing* (NLP)

The first point relates to the analysis of work orders from the plants. Work orders are the documents edited by the maintenance teams when any maintenance activity has been carried out. They include the date and duration of interventions, the equipment, the type of failure, use of spare parts, and an optional comment section where the problem encountered can be detailed. This

⁷Work order: request document that describes the corrective maintenance intervention that needs to be carried out

3.4. CASE OF FAILURES WITH LOW OCCURRENCES

work allowed to determine a first list of topics to be addressed, where they were split into two categories: low occurrence with high costs and high occurrences with low/moderate costs. Figure 3.13 illustrates the last statement, as discussed previously the methodology is cost-oriented. The topics having low occurrence and low costs are not suited for implementation of predictive maintenance, as the costs and time to deploy a solution will be greater than the outcome. Similarly, the topics having high occurrences and high costs should be very limited, as they are most of the time due to errors in the design of the equipment. As such, these last topics are most of the time dealt with very early when the production system is installed.

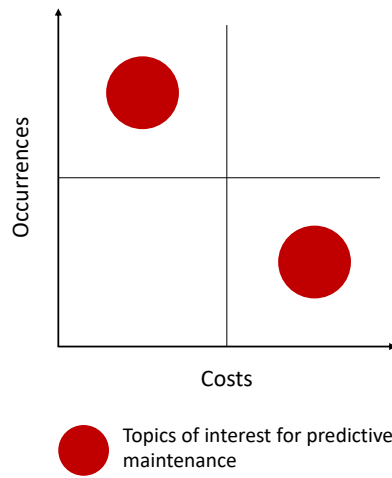


Figure 3.13: Topics considered for predictive maintenance

The second activity is part of the experts' knowledge collect, in this case plants' maintenance and production teams were interviewed to understand and aggregate their feedback on important topics to address.

Finally, in addition to the first two steps, an analysis on the previously mentioned comment section of the work orders was done. One of the major challenges of the analysis was to deal with many languages within the dataset. To obtain the results shown in Figures 3.14, 3.15 and 3.16, we first cleaned the dataset. We then translated automatically to English this data from the 16000 work orders using an API from the Google translate application. As the data is entered manually, many typos can be found, and in addition the translation being imperfect, it brought many false words that were filtered as much as possible. Three analyses were made using an NLP model, to plot the occurrences of single words, pairs of words and trigrams. The main goal was to bring new insight and confirm the data obtained from the first two activities. It is also possible to represent

3.4. CASE OF FAILURES WITH LOW OCCURRENCES

To proceed on a more detailed analysis of this topic, two main activities were defined:

- Investigation on production data, by adding current sensors
- Reproduce failure modes using a welding unit test bench

The parameters collected on the welding units (Table 3.4) were expected to be sufficient to detect failures on the band heaters, based on the analysis made with experts. However, as the PID load is a value used to control the powering of the band heater, the result of this action is missing in the dataset. That is why it was decided to add current sensors to monitor closely the behavior of the powering of the band heater. Using the maintenance data, the focus was made on the machines that had similar issues in the past.

To have more chances of collecting data related to failure events, tests were made in parallel on a welding unit test bench located in the research center (α -Alphatech) in Compiègne. The test bench is shown in Figure 3.18. It is composed of two welding operations, called "complex" because they have two band heaters. One is used to heat the part of the tank that receives the welded component, and the other is dedicated to heating the component. We performed the tests on one operation i.e. on two band heaters. For the sake of reproducing what can happen in production, both band heaters were new.

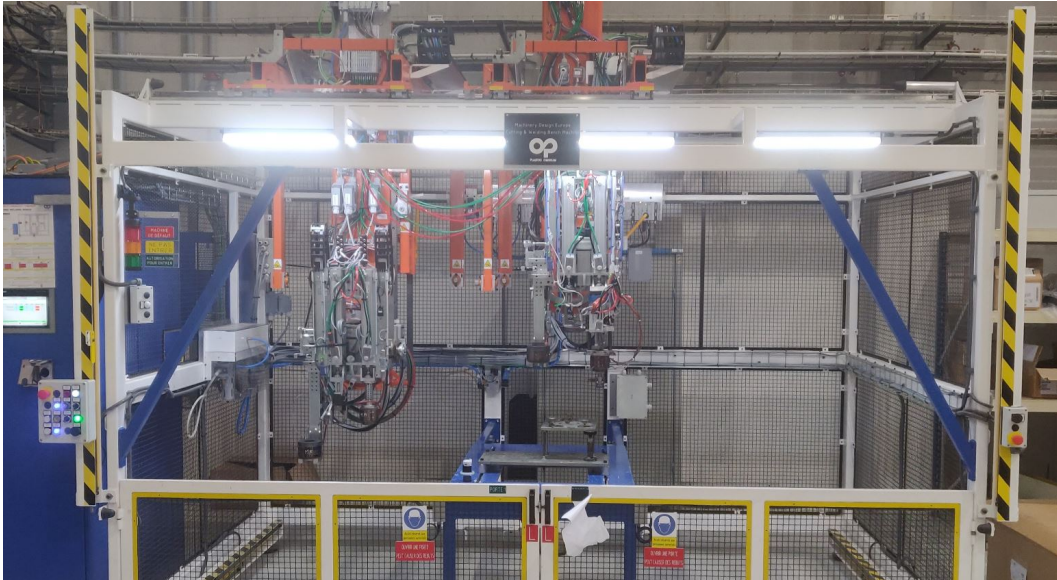


Figure 3.18: Welding unit test bench

3.4. CASE OF FAILURES WITH LOW OCCURRENCES

Table 3.5 summarizes the tests done to replicate failures, as well as the assumptions made on the causes and effects of failures on data behavior.

Table 3.5: Tests to replicate failures

Failure mode	Experiment	Expected results
Electrical issue	Repeated heating/cooling cycles	Change in resistance before failure Change of the shape of the temperature curve
Mechanical issue	Wrong installation of band heater Repeated stretching tests	Increase of regulation load
Damaged wire	Not possible with test bench	Peaks on current data

The tests related to damaged wires were not performed, due to the dangerous nature of these components. Indeed, we are dealing with temperatures up to 300°C, and extreme testing could end up generating risky situations or even create fires. Similarly, we did not push the temperature higher, as it does not reflect the use in production, and could also potentially create hazardous situations.

Some explanations and results are proposed in Appendix F.

Figure F.1 shows the solution used to create cooling on the band heaters. A simple circuit was created, using the available compressed air of the machine and two tubes operated by their respective valve. As both band heaters had different thermal characteristics, it was necessary to have one valve per component. The Edge Computing software were used to create the repeated cycles shown in Figure F.2, as Node-RED is not only able to read data from PLCs, but also to write them. This makes it possible to create scenarios to operate any machine equipped with a PLC. In our case, the process was the following:

- Start the heating phase up to 300°C
- Stop the heating (regulation switch off)
- Start blowing air by opening the valve
- Stop blowing air when temperature reaches 50°C
- Restart first step

This allowed to create many cycles to try to deteriorate the band heaters and generate a failure. The main objective was to accelerate ageing of the component.

3.4. CASE OF FAILURES WITH LOW OCCURRENCES

In production, some failures were observed during the restart of the machine, as the mirror needs to be heated from 50°C to the temperature setpoint, usually between 250 and 290°C. However, we were unable to observe changes in the behavior of the band heaters after hundreds of cycles, even less to generate a failure.

Figure F.3 shows the mechanical tests done on the band heaters. The idea behind these was to reproduce wrong conditions that can happen in production, for instance when maintenance is performed to change the band heater, and a failure is produced by this replacement. The first test involved not tightening the band heaters to their respective mirror and starting the regulation phase, to observe the impact on data. The second test was strength-based, as we stretched the band heater repeatedly before installing it again and running the regulation. Both tests provided no results, as no change in the behavior of the band heaters was observed.

Finally, as no failures were observed in production, and in addition to the results given by the tests, the study was put aside. The main difficulty being the assessment of the maintenance data coming from the 40 plants, it has been assumed that the failures reported were either due to wiring issues, or a combination of several factors that we were not able to replicate. However, by using the monitoring developed for the welding units, primarily with the load of the PID, we can detect issues that can impact the band heaters. In the case that the load is high during the regulation phase (after reaching the temperature setpoint), the plant's team can either check that the parameters of the PID are correct, or else if any issues appeared on the band heater itself.

3.4.3 Blow Molding Machines: rotating equipment and hydraulics

An important work has been conducted regarding vibration analysis on the Blow-Molding Machines (BMMs) and linked to the top failure mode impacting the division. These failures have a low occurrence, but the costs of repair and non-production are important.

The main reason why vibration is used for monitoring of rotating elements is because of the early changes in the behavior of the data before a failure happens. To visualize this statement about vibration, it is interesting to use a potential failure curve (P-F curve). This curve has first been introduced by Moubray (2001) and plots the evolution of the condition of any equipment regarding time,

starting when it is first installed. On this curve also appear the points P (potential failure apparition) and F (functional failure apparition). The distance between these two points regarding time is called P-F interval, it is therefore the estimated time between the actual failure and the first signs that indicate its occurrence. Finally, we can also find on the curve an indication of each physical data related to the failure, that can help detecting it between the points P and F. The closer it is to P regarding time, the better the data can help detect early stages of the issue.

An example of P-F for a ball bearing is given in Figure 3.19.

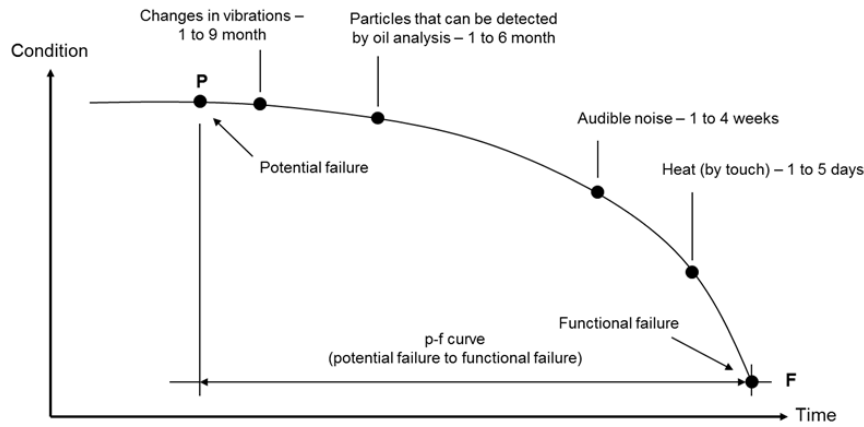


Figure 3.19: P-F curve of ball bearing (Moubray 2001)

This example of curve is true for all rotating equipment, with ultrasound analysis being even closer to P than vibration signals, but also more expensive and difficult to interpret compared to vibration. Vibration has been studied extensively over the past decades, that is why it is widely used in industry to monitor mechanical issues on production systems. This statement is even more true in the Industry 4.0 context, as the systems can compute and communicate vibration features more easily.

Figure 3.20 shows the test bench created to experiment on vibration analysis. It is composed of a servo motor, a PLC, a shaft, two bearings and a wheel. The bearing farthest from the motor can be easily changed as in the right picture, to evaluate the vibration signals on bearings having different health state. The wheel can be loaded with weight to create unbalance on the shaft. The two bearing housings were machined to easily place the vibration and temperature sensors, as close as possible to the bearings. The motor was operated using the Edge Computing architecture, as for the welding test bench (in this case, to turn

3.4. CASE OF FAILURES WITH LOW OCCURRENCES

the motor on and change its speed).

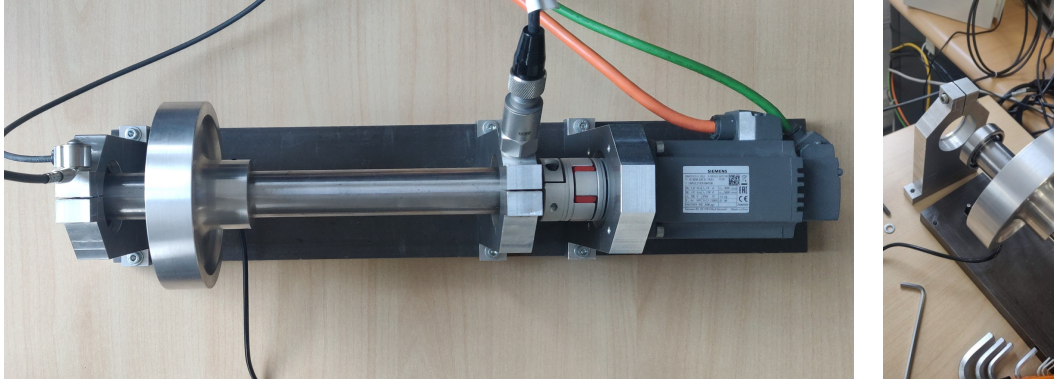


Figure 3.20: Vibration test bench

Two main objectives were set regarding the use of the vibration test bench:

- Validate the technical aspect of the solution regarding vibration analysis
- Validate the software environment linked with vibration data

To reach these goals, several tests were made on the bench, with solutions provided by various suppliers. The final objective was to select a solution to be deployed within the 40 plants.

Table 3.6: Validation of the vibration solution

Technical requirement	Related experiment
Collect vibration and temperature data	Implementation and wiring of vibration and temperature sensors
Vibration sensor frequency range higher than 4kHz (to detect issues on bearings that operate at high frequency)	Verify technical characteristics of the sensors Reproduce failures on the vibration bench
Possibility to study the data in the frequency domain Possibility to monitor common vibration indicators: unbalance, misalignment, bearings	Study available features from supplier's solution
Possibility to implement limits of standard ISO 10816-3	Test software's feature to add thresholds
Availability of the data outside of supplier's software	Collect vibration bench's data using Edge Computing

An extra requirement to choose the final solution was the possibility to integrate oil monitoring sensors in parallel. As shown in Figure 3.19, oil analysis is also interesting to detect issues coming from mechanical equipment. This set of sensors includes particle counting, pressure, flow level, temperature, water content in oil. These sensors make possible the analysis of the full hydraulic group used to operate the BMMs. The main reason for choosing to make experiments solely on vibration is because of the complexity of such analyses, compared to the ones required for the hydraulic parts.

The different tests made it possible to select a solution that is being implemented in both IES (Intelligent Exterior Systems) and CES divisions. The use of the solution is continuously being improved, and provided some successes for the company, by avoiding critical failures, as shown in Appendix G.

3.5 Overview of the results and discussion

In this section we will discuss the results from the first use case, as well as some investigations that were conducted on failures having low occurrences. In a second part, we will address the limitations and opportunities observed throughout the implementation of the predictive maintenance framework in the industrial context.

3.5.1 Results

The application of the methodology proposed in section 3.2 within our industrial context provided many results. The first noticeable one is the capability of the system to provide an efficient solution to address a specific issue, for both the developing team and the end-users. This allowed to validate and standardize the proposed approach within the company, for dealing with machine failures with a predictive maintenance strategy. As discussed, a major goal of the approach is to be adaptable to most of the machines and processes, and the flexibility of the architecture makes it possible. This flexibility results from its availability to be deployed in local computers, as for the tests done on the band heaters, but also at the plant level in its local server, to address multiple machines at once.

A second aspect of the solution is the possibility to package a predictive maintenance monitoring application. In the case of the thermocouples monitoring for the welding units, we were able to propose a simple way to deploy a standard solution within the 40 plants. This topic is rarely discussed in the literature, but

3.5. OVERVIEW OF THE RESULTS AND DISCUSSION

the implementation of a standard solution for multiple users in different countries is challenging. The solution is continuously being improved, by modifying and adding ways to monitor the issues, as well as new alerting channels and local translations.

As the monitoring application should not be an end in itself, the results found from the different use cases allowed the experts to focus on specific points to reduce the occurrence of failures. For instance for the wiring issues, an improvement on the systematic verification of cabling and routing was issued, as well as specific rules regarding bending angles during the movements. However, the application is still necessary, as the process still generates natural wear on the cables.

Finally, an observation made during the different experiments shown that extracting knowledge and value from data is not always done through complex processing, but it often starts with an efficient way of sharing it through visual dashboards. That is why selecting the correct data at the beginning of the study is important, to provide first insights to experts and daily users of the equipment. The main reason behind this statement is that most of the time, data is used within the PLC, and can be collected punctually by other systems, but the possibility to visualize its evolution closely to real-time often gives new perspectives and useful information.

