



New decision support methods for dynamic predictive maintenance based on data science and multi-objective optimization

Behnam Einabadi

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**Nouvelles méthodes d'aide à la décision
pour la maintenance prédictive
dynamique basée sur la science des
données et l'optimisation multi objectifs**

*New decision support methods for dynamic predictive maintenance based on data science
and multi-objective optimization*

Devant le jury composé de :

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MACCHI Marco	Professeur - Politecnico di Milano	Rapporteur
SIADAT Ali	Professeur - Arts et Métiers Metz- LCFC	Rapporteur
SCUTURICI Marian	Professeur - INSA de Lyon - LIRIS	Examineur
Fouzia OUNNAR	Maitre de Conférences - Aix Marseille Université,	Examinatrice
ROTHER Eva	Directrice industriel - Comeca Group-Chatenoy le Royal	Examinatrice
BABOLI Armand	Maitre de Conférences HDR - -INSA de Lyon	Directeur de thèse

Référence : TH0982_M. Behnam EINABADI

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*ScSo : Histoire, Géographie, Aménagement, Urbanisme, Archéologie, Science politique, Sociologie, Anthropologie

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Abstract

Recently, the predictive maintenance (PdM) concept has received increasing attention in industrial practices and academic research. The potential opportunities for utilizing real-time data provided by the Industry 4.0 principles and technologies are often exploited for equipment health monitoring and remaining useful life (RUL) estimation. Thereby, most studies focus on the prediction of failures, which is important in itself, while the prescription of decisions for maintenance activities is much less addressed in the literature. Furthermore, it is often neglected that in the real world, all the equipment or components cannot be maintained only through the PdM strategy and planning of this type of maintenance intervention could not be separated from other maintenance strategies and activities such as preventive maintenance (PvM).

The aim of this thesis is to propose new approaches and methods for PdM and PvM through data science and mathematical optimization. The study aims to address several key questions, such as the feasibility of estimating the health state and/or RUL of equipment/components, and the methods to use this data and information in decision-making and maintenance planning, while considering their links to other activities. In this regard, a comprehensive Predictive Maintenance Management System (PdMMS) approach is proposed. This approach covers overall maintenance strategies and involves several interconnected steps, from descriptive and diagnostic analysis to prescriptive decision-making. These steps incorporate the criticality analysis of equipment and/or components, identification of appropriate maintenance strategies for each equipment and/or component, identification and acquisition of required data and information for each strategy, maintenance monitoring system for PvM and corrective strategies, equipment health monitoring and RUL estimation for PdM strategy, and finally, maintenance planning of overall maintenance interventions. Based on this approach, various appropriate methods, algorithms, and applications were developed and applied to different use cases at the Fiat Powertrain Technologies Bourbon-Lancy (FPT-BLY) plant.

Initially, a new approach for identifying maintenance strategies is proposed. This approach relies on several methods such as multi-criteria decision-making (MCDM), ABC analysis, sensitivity analysis, and optimal frequency identification. It has been applied to one of the complex Computer Numerical Control (CNC) equipment, and the proposed approach has successfully identified critical equipment and components, resulting in a significant reduction in emergency purchases. Concerning maintenance monitoring, the most relevant maintenance indicators have been identified, and appropriate visualization dashboards have been proposed to monitor maintenance performance and facilitate the identification of improvement actions. Regarding equipment health monitoring and RUL estimation, a health indicator (HI) method and a new dynamic algorithm are proposed and applied to a use case of a conveyor chain painting system. The results demonstrate the possibility of dynamically estimating the health state and RUL based on real-time data. In the same case, a problem of simultaneous PdM and PvM planning is also studied. In this context, a mathematical optimization model is proposed to minimize overall costs, including direct (intervention costs) and indirect (expected failure risk costs, unused life losses), by considering the opportunistic grouping of maintenance interventions. This study indicated that RUL information could be integrated into the comprehensive maintenance planning system to identify optimal planning. Moreover, to validate the proposed method, an inclusive sensitivity analysis is provided, and the obtained results indicate that considering the mentioned aspects could significantly impact maintenance planning and decrease overall maintenance costs in the mid/long term. Finally, the thesis conclusion highlights the main implementation challenges of the proposed PdMMS approach in other companies, along with managerial insights and research perspectives.

Key words: Predictive maintenance, RUL estimation, Maintenance planning, real-time data, data analytics, mathematical optimization, Industry 4.0.

Résumé

Au cours de la dernière décennie, le concept de maintenance prédictive (PdM) a attiré une attention croissante dans les pratiques industrielles et la recherche académique. Les opportunités potentielles d'utilisation des données en temps réel offertes par les principes et les technologies de l'Industrie 4.0 sont souvent exploitées pour la surveillance de l'état de santé des équipements et l'estimation de la durée de vie restante (RUL). De ce fait, la plupart des études se concentrent sur la prédiction des défaillances, qui est en soi importante, tandis que la prescription de décisions pour la planification des interventions de maintenance est beaucoup moins abordée dans la littérature. De plus, il est souvent négligé que dans le monde réel, tous les équipements ou composants ne peuvent pas être entretenus uniquement par la stratégie de PdM et la planification des interventions pour ce type de maintenance ne peut pas être détachée des autres activités et stratégies de maintenance telles que la maintenance préventive (PvM).

L'objectif de cette thèse est de proposer de nouvelles approches et méthodes de PdM et de PvM grâce à la science des données et à l'optimisation mathématique. L'étude vise à répondre à plusieurs questions clés, telles que la possibilité d'estimer l'état de santé et/ou RUL des équipements/composants, la manière d'utiliser ces données et informations dans la prise de décision et la planification de la maintenance, tout en tenant compte de leurs liens avec d'autres activités. À cet égard, une approche globale de l'organisation de la maintenance prédictive est proposée. Cette approche couvre l'ensemble des stratégies de maintenance et implique plusieurs étapes interconnectées, de la description et du diagnostic à la prise de décision prescriptive. Ces étapes intègrent également l'analyse de la criticité des équipements et/ou composants, l'identification de la stratégie appropriée de maintenance pour chaque équipement et/ou composant, l'identification et l'acquisition de données et d'informations nécessaires pour chaque stratégie, le système de surveillance de la maintenance pour les stratégies PvM et corrective, la surveillance de l'état de santé des équipements et l'estimation de la RUL pour la stratégie PdM, et enfin la planification de l'ensemble des interventions de maintenance. Sur cette base, plusieurs méthodes, algorithmes et applications appropriés ont été développés et appliqués sur différents cas d'utilisation à l'usine Fiat Powertrain Technologies Bourbon-Lancy (FPT-BLY).

Initialement, une nouvelle approche d'identification de la stratégie de maintenance est proposée. Cette approche s'appuie sur plusieurs méthodes telles que la prise de décision multicritère (MCDM), l'analyse ABC, l'analyse de sensibilité et l'identification de la fréquence optimale et est appliquée sur l'un des équipements de contrôle numérique (CNC) les plus complexes. L'approche proposée a identifié avec succès les équipements et les composants critiques, permettant d'obtenir une réduction significative des achats d'urgence. Concernant la surveillance de la maintenance, les indicateurs de maintenance les plus pertinents ont été identifiés et des tableaux de bord de visualisation appropriés sont proposés pour surveiller la performance de la maintenance et faciliter l'identification des actions d'amélioration. En ce qui concerne la surveillance de l'état de l'équipement et l'estimation de RUL, une méthode d'indicateur de santé (HI) et un nouvel algorithme dynamique sont proposés et appliqués sur un système de chaîne de convoyage de peinture. Les résultats montrent la possibilité d'estimer dynamiquement l'état de santé et la RUL en se basant sur les données en temps réel. Sur le même cas, un problème de planification simultanée PdM et PvM est aussi étudié. Dans ce contexte, un modèle d'optimisation mathématique est proposé pour minimiser les coûts globaux contenant le coût direct (coûts d'intervention) et indirects (coûts estimés du risque de défaillance, pertes de durée de vie inutilisée) tout en prenant en compte le groupement opportuniste des interventions. Cette étude a indiqué que les informations de RUL pourraient être intégrées dans le système de planification de maintenance global pour identifier une planification optimale. De plus, pour valider la méthode proposée, une analyse de sensibilité complète est fournie, et les résultats obtenus indiquent que la prise en compte des aspects mentionnés pourrait avoir un impact significatif sur la planification de la maintenance et pourrait permettre de réduire les coûts de maintenance globaux à moyen/long terme. Enfin, les défis de la mise en œuvre de l'approche proposée dans d'autres entreprises, les issues managériales et les perspectives de recherche ont été discutés.

Mots clés : Maintenance prédictif, Estimation RUL, Planification de la maintenance, Données du temps réel, Data analytiques, Optimisation mathématique, Industrie 4.0.

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Abbreviations

AI	Artificial Intelligence
AM	Auto Maintenance
ANN	Artificial Neural Network
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
BD	Big Data
BM	Breakdown Maintenance
CBM	Condition-based Maintenance
CC	Cloud Computing
CIFRE	Industrial Conventions for Training through Research
CNN	Convolution Neural Network
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
CRITIC	Criteria Importance Through Inter-criteria Correlation
CS	Cyber Security
DF	Distribution Function
DL	Deep Learning
DR	Discriminant Ratio
DSS	Decision Support System
EcD	Economic Dependency
EDA	Exploratory Data Analysis
EqG	Equipment Grouping
ERP	Enterprise Resource Planning
FFT	Fast Fourier Transform
FMECA	Failure Mode, Effects Criticality Analysis
FPT	Fiat Powertrain Technologies
FPT-BLY	Fiat Powertrain Technologies- Bourbon Lancy plant

FPTF	Fiat Powertrain Technologies France
FuD	Functional Dependency
GMC	Gross Maintenance Costs
HBM	Hit based Maintenance
HI	Health Indicator
HMI	Human-Machine Interface
HMM	Hidden Markov Model
HS	Health state
HSMM	Hidden Semi-Markov Models
I&R	Inspection and Repair
i.i.d	independent and identically distributed
I4.0	Industry 4.0
ICT	Information & Communication Technology
IIoT	Industrial Internet of Things
IoS	Internet of Service
IoT	Internet of Things
IT	Information Technology
JIT	Just in Time
KNN	K-Nearest Neighbor
KAI	Key Activity Indicator
KPI	Key Performance Indicator
K-S	Kolmogorov-Smirnov
LCL	Lower Control Level
LSTM	Long Short-term Memory
MAPE	Mean Absolute Percentage Error
MCDM	Multi-Criteria Decision Making
MES	Manufacturing Execution System
ML	Machine Learning

MLP	Multi-Layer Perceptron
MSME	Multi-Spindle Machining Equipment
MTBF	Mean Time Between Failure
MTTR	Mean Time to Repair
NN	Neural Network
OEE	Overall Equipment Effectiveness
OFV	Objective Function Value
PCA	Principal Component Analysis
PDF	Probability Density Function
PdM	Predictive Maintenance
PdMMS	Predictive Maintenance Management System
PHM	Prognostic and Health Monitoring
PLC	Programmable Logic Controller
PM	Professional Maintenance
PoC	Proof of Concept
PQCDMS	Productivity, Quality, Cost, Delivery, Morale, and Safety
PvM	Preventive Maintenance
R&D	Research and Development
R2F	Run-to-Failure
RCM	Reliability-Centered Maintenance
RFID	Radio-Frequency Identification
RL	Reinforcement Learning
RMS	Root Mean Square
RMSE	Root Means Square Error
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
SMART	Simple Multi-Attribute Ranking Technique
SMP	Standard Maintenance Procedure

SrD	Structural Dependency
SVM	Support Vector Machines
TBM	Time-based Maintenance
TIE	Total Industrial Engineering
TPM	Total Productive Maintenance
TQC	Total Quality Control
TTR	Time to Repair
TPS	Toyota Production System
UCL	Upper Control Level
WCM	World Class Manufacturing

Part 1: Introduction, motivation, and literature review

In this part, the global context of this thesis is presented. In **chapter 1** the thesis subject and the research objectives, questions, and motivation are provided. This thesis is carried out in the context of a CIFRE (Industrial Conventions for Training through Research) which is an industrial agreement between research institutes and Fiat Powertrain Technologies (FPT) company. Knowing that in the CIFRE thesis, the reach activities are planned and performed based on the industrial requirements, the presentation of the company, its challenges, and complexities in maintenance planning are presented in **chapter 2**. Furthermore, the opportunities for digital transformation projects in this company are also presented. **Chapter 3** is dedicated to the literature review that has been surveyed in predictive maintenance state-of-art, approaches, and methods. The conclusions of the literature review are stated at the end of this chapter.

1 Chapter 1: Introduction

In today's highly competitive global market, manufacturing companies should offer a family or a range of products for the same function on the one hand, and to propose personalized and customized products on the other hand to achieve the maximum part of the market. In this context, flexibility, agility, efficiency, and proactivity in production systems become highly important. In this regard, during the last decade, a new industrial evolution has been introduced to increase the efficiency and integration of production systems. This is called as “Factory of future, Industry 4.0, Cyber-Physical Production Systems (CPPS), Smart Factory, etc.” (Liao et al., 2017) (Zhong et al., 2017) (Y. Liu et al., 2017). In these cyber-physical systems, using information and real-time data, a better exploitation of the production system could be obtained.

Due to technological progress in the field of Information and Communication Technologies (ICT), these systems provide access to large amounts of information and data in real-time from various structures of the value chain, such as production machines and equipment. These data are mainly obtained through infrastructure technologies such as the Internet of Things (IoT), Big Data, etc. Moreover, the integrated network of information and knowledge should also create new value-added in the organization of production systems. Traditional data analysis methods such as data mining could not allow exploring efficiently these huge quantities of data as inputs in a decision-making process. Therefore, supplementary technics and methods, such as artificial intelligence, mathematical optimization, and simulation should be simultaneously exploited in order to develop predictive decision-making models or Decision Support Systems (DSS). The objective of these models or DSS is mainly to make efficient intelligent decisions compared to traditional decision-making. Furthermore, the decisions can then be readjusted by integrating real-time data and information.

One of the important challenging aspects of a smart factory concerns the maintenance activity allowing to increase proactively the availability and efficiency of the production machines/equipment (Chiu et al., 2017) (Z. Li et al., 2017). In this way, it is important to have proactive maintenance planning based on real-time data and historical information. In general, maintenance planning is an interdisciplinary domain that is inevitably followed by several complexities. Firstly, maintenance planning has been introduced mainly by understanding the major risk and impacts of pursuing the breakdown or Corrective Maintenance (CM) strategy (reactive strategy). Wheels iron hubs and regular lubrication (greasing) of the axis to avoid the risk of breakdown could be considered as the first maintenance activities (900-700 B.C.) (Timothy C.Kister, 2006). In manufacturing companies, the risk is mainly concerned with the stoppage of the production line, extra cost, and time of performing urgent maintenance. The first systematic maintenance planning has been implemented since the first industrial revolution (18th century) (Timothy C.Kister, 2006). Implementing a proper maintenance planning system requires having a maintenance management structure (centralized and/or decentralized) supported by industry-related resources (such as maintenance experts, and tools), and a proper maintenance planning method. The maintenance planning method should be developed as much as possible close to the shop floor reality. To avoid disruptive events and breakdown of machines and equipment, Preventive Maintenance (PvM) strategy could be applied. PvM planning activities are related to maintenance interventions in predetermined frequencies (regular or irregular). However, the PvM strategy is not always applicable to all components and machines (especially in manufacturing industries). This is because the planning is principally based on Mean Time Between Failures (MTBF). MTBF is generally communicated by the constructor/manufacturer of the equipment or calculated based on historical

failures of the components or machines if they exist. Moreover, the MTBF is less able to capture the operational conditions, and loads on the components, and machines (Oakley et al., 2022) (Wakiru et al., 2019) (Carvalho et al., 2019a). Therefore, following the defined frequency of preventive activities may take unnecessary extra cost, time, and energy from the industrial actors (Chuang et al., 2019).

In the context of Industry 4.0, access and use of real-time data, and the idea of Prognostic and Health Monitoring (PHM) with data connections have brought the means to monitor the operational conditions and the loads on components or machines (Yu et al., 2020a) (Ahmad & Kamaruddin, 2012). The monitoring data and information are normally obtained from the sensors installed in the equipment (Rabatel et al., 2011). The interesting and challenging point here is not only to monitor the equipment's health but also to predict the next failure and estimate the Remaining Useful Life (RUL) to avoid over-maintenance and/or breakdown costs. It should be considered that sensor data is not the only source of the decision-making process in maintenance. There is also information about past maintenance activities and breakdowns which are also important to consider. Although we cannot monitor the equipment health state in PvM strategy, the PvM strategy is still compulsory to be followed for many cases, even in Industry 4.0, due to the lack of resources to apply PdM in the plant physical assets.

This CIFRE thesis is related to the implementation of PdM, PvM, and maintenance planning and was carried out jointly with the LIRIS laboratory of INSA Lyon and the Fiat Powertrain Technologies (FPT) company (The Bourbon-Lancy plant in FPT Industrial Group), a manufacturer of heavy engines intended for various industrial, public transport, nautical, military, and energy applications. It produces more than 35,000 engines/per year and employs more than 1,200 people. This company has a global project for transforming its production system into the factory of the future. One of these important projects is concerned with transforming maintenance activities into PvM and PdM, if possible. This thesis is focused on the optimization of maintenance activities by developing decision support methods for better organization, prioritization, and planning of predictive maintenance activities. As use cases and Proof of Concept (POC), some of the production equipment of FPT are selected to develop appropriate decision-support methods.

1.1 Research objectives

The main objective of this thesis is to study the applicability of PdM and then, develop models and optimization methods for dynamic PdM in production systems. The possibility of exploiting the main principles of Industry 4.0 as Industrial IoT (IIoT), Big Data, Edge, Cloud computing, etc. are also another objective of this thesis. Although the focus of this thesis is on the PdM strategy, other methodological aspects of maintenance, such as the PvM strategy and maintenance system monitoring, are also within the scope of this thesis. To achieve this objective, four steps or scientific contributions are considered.

Firstly, it is necessary to develop methods to classify equipment and components/spare parts to identify the most relevant maintenance strategies for them (PvM, PdM, CM). In continue, it is necessary to identify appropriate policies and methods for equipment/components that are either connected via IIoT or not connected to condition or real-time monitoring systems.

Secondly, it is important to follow the descriptive analysis through the proposition of the right methods to monitor the current equipment condition and the state of maintenance system. The objective here is to develop Health Indicators (HIs) or maintenance Key Performance Indicators (KPIs) through real-time

condition monitoring data and historical information to identify and monitor the equipment's health state and maintenance system.

The third step is related to the estimation of RUL for machines or group components. In this way, it should be focused on exploiting sensor data and information collected from other sources and HIs developed in the previous step. To do so, predictive models should be developed based on AI and learning techniques (statistical, machine learning, deep learning, etc.).

The Fourth step focuses on the planning of maintenance tasks. In this step, all the parts, sub-functions, and equipment, resulting from the first step, should be taken into consideration for the planning. Regarding the PdM planning, the RUL and health state information should be used, while for PvM planning the MTBF information must be considered. The planning should also consider the technical constraints and find the best trade-off between intervention costs, failure risk costs, etc. In this way, the development of mathematical modeling is expected to identify optimal maintenance planning.

1.2 Research questions

Some of the main important questions that need to be answered in this research are as follows:

- For which equipment/machine Preventive and/or Predictive Maintenance strategies could be applied? Which of them should remain in corrective maintenance?
- What are the criteria for identifying the strategy of maintenance for each equipment/machine?
- Knowing that is impossible to apply PvM and PdM for all components of a machine, which component could be under PvM and/or PdM?
- For the component in the PvM strategy, what is the best frequency of performing maintenance?
- How can we identify the current health state of the machine and its components? How can we identify the performance of a maintenance system? Through which information, data, and indicators? How to monitor and visualize maintenance indicators?
- How it is possible to calculate/estimate the health state or Remaining Useful Life (RUL) of the equipment/parts? Through what kind of methods?
- In the case of RUL estimation possibility, how we can utilize them for maintenance planning? through which mathematical/ optimization models?

1.3 Motivation

Maintenance management and planning is an interdisciplinary domain that is inevitably followed by several technical, economical, and time complexities to be properly applied in various types of industries and management systems. Some of them can be mentioned as follow:

- The risk of production stoppages
- Limitation of maintenance resources (man, machine, spare part)
- The cost of maintenance operation and spare parts

- Lack of reliable information, and tools for decision-making
- The uncertainty of the useful life of the components
- The complexities in the structure of machines
- The dependencies between the components

The concept of industry 4.0 and access to the real-time data of equipment and integration of information systems has brought the opportunities to overcome to abovementioned complexities. In this way, it is important to study how we can use the data and information opportunities in the decision-making of maintenance problems.

In this regard, developing decision support methods and tools for maintenance and especially simultaneously PvM and PdM planning problems are the main motivation of this thesis.

1.4 Main contributions

In summary, this thesis contributes to the field by proposing approaches and methods in the following areas based on real-time and historical data and information:

- I. Robust multi-criteria decision-making (MCDM) for identifying the maintenance strategies of equipment/ components
 - a. Proposing new intercorrelated sensitivity analysis methods
 - b. Application of an optimal maintenance frequency identification method
- II. Proposing a health monitoring and visualization system based on real-time and historical data and information
 - a. Experimentation of Health Indicators (HIs) in a complex use case
 - b. Identification and proposition of most important maintenance indicators
 - c. The proposition of appropriate visualization dashboards for the decision-makers
- III. RUL estimation /State prediction by using statistical and/or learning approach
 - a. Providing a dynamic predictive approach for readjustment of RUL/health state
 - b. Proposing a dynamic RUL estimation algorithm
- IV. Proposing optimal Maintenance planning for PvM and PdM activities
 - a. Studying the maintenance planning problem Considering PdM, and PvM strategies together and proposing a new approach
 - b. Developing a maintenance planning method in the manufacturing industry with multiple machines and multi-components based on RUL and MTBF
 - c. Considering the economic grouping of multiple maintenance activities
 - d. Integrating the dynamic RUL estimations in the optimization model
 - e. Considering the failure risk and unused life of components
 - f. Considering the uncertainties of MTBF and RUL information

On top of these contributions, the provided Predictive Maintenance Management System (PdMMS) approach by considering the relationships between the main maintenance aspects such as maintenance strategy identification, maintenance monitoring, equipment health monitoring, RUL estimation, and maintenance planning of the entire maintenance strategies is the most important contribution of this thesis.

2 Chapter 2: Company and Problems

2.1 Presentation of the group FPT Industrial

FPT Industrial is a brand of Iveco Group that is attached to FIAT group and specializes in the design, production, and marketing of engines for on-road and off-road vehicles, as well as in marine applications and generators. All the engine types and applications are shown in Figure 1. The wide range of products (six big engine families, and more than 2000 engine references), as well as a large number of research and development activities, make FPT Industrial one of the main global industrial players in the industrial transmissions sector. FPT Industrial plants are in 8 countries around the world, which are 10 production plants and 6 R&D centers. FPT offers a wide range of products: seven engine families with power from 240 to 1000 HP and transmissions with a maximum torque of 200 to 500 Nm. In 2017, 607,000 engines were produced in 10 factories around the world for revenue of \$4.4 billion.

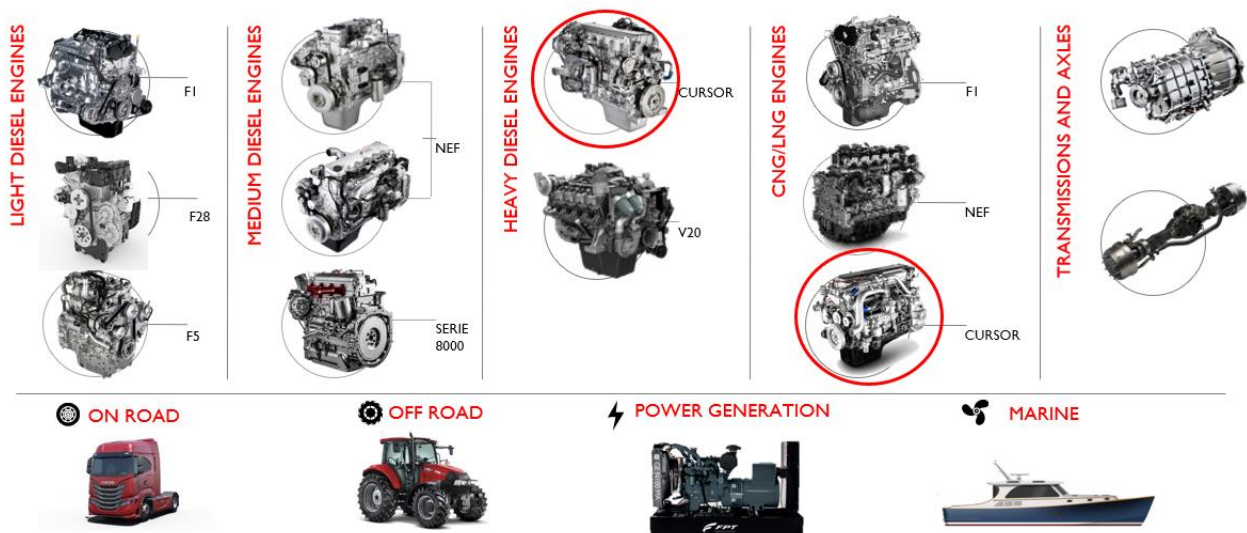


Figure 1. Engines and power generators fabricated by FPT Industrial

2.2 Presentation of the FPT Bourbon-Lancy plant

The FPT Bourbon-Lancy plant (which is called FPT-BLY abbreviately), part of Fiat Powertrain Technologies France (FPTF) where this project is being carried out, is the only FPT site that manufactures all the engines in the Cursor range (see Figure 1 which are circled in red). FPT-BLY has a capacity of around 50,000 units per year with more than 5700 variants. FPT-BLY produces the 6 big CURSOR engine families as follows:

- CURSOR 8 - 6 cylinders of 7.80 liters - power from 240 to 360 hp
- CURSOR 9 - 6 cylinders of 8.70 liters - power from 290 to 400 hp
- CURSOR 10 - 6 cylinders of 10.3 liters - power from 390 to 430 hp

- CURSOR 11- 6 cylinders of 11.1 liters - power from 420 to 480 hp
- CURSOR 13 - 6 cylinders of 12.9 liters - power from 460 to 680 hp
- CURSOR 16- 6 cylinders of 12.9 liters - power from 480 to 1000 hp

The factory covers an area of 21 hectares, 11 of which are covered. It employs nearly 1,300 employees, 80% of whom are operators, 17% technicians, and 3% executives and senior managers. It works with more than 260 suppliers, 96% of which are European, that supply more than 4,800 different references.

FPT-Bly is composed of three main buildings as A1, B1, and C as it is seen in Figure 2. Building A1 is related to the cast iron machining of the engine block and cylinder head. Building B is dedicated to the machining of steel conrod, camshaft, and crankshaft, and the assembly line of Cursor 8 and 9. The assembly lines of Cursors (C10, C11, C13, and C16), painting, and test stations are located in building C.

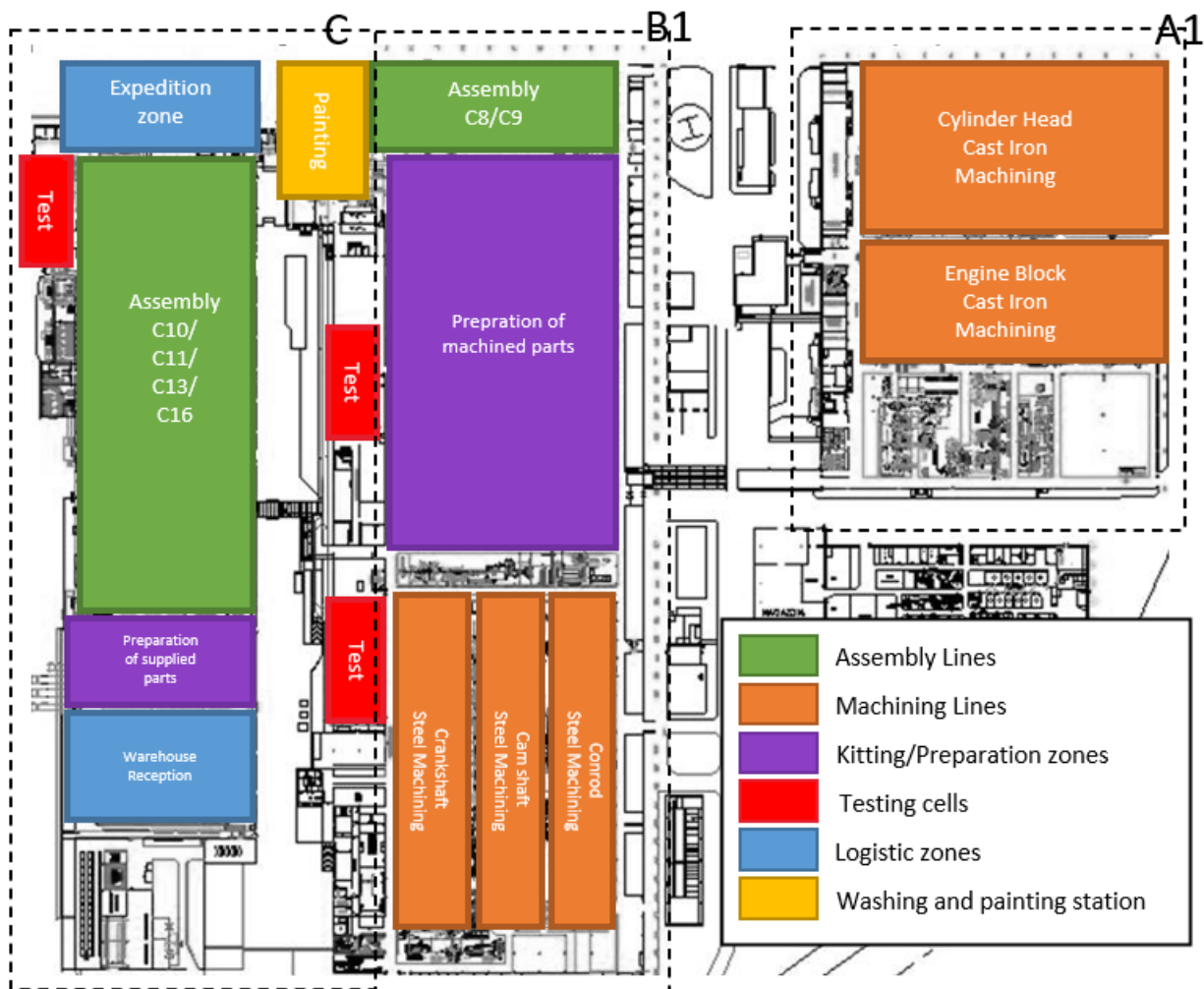


Figure 2. FPT-BLY plant layout

The main customers of FPT-BLY engines are Iveco and CNH subsidiaries such as New Holland, Case, Steyr, Heuliez Bus, Magirus, and CLAASE Tractor, etc. which are distributed mainly in Europe, north and south America.

The site has 3 main activities summarized here in a few key information as indicated in Figure 4. These are as *i)* cast iron machining, *ii)* steel machining lines, and *iii)* assembly lines. In the machining line, the main engine components as the engine block, cylinder head, crankshaft, Camshaft, and Conrod. It is shown in Figure 3. The remaining components are supplied and assembled in the assembly lines.



Figure 3. Main machining components in FPT Industrial

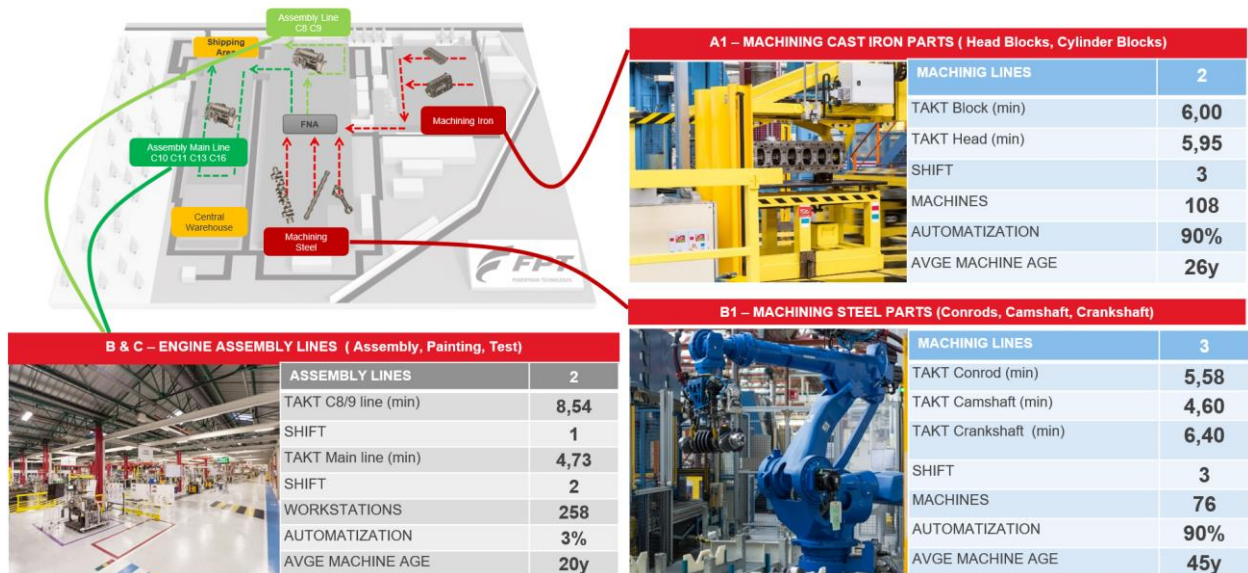


Figure 4. The key figure of main activities in the FPT-BLY plant

2.3 Complexity and specificities of the FPT-BLY plant

The great complexity of the existing FPT-BLY system comes from the very large number of engine variants and references (especially for agricultural machinery) and a high level of uncertainty regarding orders that depends on the policy of the parent company. Engine orders must be confirmed by the customer 6 weeks before the delivery date, but it is often observed that these are totally or partially modified until the manufacturing day. These specificities complicate the configuration, organization, planning, and scheduling of production. This is also the case for activities related to replenishment, logistics, and storage of components, kitting, supply of production lines as well as the distribution of operations, line balancing, etc. Knowing that there are no decision-support tools on these points, decision-making in this uncertain environment has become very complex.

2.4 History and evolution of FPT-BLY plant

Figure 5 summarizes the history of the FPT-BLY plant. At the end of the first industrial revolution in 1874, the small company initially called "Emile Puzenat & Fils" set up a factory to manufacture agricultural equipment. "Puzenat" became the largest French manufacturer of agricultural equipment in 1935. Twenty years later, Puzenat was taken over by SIMCA (Société Industrielle de Mécanique et Carrosserie Automobile) and began the renovation of its equipment to manufacture the engine of the SIMCA ARONDE and VERSAILLES models. At the beginning of the third industrial revolution, in 1962, the factory became a tractor manufacturer named SOMECA (Société de Mecanique de la Seine). Later, this company made a joint venture with Fiat. Ten years later and in 1972, the Fiat-Someca plant in Bourbon-Lancy started to manufacture heavy-duty engines for UNIC trucks. At the beginning of 1975, the creation of IVECO (Industrials Vehicles Corporation) completed the merging of the FIAT VI, OM, LANCIA VI, UNIC, and MAGIRUS-DEUT brands. In 1998, the plant renewed the production process and system for the Cursor engine range. The FPT Industrial group was created in 2005 and the plant took the name of FPT-BLY. Following the split between the automotive and industrial activities of the Fiat group in 2013, FPT was attached to the CNH Industrial group, the industrial branch of the parent FIAT group which is today a world leader in the capital goods sector. Recently in 2022, in the company spinoff, the FPT industrial group is now attached to the IVECO group.

New versions of Cursor engines were developed in 2014, and currently, a challenging project toward a completely new engine of XC13 is ongoing to produce the prototype engines by 2023.

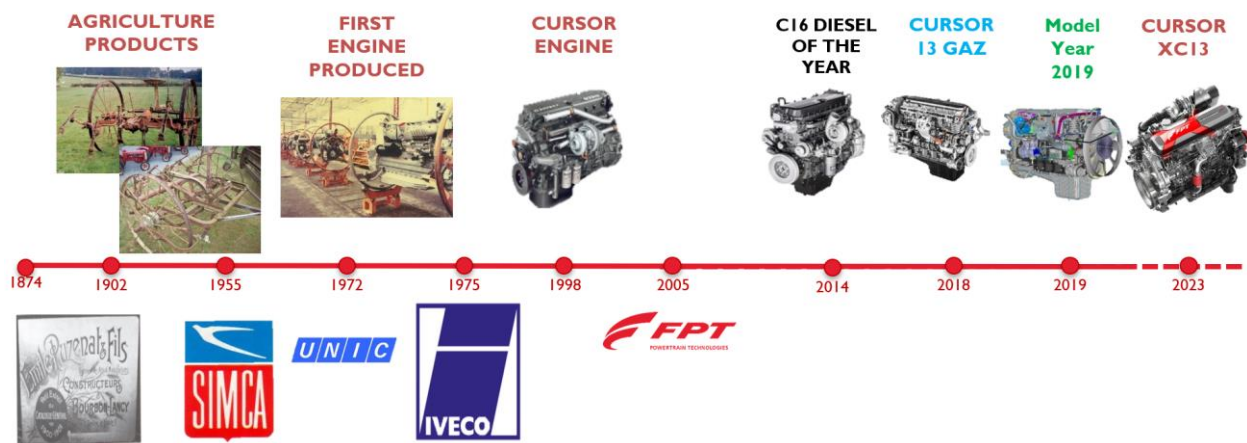


Figure 5. History and evolution of FPT-BLY plant

The company is committed to proceed a lean manufacturing system and enterprise excellence, particularly the World Class Manufacturing (WCM) standard has been followed. WCM is an international methodology for the manufacturing process adopted by the most important businesses in the world. Between 2008 and 2010, the company reached the bronze and silver levels of the WCM standard through several continuous improvement projects and audits. During this journey, it achieved the American AME Excellence Reward in 2018. In continue, the company adopted the digital transformation and industry 4.0 approach which will be detailed further. Based on the advancement of its activities, it was recognized nationally in France as “Vitrine Industrie du Future” and “Territoires d’Industrie” which indicate the companies that are engaged in the industry of the future. In 2020, FPT-BLY was founded as the digital champion of the entire CNH Industrial group. In 2021, after considerable transformations and

improvements, the company achieved the gold level of the WCM standard which is the 7th enterprise out of 207 enterprises in the world that get this award. To evaluate and prove the digital competencies in the company, I was the representative from the research and innovation team of FPT-BLY, and I won the GoldenTech” competition in 2022. This competition was in the “Data Automation Manager” category that was organized in the “Globale Industrie” the biggest industrial exhibition in France. All these activities also have been validated by AGAMUS audit in 2022 which is specialized in auditing digital operation excellence in the automotive industry. The results of all these projects have brought the above awards for FPT-BLY which are presented in Figure 6.

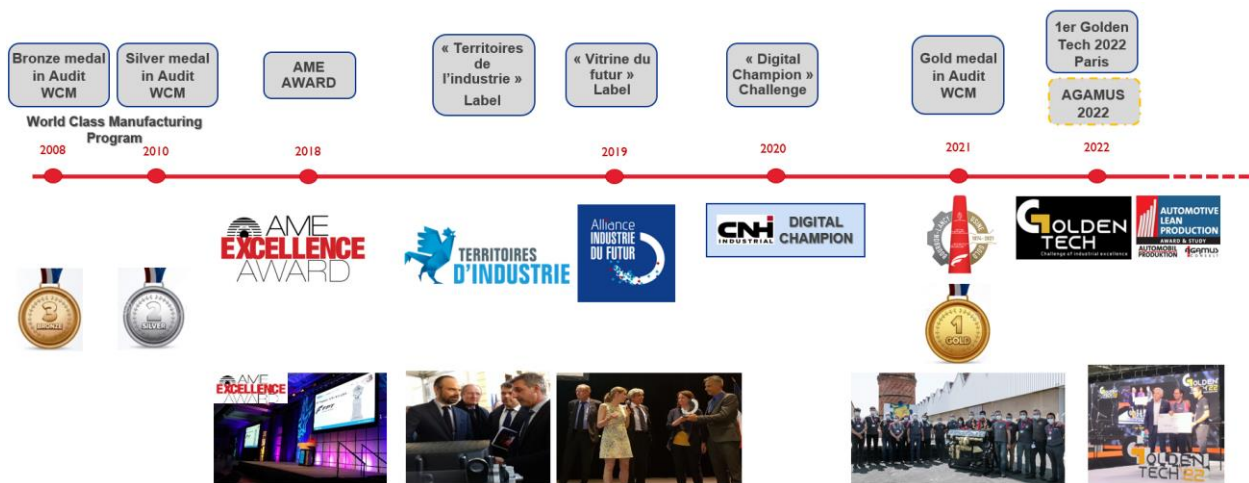


Figure 6. Achieved awards in the FPT-BLY plant

The innovative digital transformation approach that has been begun since 2015, has brought the opportunity for the implementation of industry 4.0 projects. Dynamic predictive decision-making is the main theme, and topic of these projects. One of them was concerned with “Dynamic Predictive Maintenance” and the current thesis was defined as a research opportunity in this context.

2.5 Production machinery - equipment park

The company owns 1723 machine assets, which are of 28 types and supplied by 261 constructors, the average age of all assets is around 42 years. These assets are categorized as below:

- Building → 69 machines
- Installations → 85 machines
- Manutention → 870 tools
- Screwdrivers → 201 tools
- Quality control → 131 equipment
- Machining tool assets → 99 equipment
- Production → 270 machines

The main perimeter of professional maintenance in FPT-BLY is regarded as the 270 production machines. 109 of them belong to the iron cast machining line and 76 of them to the steel machining line and the rest to the assembly line. Among them, the most important production equipment in terms of maintenance is the engine block and cylinder head and steel machining lines, in which most of the Computer Numerical Control (CNC) machines, robots, washing machines ...etc. belong to these production lines. However, there are also key pieces of equipment in assembly lines that can have a great impact on the assembly line stoppages such as conveyor chains. In terms of maintenance costs, a considerable amount of the costs is generated from these lines. CNC machines are used for several types of machining activities, and these machines more often fall into failure and impact the availability of production lines and product quality.

2.6 Context and challenges

2.6.1 Maintenance strategies in FPT-BLY

As described, the Company follows the WCM standard which is developed based on the experiences and the concepts of Total Quality Control (TQC), Total Productive Maintenance (TPM), Total Industrial Engineering (TIE), and Just in Time (JIT). WCM standard has 10 technical and 10 managerial pillars, Professional Maintenance (PM) and Auto Maintenance (AM) are two of the important pillars in which the maintenance activities are continuously improved. In AM the objective is to follow some basic maintenance operations to reduce and eliminate dirt and deterioration sources. AM activities are performed by the production team and are not considered in this study. However, the PM is followed by the maintenance team for more advanced interventions. In each pillar, seven main improving steps are defined for the excellence of each pillar. The 10 WCM pillars and the 7 steps of the Professional Maintenance pillar are depicted in Figure 7.

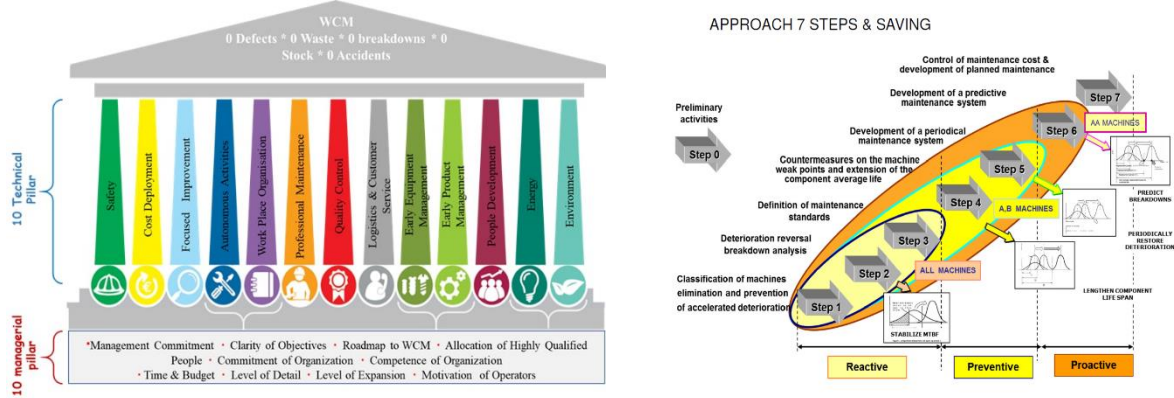


Figure 7. 10 WCM pillars and 7 steps of PM pillar

PM pillar in the WCM standard is an important guideline for the enterprise for the advancement of developing projects in the maintenance field and continuous improvement. In general, this standard follows an approach for achieving a zero-breakdown production system which is the ideal goal of any manufacturing system. This approach is composed of four phases which are provided in Figure 8.

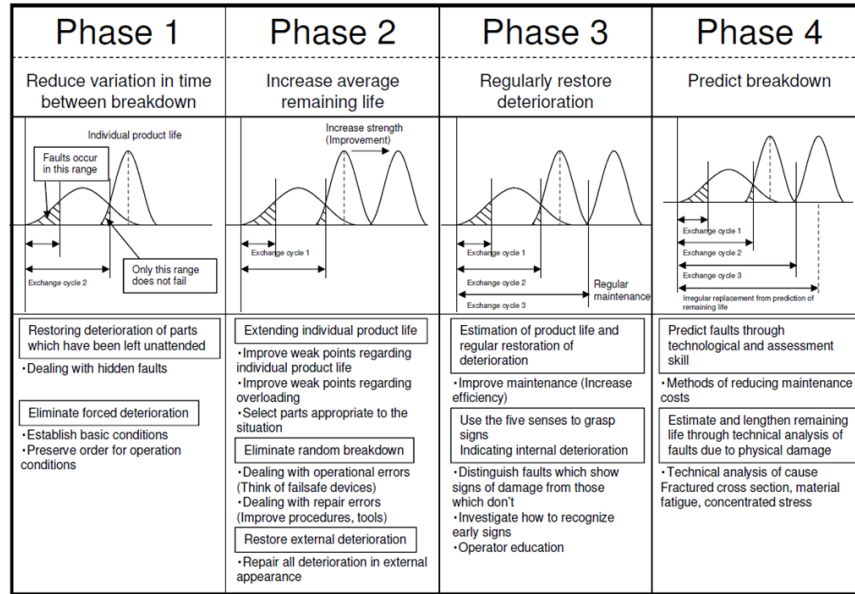


Figure 8. WCM Approach to achieving zero-breakdown system

2.6.2 Maintenance activities modeling

In resume, the maintenance department performs mainly CM and PvM activities. The PM activities are managed by 64 technicians, 53 technicians work generally in the machining line, and 11 technicians in the assembly line. The process of current professional maintenance activities in FPT-BLY at the machining lines is presented in Business Process Mapping (BPM) format in Figure 9.

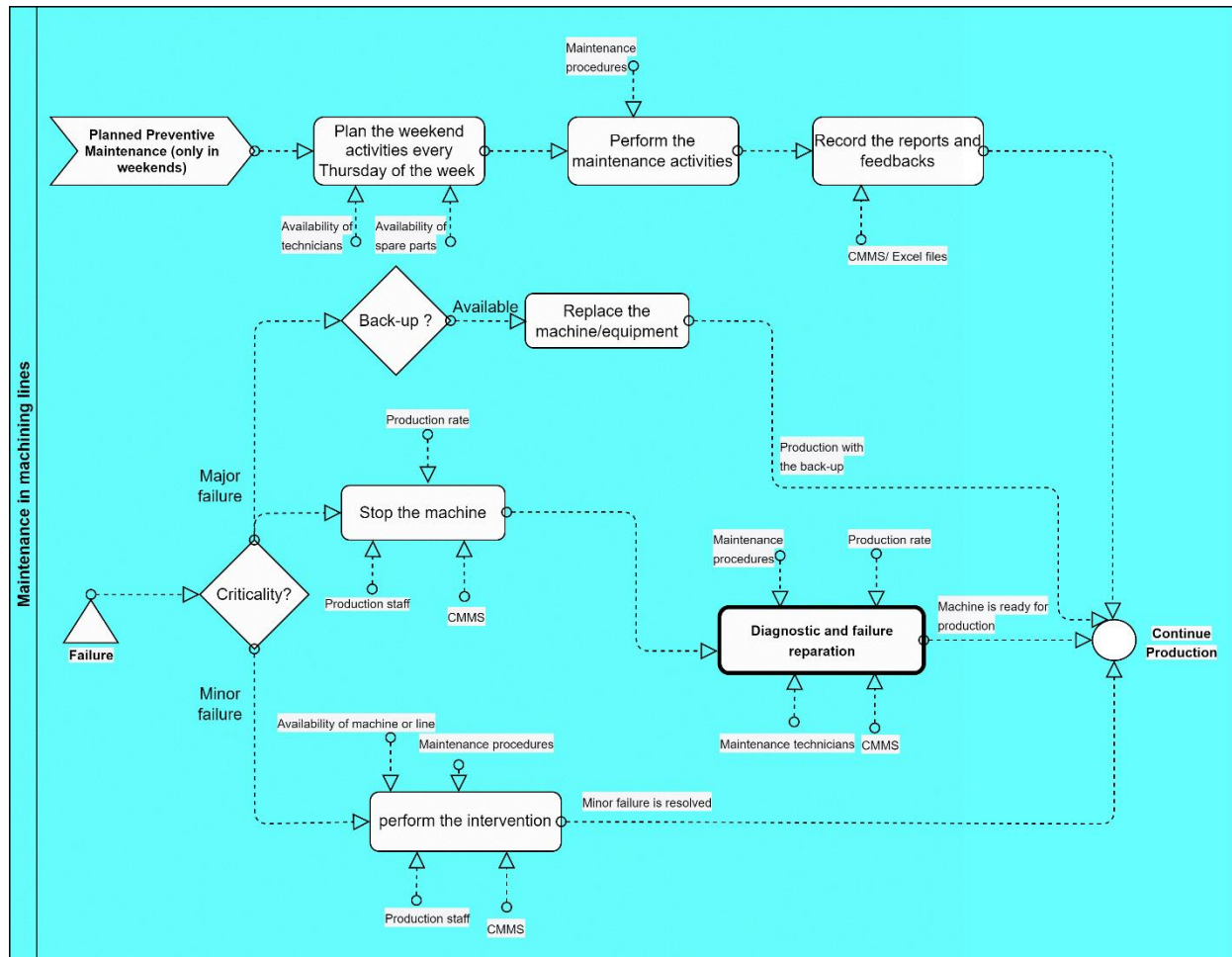


Figure 9. The current process of maintenance activities at machining lines in FPT-BLY

As seen in the above process, planned maintenance activities and failures are the two principal triggers of maintenance activities. Regarding the failures, depending on the severity of the breakdown, related actions are followed with the cooperation of the production department. Regarding the major failure, it is necessary to perform a diagnostic and repair process, which is presented in the following schema in Figure 10 in more detail. In the event of prolonged stoppages, the equipment/machine can be operated in a degraded mode, allowing it to continue running at reduced capacity. In this case, the relevant maintenance activities are planned for the upcoming weekends to restore the equipment/machine to normal operating mode.

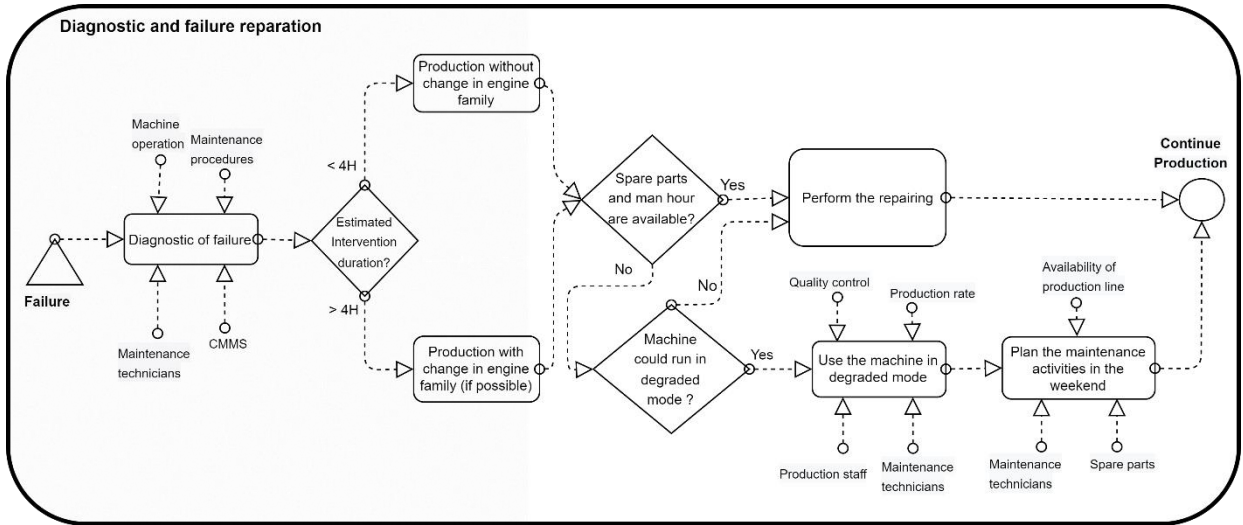


Figure 10. Details of the diagnostic and repairing process in FPT-BLY

Implementation of the PM pillar in FPT-BLY has improved the maintenance management system until step 3 which is related to the reactive maintenance aspects. However, regarding the preventive and proactive aspects of maintenance (after step 3), the concepts and methodology are less clear, and the resource limitations are not previsioned in this methodology. Due to these limitations, following the next steps has become complicated. All these factors have caused the WCM-PM not to be applied integrally, hence FPT-BLY desires to improve its performance with new methods and the existing constraints.