3.5.2 Limitations and opportunities

In parallel of the satisfying results discussed above, we faced many challenges that opened new areas of investigation and provided room for improvements on some aspects of the predictive maintenance framework.

The first topic is related to the maintenance data coming from the ERP system, which was used to determine the topics to be addressed with the predictive maintenance approach. As mentioned in section 3.4.1, work orders coming from the plants were analyzed. However, to perform this job, it was necessary to make manual extractions of the databases and aggregate all the data together. As this process was not optimized, one project was started to create a global application to automatically collect and visualize the data from the plants. This allows to refresh periodically the Pareto of costs and occurrences of the failures.

Similarly, as presented in section 3.4.2, the work on band heaters was unsuccessful. A thorough analysis of the maintenance data highlighted some issues

regarding the data quality on the work orders. As the work orders were entered manually in the system, some data was incorrect, due to lack of time or errors from the users when typing back the work orders. This led to reconsider and update the list of candidates for predictive maintenance. Consequently, a second project was started to automatize the entry of maintenance data within the system. The main goal was to standardize and quickly identify the categories of failures to put the work orders in, to have clean data. This work was performed in parallel of the first one mentioned just above, to propose a precise global visualization of maintenance data.

The work conducted on the welding units provided a good insight linked to the challenge to observe failures on any given equipment. This reinforces the necessity of the predictive maintenance system to be flexible and easy to deploy on new use cases or machines. In addition, having physical data available on the monitored equipment is a strong requirement, to have a chance to observe its degradation over time. Hence, the study of implementation of vibration and oil analysis sensors on the BMMs was necessary, to get the early signs of failures on rotating equipment. Similarly, collecting the current of the band heaters was relevant, even though we could not find a way to detect issues on these components.

As part of the improvement of the application developed for the thermocouples of the welding units, it is necessary to assess the performance of the model. This assessment can be demanding, as the model is installed globally in the plants of the division, addressing dozens of machines. Because the application alerts the maintenance teams to go check the data, and if necessary to assess physically the state of the thermocouple, there is a limitation on the automatic assessment of the performance of the model. Currently, manual feedback from the plant's team regarding work orders linked to thermocouples interventions is provided, to check whether an alert from the application has led to this intervention or not. Two ways to improve this process are shown in Table 3.7, both having their limitations. These investigations are valid for the topics using the framework, not only for the assessment of the thermocouples monitoring.

A general observation on the different projects linked with predictive maintenance is that even though the framework proposes remote tools to address the use cases, local insights and collaboration from plants are essential. The pre-conceived idea that a maintenance issue can be solved only remotely using data analyzed by experts is far from reality. Paradoxically, close work between experts and local users of the equipment is required, but time spent on these topics can

3.6. CONCLUSION

Table 3.7: Improvements linked to the performance assessment

Possibility of improvement	Benefit	Drawback
Include semi-automatic feedback from user in the performance assessment data	Ensures the quality of the feedback	Rely on users with possibility to forget, or make mistakes
Automatic work order triggered by the predictive maintenance framework	Possibility to assess the performance through the work orders Process tested and validated within the framework	Possibility to generate work orders on false alarms

be an issue locally, as well as necessary skills that are not yet well developed. And as mentioned, many of the ideas and feedback to work on predictive maintenance topics arise from the local needs. All these statements add extra complexity to such a study.

Finally, from the proposed framework and operational methodology to implement it, there is a necessity to anchor such process within the company. To achieve this goal, a modelling of these steps was done as shown in [Appendix D](#) as well as training and presentation materials.

3.6 Conclusion

In this third chapter, we detailed the methodology behind the predictive maintenance framework. It was applied on a first local use case, before being extended to several plants of the company. It provided satisfying results, to validate and evaluate each step of the process of implementation of a predictive maintenance solution. An investigation on cases with low occurrence was conducted, generating some mixed results that were used to highlight weak points and possibilities for improvements. From all the listed points of the previous section came the necessity to develop a specific environment for predictive maintenance within the Edge Computing architecture presented previously. Multiple goals are addressed with the use of this new solution, enabling an efficient way to test, develop, package, and deploy monitoring applications. This *Intelligent Maintenance System* (IMS) will be described in [Chapter 4](#).

3.6.1 Scientific contributions

The goal of these first steps to develop and deploy the predictive maintenance framework was to confront the existing standards proposed by PHM to a global industrial context. The technical aspect of the methodology is validated, however the choice of tools used to embody the framework differs and arises from this global context, as well as the features of Industry 4.0 linked to communication protocols and IoT. We showed that many aspects related to industry need to be considered for the development of the methodology, that is why in this work the development of the framework was supported by results from its implementation. Some key aspects are proposed below:

- There is often a trade-off between money investments put in a standard solution that will not meet all requirements from the framework, time investments to develop specific solutions linked with contextual needs, time objectives linked with the expected availability of the solution, and available resources with proper skills to work on the previous points
- The predictive maintenance system has two levels, related to the development of the end-solution by experts, and how it will be implemented and used locally
- The management and development of internal skills to support the lifecycle of the system greatly impacts the global study, from the development to the implementation of the solution
- The financial feedback of the solution is not often easy to apprehend, as it requires an efficient way to track and collect feedback linked to its usage. This complexity is increased in a global context

3.6.2 Industrial contributions

In this chapter, we presented several works that contributed to improve different aspects of our industrial context:

- A monitoring solution deployed globally for thermocouples issues
- A new way to perform tests by collecting and analyzing data locally, using the Edge Computing architecture
- A sensor solution for rotating and hydraulic equipment that was assessed and tested to match technical and financial requirements
- Data quality issues for maintenance work orders allowed to improve the ways to collect and organize the data, and provided a global visualization to select potential candidates for predictive maintenance

3.6. CONCLUSION

Chapter 4

Development of an Intelligent Maintenance System for predictive maintenance

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In this chapter, the motivations previously discussed behind the development of such system are detailed. We will then describe the methodology that was followed to create the IMS, as well as its architecture. Its practical deployment will be explained, and some examples of its application will be given, by emphasizing on the flexible and reconfigurable aspect of the solution, facilitating the implementation of predictive maintenance topics.

4.1 Motivations

Many observations from the implementation of the predictive maintenance framework highlighted the necessity to develop a specific application to deal with it, in addition to the implementation of the Edge Computing architecture. Some important features specific to predictive maintenance activities should be included within the solution. Such features are summarized below.

- Propose a standard way of collecting data from numerous sources, using different communication protocols
- Apply different processing on the data, with the flexibility to add extra types of processing
- Monitor each data with a specific approach (threshold for instance), with the flexibility to add extra approaches
- Assess the state of each data, to propose indicators to follow the evolution of its behavior
- Alert the maintenance teams and create action plans regarding the prognostics that was done
- Propose efficient visualizations for all the different steps linked to data manipulation

Figure 4.1 helps understanding where this IMS intervenes on the different steps of the framework.

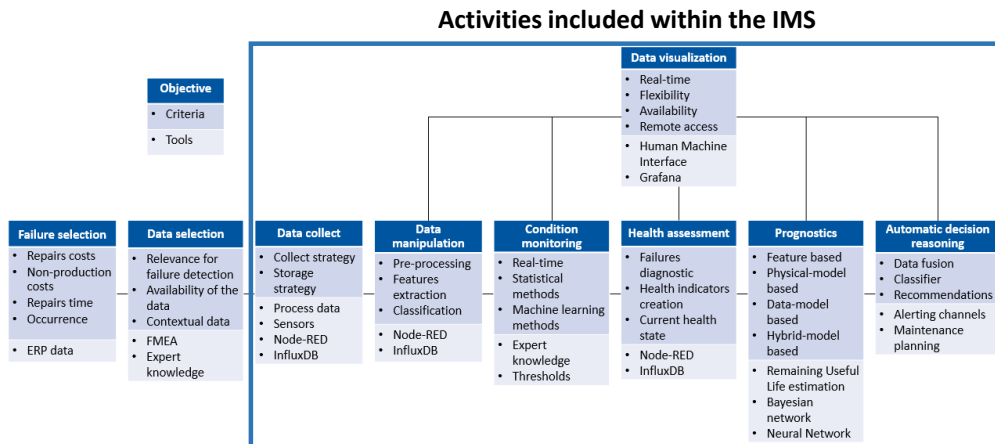


Figure 4.1: Perimeter for the IMS activities

The only steps not included are linked with failure and data selections, as they require maintenance data from the ERP system, as well as knowledge from experts on failure modes. The rest of the activities are incorporated inside the system, to provide a standard way of developing and deploying predictive maintenance solutions. The methodology used to develop the IMS is detailed in the next section.

4.2 Methodology behind the application

The model that was developed around the first framework can be found in Figure 4.2. It presents an overview of the different steps taken to implement predictive maintenance. The application that integrates a large part of the methodology was named Machine Health Management (MHM), and proposes a set of tools that tackle the different challenges of predictive maintenance. The various parts of the methodology will be described below.

The first part of the process starts with the studied machine or production system. Because machines can be quite complex with different parts dealing with different functions or steps in the production process, it is quite important to understand the failures modes. As proposed in the first use case, the studied failures are first and foremost chosen regarding their impact on availability time and productivity of the machine. The interesting failures to study are most of the time the ones with high impact on costs and low occurrence, or the ones with high occurrences and low impact on costs.

The failures that have low occurrence and low impact on costs will not benefit from the deployment of a predictive maintenance solution. The failures with high costs and occurrences should normally be dealt with very early when the production system is started, because mostly coming from design issues.

To study the relevance of failure modes to be studied, we propose three main solutions that are studied in parallel. These steps are the most important ones because they will define the final solution that will be implemented.

4.2. METHODOLOGY BEHIND THE APPLICATION

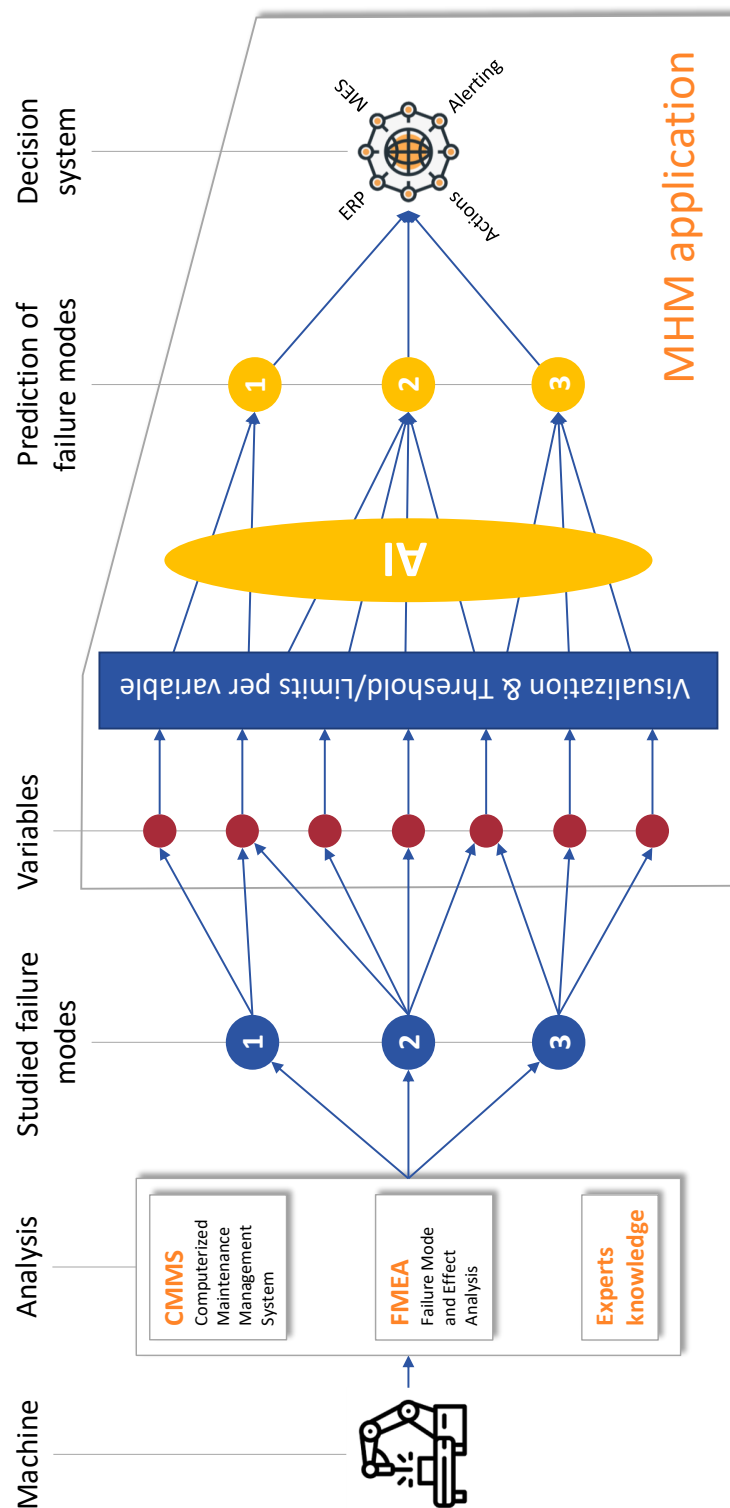


Figure 4.2: Machine Health Management application model

1. The Computerized Maintenance Management System (CMMS) is a tool used to manage the maintenance within a company. Its main goal is to organize maintenance activities, follow-up on the different interventions and keep an historic of all this data. The interest here is to be able to analyze past data on the production system, to rank the different failures observed according to their costs and occurrences. The CMMS system is often linked to an ERP system, which allows to understand the costs involved on spare parts. In the case of a new production system with no historical data, this system will help updating the list of chosen failure modes from the two other steps at a later time.
2. FMEA is widely used in industry to understand the potential failures that can occur and know them better by analyzing their causes and effects on the impacted equipment. This tool can have different variations, by analyzing the process (PFMEA) for instance, or adding a criticality score to the failure modes (FMECA). However, its use in this methodology remains the same, and provides information on several steps.

First, it provides a list of failure modes that can be studied for predictive maintenance, probably not exhaustive, but enough to start the analysis. The main benefit is that it does not require the production system to be already in use, and therefore this study can be performed even in the early stages of conception.

Second, the a priori knowledge of causes and effects can help choosing a first set of data to be collected by the predictive maintenance system, and even help implementing extra sensors on the production system.

3. Finally, experts' knowledge also matters, similarly to FMEA, to choose the correct failure modes and the data to be collected. Some of this knowledge can be found within the FMEA, but experts here relate to several groups of people within the company that have knowledge about the way the production system operates. It includes for instance process engineers, automation engineers, machinery design department, maintenance technicians, operators and more. The importance of involving a wide range of "users" is to have theoretical and practical knowledge about failures that can, did or will appear on the equipment.

There is a practical reason behind the selection of only several impacting failure modes to be studied, compared to, for instance, a full assessment of the production system. The latter study can be successful but involving several failure modes and a large amount of data in the predictive maintenance system can prove to be very challenging to tackle. **The risk is to propose a final**

solution that will be too fuzzy for the end user regarding prediction of health state, or not precise enough to take the correct actions. That is why, even if the solution is identified as data-driven, meaning that the model uses data analysis to propose solutions, there is still a necessary part of physics understanding involved, to correctly apprehend the failure mechanisms. When implementing a predictive maintenance system, it is often more meaningful to have a smaller dataset, but with data that has high correlation with the failure mechanism that is being studied. Knowing key characteristics related to the process can also help finding the relevant parameters to be monitored.

The previous steps give a first interpretation of the dataset that will be needed to study the selected failure modes. The next step is to identify if this data is available in the production system, i.e., the application will be able to connect to the source of the data to collect it. Many ways exist to connect and collect data through different protocols, and some will be presented in Section 4.3. To be successful in this step, knowledge about the automation system used, as well as Information Systems and Services (IS&S) is required. If extra sensors need to be implemented in the system, it is necessary to verify that the addition of such means of measurement will not create extra failure modes or weaknesses in the system. It means that the sensors should be as less intrusive as possible regarding the way they are implementation on the studied equipment.