In this way, maintenance methods, approaches, and strategies should be readjusted to be adopted for the company. It should be specified that the developed methods and approaches in this thesis are not contrary to the WCM, while it would improve and add other steps.

There are other technical, and economical challenges for the maintenance planning that are mentioned in the following.

2.6.3 The challenge of maintenance planning in FPT-BLY

As stated in the previous subsection, an important aspect is the lack of proper methods for maintenance planning which makes maintenance planning more difficult. Furthermore, three main limitations make the management of maintenance activities complex. These are concerned with the limitation of manpower, spare parts resources, and availability of machines for maintenance intervention.

Moreover, maintenance activities become more complex when the number and types of machines and components are increased. This arises the need for multiple maintenance competencies and a high variety of spare parts. The other complexity of the FPT-BLY for the maintenance activities comes from the age of the machining equipment which is about 40 years. This increases the uncertainty of the equipment's reliability and makes it hard to identify the right planning for this production equipment. Due to this reason, the FPT plant in Bourbon-Lancy often faces considerable breakdowns that result in production stoppages costs and over-maintenance on the other hand.

Managing the plant production assets and PvM and CM activities with the mentioned aspects is the main challenge of the maintenance department. It is often quite difficult to organize maintenance activities and allocate the right technicians with the availability of spare parts.

The mentioned limitations and problems exist since the current approaches and knowledge in FPT-BLY are imperfect. However, the protentional of the industry 4.0 approach, tools, and projects, which is going to be explained in the next subsection, would be utilized to improve the maintenance performance.

2.6.4 Digital transformation and Industry 4.0 projects in FPT-BLY

The concept of continuous improvement has been applied in this company for several years and encouraged managers to reflect and work on the evolution of existing systems toward Industry 4.0. In this context, based on the mentioned complexities and specificities of the FPT-BLY plant and based on the company's strategical point of view, using real-time data and dynamic predictive decision-making in maintenance activities has been identified to be one of the important methodological projects toward Industry 4.0 that can help to improve and optimize maintenance activities. In this way, the company has engaged itself to connect the machines via IIoT and get real-time data for visualization, analysis, and better decision-making purposes. Hence, an IIoT platform has been selected which is explained in the following. Furthermore, the information systems in FPT are presented.

Real-time data and information systems in FPT-BLY:

The architecture of the data collection and information management system in FPT-BLY is provided in [Figure 11](#). In the initial experimentation phase, FPT has performed the projects to send the raw data from the machines, and process, ... into a cloud system for the objectives of monitoring, visualization, data analysis, and decision-making support systems.

This objective has been realized with the integration of “MindSphere[®]” software which is an IIoT platform developed by SIEMENS[®] Corporate. Due to the complexities of integration into the IT management system, this platform helps the FPT-BLY in the research phase, and for further applications, once the POC has been done, other solutions such as Edge computing will be also considered to apply in the plant. It should be noted that the information available in the Enterprise Resource Planning (ERP), and manufacturing Execution System (MES) are valuable and necessary to be integrated into the study. However, at the current and earlier state, there is not interesting to connect the information systems with the real-time data platform. Nevertheless, in the future, there is a general vision to combine the output through real-time data analytics (information or acquired knowledge) with information systems.

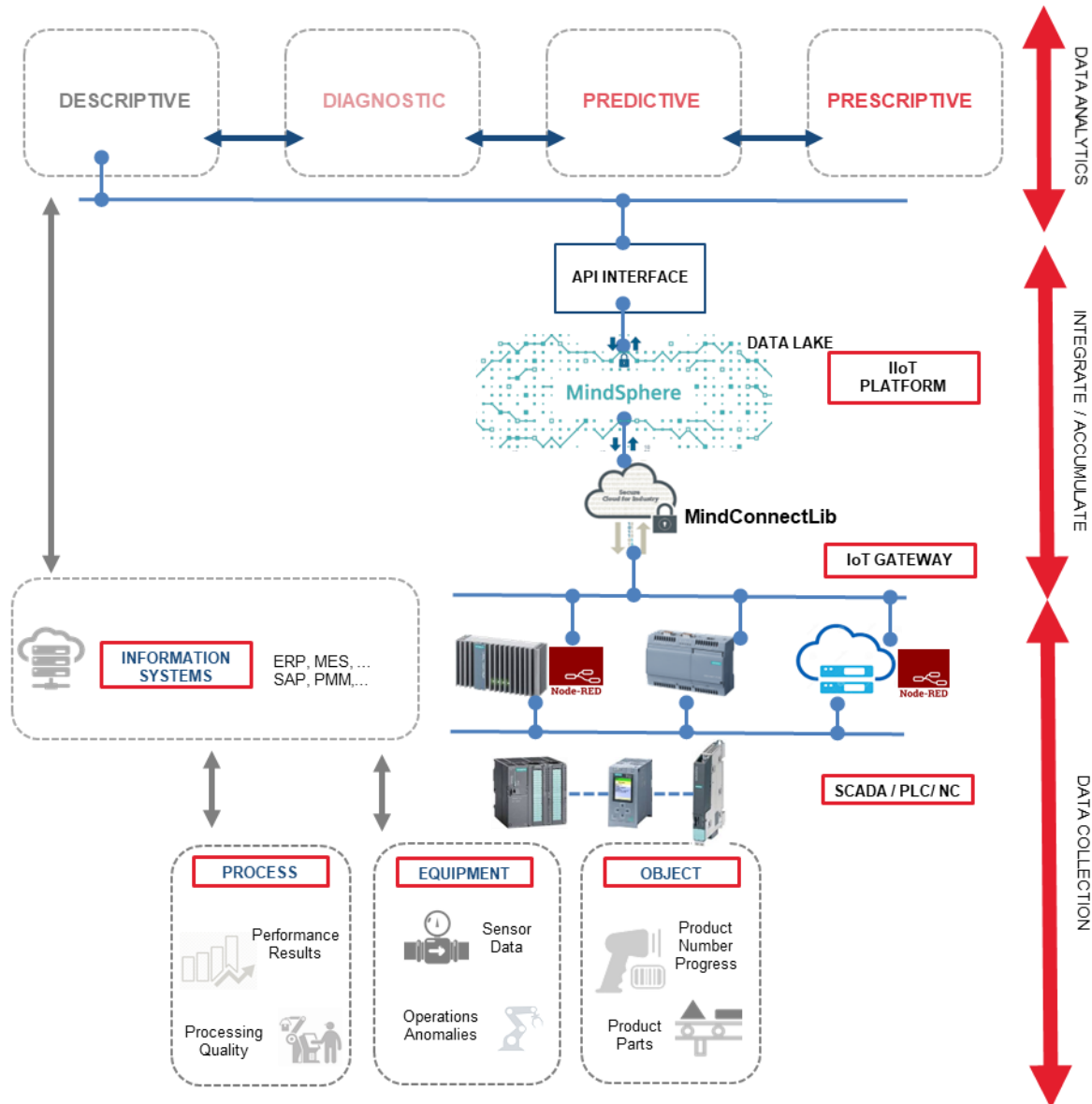


Figure 11. The architecture of data and Information system in FPT Industrial

Regarding the information system of maintenance historical activities, the FPT Industrial plant currently manages its activities by the ERP system of SAP. Recording the different types of maintenance activities along with spare part utilization, inventory control, and cost management are all managed by SAP.

2.7 The interest of the thesis for FPT-BLY:

As stated, the application of the WCM approach in FPT-BLY has greatly contributed to the resolution of maintenance and other problems in a continuous way. However, due to the mentioned limitations of the WCM standard in professional maintenance methodologies, an innovative methodological DSS seems to be necessary for the proper operation of the maintenance system. In this way, based on the mentioned technical, and economical complexities in FPT-BLY, this company desires to improve its methodologies

and decision-making methods and tools in production engineering such as maintenance based on data-driven approaches. On this basis, FPT-BLY attempted to make the real-time data of machines, objects, etc. available for further advancement. This has begun with the mentioned implementation of the IIoT platform and data acquisition.

In connection with the internal projects for the transition to the Factory of the Future, one of the objectives is to increase the machine and process flexibility. The interest of this thesis for FPT-BLY is to achieve a reliable and efficient production and maintenance system, to have better visibility of the operation in the production system. This would help the enterprise to better control maintenance activities and costs.

3 Chapter 3: Literature review

To overcome the mentioned challenges in section 2.6, a comprehensive study in the literature on maintenance strategies, PdM methodologies, and industry 4.0 topics has been performed. This literature review contains both articles which are theory and practical-based. As this thesis has an industrial applicative approach, more focus has been given to the articles with application and practical cases. Initially, the general concepts of Industry 4.0, its technologies, and tools are reviewed (section 3.1). This would allow for identifying the advantages, and opportunities of I4.0 for maintenance decision-making process. Then, a brief history of maintenance activities with classification of maintenance strategies, and the importance of maintenance planning are provided in section 3.2.

Even though Industry 4.0 offers advanced resources to monitor equipment health, PvM strategy remains mandatory in many cases due to insufficient resources to implement PdM for plant production assets. In this way, we then focus on maintenance strategies with a preventative nature, including PvM, CBM, and PdM (section 3.3.1). It is worth noting that PdM is a subcategory of the PvM strategy, with both sharing a preventative nature. However, PdM primarily relies on real-time data and information for predictions to determine the remaining useful life (RUL), whereas PvM uses predefined mean time between failures (MTBF) values. The main difference between CBM and PdM is that CBM does not necessarily rely on real-time data and can be performed through discrete measurements. Unlike PdM, CBM does not provide a prediction of failure time.

In continue, PdM literature study is detailed into three categories: Health Monitoring, RUL estimation, and maintenance planning. While the primary emphasis of this thesis is on the PdM strategy, we also explore the PvM strategy and maintenance system monitoring. To this end, we cover the relevant topic of maintenance monitoring systems in the health monitoring section (3.3.3) of the PdM literature review. Similarly, the PvM planning methods are reviewed in the maintenance planning section (3.3.5) in PdM review. The different methods in the context of the thesis problem have been studied and a structure to organize these articles has been proposed. Studying the methodology of these sources has brought inspiring visions and overviews for this thesis.

Before detailing this literature review, a general statistical analysis of the documents in the ScienceDirect database has been performed regarding the main keywords of this thesis. The keywords are concerned with “Predictive Maintenance”, “Industry 4.0”, and “Maintenance Planning”. Moreover, the survey includes the research documents from 2000 to 2022 which are included in the title, abstract, or author-specified keywords. Initially, these keywords are assessed separately which are presented in Figure 12 (a, b, c). Then the intersection of pair keywords and the three keywords together are also evaluated and presented in Figure 13 (a, b, c), and Figure 14.

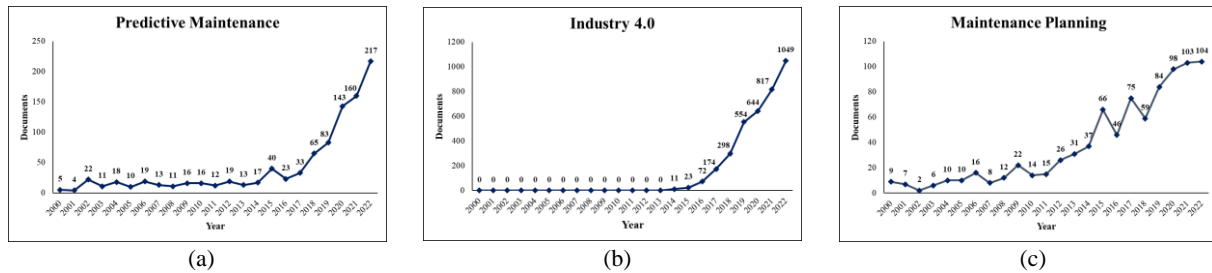


Figure 12. Published documents containing “Predictive Maintenance”, “Industry 4.0”, and “Maintenance Planning” keywords

As demonstrated by the above trends and charts, the interest in Predictive Maintenance (PdM) has steadily grown over the years, while research documents related to Industry 4.0 (I4.0) have emerged since 2014. Maintenance planning has also been an area of research with a notable increase in the number of documents published in the last decade. These trends suggest that PdM was not limited to the emergence of I4.0, but rather that its popularity has been further amplified by the increased focus on I4.0.

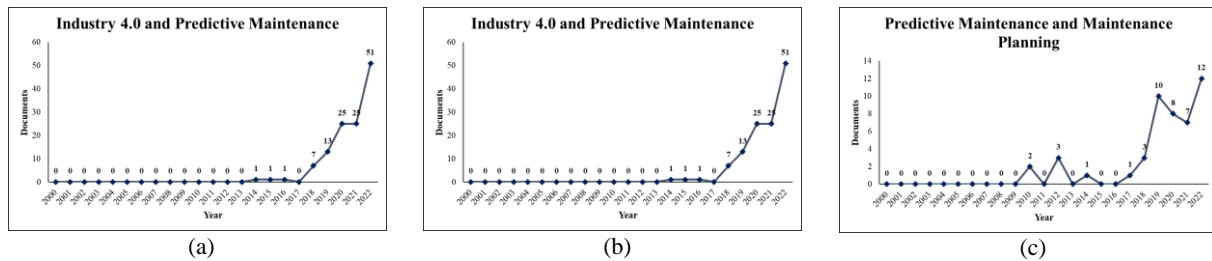


Figure 13. The published documents containing the pair intersection of keywords

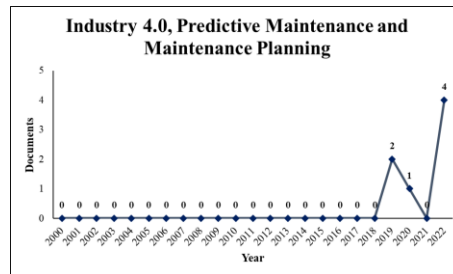


Figure 14. The published documents containing the triple intersection of keywords

The pairwise and triple analyses of the intersection of the three main keywords indicate that the problem of maintenance planning in the context of Industry 4.0 means and Predictive Maintenance (PdM) strategies have been rarely studied in the literature. This indicates that further research should be conducted to explore the implications of such a combination of technologies on maintenance planning.

In continue, the literature review of Industry 4.0, predictive maintenance, and maintenance planning are presented.

3.1 Industry 4.0

The concept of Industry 4.0 (I4.0) first appeared in November 2011 by the German government following an initiative regarding a high-tech strategy for 2020 (“Cyber-Physical Systems: Driving Force for Innovations in Mobility, Health, Energy and Production,” 2011) (Henning Kagermann, Wolfgang Wahlster, 2013) (Zhou et al., 2015). “The Industrie 4.0 Working Group”, led by Dr. Siegfried Dais (Deputy Chairman of the Board of Management of Robert-Bosch GmbH) and Prof. Henning Kagermann (President of Acatech), created the first set of implementation guidelines between January and October 2012. Although the origin of I4.0 lies in the German manufacturing industry, the conceptual idea has been widely adopted by other industrialized countries within the European Union, as well as in China, India, and other Asian countries (Gilchrist, 2016).

I4.0 considers a new model for organizing (Bartodziej, 2017) and controlling the entire value chain throughout the product life cycle from the product design phase to production and product delivery to end customers. I4.0 deploys the tools provided by technological advances in communication and information exchange to increase automation and digitization levels of production in manufacturing and global industrial processes (Gilchrist, 2016). This is the paradigm of different connectivity types of physical devices enriched by embedded electronics (sensors, actuators, RFID, etc.) and connected to networks or the internet to interact with all system components. In the vision of I4.0, continuous interaction and information exchange occur not only between machines, but also between humans, and between humans and machines (Wan et al., 2016). In this paradigm, cyber-physical systems (CPS) or cyber-physical production systems (CPPS) monitor the physical process, create a virtual copy of the physical world, and offer decentralized decisions in real time (Posada et al., 2015).

I4.0 could have significant influences on the production environment in the execution of operations, enabling real-time production planning and control (Sanders et al., 2016). In this environment, companies should increase the level of digitization and collaboration with their customers and suppliers in digital ecosystems (Tupa et al., 2017).

In summary, I4.0 can be seen as an interoperable manufacturing process based on the integration of heterogeneous data and knowledge through advanced algorithms, Big Data (BD), and advanced technologies such as the Internet of Things (IoT) and the Internet of Services (IoS), industrial automation, cybersecurity (CS), cloud computing (CC), and smart robotics (Liao et al., 2017) (Peruzzini et al., 2017) (Baena et al., 2017). The main technologies of I4.0 are presented in [Figure 15](#). In I4.0, an intelligent flow of parts, machine by machine, station by station, with real-time communication between all elements of the system is expected. In this environment, CPSs will make manufacturing smart and adaptable with flexible and collaborative systems that make the best decisions (Peruzzini et al., 2017).

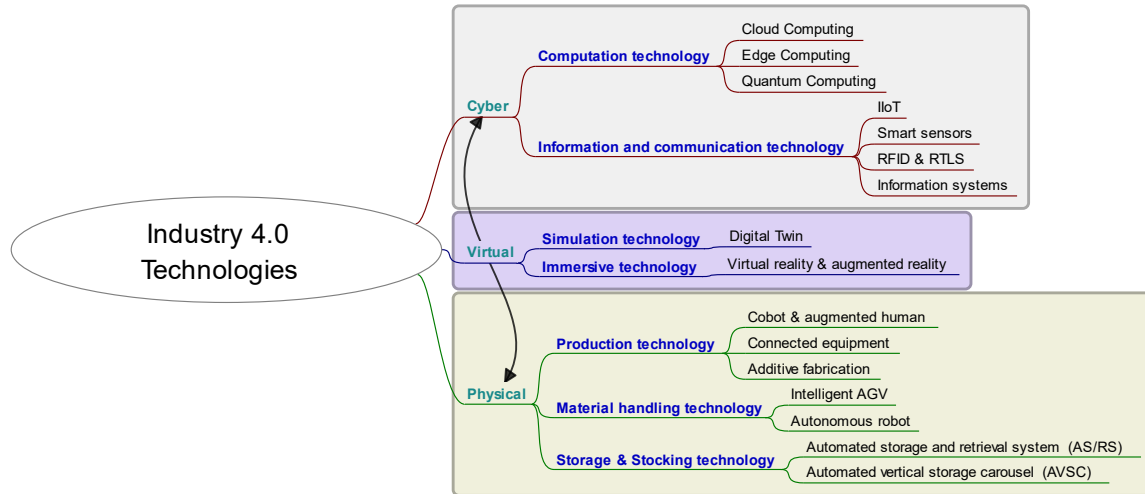


Figure 15. Industry 4.0 technologies

The basis of I4.0 is the real-time availability of relevant data and information by linking all actors in the value chain. I4.0 can bring the possibility to integrate learning models from data at any time, allowing a more accurate description, diagnosis, prediction, and prescription of the system behavior which enables to have autonomous control. In this system, we should be able to propose a decision-making process with data analytics (called in our approach "Dynamic Predictive Decision Making" (Ebrahimi et al., 2019) which is based on historical and real-time information and data. This feature allows us to predict certain events using historical data and information and to prepare the decision for these events, then readjust them if necessary, using the latest information and real-time data. This capability would help to drive the factory of the future more efficiently and it would become a necessity over time.

Although the basis of the three previous industrial revolutions was the development of technologies, based on our point of view, the core aspect of I4.0 relies on methodology development rather than technology. Nevertheless, there is also a third important aspect concerning management, which is at the center of the transformations and identifies the I4.0 opportunities for human resources. Proper management of human resources is therefore essential for realizing the full potential of I4.0. These three pillars of I4.0 evolution as presented in Figure 16 can be briefly characterized below:

1. Technological evolution
 - Data collection, storage, and exchange technologies
 - Edge, Fog, and Cloud technologies
 - IIoT, Cyber-physical System, cybersecurity
2. Methodological evolution
 - Holistic vision and End to End value chain
 - Product Lifecycle Management
 - Data Analytics (Descriptive, Predictive, and Prescriptive Analytics)
 - Visualization, Digital Twin & Dynamic readjustment

- Smart Decision Support Systems (Using learning approaches, mathematical optimization, simulation, knowledge graph, expert system, etc.)
3. Human-centered evolution
- Removing barriers, training, and developing (growing) new skills
 - Change in the organization's culture, knowledge of employees, and method of management

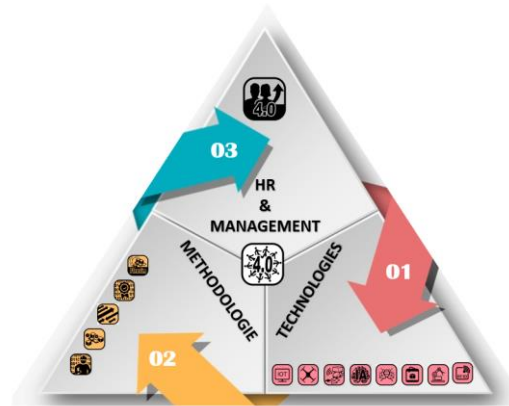


Figure 16. Three main aspects of I4.0 development (Ebrahimi, 2020)

As shown in Figure 17, we emphasize that data is at the heart of Industry 4.0 and digital transformation. In our perspective, Industry 4.0 is accompanied by three major challenges: *i*) data generation and sharing, *ii*) data security and storage, and *iii*) data analytics and action. Additionally, the outer layer of Figure 17 illustrates the seven key elements of I4.0 in manufacturing companies

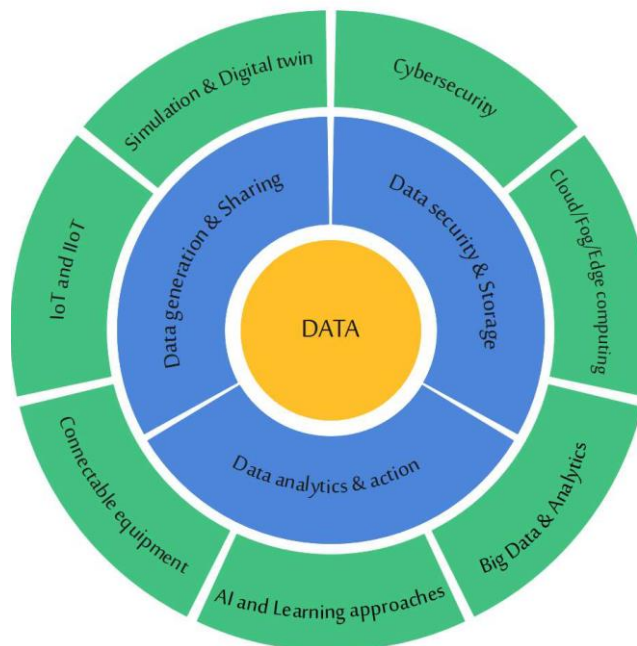


Figure 17. Importance of Data in Industry 4.0 & Digital Transformation

Based on the four main axes of a value chain, namely "design, production, distribution, and marketing", there are two types of activities. Primary activities are directly linked to the production chain and relate to each step of the production process. Support activities cover from business, traversing human resources, IT, purchasing, etc., to administration (Gilchrist, 2016).

The position of maintenance is in the support activities of the value chain, and through the I4.0 integrations, it would be able to increase visibility and better decision-making. Based on Figure 17, in the context of Industry 4.0, the challenges in PdM are mainly related to data generation & sharing, and data analytics & action. The technological aspects of PdM are more concerned with IIoT, Connectable equipment, Big Data & Analytics, AI and learning approaches, and cloud/fog/edge computing.

3.2 Maintenance strategies

Historically, primitive maintenance activity started with the appearance of the hand tool (stone flake, 35000BC) which concerned the sharpening of cutting parts and replacing or repairing the wood or bone handles (9000BC). These maintenance activities could be considered "Corrective Maintenance (CM)". The wheel's iron hubs and lubrication (greasing) of the axis to avoid the breakdown risk could be considered the first "Preventive Maintenance (PvM)" activity (900-700 B.C.) (Timothy C.Kister, 2006). One of the earlier systematic maintenance activities dates back to the time of the Achaemenid (Persian) empire (550-330 BC), where the repair and maintenance of the Royal Road, an ancient highway, and the express courier system (known as Chapar Khaneh) (Briant, 2002) were carried out by skilled Persian engineers through municipal organizations (Khazai, 2016).

In terms of modern maintenance strategies, it could be referred to the first industrial revolution where "Shutdown Maintenance" was introduced (1708-1803). This was due to the overproduction of cotton and iron products (for the market loss compensation objectives) and the essential need for a stoppage period of about one or two months. In the twentieth century, the emergence of electrical power and engines which led to the second industrial revolution accelerated technological and production advancement. At the beginning of the twentieth century the modern and productive assembly lines, introduced by Henry Ford (1908-1913), required the "Planned Maintenance" method to ensure the consistent flow of automobile production. In the First World War (1914-1918), a pre-post flight maintenance checklist control was begun in military aircraft. The developments of armored tanks, the "Time-based" oil replacement, and "Condition-based" oil, fuel, and air filter replacement were the other innovations in maintenance activities during the First World War. During the period between the First and Second World Wars, there were fewer incentives for innovations in maintenance activities due to the overcapacity of the manufacturing plants. However, the second world war ignited the demand for more technological advances (more mechanizations due to workman shortages) to comply with the military and consumer goods. In the meantime, equipment downtime and reliability became crucial, and several planned, and periodic maintenance programs were developed. After the second world war, the "lean manufacturing" and "lean thinking" concepts were brought by Toyota Production System (TPS). Initially, lean thinking was the identification of wastes in the production processes and their elimination. Whereas manufacturers found that improving the production rates resulted in reliability and downtime issues. This has made it important to implement "lean maintenance" (Timothy C.Kister, 2006) and consider maintenance objectives beside production objectives. Total Productive Maintenance (TPM) was introduced in 1969 (Nakajima, 1988) which emphasizes on

equipment care by the operators through cleaning, controls, etc. Furthermore, the start of the third industrial revolution can be traced back to the invention of the first Programmable Logic Controllers (PLC) in 1969, which was linked to the rise of automation, electronics control, and the growth of information technology. After this while, the first type of “Condition Based Maintenance (CBM)” was initiated by the advancement of sensors, monitoring tools, and the application of statistical models (Poor et al., 2019) (Roser, 2021). In 1978 Reliability Centered Maintenance (RCM) was introduced (Nowlan & Heap, 1978) for optimal maintenance identification in the aircraft industry. The contribution of RCM was to look at the life cycle of the equipment from the conception and increase the reliability from the conception and elimination of failure sources. As we have seen in the historic voyage, several maintenance strategies and activities were developed, and the importance of fundamental needs and the prerequisite role of maintenance is now widely understood. Finally, as stated in previous subsection 3.1 the emergence of Industry 4.0, has opened up opportunities to implement “Predictive Maintenance (PdM)”.

To summarize, the initial, basic and traditional maintenance strategy was run-to-failure (R2F) or Corrective Maintenance (CM), based on this strategy manufacturing has been continued until there was a failure or breakdown in the machines, and afterward, related activities triggered in order to repair equipment (Doyen & Gaudoin, 2011). If this is used to just resolve the temporary provisional failure, this is called a Breakdown Maintenance (BM) or Palliative Maintenance strategy. On the other hand, if the maintenance activities are focused to resolve certain issues in the machine once forever, then this is called Curative Maintenance. (Gouriveau et al., 2016) Have presented a comprehensive overview of different types of maintenance strategies based on the standard EN 13306 (2001), which is illustrated in Figure 18.

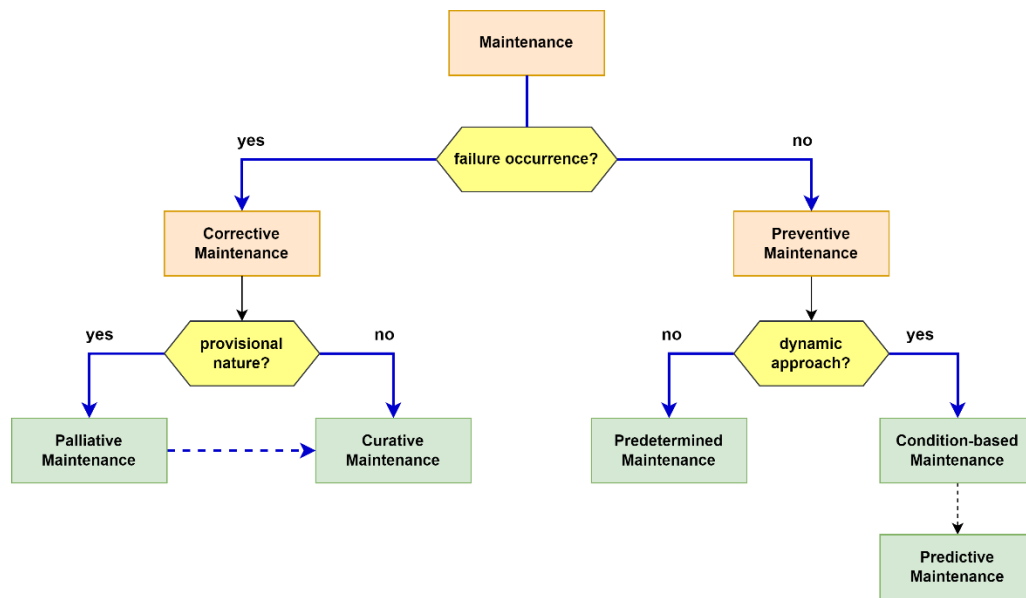


Figure 18. Maintenance strategies according to standard EN 13306

3.2.1 Maintenance planning

The goal of effective maintenance planning and scheduling is to maximize the efficiency of maintenance resources, ultimately leading to improved equipment reliability and performance. By optimizing the allocation of maintenance tasks per equipment needs, it is possible to ensure that maintenance resources are used most effectively and efficiently as possible. This will help to reduce downtime, improve equipment performance, and reduce overall maintenance costs. Without proper planning, the resources utilized in the

production process or for maintenance services are being utilized inefficiently. (Timothy C.Kister, 2006). It should be noted that it is not possible to have only one kind of maintenance strategy in a company. In another word, PvM or PdM planning strategies could not be applied for all components or machines due to technical and/or economical limitations. PvM and PdM planning methods are reviewed in subsection 3.3.5. furthermore, maintenance planning is developed more extensively in chapter 6.

In continue, the preventive maintenance family is presented in the following:

3.3 Preventive maintenance

Each machine or equipment has a life cycle, the statistical aspect of the machine's life cycle is illustrated in Figure 19. This represents that the new machines may have a high probability of failure during the early phase of installation, then the machine would have a quite stable life, then in their late age, the failure rate increases more and more (Mobley, 2002). To avoid the important cost of breakdowns, increase the availability level of the production equipment, especially in the normal life of the equipment, and slow down the failure process, PvM has been used (Silver & Fiechter, 1995). This strategy has a static aspect which means that it is followed based on a schedule. This schedule could be based on the calendrical schedule, the hour of work, or the completed kilometer. In the industry and based on the World Class Manufacturing (WCM) standard book of knowledge (S. D'APRILE, 2020), timely predetermined maintenance is called time-based maintenance (TBM) (Gajdzik, 2014), and the maintenance that is based on an hour or level of work is called Hit-based Maintenance (HBM).

There exist, different definitions of PvM but time-based maintenance (TBM) is the common point between them. In practice for this maintenance strategy, Industrial actors may use the term Inspection& Repair (I&R) and PvM. I&R activities are more related to checking, controlling, and repairing the part if it is necessary. They may refer to the PvM for the activities in which components are changed systematically.

Although PvM can reduce the risks of sudden failure, even in well-implemented PvM systems, two risks increase the cost of maintenance and production. This refers to performing the maintenance where the component could have worked more which results in over-maintenance costs. Furthermore, the failure in production equipment can also lead to breakdown costs that are often substantial. The analysis has shown that this cost could be three times more than the PvM in the normal running machine condition.

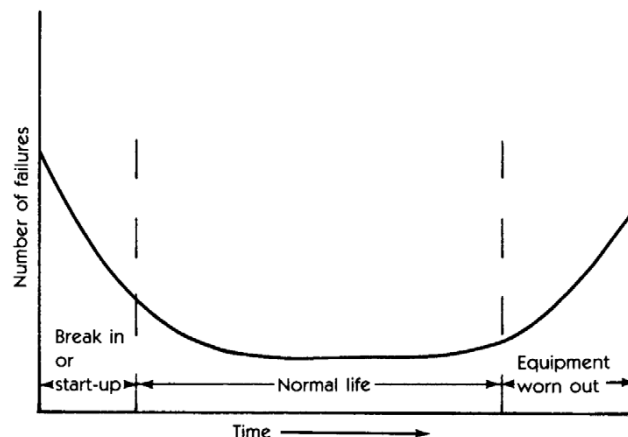


Figure 19. The failure rate in the life cycle of machine/ equipment (Mobley, 2002)

In order to update the MTBF of production equipment based on the last information on equipment condition ‘Dynamic PvM’ strategy has been taken into action. In this strategy, the maintenance periods are dynamic and there is no fixed period (Gao et al., 2015).

In continue, the other recent types of maintenance as condition-based maintenance (CBM) and PdM are explained:

3.3.1 Condition-based maintenance

Condition-based maintenance is a branch of the PvM family that is developed by relying more on the actual state of the equipment. In the PvM strategy, the components are changed regardless of the actual condition of the component. In another word, each component is replaced when it arrives at its degradation level rather than its age (Heping Li, 2016). CBM is performed in predefined cycles, in this vision it is somehow similar to PvM, but the difference is that the maintenance is only triggered where an anomaly or change in the characteristic of the equipment is detected in the moment of condition monitoring. (Gouriveau et al., 2016) have defined the CBM as “*a preventive maintenance based on performance and/or parameter monitoring and the subsequent actions*”. This strategy is quite the same as already stated I&R however, the difference is in the control tools for the inspection. In CBM strategy, condition monitoring is performed by the application of certain measurement technologies such as vibration monitoring and thermography devices. However, in traditional I&R activities, control and inspections are usually performed manually. Furthermore, maintenance is generally scheduled when it is needed based on the regular measurements and assessment of the machine or component condition (Beebe & Beebe, 2004), and the maintenance periods are dynamically updated based on the last assessments.

The concept of CBM strategy is well presented in Figure 20. Black points are the measured value of a defined parameter at different time intervals. Initially, the aim is to establish the normal operation condition data by testing the parameters at different periods, this is to have a normal baseline condition in order to compare with future measurements. As the measured parameter arrives at its variation limits, a prediction should be made for the failure of the component or machine.

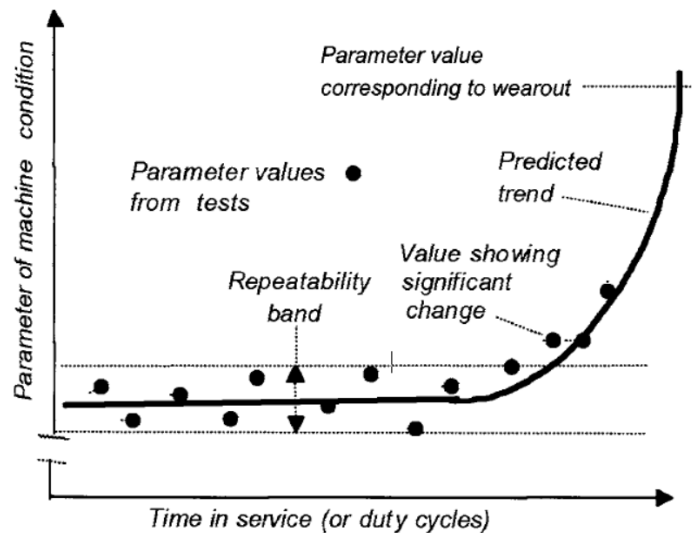


Figure 20. The principle of CBM strategy (Raymond Beebe, 2004)

There are several monitoring tools and methods that can be used for different types of equipment. These are well presented in the technical support of the WCM standard provided by Professor Hajime Yamashina (Yamashina, 2011). This can be a good basis for developing and implementing industrial solutions in CBM (Figure 21).

Detecting method of Judgment parameters Equipment to check		By active method																			Check by passive method												
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	1	2	3	4	5	6	7	8	9	10	11	12	13
Rotating equipment	Bearings, reduction gears, Slow rotation bearings Transmission Pumps, blowers,	○	○	○	○					○				○		○						△											
Structural equipment	Rolling mill, cargo handling machine, Pipes, pressure containers, Trestles • frames Refractory bodies, chimneys		○					○		△											○	○	○	○			○						
Lubrication equipment	Hydraulic apparatus, Sliding bearing apparatus, Lubrication oil • grease	○							○	○				△	△			○								△							△
Electric / control equipment	AC, DC motors, Oil transformers Electric power cables Electric power condensers High pressure distributors Automatic control systems	○		○	○					○	△						○		○	○		△				△		○	○	○	○		○

Figure 21. Monitoring Techniques in CBM (S. D'APRILE, 2020)

3.3.2 Predictive maintenance

A new branch of the PvM family is called Predictive Maintenance, which mainly relies on real-time data (Lughofer & Sayed-Mouchaweh, 2019) that are used for the failure and degradation trend prediction of components or machines. The challenge in this new PdM strategy is to avoid over-maintenance and breakdown costs by finding prognostics to predict the next failure of the machine and perform the maintenance before the predicted time. As the PdM strategy tries to consider the current state of the equipment, its nature is more dynamic compared to CBM (Gouriveau et al., 2016). In the case that the PdM strategy could receive and consider the new (last updated) condition monitoring data and information and, then update the maintenance planning, this strategy is then called 'Dynamic PdM' (Van Horenbeek & Pintelon, 2013).

There are several advantages for the PdM strategy as follows:

1. Optimization of PvM planning by reduction of unnecessary maintenance interventions,
2. Identifying early degradation and failure signs and avoiding severe and sudden breakdowns,
3. Decreasing spare part cost and spare part management cost,

4. When the component is used maximally without failure, then the spare part cost would decrease automatically,
5. With the early prediction of components, there would be less need for emergency purchases which normally cost two times or more than in a normal situation,
6. Reduction of production stoppages,
7. Increasing the availability of production equipment,
8. Identifying diagnostic rules by condition monitoring,
9. Reducing time to repair by root cause diagnostics analysis,
10. Increasing product qualities by resolving the degradation problems of machines

As a PdM strategy has direct communication with sensor/real-time data, the role of big data management in the decision-making process becomes important. An interesting big data framework has been developed by (C. K. M. Lee et al., 2017) for the diagnostic and prognostic aspects of PdM. This framework is illustrated in Figure 22, where the data flow begins with data collection from physical assets. Then, several kinds of methodologies as machine learning (ML), data mining, and knowledge-based systems are utilized in the diagnostic and prognostic aspect of PdM to propose certain potential failures in the context of the prognostic aspect of the PdM strategy.

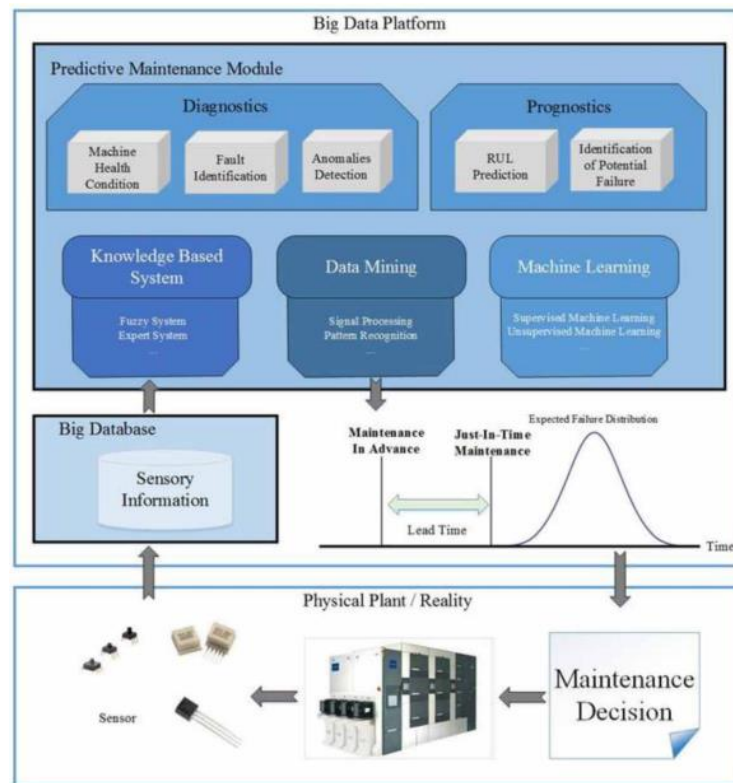


Figure 22. Big data framework for PdM (C. K. M. Lee et al., 2017)

The common sensor data that are usually used in the PdM strategy are vibration, temperature, current, voltage, lubricating oil, noise level data, etc. It depends on the technical issues of each specific equipment. The effort is to analyze and monitor these data to find a model, method, or strategy to predict the state of the component, or machine or predict the potential of the next failure.

Several types of research are dealing with developing and installing sensors in the machine and equipment in different industries and applications and the main concern is technological rather than methodological. In this thesis, the main focus is on methodological research, in which the PdM problems are separated into three general categories (Gouriveau et al., 2016) (Chebel-Morello et al., 2017):

- 1) Health monitoring, diagnostic, and visualization
- 2) Prognostic, RUL estimation
- 3) Maintenance planning

The main objective of health monitoring systems in PdM is the preparation of the basis for the evolution from reactive (diagnostic) to proactive (prognostic) maintenance. The main problem in health monitoring is finding the right indicators for monitoring the state of components, machines, or equipment (which we call supervision cases). The visualization of these indicators is the other subject to illustrate the information in the best possible manner. The indicators would be helpful for the diagnostic of the supervision cases in order to find out the initial faults based on threshold analysis to identify the normal and abnormal conditions. In the health monitoring phase, some maintenance activities could be triggered regarding the thresholds, and/or the accordance of experts.

RUL estimation is one of the important challenging problems in the PdM strategy. Regarding the methodological aspect of RUL estimation, there are three main categories: model-based, data-driven-based, and hybrid models. In model-based methods, the effort is to model the physical dynamics of the equipment/system and to develop scientific models to model the vital failure feature that describes the degradation process (WANG et al., 2017) while, in the data-driven methods, the attention is to use the available data and use of statistical models (X. S. Si et al., 2011). However, in the considered classification, data-driven models could contain not only past historical data but also every data that has worth thinking about and considering in the model and the working environment. This could be real-time data received from the shop floor, sensors, etc.

Regarding the maintenance planning, the big difference in the PdM strategy concerns the existence of supplementary information on the RUL of components, which does not exist in the other maintenance strategies. As maintenance planning contributes to cost optimization, different information should be available in this regard. Those are as cost of the components, real-time state of components, maintenance resources, and spare parts inventory.

Maintenance planning problems have been investigated in the multi-component environment in the PvM and PdM strategies. Maintenance planning of multi-components that have inter-relationship with each other and it is even more complex. The complexity comes from the three main dependencies between components that are available in the literature: 1) Stochastic (Functional) dependencies, 2) Structural dependencies, and 3) Economic dependencies.

1. *Stochastic or Functional Dependencies*: degradation or failure of one component affects the degradation level or maybe the failure of other components (Olde Keizer et al., 2017)

2. *Structural Dependencies*: refers to the physical position of the components when there is a need to replace or repair one component, other components have to be dismantled at least. (Olde Keizer et al., 2017)

3. *Economic dependencies*: If one component needs maintenance, it may be cost-effective to do maintenance on any related components at the same time. Positive economic dependencies exist if the combined maintenance is cheaper than the individual maintenance, and negative economic dependencies

exist if it is more expensive. This could be due to setup costs, manpower restrictions, safety requirements, etc. (Nicolai & Dekker, 2008).

According to the study of bibliography, resources such as (Mobley, 2002) (Gouriveau et al., 2016) (Chebel-Morello et al., 2017) (Daher, 2018) (VEGA ORTEGA, 2019) (Lei et al., 2018) (Jardine et al., 2006a), the structure of the literature review in PdM problems has been proposed in Figure 23.

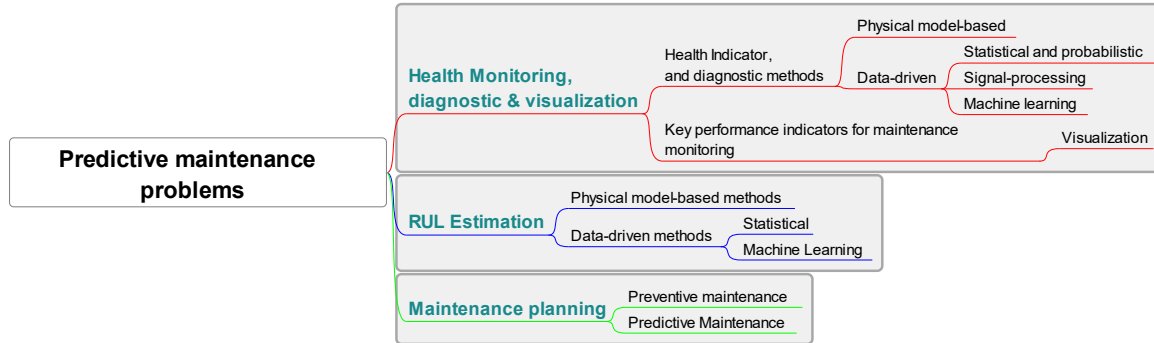


Figure 23. Proposed structure of the predictive maintenance problems

For a better perception of the proposed structure of the PdM literature, the general prognostic and health monitoring (PHM) cycle could give a general vision of PdM steps. This cycle has seven steps as shown in Figure 24.

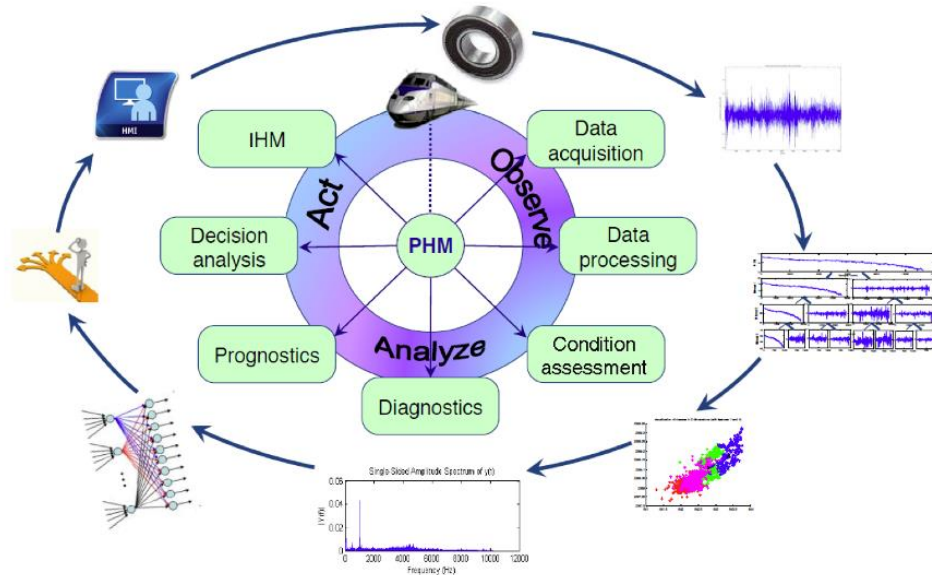


Figure 24. Schematic of the process, from data to the decision (Gouriveau et al., 2016)

Data acquisition is mainly followed by sensors or transducers, acquisition of event data can also be considered. The acquired data should be processed in order to extract the features that can suggest the anomaly or degradation of the monitored component or machine. After the *data processing*, the diagnostic is the first step to come across the PdM. *Diagnostics* begins with *condition assessment (detection)* so that the real-time data would be compared with pre-defined thresholds and the alerts should be generated. In the case of faulty state detection, the diagnostic tool should be able to determine whether the monitored component or system is degraded or not, and it should be able to find the root cause of faults or failure. The

prognostic is the next step in which the future state of a component or machine should be predicted. This can be in terms of estimation of RUL or machine state. The prognostic is relying on the data and information of the diagnostic step since it is necessary to have the current state of the component or machine for further predictions. It should be noted that in practice, this RUL or state could be dynamic rather than static. Afterward, *decision-making analysis* is the important step in which the inspection or maintenance action and its schedule should be proposed. This is mainly based on the RUL that should be followed by a decision that optimizes local maintenance costs in the first step, and in the continue that could globally optimize the costs. Finally, there should exist an online tool that contains all previous steps in the form of a human-machine interface (HMI).

In this literature review, the *data processing*, *condition assessment*, and *diagnostic* are included in section 3.3.3, the *prognostic* in section 3.3.4, and the *decision analysis* in section 3.3.5. Finally, a conclusion of the PdM topic from a general overview is provided in section 3.3.6.

3.3.3 Health monitoring, diagnostic, and visualization

In general, health monitoring and real-time supervision systems are proposed to reduce CM costs by actively monitoring the integrity of the machine or systems (Xu & Xu, 2017). The main objective of health monitoring systems in PdM is to be capable of monitoring the current state of the machine or systems through metrics and indicators. When there is a proper assessment of the current conditions, it could be the right basis for the prognostic which will be detailed in the next subsection 3.3.4.

Health Indicators are the main objective of health monitoring and diagnostic analysis. These indicators can come whether from some methodologies based on the input data or expert knowledge (Lei et al., 2020). The main idea of the HI problem is to develop methods in order to obtain the health state of equipment through field knowledge or based on the identification of a function from sensor data (Balcázar et al., 2010). There is a wide range of data and information that can be considered for the health indicators as historical maintenance activities and failures, operating parameters, and condition sensors. HIs can help the maintenance team to track and detect faults and failures (Kronz, 2006).

The main objective of diagnosis is to identify the faults and failures in the components and to find the root cause of the faults or failures. In order to be clear in the two terms of fault and failure, let's explain that fault is the deviation from the normal characteristic of a component, machine, or system that comes from abnormal behavior. When a fault occurs in a component or machine, despite the abnormal behavior the system is capable to continue working. Whereas, when a failure happens the effect is harsher and the machine is stopped (Phillips, 2012). Diagnosis is the process of identification of the nature and cause of a condition, or problem (J. Lee et al., 2014). Diagnosis analysis would define the healthy or degraded state using the provided information by the health monitoring system, and/or the expert's knowledge. The diagnosis process involves three steps: fault detection, localization, and identification. Fault detection indicates whether something is going wrong with the monitoring system. Fault localization locates the faulty component and fault identification determines the root cause of the fault.

Most often, the diagnostic activities are carried out by competent technicians and engineers when the machine is in breakdown or degradation mode with their physical presence. These experts have domain knowledge about the machine's structures, operation conditions, failure modes, and causes. As in the industry, there are availability limitations of maintenance experts who have to manage a set of industrial machines, they could not be always present for continuous diagnostic activities. However, in PdM or CBM,

the idea is to develop an automatic diagnosis methodology that can increase the visibility of the health state of components or machines, in real-time. This visibility could help in detecting faults and anomalies.

The other relevant aspect of this section is concerned with KPIs for maintenance system monitoring and the visualization which is an appropriate tool for triggering human inference from large data sets and helping in making better-informed decisions (Lebanon & El-Geish, 2018a) (Huynh et al., 2017). Different kinds of visualization plots could be (S. Liu et al., 2017) to propose and create dashboards, particularly for maintenance activities (Arulraj et al., 2019).

3.3.3.1 Health monitoring and diagnostic steps:

The application of health monitoring and automatic diagnostic needs to follow some steps that are presented in Figure 25. The first step is to detect the phenomenon, process, or targeted components for health monitoring. Then the measurement method by the suitable sensors should be identified, and the data should be acquired and validated. Researchers mainly use feature selection and/or feature extraction methods for dimension reduction purposes as there are large data sets in the PdM strategy, however, some researchers may prefer not to use feature extraction or selection methods and apply their model directly to the raw data. The next step is to develop health indicators (HIs) that are capable to detect faults or refer to some symptoms. Fault detection is mainly followed by a statistical test or threshold analysis, the effect of noises should be considered in fault detection. In continue, the components that are the cause of the faults should be localized. The final step is taking some actions which are to define what should be done in order to maintain the desired performance of the system under surveillance. The necessary actions should be followed to return the system to its normal operating characteristics (Daher, 2018). It may also be proposed some development projects to identify and remove the root cause of the fault or failure at this point.