There is also a requirement during this step to study and estimate the amount of data that will be collected and stored. The choice of data retention (meaning how long the data will be stored before being backed up or deleted) is of importance, as the system will grow more and more with new studies being implemented. As shown in Figure 4.2, this data (or variables as named in the figure) is the input of the system that composes the predictive maintenance application. Most of the data collected from the production system is time series data, but other types of data can be integrated, such as images (from 2D cameras or thermal cameras for instance). As per the figure, one variable can be used to analyze multiple failure modes, although it is only collected once.

As mentioned before, the first knowledge coming from data is most of the time with an efficient way of visualizing it. The main reason is that until implementing such system on the industrial equipment, it can often be seen as a "black box", meaning that the users cannot fully understand what is physically happening during the process. Time series data show evolution of the system over time, and close to a real-time visualization (data can be collected every few milliseconds). It is a first strong step for the users to understand the machines and processes

better and can also generate ideas about how the data should be monitored. An explanation is proposed in Section 4.3 regarding the users' interactions with the application.

Thresholds or limits are often the first type of monitoring that will be done on new studies of failure modes. These values can be known a priori from how the process works, or the acceptable limits of the mechanical parts that compose the production system. This first monitoring will also help implementing a first set of alerts for the users, in case of deviation.

After these first interactions with the collected data, the next step is linked with Artificial Intelligence (AI), in its broad definition. The main goal at this stage of the methodology is to be able to create correlations between selected data to predict appearance of the failure mode. It can be reached using various methods involving several manipulations and transformations on the data, which are available in the application. The data management system must integrate modules to perform these actions, such as implementation of machine learning models. Most of these analyses are multivariate because interactions and correlations between state of several data must be studied and taken into consideration. The idea here is to create a specific monitoring for the failure mode, to be able to alert afterwards and point as precisely as possible where the issue is located on the impacted production system. This precision allows the maintenance teams to be more prepared and plan specific actions related to the result proposed by the system.

Finally, the decision system is composed of numerous tools to share the correct information at the correct time and to the correct information system or user. There is a necessity to connect this predictive maintenance application to the most important information systems of the company, such as the ERP described at step 1, or the MES to plan maintenance actions without disturbing the production. The system should also have the possibility to send action plans or work orders through the CMMS. It is also important that alerts can be sent from different channels to reach the users, the most commons being emails, SMS, internal communications applications such as Microsoft Teams. Standard alerting dashboards exist for visualizing data in different ways, and users also have the possibility to create new ones, so that the production and maintenance teams can easily check the evolution of the equipment's state.

4.3 Architecture of the application

In this section, the actual architecture is described, as well as the different possible ways to use this application. To understand how the application works, a simplified overview is proposed in Figure 4.3.

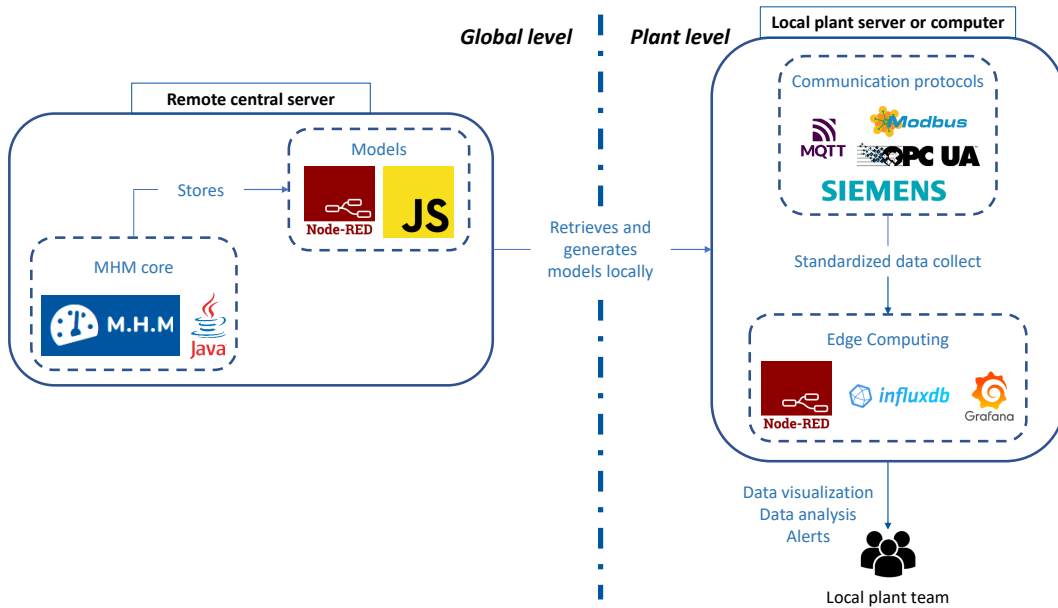


Figure 4.3: Overview of the structure of MHM

The application can be seen as being on top of the Edge Computing architecture. It interacts directly with it through a web interface, which will generate code without having to type it. The benefit is that it helps users visualize and understand how the machines behave, by using standardized applications. The different modules of the application are described below.

MHM is a central tool developed during the thesis in Java, which stores each models used to collect, store, and analyze the data at a global level. It is accessible through a web page for any user having the necessary credentials. It implements all the previous models locally in the plant, where the user wants to create a monitoring. Once this code is pasted, it runs on the local server or computer of the plant. One of the main advantages is that MHM opens this kind of monitoring to workers that do not necessarily have a coding background.

As a result, they can use the visual interface to configure what machine they want to address, what data they want to collect, how long they want to store it and what data manipulations and monitoring they want to add. Once this

configuration is done and validated, the application will automatically generate all the necessary code with the correct configuration inside the local plant device.

Because the local device is connected to the same network as the machines, it can connect to them using various communication protocols, for instance OPC UA (Leitner and Mahnke 2006), Modbus (Swales et al. 1999), MQTT (Hunkeler et al. 2008), and directly to the Programmable Logic Controller (PLC) of the machine through its proprietary protocol: Siemens S7 protocol for example (Beresford 2011). Once this connection is done, data is stored locally, in a standard way, with possibility to add some extra information on the data, such as tags. This allows filtering the data for visualizations and analyses.

Some pre-configured dashboards were developed during this work, so that the users can visualize directly the newly collected data. Dedicated dashboards can also be created in Grafana, which can then be shared amongst plants. There is also the possibility to put in place some alerting regarding the monitoring rules, through the communication channels described before.

The different rules are part of the "AI" block shown in Figure 4.2. They are based in the current version on static thresholds, duration of known anomaly states, catching and counting events in the incoming data or dynamic thresholds using SPC (Statistical Process Control (Oakland 2007)). SPC allows calculating thresholds dynamically, by selecting a time window reference for the data. It makes it possible to create efficient control charts, to understand if the data is stable or deviating. Each rule can trigger a specific alarm to alert the maintenance teams, and the most advanced rules can also generate work orders to plan corrective actions directly with the ERP-CMMS system. There is also a possibility to combine several rules and generate targeted alerts if the root cause of the failure detected is known.

Finally, the importance of this step is that the user is still able to reach the "back-end" of the application (directly in Node-RED), to make some manual modifications, or even adding specific local monitoring. Plants tend to have more and more local skilled people on these topics, able to help with the coding process. In this case, the code can be written in JavaScript in Node-RED and there is also a possibility to create analyses in R or Python.

This final step is important to underline, because as mentioned before, it is quite challenging to address all the existing machines within a company. For

4.3. ARCHITECTURE OF THE APPLICATION

the Clean Energy Systems division as an end user, the machines may differ, not in terms of process but of components used to build the machine. Therefore, the behavior of one machine to another may drastically change, and can also be impacted by the environment in which they operate. That is why this notion of flexible tool matters, because it is not only a top-down application, but also bottom-up, similarly as mentioned in Figure 1.6 in Chapter 1.

The top-down aspect is linked to the developments made by the central team working on Industry 4.0 topics, which proposes specific monitoring on top failure modes directly to the end users, i.e., the plants. Using the application, they can replicate a model developed by experts, and operate it directly with the correct configuration.

The bottom-up aspect is linked to the local developments made on specific issues, which can be also of interest for other plants. One of the main interests is that these developments can be done easily and quickly, on faulty equipment, which can increase the efficiency of the model created. These local developments can then be reinjected locally to other plants that may find themselves in the same situation as the original plant. Storing the models centrally, like in MHM, allows this way of working: the application can be seen as an "application center" similarly to what can be found in smartphones. A summary of these activities is shown in Figure 4.4.

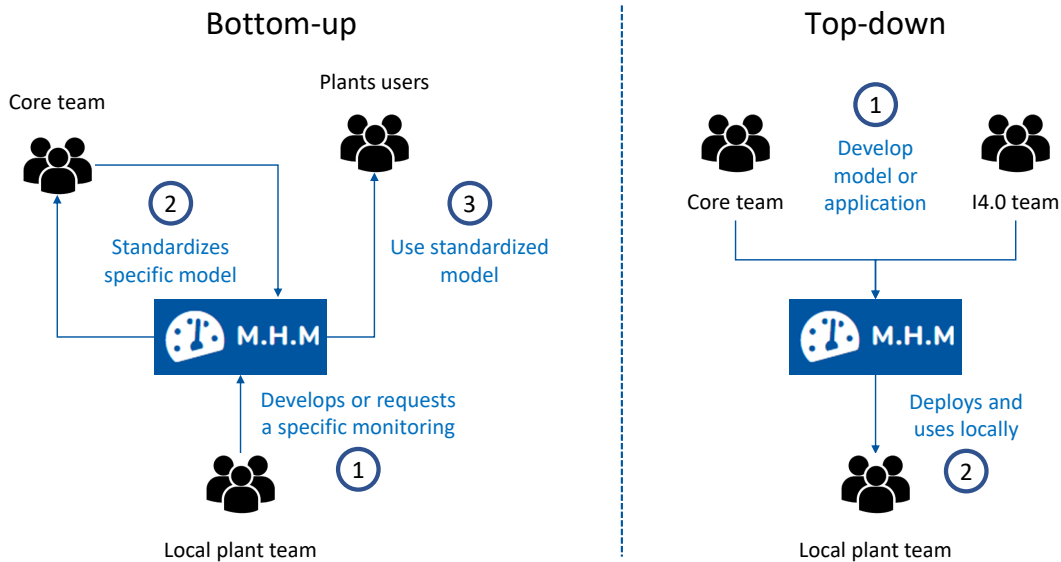


Figure 4.4: Top-down and bottom-up aspects of MHM

4.4 Deployment and validation on industrial cases

After understanding the methodology behind MHM and its architecture, we will analyze its use in the industrial context on two different topics. Although it has been used on several cases, the two cases presented below are the most advanced applications that provided good results and perspectives for future improvements.

4.4.1 Helium Leak Testers

4.4.1.1 Principle of the process

The first topic deals with helium testing machines, also called Helium Leak Testers (HLTs). These machines intervene at the end of the production process, as mentioned in Appendix C. Their goal is to ensure that each produced fuel system is within acceptable range regarding leakage. Indeed, as mentioned previously some cutting and welding operations are done on the tank, which can create internal leaks if the operation is not performed under good conditions.

To verify this, tanks are tested inside the HLTs. A basic principle is proposed in Figure 4.5.

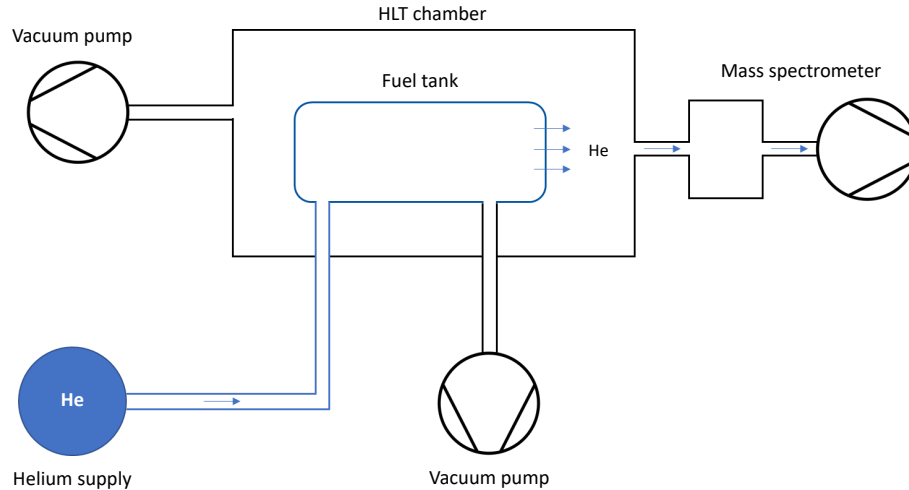


Figure 4.5: Helium leak test principle

The machine is composed of a chamber where the tank is installed. It is sealed, and vacuum pumps evacuate the air in both the chamber and the tank. Once it is complete, a fixed quantity of helium is injected inside the tank, and a

mass spectrometer coupled with a pump observes the number of particles located inside the chamber, i.e. the estimation of the leak rate of the tested tank. The acceptable limit is given per product, and if it is crossed, the tank can be re-tested or defined as a scrap. Helium is used during this test as it is the smallest known atom, therefore giving a good idea of possible leakage issues on the product.

4.4.1.2 Topic definition

Issues on the HLTs are part of the list established in section 3.4.1, the main reason being the lack of internal knowledge regarding their failure modes. Indeed, these machines are historically less common to perform the leak tests, Water Leak Testers being more used globally (cf. Appendix C). However, HLTs are much more complex, and more efficient in the detection of leaks, therefore they are becoming standard machines to be used in production lines nowadays.

HLT is a good example of what usually happens in the industrial context: these machines are quite complex and have many unexploited internal data that could help understanding better their behavior. Consequently, HLT machines were selected as a first topic to be worked on using the MHM application. This use case started as a Top-Down project, as the main goal was to propose a global solution to be deployed and used within each plant.

As a first step to define the study, four activities have been performed in parallel, to understand better the issues related to this family of machines:

- Analyze maintenance history data to understand common failures
- Interview experts from the research center, and plants
- Work in collaboration with the supplier of machines
- Use the test machine located in Alphatech¹ to have a better understanding of the process

The result of these steps is proposed in Table 4.1. It gives an overview of the issues related and the current processes in place to correct and detect them. To understand the data inside the table, as presented before the machine has several pumps, for various purposes such as removing air from the chamber and tested part, or to remove the helium still inside the chamber after the test is done. Filters are used to restrain particles that could damage the equipment, such particles can be dust, or plastic parts that could still be on the product. Seals are important on the machine, as they ensure that the process is performed

¹Alphatech: research center of Plastic Omnium CES, located in Compiègne - France

properly. Finally, many valves can be found on the machine, to redirect the different gases in the correct places.

Table 4.1: Known failures on HLT machines

Issue	Effect	Verification in place
Faulty pump	Increase cycle times Impossibility to reach vacuum level required	Oil check Biannual pump's performance assessment
Filter clogged	Contaminate oil Increase cycle times Pump deterioration	Cyclic cleaning Replacement of part with spare
Deteriorated seal	Impossibility to run full cycle Increase cycle times	Cyclic check Replacement of part with spare
Broken valve	Impossibility to run full cycle	Replacement of part with spare

4.4.1.3 Proposed solution

The machine has internal alarms, and a Human-Machine Interface (HMI) to display them to the users. However, it is possible that some alarms can be missed, due to the fact that they are not critical to the process itself, but can still indicate the start of an issue on the machine. Consequently, one of the first objectives of this topic was to collect the correct data, to start creating a history and propose valuable visualizations. With the help from experts (on the supplier and company side), a first list of data was edited, most of them being in the following list:

- Cycle times: the duration of each phase of the process is calculated within the machine
- Pressures: many pressures are measured by internal sensors, at different locations on the machine
- Leak rate: calculation the observed leak rate by the mass spectrometer
- Other data: identification of the tested part, results of the tests, number of parts tested, number of hours run for the pumps

The data is split and tagged under two categories:

- Chamber: machines can have multiple testing chambers, so each data specific to a chamber is identified here
- General: the rest of the data, common for all chambers, is identified here

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Splitting the data as such also allowed to create an interactive dashboard where the general data and data specific to chambers are visualized independently. An example of the visualization is proposed in Figure 4.6. Selecting one or both chambers will modify the dashboard, to display the correct data. This allows the users to quickly check the interesting data. Appendix H shows an example of data visualization, in the case of a machine having two testing chambers.