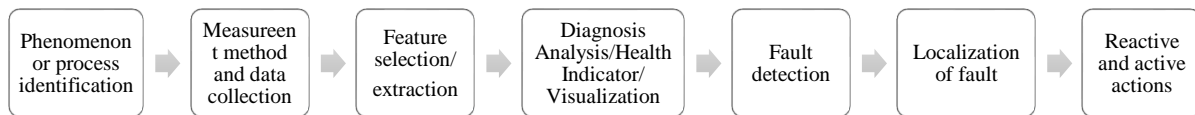


Figure 25. Diagnosis steps in health monitoring

In continue, the health state monitoring, diagnostic, and visualization methodologies, and application areas are reviewed based on scientific sources like journal articles, books, and related thesis reports.

3.3.3.2 Health indicator and diagnostic methodologies

One of the reference books that is a basis in health monitoring and PdM, is “from prognostic and health system management to PdM” (Gouriveau et al., 2016). In this book, the diagnostic steps, from data acquisition, and feature extraction to health state identification are explained. Regarding the authors, the current health state can be obtained based on two approaches. The first is to develop the features from the raw data and classify the evolution of the features. The second approach is to construct the health state estimators (through Markov and/or Bayesian models) that can represent the health state of the components, or system. In addition, several review papers have investigated the diagnostic problems in different application areas and methodologies that are presented in Table 1. Although these studies may include the prognostic aspect, in this section we have concentrated only on the diagnostic and current state estimation aspect of the studies.

Table 1. Summary of the review papers in health monitoring and diagnostic studies

Reference	Reference type	Main perimeter of study	Application area	Methodology types
(Gouriveau et al., 2016)	Book	Health state identification through feature extraction, and health state estimators	Machining test bench, Bearing, Turbofan	Hidden Markov Models (HMMs), Dynamic Bayesian Networks (DBNs)
(Daher, 2018)	Thesis	Fault detection, health state identification	Chemical process, distillation column	Fuzzy c-mean clustering, Artificial Neural Network (ANN)
(Phillips, 2012)	Thesis	Fault detection	Electrical actuators, landing gear actuators	Model-based, threshold analysis
(Jardine et al., 2006b)	Review article	Fault detection	Machinery equipment	AI/ Statistical approaches
(R. Liu et al., 2018)	Review article	Health Indicator, Health state identification	Rotating machinery	Artificial Intelligence (AI)
(Lei et al., 2018)	Review article	Health Indicators Health state, and threshold identification	Rotating machinery, Bearing	Signal processing, Statistical methods (RMS, PCA, etc.)
(McKee et al., 2014)	Review article	Fault detection	Centrifugal pumps	AI, Statistical, Expert systems, Fuzzy logic approaches
. (El-Thalji & Jantunen, 2015) and	Review article	Health monitoring, fault detection	Bearings	Signal processing, ANN, Statistical, Expert systems, Fuzzy logic, model-based approaches
(Cerrada et al., 2018)	Review article	Fault detection	Rolling bearing	Signal processing, AI learning approaches
(Khan & Yairi, 2018)	Review article	Anomaly and fault detection	Bearing, Rotating machines, Pump, Gearbox	Deep Learning (DL)
(T. Wang et al., 2019)	Review article	fault detection through vibration condition monitoring	Turbine gearbox	Signal processing, Statistical approaches

As early discussed, there are different range of review articles in the condition monitoring diagnostic area that has reviewed the methods from their point of view. The idea here is to have a comprehensive classification that contains as much as possible the range of available methods into one structure. In this way, they are separated into three general categories: *i)* Model-based, *ii)* Data-driven, and *iii)* Hybrid models (Tahan et al., 2017) which are seen in Figure 26.

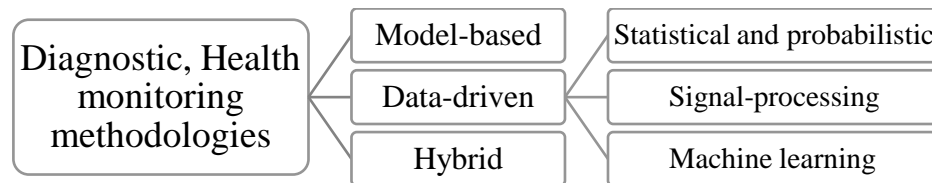


Figure 26. Classification of diagnostic methodologies in PdM

Model-based methods often need deep physical domain knowledge of the component such as the engineering design of the equipment which is more complicated to develop. Since this methodology is not in the scope of this project, we have less concentrated on this method, but it is interesting to consider the requirements for developing such methods. As an example (Abdel Fatah et al., 2019) have developed 3D computational fluid dynamics, pressure pulsation, and pump casing dynamic models into the centrifugal

pumps to monitor the forces, pressures, and possibility of cavitation that may impact the performance of the pump. In this case, the researcher should have knowledge of mechanical fluids and severe failure types in pumps such as cavitation.

3.3.3.3 Data-driven methods

An important point to note here is that the review of data-driven methods provided does not necessarily imply that they will be applied exactly in the thesis methodology. Rather, the state-of-the-art study provides us with a better vision and inspiration for the application of health monitoring and health indicators.

The methodologies in this category are very wide and large, the common point in the whole data-driven methods is that they are fed with the signal and the data that comes from the sensors. According to the literature and reviewed methodologies, the data-driven methods have been divided into three main subcategories: i- Statistical, ii- Signal processing-based, and iii- Machine learning methods.

For a better comprehension of the data-driven methods, it is valuable to take a look at the definition of data and its difference from the signal. The data is a measurement that is raw and it does not have a meaning (Bellinger et al., 2004) by itself. A signal can be generated by electrical or electromagnetic pulses, a signal is a function that conveys information about a phenomenon (Priemer, 1991). In this way, it makes it possible to track the changes with the signals. It could be analog as continuous or digital as discrete. Differences between data and signal are given below:

- Data is what we need to send whereas the signal is what we can send.
- Data is being carried whereas the signal is the carriers
- Data cannot transmit signals whereas signals can transmit data (*Networking Data and Signals*, 2012)

In general, based on the study of the literature, there are three types of data which the category is depicted in [Figure 27](#):

Value type: Data collected at a specific time epoch for a condition monitoring variable are a single value. For example, oil analysis data, temperature, pressure, and humidity are all value-type data.

Waveform type: Data collected at a specific time epoch for a condition monitoring variable are a time series, which is often called time waveform. For example, vibration data and acoustic data are waveform types.

Multidimensional type: Data collected at a specific time epoch for a condition monitoring variable are multi-dimensional. The most common multidimensional data are image data such as infrared thermographs, X-ray images, visual images, etc.

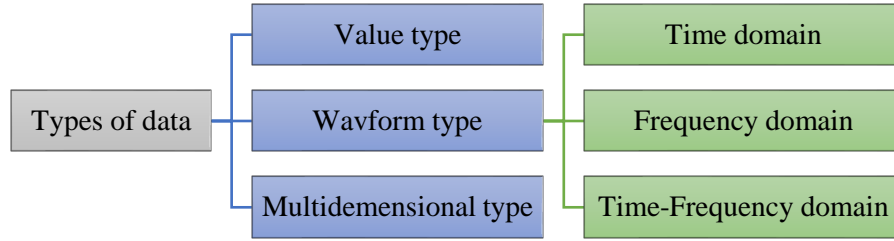


Figure 27. Category of data types

For more information, different aspects of the time and frequency domain of a signal data type are depicted in Figure 89 which is in Annex I. In fact, frequency variations of data are the hidden aspect of time-domain data that can be achieved by performing the Fast Fourier Transform (FFT) method. There are also other transformation methods like *Wavelet transform* that are explained in Annex I.

3.3.3.4 Statistical and Probabilistic Methods

Statistical methods concern several types of methods such as failure probability identification, hypothesis test, statistical process control, statistical feature extraction, degradation modeling, and Markov models. These methods are presented in the following:

Probability methods in general, are very suitable for the analysis of a phenomenon through the estimation of the Probability Density Function (PDF) of the phenomenon based on the acquired data. The statistic and probability field applies mathematics to the data and tries to find relationships between the data and inferences, by the creation and fitting of a probability model (Bzdok et al., 2018). In diagnostic applications, PDF estimation is not that much easy, as routine data like demand data, to apply directly. Since there are numerous data with a large variation level, so that it may not be possible to fit a PDF directly to the sensor data. However, it may be possible to suppose that sensor data amplitude is a stochastic process. As an example, if we consider the percentage of times that a sensor parameter has a certain amplitude, then this may be assumed to be a stochastic process that fits some Distribution Functions (DF). Thus, by supposing that the sensor data amplitude is fitting to a certain DF, then it would be possible to run some hypothesis test problems. In this way, the null hypothesis H_0 is that the fault exists in the sensor monitoring data, and H_1 is the opposite side. For example, (Ma & Li, 1995) applied statistical analysis of vibration data in the rolling element bearings. They analyzed the vibration data in normal and damaged conditions. They supposed that the vibration of a damaged bearing fits the two Gaussian distributions with a zero mean and two different variances. Based on this assumption that the N observations are independent and identically distributed (*i.i.d*), they proposed a hypothesis test based on the Gaussian distribution. According to the vibration monitoring data and the test statistic, it should be decided whether to accept the null hypothesis or not.

Another method is concerned with statistical process control that is applied in maintenance diagnostic applications despite that they are mainly developed in quality control. The basis of the SPC theory is to compare the concerning variable or parameter with the Upper and/or Lower Control Level (UCL/LCL), in order to see if the variable or parameter is in the control limit or not. In the PdM strategy, the control variable can be the features that are selected or extracted from raw sensor data. For example, (Du et al., 2020) studied the vibration sensors in the motorized spindle of a CNC machine. They implemented a Proportional Hazard Model to find the best health indicator through the Kolmogorov-Smirnov (K-S) Goodness-of-Fit Test. Based on the (K-S) statistic and the highest p -value the best feature is selected for the statistical process

control, and the outputs are depicted in the form of Shewhart-I and EWMA control charts. There are other examples of the application of control charts and SPC for the health monitoring of equipment such as bearing (Guoqing et al., 2016) and aero engines (Vassilakis & Besseris, 2010).

Statistical feature extraction methods are the other methods which a wide range of them are based on statistical calculations. Generally, one of the initial steps in the data-driven methodologies after data acquisition is feature selection or feature extraction. This is to reduce the complexity of multivariate problems. Some of the famous time-domain statistical indicators (T. Wang et al., 2019) are presented in Table 2, with their calculation formula. Note that in each feature there is N number of data and $x(i)$ is the i^{th} data in the N data set.

Table 2. Statistical indicators

Feature name	Formula	Feature name	Formula
Maximum value	$\max x(i)$	Standard Deviation	$\sqrt{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^2}$
Minimum value	$\min x(i)$	Root mean square (RMS)	$\sqrt{\frac{1}{N} \sum_{i=1}^N x(i)^2}$
Average value	$\frac{1}{N} \sum_{i=1}^N x(i)$	Skewness	$\frac{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^3}{(\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^2)^{\frac{3}{2}}}$
Average absolute value	$\frac{1}{N} \sum_{i=1}^N x(i) $	Kurtosis	$\frac{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^4}{(\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^2)^2}$
Variance	$\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^2$	Shape factor	$\frac{\sqrt{\frac{1}{N} \sum_{i=1}^N x(i)^2}}{\frac{1}{N} \sum_{i=1}^N x(i) }$

As an example, (Babbar et al., 2009) have studied diagnostics with RMS analysis for determining aircraft engine performance.

Degradation modeling is another type of method in which the deterioration process is studied to identify a probability function representing the degradation (Z. Zhang et al., 2015). For example, (Zhao et al., 2010) presented a reliability function based on degradation probability. (Cattaneo & MacChi, 2019) have used an exponential degradation model for identifying the degradation rate of the most critical failure mode. In this way, they have installed sensors and applied statistical methods due to the lack of run-to-failure data. Other studies have proposed stochastic degradation models (Kaiser & Gebraeel, 2009) (Curcucu et al., 2010) (Omshi et al., 2020). Covariate-based hazard model, and Weiner process methods are also used for the degradation analysis (Z. Zhang et al., 2018).

The Markov models are the other category of statistical methods, which are inspired by Markov chains and can be used for health state identification based on the probability of transition between the states (Gouriveau et al., 2016). Hidden Markov Model (HMM), and Hidden Semi-Markov Models (HSMMs), are

some of the examples (X.-S. Si et al., 2011) which consider the predefined states and also the observations such as sensor monitoring data. For example, (Q. Liu et al., 2013) HSMM model with aging factor.

3.3.3.5 Signal Processing-based Methods

Signal processing-based methods are mainly used for fault detection, severity analysis, fault size, and fault location purposes. This is principally followed by feature extraction, as a result getting indicators from the signal/data is the most important objective in health monitoring and PdM. As previously discussed, signals and data have some similarities and dissimilarities. One can think that both are set of values (whether in time series or not), and it seems to be the same as data. However, the hidden frequency changes can be traced in the signals and not in the data which is the key point that makes the difference. For example, in Fourier Transform the time-domain data would be transformed to frequency-domain data. This makes it possible to have frequency domain indicators such as mean frequency, frequency RMS, and standard deviation. These indicators are used in the signal-processing-based methods for the waveform data type.

Supposing that a signal is received within a frequency of 50 Hz (this receiving frequency is different from the spectrum frequency of a signal), then it means every 0.02 seconds, one data is obtained. However, regarding the amplitude of the signal, the spectrum of the signal shows the frequency of the signal waves (see [Figure 89](#) in [Annex I](#)). Therefore, signal processing-based methods work with signal waves and waveform data types.

Based on a general review of the signal processing methods, a global vision of the signal processing methods is achieved to structure them in the PdM framework. These methods here are presented based on the waveform data types, considered signal, and the studied component.

Some of the signal processing-based methods that are used in the feature extraction objective are presented in ([Table 17](#) of [Annex I](#)). The details of the methods are not discussed here, but the references for those interested are provided. As a general note, time-domain and frequency-domain methods are suitable for stationary signals, and time-frequency domain methods should be applied to non-stationary waveform signals. In stationary signals, the existing frequencies (could be one or more in each signal) in the wave do not change and it is constant, however, in non-stationary signals, the frequency values change over time. In this case, the frequency and time domain should be investigated at the same time (Jardine et al., 2006a). Once again, it should be emphasized that the interest in using signal processing-based methods is to extract features for further utilization in the prognostic analysis. Another application of signal processing methods is de-noising techniques, as the waveform signal as an example in the vibration signals may contain noises that are due to other faults in the equipment (Cerrada et al., 2018).

Regarding the time domain analysis, the study of (Cattaneo & MacChi, 2019) (is presented here, in which they have implemented a vibration sensor (accelerometer) in a laboratory drilling machine. They recorded the acceleration parameter in the sampling frequency of 200 Hz, and they considered the cycle of 11 seconds in which 2200 acceleration data is recorded for each cycle. In continue, they calculated the RMS of each cycle and as a health indicator, the maximum acceleration of the three axes of x , y , and z is considered as a HI. This has been presented in [Figure 28](#), where each data point represents a set of 6600 vibration data in three axes. The envelope curves are on the top of the figure.

For state detection, as there is not sufficient Run-to-Failure (R2F) data, they have run the drilling machine for 100 pieces of parts. The normality test has been applied to the HI values in order to model the healthy state which means the degradation classes. After confirming the normality test, the degradation

class has been defined by $\mu+3\sigma$ that is dynamic through time and new inputs. This HI and the degradation level are a basis for developing prognostic and predictions.

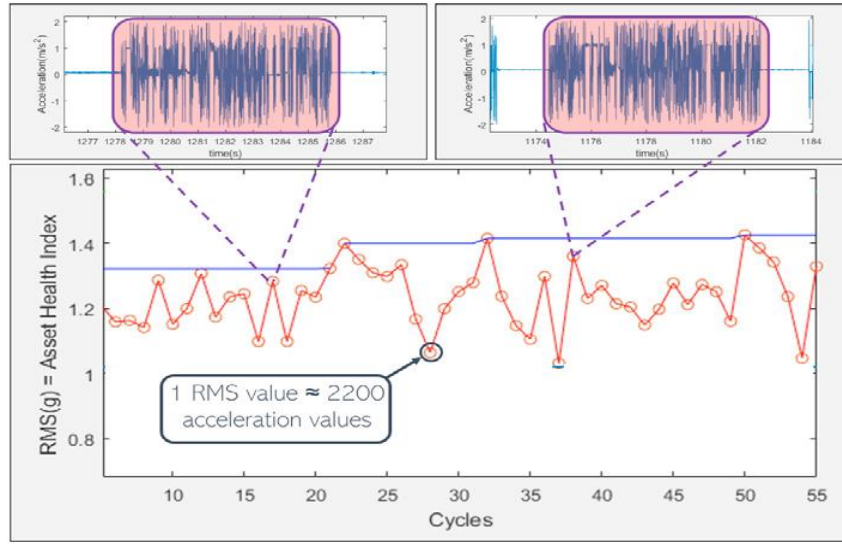


Figure 28. RMS values of vibration signals (Cattaneo & MacChi, 2019)

Another example of signal processing methods that have been used from the time domain and also frequency domain data type is the study of (Devendiran & Manivannan, 2015) that has been performed on the vibration signals in the laboratory test gears of rotating machinery. They have acquired the vibration data at the frequency of 12800 Hz which contains 6400 datasets per second and used it for HI development. In terms of industrial application, (Polenghi et al., 2022) have studied vibration analysis in order to identify the health state of the industrial centrifugal fans in a foundry plant. Based on the FMEA analysis, the engine, coupling, and support were selected for monitoring. Based on the installation of three accelerometers on the bearings, they have used the vibration data and applied time-based (as RMS) and frequency-based indicators to develop HI based on the ISO 10816-3 and ISO 13373-3/5 guidelines. Their study has shown that vibration data analysis could bring better knowledge of the equipment for further maintenance decisions. Nevertheless, the vibration analysis has provided the working state information rather than the health state of the components, or equipment.

3.3.3.6 Machine learning methods

Machine Learning (ML) methods are another category that could be used in the literature for health monitoring and diagnostics. ML was introduced in the late 1950s as an AI technique (Tiwari, 2017) which is a branch of AI that uses statistical techniques and mathematical algorithms to enable a machine to learn from data, analyze data patterns, and make decisions with minimal human intervention. ML has been classified into three groups, namely *i*) supervised learning, *ii*) unsupervised learning, and *iii*) reinforcement learning (Alsheikh et al., 2014). In continue, ML, statistical learning, AI, and data-science and their differences are explained.

The basis and principles of Statistical and ML, are mathematics and statistics, which means without statistics there is no Machine Learning. However, some differences between them should be noted to avoid ambiguity of the terms like “Statistical Learning”, “Machine Learning”, “Data-science” and “Artificial-Intelligence”. Statistics and statistical learning are often based on some assumptions such as normality, equal variance, etc. however ML methods do not consider the assumptions. Statistical learning is based on

probability spaces with the samples, population, and hypothesis and helps us formalizing the relationships between the variables, however, ML uses the statistics theory, optimization, linear algebra, and computer science in order to find and learn the patterns in the data to make the prediction. In terms of computational capabilities, statistical methods are suitable for smaller data sets with few variables, however, in Machine learning, it is possible to process large data sets and variables.

Figure 29 has well illustrated the schematic domain of AI, ML, Deep Learning (DL), and data science. As it is seen, mathematics and statistics are fundamental in all methodologies. Machine learning is a subset of AI in which the machine is trained and taught to make predictions, classifications, or clustering based on previous data. In fact, AI has a larger application rather than just machine learning as it is dealing directly with humans and the methods and algorithms are more complicated. Data-science and statistics are not equally the same, as data-science uses computational and statistical methods, Exploratory Data Analysis (EDA), computer science, and big data in small and large data sets. In fact, in data-science, the data is taken from databases and servers to do preprocessing as data cleansing, then by EDA the data would be examined for better understanding and visualizing the data. One may confuse statistics with data-science and ML, but as it was described once again, we should notice that ML and data-science use mathematics and statistics in order to develop some real-world applications based on billions of data and variables. One can do statistics without a computer, but the opposite side is not possible (*Machine Learning Vs. Statistical Learning*, 2018) (Stewart, 2019).

As stated, AI is the broader category of ML methods that work more with humans. The goal of AI is to develop computers so that they could act like humans. Some good examples are as expert systems, rule-based learning, fuzzy logic systems, and neuro-fuzzy expert system. As an example, (Ruiz-Sarmiento et al., 2020) proposed a Bayesian Filter, which includes an expert system to estimate the degradation of equipment in the hot rolling process.

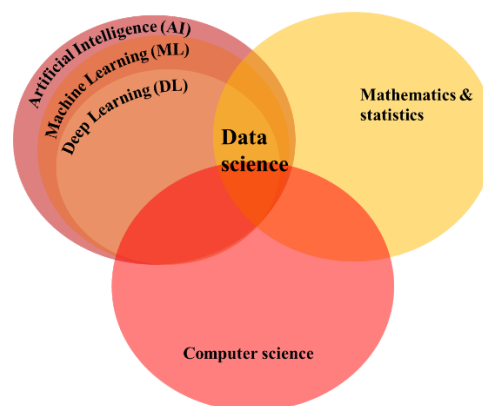


Figure 29. AL, ML, DL, and data science framework

Following the review of applied ML methods for the prognostic and precisely anomaly detection objectives, the most commonly used ML methods are as following: Artificial Neural Network (ANN), Support vector machine (SVM), K-nearest Neighbor (KNN), Naïve Bayes classifier, deep learning. The ML methods have been categorized and depicted in Figure 30 based on the learning types that are supervised, unsupervised, and reinforcement learning. This category gives us a general and global vision to

investigate ML methods. In a case where the target variable/s are continuous value/s, regression-based methods are applicable, and if the target variable/s are categorical then classification methods are suitable to apply.

Supervised learning is a methodology that tries to calculate the dependent variable based on some independent variables. The dependent variable named as output can be presented as Y , and the independent variables named as inputs can be presented as X_1, X_2, \dots, X_n . In supervised learning the data and information of inputs and outputs are available, and the challenge is to find the outputs for the new receiving inputs. As discussed, in the case of output data availability, which is called labeled data in the literature, supervised learning methods can be applied for classification or prediction objectives

Unsupervised learning methods deal with the data type where no target or label data is available. Clustering and dimension reduction are the main applications. Reinforcement learning tries to make a continuous classification based on the interaction with the environment to maximize the reward and minimize the penalties.

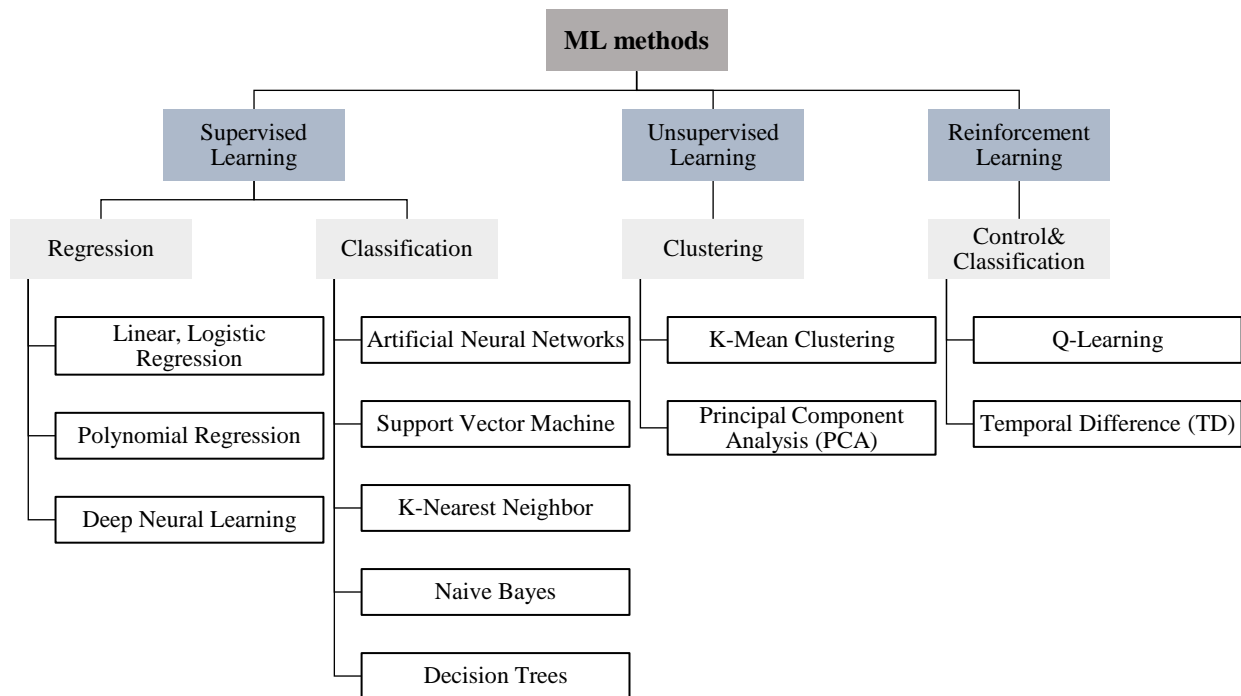


Figure 30. Category of ML methods in health monitoring and diagnostic applications

As the PdM problem deals with the large size of data, the utilization of statistical models may make it difficult for analysis. Therefore, ML methods have shown to be efficient enough in developing intelligent predictive algorithms and processing high dimensional and multivariate data in large application areas. ML methods can be used in health monitoring to estimate the current state of components or machines. In this way, Machine Learning methods are could be used in features extraction, classification of degradation levels, fault detection, and health indicators proposition (Cerrada et al., 2018) (McCoy & Auret, 2019), (Carvalho et al., 2019b). Regarding fault detection, it should be tried to find the fault pattern, in this way the faults should be classed into different degradation classes. This problem has been found in the literature as Health State (HS) division, in which ML methods can be applied for this objective (Lei et al., 2018)

In PdM, supervised learning requires a large volume of data that are accompanied by abnormal events or breakdowns in machines, however, this is not easy to have such data and it may take a long time. Unlike this, unsupervised learning methods can help in developing ML methods for degradation analysis and anomaly detection purposes. Unsupervised learning is in contrast with supervised learning, which deals with only input data and no corresponding output vector, meaning that there are no correct answers in this method. Clustering is the most common unsupervised learning technique, which is used to classify datasets into different groups or clusters based on the similarity between input data (Ghahramani, 2003). In continue, some of the most important methods are explained and a review has been done.

(Bekar, Nyqvist, & Skoogh, 2020) Have used from Principal Component Analysis (PCA) method for dimension reduction and then the K-mean method for the clustering of the anomalies in the case of machining shops for the spindle parts. In this regard, they have considered process parameters data such as motor consumption, temperature, torque, and the sensors data such as temperature, and flow rate. In another study, (Hiruta, Maki, Kato, & Umeda, 2021) used of Gaussian Mixture Model which is an unsupervised ML method in the case of experimental electrical motors for the anomaly detection of bearing. Bearing data set has been widely used in the literature for diagnostic and prognostic applications. (H. Yang, Sun, Jiang, Zhao, & Mei, 2020) have proposed to use scaled HI construction with unsupervised learning. They have used form time domain and frequency domain features for the construction of health indicators. (C. Li & Zhou, 2014) worked on the fault diagnosis of bearings with a weighted kernel clustering algorithm.

3.3.3.7 Key performance indicators for maintenance monitoring

Maintenance KPIs could be used for the monitoring of the machines, and maintenance performance. In the KPI study, KPI identification, measurement, visualization, and interdependencies between indicators are the main subjects that could be investigated. In this study, it is more focused on KPI identification, measurement methods, and visualization. On this basis, a brief review of KPIs, which are mostly related to maintenance, has been presented. Furthermore, in the next section 3.3.3.8, the visualization is briefly reviewed.

KPIs can be used in different areas such as energy, raw materials, control and operation, and maintenance to assess performance. The KPIs are criteria for measuring a company's progress against its objectives so KPIs can influence the decision-makers (Gonzalez et al., 2017). They can be used in different organizations, for example, in a healthcare organization, many indicators can affect the performance and quality of healthcare services (Jiang et al., 2020).

Different standards have defined various KPIs; for example, ISO 50006 has defined KPIs related to energy in the Swedish pulp and paper industry (Andersson & Thollander, 2019) and ISO 22400 has defined KPIs for mineral processing (Bhadani et al., 2020a) ISO 50006 also defined three levels of KPIs. The choice of a KPI level depends on its main user and the situation. Different KPIs can be used to measure maintenance performance. (Raza et al., 2016) discussed different methods of measuring maintenance performance through KPIs such as reliability, availability, maintainability, and safety at different levels. The following KPIs have been studied in the literature: operation, performance control, maintenance, and planning KPIs (Aceto et al., 2020), Reliability, Availability, Maintainability, and Safety KPIs (Shafi et al., 2018). In general, MTBF, Mean Time to Repair (MTTR) (Pilar Lambán et al., 2022), availability, and preventive maintenance compliance are the most used maintenance KPIs in the literature (Raza et al., 2016). More details of the literature KPIs and the proposed KPIs are provided in chapter 5.

3.3.3.8 Visualization

Data visualization helps humans to take a quick vision of the system or process. It helps to uncover hidden information in the data. One of the benefits of data visualization is the incorporation of human capabilities into an intuitive visual interface. In other words, data visualization is an appropriate tool for triggering human inference from large data sets. Data visualization is the main key in data analytics (Lebanon & El-Geish, 2018a) (Huynh et al., 2017). The idea of visualization is to help in making better-informed decisions. Visualization techniques are not limited to bar charts and graphs or the display of KPIs. A dashboard is the main tool used to visualize the data. Different kinds and types of plots could be used in data visualization, such as single variables, bi-variables, ... and Strip Plots, Histograms, and Line Plots (Thomas & Cook, 2006) (S. Liu et al., 2017).

A dashboard can be used to monitor product quality, project progress, or customer satisfaction. The dashboard presents quantitative data visually. It also makes it possible to disseminate information in a more user-friendly way and to help stakeholders make decisions. A dashboard closely tracks and monitors KPIs. A dashboard is based on analyzing large amounts of historical data and real-time data. With dashboards, it is required to combine data from different sources and model it correctly to get an immediate view of the effect of the actions you have taken on the results you see. A successful KPIs dashboard should provide real-time updates. The objectives include discovering trends, setting forecasts and targets, predicting outcomes, and determining the mutual effect of different variables (Staron et al., 2015). There are different types of dashboards, including strategic, operational, and analytical level dashboards. The content of the dashboards may consist of tables, graphs, or visual KPIs (Pappas & Whitman, 2011). Depending on the purpose of the dashboard, it may vary in terms of applied technology, visualization, or user interactivity (Staron et al., 2015). Regarding the creation of dashboards for maintenance activities, there are some studies such as (Arulraj et al., 2019) and (Okoh et al., 2017).

3.3.3.9 Conclusion of literature review in health monitoring

The state-of-art indicates that initially classical hypothesis tests, statistical process control, and degradation modeling based on failure probability identification are used for health monitoring of components, or systems. Moreover, advanced signal processing and ML methods are more and more developed to analyze real-time data and signals for automatic and online health monitoring and diagnostics. However, the complexity and needed time and cost of developing such methods should be considered for industrial applications. This would depend on the required precision level of the analysis. Furthermore, the output of these health monitoring analyses should bring meaningful information for further RUL or decision-making applications.

Aside from the component vision, the monitoring of the whole maintenance systems and machines is also another vision that is reviewed here. Maintenance monitoring systems are often through maintenance KPIs which should be identified, measured and visualized to provide actionable feedback for the decision-makers.

The reviewed methods could be used for the prognostic aspect and RUL estimation methods which are reviewed in the next section.

3.3.4 RUL estimation

The prognosis is to analyze and predict accurately the future and the failure before it occurs. Failure prediction determines whether a defect is imminent and estimates the timing and probability of its

occurrence. The estimation of RUL is one of the main prognostic issues (Jardine et al., 2006a) (Tahan et al., 2017). In fact, the final objective of prognostics is to help in making correct decisions (Gouriveau et al., 2016). RUL estimations always come along with errors as illustrated in Figure 31. The RUL and threshold values can intrinsically have uncertainties that should be taken into account.

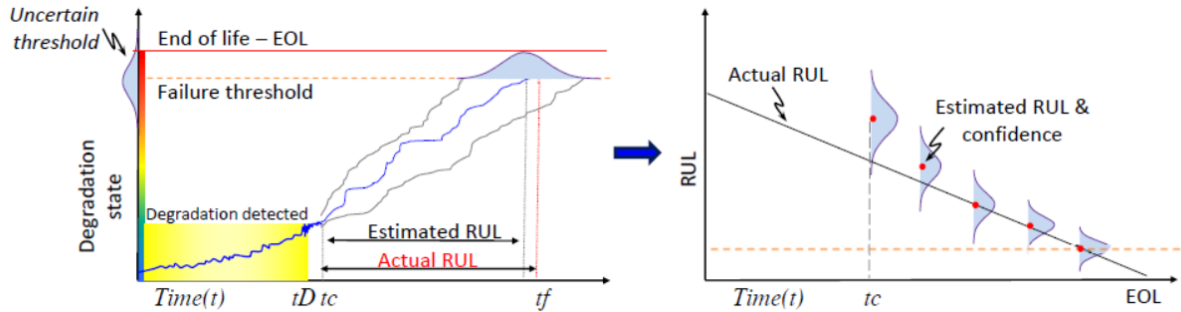


Figure 31. RUL schematic diagrams with uncertainties

Another aspect that should be noted in RUL estimation is related to the fault or failure trend. Most often it is supposed that this trend is smoothly changing and becoming worse however, this is not always true. There are different types of fault or failure trends that are well depicted in Figure 32.

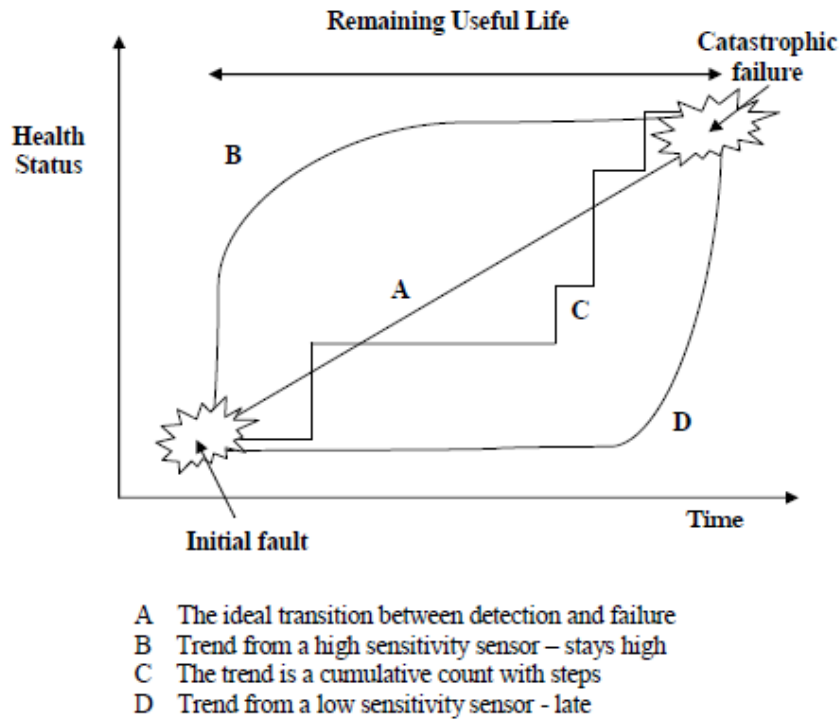


Figure 32. Different types of failure progression trends (Phillips, 2012)

Based on the study of different reviews and PHM standards we can state that the prognostic methods are divided into three groups, namely the Physical Model-based, the Data-driven, and the Hybrid methods. Physical Model-based approaches incorporate a physical degradation model with measured data to predict

the RUL and the future degradation pathway. Data-driven approaches construct a mathematical model or numerical algorithm to describe degradation behavior using a set of training data. Hybrid approaches combine model-based and data-driven approaches (J. Wu et al., 2020) (Chen et al., 2020). The advantage of data-driven approaches is that they do not require a deep domain and a priori knowledge and understanding of complex physical damage behavior. Therefore, these approaches have become the most popular in recent years (Han Li et al., 2020). The classification of prognostic methodologies is presented in Figure 33.

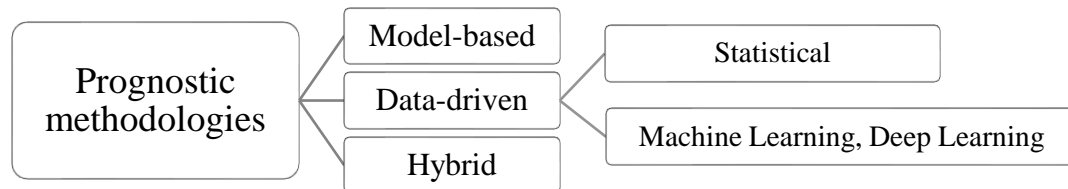


Figure 33. Prognostic Methodologies

Regarding the data-driven methods, as it is previously presented in Figure 23 there are two main types of methods as statistical methods, and machine learning (ML) methods. RUL estimation based on statistical methods and approaches is well-reviewed by (X.-S. Si et al., 2011). Machine learning methods have been reviewed by (Carvalho et al., 2019b) for the prognostic aspect of PdM. There are also some other reviews (for the interested ones) that have considered the RUL estimation methods for certain types of equipment, for example (Lipu et al., 2018) have reviewed ML, statistical, and physics-based models in the case of lithium-ion battery in electric vehicles. Rotating machinery is one of the most targeted types of equipment studied in the literature, so (J. Lee et al., 2014) reviewed the prognostic methodologies in critical components based on the condition monitoring data, health indicators, algorithms, and methods. Another study in this way is the paper of (Kan et al., 2015) which reviewed prognostic methods in the case of non-stationary rotating systems like pumps, aircraft, turbines, and electric motors.

One of the very interesting and comprehensive reviews in machinery prognostics is the study of (Lei et al., 2018) in which the whole types of RUL estimation methods, HI calculation methods, and health state (HS) division methods are well investigated. In this study, a comparison chart of different methods and models is provided in Figure 34 which is valuable to consider. As seen in the pie chart, statistical and ML methods are the most used methods in this field.

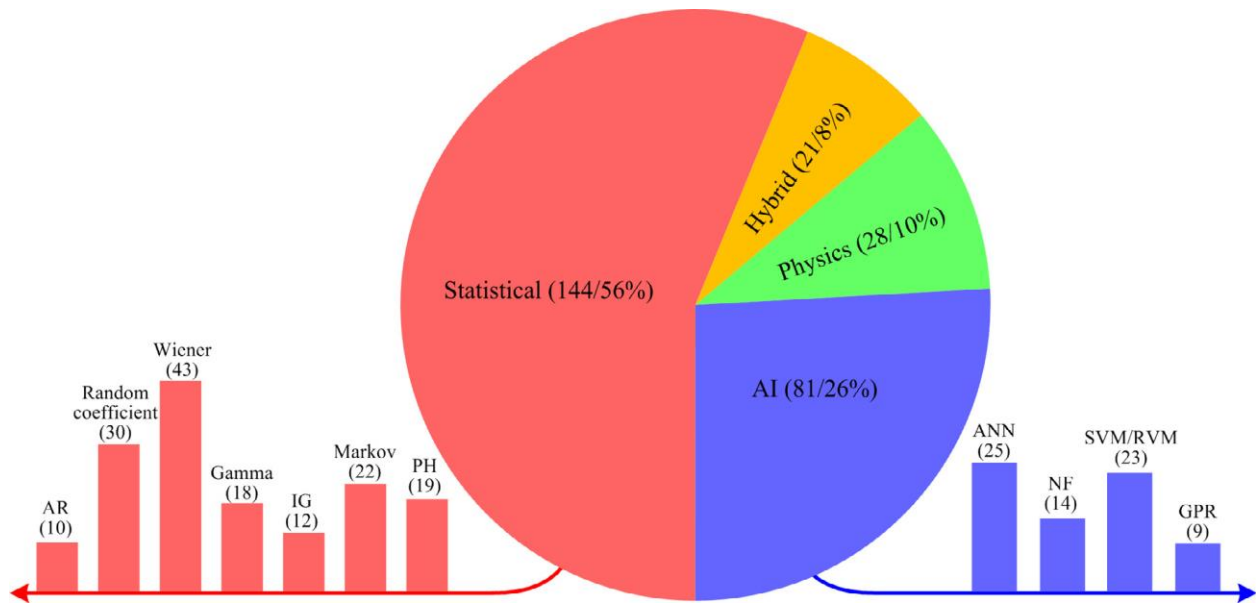


Figure 34. Categories of RUL estimation methods and models (Lei et al., 0218)

In continue, the RUL estimation methods are reviewed:

3.3.4.1 Physical Model-based RUL estimation in PdM

As it is discussed, researchers tried to make mechanical or physical analyses to model the certain failure behavior of the components such as mechanical fatigue. In this way, mechanical fatigue which results in crack failure growth in the fuselage panel of aircraft has been modeled by (WANG et al., 2017) as a prognostic to quantify the distribution of future damage size. By monitoring crack failure proper maintenance would be triggered to ensure a certain level of reliability. Mechanical fatigue has also been used in the study of (Lanza et al., 2009) since a large load incurs stress into the component and when this stress passes the ultimate strength of the material, there is a high probability of failure. They have analyzed the effect of loads that are subjected to certain components of the equipment.

In the same context, the system dynamics of biomass-fired boilers have been analyzed by (Macek et al., 2017) to identify their efficiency. Their goal was to analyze the main failure which is soot accumulation during its operation. Soot accumulation reduces efficiency in heat transfer.

(Aivaliotis et al., 2019) have studied a physical-based simulation modeling for predicting RUL in a real case study of a welding robot, they have used form sensor and machine-controlled data as the input for the simulation model.

3.3.4.2 Data-driven models for RUL estimation in PdM

Several types of data have been considered and employed RUL estimation such as sensors data (Yan et al., 2017), process parameters information (Q. Liu et al., 2013) and (Kaiser & Gebraeel, 2009), operational data (He et al., 2018) and output quality data (Lindström et al., 2017). Depending on the studied case vibration, acoustical, temperature, 3D laser image, and power sensor data have been taken into account. For the process parameters, the flow rate of pump reactor pressure, reactor liquid level, reactor temperature, and compressor working power... are some examples that are identified in the process of studied cases.

In some studies, only historical data has been incorporated (Zhao et al., 2010), (Márcia Baptista et al., 2018), (Dong et al., 2017), while in some other real-time data has also been taken into account (Q. Liu et al., 2013), (He et al., 2018) and on this basis, they have developed dynamic models.

Regarding the data-driven methodologies of RUL estimation, statistical methods incorporated a wide range of studies classically. ML and DL methods are also new techniques that have been used recently that can be implemented easier than Physical Model-based methods. It should be emphasized that the data-driven methods in RUL estimation, lie more in supervised learning, deep learning, and statistical regression methods, while the data-driven methods in health monitoring are more in unsupervised learning and signal processing-based methods.

There are a variety of industries, real cases, and applications that have been under the magnifier of researchers from mining to automotive, etc.

3.3.4.3 Statistical methods in RUL estimation

The similarity model, the degradation model, and the survival model are statistical RUL estimation models. Depending on the available data and information, one of these models may be used. Similarity models can be applied when the run-to-failure data of similar components exists and the run-to-failure data exhibit similar degradation behaviors (Yu et al., 2020b). The idea of similarity models and lifetime survival modeling for RUL estimation is presented in Figure 35. Regarding the similarity models, it is important to have available life-span information of similar components. Then, based on the health state values of the monitored component, the most similar trend and hence the life cycle time of the monitored component is identified compared to the historical information of similar components. Lifetime survival models identify the Probability Distribution Function (PDF) of the component and estimate the cycle times that a component may work in the right condition.

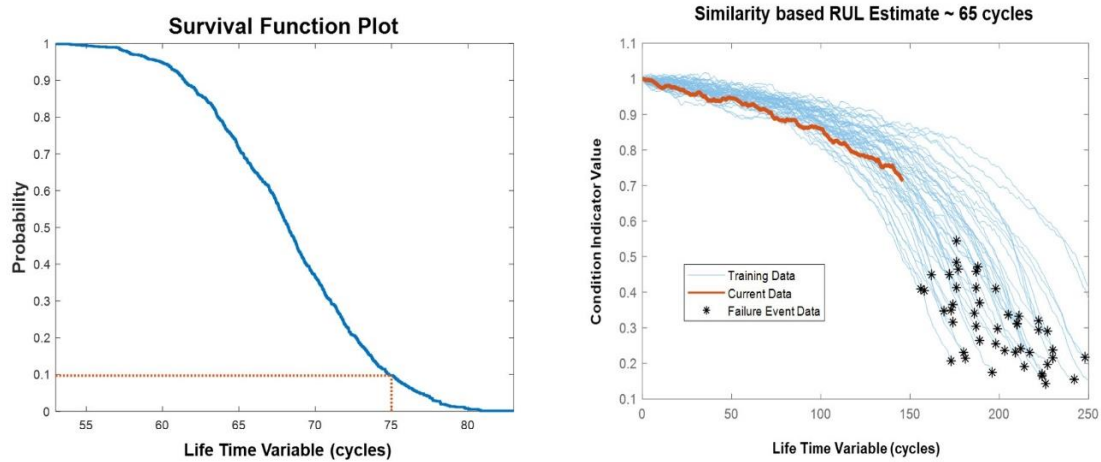


Figure 35. Run-to-Failure degradations and similarity modeling of current investigating data (Baru, 2018)

Degradation models attempt to predict the future state by taking into account past behavior. It is important to have available threshold information for further modeling and analysis. It adopts a model for the degradation of a condition indicator. This fitted model can be linear or exponential, then it uses the degradation of the test component to statistically calculate the time remaining until the indicator reaches a certain prescribed threshold. These models are particularly useful when there is a threshold that is a known value of the failure state indicator. (Yea & Xie, 2015) Presented several degradation models and compared

them. Figure 36 have depicted the idea of degradation modeling for RUL estimation, once the degradation is modeled through one or more health indicators, then the time that RUL crosses the threshold should be predicted. As stated in section 3.3.3.4, the degradation modeling is mainly performed with Gamma and Weiner process models, Markov models, Inverse Gaussian (IG), Auto regressive (AR), and proportional hazard (PH) models (Lei et al., 2018).

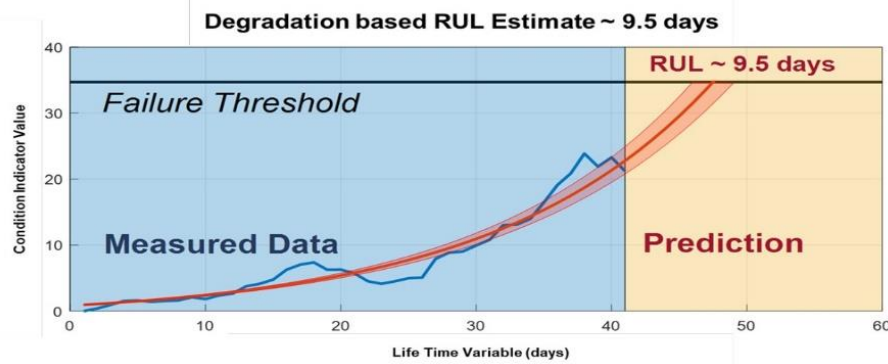


Figure 36. Degradation modeling for RUL estimation (Baru, 2018)

3.3.4.4 Machine learning, and deep learning methods in RUL estimation

Once again as previously stated, Fault degradation estimation and Health State (HS) division is the initial and necessary step in the estimation of RUL. Prediction of failure is often modeled as a regression problem or classification problem using supervised learning and deep learning methods.

Prediction is based on quantitative data that estimates a value based on the analysis of input data and its relationships with the output or labeled data. Regression is a well-known method for prediction purposes. Regression is generally defined as the determination of relationships between two or more variables. Linear regression, logistic regression, and polynomial regression are commonly used as regression models. In classification, the output data is not quantitative but qualitative, it means that there are limited defined classes and each input data corresponds to a discrete class. The objective is to make the prediction of new inputs and categorize them into the best class. Several classification techniques can be selected depending on the type of dataset such as K-nearest neighbor, Decision trees, Naïve Bayes, and Support vector machines (SVM) widely used as traditional classification techniques (Hastie et al., 2009).

Regression-based models for the RUL estimation of bearings are well studied by (C.-Y. Lee et al., 2019). They have used regression-based models as Support Vector Regression (SVR) for the RUL estimation of electrical motors. They have used the vibration sensor data and they have found that time domain data can be more relevant to the RUL. Based on the time-domain data, they have analyzed some features to use in the SVR method for the objective of RUL estimation. Furthermore, SVR on the Turbofan (C-MAPSS) dataset is largely used in the literature (Khelif et al., 2017). Auto-Associative Kernel Regression (AAKR) has been applied by (Chen et al., 2020) for modeling the degradation process in the railway turnout system. (Marcia Baptista et al., 2018) have used Auto-Regressive Moving Average (ARMA) model, alongside some classical ML methods to increase the precision and efficiency level of the next failure prediction in the case of critical valves of engine craft. Gaussian Process Regression (GPR) was applied to the lubrication oil remaining useful life (Tanwar & Raghavan, 2020). (Cattaneo & MacChi, 2019) have used an exponential degradation model based on the random coefficient statistical method for health state prediction. The triple

exponential smoothing method has been used for RUL estimation of the cyclic process by (De Marco et al., 2019). The Autoregressive Integrated Moving average (ARIMA) method has been adopted by (W. Wu et al., 2007) on the rotor test rig for state prediction purposes.

As it was depicted in Figure 29, DL is a sub-domain of ML that deals with algorithms inspired by the structure and function of the brain called artificial neural networks. DL methods are widely used in image processing and voice recognition applications and less in the RUL estimation domain (Y. Wang et al., 2020). However, researchers are attempting to find solutions for RUL estimation by configuring input, hidden and output layers in different formats to provide a Neural Network (NN) that adapts to each kind of problem.

Artificial Neural Network (ANN) as a feed-forward NN (Tian et al., 2010) has been deployed on the historical and vibration data of a rotatory pump. Vibration data is also used in a Multilayer Perceptron (MLP) Neural Network for the RUL estimation of rolling-element bearing (Rohani Bastami et al., 2019). (Yan et al., 2017) have predicted the remaining life of the critical component of the CNC machining center, by structuring multi-source heterogeneous information and using the ANN method. (Chuang et al., 2019) have used different sensors and have performed statistical analysis and ANN for the RUL estimation. Convolution Neural Network (CNN) is been applied in the famous turbofan data set (X. Li et al., 2018). These methods utilize forward direction which means the process is started from input layers, then hidden, and finally output layer. Moreover, the seasonality changes are not captured in these methods. While Recurrent Neural Network (RNN) is another DL method that has feedback connections between hidden and output layers, and it is said to be more pertinent for the prediction of sequential data as time series data. Long Short-term Memory (LSTM) is a type of RNN that has been proposed by (Zheng et al., 2017) to expose the hidden pattern of sequential data, and they have used LSTM to estimate the RUL of the Turbofan engine in the C-MAPSS data set. Neuro-Fuzzy (NF) systems or predictors (which are NN-based fuzzy systems) are also used for state prediction of gears (W. Q. Wang et al., 2004).

Although DL methods are developed and applied in time series data, other aspects of interpretability and complexities should be considered. The black-box nature of DL methods may be complex for parameter indications and interpretation (Triebe et al., 2019). On the other side, statistical methods such as ARIMA may not capture the seasonality patterns (long fitting time or hard tuning of autoregressive parameters) and imply large trend errors. However, the Prophet prediction method has shown the capability of self-adjusting and tracing long trends and seasonality patterns for large data sets (Taylor & Letham, 2018). This method is more developed in chapter 5 along with a use case.

3.3.4.5 Conclusion of literature review in RUL estimation

In case of the existence of run-to-failure data in multiple similar components, the similarity-based, and survival models could be used for RUL estimation. Otherwise, the condition monitoring data is imperative to apply the learning or regression models. Although several advanced learning methods are recently developed, the choice of the method for RUL estimation depends on the application area. For example, in the automotive industry, the exact precision of RUL is less important as the response time is not instant. This means that the relevant maintenance activity would not be exactly at the predicted failure time, while this would be in further periods. The reason is that more complex learning methods may have more precision, whereas the complexity, required development time, and required calculation capacity are the other aspect that should be considered in the selection of the right RUL estimation method.