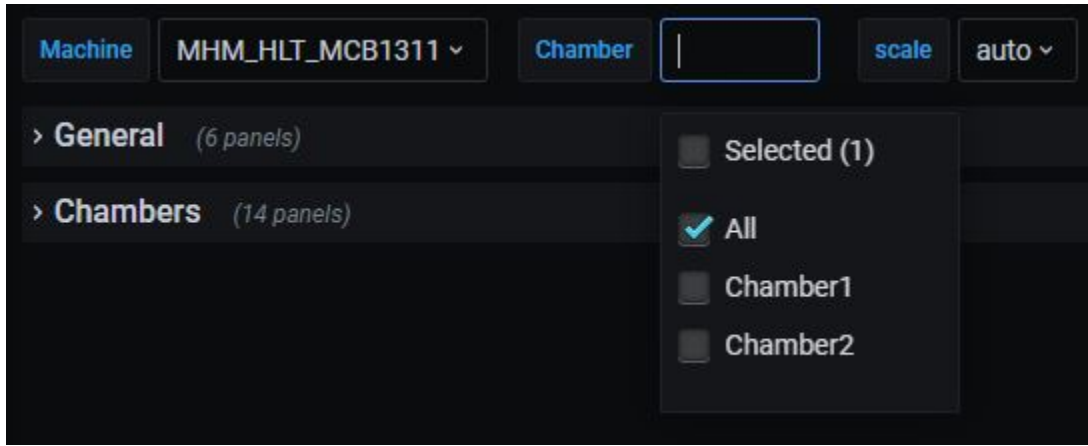


Figure 4.6: Split visualization for HLT machines (Grafana)

In addition, first thresholds and alerts were implemented, based on experience and knowledge on the process. The package standardized and deployed from MHM was composed of the data collection of the previous list, which represents around 65 variables, and the dashboard discussed previously. This first solution was the basis on which more knowledge about the machine's behavior has been built.

4.4.1.4 Improvements and perspectives

After implementing the first package, the second step of the work was dedicated to improving the solution. The final goal being the proposition of meaningful messages for the maintenance teams, based on the results of the analyses done on the data, the current work is oriented towards this objective. Table 4.2 summarizes the various actions related to the improvement of the package.

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Table 4.2: Leads to improve the monitoring of HLT machines

Idea	Expected result	Related action
Observe trends on specific pressures and cycle times data	Increase or decrease of the value over time should indicate an ongoing deterioration	Implement linear regression analyses
Analysis of gases consumption	Comparison of data over time can indicate seal or filter issues	Calculate consumption periodically, or per gas bottle, and verify number of tested parts
Verify opening times of valves	An increase of duration during opening and closing phases of the valve can alarm on a failure of the valve	Calculate and monitor the evolution of the opening and closing duration
Add extra sensors on pumps	New physical data related to the pumps can help detecting oil or mechanical issues	Implement sensors defined in section 3.4.3

An example of the User Interface is proposed in Figure 4.7. Here, we can find the list of machines monitored within the plant, the status of the machine according to the monitoring rules in place, and a summary of issues per machine. The user can click on the specific issues, to give more details and provide a direct link to the data visualization.





Machine health		
Machine	Status	Details
		
		
		
		The average Leak Rate of Chamber1 is quite high

Figure 4.7: User Interface for the HLT machines (Node-RED)

All these developments gave the opportunity to improve the core of the application, as they can be proposed as new ways of monitoring the data collected

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by MHM. Figure 4.8 below shows the two main contributions of the use of MHM for the HLT machines topic:

- As mentioned previously, the complexity of the machine, the lack of internal knowledge and the availability of unused data provided a strong basis to build efficient data collection, data visualization and first monitoring rules to alert on potential problems
- A second step, still under improvement, gave the opportunity to list and develop specific analyses, to propose a first diagnostic related to issues on the HLT machines. The objective is to identify clearly the observations made on data, and propose maintenance actions to try and improve the health state of the machine

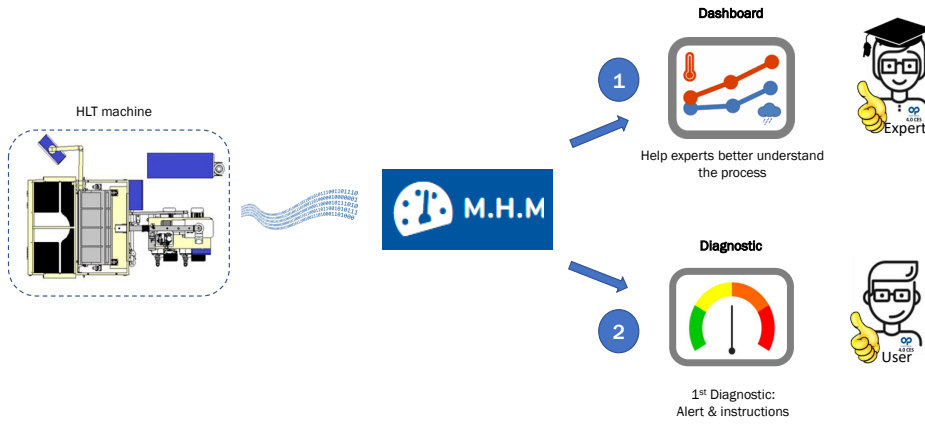


Figure 4.8: Current contributions on HLTs

4.4.2 Blow Molding Machines: band heaters

4.4.2.1 Principle of the process

As partially presented in section 1.2.2, heating systems are found on the BMMs, on the extruders and on the head. Their goal is to keep the material melted and at the correct temperature. Similarly to the welding units presented in sections 3.3 and 3.4.2, the system is composed of one or multiple band heaters, and one thermocouple per "zone". The zones are shown in Figure 1.3, and correspond to the physical location of each heating system, from the feed hopper to the start of the head. Such zones are defined in the same way for the head tooling, from the top of the head, to the start of the parison creation.

The size of each zone defines the number of band heaters that can be installed, and a regulation system powers the band heaters to reach a temperature setpoint,

similarly as shown in Figure 3.8. An internal monitoring within the machine ensures that the temperature is correctly regulated in each zone, and a detection of wrong temperature based on a plausibility test is performed, which can stop the machine if necessary. The heating systems are critical components of the machine, as any failure can lead to quality issues and severe damages on the extruders and the head tooling.

4.4.2.2 Topic definition

Differently from the band heater topic on the welding units that originated from maintenance data analysis, this topic was a request from three plants. The need came from several issues observed on band heaters located on the head tooling of different machines, in different plants. Therefore, contrary to the HLT study, this one can be categorized as a Bottom-Up topic, as per the definition of Figure 4.4. The plant located in Pfaffstätt, France, was selected as a first pilot for this project as several failures were reported on a specific zone of the co-extrusion machine (c.f Appendix B).

Following the same steps as for the HLT machines study, we propose a summary of known failures on these components, in Table 4.3. The main difference with the welding units is that band heaters located on the BMs are not moving, therefore the cabling issues on both the thermocouples and band heaters are not present in this case. The install on the extruder side is very robust, and few issues are reported. However, the setup on the head tooling can be changed depending on the production, and therefore the maintenance actions can deteriorate the components, if a wrong action is applied during this change.

The verification currently in place on the system is linked with the evolution of the temperature, and any detection of an issue based on this analysis can stop the machine. The monitoring of the current gives alarms to the users through the HMI of the machine, but does not currently stop the process in case an issue is detected. Therefore, after understanding the potential failures on the heating system, the next step presented below is dedicated to describing the available data to be collected to monitor such issues.

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Table 4.3: Known failures on the BMMs' heating systems

Issue	Effect	Verification in place
Band heater electrical failure	No heating possible Brutal failure of the component	Monitoring with current transducers Evolution of the temperature over time
Band heater not positioned properly	Deterioration of the band heater Regulation disturbed by zones above or below	Monitoring with current transducers
Band heater tightened too much on its support	Breakage of the support Band heater loosening	Visual inspection
Wrong regulation parameters	Slow deterioration of the band heater Electrical failure	None
Thermocouple breakdown	Loss of temperature data Incapability to perform temperature regulation	Evolution of the temperature over time Stoppage of the machine

4.4.2.3 Data collect

The dataset has been defined after reviewing the system with process and automation experts, to understand the available and accessible parameters.

- The temperature coming from the thermocouple
- The temperature setpoint, which is a parameter that can be modified on the HMI of the machine
- The temperature high tolerance value, which should not be crossed during the production phase
- The temperature low tolerance value
- The PID load, named "ED" (similar to the value of the welding units)
- The current, that is measured for one zone, meaning that the read value can be for one or several band heaters
- The current target, which corresponds to the value that should be read
- The current tolerance, below which plants' teams should be alerted
- The machine's production status

The first 8 variables are collected for each zone of the machine, and the status just once. For a typical co-extrusion machine, having 6 extruders, each of them having between 4 and 6 zones, and a head tooling having between 6 and 8 zones, the dataset is composed of around 300 variables. Using MHM, the application

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connects directly to the PLC of the machine, to collect each parameter every second. An example of the data collection code generated through MHM to Node-RED is shown below.

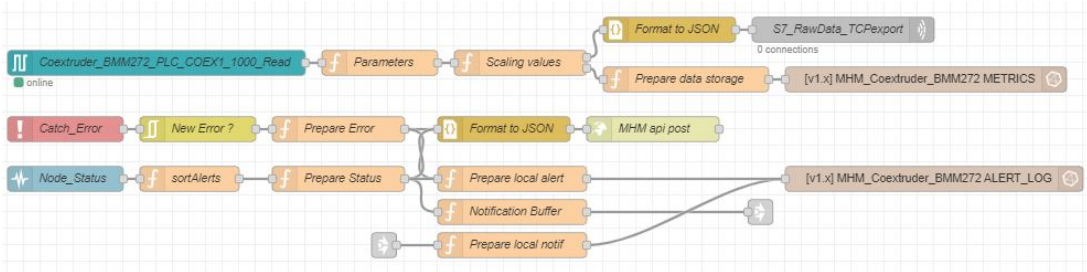


Figure 4.9: Node-RED flow generated by MHM to collect data from a PLC

Similarly as proposed for the HLT machines, Figure 4.10 shows the split visualization done in Grafana. The variables shown on top allow the selection of the necessary extruders and related zones to be displayed, and the same thing exists for the head zones. Selecting multiple extruders and/or zones will populate the dashboards with extra graphs dedicated to each of the selected items.

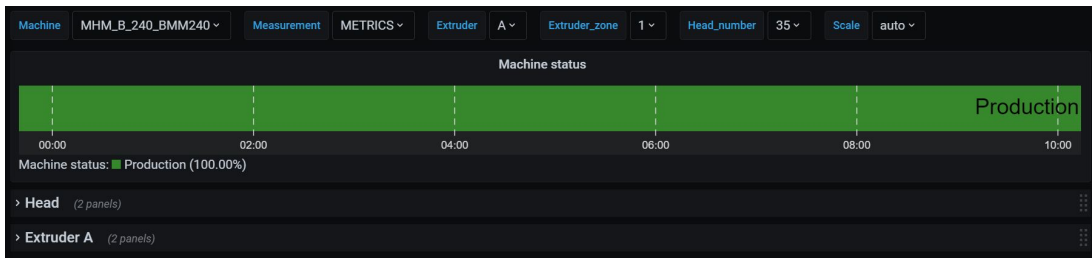


Figure 4.10: Split visualization for Blow-Molding Machines (Grafana)

The machine's status allows understanding quickly in what state was the machine when visualizing the data related to the heating systems. It is especially useful when checking a failure event from the history data, to get the evolution of the machine's state according to the rest of the monitored data.

4.4.2.4 Observed failures and proposed solutions

Based on the list of failures shown in Table 4.3, we were able to observe the first four types of failures while collecting the list of data previously mentioned. Below will be presented the different cases, and how solutions were designed within the MHM application.

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The first failure is linked with a sudden loss of the component due to an electrical failure, as shown in Figure 4.11.



Figure 4.11: Electrical failure of the band heater (Grafana)

As observed on the graphs, the value of the current that powers the band heater brutally drops to 0 on the left graph ("Head_Current_35" - green curve). After this event, we can see on the right graph that the temperature is slowly decreasing ("Head_Temp_35" - green curve) and the load of the regulation is increasing to reach its maximum value of 100% ("Head_ED_35" - blue curve with vertical axis on the right side).

Due to the inertia of the system, and the zones located close to this one trying to compensate the loss of the band heater, the heating system can continue to work within temperature ranges (green colored zone on the right graph) for several hours. However at some point the temperature crosses the bottom threshold, and the machine automatically stops, after nearly 5 hours working in a degraded mode.

The causes of the failure are numerous, and difficult to observe or replicate. The data prior to the event shows no abnormal levels of temperature, regulation, or current. Consequently, the first solution proposed to the plant's team was a monitoring based on thresholds and duration. As discussed previously, standard monitoring techniques are proposed within MHM, to be used on any collected data. In this case, the "Threshold timer" monitoring uses a threshold value and a duration of the crossing of the proposed value. An additional parameter can be used, as a verification of the first rule.

Consequently, to detect and alarm the plant on the loss of the band heater, the proposed rule are detailed below.

1. The value of the current reaches 0
2. The status of the machine is "Production" (additional verification parameter)
3. The duration of both previous rules is higher than 10 minutes

Again, the main goal is to have a pragmatic approach, and setting up this monitoring to 10 minutes allows to verify that the signal is really lost and that the machine is still producing parts. Similarly to the thermocouple case on the finishing centers, the alerting allows the maintenance team to quickly react and organize an emergency intervention on the identified zone. As observed on the figure, the intervention took more than an hour, as it can be difficult to clearly identify where the issue is located. The current alert allows both to reduce the time of production with the broken part, and to know here the replacement will be done, saving a lot of time.

The second failure observed is associated with lines 2 and 3 of the failure table. It can happen after a change of the head tooling, or replacement of a defective band heater. Such event can be observed in Figure 4.12, and follows the previous event where the band heater was lost.

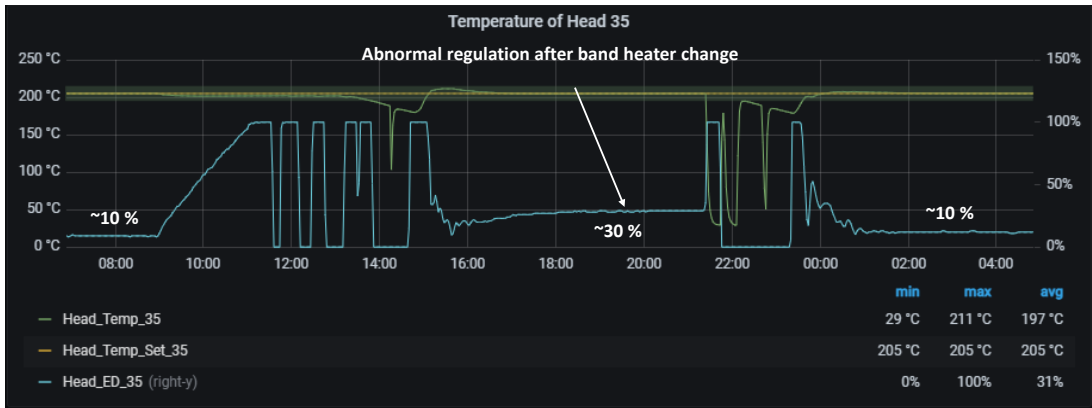


Figure 4.12: Wrong positioning of the band heater (Grafana)

We can see from the data that after the initial replacement of the band heater, the regulation (blue curve) is following a different trend compared to the normal levels before the first failure, and after the second replacement. After investigating this event, the plant's team observed that the band heater was tightened too much on its support, creating a perturbation on the regulation loop. Eventually, the support started to break and lead to a second stoppage of the machine.

4.4. DEPLOYMENT AND VALIDATION ON INDUSTRIAL CASES

Similar events were observed, in the case where the band heater is not placed properly, and the zones above/below on the head tooling will generate a perturbation on the regulation loop. Current work is to propose a monitoring for such issue, and the first lead is to study a linear regression of the load of the regulation. Implementing such new rule will in the end also benefits other users, as a standard monitoring "Linear regression" will be developed and implemented within the application.

Finally, a failure linked with the fourth issue was identified using MHM. Even though it is not a common problem, it still benefited the plant and reduced failures due to such event. Investigation on the cause of the problem was quite difficult without the monitoring system in place with the application.