3.3.5 Decision-making /Maintenance Planning

Looking back to the data analytics approach, health monitoring, visualization, and RUL estimation are on the perimeter of descriptive, diagnostic, and predictive analysis. The majority of PdM studies focus on the RUL or stat predictive aspects and less on prescriptive analysis. In fact, the final objective of health monitoring, diagnostics, and prognostics is to help in making correct decisions (Gouriveau et al., 2016). Several types of decisions can be imagined in the final output of the PdM. These are such as automatic rules or actions, maintenance optimization, spare part management, and production planning. The typology of these different types of decisions regarding the reaction time for taking decisions is well presented in Figure 37. Fast and immediate decisions, auto diagnostic, and real-time control happen in very short terms. Then for the medium term, semi-autonomous decisions impact the scheduling and re-scheduling of maintenance. Finally, for the mid-long term, decisions deal with maintenance planning, production planning, and spare part management. The maintenance planning is obtained mainly by cost optimization. Cost of maintenance activities, production stoppages, and spare part management are some of the main cost optimization examples. This could be often achieved through mathematical modeling and optimization. In continue, the review of PvM and PdM planning methods is provided:

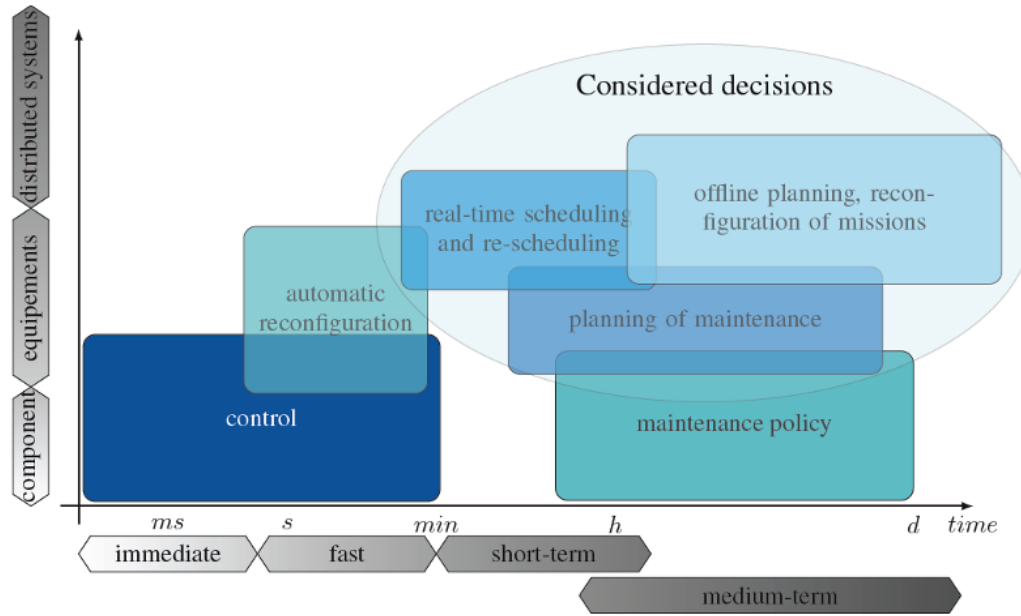


Figure 37. PdM decision types based on decision periods (Chebel-Morello, Nicod, & Varnier, 2017)

Regarding the decision aspects of PdM, the current literature review has been focused mostly on maintenance planning of PdM and other maintenance strategies, to manage better the maintenance activities and resources. This objective is to maximize the availability and efficiency of maintenance and production systems through the minimization of overall maintenance costs. The relevant research and studies, in the scope of preventive and PdM planning, are reviewed in this section. First, studies of PvM planning are addressed, and then PdM planning studies (those that try to see the effect of monitoring data for predictive and planning purposes) are presented.

We have assessed the state-of-art of maintenance planning methods with the below key aspects:

- Industry type (manufacturing, infrastructure, transport...)

- Existence of real-world cases or numerical tests
- The perimeters of planning (for single or multiple machines/equipment, and single or multiple components)
- Modeling considerations (Ex: machine and maintenance experts' availability)
- Maintenance strategies considered in the planning
- Existence of condition-monitoring data
- Existence of HI for the monitored components
- Existence of RUL for the monitored components

3.3.5.1 Preventive Maintenance planning methods

As discussed earlier, there are different dependencies between components. These will produce more complexity in the modeling and prediction. Earlier studies on multi-component maintenance have been carried out by finding a grouping policy for triggering maintenance on a specific group of components. These studies are typically applied over a single system (or machine). (Wildeman et al., 1997) considered maintenance setup costs, and the authors developed an approach to minimize costs. They initially determined the optimal frequency (MTBF) for each component individually. Next, possible grouping policies for the set of activities in a single machine were analyzed, and the optimal policy was selected, based on reduced costs. The same framework for the problem was studied by (Gustavsson et al., 2014), while they considered the risk cost of failure (hence the CM) in the mathematical model they presented. The objective was to make a trade-off between preventive maintenance setup cost, cost of components, and expected CM cost. (Mena et al., 2021) and (Tambe, 2022) modeled a similar problem, but also considered the availability of maintenance resources. Stochastic dependency is the other dependency type, for which (L. Zhang et al., 2022) developed a maintenance planning method for a single machine with multiple components. They proposed an optimization model for identifying the replacement period of the components or the whole ball screw system. Studies by (Wildeman et al., 1997), (Gustavsson et al., 2014), (Mena et al., 2021), and (Tambe, 2022) were related to numerical experiments. (L. Zhang et al., 2022) applied their method in the industry of manufacturing and the case of the ball screw system in a numerical control (NC) machine.

Up to this point, we have mentioned some studies of single machines with multi-component systems. Another side of the planning method is concerned with multi-machine studies. For example, (Moghaddam, 2013) studied maintenance planning for a multi-workstation manufacturing system and proposed a mathematical programming model for maintenance planning. (Das et al., 2007) proposed a mathematical optimization model by considering the opportunistic grouping aspect. The grouping was modeled into the maintenance of machines in a cellular manufacturing system (CMS). In this direction, (Chalabi et al., 2016) also presented opportunistic grouping maintenance planning of a multi-machine system that was in a series configuration. (C. Zhang & Yang, 2021) and (Alimohammadi & Behnamian, 2021) proposed a preventive maintenance planning method in order to allocate multiple maintenance teams to several pieces of equipment that were distributed in different locations. (C. Zhang & Yang, 2021) also considered the multi-component aspect by focusing on four critical components (rotor, gearbox, main bearing, and generator), but without dependency considerations.

(Das et al., 2007) and (Chalabi et al., 2016) applied their method in illustrative and numerical examples. (Moghaddam, 2013) considered a historical failure data set from a case of CNC machines. (Alimohammadi

& Behnamian, 2021) developed their method in an infrastructure case of multiple electrical distribution feeders, and (C. Zhang & Yang, 2021) in a wind farm case.

Based on our review of the literature, few published research papers have been focused on manufacturing systems within a holistic context of several machines and components (and seeing dependencies between them) together

3.3.5.2 Predictive Maintenance planning methods

In this subsection, we reflect on the evolution of maintenance planning in the presence of the health state or RUL information for components or machines (keeping the same previously mentioned key aspects in 3.3.5) in the presence of the health state or RUL information of the components, or machines. In another word, we keep the same vision as the published works in PvM, but those that propose maintenance planning based on the health state, and/or RUL information.

Regarding maintenance planning, few published papers have considered condition monitoring information at the same time as industrial constraints (de Jonge & Scarf, 2020). Many current studies, like (Han et al., 2021), have considered making predictions and carrying out maintenance some periods ahead of time. Despite this, there are still some relevant studies from various industries that have utilized monitoring and/or prediction techniques and are worth considering.

(Hesabi et al., 2022) applied a DL method for failure prediction for the components in a single system. They proposed a cost optimization model for the planning of maintenance activities in the limited available periods. They implemented their method on the typically used data set of a turbofan engine. In another case in the transport sector, (Consilvio et al., 2021) estimated the health state of train rails (mainly from historical geometry data collected by measurement cars). They proposed an optimization (based on cost and failure risk aspects) with the constraints of the trains and maintenance resource availability. Another case in the aviation industry for aircraft cooling units was studied by (de Pater & Mitici, 2021). In this study, maintenance planning based on RUL information was proposed. The HI was calculated through some sensor measurements, and they considered an exponential function to estimate the RUL. The constraints of equipment availability for the maintenance operation and spare part availability were considered. The planning model made a trade-off between lower and higher exploitation times based on the probability of failure and exploitation benefits of the components.

(Hesabi et al., 2022), (Consilvio et al., 2021), and (de Pater & Mitici, 2021) concerned railways or aircraft industries, for which the requirements are quite different from those for manufacturing systems. It is always interesting to see maintenance planning models in different industries since they have similar approaches. Furthermore, in these types of studies, the multi-component dependency aspect and the holistic vision of the whole maintenance planning process (as in PvM) are not considered.

Dependencies between multi-component systems and modeling were more extensively studied by (Olde Keizer et al., 2017). However, in the majority of such studies, degradation models have been utilized rather than monitoring methods for maintenance planning.

(Nguyen et al., 2015) used degradation modeling of health states in a multi-component system with economic dependency for maintenance. (Do et al., 2019) modeled degradation based on vibration data in a gearbox case (at a laboratory scale). They modeled economic and stochastic dependency for the

maintenance planning of single equipment with multiple components. The same approach was studied by (Dinh et al., 2022) in a multi-component system with economic and structural dependency considerations. They defined some opportunistic thresholds for calculation of PdM in their proposed cost model. The model was applied in numerical experimentation. According to the author's view and the reviewers in the field, such PdM models can be regarded as an interesting approach, although simple scenarios are generally modeled, and they remain mostly theoretical (Gashi & Thalmann, 2020). Yet, a general approach and method for PdM planning was proposed by (Bencheikh et al., 2022) considering RUL information and the availability of maintenance experts. These studies have generally provided inspiration for developing more realistic models that could be applied in the industry by considering industrial objectives and technical perspectives.

A summary of the literature review is presented in Table 3.

Table 3. Comparison table of the PvM and PdM planning state of art

Published papers	Maintenance Planning Aspects								State/Prediction Information			
	Case structure					Other Modeling Considerations			Monitoring (Real-time) data	Health Indicator	RUL	Method (Modeling and solution method)
	Industry Type	Real/ Numerical Case	Multi/ Single Machine	Single/ Multi-component	Multi-Component	Maintenance Resources Availability	Equipment Availability	Maintenance strategies				
(Mena et al., 2021)		Numerical	Single	Multi	EcD*	✓		PvM				MILP
(L. Zhang et al., 2022)	Manufacturing	Real Case/ Ball screw system in NC machine	Single	Multi	FuD*			PvM				Optimization
(Pires et al., 2019)	Manufacturing	Real Case/Stamping machine	Single	Multi	EcD		✓	PvM CM				Mathematical Modeling
(Das et al., 2007)	Manufacturing	Numerical/ CMS	Multi	Single	EqG*			PvM				Mathematical Programming-Exact approach
(Tambe, 2022)		Numerical	Single	Multi	EcD		✓	PvM				Mathematical Programming-SA
(Chalabi et al., 2016)		Numerical	Multi	Single	EqG			PvM				Mathematical Programming-Particle Swarm
(Alimohammadi & Behnamian, 2021)	Infrastructure	Real Case/Electricity Distribution feeders	Multi	Single		✓		PvM				Mathematical Programming-Heuristics
(Moghaddam, 2013)		Numerical	Multi	Single			✓	PvM				Mathematical Programming-Hybrid Simulation& Goal Programming
(de Pater & Mitici, 2021)	Aircraft	Real Case	Multi	Multi			✓		✓	✓		Linear Integer Program/ Rolling horizon Approach

(Do et al., 2019)	Laboratory/ DC motor/ Gear Box	Real Case	Single	Multi	EcD FuD			PdM	✓	✓	Mathematical Modeling
(Geng & Wang, 2022)	Infrastructure/Power Transformer	Real Case	Multi	Single		✓	✓	PdM		✓	Mathematical Modeling/Full Enumeration
(Zonta et al., 2022)		Numerical	Multi	Single			✓	PdM	✓	✓	Simulation
(Hesabi et al., 2022)		Numerical	Single	Multi			✓	PdM		✓	Mathematical Programming
(Dinh et al., 2022)		Numerical	Single	Multi	EcD StD*			PdM		✓	Mathematical Modeling/Particle Swarm
(Consilvio et al., 2021)	Transport /Railway	Real Case	Single	Multi		✓	✓	PdM		✓	Mathematical Programming (MILP)/Metaheuristic
(Bencheikh et al., 2022)		Numerical	Multi	Multi		✓	✓	PdM PvM		✓	Mathematical Modeling
This Paper	Manufacturing/conveyor chain system	Real Case	Multi	Multi	EcD StD	✓	✓	PdM PvM	✓	✓	Mathematical Programming (MILP)

*EcD (Economic Dependency), FuD (Functional Dependency), EqG (Equipment Grouping), SrD (Structural Dependency)

3.3.5.3 Conclusion of literature review in maintenance planning

As we have seen, on the one hand, PvM planning methods are widely used in the multi-component (Wildeman et al., 1997) (Gustavsson et al., 2014) (Mena et al., 2021) (Tambe, 2022) (L. Zhang et al., 2022) or multi-machine configurations (Moghaddam, 2013) (Das et al., 2007) (Chalabi et al., 2016) (C. Zhang & Yang, 2021) (Alimohammadi & Behnamian, 2021) that have been explored. On the other hand, PdM studies are concerned mostly with HI and/or RUL development (Jardine et al., 2006b) (R. Liu et al., 2018) (El-Thalji & Jantunen, 2015) (Cerrada et al., 2018) (T. Wang et al., 2019). Regarding maintenance planning in PdM strategies, few papers have simultaneously considered both condition monitoring information and industrial constraints (de Jonge & Scarf, 2020). Many PdM studies have focused on predicting failures or RUL and allocating maintenance before failure (Han et al., 2021) (Aivaliotis et al., 2019) (Gohel et al., 2020). Nevertheless, some studies have considered HI and/or RUL information for maintenance planning, but multi-component dependencies have not been included (Hesabi et al., 2022) (Consilvio et al., 2021) (de Pater & Mitici, 2021). However, in interdependent manufacturing systems, it is important to see the relations between predictions, and the dependencies between components and maintenance/operation aspects. Other types of PdM studies have considered multi-component dependencies. However, most studies have tended to focus on the use of degradation models rather than monitoring methods or PHM steps (Olde Keizer et al., 2017) (Nguyen et al., 2015). Furthermore, these studies have mainly been carried out through numerical experimentation or laboratory-scale equipment (Do et al., 2019) (Dinh et al., 2022) (Bencheikh et al., 2022), and their application in industrial cases was not developed. Such PdM models can be a useful foundation for the development of applied industrial models, although they tend to be simplistic in nature (Gashi & Thalmann, 2020).

To the best of our knowledge, there is no literature addressing PdM planning in real-world manufacturing cases that takes into account all of the following aspects together.

- Simultaneous PdM and PvM planning
- PdM planning based on monitoring real-time data, HI, and RUL estimation
- Maintenance planning with multi-component dependencies (economic and structural)
- Maintenance planning by considering industrial constraints (maintenance resource and machine availabilities)
- Considering failure risks and prediction errors of RUL
- Application in a real-world industrial case

3.3.6 Conclusion of literature review

The overall review has been done on a wide range of research, books, thesis, and papers. We focus mainly on implementing the PdM strategy in industrial and laboratory-applied cases. Regarding the investigated methods, there are three main objectives for the applied methods in this context: i) health monitoring, ii) prognostic (predicting the future state), and iii) decision-making (maintenance planning and scheduling).

Health monitoring, diagnostic and prognostic help us to determine better the current and future state of a component, group of components, machine, equipment, or production system. RUL estimation or state prediction are the main objectives of prognostics while having RUL or state information is not the final goal in the industry if it does not end up with the decision-making. In this way, the whole PdM process should be followed by a decision or prescription of decisions that help to avoid sudden failures and optimize the overall maintenance costs. PHM has also covered the decision-making aspect after the prognostic step such as automatic rules, maintenance scheduling, re-scheduling, and maintenance planning. However, considering RUL information in a more global context of maintenance planning or scheduling with other maintenance activities is rarely addressed.

Health monitoring studies are concerned with the component or equipment level. In this regard, statistical methods like degradation modeling were traditionally used based on failure probability studies. In these methods, historical information is used rather than real-time data. Whereas ML and signal processing methods are used more to apply in condition monitoring real-time data (mainly vibration data). In this way, feature extraction and feature selection methods play functional roles to construct the HI for the monitoring cases. In literature, health monitoring individual components such as bearings, gears, etc. widely surveyed while the study of complex systems such as CNC machines is less focused.

Regarding the monitoring of the whole maintenance system, the most appropriate indicators, or KPIs should be identified and visualized. Although some studies have proposed maintenance KPIs, the most appropriate and relevant indicators should be identified and tailored to the specific industrial context. Thus, it is necessary to conduct further research to determine the best-suited indicators, and the best visualization form using the historical and real-time data of our automotive use case.

Concerning the prognostic aspect (RUL estimation or state prediction) statistical methods, learning, and hybrid methods are mainly used in the literature. In the case of R2F data availability of similar components, similarity-based methods are addressed. Moreover, statistical regression-based, ML, and DL predictive models are also widely covered recently for RUL estimation based on condition monitoring data. The

precision, complexity, and calculation times of predictive models are other aspects that were taken into account for the selection of best suited RUL estimation or state prediction method. In the automotive industry, R2F data is rarely available (due to the long useful life of the components, etc.), in this way the appropriate methods should be studied for RUL estimation of automotive use cases.

Although there has been a significant amount of research in the field of health monitoring and RUL estimation, the challenging decision-making aspect as maintenance planning is less developed in real-world industrial cases. In other words, in most PdM studies, maintenance planning and scheduling is limited to the component being studied based on real-time data monitoring, and without considering industrial constraints and conditions. However, in the production or manufacturing industries, proposed methodologies and solutions should be responsive to the needs of the entire production system. On the other side in PvM studies, although maintenance planning models have been more developed in the literature, the identification of an appropriate PvM method for a specific industrial use case should be investigated. Moreover, simultaneous PvM and PdM planning methods in production systems are the other important aspect that is not studied in the literature and needs to be developed.

Part 2: Methodology and results

For the efficient implementation of maintenance, the appropriate methods or in more general terms, a Decision Support System (DSS) should be developed. The main objective of a maintenance DSS is to manage all kinds of preventive, predictive, and corrective maintenance activities. As PdM cannot be applied to all components or equipment, hence the DSS should incorporate the whole maintenance strategies and activities.

Generally, the DSS has a support role for the business function (as production, maintenance, etc.) through a data analytics approach based on the output data, information, constraints, and events of the business function. The DSS would return the inputs, and/or rules for better decision-making. This process is depicted in Figure 38 by using IDEF0 modeling.

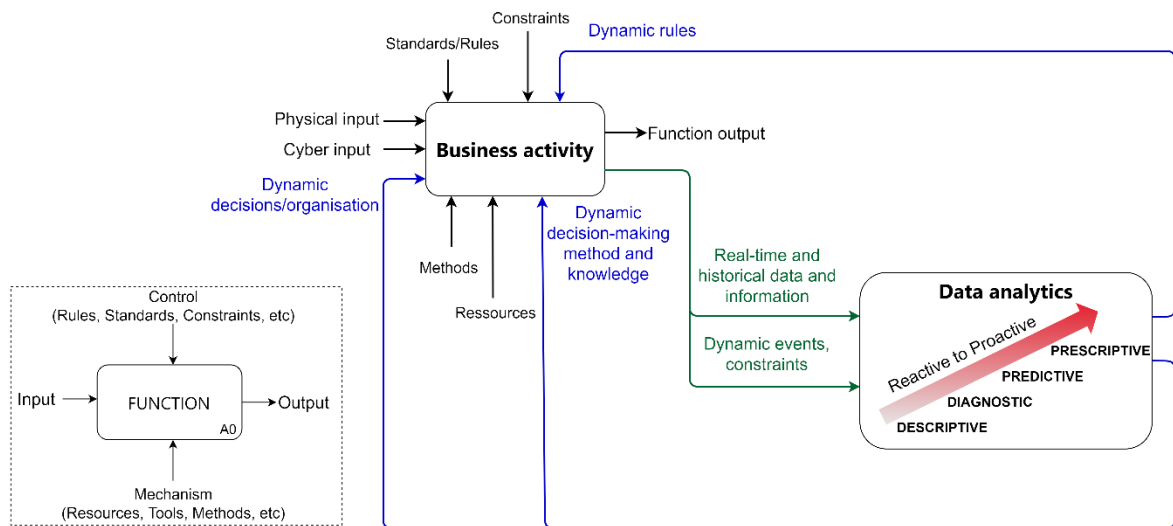


Figure 38. Decision Support System model for the business activities

The main challenge in this thesis concerns how to evaluate and develop DSS for the maintenance function, particularly regarding predictive maintenance by using real-time and historical data and information. Based on the inspiration of the data analytics and DSS approach, these points are studied to be applied in the maintenance function of manufacturing businesses.

The research studies, contributions, developments, and experimentations in this thesis are summarized in several steps which are presented in Figure 39. In fact, these steps are also proposed for the implementation of the PdM management system (PdMMS). In the following sections, these steps are detailed and followed with the use cases in the FPT-BLY plant. These steps cover all maintenance problems from the criticality analysis to the maintenance planning. Finally, the conclusion and the challenges to efficiently implementing PdMMS are discussed in part 3.

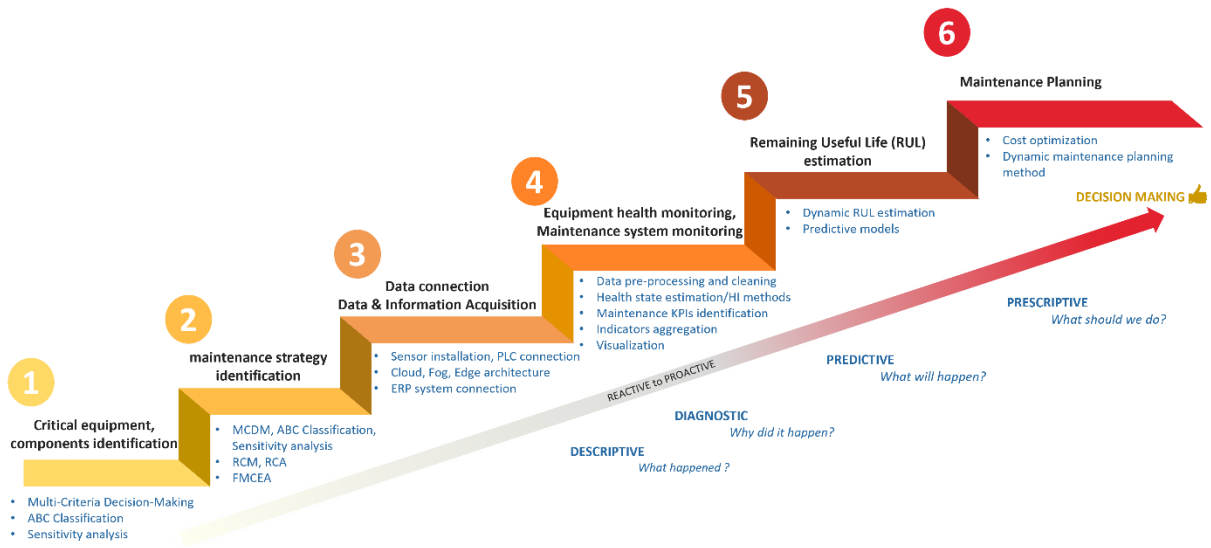


Figure 39. Proposed steps toward the predictive maintenance management system

For more detail the proposed approach is indicated in the following Figure 40 based on the IDEF0 process format:

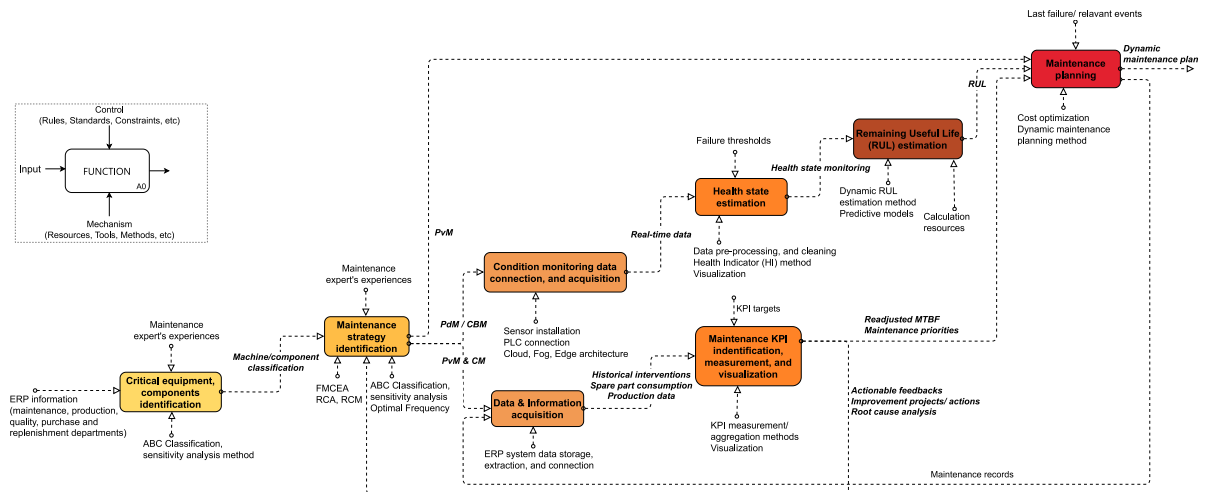


Figure 40. Proposed predictive maintenance management system in IDEF0 format

In Figure 39, firstly the objective of each step is remarked, and the related methods and/or procedures are provided below the steps. Furthermore, these steps begin from reactive and continue to proactive maintenance inspired by the data analytics approach.

As stated in the conclusion of the literature review (section 3.3.6), the maintenance system should manage the whole maintenance strategies, and furthermore, all machines and components cannot be followed through preventive strategies due to several limitations. Therefore, a prerequisite study is required to identify the maintenance strategies of machines before delving into PdM, PvM, and maintenance planning topics. In this way based on Figure 39, the initial step (steps 1 and 2) concerns the development of methods to analyze the criticality of machines and components. This analysis would be used to classify and identify the most relevant maintenance strategies for the machines and

components. The stability/robustness analysis of the criticality studies is the other aspect that is needed for the assurance of the decision-maker which requires appropriate sensitivity analysis methods. Moreover, the study of optimal maintenance frequencies and readjustment of frequencies over time is another aspect of maintenance strategy identification. The mentioned problems in **steps 1 and 2** and the proposed methods with use cases are presented in chapter 4.

Data and information accessibility is essential to achieve the appropriate maintenance planning or decision-making system. In this way, **step 3** concerns finding the appropriate methods, procedures, and technologies for real-time and historical data and information acquisition from the sensors, Programmable Logic Controllers (PLCs), Information Systems (IT), etc. This is often followed by technical complexities and challenges. Although the data and information acquisition systems are not the principal objectives of this thesis, the architecture of real-time data, IIoT platform, and information systems in FPT-BLY are presented in chapter 5.

Step 4 concerns the health monitoring, diagnostic, and maintenance system monitoring that could be served to monitor the current state, detect, and diagnose the probable weak points or trigger and define other maintenance activities. Health monitoring and maintenance system monitoring are mainly followed through the visualization dashboards to take a quick vision of the machines. In this step, the main challenges include the identification, measurement, and visualization of the health indicators, and/or the most relevant KPIs of the components, machines, and maintenance system. This step is developed and presented in chapter 5.

The main problem of **step 5** is concerned with the study of the state prediction or RUL estimation of the components or sub-assemblies (group function) of the machines. The main challenge of this step is related to the possibility study of dynamic RUL estimation development based on the available real-time data from the use cases. In this way, dynamic predictive models for an industrial use case are studied and presented in chapter 5.

The last **step 6** concerns the prescriptive aspect and maintenance planning of the previously identified maintenance strategies. The main challenge is this step is related to the identification of an appropriate cost-effective maintenance plan that considers the overall maintenance costs (including breakdown stoppages cost). This requires the development of a mathematical optimization model with appropriate objective functions, cost elements, and constraints. Concerning the equipment/machines that are not connectable for real-time data acquisition, an appropriate PvM method is proposed and applied. Regarding the simultaneous planning for PdM and PvM a new dynamic maintenance planning cost optimization model is proposed and presented in chapter 6.

4 Chapter 4: Maintenance strategy identification by criticality analysis

Implementing preventive maintenance interventions for all plant production assets would not necessarily reduce the failure risks. Moreover, there are often limited resources (manhours, spare parts, ...) and limited available times for performing maintenance action in the whole plant production assets. In this way, it is very important to target the most critical equipment and components through the criticality analysis to ensure effective maintenance by defining the appropriate maintenance strategies. The criticality analysis can be also used for spare part management in which the strategic spare parts are identified and provisioned. Criticality analysis often returns the ranking of the alternatives (as equipment, and components). However, in industry, classifying equipment and components is more advantageous, as it enables efficient resource allocation and effective management. This approach prioritizes the most critical items and allocates resources accordingly while reducing waste and maximizing efficiency. In this way, we need to classify the parts and components to define maintenance strategies on one hand and the spare part strategies on the other hand. Furthermore, the robustness of the analysis is crucial to attack the most appropriate components, systems, or equipment. In another word, the result of the analysis should be stable enough to ensure the decision-makers of their right decisions. In this way, the study, and development of robust criticality analysis methods to be applied in a real use case are the main problems of this chapter. In addition, this chapter also covers the development of the optimal frequency for maintenance interventions in PvM activities. It is essential to determine the optimal frequency as following the MTBF or manufacturer's recommended frequency may not always be the best approach, since the readjustments of maintenance frequency is necessary to maintain the efficiency of the maintenance system.

To develop appropriate methods and/or DSS, based on the priorities of the FPT-BLY plant a complex and crucial set of equipment have been considered to improve the efficiency and reliability of these types of equipment. This case was concerning the Multi-Spindle Machining Equipment (MSME) which is used in the CNC machines for machining operations.

In this chapter, our new approach to maintenance strategy identification through multi-criteria decision-making, ABC classification, and sensitivity analysis is presented. Furthermore, new sensitivity analysis methods are proposed and presented. Then, an application is developed and presented based on the explained methods. In continue, an appropriate optimal frequency identification method is presented for PvM activities. Next, the methods have been applied to the mentioned use cases, and the conclusion and contributions are provided at the end of the chapter.

4.1 Criticality analysis method

Several approaches and methodologies exist in literature to define the best maintenance strategy regarding each industry, equipment, spare parts, etc. such as the Reliability-Centered Maintenance (RCM) approach to find the failure sources and propose intervention lists or tasks with the frequency and required resources. The Failure Mode Effects Criticality Analysis (FMECA) method is often used in this regard. However, in some industrial cases, it is needed to consider other specific criteria. Hence, we suggest utilizing Multi-Criteria Decision-Making (MCDM) methods to prioritize the machines, equipment, or components. Since the output results are very dependent on the evaluation of the criteria weights, sensitivity analysis methods are proposed to ensure the stability/robustness of the achieved results.

The general process of this methodology is as following steps:

1. Definition of problems and the objectives (ranking, sorting, selection)
2. Identification and selection of the most appropriate criteria
3. Selection of the method to estimate the weight of each criterion
4. Calculation of the weight of each criterion
5. Evaluation/calculation of the score of each alternative regarding each criterion
6. Normalization of the evaluation scores
7. Selection of the MCDM method
8. Calculation of the ranking of each alternative
9. Sorting and classing the results
10. Sensitivity analysis

Based on the problem and objectives (step 1) the most important criteria could be selected (step 2) with brainstorming or the domain knowledge. Then, identification of the weight of each criterion (steps 3&4) should be done if the criteria do not share the same weights. Some weighting methods in the literature are classified and provided by (Odu, 2019) which are listed in Table 4. In general, direct rating, ranking method, pairwise comparison, and Delphi methods which are in the category of subjective methods are the most commonly used methods, especially in the industry. This is because they do not need to follow complex mathematical computations and they are easy and fast to apply. However, for example in the pairwise comparison method (AHP) method, a high level of comparison between criteria may put the experts into error and comparative conflict (inconsistency). For example, they may say Criterion A is more important than criterion B, criterion B is more important than criterion C, and criterion C is more important than A. This conflict of comparison may happen especially when the number of comparisons increases. To avoid this error, it is proposed to use the integrated quantitative and qualitative method of Best Worst developed by (Rezaei, 2015). In this method, only the comparison occurs once between the most important criterion and the others, and once between the others and the less important criterion, and through a mathematical model, the appropriate weights are identified.

Table 4. Weighting methods in multi-criteria decision-making

Subjective weighting methods	Objective weighting methods	Integrated Weighting methods
Point allocation	Entropy Method	Best Worst Method
Direct rating	Criteria Importance Through Inter-criteria Correlation (CRITIC)	Additive synthesis
Ranking method	Standard deviation	Multiplication synthesis
Pairwise comparison (AHP)	Statistical variance procedure	Optimal weighting based on sum square
Ratio method	Ideal point method	
Swing method		
Delphi method		Optimal weighting based on the relational coefficient of graduation
Nominal group technique		
Simple Multi-Attribute Ranking Technique (SMART)		

In continue, the evaluation of the scores for each alternative and criterion (step 5) are often obtained through information systems or experts' knowledge. Then, these values should be normalized (step 6) with normalization techniques (Vafaei et al., 2016). As an example, a linear fuzzy technique normalization method is presented below:

For the benefit criteria

$$N_{ij} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}} \quad (4.1)$$

For the cost criteria

$$N_{ij} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}} \quad (4.2)$$

In general, there are two types of criteria which are 1: benefit criteria, and 2: cost criteria. In benefit criteria, the higher value indicates the importance of that alternative, however, for the cost criteria is vice versa. N_{ij} is the normalized value of alternative i for the criteria j . r_{ij} is the real value of alternative i for the criteria j . r_{min} and r_{max} are the minimum and maximum values of criteria j in the whole alternatives (Vafaei et al., 2016).

In the next step, the MCDM method (such as TOPSIS, DEA, Weighted sum, etc.) should be selected (step 7) and the rankings are identified (step 8) based on the selected method. Due to the simplicity of the weighted-sum method in the industry, the weighted sum method is selected and presented below where there is n number of criteria, and m is the total number of alternatives:

$$A_i^{WSM-Score} = \sum_{j=1}^n w_j N_{ij}, \quad i = 1, 2, \dots, m \quad (4.3)$$

Then through classing/sorting methods (such as ABC classification), a range of alternatives could be classified (step 9) together which represent nearly the same degree of importance. Classing the alternatives helps in targeting the most critical alternatives in the categories to allocate resources efficiently. Although classification methods based on Machine Learning (ML) are prevalent, however, they require more effort and technical expertise from the users. In the industry, such ML methods may prove to be complicated for the users. Hence, for more simplicity, the ABC classification method is proposed for classifying the alternatives. Furthermore, the three A, B, and C categories are easily understandable for industrial users.

There exist several methods for this objective, while the basis is the use of the Gini index and Pareto chart. Corrado Gini, an Italian statistician, created the Gini index in 1912, to measure the inequality of income share in countries (Sitthiyot & Holasut, 2020). In this way, the Lorenz curve is used to measure the Gini index (Figure 41):

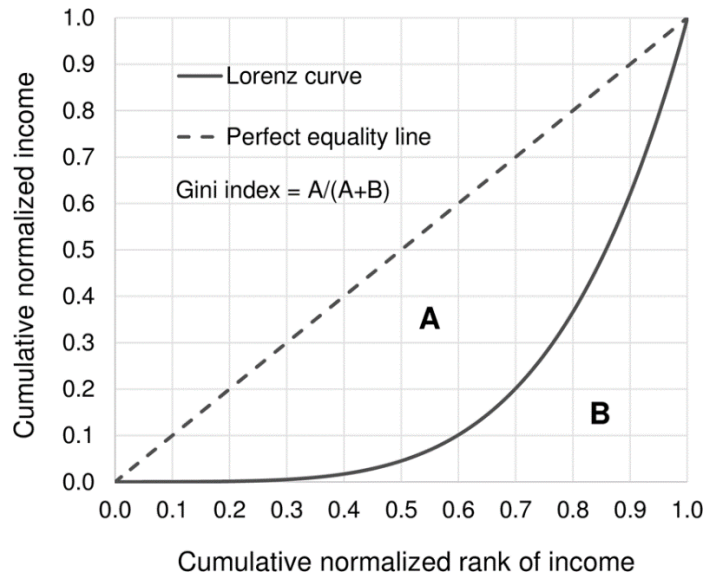


Figure 41. Lorenz curve and the Gini index (Sitthiyot & Holasut, 2020)

(Ultsch & Löttsch, 2015) have proposed an ABC calculation method, in which the A limit is identified through the maximization of yields (for example ranking scores) and the minimization of efforts (for example number of alternatives) at the same time. In other words, it is tried to identify the fewer alternatives which represent the most value. Furthermore, the yields and efforts of B and C are minimized. In this method, the A and B limits are exactly calculated. However, more practically, the discriminant Ratio (DR) method (Jackadit, 2020) which is inspired by the Gini coefficient and Pareto method is widely used in industry. In this method, initially, the Pareto chart of all alternatives with their cumulative ranking scores is obtained. Then based on Figure 42, the DR is calculated as $DR=CB/AB$. Finally, regarding Table 5 the number of each class is identified.

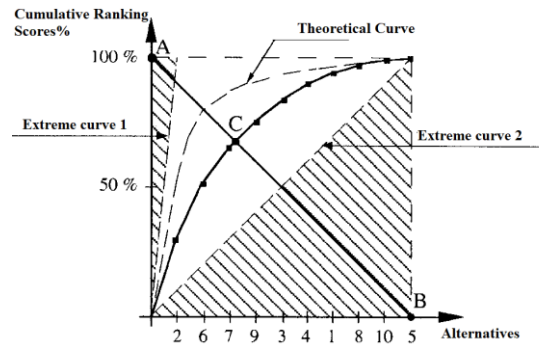


Figure 42. Pareto chart of the cumulative ranking scores

Table 5. ABC class determination based on DR value

DR Value	Zone	A	B	C
$1 > RD > 0.9$	1	10	10	80
$0.9 > RD \geq 0.85$	2	10	20	70
$0.85 > RD \geq 0.75$	3	20	20	60
$0.75 > RD \geq 0.65$	4	20	30	50
$0.65 > RD$	5	Non interpretable		

4.2 Sensitivity analysis method

In the last step, the stability/robustness of the decision-making method and the results are assessed. In this regard, it is proposed to perform the sensitivity analysis based on the variation of the weights. It should be noted that this analysis could be also implemented on the evaluation scores, however, in the industrial context the criteria weights are more estimative with possible errors. Thus, it is assumed that if the experts may have had an error in weighting (step 4), this will not impact the obtained results, rankings, or classifications. In other words, the objective is to identify the limits of the variations of the weight so that the rankings or classifications remain unchanged (Mareschal, 1988). The shorter these limits, the more the criteria are sensitive and vice versa. The limits could be presented in the form of a tornado chart for all the criteria so that the more sensitive criteria are on the bottom and the less sensitive criteria are on the top.

Another important sensitivity analysis objective is to consider the correlation between criteria. This is because multiple criteria often have correlations that can significantly impact the final rankings or classifications. Considering the criteria correlation effect helps to understand the interdependencies

between criteria and their impact on the overall decision. A positive correlation between criteria can amplify the importance of certain criteria, while a negative correlation can reduce it. Ignoring correlation can lead to inconsistent or unreliable results. By taking correlation into account, the sensitivity analysis provides a more accurate and robust assessment of the impact of each criterion on the overall decision.

For this purpose, three methods are proposed and all of them follow general steps in a proposed algorithm that is depicted in Figure 43. In short, firstly the criteria weights are updated, secondly, it is checked if the initial ranks or classes remain unchanged. If the initial result differs, the positive or negative limits of each criterion are recorded, else the weights will be again updated with greater values of variations. The three methods are as follows:

1. Simple single side
2. Weighted single side
3. Correlated weighted

In the first method, the weights are updated linearly based on a delta (δ), so that one criterion is added with δ (equation 4.4), and the other criteria weights are subtracted uniformly (equation 4.5). While in the second method, other criteria weights are subtracted based on the impact of the importance weight of each criterion (equations 4.6 and 4.7). In the third method, the pair correlation effect is considered in addition to the importance weight of each criterion (equations 4.8, 4.9, and 4.10). Here, if the other criterion (i') has more correlation with the initial criterion (i), its updated value would be less important. This is to consider the pair relationships of all criteria and give less updated weights to the correlated criteria and more updated weights to the less correlated criteria.

$$w(i) = w(i) + \delta \quad (w(i) \rightarrow \text{Weight of each criterion } i) \quad (4.4)$$

$$w(i') = w(i') - \frac{\delta}{n-1} \quad (4.5)$$

$$Sum_Weights(i) = \sum_{i'=1, i' \neq i}^n w(i') \quad (4.6)$$

$$w(i') = w(i') - \frac{\delta w(i')}{Sum_Weights(i)} \quad (4.7)$$

$$Cor(i, i') = \frac{\sum_{j=1}^m (N_{ij} - \bar{I})(N_{i'j} - \bar{I'})}{\sqrt{\sum_{j=1}^m (N_{ij} - \bar{I})^2 (N_{i'j} - \bar{I'})^2}} \quad (4.8)$$

($\bar{I}, \bar{I'}$ \rightarrow Average of the normalized evaluation scores for criterion i, i')

$$Sum_Cor(i) = \sum_{i'=1, i' \neq i}^n (1 - |Cor(i, i')|) w(i') \quad (4.9)$$

$$w(i') = w(i') - \frac{\delta w(i') (1 - |Cor(i, i')|)}{Sum_Cor(i)} \quad (4.10)$$

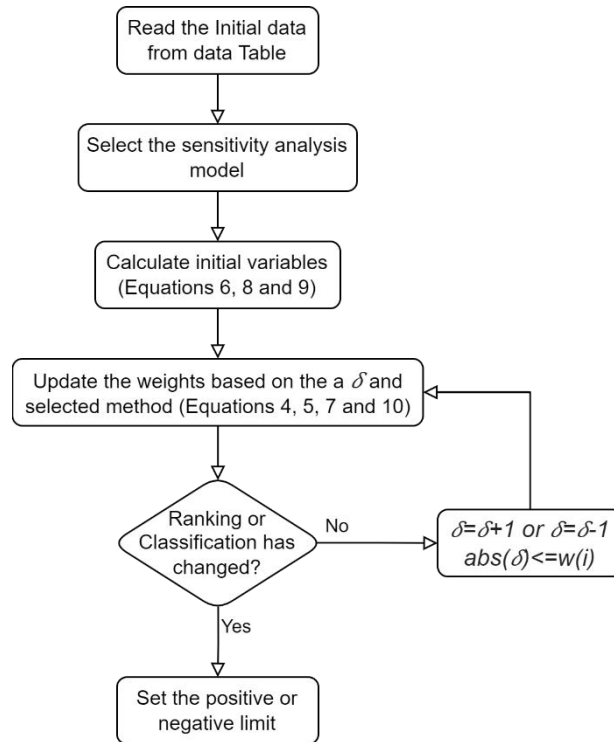


Figure 43. Proposed algorithm for identifying the range of sensitivity limits in the importance weights of criteria

4.3 Decision-making support application

Based on the explained methodology, a generic decision-making support application has been developed via Microsoft Excel VBA to integrate the MCDM, ABC classification, and sensitivity analysis. The developed application can be applied to the desired number of criteria and alternatives and automatically obtain the result. The principal command page of the application is shown in Figure 44. For each new project, the data entry should be followed in different steps to be prepared for the analyses. In each data entry step, the data validation is controlled to assure the existence of the right data. An example of data entry is presented in Figure 45. It should be noted that the data entry is formed based on the user's desired number of criteria and alternatives and the user can modify the data.

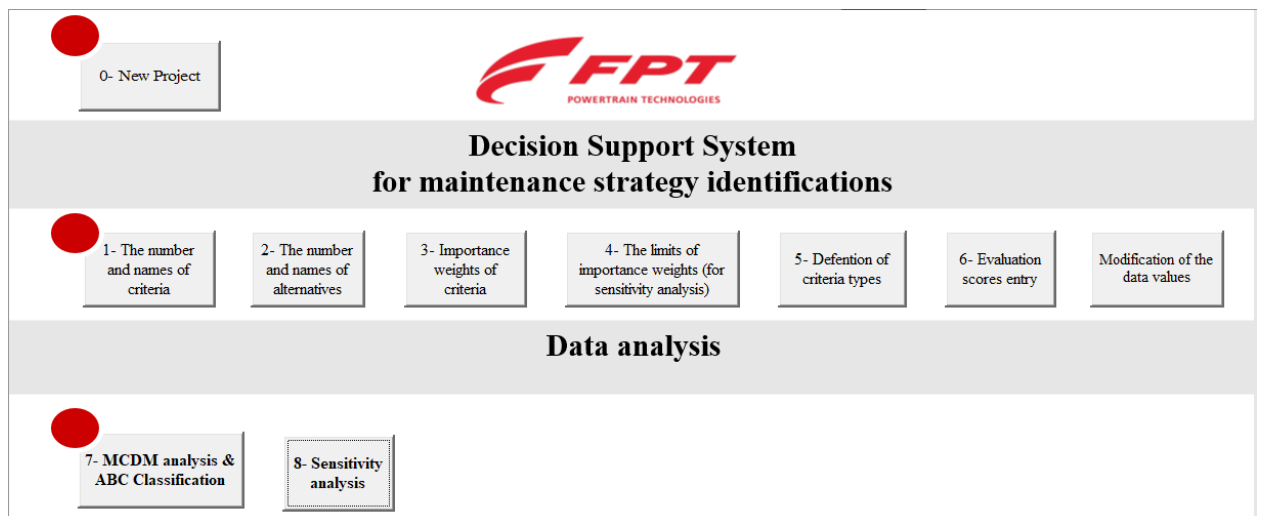


Figure 44. Developed tool for decision-making support

Nom des critères	Critère 1	Critère 2	Critère 3	Critère 4
Poid d'importance des critères (%)	Cost	Severity	Lead-Time	Occurence
Les limites supérieures de poids d'importance(%)	10%	42%	24%	24%
Les limites inférieures de poids d'importance(%)	20%	62%	44%	44%
Type des critères 'Impact Bénéfique/Non-Bénéfique'	0%	23%	5%	5%
	Bénéfique	Bénéfique	Bénéfique	Bénéfique

Nom des Alternatives					
Alternative 1	Roulement de broche	300	7	120	7
Alternative 2	Roulement de boîte	3	9	15	8
Alternative 3	Bague d'étanchéité	10	8	7	6
Alternative 4	Clavette	2	8	7	6
Alternative 5	Etoile d'accouplement	5	5	15	6
Alternative 6	Accouplement	200	2	15	3
Alternative 7	Pignon de boîte	250	2	15	2
Alternative 8	Bague, Entretoise	3	2	7	3
Alternative 9	Arbre de broche	170	1	5	2
Alternative 10	Arbre de boîte	170	1	5	2
Alternative 11	Bride	30	2	5	1

Figure 45. Example of data entry in the developed tool

The sensitivity analysis methods are also integrated, and the user can select the type of sensitivity analysis (as shown in Figure 46) and obtain the results.

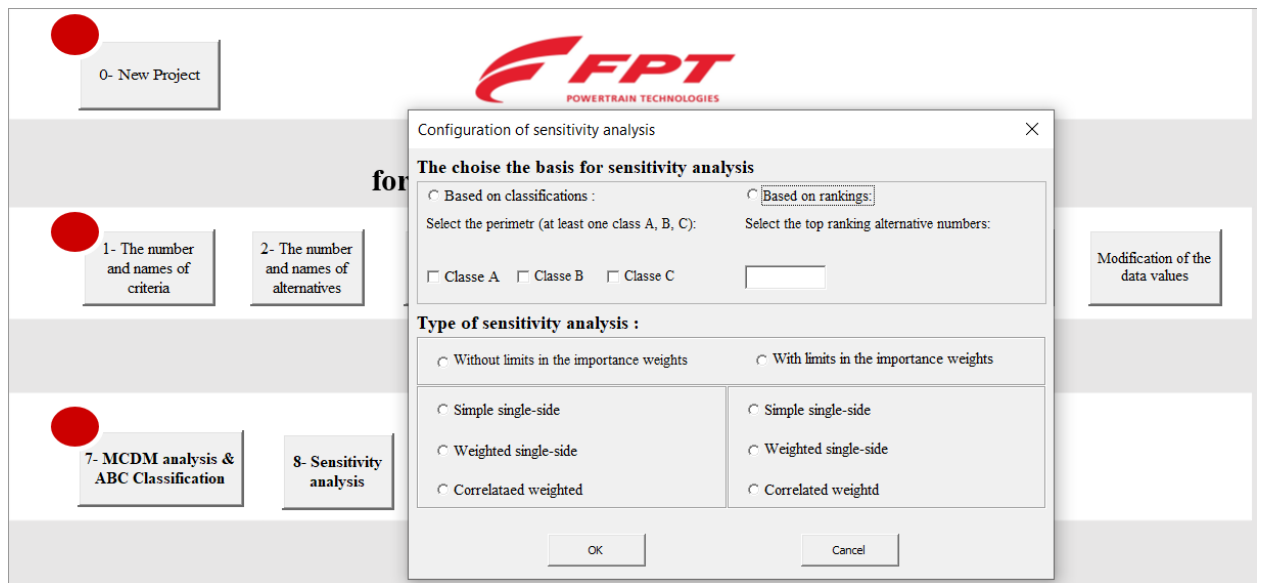


Figure 46. Sensitivity analysis menu in the developed tool

The proposed application is used by other users in the enterprise for generic decision-making problems. Moreover, the example results of case studies based on the proposed tool are presented in the following section:

4.4 Identification of maintenance strategy: Use case

In this study, a perimeter of Multi-Spindle Machining Equipment (MSME) in FPT-BLY has been chosen for the case study. MSMEs are an important function in CNC machines which perform the machining operation of engine blocks or cylinder heads simultaneously in multiple axes. They are crucial functions in the machining production line, and their failures have considerable impacts on the line's stoppage or changing the machining program. MSMEs are composed of tools, gearboxes,

intermediate axes, bearings, lubrication systems, etc. MSME is very complex equipment that is used in FPT-BLY and some examples are shown in Figure 47.

In the FPT-BLY plant, there is 151 number of this equipment distributed in 14 HULLER RT machines as illustrated in Figure 48. Each of them performs a unique operation in each machine, which means there is no reserve in case of failure. Each MSME is capable to do a certain type of machining operations in different diameters and depths such as milling, drilling, threading, boring, and chamfering.



Figure 47. Multi-Spindle Machining Equipment (Internal and external views)

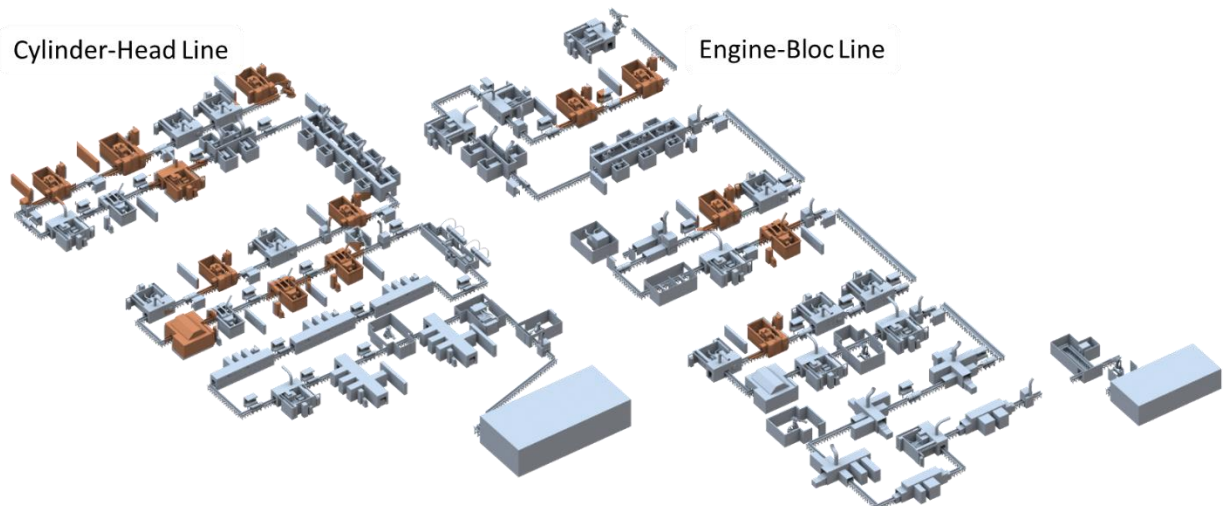


Figure 48. Huller RT machines that include MSMEs in the flow shop machining lines

FPT-BLY manufactures several types of diesel and gas engines regarding the capacity of the engine such as C8, C10, and C16 in different versions as Euro4 and Euro6. Each MSME is designed to perform the machining for certain engine types and some of them are designed for all types of engines.