Figure 4.13 shows the effect of a regulation having wrong parameters. High instabilities are generated for several hours, and the source of the perturbation is unknown so far. However, the response of the regulation was too much compared to the effect of the initial perturbation, therefore creating an even greater issue.

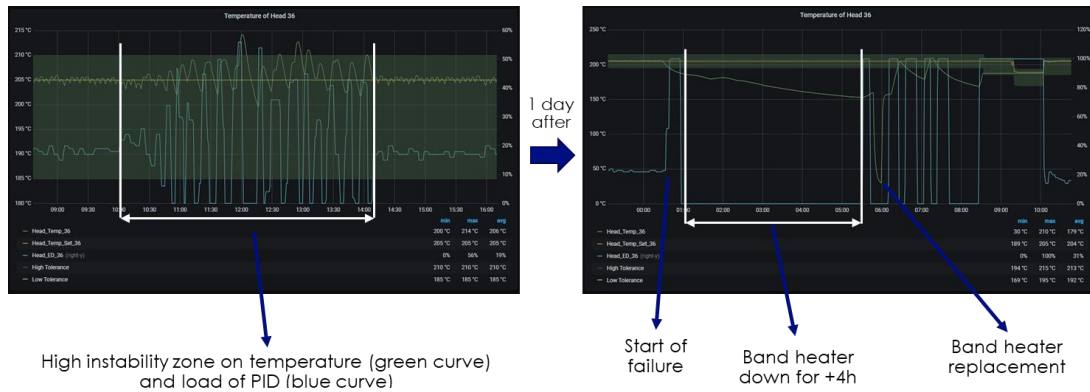


Figure 4.13: Wrong regulation parameters (Grafana)

These sudden changes within the regulation loop create a deterioration of the electrical system of the band heater, and eventually lead to a failure, as observed on the right graph. This failure event took place after several occurrences of the perturbation event shown on the left graph. Consequently, a specific monitoring was created, to alert the plants in case a similar issue is observed on the data, and can be linked with a wrong regulation of the system. It allows the automation engineer on site to verify and modify the parameters of the PID, if necessary.

4.4.2.5 Results and perspectives

This second example provided the opportunity to explore a concrete use case coming from plants' requests. It has been beneficial to first understand better the verification in place within the machine, to detect issues on the heating systems. From this, we could edit a list of data to be collected, which provided an interesting source of information regarding the different failures observed on the system.

For this specific topic, the monitoring will be extended to mono-extrusion machines (cf. Appendix B), and extra means of verification are being requested by the plants, to monitor even closer the heating systems.

The standard monitoring techniques available inside the application allowed to create ways of detecting these issues early, and point out precisely which part of the system generated a problem. This information is crucial for maintenance teams because they enable them to act quickly on the correct location of the source of the failure, as discussed previously.

We have also observed that extra monitoring are necessary, to be able to treat the various cases that can be encountered in the industrial context. This leads to improving the end-solution, and providing a wide range of possibilities for the users to analyze their collected data.

4.5 Conclusion

In this chapter, we discussed the solution developed throughout this thesis work, to tackle the current challenges regarding implementation of intelligent maintenance systems in the industrial context. The methodology that was developed behind the maintenance application is described, with all the different steps necessary to work efficiently on the failure modes of any production system. This methodology is not limited to the automotive industry but can be used in other fields, and can be implemented for machines having history as well as for new equipment. The architecture that was implemented in the industrial context was presented, with a description of each module composing the system. The term flexible is employed because the application allows working in a top-down and a bottom-up way.

The main benefit of the solution is that it is built on open-source software, and can be operated by users having different profiles and knowledge. It allows

4.5. CONCLUSION

data exploration and creating efficient monitoring that can be used for predictive maintenance, and proposes an easy way to implement solutions developed by the central team, or other users. There is a strong belief that most of the knowledge regarding machines' health state is coming from the daily users within the plants, and this tool gives them the opportunity to experiment and create broader solutions for the rest of the users.

Several improvements on the "AI" block proposed in Figure 4.2 will be conducted. One of them being the possibility to use statistical models such as ARIMA (AutoRegressive Integrated Moving Average (Box et al. 2015)) to predict timeseries, and train machine learning models directly on the data collected by the application. One of the key approaches that will be investigated is to train models on "healthy" data, to find anomalies when new data is checked by the model. The main reason being that in most cases, the machine or system will run in its correct state for long periods of time, and sometimes catching faulty data can be difficult. For instance, Novelty Detection models can help detecting anomalies on new data by comparing calculated scores, or Autoencoders, which learn a representation of the data and compares the expected outcome to the new data. The Edge Computing solution used in combination with MHM, offer the possibility to do so and propose new features for the users. These new developments are made available because of the flexibility discussed throughout this work, and they can be implemented easily to improve progressively the end-solution.

4.5.1 Scientific contributions

After having confronted the methodology developed in Chapter 3 with the industrial context, several improvements were deemed necessary to propose an efficient predictive maintenance system. In this chapter, we propose to move from a "low-code" solution (i.e. the Edge Computing solution) to a "no-code" solution using the Machine Health Management application. This "no-code" aspect means that users do not need a coding background to use the solution, as everything can be configured through a web page, and the correct code is generated automatically.

This flexibility discussed throughout the chapter is necessary to palliate two critical and limiting aspects of the predictive maintenance topic:

- Observations and analyses on data to create a predictive maintenance solution is demanding in terms of required time and available resources: skilled

users, information system to develop and implement the solution

- Most of the knowledge regarding equipment's failures is located in the plants, where users have a daily experience on the systems

Consequently, proposing a system that can be used as both a platform to develop and deploy the solutions for predictive maintenance is important. It allows reducing the time of development, as experienced users on the machines can experiment with data and propose beginning of solutions that can be shared in their turn to other users. It also allows to implement these data analyses directly on faulty equipment, and local users are involved to verify the equipment's condition and make the link between events observed on the data and on the machine itself. Finally, it contributes to having more and more local skilled people to work on such topics, to balance the top-down and bottom-up aspects of the predictive maintenance solution.

4.5.2 Industrial contributions

First and foremost, the MHM application provides a simple way for users to connect to machines using various industrial protocols, collect specific data, visualize them, implement different techniques to monitor them and receive alerts through their preferred channel of communication, all this in a standardized way.

Two use cases were presented, showing different ways of working with the application. The Helium Leak Testers topic was linked to a development coming from the central team to the plants, to provide a better way of understanding the machines and first monitoring rules linked to maintenance actions.

The heating systems topic for the Blow Molding Machines arose from plants' needs, and was developed jointly with local users. It allowed working on a faulty machine, and provided some good results to feed the application with new requirements in terms of data analysis. The solution developed locally can then be proposed back to other users, its implementation being carried out directly through the application, in a standardized way.

Developing successful and useful topics for plants is a way to promote the application, facilitate its adoption and generates local interest for such studies. By doing so, more local needs are created, and it enables the users to develop new skills linked with Industry 4.0.

4.5. CONCLUSION

Conclusion

The works presented in this document were conducted during a CIFRE thesis between the automotive company Plastic Omnium, the LCFC laboratory of the engineering school Arts et Métiers. The main objective was the development, design, and deployment of a predictive maintenance framework in a global industrial context. Many researchers contributed to the predictive maintenance topic over the past two decades, and it seems to have gained even more attention over the recent years. The main explanation behind this observation is that industrial actors are investing more and more in the Industry 4.0 topics, which also cover predictive maintenance. Indeed, data has become an invaluable source of knowledge and enables new ways of enhancing the performance of manufacturing systems, which is critical in today's global competitive market. Understanding better the behavior of a production system is one of the goals of predictive maintenance, and allows eventually to make early detections to prevent catastrophic failures. Therefore, our initial objective to propose a methodology and a set of tools to implement predictive maintenance led to the development of an Intelligent Maintenance System, capable of handling a large part of the activities of this methodology.

To reach this state, as an answer to both the scientific and industrial issues presented in [Chapter 1](#), we organized the document as follows.

In [Chapter 1](#), we defined our scientific and industrial contexts. The scientific topic of this thesis work revolves around predictive maintenance, and the necessary methodology to implement it thanks to Industry 4.0. In a second time, we presented the industrial context, as the automotive industry historically contributed to many advances for the whole industry, mainly due to its competitive nature. Although the main objective was to propose a non-domain centric solution, the industrial context gave the opportunity to experiment on concrete examples, with high requirements behind the goals of the thesis work.

Finally, the main objective of the thesis was summarized into a research question that needed to be answered, with the help from four industrial and scientific issues.

A literature review is proposed in [Chapter 2](#), to give a global vision of how maintenance is handled in the context of Industry 4.0. Indeed, we observed a real shift of mindset regarding the role of maintenance in the industrial context, going from "necessary evil" to one of the activities most invested on by manufacturing companies. These investments are mostly linked with the information systems required to handle the data in an efficient way. In addition, a methodology is necessary to deal with predictive maintenance, and we showed that most of the systems proposed in the literature are based on PHM. The process goes from data selection and collect, to the design of decision-making systems to support the communication of analyses made on data. We then reviewed the current challenges coming from the implementation of this methodology in the industrial context. The main difficulties are linked with the costs of such solutions, and often the lack of visibility regarding the return on investment. This can be explained by the complex nature of the predictive maintenance topic, and the necessary skills that are still scarce in the industrial context. From these observations was proposed a framework for predictive maintenance, to understand its numerous activities and how they can be implemented in industry.

The application of this framework was detailed in [Chapter 3](#). We presented the extended methodology behind the framework, as well as the first use case selected for predictive maintenance. The study provided satisfactory results regarding the different activities of the framework, and the proposed tools to implement them. The solution enabled detecting early issues on a critical component of the welding units, and was packaged and deployed in many plants of the company. This work, in addition to parallel studies on cases having low occurrences but generating high costs, highlighted some limitations and possible improvement points. The main outcomes were the necessity to propose a tool not only for experts, but also for the daily users of the production systems who have experience on their behavior. Integrating this experience and knowledge within the predictive maintenance is the real challenge of this work, to propose efficient and relevant ways to detect and predict failures. In regard to the scientific and industrial issues defined in [Chapter 1](#), we can say that the first application provided partial answers to the four topics, by:

- Providing a way to select meaningful cases for predictive maintenance, and identifying key parameters to be collected and monitored

-
- Describing the data management system used and developed throughout this thesis work, based on open-source software and tools
 - Proposing analyses on data, to detect early patterns of an incoming failure mode
 - Defining a decision-making system based on data visualization and results from the data analyses, communicated to the end users through alerts by emails

Consequently, we proposed a global solution to provide satisfactory answers to our research question in [Chapter 4](#). The application developed was baptized "Machine Health Management" (MHM), and was designed to serve as a development tool for experts and non-experts, and a channel to deploy the predictive maintenance solutions globally. We emphasized on the term "flexible" to qualify this solution, as it is built on open-source standards, and can be improved based on new findings from the literature, or specific needs from the industrial actors. We presented two use cases where the use of the application provided good results, as well as new opportunities to improve it. The main contributions coming from the application are the standardization of the data collection, the use of numerous industrial communication protocols to address this data, standard visualizations proposed to users, as well as means to create specific ones, standard monitoring techniques on the collected data and various channels to alert based on the previous analyses. These contributions are the answers to the four scientific and industrial issues. The proposed framework, as well as the MHM application are the two main contributions of this thesis work, to provide an answer to our research question:

How can industries implement predictive maintenance with the help of Industry 4.0?

A summary of the contributions is proposed in [Table 4.4](#).

During this thesis work, we worked jointly and took advantage of three principal features that were made possible thanks to the dual scientific and industrial contexts of the CIFRE agreement:

- The academic study, to understand and develop methodologies, based on works proposed by researchers from various fields
- Work on concrete use cases to confront the scientific findings to the real world and industrial requirements, which can greatly impact the proposed solutions. Including the users in the process also greatly matters

Table 4.4: Summary of the contributions

Scientific issues	Contributions
N°1: Formalization of the criticality of failure modes based on the understanding of their causes and effects	<p>Selection of candidate topics for predictive maintenance through the analysis of costs and occurrences of failure modes from the CMMS data</p> <p>Understanding of the criticality of a candidate failure mode through the FMEA</p> <p>Integration of experts' knowledge, to add factual experience in the selection process</p>
N°2: Structuring of the data management system to integrate multiple sources of data	<p>Use of open-source software to develop the data management system</p> <p>Integration of multiple data sources using different communication protocols, and standardization of the data collection and storage</p>
N°3: Creation of health check on the production system based on processed data, to anticipate failures	<p>Development and standardization of monitoring techniques, to detect early signs of changes in the data and prevent issues</p> <p>Integration of state-of-the-art techniques, and new means to create knowledge from the data on the health state of a given equipment</p>
N°4: Elaboration of relevant indicators to support operational and business-oriented decisions on predictive maintenance	<p>Use of standard visualizations and offer the possibility to create specific ones</p> <p>Integration of various means of communication to alert the end-users on potential incoming failures</p>

- Define a global technical solution, to experiment on data coming from various production systems, devices and sensors. This system must be compliant with the requirements coming from the scientific and industrial studies

Perspectives

Many opportunities and perspectives drew our attention while conducting this research work. We want to highlight three main topics that in our opinion will be necessary to propose an improved solution, based on this work. The first one discusses the architecture of the solution. The second topic is linked with the data selection activity that is outside of the scope of the MHM application. Finally, the last point deals with data analyses for predictive maintenance.

We would like to emphasize first on the design of the information system responsible for handling the predictive maintenance activities. We presented in this document an architecture capable on sending data to a data lake for global analyses, using machine learning algorithms to analyze the data or even generate automatic work orders for maintenance teams based on the alerts of the monitoring applications. The main point of attention on these features is that even though they were not directly used in the presented work, it is important to consider them when designing such system, as it needs to be flexible and reconfigurable. Based on the evolution of the predictive maintenance topics in the industrial context, the new findings and the results of the studies, the end-system needs to be able to adapt to the requirements of the users. Consequently, these features were tested and validated in the system, to be ready for future use.

The MHM application proposes a standard way of dealing with the predictive maintenance activities linked with data handling. One of the improvements for the framework is related to data selection for failure analysis. It is a crucial step that is not always easy to perform correctly the first time. Most of the time, the choice is based on expert knowledge when it is a known issue on the equipment, however it can happen that the failure is not known or documented. As a result, there is an interest in proposing a systematic approach to select the proper data to detect and predict a given failure. To do so, a first proposition was to work on an existing approach proposed by [Echeverri et al. \(2021\)](#), from the LCFC laboratory. This approach aims at defining the best solution during the conception phase of a production system, using the Energetic Technical Functions (ETF). It is a representation of the energies involved in the process, in order to identify risks coming from them.

In the case of maintenance, the interest of this approach is to make the ETF

representation of the equipment or component to be monitored, in order to understand its function and the energies involved. By doing so, it is possible to then identify the data to be monitored, by linking the physical phenomena involved in the production of the ETF, and the risks of failures identified on the equipment. The first approach is proposed in Appendix E. Figure I.1 shows the ETF model as proposed by (Echeverri et al. 2021). In the case of maintenance activities, the component or equipment studied is part of a larger entity, that is why there is an interest to also involve energies exterior to the system that can also have an impact on equipment. The energies losses are also represented, as they can help quickly identifying the proper data to be monitored. Figure I.2 describes the currently proposed approach to select data for maintenance, and Figure I.3 details the different steps to be performed. This process is still under investigation, but can help proposing a systematic approach to select the relevant data for failure analyses.

Finally, from the observations coming from the different use cases studied during this work, we highlighted that catching faulty events can sometimes be a difficult task. Having failure data is not always a possibility while working on predictive maintenance topics, as for instance the case presented in Chapter 3 for the rotating elements that are costly. In the recent years, many researchers proposed to work on data collected during a known healthy state of the equipment, to learn its representation using mathematical models. There is a high interest for predictive maintenance of some critical systems where it is not possible to generate or simulate failures. One of the possibilities is called Novelty Detection as proposed by Finch (2020). It enables to create an anomaly detection system when the incoming data is outside of the known healthy state from the model. A second possibility is linked with the transformation of timeseries data into images, to use machine learning models for image classification, as proposed by Hatami et al. (2018) and Yang et al. (2019). Similarly, the main idea is to label images for the healthy state of the equipment, and detect faulty states as anomalies by the model.

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Résumé en français

Ce document présente les résultats d'un projet collaboratif entre Plastic Omnium et le laboratoire LCFC d'Arts et Métiers. L'objectif du projet était de créer un cadre de maintenance prédictive à utiliser dans les milieux industriels. La maintenance prédictive (ou prévisionnelle), qui consiste à utiliser des données pour prévoir et prévenir les défaillances de l'équipement, a suscité de plus en plus d'attention ces dernières années dans le cadre des activités liées à l'Industrie 4.0. Le développement d'un système de maintenance intelligent capable de gérer une grande partie des travaux nécessaires à la mise en œuvre d'une approche de maintenance prédictive a été un résultat clé du projet. L'objectif du système est d'améliorer les performances des systèmes de production en ayant une meilleure compréhension leur comportement et en détectant les défaillances de manière précoce, afin de les prévenir.

Au **Chapitre 1**, nous avons présenté le sujet de cette thèse, qui porte sur la maintenance prédictive et son application grâce à des techniques de l'Industrie 4.0. Nous avons également décrit le contexte industriel dans lequel le travail a été mené, en particulier l'industrie automobile, qui a une longue tradition de conduite de l'innovation dans ce domaine. L'objectif du sujet était de développer une solution qui pourrait être appliquée à différents domaines, mais le contexte industriel a fourni un cadre pratique pour tester et affiner les méthodes proposées. L'objectif principal de la thèse a alors été résumé sous la forme d'une question de recherche, ainsi que de quatre verrous scientifiques et besoins industriels connexes qui devaient être traités.

Le **Chapitre 2** présente une revue de la littérature sur l'état actuel de la maintenance dans le contexte de l'Industrie 4.0. Dans ce chapitre, nous avons constaté un changement dans la façon dont la maintenance est perçue par les entreprises de fabrication, passant d'une image de "mal nécessaire" à un élément clé pour l'industriel. Nous avons également discuté de la méthodologie util-

isée pour mettre en œuvre la maintenance prédictive, qui implique généralement l'utilisation du PHM (Prognostics & Health Management). Le processus de mise en œuvre de la maintenance prédictive comprend des étapes telles que la sélection et la collecte de données, et la conception de systèmes de prise de décision pour soutenir la communication des analyses réalisées. Nous avons examiné les défis associés à la mise en œuvre de cette méthodologie dans un contexte industriel, y compris les coûts et la difficulté de démontrer un retour sur investissement. Pour aider à surmonter ces défis, nous avons proposé un cadre de maintenance prédictive qui décrit les différentes activités impliquées et comment elles peuvent être mises en œuvre dans l'industrie.

Le **Chapitre 3** décrit l'application du cadre de maintenance prédictive introduit au **Chapitre 2**. Nous avons décrit la méthodologie étendue derrière le cadre et présenté une étude de cas dans laquelle le cadre a été utilisé pour détecter des problèmes avec un composant critique dans les unités de soudure. L'étude de cas a montré des résultats satisfaisants concernant les différentes activités du cadre et des outils utilisés pour les mettre en œuvre. La solution a été en mesure de détecter de premiers problèmes avec le composant et a été déployée dans plusieurs usines. Cependant, l'étude a également identifié certaines limites et domaines d'amélioration, notamment la nécessité de développer un outil accessible à la fois aux experts et aux utilisateurs non-experts des systèmes de production. L'intégration des connaissances et de l'expérience de ces utilisateurs dans le processus de maintenance prédictive est un défi clé afin de détecter et de prédire efficacement les défaillances. En ce qui concerne les problèmes scientifiques et industriels décrits au **Chapitre 1**, l'étude de cas a fourni des réponses partielles en:

- Développant une méthode pour sélectionner des cas significatifs pour la maintenance prédictive, et en identifiant les principaux paramètres à collecter et à surveiller
- Décrivant le système de gestion de données utilisé et développé dans le projet, qui est basé sur des logiciels et des outils open source
- Effectuant des analyses de données pour détecter de premiers modèles d'un mode de défaillance imminent
- Concevant un système de prise de décision basé sur la visualisation des données et sur les résultats de leurs analyses, et qui alerte les utilisateurs finaux par e-mail

Par conséquent, au **Chapitre 4**, nous avons proposé une solution globale pour répondre à la question de recherche énoncée au **Chapitre 1**. La solution,

appelée "Machine Health Management" (MHM), a été conçue pour servir à la fois d'outil de développement pour les experts et les non-experts, et d'une plateforme pour déployer des solutions de maintenance prédictive à l'échelle mondiale. Nous avons souligné la flexibilité de la solution, qui est construite sur des normes open source, et qui peut être adaptée aux nouvelles découvertes de la littérature ou aux besoins spécifiques des acteurs industriels. Nous avons présenté deux études de cas dans lesquelles l'utilisation de l'application MHM a fourni de bons résultats et a identifié des opportunités d'amélioration. Les principales contributions de l'application MHM sont la normalisation de la collecte de données, l'utilisation de divers protocoles de communication industrielle pour transmettre les données, des visualisations standard pour les utilisateurs ainsi que la possibilité de créer des visualisations personnalisées, des techniques standard pour surveiller les données collectées et différents canaux pour alerter en fonction des analyses de données. Ces contributions répondent aux quatre problèmes scientifiques et industriels énoncés au **Chapitre 1**. Le cadre proposé et l'application MHM sont les principales contributions de cette thèse pour répondre à la question de recherche : "Comment les industries peuvent-elles mettre en œuvre la maintenance prédictive avec l'aide de l'Industrie 4.0?"

Ce projet de thèse a profité de trois aspects clés rendus possibles par le contexte scientifique et industriel double de la convention CIFRE :

- La possibilité de mener des recherches scientifiques et de développer des méthodologies sur la base du travail de chercheurs de différents domaines
- La possibilité de confronter les solutions proposées sur des cas réels, et aux exigences industrielles, et d'impliquer les utilisateurs finaux dans le processus
- Le développement d'une solution technique capable de gérer les données de divers systèmes de production, appareils et capteurs et de répondre aux exigences des études scientifiques et industrielles

Appendices

A Plastic Omnium Clean Energy Systems presentation

The Clean Energy Systems division of Plastic Omnium is specialized in plastic fuel tanks systems, and depolluting systems, mostly for private and commercial vehicles. Some numbers about the division can be found in Figure A.1. In 2018, more than 22M fuel systems have been delivered, representing 1 out of 4 commercialized vehicles equipped with a CES fuel system. Since 2021, the company is also evolving towards electrification of vehicles, by producing battery packs, and proposing high-pressure tanks for hydrogen-powered vehicles.

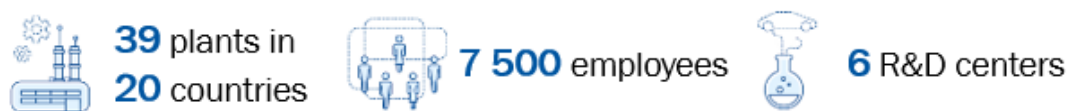


Figure A.1: CES division numbers

The material used for producing the fuel tanks is High-Density Polyethylene (HDPE). There are several reasons why they are made of plastic and not in metal as they used to be (for cars):

- Plastic is lighter than metal (about 30%); which allows a reduction of fuel consumption
- The raw material is less expensive
- A plastic tank cannot explode: it will melt, and the fuel will be spilled on the floor

However, one issue is the permeability: as plastic is a porous material, fuel will eventually end up going through it and that leads to two major issues: the



Figure A.2: Plastic fuel tank



Figure A.3: Filler pipe

consumer will lose some of his gas, and this one will go into the air and pollute the atmosphere. That is why a fuel tank is not a simple container of fuel: it is a real part composed of complex technologies, from the production processes to the material used, and also the parts attached to the fuel system; filling system, pump gauge module, ventilation. These are used to make the fuel system less permeable to cope with the different regulations. Figure A.2 shows an example on a plastic fuel tank, and the different parts welded on it.

A fuel system A.4 is composed of a fuel tank and a filler pipe A.3, the latter is the only part visible of the system by the end user, to refill the tank at the station.

The system called SCR (Selective Catalytic Reduction) stores a fluid named Adblue, which reduces the polluting emissions for diesel vehicles, as shown in Figure A.5.

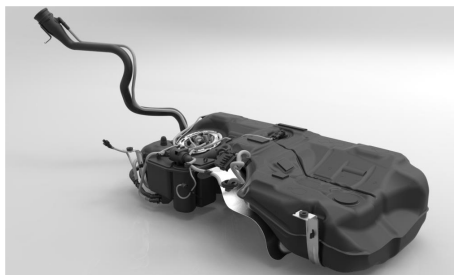


Figure A.4: Fuel system



Figure A.5: SCR product

B Fuel tanks production: the different processes

Several processes exist to produce a fuel tank. Each of them are quite different, and the resulting tanks have their specific properties.

Mono-layer tank It is the basic process used to produce a plastic fuel tank. The material used is HDPE as mentioned in the previous appendix, it is melted and transported through an extruder until the “head” of the machine that will deliver the right quantity of material to produce the part. A “parison” is created by the head, such as in Figure B.1; it is then captured by the mold that is composed of two parts, and then the parison is blown so that the material will take the shape of the mold. Then, the tank is going through a fluorination phase, so that its permeability is improved.

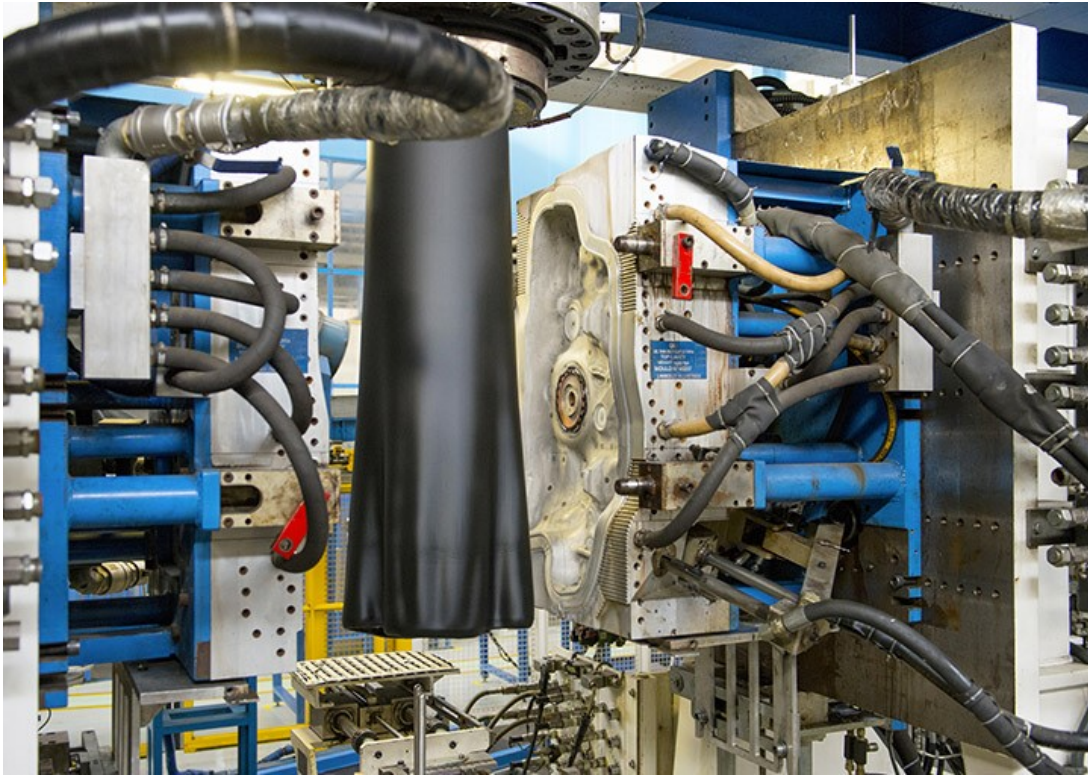


Figure B.1: Plastic parison

The different steps are depicted in Figure B.2:

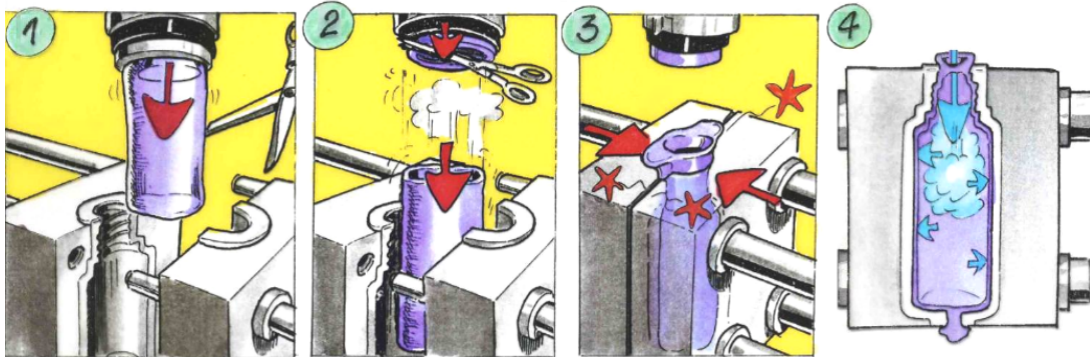


Figure B.2: Blow molding process (training material Plastic Omnium)

For all the processes presented, the next step after the extrusion and the blowing of the tank are the same: it goes through a post-cooling phase where the temperature of the tank is reduced, then a finishing phase where the different components are welded on the tank, and finally, the filler pipe is assembled on the fuel tank.

Co-extrusion To get rid of the fluorination phase of the mono-layer tanks (because of its toxicity and dangers) and to solve the problem of permeability to respect the norms, a co-extrusion process has been designed by the division. The steps are like the mono-extrusion, though in that case, up to seven extruders can be used instead of one. The goal is to create a multi-layer tank with the use of different material, as shown in Figure B.3:

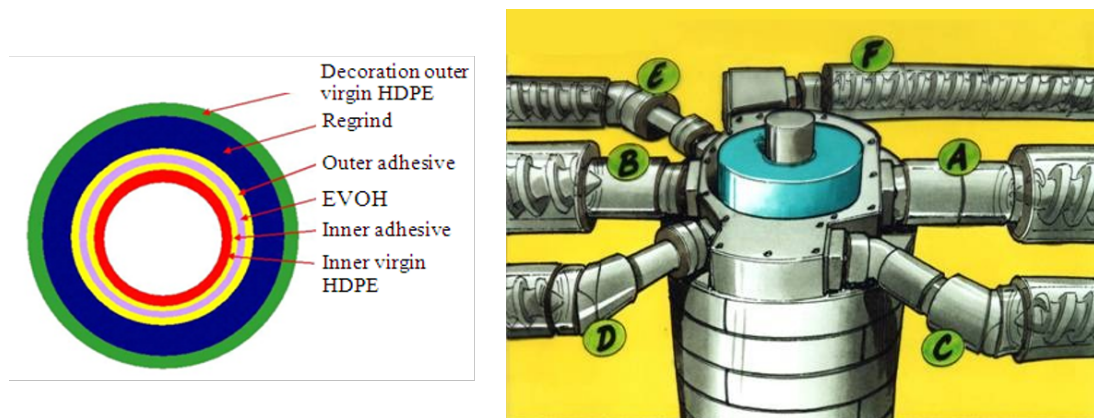


Figure B.3: Co-extrusion process (training material Plastic Omnium)

A new material appears, to replace the fluorination phase: the EVOH (Ethylene Vinyl alcohol). It allows a high degree of permeability, so that the fuel leaks

B. FUEL TANKS PRODUCTION: THE DIFFERENT PROCESSES

can sustain the norms. Though, as it is a highly volatile substance, it requires layers of adhesives to stay in place.