On the shop floor, the failure of this equipment can significantly impact production, leading to costly line stoppages or even the need to change production families. Other complexities with this equipment include the long and substantial diagnostic and Time to Repair (TTR), as well as the significant lead time for obtaining replacement parts. Furthermore, the degradation of this equipment can directly cause problems in the quality of cylinder heads and engine blocks. Purchasing backup equipment for each MSME is cost-prohibitive and not a cost-effective solution. One of the main challenges in MSMEs is that the breakdown of a single component can lead to the failure of multiple other components (directly or indirectly connected), which is where PvM strategies could be beneficial in preventing such issues. However, due to complexities such as missing technical and maintenance documentation, inadequate human resources, and difficulties in sensor installation, PvM or PdM strategies have not yet been implemented in MSMEs.

The general objective of this study is to identify and classify the criticality of the MSMEs and their components by applying the proposed method presented in the previous sections 4.1 and 4.2. The results of this study would be used for further PvM planning in the maintenance planning chapter6.

In this way, regarding MSMEs, several criticality criteria have been identified through a collaborative process involving experts from maintenance, spare parts purchasing, production, and quality departments, based on technical, cost, and production aspects which be detailed in the next subsection.

4.4.1 Criticality analysis of multi-spindle machining equipment

Based on the mentioned aspects of the criteria, the following data, information, and documents are collected to be served as an input resource for the analysis.

1. Historical breakdowns and interventions information of the MSME,
2. Historical production information regarding different engine types,
3. Historical information of used spare parts for each maintenance order,
4. Human resource information regarding the number of maintenance technicians per sector,
5. Technical information about the type of machining operations and its details in PDF documents,
6. Quantities and types of components in the drawing (DWGs) from hard copy documents,
7. The weighted average purchasing price of the components
8. Standard Maintenance Procedure (SMP): Control frequencies for inspection and cleaning purposes

It should be considered that some of them are not complete and precise information that is needed for this study. They could be categorized as below:

1. Structured ►Ex: Databases
2. Semi-structured ►Ex: Excel Files
3. Unstructured ►Ex: PDF Files
4. Information on paper (these are not data) ►Ex: Technical Drawing Plans

Criteria explanations:

In this project, as it is explained previously, the goal is to identify the criticality level of 151 MSMEs with three families of criteria concerning cost, production, and technical, which are presented in [Figure 49](#) and explained as follows:

- **Cost:** More critical equipment would generate more cost of interventions and/or machine stoppage duration

Calculation of this criteria could be based on historical data of failures by considering the following four sub-criteria:

- MTBF of the machine relating to each MSME,
- Number of more impacting interventions in the related machine,
- MTBF of each MSME,
- Number of more impacting interventions in the MSME,

- **Production:** The equipment that is dedicated to producing more volume and engine types, comes to be more critical.
- **Technical:** In general, the equipment types that bear more force due to the kind of machining operation or other technical parameters, should come to be more critical. Thus, two sub-criteria are considered for the technical aspect:
 - Machining type
 - Machining diameter

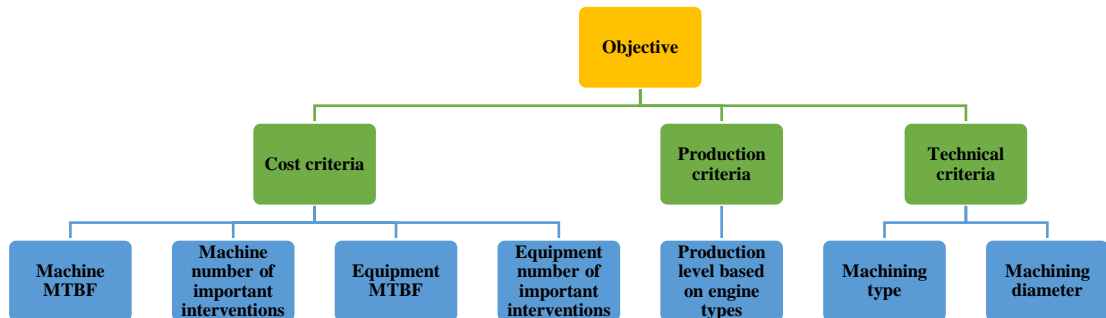


Figure 49. Structure of the criteria in this study

For the calculation of the cost criterion, the MTBF and number of important interventions of each machine and equipment regarding the mentioned sub-criteria have been calculated. The fewer MTBF values represent that more cost could be generated by the equipment which means that MTBF is a cost sub-criterion. Due to the incompleteness of the maintenance interventions for the precise MSME, this criterion has been calculated for the machine, and for the equipment regarding the available historical information.

Information on the production level of the different types of engines is indicated in Figure 50. The production level in percentage in a year based on the engine types is indicated in the charts. It should be noted that different combinations of engine types that the MSMEs could produce them. Based on historical production information, a production importance rate has been dedicated to each combination. These individual combinations and their weights are presented in Table 6.

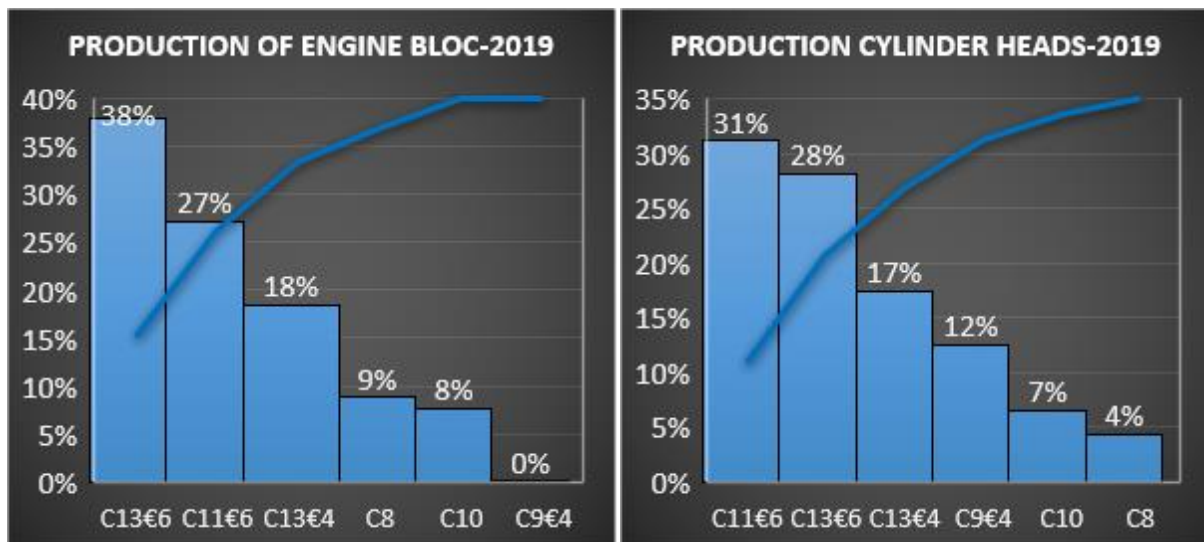


Figure 50. The production level of engine types for both machining lines

Table 6. Production importance rate of individual MSME types in the engine block and cylinder head machining line

MSME Types	Engine types						Production importance rate	
	C8 Euro4	C9 Euro4	C10 Euro4	C13 Euro4	C11 Euro6	C13 Euro6	Cylinder Head	Engine Blocks
Type 1	✓	✓	✓	✓	✓	✓	100%	100%
Type 2	✓		✓	✓	✓	✓	88%	100%
Type 3			✓	✓	✓	✓	84%	91%
Type 4					✓	✓	60%	65%
Type 5	✓	✓	✓	✓			40%	35%
Type 6					✓		32%	27%
Type 7			✓		✓		39%	35%
Type 8						✓	28%	38%
Type 9						✓	45%	56%
Type 10			✓	✓			24%	26%
Type 11	✓		✓	✓			28%	35%
Type 12				✓			17%	18%
Type 13	✓	✓					16%	9%
Type 14		✓					12%	0%
Type 15	✓						4%	9%
Type 16			✓				7%	8%

Regarding the technical criteria, the machining type is one important criterion as each equipment is capable to do certain types of machining and certain machining types exert more force on the MSME which is more critical. According to the expert's knowledge, the criticality level of the equipment is based on Figure 51 in which drilling and boring are more critical compared to spot-facing and chamfering operations. Hence, a score between 1 and 10 is dedicated to each operation type.

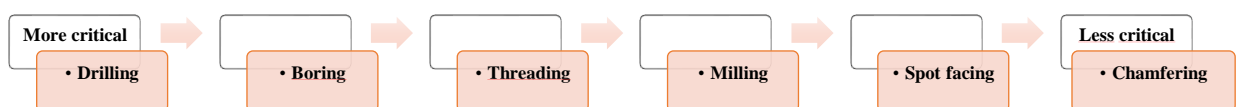


Figure 51. Criticality priority of the machining types

The other technical criterion concerns the diameter of machining in each equipment which has been taken from drawing files/hard copies. The bigger diameter indicates the more force that the equipment would tolerate.

Criticality ranking of MSMEs:

In this case, the Delphi method was used to estimate the importance weights of criteria with the assessment of different experts in several rounds until arriving at a consensus with minimum variance and mean of the evaluations are considered for further decision making. Regarding the MCDM method, the simple weighted-sum method has been selected as it could be useful for real case studies (Vafaei, Ribeiro, & Camarinha-Matos, 2016). In this way, based on the evaluation scores and equation (4.3), the ranking of the alternatives (MSMEs) is obtained based on the product of the criteria weights into the normalized evaluation scores of the alternatives. The classification and sensitivity analysis is performed based on the explained method in section 04.1. The 11 most critical MSMEs are classed in class “A” which are the target for further PvM planning. To assure the stability of the chosen alternatives, the values of the criteria weights have been varied by $\pm 10\%$, and the result of the class “A” did not change. In Figure 52 the 11 most critical MSMEs are indicated as the belonging machine of each MSME, the MSME specification number, and its engine.

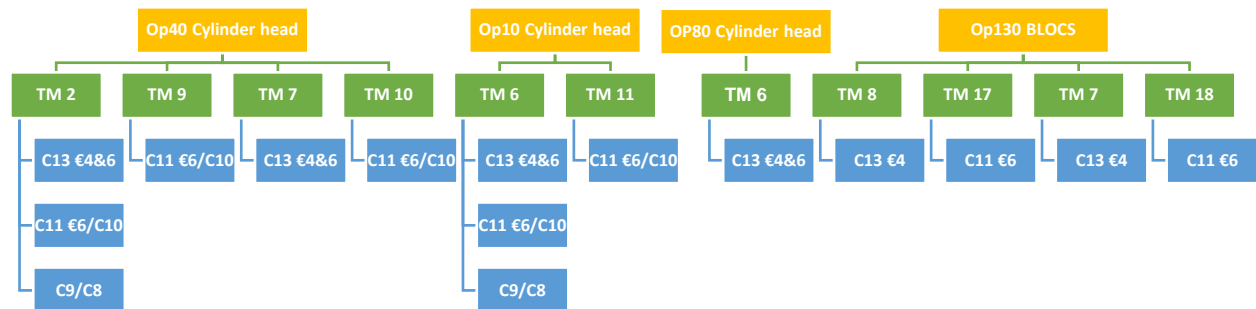


Figure 52. The result of MCDM for the most critical equipment (to proceed for PvM)

4.4.2 Criticality analysis of the components of multi-spindle machining equipment

Once the critical types of equipment are selected, the most critical components should be identified for the PvM or PdM policies. Each equipment has several parts that can be categorized into component types such as gears, ball bearings, angular contact bearings, spindle axis, etc. However, different references may exist for each component type. Therefore, it is possible to conduct a general analysis of critical components for all types of MSMEs.

A cause-and-effect analysis has been performed on the components to identify the most relevant ones. This analysis was conducted on the most critical MSMEs. Historical data on the causes of failures was used to identify the causes that have occurred most frequently. Subsequently, the most relevant components were identified. For instance, Figure 53 illustrates the failure causes of a particular machine, with mechanical displacements being the most frequent cause. Based on this finding, the components that are affected by this type of failure were identified and are listed in Table 7. The identification of these components was carried out through expert knowledge and investigation of drawings.

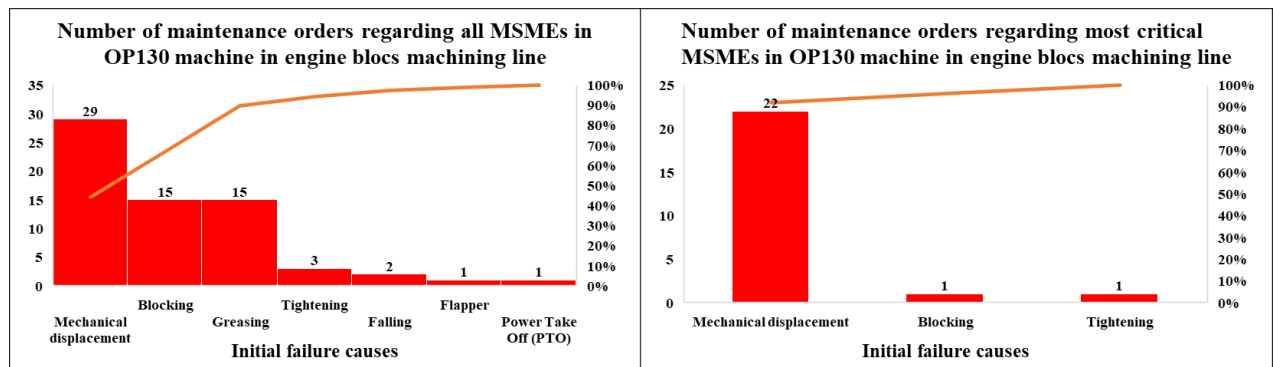


Figure 53. The failure causes in one critical MSME


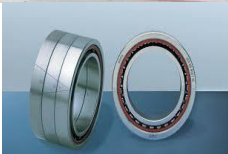
The listed components in Table 7 are the alternatives for the criticality identification study.

To do so, the FMECA method has been often used in the literature, (Gong, Luo, Qiu, & Wang, 2020) which is based on the three criteria concerning the detectability (D), the severity (S), and the occurrence (O). However, in this case, the detectability level for each component before opening MSMEs is very low (nearly impossible to detect).

Considering the simplicity of its application in industry, we use one of the most applied MCDM method called the Weighted Sum Method. Some criteria come from the FMECA method and two more criteria are from cost and technical aspects. It is proposed to use the following criteria as the basis for the identification of the critical components.

1. Cost: Components with more cost become more critical (Ascending criteria).
2. Lead-time: The components with the higher lead-times are more critical (Ascending criteria).
3. Occurrence: The components that have failed more in history become more critical (Ascending criteria).
4. Severity: If the failure of a component results in considerable failures in the equipment, it comes to be more important (Ascending criteria). Severity can be decomposed into two items:
 - Severity on service level which is related to the impacts on the client in the terms of quality and lead-time,
 - The severity of the breakdown is related to the internal impacts such as breakdown cost, security, and environmental aspects

Table 7. MSME components related to mechanical displacement cause

Component name	Photo
Axe of the Spindle	
Bearing of the Spindle	

Coupling
Coupling star



Axes of the box



Gear of the box
Key
Ring, Spacer



Bearing of the box



Waterproof ring



Flange



As explained in section 4.1, to define the weights of each criterion, several weighting methods exist in the literature. In this case, considering the simplicity of its application and its advantages, the Best Worst method (BWM) has been used. Then, through the weighted sum method, the most critical components of the PvM policy have been identified based on the following equation:

$$\alpha W_{Cost} + \beta W_{Technical} + \gamma W_{Lead-Time} + \delta W_{Historical} = \mu \quad (4.11)$$

The application of BWM by considering the opinion of several experts allows to identify of the criteria weights as $\alpha = 10\%$ for the cost, $\beta = 43\%$ for the severity, $\gamma = 24\%$ for the lead time, and $\delta = 24\%$ for the occurrence. On this basis, the score of weighted sum values of each spare part is calculated and presented in Table 8.

Knowing that the importance of the spare parts is different, classifying the components would allow us to prioritize more critical spare parts for further resource allocation and maintenance strategy identification. As stated in 4.1, for more simplicity in the industry, the ABC classification method has been applied and the result of critical component ranking has been shown in Table 8.

Table 8. Result of component criticality analysis

Components	Cost €	Severity (1-10)	Lead-Time (Days)	Occurrence (1-10)	Weighted sum value	Class
Bearing of the Spindle	300	7	120	6	81%	A
Bearing of the box	3	9	15	8	67%	A
Waterproof ring	10	8	7	6	53%	A
Key	2	8	7	6	52%	A
Coupling star	5	5	15	6	37%	B
Gear of the box	250	4	15	3	33%	B
Ring, Spacer	3	4	7	3	19%	B
Coupling	200	2	15	3	19%	B
Axe of the Spindle	170	2	5	3	16%	C
Axe of the Box	170	2	5	3	16%	C
Flange	30	3	5	1	7%	C

This classification is valuable to define the maintenance and spare part strategies simultaneously. The above classification results indicate that the components in class “A” could be followed by PvM strategy, class “B” may need more analysis, and class “C” can stay at CM strategy. In the case of real-time data acquisition possibility, and economical justification, class A also could be followed as a PdM strategy.

To provide decision-makers with confidence in the classification and the stability/robustness of the results, a sensitivity analysis was conducted on the criteria weights using the third model explained in section 4.2. This analysis was conducted on the most critical components belonging to class “A”. The objective was to identify the lower and upper weights of each criterion for which the class “A” classification remains unchanged. The results are presented in Figure 54, which shows that the assigned parts in class “A” are more sensitive to variations in the severity criterion, but less sensitive to the cost criterion. Hence, the positive and negative ranges indicate that the decision model and the results are highly stable. Therefore, the possible estimation errors in the weights do not affect the initial results in class “A”. Figure 55 presents the interval of the criteria weights and the initial weights so that the result of the analysis stays unchanged in these ranges.

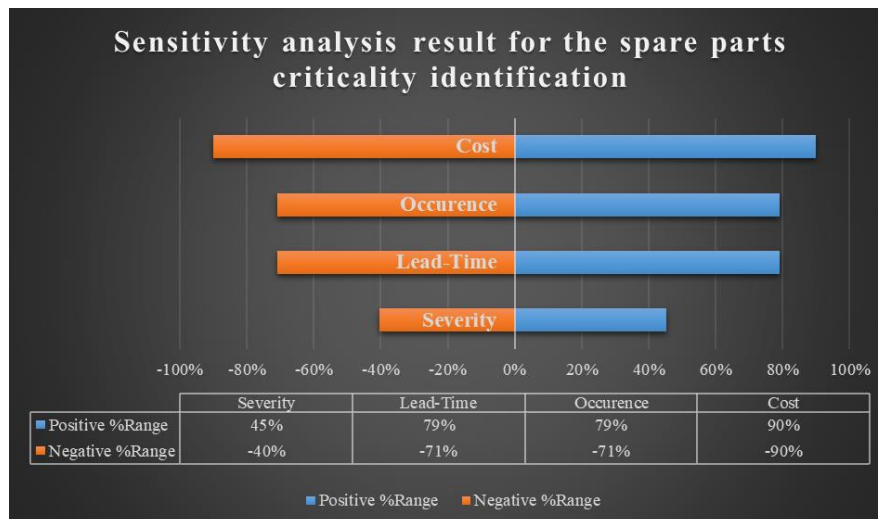


Figure 54. Sensitivity analysis result for the components

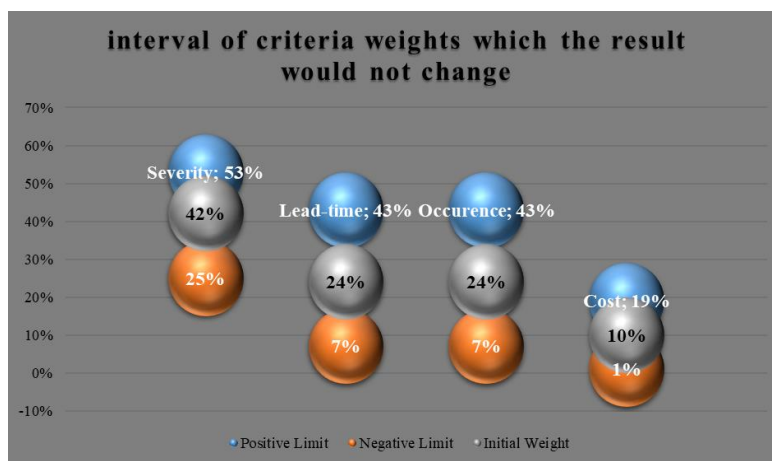


Figure 55. The interval range of criteria weights that the results stay stable

The above sensitivity results indicate that the criticality analysis of the components in this study is quite stable and reliable. In this way, based on the obtained results the optimal maintenance frequency is developed and presented in the next section.

4.5 The optimal maintenance frequency

In preventive maintenance, it is common practice to set maintenance frequencies based on the Mean Time Between Failures (MTBF) or information provided by the equipment's manufacturer. However, in many cases, following the MTBF or manufacturer's recommended frequency may not be the most optimal approach. Additionally, in some production assets, the manufacturer's information may not be available. Even if it is available, over time, it may lose its optimality through the time and require readjustment of maintenance frequencies. Therefore, it is important to conduct optimal frequency analysis to increase the efficiency and availability of equipment/machinery.

The optimal PvM frequency could be applied for the important components that are already identified in class “A” and/or “B”. The PvM frequency could be in terms of the calendarial periods or the number of production cycles. In this way, a mathematical method is studied and proposed for optimal PvM planning, which will be detailed in the following:

Based on the review of the reference books (Jardine & Tsang, 2013) (Todinov, 2006) and the literature study provided in section 3.3.5.1, the best model appropriate model is selected to determine the optimal frequency. Estimating the optimal replacement of the component in PvM is always followed by some assumptions:

- As pointed out in (Jardine & Tsang, 2013) book, in the probabilistic models two conditions of an equipment/component are considered as “good” and “failed” which is logical in the production systems that failure of one piece of equipment is identified rapidly. The second one is that replacement of equipment makes it “as good as new”.
- Running PvM is cost-effective so that the cost of breakdown maintenance (containing spare parts, man-hours, and production stoppages and losses) is greater than the cost of running PvM.

Regarding the single component condition, the following model (Laggoune et al., 2009) has been found important that could help the decision-makers to set the cost-efficient PvM. This model tries to find the best trade-off between PvM and breakdown maintenance costs in each horizon of time. In this model, the expected number of failures is taken into account which can be considered as the reliability of the machine.

The total maintenance cost function at each specified time is calculated as follows:

$$Cpm * \frac{T}{Fr} + Cbrm H(Fr) \quad (4.12)$$

Where Fr is the optimal PvM frequency that should be defined by solving the optimization equation. The Cpm is the cost of maintenance intervention in preventive conditions, and the $Cbrm$ is the maintenance cost in a sudden breakdown situation which is often more than the Cpm . $H(Fr)$ is the number of breakdowns that are expected to occur in the interval $(0, Fr)$. T is the horizon of time that we consider to be acceptable if can optimize maintenance costs. This is because the total PvM cost is dependent on the number of PM cycles in the considered horizon of time.

Based on these parameters and the Fr variable, at each specific time, the total cost is obtained which can be used as an optimization function to find the optimal frequency for PvM.

The function of $H(Fr)$ is calculated based on the following equation which is driven by the Laplace transform:

$$H^*(Fr) = \frac{f^*(Fr)}{s[1 - f^*(Fr)]} \quad (4.13)$$

Where $f(Fr)$ is the density function of the given probability distribution, and $f^*(Fr)$ is the Laplace transform of $f(t)$. The Laplace transforms are usually found in the reference tables. On this basis, the $H(Fr)$ function is achieved via $H^*(Fr)$. As an example, for the exponential density distribution, the $H(Fr)$ is equal to $\lambda \times Fr$.

In this equation, the risk of failure is represented by the λ parameter. In the exponential distribution, this parameter is constant, which leads to a stable hazard rate over time. According to information from two sources on reliability (Jardine & Tsang, 2013), (Laggoune et al., 2009), it is understood that a constant hazard rate in failure patterns can be caused by random stresses and extreme conditions. This failure model applies to complex equipment in which the failure of one or more internal components can lead to equipment failure and subsequent downtime.

In the problem of MSME, the condition of this equipment is fairly confirming the above-mentioned condition. As a result, we have considered the failure probability distribution of this equipment as an exponential distribution failure.

The optimal Fr is obtained via equation (4.14) by performing the derivation of equation (4.12). The frequency of PvM activity can be measured in operational hours/weeks or the number of produced parts.

$$Fr(*) = \sqrt{\frac{Cpm * T}{\lambda * Cbrm}} \quad (4.14)$$

The application of this proposed method is presented in the following section.

4.6 Optimal maintenance frequency in multi-spindle machining equipment use case

To implement the optimal PvM frequency method proposed in the previous section, initially, it is necessary to estimate the required resources such as spare parts and human resources. The needed information has been collected based on the drawings, warehouse, supply departments, and technical information from the experts in FPT-BLY. In continue the processes of information collection are detailed:

Estimation of spare part requirements:

Accurately estimating spare part costs for MSMEs requires detailed information on the types and number of spare parts and their unit purchasing costs because the spare part types and numbers are not the same in different MSMEs. Since MSME equipment is complex and contains numerous detailed parts, it may not be feasible to obtain all the necessary information. In such cases, an alternative approach is to use available data on the costs of spare parts for similar equipment as a basis for estimation.

To do so, in general, it has been considered the spare part types that were considered for the criticality/maintenance strategy identification analysis in Table 7 in section 4.4.2. Information on the bearings was initially available, but for the remaining components, the appropriate spare parts references and quantities were found by thoroughly reviewing technical drawings and documents. For cost identification, some of the spare parts are already codified and the references are available in the ERP (SAP) system. Whereas some others do not have registered ERP codes, and the costs are not available. For these types of spare parts, it has been tried to interpolate the cost based on the previous similar commands. Furthermore, for certain types that FPT-BLY is capable to manufacture internally, the spare part cost has been estimated with the internal resources.

Due to the significant amount of time required to obtain detailed information for the other MSMEs, an interpolation method is proposed to estimate the cost of this equipment based on the number of spindles and box axis. To understand this, let's explain that in each MSME there is a certain number of spindle and box axis that do the machining operations. An example is seen in Figure 56, by considering the assumption that the spare parts cost is quite the same per each axis, the cost of spare parts for the other equipment could be calculated proportionally.

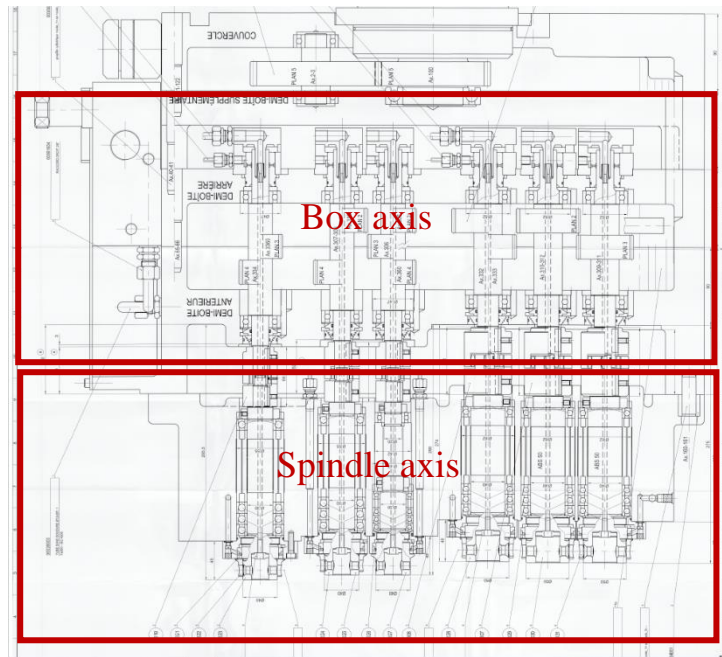


Figure 56. Drawing example of multiple-spindle machining equipment axis

Estimation of human resource requirements:

With the same logic of the spare parts estimation, the human resource has been estimated based on the fixed duration of opening and closing the equipment and the variable duration that is based on the number of spindle axis in each MSME type. Following the information acquired from the experts, [Table 9](#) represents the maintenance times of MSME based on its machining type:

Table 9. Estimated maintenance times based on the type of machining

Equipment machining type	Preparation, opening, and closing time (hours)	Cleaning and fixing components for each axis (hours)
Milling, chamfering	4	8
Threading	8	2
Drilling, boring, counterboring	0	1,5-2

Once the required resources for preventive maintenance are estimated, the optimal Fr of the components which are dedicated to the PvM policy could be identified using the proposed method in the previous section. The results of the MSME optimal planning are explained in continue:

Optimal PvM frequency results:

Regarding the proposed method, the optimal frequency and the components are identified for the 11 most critical MSMEs which are found as the most critical in section **4.4.1**. In this regard, based on the proposed method, this could be identified though three main parameters which are MTBF, PvM costs (Spare parts and human resources costs), and breakdown maintenance costs which have supplementary emergency costs in addition to PvM costs.

As previously found in the component criticality analysis in section 4.4.2, the parts in class “A” are included in PvM, and parts in class “B” should be identified by the method and cost analysis to be included or not. In this way, for the simplification of the solution for industrial utilization, we have used the single component model, so that the whole components of the equipment are considered as one component. In order to identify if the components in class “B” should be considered in PvM policy or not, the cost analysis scenarios have been performed. In each scenario, the multiple combinations of the presence of class “B” components have been considered. Therefore, the optimal frequency and the optimal number of components are calculated by considering all the scenarios of components in class “B”. One example of the obtained result is presented in Figure 57:

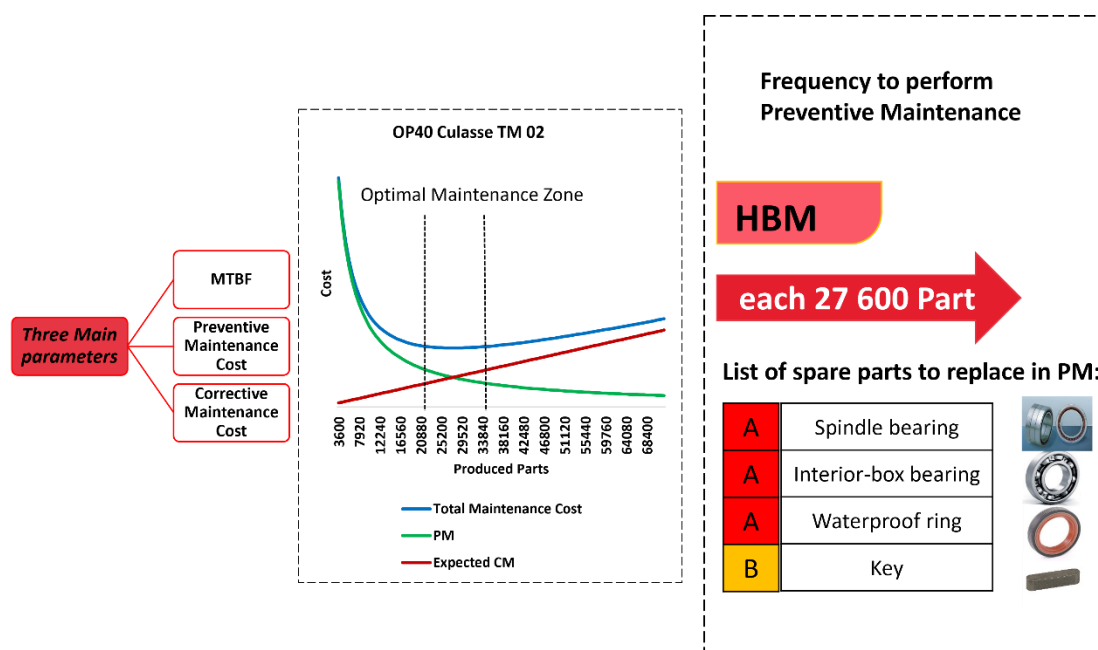


Figure 57. One example of an optimal PvM policy identification result

In the same way, the optimal frequency and spare parts are calculated for the other 10 equipment, which is provided in the following Table.

Table 10. Optimization result of 11 MSME equipment

Multi-Spindle Tooling Equipment	Optimal Fr to perform PvM	Spare parts-Class A			Spare parts-Class B		
Op40 CULASSES TM 2	27598	✓	✓	✓	✓		
Op80 CULASSES TM 6	29052	✓	✓	✓			
Op40 CULASSES TM 9	34991	✓	✓	✓	✓	✓	
Op10 CULASSES TM 6	37368	✓	✓	✓	✓	✓	
Op130 BLOCS TM 8	24569	✓	✓	✓	✓		
Op10 CULASSES TM 11	24742	✓	✓	✓	✓	✓	
Op130 BLOCS TM 17	22697	✓	✓	✓	✓		
Op130 BLOCS TM 7	17373	✓	✓	✓			
Op40 CULASSES TM 7	41085	✓	✓	✓	✓		
Op40 CULASSES TM 10	22907	✓	✓	✓	✓		
Op130 BLOCS TM 18	16049	✓	✓	✓	✓		

The obtained results have been validated by the maintenance experts and a maintenance procedure for this type of equipment has been created for the maintenance team. Following this developed foundation, a maintenance policy is proposed which considers the last maintenance intervention and proposes the next optimal PvM period for each MSME. The PvM policy also provided a basis for better management of the MSME's spare parts. It should be noted that the results of this study have been applied and consequently improved substantially the efficiency of the MSMEs management. For instance, the emergency purchase of spare parts has been considerably decreased as the most important spare parts are available with the optimal or minimum investment costs.

4.7 Chapter conclusion

In this chapter, a new approach to identify maintenance strategies through criticality analysis has been presented. An analytical approach has been developed using criteria weighting, MCDM, classification, and sensitivity analysis. Indeed, FMECA analyses are often commonly applied for maintenance strategy identification, however, based on the on-site experiences and the proposed approach, severity, failure effects, and probability information are not always accessible. In this way, the criticality is obtained based on other technical criteria or indicators depending on the use case features and using the MCDM, classification, and sensitivity analysis methods. Given the complexity of applying sophisticated methods in the industrial environment, the proposed approach focuses on using simple yet efficient methods. To reduce the pairwise comparisons of the criteria, the Best Worst method for criteria weighting has been proposed compared to the AHP weighting method which is often used in industry. For MCDM and classification analysis, the weighted sum and ABC classification methods have been used instead of more complex ML methods, as they are easier to understand and implement for industrial users. Additionally, to ensure the stability and robustness of the results, three sensitivity analysis methods have been developed for the weight of criteria, including single-sided and multi-sided analysis. The proposed correlated weighted sensitivity analysis method considers the correlation and importance weights between the criteria, enabling the interdependent sensitivity analysis of multiple combinations of the criteria weights. This approach ensures the robustness of the results by achieving upper and lower limits considering the interdependency, and correlation between criteria.

After identifying the critical machines/components, the next step is to perform a secondary analysis based on various factors such as the obtained classification of machines, components, historical analysis, and maintenance expert's experiences to define an appropriate maintenance strategy. For a PdM strategy, it may be necessary to conduct another MDCM analysis, taking into account other criteria such as the possibility and cost of PdM implementation to identify the most suitable strategy. This approach has been applied in Multi-Spindle Machining Equipment (MSME) use cases and has produced promising and relevant results when compared to the actual on-the-ground reality.

Determination of the optimal maintenance frequency is essential after identifying the maintenance strategy. While MTBF or manufacturer information are typically used as maintenance frequencies, these methods may not always be optimal and may require adjustments over time. Therefore, performing an optimal frequency analysis is important for increasing equipment/machine efficiency and availability. Based on a literature review and experimentations, an appropriate method was proposed and applied to the MSME use case, which yielded acceptable results in terms of the precision of the identified maintenance frequencies compared to the actual failure time. In most cases, the proposed PvM frequencies were proven to be efficient and the emergency purchase due to breakdown events was considerably decreased.

In this chapter, the general **steps 1** and **2** (Figure 39 and Figure 40) are presented, and in the next chapter the data acquisition, equipment health monitoring, and RUL estimation would be presented (**steps 3, 4, and 5**).

5 Chapter 5: Data acquisition, health monitoring, RUL estimation, and visualization

The developed criticality and maintenance strategy analysis presented in the previous chapter allows to create an appropriate basis to prioritize and identify the maintenance strategies for the machines, and/or components. To effectively track and maintain a manufacturing plant's production assets, it is essential to implement monitoring systems that can track the condition and performance of machines. Such systems allow for preventive and/or predictive maintenance and can help improve the overall efficiency and productivity of the plant. Hence, this chapter addresses two distinct but interconnected topics: *i*) Equipment health monitoring, and RUL estimation, and *ii*) Maintenance monitoring. The equipment health monitoring is necessary to build real-time diagnosis and health indicators for RUL estimation purposes. This would help to detect potential failures early, predict them, and take appropriate actions to prevent unplanned downtime. Maintenance monitoring, on the other hand, focuses on the overall production system. It involves tracking the performance of equipment and maintenance activities, identifying any areas that may require improvement, and readjusting maintenance activities or strategies if necessary to optimize maintenance effectiveness and reduce downtime. Implementation of equipment health monitoring, RUL estimation and maintenance monitoring require a data and information connection and acquisition system to develop the real-time supervision system. Maintenance and health monitoring are mainly followed through the visualization dashboards which are useful to take a quick vision of the machines, and maintenance system.

The mentioned aspects of this chapter are in accordance with the descriptive, diagnostic, and predictive phases of data analytics, and they correspond to **steps 3, 4, and 5** of the proposed predictive maintenance management system ([Figure 39](#) and [Figure 40](#)). The main objective of this chapter is to conduct a feasibility study on the identification of health indicators (HI) and the RUL estimation using real-time data. While most RUL studies focus on specific equipment, we aim to explore whether we can obtain HI or RUL using the available real-time data from connected use cases in FPT-BLY, and how we can utilize this information. In this way, the main problems in these steps concern the *i*) identification of relevant health indicators, Key Activity Indicators (KAIs), and KPIs, *ii*) indicators measurement method, *iii*) RUL estimation method, and *iv*) visualization technique.

Traditionally, information on preventive and corrective maintenance activities has been mainly managed through information systems such as Manufacturing Execution Systems (MES) and Enterprise Resources Planning (ERP). Regarding PdM activities, an IIoT system should be implemented to ensure accessibility and/or availability of real-time data and information. This would allow for the collection of data from connected devices, sensors, and other sources in order to automatize the process of collecting, analyzing, and interpreting data to enable a predictive maintenance strategy. The technical complexities of data connection and acquisition are not within the scope of this thesis. However, in this chapter, we present the architecture of the real-time data, IIoT platform, and information systems in FPT-BLY. We then introduce a dynamic prognostic approach that outlines appropriate methods, steps, and features for HI and RUL estimation. Next, we present a study of Health Indicators (HIs) and RUL estimation using real-time data from use cases in FPT-BLY. We also outline maintenance monitoring KPIs and their measurement methods. Using historical and real-time data from machines in FPT-BLY, we propose visualization dashboards that include the identified KPIs and HIs. Finally, we provide concluding remarks at the end of the chapter.

5.1 The architecture of data connection and acquisition

The importance of this section is that it provides one of the inputs of the research. Furthermore, the data collection and acquisition architecture provides a comprehensive overview of the means required for the maintenance decision support systems. It is essential to have an integrated and comprehensive system that enables the efficient acquisition and management of data for accurate and timely decision-making.

The implementation steps of the IIoT architecture involve selecting the appropriate sensors and data acquisition devices, ensuring that the data communication protocols are compatible with the existing system, setting up the data storage infrastructure, and selecting and configuring the visualization and analytics tools. The architecture should be designed to be scalable and compatible with the existing system, and the data collected should be analyzed using various data analytics tools to generate insights and improve the maintenance strategy. The IIoT architectures generally include sensors, data acquisition devices, data communication protocols, data storage, and visualization and analytics tools.

Real-time data and information in FPT-BLY

To enable access to real-time data from the machines at FPT-BLY, an Industrial Internet of Things (IIoT) architecture was implemented using the MindSphere platform. This decision was made due to several reasons, including the fact that the majority of machines at FPT-BLY use Siemens PLC, the lack of available IoT providers at the time of implementation, and the desire to avoid complexity in managing substantial real-time data.

In this way, initially, one CNC machine was configured to be connected to the IIoT platform. For external sensors, IFM sensors were used, and for the data acquisition system, a SIMATIC IOT2040 box was installed using the S7 communication protocol to the PLC. Data storage is managed in the core of the platform and in the cloud of the platform, which can be accessed via authentication for visualization and data analytics applications within the platform or via an Application Programming Interface (API) for external applications.

In order to better understand the structure of the IIoT platform, and its complexities a schema has been presented in [Figure 58](#). As it is seen, through the MindConnect (the data acquisition system), the sensor or PLC data are transferred into the core of MindSphere. Then, the data scientists/developers can have access to the data via the authentication and authorization process. This needs of creating a library for receiving the data in the desired variables in desired periods. This library has been developed in Python Programming Language.

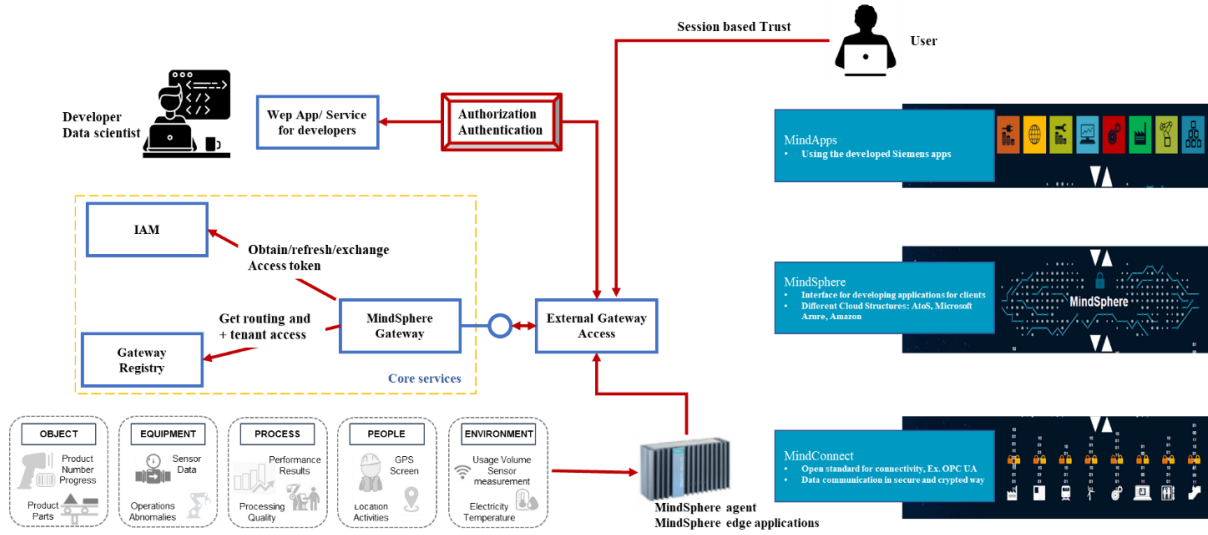


Figure 58. Detailed schema of Siemens IIoT Platform in FPT-BLY

To store data, MindSphere employs a three-fold identity format consisting of asset, aspect, and variable, which is depicted in Figure 59. This structure allows for effective data recording and management, and examples of each identity are provided in the figure.

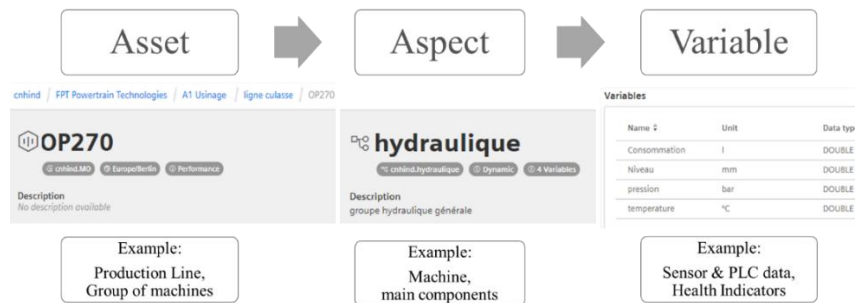


Figure 59. Data configuration in MindSphere platform with examples

It is important to note that historical information plays a crucial role in maintenance monitoring as it helps in analyzing maintenance interventions, identifying components used, calculating costs, indicators and more. However, accessing this information requires the use of ERP extraction request modules.

5.2 Dynamic prognostic procedure

In this section, we summarize the key steps for HI identification and RUL estimation based on the literature study in section 3.3.4 and our perspective, following the acquisition of real-time data.

The initial and crucial step in identifying HI and/or estimating RUL is to determine the target, which entails selecting the component/equipment to be monitored and the corresponding condition monitoring data (Tiddens et al., 2018). For the RUL estimation, the target could be a remaining life before a failure of a component or equipment, or before a specific failure condition in a part of the equipment (Angelopoulos et al., 2020). Condition monitoring data are then acquired through IIoT platforms and stored dynamically in data lakes or databases. Based on the presented approach in Figure 60 health state indicators could be defined at the instance of data acquisition and presented in the form of categorical

classes or continuous values such as a percentage. Here, specific knowledge of the equipment, and the targeted failure condition plays an important role in finding the right health indicators, as there are highly case-dependent parameters.

In terms of methodology, there are several methods to determine HIs, including feature extraction, clustering, classification, and reinforcement learning. Feature extraction involves extracting meaningful features from real-time data to identify the health status of the machine. There are three main approaches in feature extraction: time domain, frequency domain, and time-frequency domain approaches (Lei et al., 2018). Clustering methods are used when there is a lack of knowledge on the correlation between real-time data and failure. Clustering can help to identify the clusters that correspond to the real conditions of failure or healthy mode, which can then be used as featured data. Once the features are set, machine learning algorithms such as K-Nearest Neighborhood (KNN) (R. Liu et al., 2018) or reinforcement learning can be used to classify or identify the current health state as new data are received. The obtained health indicator model serves as a basis for the health assessment and monitoring of the machine or equipment. This process is illustrated in Figure 60 at the bottom left of the figure.

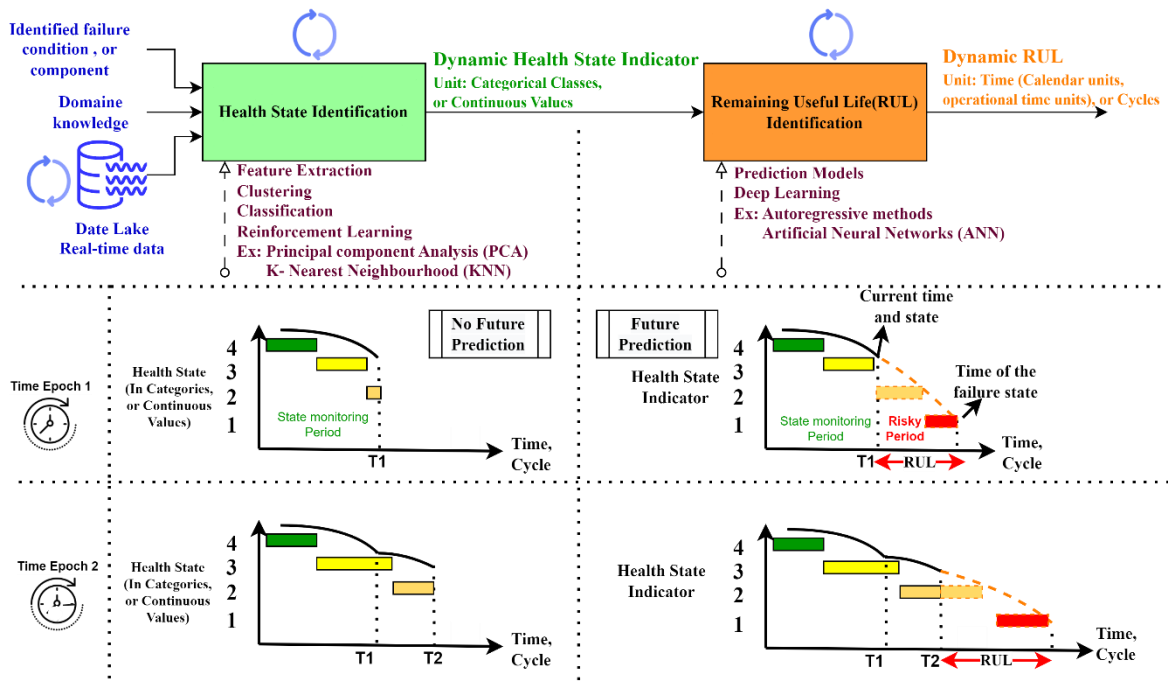


Figure 60. Dynamic Prognostic Procedure

In the HI determination phase, we are in the actual instant without any prediction for the upcoming events during the next hours, days, etc. We can maintain health monitoring when we are in a normal health state, while in a risky health state, the RUL estimation becomes more important.

For the prognostic aspect, the RUL estimation model should take the health state trend to find the failure time and calculate the RUL. The RUL unit can be the calendar units as days or production cycles as the number of produced parts. As explained in the literature section, the most pertinent methods are statistical, deep learning, or a combination of both, which could find the learning function of the health state trend. As seen on the right side of Figure 60, this is not the same approach that is presented in (Elattar et al., 2016), as the classification methods could help in identifying the current state and not the future state. While predictions and statistical methods widely help in trend prediction which is suitable for the predictions and RUL estimations.

For the dynamic aspect of the prognostic, an interval of readjustment or updating interval should be identified depending on the criticality of the case and its parameters. In each of these intervals, new real-time data are achieved and processed to update the RUL value. Furthermore, the updating interval could depend on the risky threshold of spare part replenishment lead time and the needed time for the intervention of the maintenance team. This is because the RUL value is highly dependent on the operational usage of components or equipment. It could be extended or decreased as it is depicted in the schematic example at the bottom of the figure in the time epochs.

We have presented some main methodologies for HI and RUL estimation, while the selection of appropriate methods depends on several parameters of the studied use case as listed below:

- *Safety and security risks:* Security is always the most important target in any operating system. For example, in the aerospace industry, sensitive equipment and systems are often used in critical applications such as aircraft engines. Therefore, selecting appropriate HI and RUL estimation methods is critical to ensure safety and prevent catastrophic failure risks.
- *Cost:* The required cost and time of implementing and maintaining HI and RUL estimation methods is an important factor to consider, as some methods may be more expensive than others.
- *Equipment criticality:* In the energy sector, power generation equipment such as gas turbines and wind turbines are critical for ensuring a reliable power supply to prevent unexpected downtime and ensure high availability.
- *Technical complexity:* Complex systems with numerous components requires sophisticated methods. For example, engine components may require vibration-based methods.
- *Data availability and quality:* The amount and quality of available data are crucial as some methods require large amounts of data to work effectively, while others may work with fewer data. Insufficient or poor-quality data can lead to inaccurate predictions, resulting in costly errors.

5.3 Equipment health indicator identification

In the HI identification study, we first introduce the HI method and then present the use case that we selected for equipment health state experimentation, followed by a discussion of the results.

The overall process of data-driven HI development generally involves data acquisition, data cleaning, feature extraction, and/or model development. The first step is typically identifying the relevant raw data and performing pre-treatment and cleaning to prepare the data for feature or indicator extraction. In real-time monitoring, there may be numerous observations for multiple variables. The main source of data for health indicator development is often sensor and PLC data, which consists of several variables X_1, \dots, X_m without an associated response or label data Y . Since labeled features and run-to-failure data are often unavailable and the data may include multiple variables, it is important to reduce the correlation effect between variables and identify the most relevant parameters. To address this issue, we propose using the non-supervised Principal Component Analysis (PCA) method for developing HIs, which is explained in the following section:

5.3.1 HI identification through Principal component analysis

PCA method is used to analyze multi-dimensional data to reduce the dimensionality of a dataset, which means reducing the number of variables or features while still retaining as much information as possible. In other words, the PCA method reduces the dimensions so that the dimensions represent as much as possible the variations in the whole dataset (Jolliffe & Cadima, 2016). The resulting new variables are called principal components, which are linear combinations of the original variables. The first principal component explains the most variation in the original data, with each subsequent component explaining less and less variation. Each dimension/principal component of PCA analysis is a linear combination of the m variables and the number of dimensions/ principal components that are retained depends on the results of each PCA analysis. For instance, the first dimension/component can be expressed as:

$$Z_1 = \varphi_{11}X_1 + \dots + \varphi_{m1}X_m \quad (5.1)$$

$$\sum_{j=1}^m \varphi_{j1}^2 = 1 \quad (5.2)$$

Where $\varphi_{11} \dots \varphi_{m1}$ are the loading of each variable on the first component, and X_j is the standardized value of variable j . Z_1 is a normalized linear combination of m variables. To find the best $\varphi_{11} \dots \varphi_{m1}$ for the first component, PCA uses of the optimization problem to maximize the variance of the observation that is subjected to the constraint of equation (5.2). In the following, the linear combination of the first principal component based on the observations (each i corresponds to one observation of each variable j) and the optimization equation is presented:

$$Z_{i1} = \varphi_{11}x_{i1} + \dots + \varphi_{m1}x_{im} \quad i=1 \dots, n \text{ (number of observations)} \quad (5.3)$$

$$\max \left\{ \frac{1}{n} \sum_{i=1}^n \left(\sum_{j=1}^m \varphi_{j1}x_{ij} \right)^2 \right\} \quad \text{st.} \quad \sum_{j=1}^m \varphi_{j1}^2 = 1 \quad (5.4)$$

where φ_{j1} is the loading of variable j on the first principal component, and X_{ij} is the standardized value of observation i in the variable j .

The process for identifying the second and other components ($Z_2, Z_3 \dots$) is the same, while there is a difference that the linear combination of Z_2 should be uncorrelated to the Z_1 and so on (James et al., 2013).

The results of PCA analysis are often visualized in a biplot, such as the one shown in Figure 61 (Two components in 2D). In this plot, green vectors represent variable loading vectors based on principal component one (PC1) and principal component two (PC2). The loading vectors can be used to identify correlations between variables, as well as the impact level of each variable in terms of the variations represented by the principal components. The impact level is identified based on proximity to the principal components.

It is important to note that before conducting PCA analysis, the raw data variables should be scaled. This is because each variable may have different measurement units and variances, and scaling ensures that the interpretation is not biased.

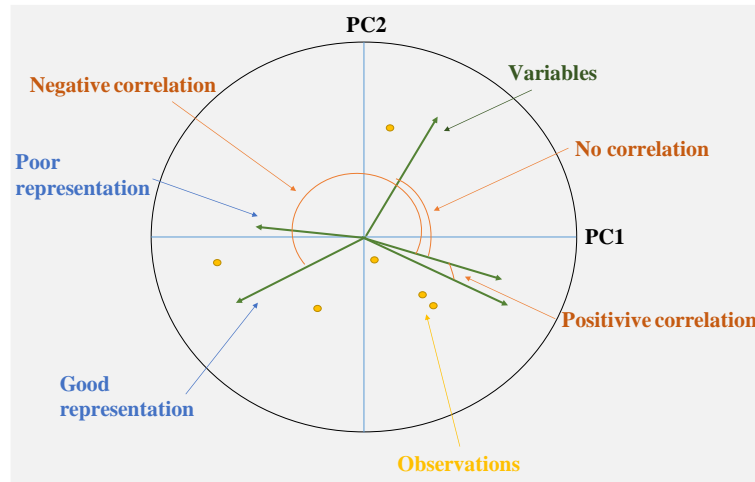


Figure 61. PCA bi-plot and the interpretations

Regarding HI development, it is proposed to utilize the principal components obtained from PCA analysis as potential health indicators. By using PC1, PC2, and so on, we can monitor the most influential variables that represent the majority of variations in the entire dataset. This approach can effectively reduce the dimensionality of the data and facilitate the identification of potential anomalies or faults in the system. However, the specific choice of principal components for each use case should be based on the experimentation and analysis of the dataset.

5.3.2 HI identification in CNC machine use case

The first use case in the IIoT platform, which was studied for PdM, is shown in Figure 62 and concerns a CNC machine of the HULLER brand. In this use case, the real-time data from both Numerical Command (NC) and external sensors are accessible. Aside from this use case, other types of machines/equipment such as conveyer chains, robots, etc. are connected for data acquisition, which would be presented in the corresponding chapters or sections.



Figure 62. CNC machine use case for HI study

To synthesize all the available data from this machine, the relevant data from the PLC and external sensors were chosen with the help of experts to identify the possible risks associated with the machine. The real-time data schematic for this use case is shown in Figure 63.

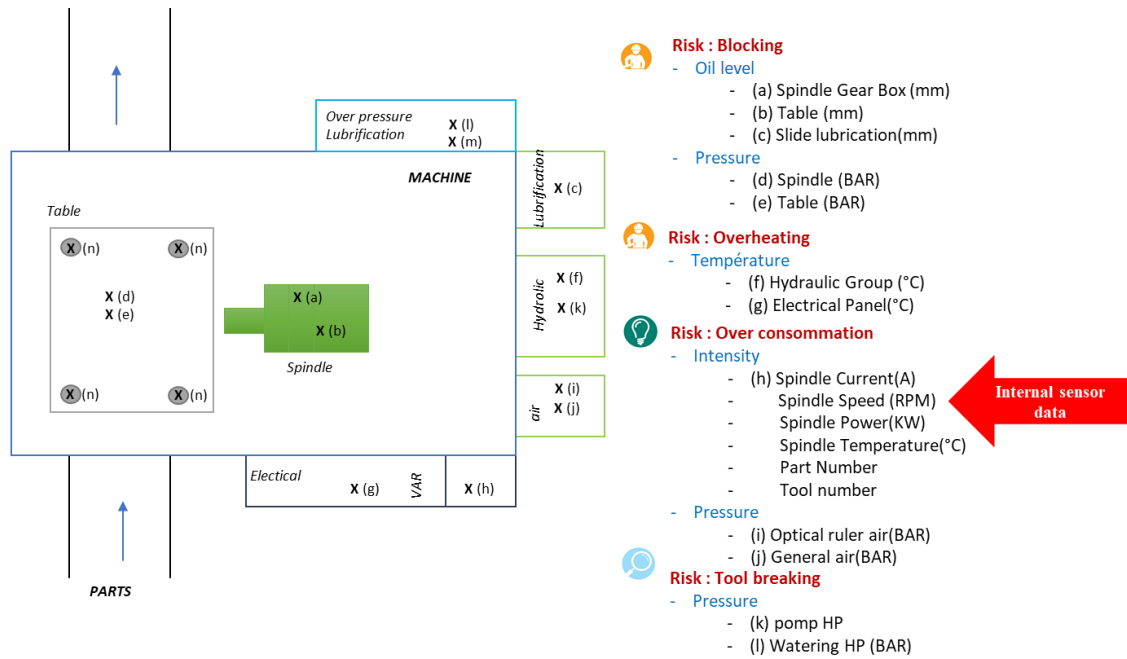


Figure 63. Schematic of Real-time data

In the HI study, the focus was on monitoring the spindle engine using real-time data on spindle speed, power, current, and temperature, as this is one of the most critical functional groups of the CNC machine. To identify relevant health indicators from the sensor data, the PCA method (explained in section (5.3.1)) was used for feature extraction. As stated earlier, PCA is a useful technique for analyzing multi-dimensional data, especially in cases where there are many variables and a high correlation between them. By reducing the dimensionality of the data, PCA can help identify the most influential variables that represent the most significant variations in the dataset, making it easier to identify relevant indicators for health monitoring. Without PCA, it can be challenging to identify relevant health indicators from large datasets with many variables, as the correlation between variables can make it difficult to distinguish between the most significant factors.

The PCA was initially applied to the entire dataset containing four variables, and the analysis was performed using two principal components. The resulting biplot (Figure 64) showed that the first and second principal components captured 71% and 17% of the total variation in the dataset, respectively, resulting in a cumulative total of 78%. These results indicate that the two principal components are sufficient to represent the majority of the information in the original dataset.

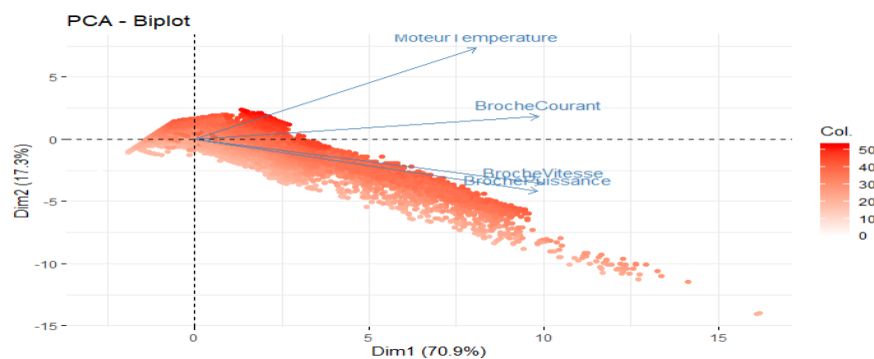


Figure 64. The PCA biplot for the sensor data of the CNC motor

The biplot provides insights into the correlations between different variables. As seen in Figure 64, there is a high correlation between the speed and power consumption of the motor. The motor temperature shows less correlation with speed and power, while the motor current exhibits a higher correlation.

The results also indicate that a significant portion of the variations can be captured by monitoring these two principal components. Therefore, instead of tracking the four individual real-time data variables, it is proposed to monitor the PC1 and PC2 as health indicators to supervise the variations and stability of the spindle engine. This health indicator can be included in the machine-level dashboard, as shown in Figure 65.

In this study, a stable state of the CNC engine is reflected in the real-time data and principal components display (Figure 65). Significant deviations from the normal state that continue for a considerable duration could indicate mechanical or electrical problems in the CNC spindle motor.

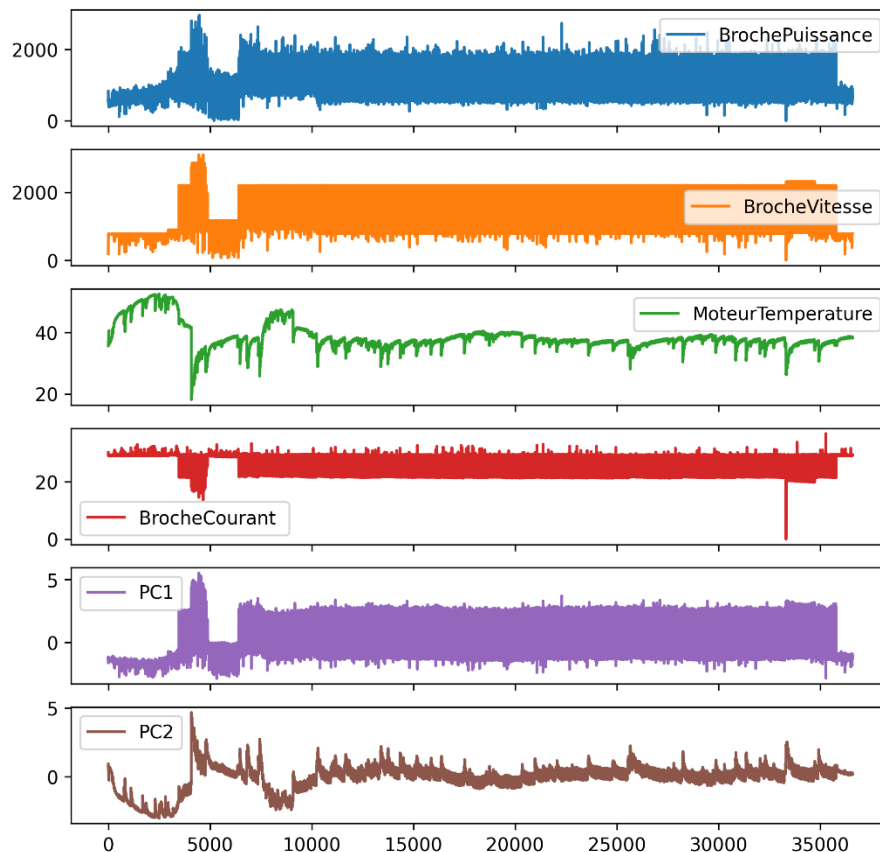


Figure 65. PCA visualization regarding component state

Although the PC1 and PC2 could be used as health indicators, the PCA result may not be directly interpretable or understandable by domain experts, especially when dealing with complex and high-dimensional datasets. While PCA can provide a useful method for dimensionality reduction and feature extraction, it is important to keep in mind that the resulting principal components may not have a clear physical or intuitive meaning. In this way, the number of principal components could be identified depending on the variance ratio (the variation representativity of the whole dataset) and the Sum of

Squared errors (SSE). SSE is a measure of how well the principal components derived from PCA analysis capture the variability of the original data. SSE represents the sum of the squared distances between the actual data points and their projection onto the principal components. The lower the SSE value, the better the principal components are at representing the original data. The SSE results of this study regarding the principal components are depicted in Figure 66.

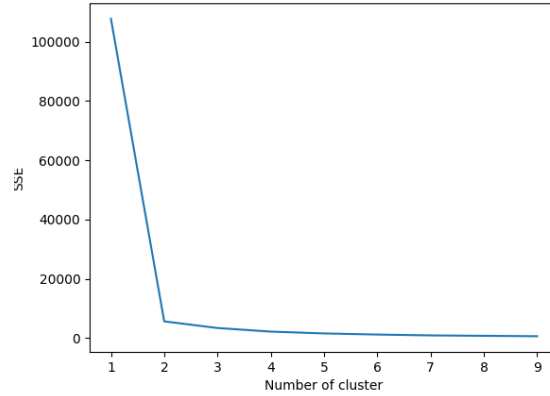


Figure 66. SSE results of PCA analysis in use case data

In our study, PC1 represents 71% of the variations, which suggests that it may be sufficient to keep only one principal component instead of two. On the other hand, keeping more than two principal components can lead to highly complex and uninterpretable health indicators.

In the following section, we will present the RUL estimation method that was used to estimate the remaining useful life in the FPT-BLY use case.

5.4 Dynamic RUL estimation

As discussed in the dynamic prognostics section, selecting an appropriate RUL estimation method depends on several factors, including the criticality of the equipment in terms of safety, security, functionality, and financial impact; the technical complexity of the equipment and the required level of precision; and the cost of implementation, including data acquisition and model building. Based on these considerations and the available real-time data in our use cases, our main objective is to determine whether we can utilize these data to estimate the RUL and, if possible, how we can utilize this information for maintenance planning purposes. Given the high variability, seasonality, and trend presence in the available real-time data, and considering a comprehensive analysis of the literature that evaluates the pros and cons of different RUL estimation methods, their applicability, and ease of use in real-world scenarios, using the Prophet method (Taylor & Letham, 2018) seems to be an appropriate method for RUL estimation. It is important to note that our objective is not to use overly complex methods, as feasibility is a more significant consideration. However, to ensure the obtained results and the selected prediction method, three other well-known prediction methods are also used in our study and their performance is compared. The comparison is presented in section 5.4.1.

Prophet prediction method:

Prophet uses a decomposable time series model that is seen in (27). This model aside from the trend prediction function $g(t)$ considers the periodic $s(t)$ variations (as daily and weekly changes) and

irregular events effects $h(t)$ as holidays. These last two features are less considered in the other prediction models. The ε_t represent the peculiar changes supposed to be normally distributed.

$$Y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (5.5)$$

Regarding the trend function, Prophet mainly uses linear piece-wise growth functions (5.6).

$$g(t) = (k + a(t)^\top \delta_t)t + (m + a(t)^\top \gamma) \quad (5.6)$$

Trend changes are incorporated in the growth function by defining changepoints S_j $j = 1, \dots, S$ and δ_j responds to the change rate that happened in changepoint j . Where k is the basic growth rate, $a(t)^\top \delta_t$ is the change rate at time t . m is the offset parameter, $a(t)^\top \gamma$ is the offset adjustment at time t . Automatic changepoint detection is based on (5.6) with a sparse prior on $\delta_j \sim \text{Laplace}(0, \tau)$ that impacts the growth rate model.

Seasonality and periodic change effects are obtained based on (5.7) by inspiration from the Fourier series:

$$s(t) = \sum_{l=1}^N \left(a_l \cos\left(\frac{2\pi lt}{P}\right) + b_l \sin\left(\frac{2\pi lt}{P}\right) \right) \quad (5.7)$$

Where P is the regular period value based on days, $2N$ is the number of parameters to be estimated that best fits the prediction problem. Equation (5.7) can be written in the form of $s(t) = X(t) * \beta$ as $\beta = [a_1, b_1, \dots, a_N, b_N]$. To impose a smooth prior β is considered as $\text{Normal}(0, \sigma^2)$.

Effect of the event in the daytime as D_i on the past and future days are considered by an indication function to check if date t is in the events or not, and a seasonality prior scale of $k \sim \text{Normal}(0, v^2)$.

Three main components are most important to avoid overfitting and underfitting as *i*) Changepoint scale (τ), *ii*) Seasonality scale (σ) and *iii*) Predictable events (like holidays) scale (v).

The best Prophet prediction parameters can be identified using a cross-iterated table of changepoint, and seasonality prior scale values. The performance metrics as Root Means Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) could be obtained to identify the best prediction parameters where y_i is the actual value, and \hat{y}_i is the predicted value. RMSE is calculated based on $\{\sqrt{(1/n) \sum (y_i - \hat{y}_i)^2)}\}$ and MAPE based on the $\{(1/n) \sum (|y_i - \hat{y}_i| / |y_i|) \times 100\}$ formulas. One advantage of RMSE is that it gives more weight to larger errors, while also measuring errors in the units of the predicted variable. On the other hand, MAPE is suitable when working with datasets of different scales.

Dynamic RUL estimation by Prophet prediction method:

In PdM, real-time data is crucial, and prediction methods must be able to capture the evolution of health state trends with respect to changes in the operational conditions of the components/equipment. To achieve this, dynamic models are necessary to provide the most accurate predictions based on the most up-to-date information, with the ability to automatically adjust and adapt to changing conditions. In this way, a new algorithm has been proposed by using real-time data which is depicted in Figure 67. In this algorithm, the predictions are done based on a risky period which refers to the period required for the maintenance team to react or replenish any necessary spare parts. When the predicted health state values reach the failure threshold in the risky period, the RUL value is calculated. The failure threshold is typically determined using technical documentation related to the use case, input from experts, or other relevant sources.

The first step of this algorithm involves obtaining a set of historical real-time data. Then, health state values would be identified based on the HI method specific to each use case. Next, the best-tuned prediction parameters are achieved with the cross-validation function which has the minimum performance error. The RUL is then estimated by predicting the health state value over a defined risky period. If the estimated RUL value within the risky period reaches the failure threshold, the RUL is calculated and sent to the decision-maker or maintenance planning system. If the predicted health state value does not reach the failure threshold, the algorithm waits for the next updating interval to obtain new real-time data and repeats the prediction process with the failure threshold.

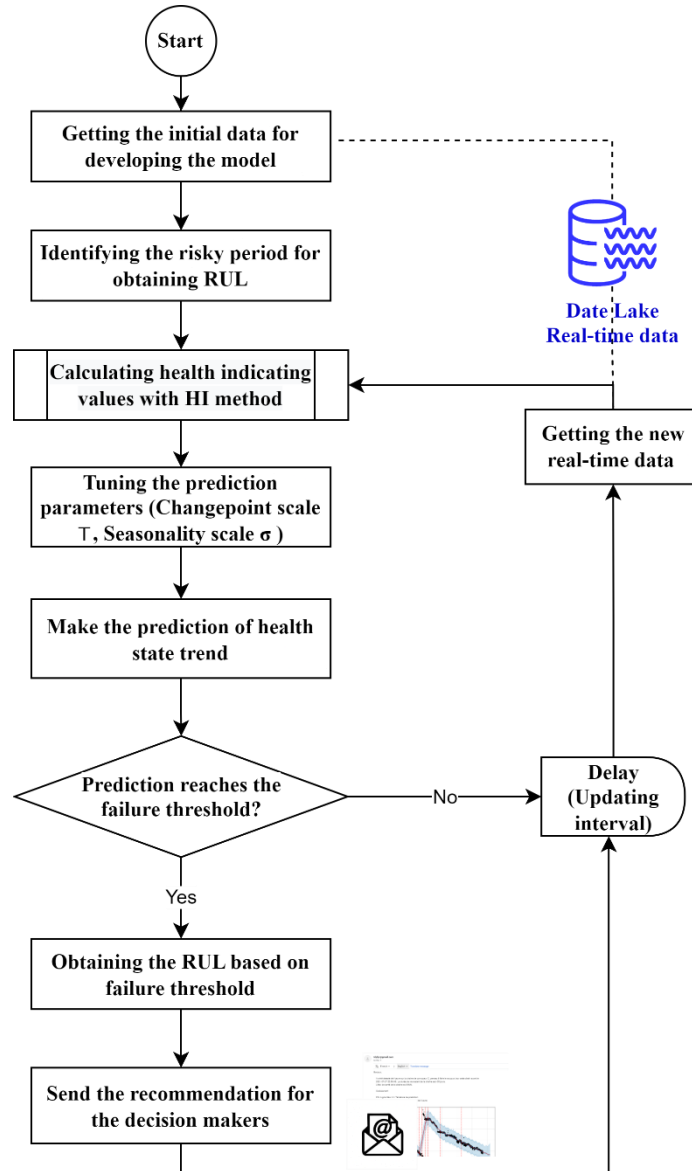


Figure 67. Dynamic RUL methodology

The proposed algorithm utilizes the Prophet prediction method and operates continuously, adapting to the most recent real-time data obtained within a predefined updating interval. At each interval, new data are collected and added to the existing dataset, allowing for the creation of an updated failure trend in RUL estimation. This is crucial since the RUL value may vary depending on the operating conditions

of the equipment. The length of the updating interval depends on factors such as the criticality and importance of the use case, the time required for the preparation/planning of maintenance intervention, etc. It is generally recommended to use shorter intervals for more critical systems. Although this algorithm is primarily based on the Prophet prediction method, it can be adapted to incorporate any other prediction methods as well. The key differences would lie in the identification of the optimal prediction parameters at each updating interval, which would depend on the specific features and requirements of the selected prediction method. This algorithm remains fundamentally similar regardless of the specific prediction method employed.

5.4.1 RUL estimation in conveyor chains use case

Regarding the application of the proposed RUL estimation algorithm and based on the availability of real-time data in different use cases of FPT-BLY and the possibility of failure prediction, we have selected one of the critical conveyor chains (shown in Figure 68 on the left) to apply the proposed RUL estimation algorithm.

These conveyor chains are driven by a motor and two gears. There is also a tensioner system with the help of 6 bar jack that keeps the tension of the chain and maintains the equilibration. These chains are degraded until they are broken or stretched enough to cause production stoppages. There are male and female I-Beam chain links that are connected in series. The principal causes of degradation are due to the weight of lifted engines as well as the ups and downs of the conveyor chain path (causes the elongation of the chain). The whole chain behavior is monitored based on the position of the tensioner system.

Concerning the experimentation of the proposed prognostic approach and dynamic RUL, it is targeted to estimate the dynamic RUL of the whole chain. This has been put into action using an ultrasonic sensor that measures the position of the tensioner system in real-time per second and is registered in the cloud Data Lake. The information on the failure threshold is available from technical documentation in this case.

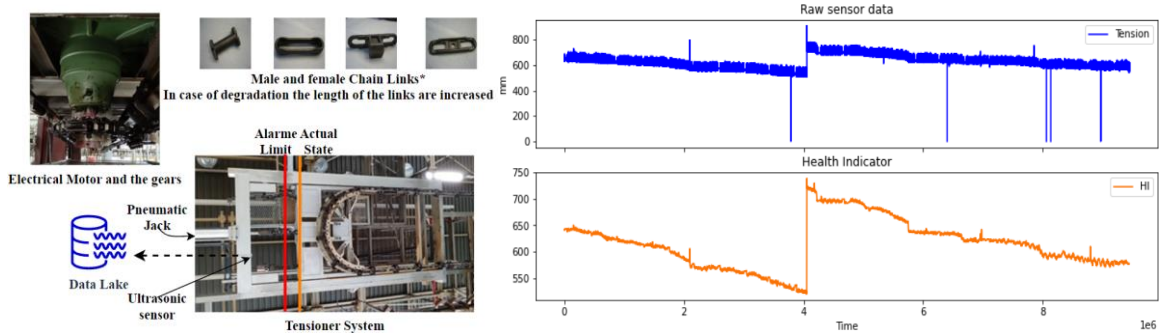


Figure 68. Left: Conveyor chain system and its elements, Right: Raw sensor data and Health Indication data

To find the RUL of the whole conveyor chain, as described in the dynamic prognostic procedure, a HI is obtained based on a statistical approach for this case. In this regard, Root-Mean Square (RMS) (Cattaneo & MacChi, 2019) has been selected for identifying the health state. RMS is calculated in a regular period (P) that can keep the degradation characteristics. therefore, the RMS of period j is obtained by (5.8) which p_j is the starting time of period j and N is the total number of periods in the dataset.

$$RMS_j = \sqrt{\frac{1}{P} \sum_{i=p_j}^{P+p_j} x_i^2}, \quad j = \{1, \dots, N\} \quad (5.8)$$

Figure 68 (right) illustrates raw data without a health indicator (the top chart) and the data after HI transformation (the bottom chart). Based on the replenishment, time to intervention, and criticality of the case, the prediction horizon is identified as 14 days. If the prediction of health state values reaches the failure threshold in the prediction horizon, then the prediction parameters are tuned, and the RUL value is calculated. This will continue in every updating interval as the new data are achieved. The result of the prediction model and RUL estimation is illustrated in the following Figure 69:

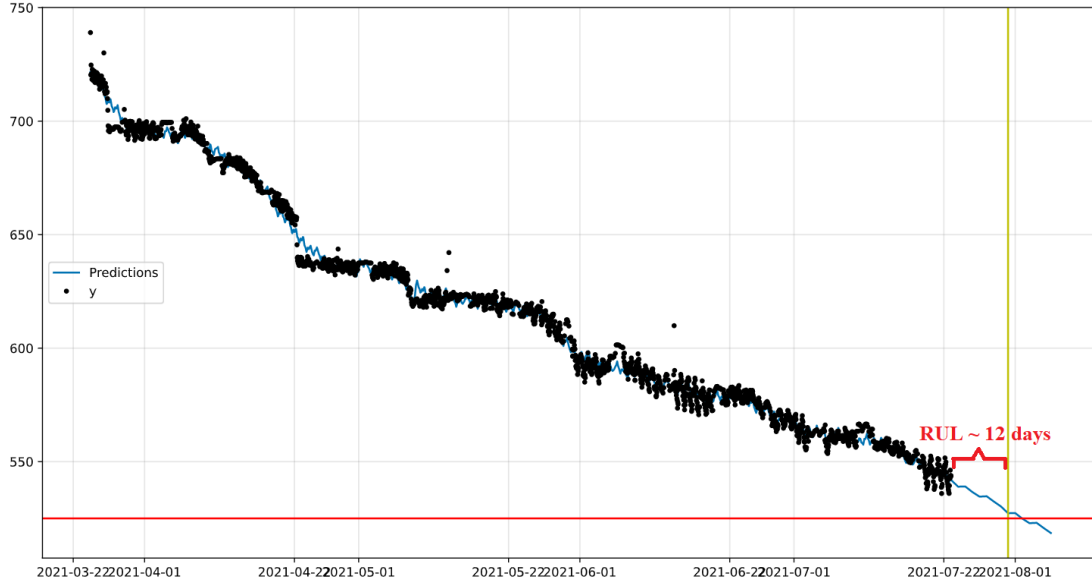


Figure 69. HI, Prediction, and estimated RUL

It is clearly seen that the periodic changes are well captured and based on the failure threshold the obtained RUL is well achieved from the health indicator data points. In order to compare the results and performance of the Prophet method, we considered Autoregressive Integrated Moving Average (ARIMA) as a statistical method (W. Wu et al., 2007), Holt-winter (Triple exponential smoothing) as an exponential method (De Marco et al., 2019) and LSTM as a deep learning prediction method (Zheng et al., 2017). These methods are widely used for RUL estimation in the literature, and they are well known for their ability to capture pattern variability, trend, and seasonality features. Here is a brief explanation of each method:

- Triple Exponential Smoothing (Holt-Winters) is a time series forecasting technique that is used to model data with a trend, seasonal component, and random noise. It is an extension of simple exponential smoothing and can capture both trend and seasonality. The method uses three smoothing factors (alpha, beta, and gamma) to estimate the trend, and seasonality components of the time series (De Marco et al., 2019).
- ARIMA is a time series forecasting method that models the dependence between an observation and a lagged value of the time series. ARIMA models are widely used in RUL estimation because of their ability to model non-linear trends and seasonality. The method involves three components: the autoregressive (AR) component, the integrated (I) component, and the moving average (MA) component (W. Wu et al., 2007).

- LSTM is a type of Recurrent Neural Network (RNN) that is capable of modeling long-term dependencies in time series data. LSTM models are popular in RUL estimation due to their ability to handle non-linear trends and capture complex patterns in data and they are trained using backpropagation through time (Zheng et al., 2017).

To compare the performance of the selected methods, the dataset was divided into a training set (80%) and a test set (20%). The results of each method are presented in Figure 70, where the blue points represent the training set, the orange points represent the test set, and the green points represent the predicted values.

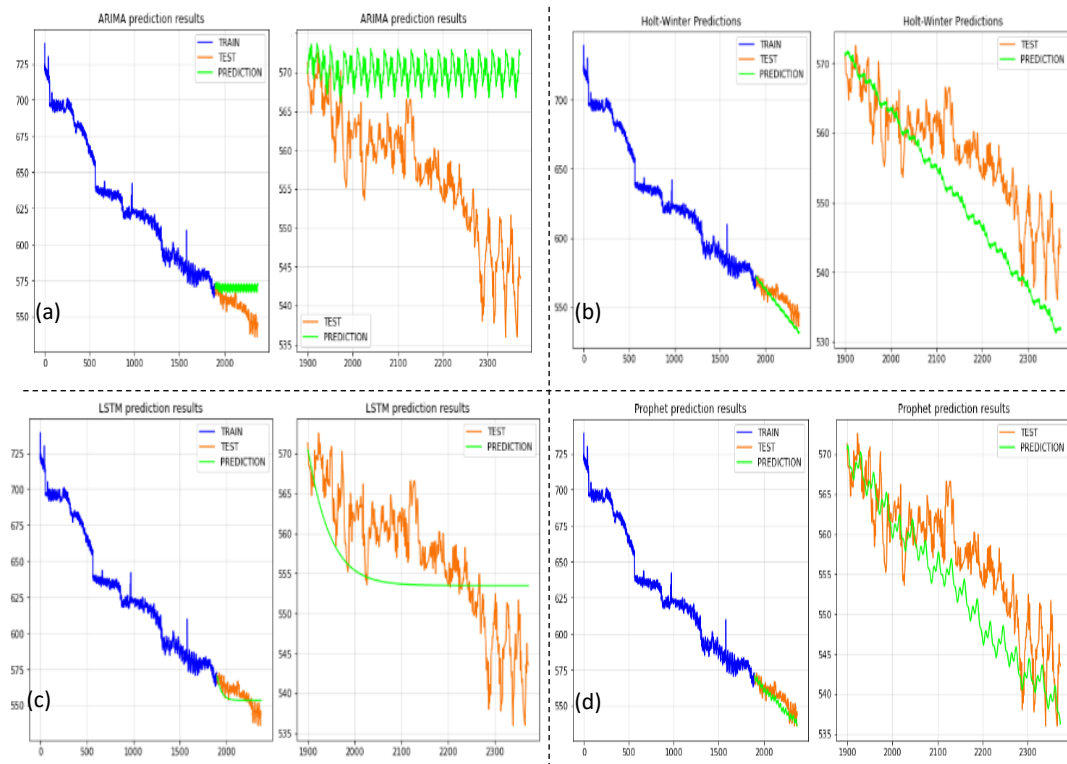


Figure 70. ARIMA (a), Triple Exponential Smoothing (Holt-Winter) (b), LSTM (c), and Prophet (d) prediction results

It is observed that the prophet and Holt-Winter's model can provide mid-term prediction, however, the ARIMA and LSTM methods give better predictions for closer times rather than longer times. In fact, despite their right training, for instance, LSTM worked well in less than 10 periods, but as the number of periods increased, it worked with less accuracy. This is probably due to the sequential nature of LSTM that gives predictions in different iterations based on the trained model. On the contrary, we observe that Holt-Winter can trace the seasonality, but not as well as the Prophet model. Concerning performance metrics, the RMSE and MAPE of the four models are obtained in Table 11, which Prophet method has the best overall performance among the four methods. The Halt-Winter method also has a relatively low RMSE and MAPE indicating it is the second-best method. The ARIMA and LSTM methods both have significantly higher RMSE and MAPE values, indicating that they may be less effective in estimating RUL in this use case. The results also indicate that although Prophet was created for business time series, we observed that it can also work well for the RUL estimation. It can provide a prediction for the data with a non-fixed interval of period, while the three other methods need a fixed interval between the periods.

Table 11. Performance metrics of prediction methods

	Prophet	ARIMA	Holt-Winter	LSTM
RMSE	5.510	15.438	7.990	14.988
MAPE	0.091	0.154	0.110	0.155

The presented algorithm allows for continuous estimation of the RUL of the entire chain, and the developed model runs in a local Edge system. The next step is to adopt an applied maintenance strategy based on RUL information. When the RUL is identified within the defined prediction horizon, the maintenance team inspects the length of 10 chain links randomly. If the lengths of the chains show relatively equal degradation (homogeneous), two chain links should be removed to maintain the equilibrium of the entire chain. If not, the degradation is not homogenous, then fault localization should be done and, on this basis, most degraded chain links are identified and changed.

As a concluding remark for the RUL estimation section, it can be noted that the Prophet prediction method is an interesting approach for estimating RUL. Based on our review of prediction methods in the state-of-the-art literature, it appears that the Prophet method is rarely utilized for RUL estimation, at least to the best of our knowledge. In this problem, deep learning methods, like LSTM, may increase the complexity of parameter tuning leading to a longer training time. LSTM and ARIMA models do not perform well in mid/long-term predictions. On the other hand, the triple exponential smoothing model can provide better predictions, but still, it requires the identification of the seasonality period. While the Prophet model self-detects the changepoints and seasonality periods, and it captures the seasonality and irregular events better than the triple exponential smoothing method. Its performance is proved by comparing it with ARIMA, triple exponential smoothing, and LSTM methods that can provide more reliable predictions and hence RUL estimation. Regarding industrial problems, triple exponential smoothing, or the Prophet method may be sufficient for RUL estimation that depends on the desired level of prediction exactitude.

The proposed dynamic RUL algorithm self-tunes the model parameters and re-estimates the RUL following the new real-time data in the time epochs. The efficiency of computational time and needed resources for application in an industrial environment (as in, Edge, Fog, or Cloud) can be studied by the research community. RUL calculation remains part of the information that must be served for maintenance strategy identification and maintenance planning which will be presented in the next chapter.

So far in this chapter, we have presented the equipment health monitoring and RUL estimation and their application in the use cases. As mentioned in the introduction, the next section will focus on the maintenance monitoring systems and KPIs.

5.5 Maintenance indicators identification and measurement

Based on the study of maintenance KPIs in the literature, the most important maintenance monitoring indicators are identified which are presented in Table 12. It is necessary to identify relevant indicators (Bhadani et al., 2020b) for each use case. It is often neglected that all indicators may not be relevant to the different decision-making levels. Hence, it is proposed that each indicator could be suitable for certain decision levels, and it is important to allocate them to the suitable ones as follows:



Strategical: At this level, top management is engaged.



Tactical: At this level, maintenance managers and supervisors are engaged.


















Operational: At this level, lower-level supervisors and technicians are engaged.

Planning indicators provide a quick overview of the machine's maintenance schedule, delays, and the PvM compliance rate. *Maintenance cost indicators*, three important costs are related to the maintenance operation (labor), spare parts, and downtime. are essential to understand the costs associated with maintenance operations, such as labor, spare parts, and downtime. The ratio of these costs per total produced items over a defined period can be an interesting indicator from a management perspective.



Maintenance indicators are related to the performance of the maintenance system and machines. For example, tracking the type of maintenance activities and failure types per machine and component can provide insight into the maintenance situation. OEE (Overall Equipment Effectiveness) is a crucial indicator that is based on three criteria: availability, performance, and quality. However, the availability indicator is more closely related to maintenance. Availability shows the uptime level of each machine, which is the time when the machine is ready for operation. Performance measures the percentage of produced items compared to the capacity of production, while quality indicates the ratio of confirmed produced items to the total produced items.

The *spare part KPI* provides a global view of the spare parts resources and their consumption and purchase trends. *Equipment KPI* is a real-time HI based on sensor data which can represent the state of the component, part, or machine. It is important to assess the real-time state of an asset because of its impacts on maintenance planning, spare parts provision, and operational performance (Qiu et al., 2020). Monitoring the presented KPIs and HIs and tracing their evolution could help in obtaining visions of the maintenance situation, the machine's performance, and most important identification of possible improvement actions based on the indicator results.

Table 12. Selected maintenance indicators

Maintenance Indicator	Indicator type	Indicator boundary	Description	Decision Level
Planning indicators	KAI	MS ¹	Last inspection or maintenance	
	KAI	MS	Number delayed periods for preventive maintenance (PvM)	
	KAI	MS	Realized PvM/ Planned PvM per period	
Cost indicators	KPI	MS	Cost of failures (spare parts + maintenance operation)	
	KPI	MS	Maintenance operation cost per production output over a period	
	KPI	MS	Maintenance spare part cost per production output over a period	
	KPI	MS	Downtime cost per production output over a period	
Operational indicators	KPI	Machine & MS	Overall Equipment Effectiveness (OEE)	
	KPI	Machine	Availability	
	KAI	Machine	Reliability	
	KPI	Machine	MTBF	
	KAI	MS	Mean Time to Repair (MTTR)	
	KAI	MS	Stratification of corrective, preventive, and predictive maintenance	
	KAI	Machine	Stratification of failures in technological groups (Mechanical, Electrical, etc.)	
	KAI	MS	Number of Emergency Work Orders (EWO)/Root cause analysis	

¹ MS : Maintenance System

Spare parts indicators	KPI	MS	Total spare parts stock value per period	
Equipment indicators	HI	Machine	Real-time health indicators at the equipment level	

Measurement of maintenance KPIs is typically based on mathematical and statistical approaches. Some of the most important KPIs for maintenance monitoring are outlined below. To calculate OEE, the formula presented in equation (5.9) is commonly used. To calculate availability, information on planned and unplanned downtime, and failures of each machine is required. MTBF indicators only consider operational times (not calendar times) and the number of failures. The calculation methods for these KPIs are described as follows:

$$OEE = Availability \times Performance \times Quality \quad (5.9)$$

$$Availability \% = \frac{Operating\ time}{Planned\ production\ time} \quad (5.10)$$

$$Operating\ Time = Planned\ production\ time - Unplanned\ downtime \quad (5.11)$$

$$Planned\ Production\ Time = Shift\ length - Planned\ downtime \quad (5.12)$$

$$MTBF = \frac{Total\ hours\ of\ operation}{Total\ number\ of\ failures} \quad (5.13)$$

$$MTTR = \frac{Total\ hours\ of\ maintenance}{Total\ bnumber\ of\ repairs} \quad (5.14)$$

$$Performance \% = \frac{Total\ parts\ produced}{Capacity} \quad (5.15)$$

$$Capacity = \frac{Operating\ time}{Ideal\ cycle\ time} \quad (5.16)$$

$$Quality \% = \frac{(Total\ produced\ items - Total\ scrapped\ items)}{Total\ produced\ items} \quad (5.17)$$

Reliability is the probability that a system performs correctly during a specific time duration. The reliability distribution function is calculated based on failure rate λ (Woo, 2017):

$$\lambda = \frac{1}{MTBF} \quad (5.18)$$

$$Reliability \rightarrow R(t) = e^{-\lambda t} \quad (5.19)$$

5.5.1 Aggregation of indicators

Indicator aggregations are often necessary to summarize large amounts of data into meaningful and interpretable information for decision-making at higher levels. In some cases, detailed data is not necessary or relevant for top-level decision-makers. Aggregations can provide a more concise and simplified representation of the data, allowing decision-makers to quickly identify patterns, trends, and areas that require attention or improvement. Additionally, aggregations can help reduce data complexity, making it easier to analyze and interpret large datasets. Ultimately, aggregations can save time and resources by providing a more efficient way to communicate important information to decision-makers.

Aggregation can be performed on both equipment health states and maintenance KPIs or KAIs. When aggregating the health states, the process can start from the component level and move up to the machine level (Laloix et al., 2019). On the other hand, when aggregating maintenance KPIs or KAIs, the process

can start from the machine level and move up to the production lines, units, and finally the plant production level. Here are some of the main steps for aggregating indicators:

- 1) Identifying and proposing the appropriate KPIs
- 2) Calculation of the KPI: using appropriate methods
- 3) Finding the importance weight of the KPIs: such as mentioned weighting methods in [Table 4](#) (in section 4.1)
- 4) Normalization: remove the measurement unit so that all KPIs have uniformed values
- 5) Aggregation: based on the weights and normalized values, and using aggregation method (Ex: weighted sum)
- 6) Evaluation: evaluate the aggregated result and adjust the weights and aggregation method if necessary

5.6 Visualization dashboards

Data visualization techniques are being developed because of the constant change in data and the importance of transforming raw data into useful information. Data visualization is important for effective data analysis. Different types of plots can be used for KPI visualization (Lebanon & El-Geish, 2018b). For instance, a scatter plot or joint plot is a classic type of visualization allowing to show two numerical variables along two axes ([Figure 71-a](#)). Box plots illustrate ranges, minimum, maximum, and median values of a dataset, as well as first and second quartiles and outliers ([Figure 71-b](#)). The line plot, line chart, or seismograph chart displays information as a series of data points connected by a straight line. Time series are line plots that are useful for understanding trends over time ([Figure 71-c](#)).

The area plot is used when the area covered under a line plot is important. The greater the area is covered, the bigger the importance is ([Figure 71-d](#)). A bar chart shows categorical data with rectangular bars. The bar chart can be used to compare numerical values or data from several groups ([Figure 71-e](#)). A column chart is used to show a comparison between different attributes ([Figure 71-f](#)). A histogram divides data into several bins, then plots the frequency of data points in each bin ([Figure 71-g](#)). Pie charts show the proportions and percentages between categories using slices ([Figure 71-h](#)). The doughnut chart is similar to the pie chart, but with a hole in the middle. In the pie chart, the emphasis is on the size or area of the slices; however, in the doughnut one, the emphasis is on the length of the arcs ([Figure 71-i](#)). Gauge charts are a combination of pie and doughnut charts. They show the maximum, minimum, and current values of the data. There are different types of Gauge charts, such as the Speedometer ([Figure 71-j](#)), Rating meter ([Figure 71-k](#)), etc. A density plot is similar to an abstracted histogram, but instead of each bin, it has a smooth curve (kernel) through its top ([Figure 71-l](#)). Probability distribution plots are used to understand the distribution of data for a continuous variable. In prediction, forecasting, or finding trends, this kind of plot can be used ([Figure 71-m](#)). The heat map shows the correlation between all the features in a dataset using different colors ([Figure 71-n](#)). Pair plots are used to plot all possible joint plots for each pair of variables. In other words, it shows which variables are dependent or interdependent ([Figure 71-o](#)).

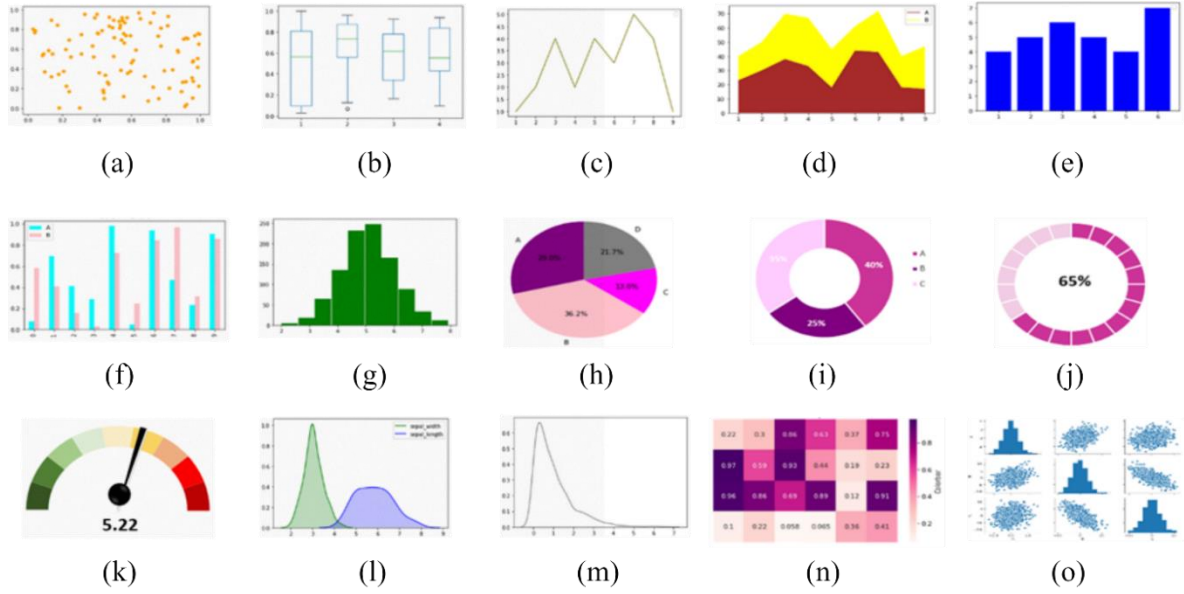


Figure 71. Visualization charts

The KPIs presented in Table 12 and the visualization charts in Figure 71, along with the health state indicators and expert opinions, provide the basis for developing visualization dashboards. These dashboards can be customized for decision-making at the machine or production system level. Based on the data and information from the CNC machine's use cases in FPT-BLY, we propose visualization dashboards to demonstrate the initial version for decision-makers and to facilitate further development of applied visualization dashboards. As a first step, we illustrate the proposed dashboard at the machine and production system level in Figure 72 and Figure 73 regarding the use cases.

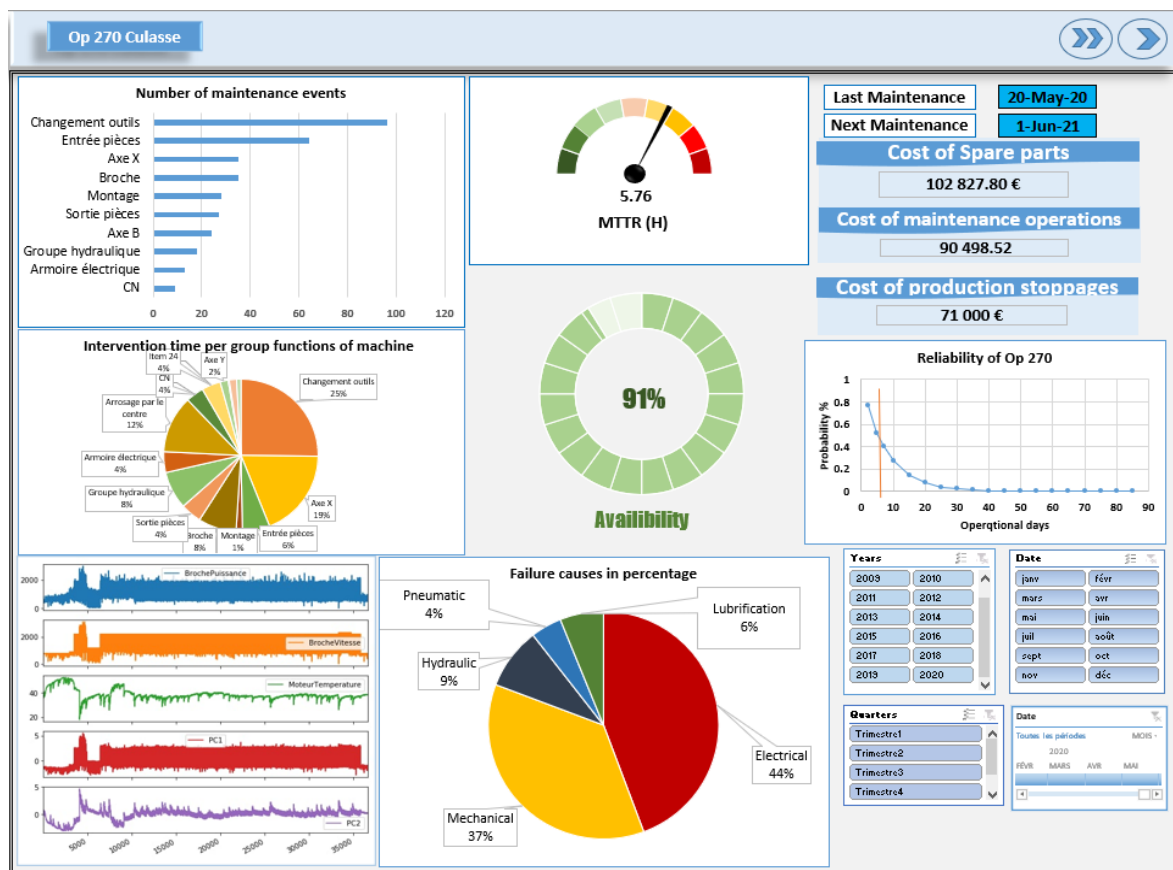


Figure 72. Dashboard at Machine Level

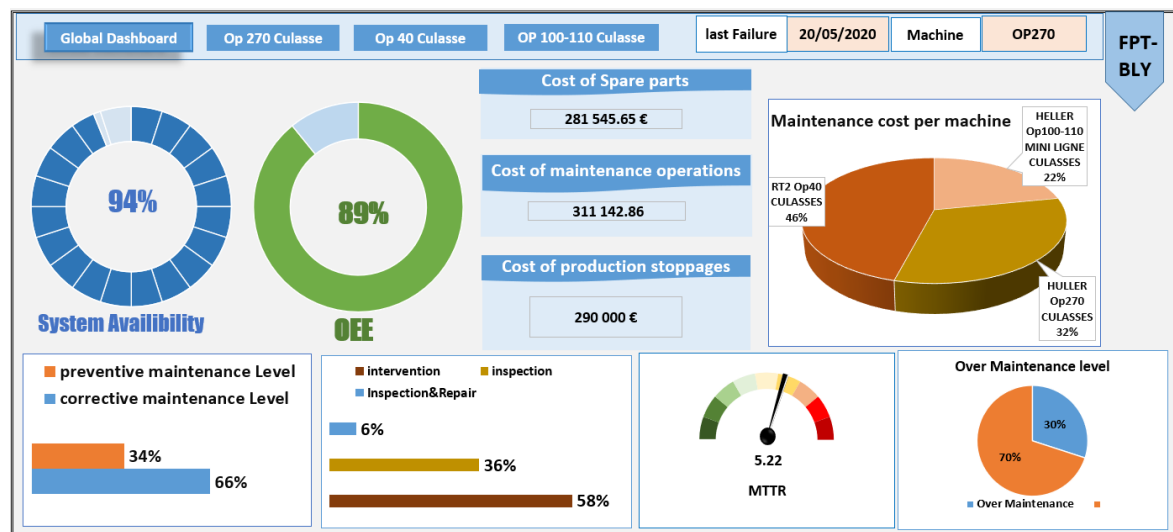


Figure 73. Dashboard at Global or System Level

The illustrated dashboards have brought better visions for the decision-makers and persuaded them to have similar dynamic visualization dashboards in their management system.

5.6.1 Application of visualization dashboards in FPT

Based on the presented indicators and dashboards, real visualization dashboards have been proposed for FPT-BLY that can be used to better analyze, monitor, and measure the performance of machines and maintenance systems. These dashboards are designed to provide users with an intuitive and interactive way to explore their data. For this purpose, it has been used of the information in the SAP system of FPT-BLY which contain the history of maintenance activities, and spare parts transactions. The extraction request of SAP is used to achieve the information. Regarding the data preparation and visualization, it has been proposed to use Power-BI Microsoft which is an interactive visualization tool. The first developed dashboard is presented in Figure 74.

The interactive dashboards enable the prioritization of the more critical machines based on the visualized KPIs in Figure 74. However, it should be noted that these dashboards are based on the available information in SAP extractions, and due to the lack of information some of the proposed KPIs were not possible to follow such as the failure stratification based on the technological group. Nevertheless, the description of the failure or intervention is available and based on the text mining visualization we can observe some of the main keywords in the interventions.