TSBM: Twin Sheet Blow Molding This is the most recent process designed by the company. To reduce even more the gas leaks within the tank, the components that were previously welded on the tank are now trapped inside the tank. Two parallel sheets are extruded, and then individually blown on the two sides of the central core that contains the components. Finally, the two sides are welded together to form the tank. The process is shown in Figure B.4:

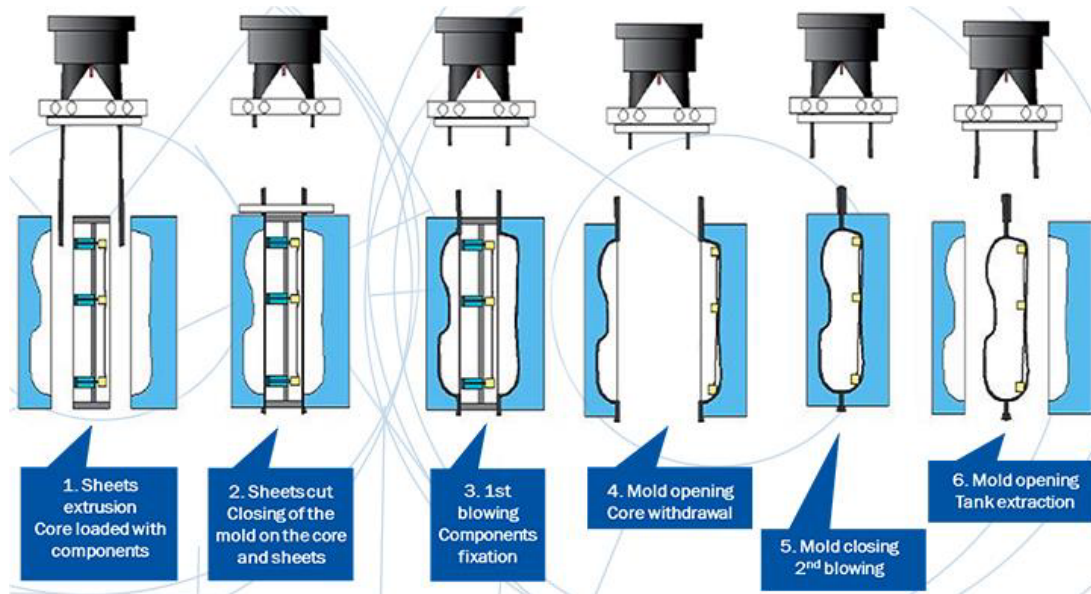


Figure B.4: TSBM process (training material Plastic Omnium)

C Full production process

Blow-molding is the first process to produce the fuel system (1). Once it has been blown, the flash around the tank is removed and regrinded (2), then it enters a phase of post-mold cooling, where its temperature is lowered with a water flow in a second mold (3/4). It is then stabilized in ambient air (5/6), before entering the finishing center, where parts of the tank will be cut, and extra components welded on it (7). Then some parts will be assembled on the tank, such as the filler pipe presented above (8/9/10). Finally, every tank is tested to detect possible leaks (11). WLT refers to Water Leak Test, which is a machine used to check the leaks of the produced tanks by immersing it into water. A trained quality operator then checks visually for bubbles, if the machine did not detect first major leakage. Other leak-testing technologies exist, such as HLT (Helium Leak Test), where helium gas is injected inside a sealed tank, then particles observed outside of the tank should not exceed a certain amount to validate the quality of the product. Finally, parts are shipped to customers (12).

In some cases, tanks are shipped in advanced locations for assembly, before steps 8/9/10.

The full process is detailed in Figure C.1:



Figure C.1: Full production process

D Modelling linked to predictive maintenance activities

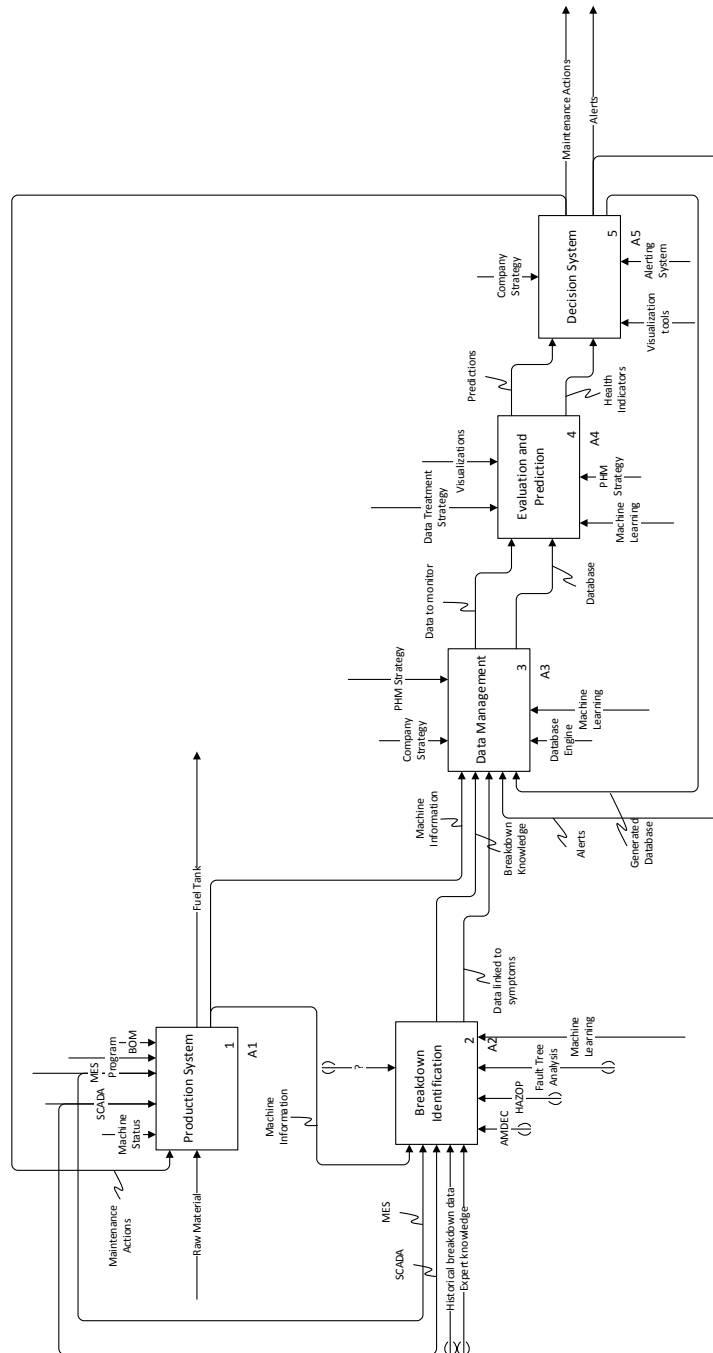


Figure D.1: SADT

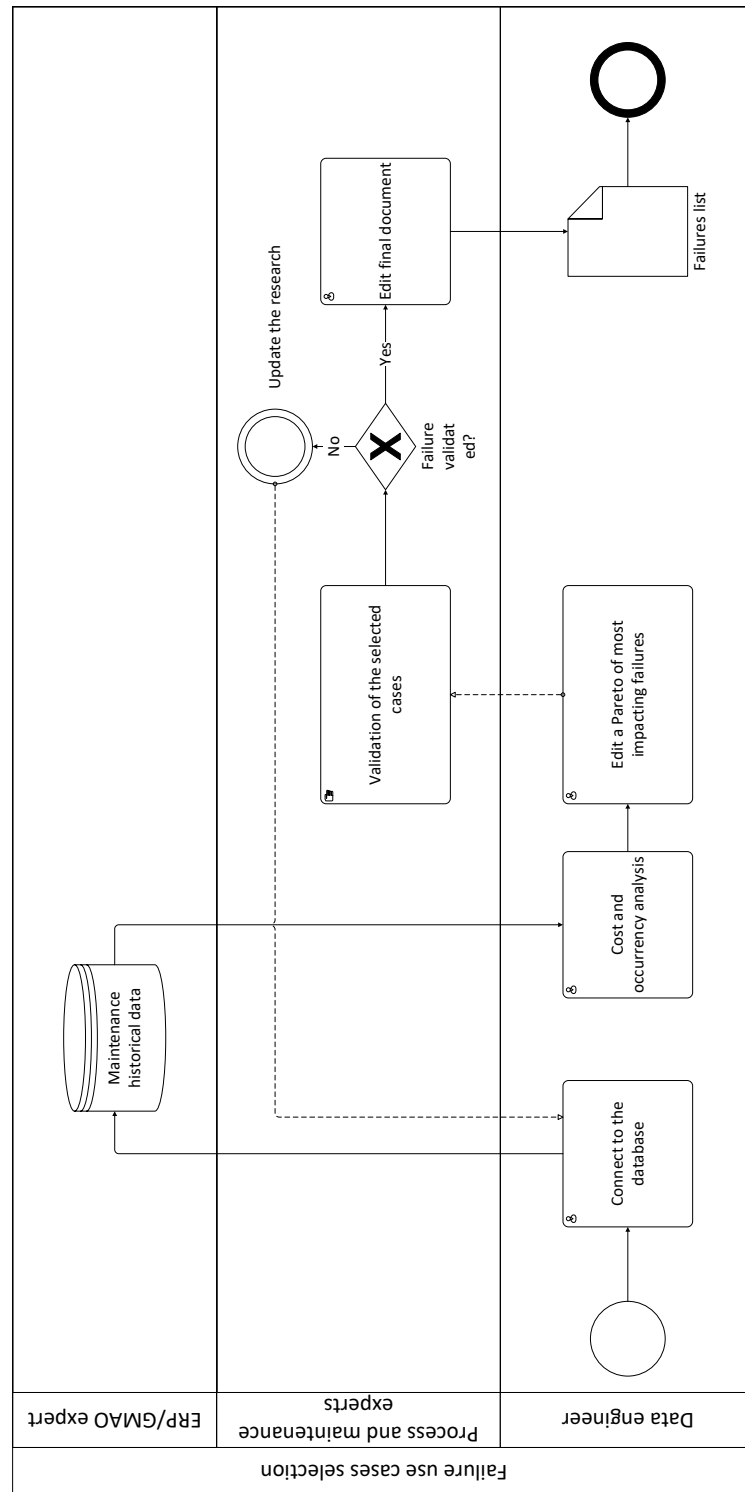


Figure D.2: BPMN

E Welding unit - thermocouples' issues detection



Figure E.1: Detection of failure on thermocouple (Grafana)

As observed on the two graphs of Figure E.1, the application is counting the peaks observed, and triggers an alert to the plant's maintenance team. From the event in the figure, maintenance team observed a cable wear issue, the wire being exposed and making contact with other parts of the machine during the movement of the unit. These contacts create the observed peaks, or micro-cuts. An example of cable issue can be seen in Figure E.2.



Figure E.2: Thermocouple cable issue

F Welding unit - band heaters experiments

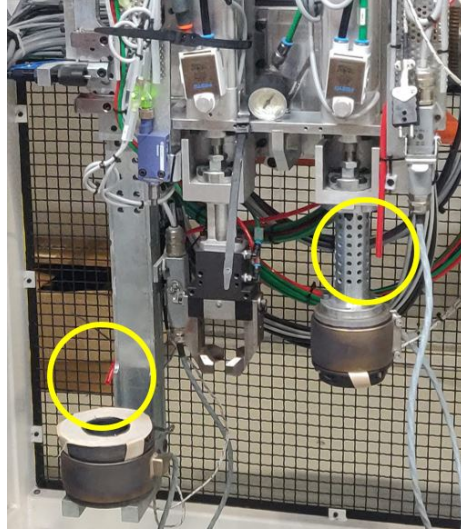
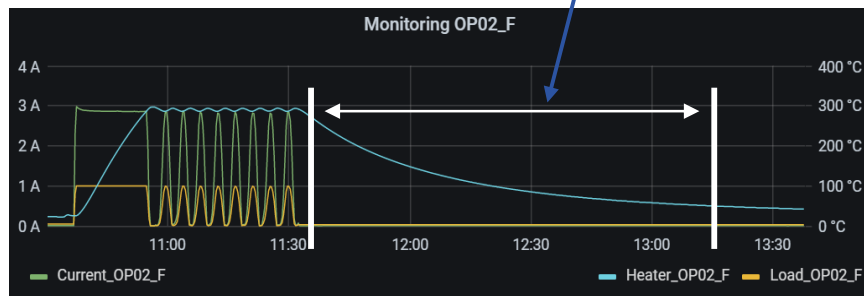


Figure F.1: Fast cooling modification

Without blowing air: 15min to heat to 300 °C / 1h30 to cool down to 50 °C



With air blowing: 15min to heat to 300 °C / 30min to cool down to 50 °C

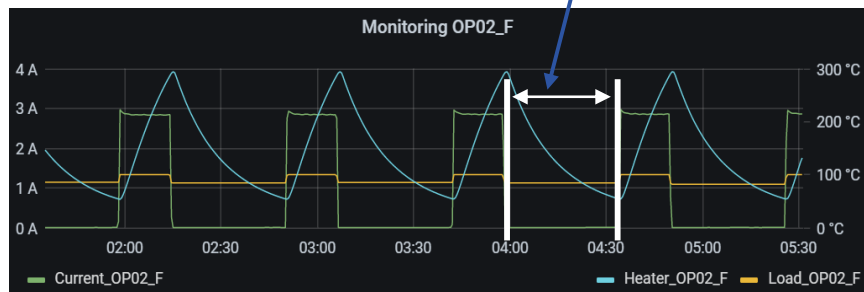


Figure F.2: Repeated cycles (Grafana)

F. WELDING UNIT - BAND HEATERS EXPERIMENTS

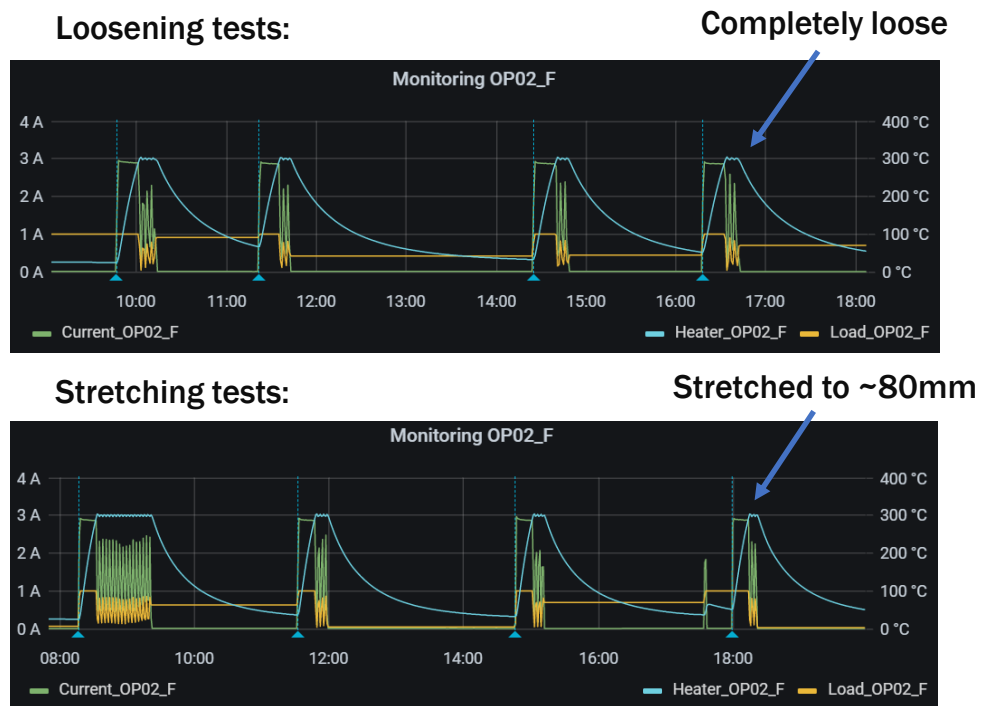


Figure F.3: Mechanical tests (Grafana)

G BMM - vibration and hydraulics

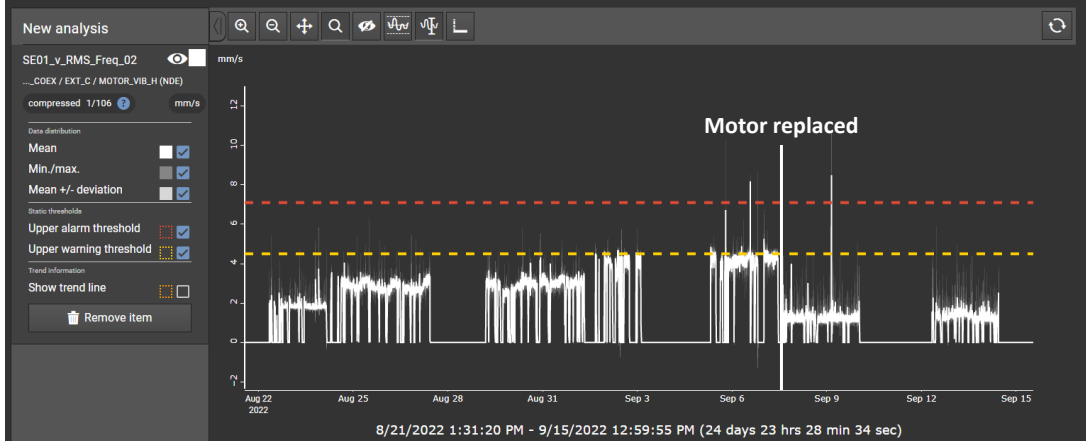


Figure G.1: Mechanical failure detection

The value displayed in Figure G.1 is the velocity of the vibration, also named Velocity Root Mean Square (V-RMS). It is linked with the energy of the vibration, and studying its trend gives a relevant indicator of the state of the rotating element.

In the case presented above, the slow increasing trend of the data until it reached the first warning level allowed the early replacement of the motor. After analysis of the non-drive end of the equipment, mechanical wear was observed on bearing flange. This damage was produced by an unbalance located on the rotating axis, which could have ultimately created an issue on the outer race of the bearing.

Despite the early stage of the deterioration, an efficient planning to verify the part allowed the plant to avoid a failure on this critical component. A low estimation of the non-production costs are around 500\$ per hour lost, in addition to the cost of the components to be replaced. Cases like this one show the relevance of the monitoring system, and also facilitates the adoption by users.

Figure G.2 shows two cases where the monitoring of the particles within the oil provided an indication on its contamination. This contamination can come from external systems, even though it is filtered, some particles can still transfer to the oil and create issues within the mechanical systems.

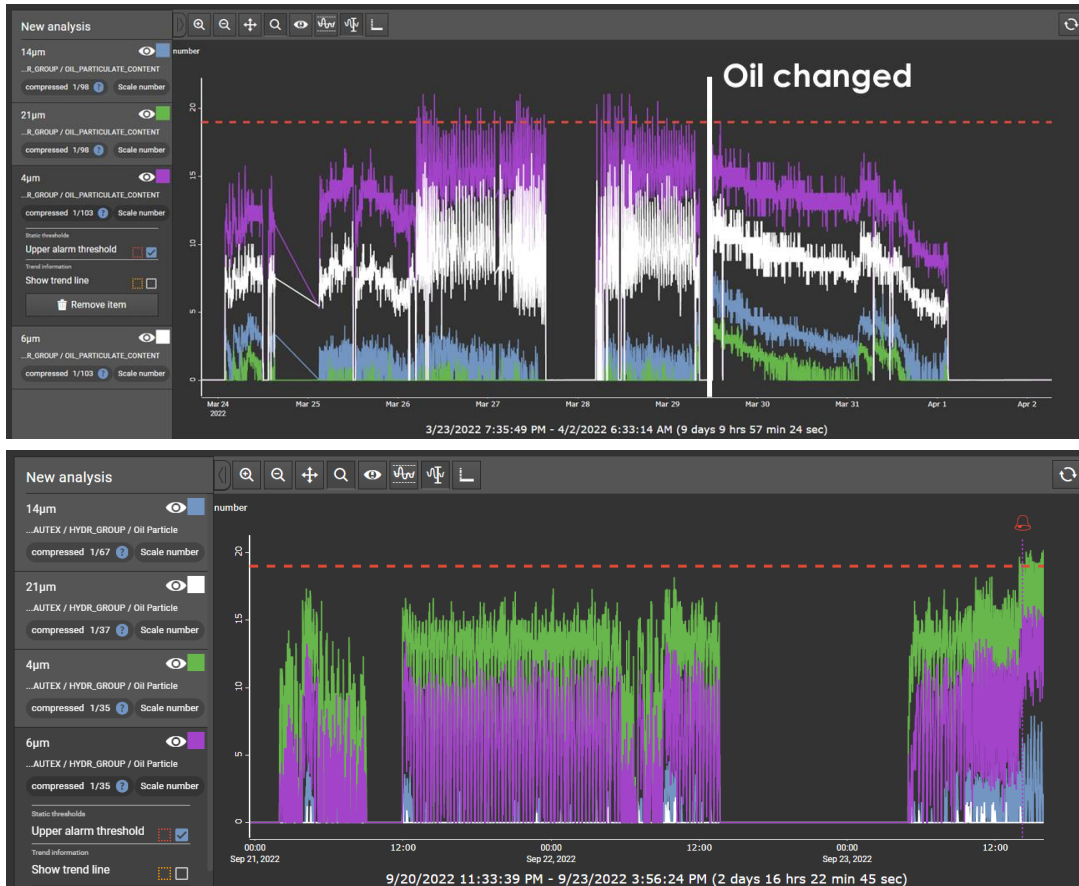


Figure G.2: Oil contamination detection

A contaminated oil is less effective in lubricating the systems, and can then generate wear on the mechanical contact points. The produced mechanical wear will in its turn contaminate the oil with metallic particles and generate further issues in the whole system. Consequently, monitoring the quality of the oil is a critical maintenance task.

To generate the alarm levels observed in the figure, the standard ISO 4406 was used. Its goal is to help determining the threshold above which the quality of the oil is deemed deteriorated. To do so, a maximum number of observed particles of different sizes (higher than 4µm, 6µm and 14µm) is taken into account, in 1mL of oil. Then, depending on the type of equipment used, thresholds can be implemented on these parameters, using the norm. In the case presented here, the particles larger than 21µm are also considered.

H HLT - data visualization

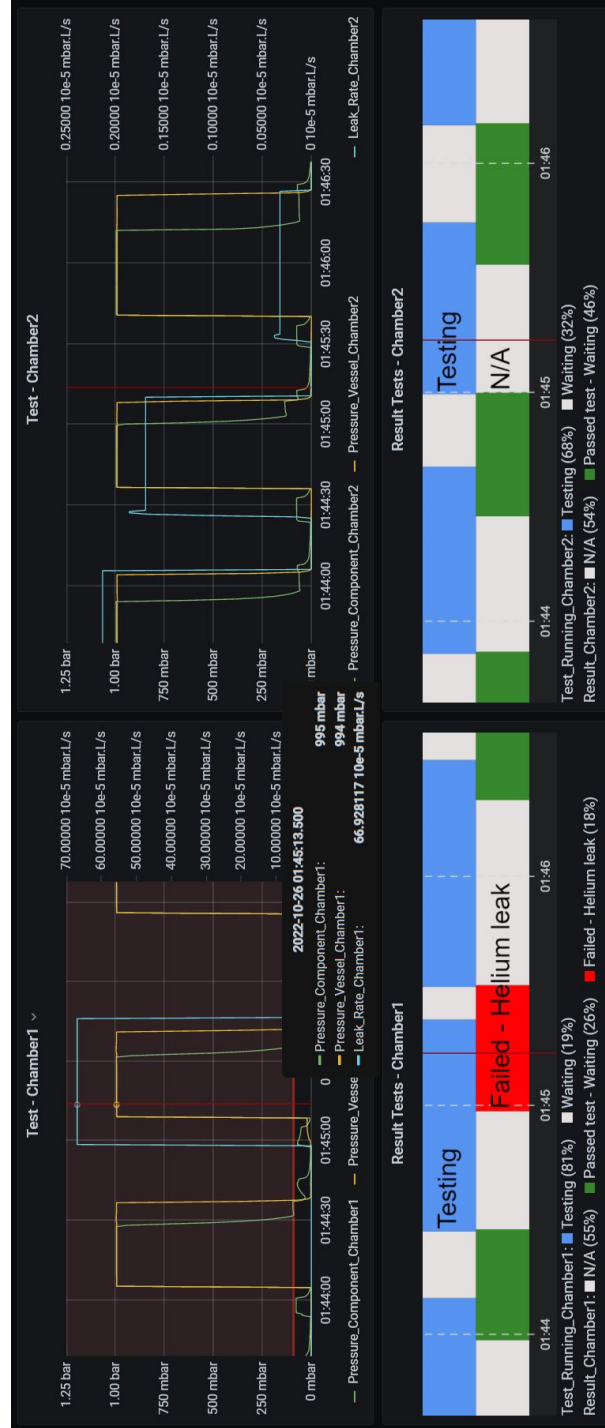


Figure H.1: Data visualization for HLT monitoring (Grafana)

I Energetic Technical Functions for systematic data selection

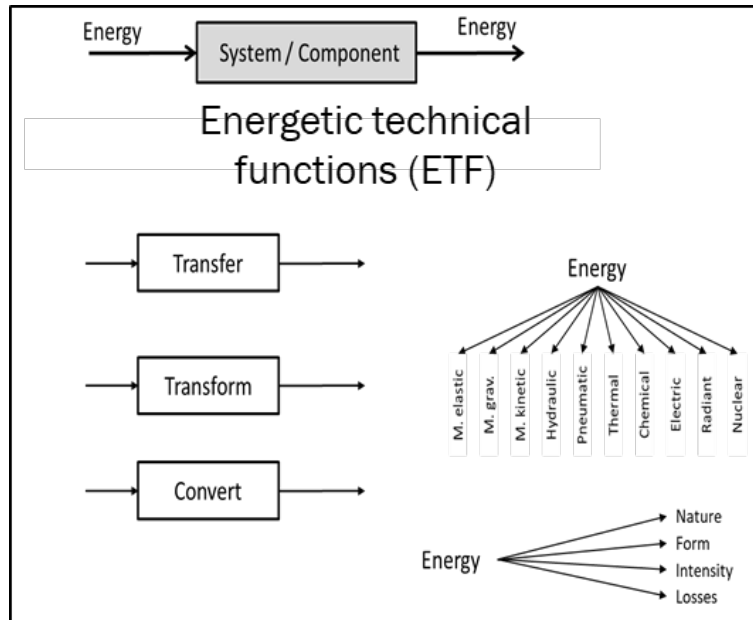


Figure I.1: Modelling of an Energetic Technical Function

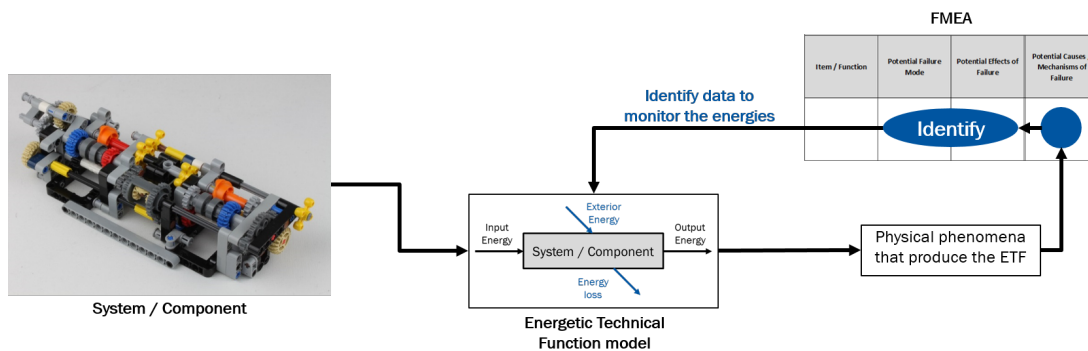


Figure I.2: Data identification process

I. ENERGETIC TECHNICAL FUNCTIONS FOR SYSTEMATIC DATA SELECTION

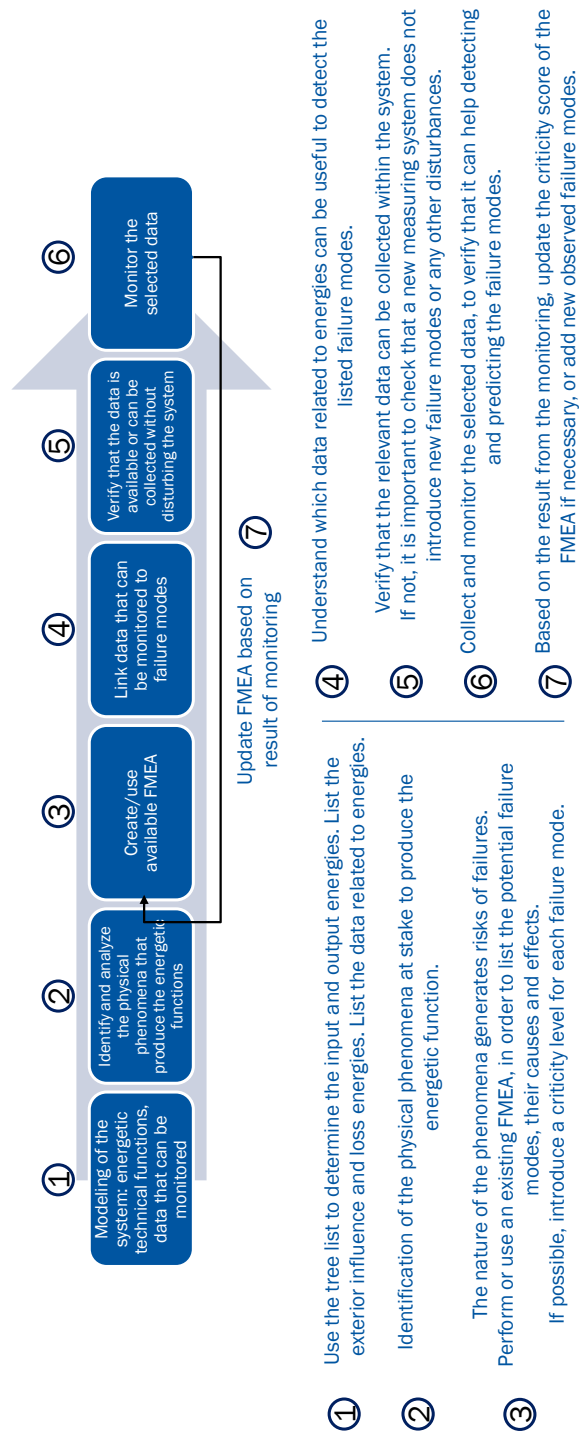


Figure I.3: Overview of the data selection process

Elaboration d'un système de maintenance prédictive basé sur l'analyse des données de production et l'expertise humaine : application à un procédé d'extrusion soufflage

Résumé

Au cours des dernières années, la façon dont la maintenance est effectuée a évolué grâce à l'incorporation d'outils numériques et de concepts de l'Industrie 4.0 au sein des entreprises. En se connectant aux systèmes de production et en communiquant avec eux, des informations peuvent être collectées sur l'état actuel et futur de l'équipement, permettant un contrôle plus efficace grâce à un processus appelé maintenance prédictive (PdM). L'objectif de la PdM est de réduire les temps d'arrêt imprévus et de répondre de manière proactive aux besoins de maintenance avant que des pannes ne se produisent. Cependant, nous avons constaté qu'il peut encore être difficile pour les praticiens industriels de mettre en place un tel système, qui gère efficacement les données pour détecter les défaillances précoces. Par conséquent, ce travail de recherche vise à proposer une méthodologie générale pour développer et déployer un système de maintenance intelligent. La méthodologie et le système développé (appelé MHM – Machine Health Management) ont été validés sur des cas industriels concrets, dans le contexte de l'industrie automobile. La principale contribution est liée à la flexibilité de l'outil, offerte par l'utilisation de normes open-source. Cela permet d'avoir un système standard utilisable dans différents contextes, et qui peut s'adapter aux spécificités lorsque cela est nécessaire.

Mots clés : Maintenance prédictive, Analyse de données, Modélisation de connaissances experts, PHM.

Abstract

In recent years, the way that maintenance is carried out has evolved due to the incorporation of digital tools and Industry 4.0 concepts within companies. By connecting to, and communicating with the production systems, information can be gathered about the current and future health of the equipment, enabling more efficient control through a process called Predictive Maintenance (PdM). The goal of PdM is to reduce unplanned downtimes and proactively address maintenance needs before failures occur. However, we have seen that it can still be challenging for industrial practitioners to implement such system, which effectively manages data to try and detect failures early. Consequently, this research work aims at proposing a general methodology to develop and deploy an Intelligent Maintenance System. The methodology and the developed system (called MHM – Machine Health Management) were validated on concrete industrial cases, in the context of automotive industry. The main contribution is related to the flexibility of the tool, offered using open-source standards. It allows to have a standard system useable in various contexts, and it can adapt to specificities when required.

Keywords: Predictive maintenance, Data analysis, Expert knowledge modelling, PHM.