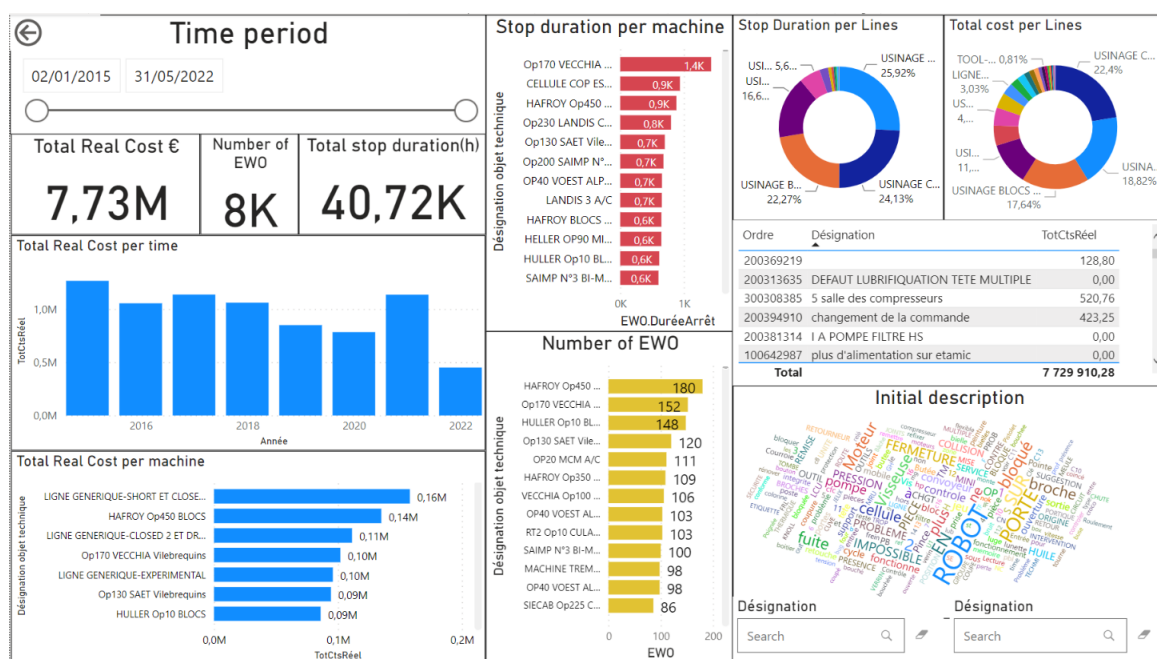


Figure 74. Applied visualization dashboard based on available information in FPT-BLY

To improve and test the implementation of KPIs, and health monitoring systems, some more indicators have been considered regarding OEE, PvM delays, and quality defects relating to machine problems. Based on these KPIs, a new visualization dashboard has been proposed for a pilot line of engine block machining, which is shown in below Figure 75:

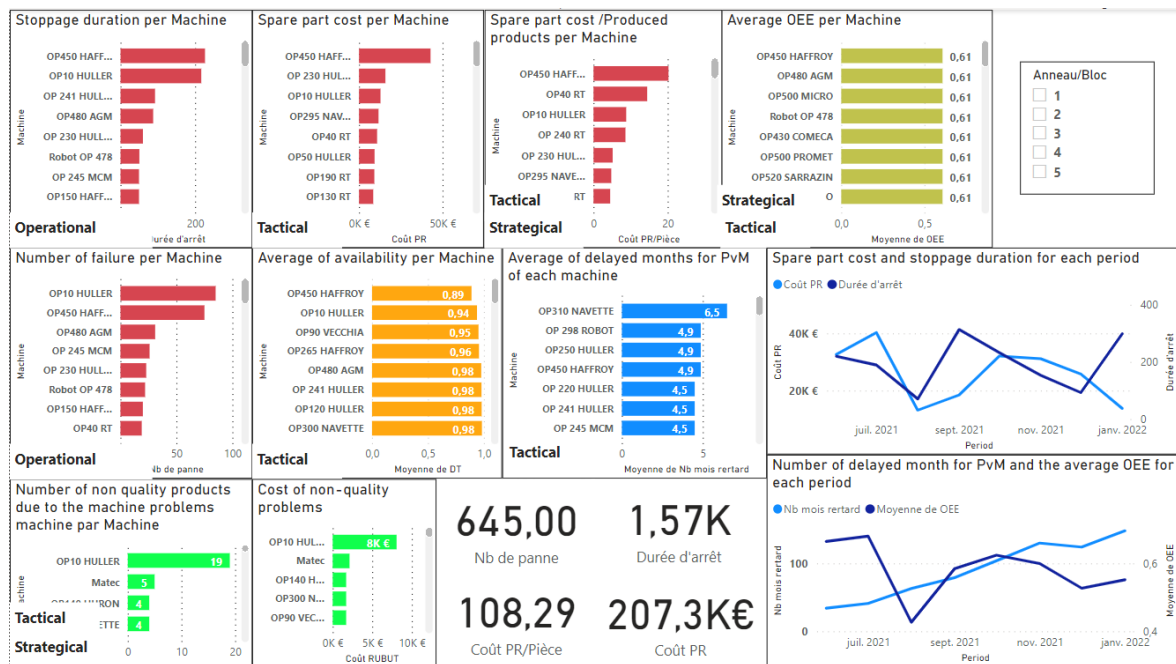


Figure 75. Applied visualization dashboard for the pilot line of engine block machining

Based on the results, and the experience more precise prioritization machines have come out from the health monitoring dashboard. Hence, further detailed root cause analysis of the group functions could be performed to identify improvement points and action plans based on the more critical machines found in the visualization dashboards. There are several areas for improvement, such as considering a different supplier for certain components, implementing a PdM activity or new PvM activities, adjusting the frequency of preventive maintenance cycles, or modifying the equipment design to enhance its reliability.

5.7 Chapter conclusion

To ensure efficient tracking and maintenance of a manufacturing plant's production assets, it is crucial to have monitoring systems that can accurately monitor and evaluate the working condition and performance of machines. There are two visions regarding monitoring systems: one in the machines/equipment and the other in the maintenance system. Equipment health monitoring and RUL estimation allow for monitoring and predicting the health state of equipment. On the other hand, maintenance monitoring systems track the performance of machines and maintenance systems. The primary goal of this chapter is to perform a feasibility analysis on the identification of health indicators (HI) and the estimation of Remaining Useful Life (RUL) utilizing real-time data. While many RUL studies typically concentrate on individual equipment, our objective is to investigate the possibility of obtaining HI and RUL using the existing real-time data from connected use cases in FPT-BLY and to explore the potential ways to leverage this information. Additionally, we aim to explore potential methods/models to obtain HI and RUL. Furthermore, this chapter aims to identify the most relevant maintenance Key Performance Indicators (KPIs) and visualization dashboards for maintenance monitoring systems, which are closely interconnected with the subject of equipment health monitoring.

Real-time and historical data management systems are essential for equipment health monitoring, remaining useful life (RUL) estimation, and maintenance monitoring. In this chapter, we initially present the IIoT platform and ERP system used by FPT-BLY, which facilitates data connection, acquisition, and historical information storage and collection.

Regarding equipment health monitoring and RUL estimation, a dynamic prognostic approach has been proposed. This approach was applied to study health indicators (HI) in the spindle engine of a CNC machine and RUL estimation in the case of conveyor chains. This study indicated that while it is possible to calculate the health state and remaining useful life (RUL) for some equipment/components, technical complexities, and unknown parameters can make it difficult or impossible to achieve accurate health HI and/or RUL estimations, even when the real-time data of machine/equipment is accessible. For example, although we obtained a health indicator for the spindle engine of the CNC machine, we could not provide RUL estimation due to the lack of run-to-failure data and a mostly constant health state trend over a long period of time. Therefore, this case was more compatible with a HI study and could be a potential focus for future research. Moreover, identifying the health indicator (HI) may be satisfactory in some cases and provide sufficient information for decision-making. In contrast, we proposed a new dynamic RUL estimation method and successfully achieved health state and RUL estimation for the conveyor chain case, and in the next chapter, we address how we can leverage this information for maintenance planning.

Since the main objective of this study is to explore the possibility of equipment health monitoring and remaining useful life (RUL) estimation, we did not aim to present complex methods of health indicator (HI) identification and RUL estimation. The precision and complexity of the models depend on several parameters such as security risks, the criticality of equipment, and implementation costs. In manufacturing cases where there are fewer security risks and equipment sensitivity, the major impact is on financial and production stoppages. Thus, simple methods may be sufficient in these cases. Furthermore, the design, tuning, precision, and interpretability of the RUL estimation models are the other aspects that should be considered in the development of dynamic RUL estimation models. For instance, the Prophet model was selected for RUL estimation due to its efficiency in capturing variable patterns, trends, and seasonality over relevant benchmark methods such as triple exponential, ARIMA, and LSTM. Although other complex deep learning methods could be studied and tested, the precision provided by the health state prediction and RUL estimation was sufficient for the use case. In these cases, dedicating a considerable amount of time to complex methods may not necessarily add value. However, the application of more advanced methods could be a perspective for future research.

We believe that these studies provide valuable insights into the decision-making aspect of equipment health monitoring and RUL estimation, such as identifying areas where advancements in health monitoring are needed, determining when RUL estimation is economically feasible, and selecting appropriate methods. To the best of our knowledge, these aspects, and the insights gained from an on-site researcher, are less addressed in the literature, and they are promising for the future of equipment health monitoring and RUL estimation.

The maintenance monitoring aspect of the study involved identifying the most pertinent KPIs and KAIs based on a literature review and on-site experience. These indicators can be used to identify the most critical areas (production lines/machines) and to determine improvement actions that increase the reliability of maintenance machines. The study also addresses visualization techniques and provides applicable visualization dashboards at both the machine and production system levels, highlighting the importance of aggregating indicators for a global view. Tracking these indicators enables monitoring of machine and maintenance team performance, which in turn provides actionable feedback for setting improvement goals and projects based on accurate measures.

Finally, it is important to recognize that while RUL estimation can provide cost savings and productivity improvements, resources for equipment health monitoring are often limited and not all machines require the same level of monitoring. Therefore, as presented in Chapter 4, it is necessary to prioritize the most critical equipment or machines for PdM implementation, as depicted in **steps 1 and**

2 of Figure 39. In the cases where it is not technically or economically feasible to install sensors for equipment health monitoring, alternative PdM approaches such as periodic inspections and controls can still be used to assess the machine's health status and reduce the risks of failure.

Looking at the general steps of the proposed predictive maintenance management system (Figure 39 and Figure 40), this chapter covered the general **step 3,4, and 5** which involves the descriptive and predictive phases. In the next chapter, the planning of maintenance activities would be presented (**step 6**).

6 Chapter 6: Maintenance planning

Maintenance planning corresponds to the prescriptive phase (step 6) of the proposed approach of the Predictive Maintenance Management System (PdMMS) (Figure 39 and Figure 40). Maintenance planning is an interdisciplinary domain that is inevitably followed by several technical, economical, and time complexities in order to be properly applied in various types of industries and management systems. Implementing an appropriate maintenance planning system requires having a maintenance management structure (centralized and/or decentralized) supported by industry-related resources (such as maintenance technicians and tools) and a proper maintenance planning method. The maintenance planning method should be as close as possible to the shop floor reality. The previous chapter focused on the feasibility study of RUL estimation. However, the main objective of this chapter is to explore how we can leverage RUL information for maintenance planning. In other words, we aim to investigate how maintenance planning would be impacted by the availability of RUL information.

The reason for studying such a maintenance planning problem is that relying solely on RUL information for maintenance planning of the entire plant production assets may not be sufficient. There are other factors to consider, such as: *i)* RUL estimation may not be available for all components due to resource limitations and technical feasibility *ii)* While there is uncertainty in RUL estimation, determining the optimal timing for maintenance is dependent on finding the right balance between the associated risk and cost. In some cases, performing maintenance earlier or later than estimated RUL may be a better option, and *iii)* The setup cost of performing maintenance on components or equipment with RUL can be significant and should be evaluated in a more comprehensive cost analysis. Therefore, it is necessary to combine both PdM and PvM strategies to optimize maintenance planning for the plant production assets. Nevertheless, RUL information could be considered as a complementary advantage for certain components or machines to reduce unforeseen failures. In industrial situations, regarding technical and economic aspects, it is often impossible to implement only one maintenance strategy. Hence, in real-world scenarios, simultaneous CM, PvM, and PdM strategies should be applied in maintenance systems. In this regard, one of the main challenges is to develop the planning of maintenance activities concerning all strategies simultaneously. It is often customary for these mixtures of strategies to be carried out through the same resources. In other words, it is impossible to utilize separate resources for each strategy, and all of them must be managed collectively.

To ensure effective maintenance planning, it is important to consider various types of complexities and aspects. In addition to the technical aspects of the machinery and equipment, other crucial factors to be included are the availability of resources such as maintenance experts and tools, as well as the availability of machines/equipment for maintenance activities. Another important consideration is the dependencies between components, such as economic/opportunistic grouping, structural, and stochastic dependencies.

It should also be noted that the level of complexity involved in maintenance planning can vary across different industries. For instance, in infrastructure projects, there are often pre-scheduled overhaul periods, while in transportation, predefined time slots make maintenance activities more manageable. Conversely, in manufacturing systems, equipment availability is typically limited due to production planning.

Following these considerations, in this chapter, a maintenance planning problem inspired by the conveyor chains system, which was addressed in the previous chapter, is studied and a new planning method is proposed. Although the problem has its roots in the automotive industry, it has a generic nature and can be applied in other industries as well. In this way, we studied the maintenance planning of several conveyors chains systems. We utilize real-time sensor data and historical information to

integrate both PdM and PvM strategies. Furthermore, we employ estimated RUL information as input in the maintenance planning method.

In continue, this chapter discusses the challenges associated with maintenance planning, including motivation, philosophy, and approach. We then proceed to define the problem and present the corresponding mathematical programming and solution method. Subsequently, we present the results obtained from an industrial case study and provide a discussion of the managerial insights gained from our findings. Finally, we conclusions are provided at the end of the chapter.

6.1 The approach of the PdM and PvM planning study

The key idea of this section is to elaborate more on the maintenance context in industrial manufacturing circumstances and to explain the approach and philosophy of PvM and PdM planning study.

As we have described, depending on the size of a manufacturing enterprise, there are several machines and equipment (or production assets) that are composed of several group functions, and components. One initial challenge or complexity in the industry is the identification of a maintenance strategy for each machine, and thereafter, the maintenance strategy for each group function or critical component in the interior of each machine. As is seen in [Figure 76](#), some components or groups of components may remain in the CM, PvM, or PdM strategies.

The emergence and evolution of the Internet of Things (IoT) technology and having access to real-time data provided an opportunity for industrial actors to move toward the PdM strategy. This approach begins with evaluating and choosing to monitor certain types of machines, group functions, or components, which are called supervision cases. Identification of supervision cases and selection of condition monitoring parameters and data concerning technical possibility, and/or financial feasibility types, remain the other challenging aspects. Although several papers have provided some guidelines about monitoring sensors, and data based on equipment type (J. Lee et al., 2014), this still needs to be identified in each industry based on its technical specifications like this study (Tiddens et al., 2018). It should again be noted that technical subjects intervene here regarding data acquisition systems, like sensor installations, programmable logic controller (PLC) data connection, Industrial Internet of Things (IIoT) architecture, data storage, etc. These aspects are represented in [Figure 76](#), which should be considered in the PdM strategy. This may require time, experimentation, and analysis to provide sufficient maturity outcomes from the condition monitoring data and to be able to monitor and observe the degradation or health state of the supervision cases. In this phase, data-science approaches, and techniques play an important role in finding predictive/machine learning (ML) models to estimate the health state and RUL of the supervision cases.

Calculation of the RUL information is not the only challenge in the industry, since the maintenance decision-making in an industrial context considers other maintenance strategies, industrial constraints, and criteria that would not be completely satisfied by RUL estimation. These aspects are listed below:

Considering several maintenance strategies together:

In industry, there may be some components/activities for which it is possible to apply and estimate RUL. However, preventive, or corrective maintenance strategies will still need to be used for a majority of other components/activities. How should we plan the maintenance activities, considering all the maintenance strategies?

Dependencies between the components:

The three main dependencies that exist in the literature are economical, structural, and stochastic (or functional). Economical dependency is related to the opportunity to perform other maintenance activities at the same time (opportunistic grouping), which would result mainly in savings of setup time. Structural dependency is related to the physical position of the components so when there is a need for the maintenance of one component, other components must be also maintained. Stochastic dependency is the degradation effects of components on each other.

Some challenges are presented by maintenance planning that is based on dependencies between the components in the same group function. As an example, in a Computer Numerical Control (CNC) machine, the motor, gearbox, and spindle could be followed together when it is necessary to maintain one of them.

Unexploited life of the components:

Planning the maintenance of components imposes a loss due to the unused life of the components. This loss is hidden since the costs of current operating spare parts are already paid. Missing this consideration would result in economic losses from excess usage of spare parts.

Interaction of several RUL information together:

Once again, the reason we remark that RUL estimation is not sufficient is that we cannot wait until the last predicted moment for performing maintenance, based on the abovementioned aspects. In the industry, we do not have only one RUL. When there are multiple RULs for different components, it is important to see the relationships of RULs with the other aspects.

In a holistic approach, the aspects mentioned in this section must be investigated in maintenance planning and/or scheduling. However, maintenance planning is performed for mid to long-term horizons by considering available capacities over longer periods. Proper maintenance planning would largely reduce failures and CM needs. In contrast, the horizon and period of decision-making in scheduling are shorter. In maintenance scheduling, the allocation of maintenance resources to maintenance activities at precise dates and times is identified. Furthermore, knowing that CM activities are still unknown during maintenance planning, they are integrated into the maintenance scheduling problem. In fact, the maintenance planning results feed into the scheduling problem, and the quality of planning has a big impact on maintenance scheduling.

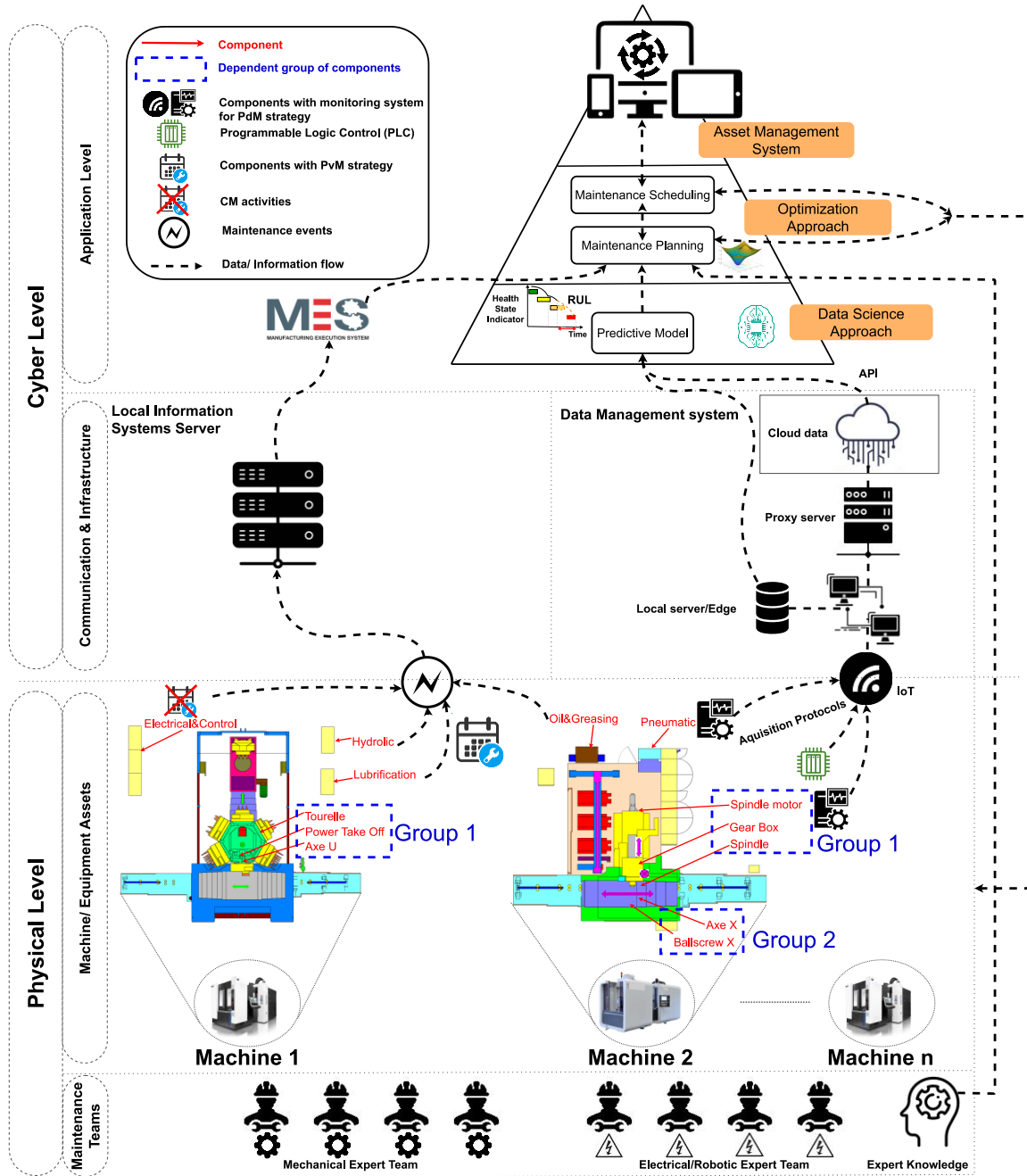


Figure 76. A general graphic of the proposed maintenance management approach with real-time data and historical information

6.2 Problem description and modeling

6.2.1 Problem definition

Based on the real-world industrial challenges stated in section 6.1, the objective of this study was to model the realistic industrial conditions of a maintenance planning system. The maintenance planning problem is made up of the set of I predefined maintenance activities included in J machines/equipment ($i \in I_j$). Based on the structural dependencies of each machine, a subset of I activities, called set G , may be included in the individual groups of maintenance activities ($i \in I_g$). Depending on the strategy for

each activity, a subset of I_j' or I_j'' is dedicated. In the case of PdM activities, they are considered in the subset $I_j' \subset I_j$, and the subset of $I_j'' \subseteq I_j$ belongs to PvM activities. PvM activities are mainly followed through a MTBF. The MTBF is mostly obtained from historical failure data, the supplier-suggested frequency for the activity, or a customized adjusted frequency considering both supplier and failure data. In this study, a general term of frequency (Fr) is considered to represent commonly the cycle of performing maintenance activities. For example, MTBF or cycle of preventive activities is considered in the developed model as Fr .

The maintenance planning is performed within the time horizon with T number of periods. Although the planning is based on the nominal frequency, it can be made into an interval of a minimum and maximum acceptable frequency. This is due to the industrial and technical conditions where a fixed interval does not work as well in practice. Hence, considering a technical tolerance as Fr^{min} and Fr^{max} is more interesting. Each activity follows a failure pattern depending on the type of activity. This failure risk increases as the number of periods increases. At the same time, a penalty cost of unused life would be allocated to the activities that have components to replace or repair. This penalty cost decreases as the planning period increases until it reaches its nominal frequency Fr (Once the components have reached their nominal Fr , they have met their anticipated service life. Thus, any additional losses after this point is not taken into consideration). This concept is presented in Figure 77.

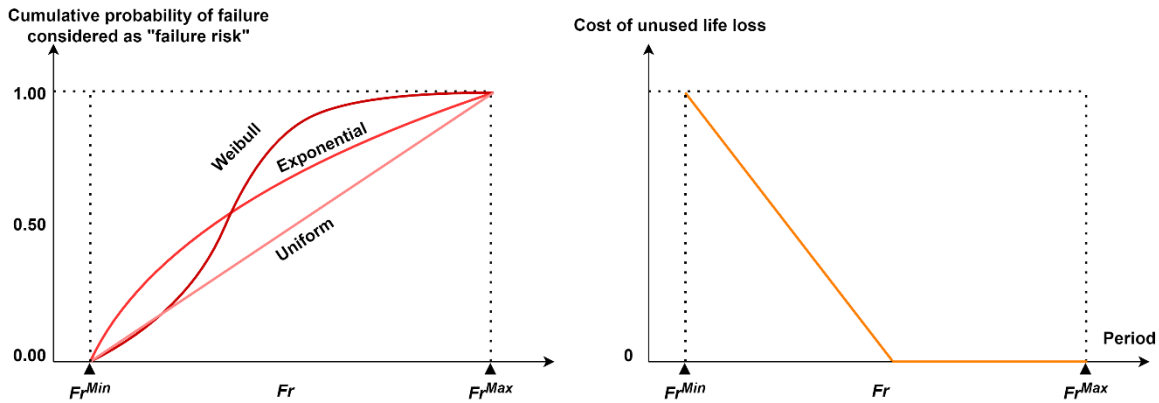


Figure 77. Illustration of Failure risk and unused life loss

In terms of maintenance resources, two groups of maintenance experts are considered: mechanical and electrical maintenance experts. For each activity, a certain number and hours of availability of experts are needed. There is a limited number of experts in each decision period. The problem is which maintenance activities must be performed in which periods (through the variable X_{ijt}), so that the total expected maintenance costs are minimized over the horizon T . Additionally, the problem is if the activities should be performed in the groups or individually and how these activities must be planned so that the limitations of the experts' availability are satisfied.

To obtain insightful results, the following assumptions are considered:

- Through the subset G , the opportunistic grouping of components (economic dependency) and structural dependency between the components in the maintenance activities are modeled.
- A reduction rate (α_{gj}) of man-hour cost related to each individual opportunistic group on the machines ($g \in G_j$) is considered to save setup costs. The more activities of the same group allocate in one period, the more setup cost saving will be applied.
- To simplify the mathematical modeling, it is considered that in general the term frequency (Fr) represents MTBF, useful life (UL) (which is the expected life of a component or equipment), or

preventive action frequency. Regardless of the maintenance strategy, the term Fr represents the cycle that a maintenance activity should take place. The difference between MTBF and UL is in their nature, since MTBF is calculated from failure data, while UL is calculated based on real-time data and not necessarily from failures (replacements instead).

- The minimum/maximum frequency can be related to the minimum/maximum time between failures (TBF) or minimum/maximum useful life, depending on the maintenance strategy.
- As presented in Figure 77, the probability of failure in each maintenance activity ranges from 0 in the minimum frequency (Fr^{min}) to 1 in the maximum frequency (Fr^{max}).
- For the activities in the PdM strategy, the probability of failure is between the upper and lower limits of RUL estimation error β . This is applied to the first intervention. For further interventions, the failure risk is between Fr^{min} and Fr^{max} . This is because the RUL information is valid only for the next intervention. For the rest of the interventions, Fr information should be used.
- Knowing that CM cannot be planned, its effect is seen in the failure risk consideration for each PvM and PdM activity.
- The failure Probability Density Function (PDF) of each maintenance activity can be customized based on its type and parameters, such as the including components, etc. The PDF of maintenance activities could be linear, exponential, or Weibull distributions. In this problem, for simplicity of linearization, we consider only uniform PDF. However, it is advised to consider linear PDF for PdM activities, exponential PDF for PvM activities that are in their constant failure period (based on bathtub curve), and Weibull in their decreasing and increasing failure period (early and wear out failure).
- The unused life cost of the components for each period is considered through a ratio of the price of components to their Fr .

The tradeoffs which make the problem more complex are as follows:

- Between the expected failure/stoppage cost and the unused life of components
- Between the grouping of activities into one period and individual interventions in several periods: See Figure 78 as an industrial example
- Between planning in an earlier period with more interventions or planning in a later period with a smaller number of interventions

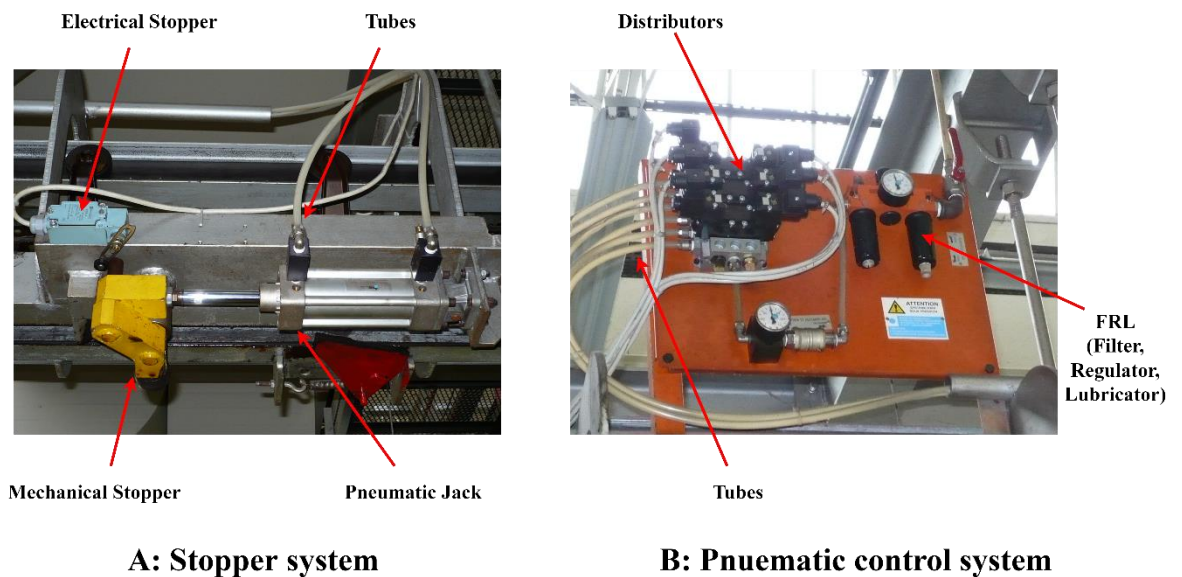


Figure 78. An industrial example of grouping maintenance interventions

In the opportunistic grouping example in Figure 78, suppose that when the pneumatic jack is predicted to be changed or controlled, then FRL, distributors, and electrical stoppers can be replaced or controlled at the same time. This is due to the functional relationship between them. When the parts are replaced, they will be repaired and returned to the spare parts stock.

6.2.2 Mathematical programming

In this section, the details of the developed mathematical model are presented. The objective of this mathematical model is the minimization of overall maintenance costs.

Sets and indices

J	Set of machines, and index $j \in J$
I_j	Set of maintenance interventions on machine j , and index $i \in I_j$
I'_j, I''_j	I'_j is the set of maintenance interventions on machine j , that have RUL. I''_j is the set of maintenance interventions on machine j , that have MTBF or frequency data, where $I'_j \cup I''_j = I_j$ and $I'_j \cap I''_j = \emptyset$
I_g	Set of maintenance interventions related to group g , and index $i \in I_g$
G_j	Set of groups of maintenance interventions on machine j , and index $g \in G_j$
T	Set of periods (month, week), and indices $t, t' \in T$

Parameters

The parameters are as follows:

P_{ij}	The purchase cost of the component for the maintenance intervention i in the machine j
D_{ij}	Passed time from the last maintenance intervention i in machine j (at the beginning of the decision-making period)
Fr_{ij}^{min}	The minimum frequency for the maintenance intervention i in machine j
Fr_{ij}	Nominal frequency for the maintenance intervention i in machine j
Fr_{ij}^{max}	Maximum frequency for the maintenance intervention i in machine j
RUL_{ij}	The remaining useful life of the component in maintenance intervention i in machine j (at the decision-making period)
β_{ij}	Accepted tolerance (or prediction error) for performing maintenance intervention i in machine j (if RUL_{ij} is available)
NMO_{ij}	Number of mechanical operators needed for performing maintenance intervention i in machine j
TM_{ij}	Needed time for the mechanical experts to perform maintenance intervention i in machine j
NEO_{ij}	Number of electrical operators needed for performing maintenance intervention i in machine j
TE_{ij}	Needed time for the electrical experts to perform maintenance intervention i in machine j
RMH	Rate of man-hour cost
$TCcm_{ij}$	Total Cost of performing CM for the maintenance intervention i in machine j . This cost involves, spare part cost, man-hour cost, and production stoppage cost
AMO_t	Available man-hours of mechanical operators at period t
AEO_t	Available man-hours of electrical operators at period t
AM_{jt}	Available number of hours for the machine j at period t for the maintenance intervention
α_{gj}	The reduction rate of man-hour cost related to group g on machine j

CMH_{ij}	Cost of man-hour for performing maintenance intervention i in machine j which is obtained as follows: $(NMO_{ij} TM_{ij} + NEO_{ij} TE_{ij}) RMH$
M	A big positive number

Decision variables

The decision variables are divided into 2 categories: the principal decision variable and the modeling decision variables:

Principal decision variable:

X_{ijt}	Binary variable, if a maintenance intervention i in machine j is planned at period t , $X_{ijt} = 1$, otherwise $X_{ijt} = 0$
-----------	--

Modeling decision variables:

Y_{ijt}	Integer variable indicating the number of maintenance interventions i in machine j until period t
Z_{ijtn}	Binary variable; if the n^{th} order maintenance intervention i in machine j is planned at period t , $Z_{ijtn} = 1$, otherwise, $Z_{ijtn} = 0$
X'_{gjt}	Binary variable; if the number of maintenance interventions related to group g on machine j at period t is equal to or greater than 2, $X'_{gjt} = 1$, otherwise, $X'_{gjt} = 0$
L_{ij}	A positive variable that indicates that unused life in the first maintenance intervention i in machine j is planned before its RUL , otherwise, $L_{ij} = 0$ (For the activities in subset I'_j)
K_{ij}	A positive variable that indicates that the unused life in the first maintenance intervention i in machine j is planned before its Fr , otherwise, $K_{ij} = 0$ (For the activities in subset I''_j)
θ_{ijn}	A positive variable that indicates that the unused life of each maintenance activity that is planned before its Fr_{ij} , otherwise, $\theta_{ijn} = 0$ (For the second or further ($n \geq 2$) maintenance intervention i in machine j)
φ_{ijn}	A positive variable that indicates the duration of each maintenance period from its Fr_{ij}^{min} . When the maintenance is planned on its Fr_{ij}^{min} , then $\varphi_{ijn} = 0$. (For the second or further ($n \geq 2$) maintenance intervention i in machine j).

For more clarification of the decision variables, the unused life losses, and the failure risk intervals in the first and subsequent maintenance interventions, see [Figure 79](#). These intervals are used in the objective function.

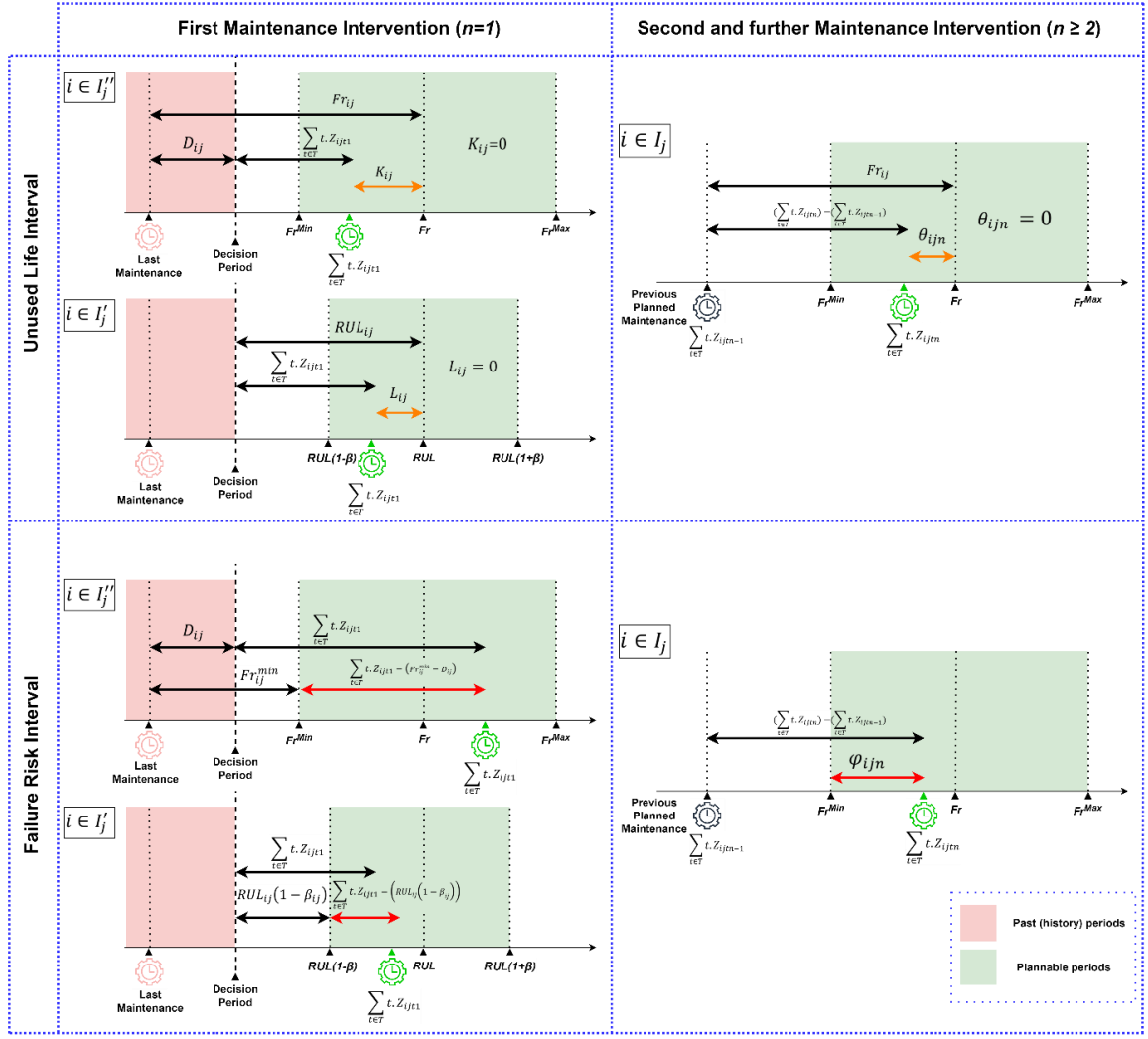


Figure 79. The illustration of unused life losses and the failure risk intervals

6.2.3 Mathematical formulation

$$\begin{aligned}
 \text{Min } \zeta = & \sum_{i \in I_j} \sum_{j \in J} \sum_{t \in T} (P_{ij} + CMH_{ij}) X_{ijt} - \sum_{j \in J} \sum_{g \in G_j} \sum_{t \in T} \left[\sum_{i \in I_g} (CMH_{ij} X_{ijt}) \times (\alpha_{gj} X'_{gjt}) \right] \\
 & + \sum_{i \in I'_j} \sum_{j \in J} \frac{P_{ij}}{Fr_{ij}} L_{ij} + \sum_{i \in I'_j} \sum_{j \in J} \frac{P_{ij}}{Fr_{ij}} K_{ij} + \sum_{i \in I_j} \sum_{j \in J} \frac{P_{ij}}{Fr_{ij}} \sum_{\substack{n \in N, \\ n \geq 2}} [\theta_{ijn}] \\
 & + \sum_{i \in I'_j} \sum_{j \in J} TCcm_{ij} \beta_{ij} \left[\frac{\sum_{t \in T} t \cdot Z_{ijt1} - (RUL_{ij}(1 - \beta_{ij}))}{2 RUL_{ij}} \right] \\
 & + \sum_{i \in I'_j} \sum_{j \in J} TCcm_{ij} \left[\frac{\sum_{t \in T} t \cdot Z_{ijt1} - (Fr_{ij}^{min} - D_{ij})}{Fr_{ij}^{max} - Fr_{ij}^{min}} \right] \\
 & + \sum_{i \in I_j} \sum_{j \in J} TCcm_{ij} \sum_{\substack{n \in N, \\ n \geq 2}} \left[\frac{\phi_{ijn}}{Fr_{ij}^{max} - Fr_{ij}^{min}} \right]
 \end{aligned} \tag{6.1}$$

Subject to:

$$Y_{ijt} = \sum_{t' \in T, t' \leq t} X_{ijt'} \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.2)$$

$$X_{ijt} Y_{ijt} = \sum_{n \in N} n \cdot Z_{ijtn} \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.3)$$

$$\sum_{n \in N} Z_{ijtn} \leq 1 \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.4)$$

$$\left(\sum_{t \in T} t \cdot Z_{ijt1} \right) \leq RUL_{ij} (1 + \beta_{ij}) \quad ; \forall i \in I'_j, j \in J \quad (6.5)$$

$$\left(\sum_{t \in T} t \cdot Z_{ijt1} \right) \geq RUL_{ij} (1 - \beta_{ij}) \quad ; \forall i \in I'_j, j \in J \quad (6.6)$$

$$(D_{ij} + \sum_{t \in T} t \cdot Z_{ijt1}) \leq Fr_{ij}^{max} \quad ; \forall i \in I''_j, j \in J \quad (6.7)$$

$$(D_{ij} + \sum_{t \in T} t \cdot Z_{ijt1}) \geq Fr_{ij}^{min} \quad ; \forall i \in I''_j, j \in J \quad (6.8)$$

$$\left(\sum_{t'=t+Fr_{ij}^{min}}^{t+Fr_{ij}^{max}} X_{ijt'} \right) + (1 - X_{ijt}) \times M \geq 1 \quad ; \forall i \in I_j, j \in J, t \in T, t \leq |T| - Fr_{ij}^{max} \quad (6.9)$$

$$\left(\sum_{t'=t+1}^{t+Fr_{ij}^{min}-1} X_{ijt'} \right) - (1 - X_{ijt}) \times M \leq 0 \quad ; \forall i \in I_j, j \in J, t \in T, t \leq |T| - Fr_{ij}^{max} \quad (6.10)$$

$$\left(\sum_{t'=t+1}^{t+Fr_{ij}^{min}-1} X_{ijt'} \right) + (1 - X_{ijt}) \times M \geq 0 \quad ; \forall i \in I_j, j \in J, t \in T, t \leq |T| - Fr_{ij}^{max} \quad (6.11)$$

$$RUL_{ij} - \sum_{t \in T} t \cdot Z_{ijt1} \leq L_{ij} \quad ; \forall i \in I'_j, j \in J \quad (6.12)$$

$$Fr_{ij} - (D_{ij} + \sum_{t \in T} t \cdot Z_{ijt1}) \leq K_{ij} \quad ; \forall i \in I''_j, j \in J \quad (6.13)$$

$$Fr_{ij} - \left(\left(\sum_{t \in T} t \cdot Z_{ijtn} \right) - \left(\sum_{t \in T} t \cdot Z_{ijtn-1} \right) \right) \leq \theta_{ijn} + \left(1 - \sum_{t \in T} Z_{ijtn} \right) M \quad ; \forall i \in I_j, j \in J, n \in N, n \geq 2 \quad (6.14)$$

$$\left(\sum_{t \in T} t \cdot Z_{ijtn} \right) - \left(\sum_{t \in T} t \cdot Z_{ijtn-1} \right) - Fr_{ij}^{min} \leq \varphi_{ijn} \quad ; \forall i \in I_j, j \in J, n \in N, n \geq 2 \quad (6.15)$$

$$\sum_{j \in J} \sum_{g \in G_j} \sum_{i \in I_j} (NMO_{ij} TM_{ij} X_{ijt}) (1 - \alpha_{gj} X'_{gjt}) \leq AMO_t \quad ; \forall t \in T \quad (6.16)$$

$$\sum_{j \in J} \sum_{g \in G_j} \sum_{i \in I_g} (NEO_{ij} TE_{ij} X_{ijt}) (1 - \alpha_{gj} X'_{gjt}) \leq AEO_t \quad ; \forall t \in T \quad (6.17)$$

$$\sum_{g \in G_j} \sum_{i \in I_g} \max(TE_{ij}, TM_{ij}) (1 - \alpha_{gj} X'_{gjt}) X_{ijt} \leq AM_{jt} \quad ; \forall j \in J, t \in T \quad (6.18)$$

$$\sum_{i \in I_g} X_{ijt} - 2 \geq (X'_{gjt} - 1) * M \quad ; g \in G_j, \forall j \in J, t \in T \quad (6.19)$$

$$\sum_{i \in I_g} X_{ijt} - 1 \leq X'_{gjt} * M \quad ; g \in G_j, \forall j \in J, t \in T \quad (6.20)$$

$$X_{ijt}, Z_{ijtn}, X'_{gjt} \in \{0,1\} \quad ; \forall i \in I, g \in G, j \in J, t \in T, n \in N \quad (6.21)$$

$$Y_{ijt}, L_{ij}, \varphi_{ijn}, \theta_{ijn} \in \mathbb{Z}^+ \quad ; \forall i \in I, j \in J, t \in T \quad (6.22)$$

Equation (6.1) is the objective function that minimizes costs of spare parts, man-hours, unused life of spare parts, and expected failures/breakdowns. Equations (6.2), (6.3), and (6.4) are the modeling constraints to create the variable Z_{ijtn} which indicates the order of intervention in addition to the variable X_{ijt} . Equations (6.5) and (6.6) control the first intervention period based on RUL information for PdM activities. Equations (6.7) and (6.8) control the first intervention period with respect to length of time that has passed since the last intervention. Furthermore, the planned period must be between the interval of Fr^{min} and Fr^{max} for PvM activities. Equations (6.9), (6.10), and (6.11) ensure the correct sequence of interventions for each activity for the second and further interventions. In equations (6.12) and (6.13), the unused life losses of the components in the first maintenance activities are calculated. The same value is calculated but for the second and further interventions in equation (6.14). In equation (6.15), the interval of failure risk is obtained for the second and further interventions. This is achieved from the difference between the current and previous intervention periods minus Fr^{max} . This is used for the expected failure cost calculation in the objective function. Equations (6.16) and (6.17) check the availability of mechanical and electrical experts in each decision period. In the case of economic grouping, the reduced values of needed experts would be applied. Equation (6.18) checks the availability of equipment or machine for each period. Equations (6.19) and (6.20) are the modeling constraints to create the variable X'_{gjt} , which indicates if the number of allocated maintenance activities of the same group in each period is equal to or more than two activities. The reduction rate of manhours (economic grouping saving) is activated when this variable takes value. Equations (6.21) and (6.22) are related to the decision variables.

Linearization formulation

In the primary formulation, there are two multiplications that violate the linearization; therefore, these have been linearized based on the following variables and equations:

Q_{ijt} Integer variable for the linearization of $X_{ijt} * Y_{ijt}$

X''_{igjt} Integer variable for the linearization of $X_{ijt} * X'_{gjt}$

$$Q_{ijt} \leq Y_{ijt}, \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.23)$$

$$Q_{ijt} \leq M X_{ijt}, \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.24)$$

$$Q_{ijt} \geq Y_{ijt} - (1 - X_{ijt})M, \quad ; \forall i \in I_j, j \in J, t \in T \quad (6.25)$$

$$X_{ijt} + X'_{gjt} \geq 2X''_{igjt}, \quad ; \forall i \in I_j, g \in G_j, j \in J, t \in T \quad (6.26)$$

$$X_{ijt} + X'_{gjt} \leq X''_{igjt} + 1, \quad ; \forall i \in I_j, g \in G_j, j \in J, t \in T \quad (6.26)$$

6.3 Implementation and obtained results

6.3.1 Use case: conveyer chain system

Once again as presented in section 5.4.1, the case of FPT-BLY is presented in this section but with more details. The problems are related to a set of conveyor chain systems that need to be maintained at the same time. FPT-BLY has several engine assembly lines, and there are 5 conveyor chains that lead the assembled engines into the painting station. In Figure 80, an engine that is lifted by the conveyer chain is presented. As can be seen, there are two rails; the upper one moves the engine, and the bottom one bears the weight of the engine.



Figure 80. An engine lifted in the conveyer chain

The conveyor chains generally have some main functions, which are: power drive, tensioner, chain links, stoppers, load/unload system, lifting system, greasing system and transfer system. These main functions are seen in Figure 81. The power drive system is composed of a motor, a reducer, two gears, and a driving chain that drives the chain links. Chain links are the male and female I-Beams connected in series. The tensioner system maintains the equilibration of the whole chain based on the lifted weights of the engines with the help of a jack. The stoppers are installed throughout the rails. Some have security functions when a chain link is broken. Others served to keep the lifted engines in the sequence of the queue for the washing and paint stations. There is also a loading and unloading system in which the engines are lifted to or discharged from the chains once the painting operation is done.

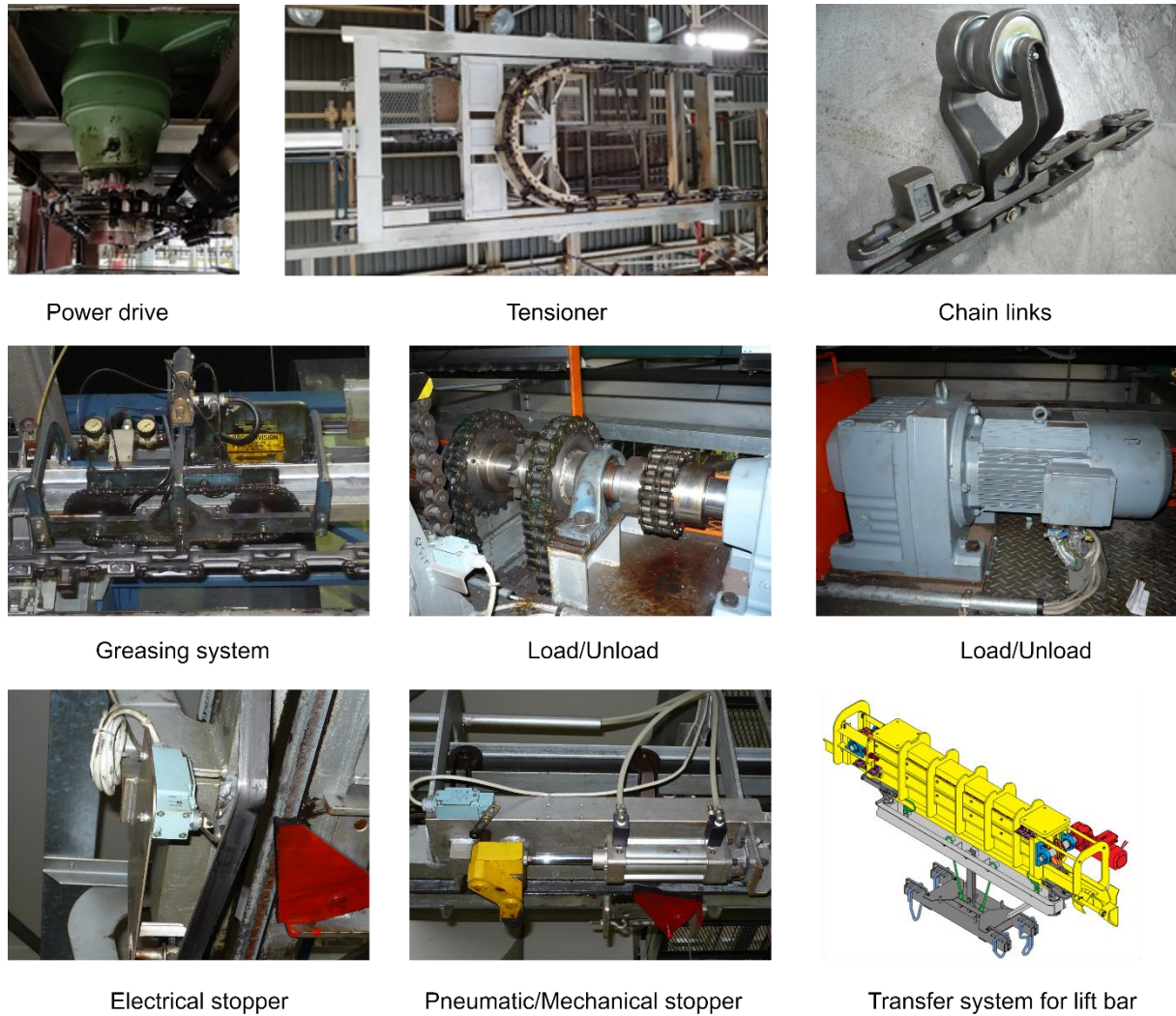


Figure 81. Main functions of the conveyer chain system

There are identified PvM and PdM activities (including inspection and repairing activities) that should be performed to keep the chain in production continuously. Regarding PdM activities, the elongation of the whole chain links can be monitored and predicted. When the chain breaks or stretches enough to reach the limit of the tensioner, the whole conveyer is then forced to stop. Through an ultrasonic sensor that measures the position of the tensioner, it is possible to monitor this elongation and estimate the RUL of the whole chain. The sensor data comes through the IoT architecture. In a previous study (Behnam Einabadi et al., 2022), the approach and the method for estimating dynamic RUL are explained. In this regard, it is worth noting that the techno-economic feasibility of adding sensors, and the value added by using real-time data collection, have already been considered.

Regarding PvM activities, the set of preventive measures is already identified by the supplier or proposals by the maintenance experts. The problem is how the maintenance activities should be planned to reduce the failure risks and minimize the maintenance costs.

6.3.2 Instance problems

Based on the explained case in the previous section 6.3.1, 21 instance problems of different sizes are extracted in order to validate the proposed model. This yields five problems with one piece of equipment (Ins.01 to Ins.05), five problems with two pieces of equipment (Ins.06 to Ins.10), five problems with three pieces of equipment (Ins.11 to Ins.15), five problems with four pieces of equipment (Ins.16 to

Ins.20), and one problem with five pieces of equipment (Ins.21). The characteristics of these problems can be found in Table 13.

To provide a general idea of the instances' parameters, the following information is worth noting. The spare part replenishment costs are between 30€ and 550€ with an average of 100€. The useful life (UL) (which is the expected life of a component or piece of equipment) and MTBF are between 16 and 30 weeks with an average of 20 weeks. The average RUL value is 11 weeks. The CM cost (involving production stoppage cost) is between 2,000€ and 5,500€ with an average of 2,600€. The expected failure cost $TCcm_{ij}$ is calculated based on these values.

Table 13. General aspects of the instances for the experiments

Instances	Equipment/ Machines	N° of maintenance activities	N° of activities (PdM, PvM)	Member number of the groups (I_g)	Available man-hours of mechanical operator	Available man-hours of Electrical operator
Ins.01	E1	8	(4,4)	(3,1,1,3)	48 h/period	48 h/period
Ins.02	E2	10	(4,6)	(5,1,1,3)	48 h/period	48 h/period
Ins.03	E3	10	(2,8)	(5,1,1,3)	48 h/period	48 h/period
Ins.04	E4	11	(3,8)	(5,1,1,1,3)	48 h/period	48 h/period
Ins.05	E5	11	(2,9)	(5,1,1,1,3)	48 h/period	48 h/period
Ins.06	E1, E2	18	(8,10)	(3,1,...,1,1,3)	48 h/period	48 h/period
Ins.07	E1, E4	19	(7,12)	(3,1,...,1,1,3)	48 h/period	48 h/period
Ins.08	E2, E3	20	(6,14)	(5,1,...,1,1,3)	48 h/period	48 h/period
Ins.09	E3, E4	21	(5,16)	(5,1,...,1,1,3)	48 h/period	48 h/period
Ins.10	E4, E5	22	(5,17)	(5,1,...,1,1,3)	48 h/period	48 h/period
Ins.11	E1, E2, E3	28	(10,18)	(3,1,...,1,1,3)	96 h/period	48 h/period
Ins.12	E1, E2, E4	29	(11,18)	(3,1,...,1,1,3)	96 h/period	48 h/period
Ins.13	E1, E4, E5	30	(9,21)	(3,1,...,1,1,3)	96 h/period	48 h/period
Ins.14	E2, E3, E4	31	(9,22)	(5,1,...,1,1,3)	96 h/period	48 h/period
Ins.15	E3, E4, E5	32	(7,25)	(5,1,...,1,1,3)	96 h/period	48 h/period
Ins.16	E1, E2, E3, E4	39	(13,26)	(3,1,...,1,1,3)	96 h/period	96 h/period
Ins.17	E1, E2, E3, E5	39	(12,27)	(3,1,...,1,1,3)	96 h/period	96 h/period
Ins.18	E1, E3, E4, E5	40	(11,29)	(3,1,...,1,1,3)	96 h/period	96 h/period
Ins.19	E1, E2, E4, E5	40	(13,27)	(3,1,...,1,1,3)	96 h/period	96 h/period
Ins.20	E2, E3, E4, E5	42	(11,31)	(5,1,...,1,1,3)	96 h/period	96 h/period
Ins.21	E1, E2, E3, E4, E5	50	(15,35)	(3,1,...,1,1,3)	96 h/period	96 h/period

As an example, in Ins.03 there is 1 piece of equipment $J = \{1\}$ with 10 maintenance activities $I = \{1,2,...,10\}$, which are 2 PdM $I' = \{1,2\}$ and 8 PvM activities $I'' = \{3,4,...,10\}$. The first 5 activities belong to one group, the 6th and 7th activities are in a single group, and the 8th to 10th activities are also in another group ($I_g = \{5,1,1,3\}$). In the same way, the other instances are defined as seen in Table 13. The planning is based on a horizon of one year, which equals 52 weeks. The related number of mechanical and electrical experts and the available time for each piece of equipment per each period are defined.

6.3.3 Experimental results

The instance problems are solved in this section. The mixed integer linear programming (MILP) models of all instances were coded in GAMS 24.1.2 (*Gams Distribution 24.1.1*, 2013). They were solved by the CPLEX 12.5.1 (“CPLEX,” 2012) solver using a PC with the characteristics of 2.8 GHz Intel Core i5-4200H, and 6 GB of installed memory.

The computational results of the instances are presented in Table 14. A limitation of 3,600 seconds as the maximum allowable time was set in the CPLEX solver. The optimum objective function values (OFV) or the optimality gaps (when the optimal solution is not found below the 3,600 s) are presented. Furthermore, the details of the OFV in 4 categories are presented in the related columns. These are as follows: i) the maintenance intervention costs, which show the spare part and man-hour costs needed for all interventions; ii) the unused life cost, which is the losses when the activity is planned before its nominal *Fr*; iii) the expected failures cost, which represents the expected losses of failure based on the planning period of the activities; and iv) the grouping saving, which is the reduced amount of man-hour cost when at least two types of activity in the related groups are planned at the same period.

Table 14. The computational results of the instances with the objective function values in detail

Problem	Time/Gap%	Elements of OFV					
		OFV (€)	Intervention cost (€)		Unused life losses (€)	Expected failure cost (€)	Grouping saving (€)
			Human resources	Spare parts			
			cost	cost			
Ins.01	0.45 s	2,973	1,678	722	124	476	26
Ins.02	1.02 s	8,378	5,635	2,423	495	304	480
Ins.03	1.36 s	7,347	5,123	2,203	498	384	861
Ins.04	0.86 s	10,123	7,561	3,251	789	91	1,569
Ins.05	1.42 s	10,329	6,748	2,902	715	873	909
Ins.06	1.61 s	11,351	7,313	3,145	619	780	506
Ins.07	1.84 s	14,823	10,087	4,337	1,057	566	1,224
Ins.08	4.86 s	15,725	10,758	4,626	993	688	1,341
Ins.09	4.42 s	19,197	13,531	5,818	1,432	474	2,059
Ins.10	6.75 s	22,548	15,157	6,517	1,638	1,343	2,107
Ins.11	6.20 s	20,233	12,436	5,348	1,117	2,699	1,367
Ins.12	6.05 s	24,736	15,722	6,760	1,552	2,406	1,704
Ins.13	3.64 s	26,688	16,835	7,239	2,133	1,772	2,975
Ins.14	12.88 s	27,575	19,167	8,242	1,927	779	2,538
Ins.15	13.05 s	29,527	20,279	8,720	2,147	1,348	2,968
Ins.16	5.03 s	30,548	20,845	8,963	2,051	1,254	2,565
Ins.17	9.11 s	29,027	19,184	8,249	1,832	2,037	2,276
Ins.18	13.91 s	32,499	21,958	9,442	2,271	1,824	2,994
Ins.19	9.58 s	33,530	22,470	9,662	2,267	1,744	2,613
Ins.20	14.78 s	37,904	25,915	11,143	2,642	1,652	3,447
Ins.21	14.14 s	40,877	27,593	11,865	2,766	2,128	3,474

As is seen in Table 14, all the instances achieved the optimal solution. The last column is related to the grouping saving, which is deducted from the costs. This will be analyzed in more detail in the sensitivity analysis section (6.4). Regarding the percentage of the costs, the cost ranges of all instances are shown in Figure 82.

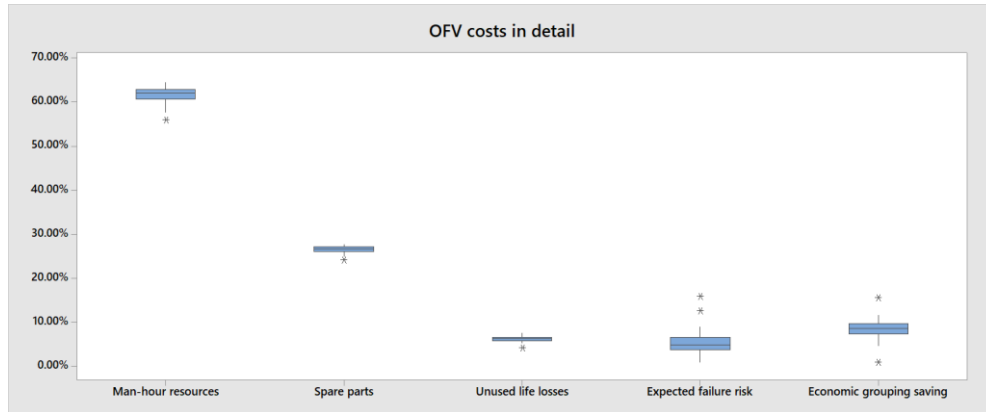


Figure 82. The interval range of each cost element in the objective function

For better understanding, an example result of Ins.07 (due to the size of the instance for a better illustration of the results) is illustrated in Figure 83-a. Furthermore, to see the impact of dynamic RUL readjustment on the planning, a scenario has also been considered in Ins.07 where 4 decision periods are passed, and the new RUL values were calculated through the real-time data and predictions. In this scenario, some of the RUL estimates were prolonged, and others were reduced due to the equipment's condition. The dynamic PdM and PvM planning results are shown in Figure 83-b.

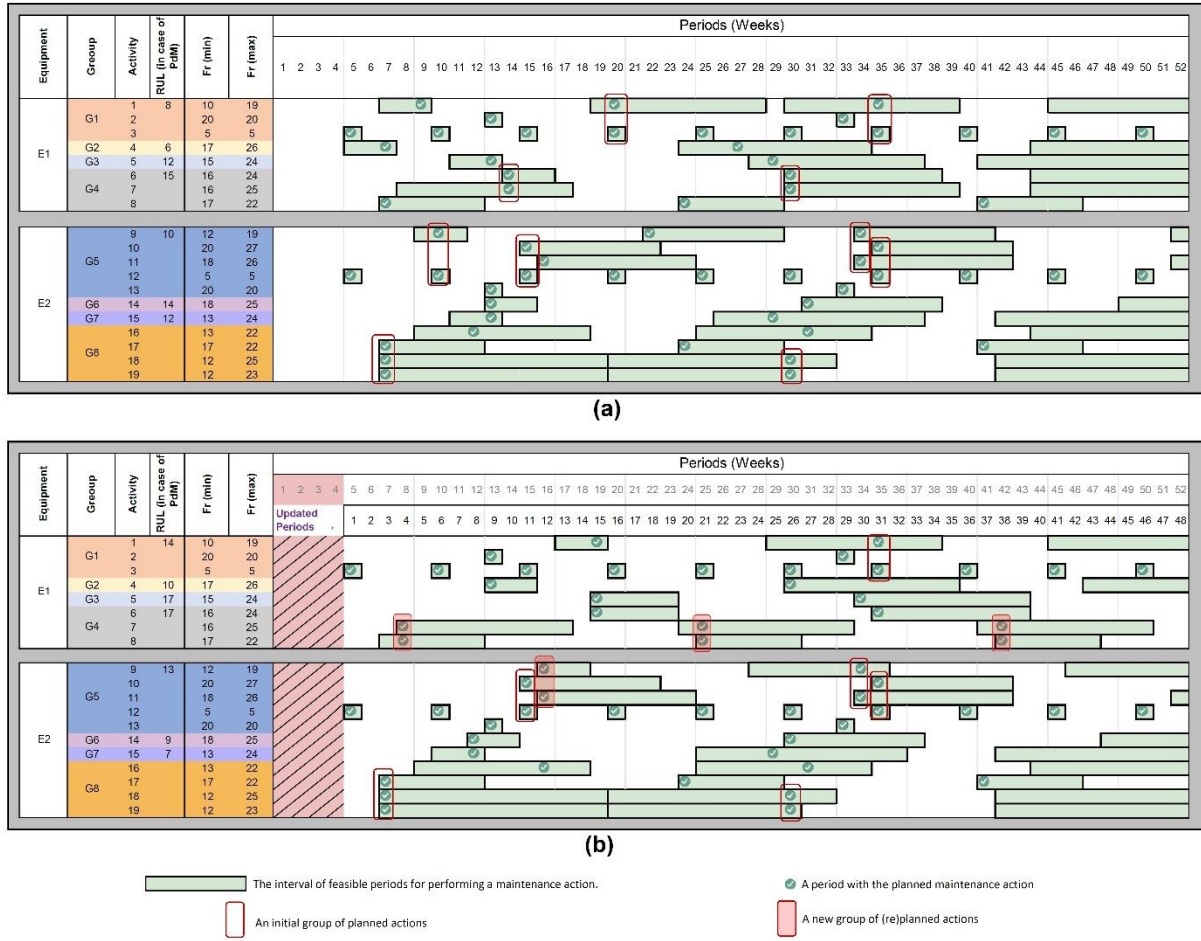


Figure 83. The result of the maintenance planning problem for Ins.07 (a), and the result of its dynamic adjustment at period 5 (b)

The plannable periods are based on $RUL [RUL * (1 \pm \beta)]$, elapsed time since the last maintenance (D), and frequency parameters (Fr^{min} and Fr^{max}). Furthermore, the plannable periods are dependent on the previous maintenance, which is identified by the optimization model. The model uses these parameters and tries to obtain the best trade-off while considering the grouping aspect. For example, in Figure 83-a and activity 5, the model planned the first intervention after its estimated RUL. The economic groupings were indicated in both figures (red rectangles), and the new economic groupings in dynamic planning were shaded in Figure 83-b. As an example, in Figure 83-b and period 16, the activities 9 and 11 are grouped in the new planning, which belongs to the opportunistic group 5 ($G5$). In some maintenance activities (like greasing), there is a fixed obligatory interval that must be respected (Ex. activities 12 and 13). In these cases, maximum, minimum, and nominal frequencies are equal.

Based on the observed results in the dynamic case, the maintenance interventions, and the corresponding overall maintenance costs, were reduced by 2%. Some previous economic groupings appeared in the same periods in the dynamic mode. Furthermore, some new economic groupings were created based on the new RUL estimates. In our case, since the calculation time is less, it would be possible to readjust the plan as soon as the dynamic RUL information arrives.

6.4 Sensitivity analysis

This section explains the sensitivity analysis that was carried out to evaluate the behavior of the model in cases of variation in the following, more important aspects:

- Expected failure/stoppage cost
- Economic grouping
- Availability of man-hour experts
- Comparison of the direct and indirect maintenance costs

6.4.1 Expected failure/stoppage cost

Based on the initial results of the instances, the expected failure cost is around 6% (on average) of the overall maintenance costs. The expected failure cost is obtained by multiplying the probability of failure by the estimated total costs of corrective maintenance (TCcm). To study the impact of this estimate, a sensitivity analysis is described in this subsection. This sensitivity analysis was done on Ins.21, which has the most maintenance activities in the defined instances. In this way, the *TCcm* values of all activities were changed in a range from -75% to +75%. The results are summarized in the [Table 15](#) and [Figure 84](#).

Table 15. Sensitivity analysis results regarding the parameter of expected failure costs in Ins.21

<i>TCcm</i> variations	OFV (€)	Elements of OFV				Intervention numbers
		Intervention cost (€)	Expected failure cost (€)	Unused life losses (€)	Grouping saving (€)	
-75%	38,084	36,249	4,086	2,053	4,303	164
-50%	39,635	39,256	1,347	2,740	3,707	171
-30%	40,174	39,256	1,746	2,747	3,575	171
-20%	40,423	39,256	1,996	2,747	3,575	171
-10%	40,664	39,458	1,915	2,766	3,474	173
0%	40,877	39,458	2,128	2,766	3,474	173
+10%	41,012	39,660	1,250	2,803	2,700	174
+20%	41,126	39,660	1,364	2,803	2,700	174
+30%	41,240	39,660	1,477	2,803	2,700	174
+50%	41,467	39,660	1,704	2,803	2,700	174
+75%	41,751	39,660	1,988	2,803	2,700	174

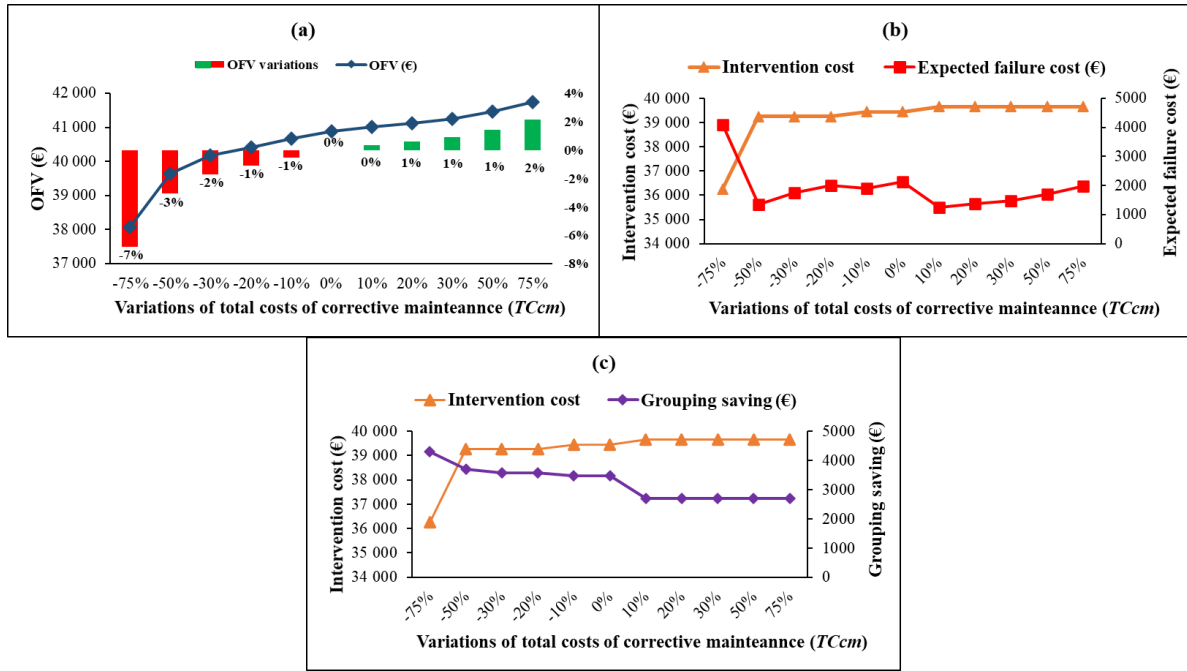


Figure 84. Sensitivity analysis results in the expected failure cost parameter (applied on Ins.21)

The results show that the OFV increases as the total costs of corrective maintenance parameters increase (Figure 84-a) and the OFV varied from -7% to 2%. As the most important result, reducing the TCcm parameter leads to a reduction in the number of planned interventions. Indeed, with a reduction of TCcm, the model allows for planning activities over longer periods. Hence, the model tries to plan fewer activities, which also results in intervention cost decreases (Figure 84-b). In contrast, the grouping saving increases as the TCcm parameter increases (Figure 84-c). That is because with smaller TCcm values, there is more space for economic grouping, and this space is reduced for larger TCcm values. The grouping saving is analyzed in more detail below.

6.4.2 Economic grouping

Based on the initial results of the instances, the grouping saving is around 9% (on average) of the overall maintenance costs. To see more exactly the impact of economic grouping on maintenance planning, two scenarios of sensitivity analysis were designed:

- Scenario 1: Studying the impact of the existence or inexistence of opportunistic groups
- Scenario 2: Studying the impact of man-hour reduction rate (α) variations

scenario 1: In this scenario, the maintenance planning problem is studied in the absence of the possibility of economic grouping. Hence, two cases are defined. In case 1, the impact of economic grouping on the mathematical model is considered. In case 2, this impact is not considered (equation 34) without considering the second term). Normally, when the economic grouping is activated, the mathematical model will plan more activities to profit from the setup or human resource cost saving. To make a cost comparison according to the same basis, the OFV of case 2 is compared to the OFV of case 1, plus the grouping saving value. It should be noted that in this analysis we call it the gross maintenance costs (GMC) which is equal to OFV plus the grouping saving. In other word, in GMC, the effect of grouping saving is removed from OFV. This scenario was applied to five instances and the results are presented in Figure 85.

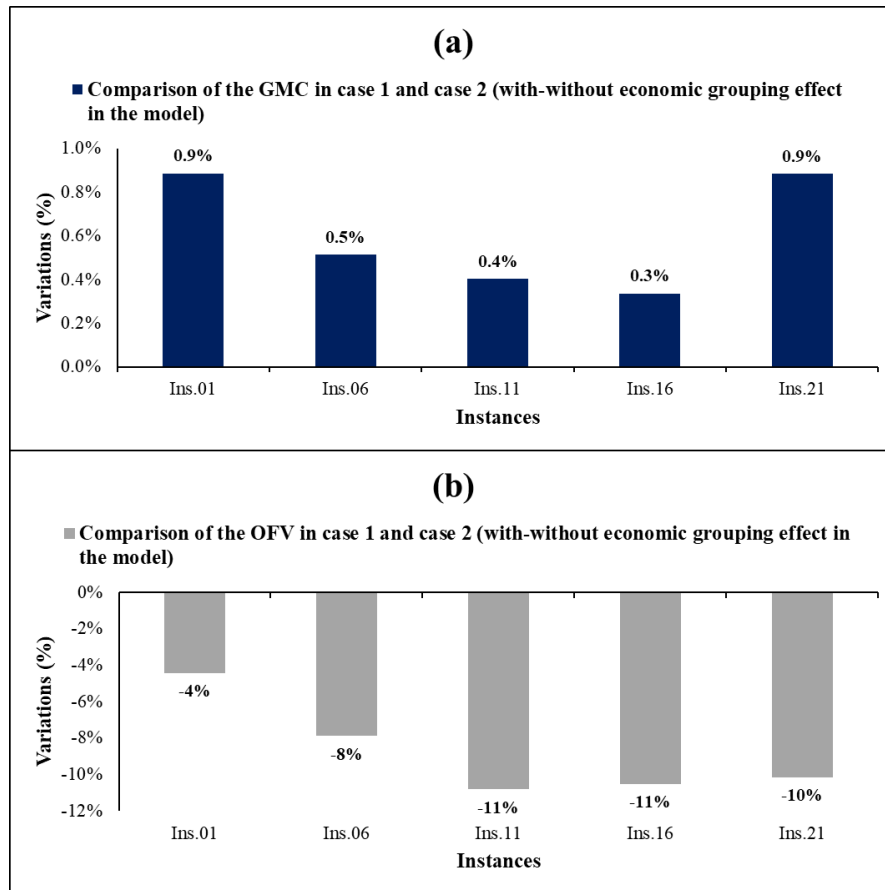


Figure 85. Sensitivity analysis results for the existence or inexistence of economic grouping

As it is seen, the GMC in case 1 is greater than in case 2 where the economic grouping impact is not considered (Figure 85-a). However, when all the whole OFV values are compared, the OFV in case 1 is decreased (Figure 85-b). This means that economic grouping would result in a small increase in the other costs, such as the intervention costs, or an increase in the expected failure costs, etc. However, all in all, with the grouping saving value the OFV decreases. Based on these observations, although economic grouping could increase the GMC about 1% on average, the whole OFV values decreased about 9% on average.

scenario 2: In this scenario, the effect of the man-hour reduction rate (α) is investigated to see the behavior of the model and the impacts on the grouping saving. Since the grouping saving depends on the estimation of the reduction rate in each opportunistic group, a sensitivity analysis scenario is designed. A range of reduction rates (0% to 50%) is considered, which are related mainly to the setup costs (dismantling and assembling the equipment). Ins.21 was selected for this analysis; it has the highest number of maintenance activities and the most opportunistic groups. The results are compared to the result obtained with initial $\alpha = 0.3$ and presented in Figure 86.

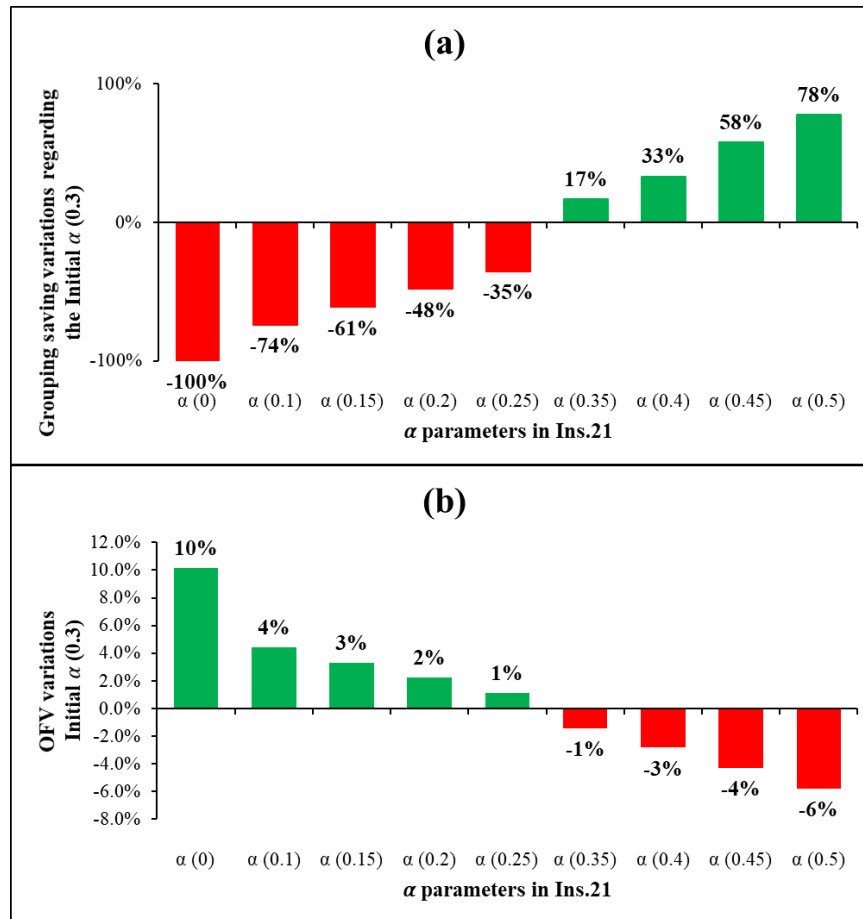


Figure 86. Sensitivity analysis results in the man-hour reduction rate parameter (α)

The results indicate that the variation of α has a direct and proportional impact on the grouping saving (Figure 86-a). Furthermore, it can oppositely impact the OFV value up to 10% (Figure 86-b). This means that the right estimation of α parameter is important.

6.4.3 Availability of man-hour experts

In this sensitivity analysis, the effect of capacity and availability of maintenance experts (*AMO* and *AEO*) is evaluated. The objective is to assess the impacts of maintenance experts' availabilities on the OFV and to evaluate the optimal needed human resources. Once more, Ins.21 was chosen and different capacities of man-hour availabilities in the periods are taken into account. The results are presented in Table 16, and Figure 87.

Table 16. Sensitivity analysis results for maintenance experts' availability

(Mechanical, Electrical) available h/period	OFV (€)	Variations regarding the
<i>Initial parameters (96,96)</i>	<i>Initial OFV (40877 €)</i>	initial solution
(24, 24)	Infeasible	N/A
(36, 24)	42,126	3.05%
(36, 36)	42,126	3.05%
(48, 24)	41,305	1.05%
(48, 48)	41,305	1.05%
(72, 48)	40,877	0.00%
(72, 72)	40,877	0.00%
(120, 96)	40,877	0.00%

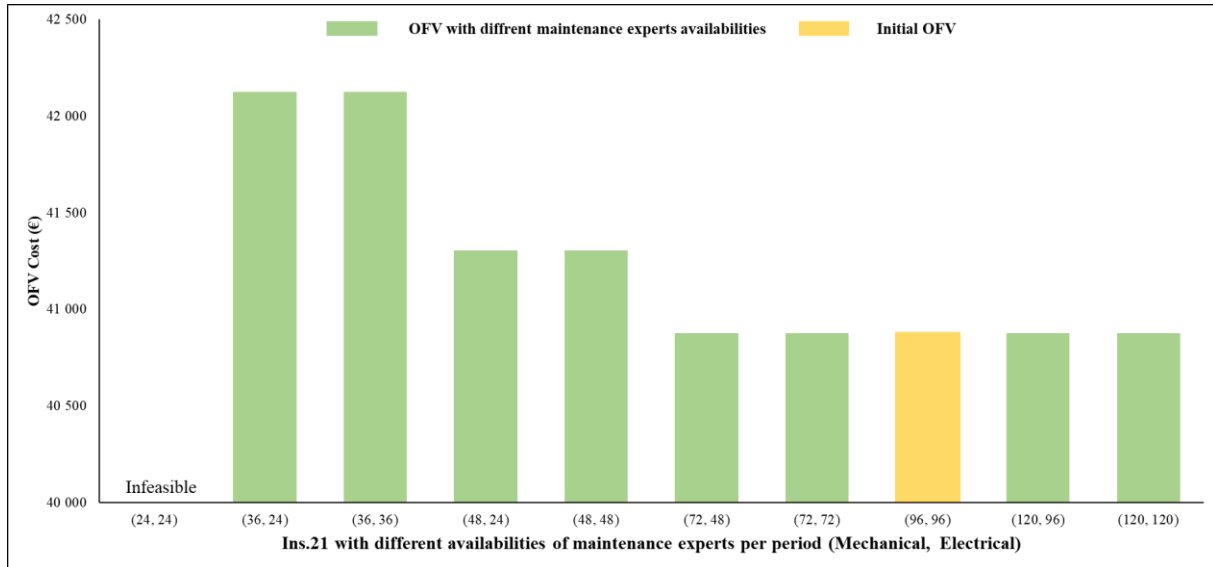


Figure 87. Sensitivity analysis results in maintenance expert availability parameter

The results show that the initial *AMO* and *AEO* parameters in Ins.21 with 5 pieces of equipment could be revised and reduced to 36 man-hours of mechanical experts and 24 man-hours of electrical experts. This has an impact of 3% increase on the overall maintenance costs. However, decreasing the availability by 24 hours/period will result in model infeasibility, which means that man-hours are not sufficient. Increasing too many resources would not decrease the OFV, and it would be unnecessary to do that. It is important to remember that regarding maintenance experts' costs, only the allocated intervention times and costs are considered in the OFV.

When the *AMO* and *AEO* parameters are reduced due to resource limitations in some periods, the model is forced to change the planning. This would result in taking more expected failure risk by planning in longer periods or ignoring the economic grouping by planning the activities individually in different periods. In both cases, the OFV is increased.

6.4.4 Comparison of the direct and indirect maintenance costs

In the last sensitivity analysis case, the effect of direct and indirect maintenance costs is studied. The direct cost is related to intervention maintenance costs (spare parts and man-hours). The indirect costs are the hidden costs of the unused life of spare parts, and the expected failure risk cost that may happen in the future. This analysis is conducted because, in most cases, direct costs are given more attention than indirect costs in industry practices.

Two cases in Ins.21 were defined. In case 1, only the direct cost (intervention cost) function is set in the objective function, while the expected failure costs and unused life losses are calculated based on the output result without keeping them in the objective function. In case 2, the direct and indirect costs (intervention, unused life, and expected failure risk cost) are set in the objective function. In this analysis, the proposed features of the model, such as the existence of PdM activities (RUL), and economic grouping, were not considered to keep the same comparison basis. The obtained results for the two cases are seen in Figure 88.

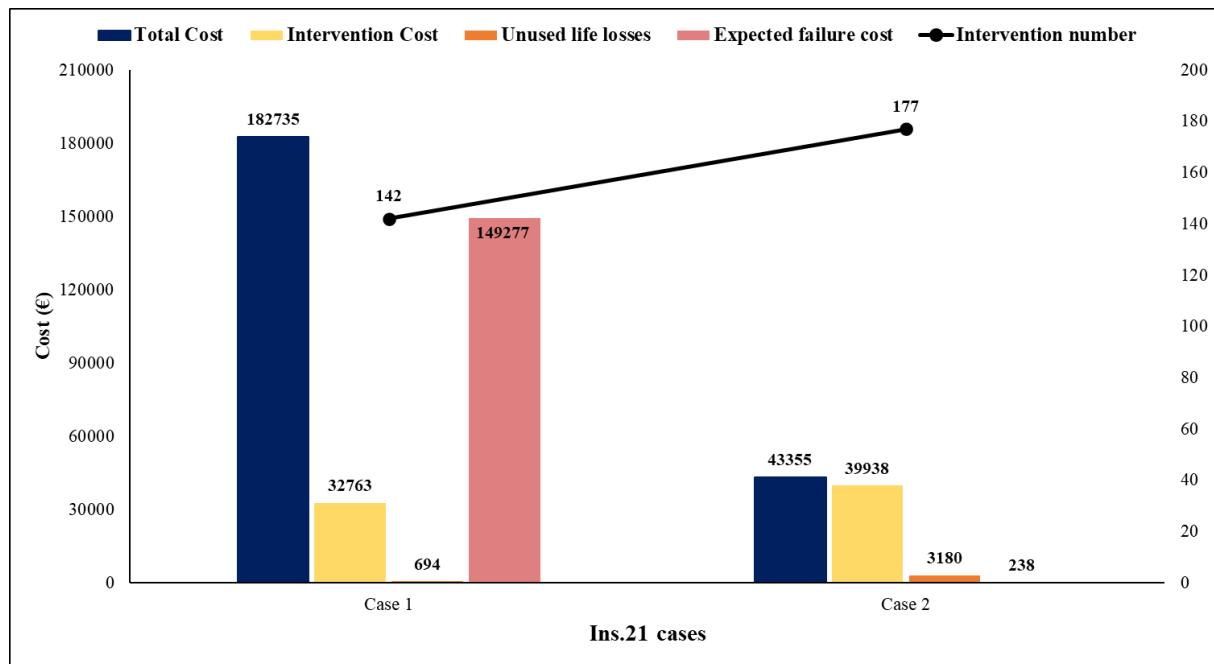


Figure 88. Detailed direct and indirect maintenance cost results in case1 and case2 of Ins.21

The results indicate that when only the direct intervention costs are considered, the intervention costs and the intervention numbers decreased by 18% and 20%, respectively. However, the indirect costs (more likely in the expected failure costs) increased extraordinarily, and the overall maintenance costs also increased by 323%, which is due to the importance of corrective/breakdown maintenance costs compared to preventive maintenance. As a result, the minimum overall maintenance costs are achieved when the direct and indirect costs are both considered in the objective function in the mid/long term horizon.

6.5 Discussion and managerial insights

Dynamic PdM and PvM planning is based on real-time data, historical information, and constructor's guidelines. Appropriate interconnected information and a real-time data management system are the preliminary elements to put into practice the dynamic aspect of PdM and PvM planning. Decision-making through maintenance planning is expected to be applicable and efficient when there is a constructive collaboration between maintenance experts, and information and communication technology (ICT) experts, data scientists, and optimization experts. In this paper, the applicability of this approach in a real-world industry was studied. Some of the important aspects of dynamic PdM, PvM planning, and optimization tools are discussed.

Implementation of real-time data acquisition, visualization, and monitoring systems should result in a health state assessment of components, group functions, or machines. This is the only case where real-time data can be included in maintenance planning through useful information like RUL or health state.

Even if the RUL is estimated, the related interventions should be implemented in the appropriate periods. This is because, in the industrial environment, resource limitations, equipment availability, and other considerations are prevalent. As an example, for some equipment in our industrial case, RUL has been well estimated (with acceptable tolerance), while maintenance teams did not perform maintenance due to lack of maintenance resources (experts) and/or unavailability of the equipment. Therefore, while

the predictions are not included in a more global vision and/or in a decision-making tool, the predictive analysis may be non-applicable.

It is true that in general, adding PdM and PvM activities will initially lead to higher costs for maintenance services. However, they will prevent equipment failures and unscheduled downtime in situations where the activities can predict or identify potential problems. Generally, due to capacity limitations, maintenance services mainly focus on short-term vision. However, implementing PdM and PvM requires a mid/long-term vision in order to consider cost optimization in the mid/long term and not the short term. In situations where there are no tools for monitoring, prediction, or identification of related preventive measures, CM is followed.

The maintenance planning method showed good performance and validity, which are presented in the sections on experimental results and sensitivity analysis. With the help of the method, it is also possible to observe the requirement trends for man-hours throughout the decision periods, which can help with better planning of maintenance activities and management of maintenance experts. Furthermore, the following points should be noted.

In the industrial context, indirect costs of maintenance, such as expected failure risk in the future and unused life losses of spare parts (a hidden cost since it is already paid), are very seldom considered for decision-making. This is largely due to lack of reliable and convenient methods and tools for estimating failure risk. In this case, it may seem that intervention costs and numbers are minimized; however, upcoming risk of failure may result in more impacts on overall maintenance costs. Thus, indirect costs are considered to have a substantial impact on maintenance decision-making.

Economic grouping in the mathematical model is considered only for reduction of man-hour cost. However, in reality, there may be other penalties that are not considered, such as fixed costs of dismantling and assembling equipment, risks of failure during machine dismantling, product quality and calibration risks (maladjustment of components), complexity of machine dismantling, etc. Since the mentioned penalties and complexities are very controversial, it is difficult to get numerical values, this could be an interesting subject for future research.

It is always important to effectively extract or estimate model parameters for better results that could keep machines and equipment at maximum uptime. Thus, providing data and information management systems, procedures for storage, and quality data are essential to having correct maintenance planning and decision-making.

Regarding PvM activities for failure costs, it is necessary to estimate the failure distribution of the components in each activity. However, in practice, this is not easy and requires reliable methods, time, and energy. In this paper, for simplicity, a linear function was considered. Nevertheless, since this parameter is very sensitive, other functions of failure probability, such as exponential or Weibull, could be studied.

6.6 Chapter conclusion

Maintenance planning in industries is a complex problem due to intrinsic uncertainties. The PdM and PvM approaches are the most pertinent that can be used in the industry. However, integration of both strategies in maintenance management systems is essential.

In this chapter, the maintenance planning problem was addressed in case of PdM strategy presence. In this way, the PdM and PvM planning problem was studied and an industrial case of a conveyer chain system in FPT-BLY plant was used to demonstrate the outcome. In overall, the study has indicated that RUL information could be integrated into the comprehensive maintenance planning system to identify

optimal planning results. In this study, a new mathematical programming model was developed to minimize the overall direct (intervention costs) and indirect (expected failure risk costs, unused life losses) maintenance costs. Moreover, the economic grouping possibility was considered in set-up times for maintenance activities based on their structural dependencies. In the proposed method, the RUL and MTBF information that are obtained from real-time data and historical information are used. The dynamic aspect of the method is studied in a scenario where the RUL values are updated through real-time data, and their impacts are studied. Optimal maintenance planning is achieved in a short amount of time, and based on the results, the model is expected to solve the problem for about 30 pieces of equipment with 300 maintenance activities within a reasonable time. Based on these observations, the proposed method could be extended to other types of equipment or cases. Moreover, based on the solution times for the instance problems, the periods could be reduced from weekly to daily for bigger maintenance scheduling problems.

Moreover, a comprehensive sensitivity analysis of the most important aspects of the method was provided and the results were discussed. The experimental results together showed the validity, efficiency, and performance of the proposed mathematical model for maintenance planning. Based on the results, the proposed model identifies the best balance between direct and indirect maintenance costs. This indicates that indirect costs have considerable impacts on maintenance planning (especially in the mid/long term). Hence, we believe that the RUL estimation and optimization method could be utilized for industrial maintenance planning of multi-machines and multi-components.

Furthermore, the impact of total costs of corrective maintenance (TC_{cm}) estimation on maintenance planning was evaluated. It was found that variations of corrective maintenance cost estimation can considerably affect the number of planned interventions and decrease the objective function value (OFV) by about 7%. Regarding the economic grouping in the proposed model, the results indicated that with this consideration, the gross maintenance costs (GMC) increased about 1%, while the OFV with grouping saving value decreased by 9% on average. In addition, the capacity and availability study of maintenance experts indicated that the optimal requirement for maintenance experts could be achieved with the proposed method.

In this chapter, the general **step 6** (Figure 39 and Figure 40) is presented, and in the next part, the final conclusion remarks of this thesis are provided.

Part 3: Thesis conclusion and perspectives

A more advanced branch of the Preventive Maintenance (PvM) family is Predictive Maintenance (PdM), which mainly relies on real-time data (Lughofer & Sayed-Mouchaweh, 2019) that are used for the failure and degradation trend prediction of components or machines. The primary objective of this thesis project was to address dynamic PdM through the identification of new methods for decision support systems (DSS) based on the use cases in Fiat Powertrain Technologies in the Bourbon-Lancy (FPT-BLY) plant. The driving motivation was concerning the exploration of the potential benefits of real-time data provided by the Industry 4.0 principles, such as Industrial IoT (IIoT), and Edge/Cloud computing to implement PdM in production systems through the data science and optimization methodologies. While real-time or sensor data is an important source for decision-making in maintenance, it is not the only one to consider. Hence, information about past maintenance activities and breakdowns is also very important. Even though we cannot monitor equipment health state in a predetermined PvM strategy, it is necessary to follow it, due to the limited available resources for implementing PdM in the overall plant physical assets. In this regard, this thesis also encompasses other methodological aspects of maintenance, including maintenance system monitoring, and PvM planning. The main research questions were to see *i)* If it is possible to identify equipment health monitoring and RUL estimation? Through which types of methods/models? *ii)* How it could be used for decision-making? *iii)* What are the boundaries that are interesting to follow a PdM strategy? and *iv)* what is the relation of PdM strategy with the other maintenance strategies in a production system? In this regard, various appropriate tools, algorithms, and methods were proposed and developed by performing a variety of studies on different use cases of FPT-BLY using the available real-time and historical data and information.

The research studies, developments, and experimentations in this thesis were summarized in six main steps (Figure 39). For more detailed information on the inputs, outputs, methods, and controls of each step, an IDEF0 is provided, which highlights the relationships between the steps (Figure 40). These steps are in line with the data analytics approach with, descriptive, diagnostic, predictive, and prescriptive aspects, and they are as *i)* Critical equipment, and components identification, *ii)* Maintenance strategy identification, *iii)* real-time and historical data and information acquisition, *iv)* Equipment health monitoring and maintenance system monitoring, *v)* RUL estimation, and *vi)* maintenance planning.

In chapter 4, the first and second steps have been presented concern the criticality analysis of machines, and components, identification of maintenance strategy, and optimal maintenance frequency. In chapter 5, the real-time data acquisition, dynamic prognostic approach, equipment health monitoring through health indicators, and maintenance system monitoring through Key Performance Indicators (KPIs) and Key Activity Indicators (KAIs) have been detailed. In chapter 6, the maintenance planning methods are developed for the simultaneous PvM and PdM activities. The novelty of this approach is that generally, most PdM studies focused on the RUL estimation (Jardine et al., 2006b) (R. Liu et al., 2018) (T. Wang et al., 2019), and the decision-making aspect and the relation of PdM with the other maintenance activities and strategies are rarely considered. Regarding the first and second proposed steps, there is a similar study (Tiddens et al., 2018) that considers the criticality analysis and other types of methods for identifying suitable equipment/components for PdM strategy. However, it lacks the consideration of the health state, RUL estimation, and decision-making aspects. Furthermore, although the presented approach in ISO 13374 Open System Architecture for Condition Based Monitoring (OSACBM) standard (MIMOSA, 2006), follows partially the third to sixth of our proposed steps, the maintenance planning based on RUL estimation and the simultaneous maintenance planning considering other strategies as PvM are not addressed. Moreover, the relationships between the maintenance monitoring systems through health indicators, and maintenance KPIs, and the relation of indicators with the Root Cause Analysis (RCA), and the Reliability Centered Maintenance (RCM) are not taken into account. As a result, in literature several approaches exist concerning separate or combination of the

proposed steps, however combining and integrating all the blocks and steps together in one structure is the novel approach that is developed in this thesis based on the on-site research, investigations, exploration, and experimentations.

Throughout the presented steps and chapters, the relevant use cases of FPT-BLY that allow us in developing the proposed steps (Figure 40) have been considered for the application of the proposed/identified methods in each chapter. In continue, the conclusion, challenges, contributions, and perspectives of these steps are provided.

i) Criticality analysis of equipment, components

The first step concerns targeting the most critical equipment and/or components. This is because performing maintenance interventions to all plant production assets would not necessarily reduce the failure risks. Moreover, there are often limited resources (manhours, spare parts, ...) and available times for all maintenance activities. Criticality analysis requires the identification of evaluation criteria, which can include key performance indicators (KPIs) as measurable criteria. Typically, productivity, quality, cost, delivery, morale, and safety (PQCDMS) criteria are used in the industry. However, it may be more interesting and pertinent to consider other types of criteria and indicators that are most relevant to the target of criticality analysis.

The main challenges in this step concern the identification of relevant criteria, indicators, and related data and information. Moreover, identification of the weights of criteria and robust criticality analysis that ensure the decision-makers of the obtained results are the other challenges of this step.

For this step, it is proposed that the Multi-Criteria Decision Making (MCDM), with ABC classification, could be applied to prioritize the machines, equipment, or components. To make it simpler for industrial users to understand and implement, less complex methods such as the weighted sum and ABC classification methods were used instead of more complicated ML methods in MCDM and classification analysis. Since the criticality analysis often requires qualitative evaluations from the experts, the stability/robustness of the obtained results could be ensured through more advanced sensitivity analysis. Three sensitivity analysis methods, including a new correlated weighted sensitivity analysis method, have been developed for the weight of criteria, which considers the correlation and importance weights between criteria, enabling the interdependent sensitivity analysis of multiple combinations of criteria weights. The mentioned aspects in this step have been developed in chapter 4, and sections 4.1, 4.2, 4.3, and 4.4.

One possible perspective is the development of advanced sensitivity analysis methods for evaluating the scores, while another is the creation of a more comprehensive Decision Support System (DSS) for criticality analysis. This DSS would allow for the selection of appropriate criteria weighting, MCDM, and sensitivity analysis methods based on industrial requirements.

ii) Maintenance strategy identification

The second step concerns identifying suitable maintenance strategies for each machine, and equipment. There exist several approaches and methodologies to define the best maintenance strategy regarding the specificity of each industry, and/or equipment. For example, Reliability Centered Maintenance (RCM) approach could be used to find the failure root sources/causes and propose intervention lists with the frequency and required resources. The failure mode, effects criticality analysis (FMECA) method is also often used in this regard. Generally, the analysis of this step allows us to define maintenance strategies of machines, and components based on the EN 13306 standard (Figure 18).

Regarding PvM, further spare part analysis, and frequency identification of PvM periods would be required. For the PdM, this would depend on the feasibility and technical possibility of real-time data access and acquisition. In this regard, the selection of the right, and pertinent condition-monitoring data is a necessity. Although there are some guidelines about the selection of sensors, regarding the equipment type (J. Lee et al., 2014), in each industry, this needs to be identified based on its technical specificities.

The main challenges in this step concern the possibility of the application of PvM or PdM activities for the machine, equipment, and/or components. For PvM, the complexity is to identify the appropriate maintenance activities through failure root cause analysis, and optimal frequency of PvM implementation through optimization studies. For PdM, the challenge is to identify of most appropriate condition monitoring data that could be used for the health state estimation of equipment/components. In addition, the feasibility of connecting and accessing real-time data, as well as the economic justification for implementing a condition monitoring system, are other challenges that need to be addressed.

A new analytical approach has been proposed based on criteria weighting, MCDM, classification, and sensitivity analysis methods developed in the previous step. Although FMECA analyses are commonly used for maintenance strategy identification, the proposed approach provides an alternative when severity, failure effects, and probability information are not available, and instead relies on other technical criteria or indicators based on the specific use case. Furthermore, an appropriate method for performing optimal frequency analysis was proposed and applied to the MSME use case, which led to improvement in equipment/machine efficiency and availability, as well as decreased emergency purchases due to breakdown events. The developed elements in this step are presented in chapter 4, and sections 4.5, and 4.4.

It is important to be precise that more critical machines or components may not automatically be interpreted as PvM or PdM strategy. Therefore, conducting a secondary analysis that takes into account machine/component classification, other relevant criteria for PdM strategy, relevant historical data, failure root cause analysis, and the insights of maintenance experts is necessary to determine the most suitable maintenance strategy. In this way, exploring and developing new methodologies and approaches for providing decision support systems can be considered as a potential area of future research.

iii) real-time and historical data and information acquisition

The third step concerns the data and information connection/collection that is required for further analysis and improvement. Traditionally, all information on PvM and corrective maintenance (CM) activities are mainly managed through information systems such as (MES, SAP, etc.). Regarding the PdM, the desired real-time data and information should be accessible through the Industrial Internet of Things (IIoT) system.

Even if the sensors and condition monitoring parameters are already identified, there are some main challenges to the implementation of the data acquisition system. These are sensor installations, Programmable Logic Controller (PLC) data connection, IIoT architecture, communication protocols (OPC UA, MQTT, etc.) data storage (Edge, Fog, Cloud), application programming interface (API), etc. The other challenge is the connection of IIoT into information systems to automatically obtain historical information and real-time data.

The relevant IIoT platform and architecture are presented in chapter 5, section 5.1.

iv) *Equipment health monitoring and maintenance system monitoring, and visualization*

v) *RUL estimation*

In the fourth and fifth steps, the identification of health indicators (HIs) for equipment health monitoring, RUL estimation through HIs, and maintenance indicators for maintenance system monitoring are mainly studied. Data and information management systems are the prerequisites for this purpose. It should be noted that appropriate health indicators would also help in the diagnostic by detecting the faults, their localization, and their root cause. Diagnostic in maintenance is often followed manually by the maintenance technicians, however, automatic diagnostic through HI is a very challenging and complex issue that needs detailed analysis accompanied by expert's validations. Equipment health monitoring provides the information on the current state, and failure trends of the machines, or components, while the RUL estimation highlights the prognostic aspect and the prediction of failures. RUL of equipment/components is generally estimated via the predictive models that need investigation of the appropriate method depending on the features of the use case. Another interconnected subject in this step is maintenance monitoring systems, which track the performance of machines and maintenance systems through visual indicators. These indicators can be used to identify critical areas such as production lines/machines and to determine improvement actions that enhance the reliability of maintenance machines.

In this step, the main challenge is the identification of appropriate health state and RUL estimation methods that can dynamically fit or readjust the health state, and RUL estimation. In this way, the main determining factors are the criticality of the use case, required precision level, required cost as computation resources and model development times, and the available data. Maintaining the precision of predictive models, and predictions over time is also another essential factor. Therefore, it is essential to identify the most balanced method based on these factors that could generate added values. There is another point in which depending on the quality of the obtained results, it may be necessary to install new sensors or connect other PLC data. In this case, a return to step three of the proposed approach is required. Furthermore, the identification of most appropriate maintenance indicators and monitoring dashboards are the other important challenges.

Steps four and five are presented in chapter 5, as a dynamic prognostic approach was proposed in section 5.2, followed by experimentation of health state study in a complex system of spindle engine based on unsupervised principal component analysis in section 5.3. A new dynamic algorithm for RUL estimation was also proposed by integrating the Prophet prediction model, which showed better performance values compared to similar prediction models in section 5.4. Additionally, relevant maintenance indicators were identified, and visualization methods were considered to propose interactive maintenance monitoring dashboards in sections 5.5, and 5.6.

The studies conducted shed light on decision-making in equipment health monitoring and RUL estimation by identifying areas that require improvements, determining when RUL estimation is economically viable, and selecting suitable methods. As a future direction, one axis could be to investigate complementary health state, automatic diagnostic, and RUL estimation methods utilizing relevant sensor, PLC, and numerical command data based on statistical and/or machine learning models. Additionally, it would be valuable to consider the required resources for these calculations and determine the most suitable models for the given resource limitations.

vi) Maintenance planning

The sixth and last step concerns the simultaneous planning of CM, PvM, and PdM activities based on the obtained outputs from the previous steps. This is because in industrial situations, regarding the technical and economic aspects, all maintenance activities are generally followed through the same maintenance resources and managed by the same system.

It should be noted that, even if the RUL information is obtained, the maintenance planning of the whole machine cannot be managed by only RUL information. There are complexities to be considered such as the integration of RUL in a more global maintenance planning, consideration of dependencies between components and/or maintenance activities, failure risk, the unexploited useful life of the components, and industrial constraints and maintenance resource limitations.

The main challenge in this step concerns the identification of well-balanced maintenance planning through a cost optimization approach. The development of a mathematical optimization model, the objective functions, the cost elements, and the mentioned constraints are some of the challenges. Moreover, the capability of the maintenance planning DSS to prescribe an initial solution and readjust it based on the last data and information is the other challenge.

Regarding the last step, a new mathematical programming model was developed to minimize the overall direct (intervention costs) and indirect (expected failure risk costs, unused life losses) maintenance costs. Moreover, the economic grouping possibility was considered in set-up times for maintenance activities based on their structural dependencies. Moreover, a comprehensive sensitivity analysis of the most important aspects of the method was provided and the results were discussed. The experimental results together showed the validity, efficiency, and performance of the proposed mathematical model for maintenance planning. Based on the results, the proposed model identifies the best balance between direct and indirect maintenance costs. This indicates that indirect costs have considerable impacts on maintenance planning (especially in the mid/long term). Hence, we believe that the RUL estimation and optimization method could be utilized for industrial maintenance planning of multi-machines and multi-components.

The final step is developed in chapter 6, where a new mathematical programming model was developed to minimize both direct (intervention costs) and indirect (expected failure risk costs, unused life losses) maintenance costs, with consideration of economic grouping possibilities in set-up times for maintenance activities. A sensitivity analysis was conducted to identify the most important aspects of the method, and the results were discussed. Experimental results demonstrated the validity, efficiency, and performance of the proposed mathematical model for maintenance planning, which effectively balances direct and indirect maintenance costs. This highlights the importance of considering indirect costs in maintenance planning, particularly in the mid/long term. Thus, the RUL estimation and optimization method could be used for industrial maintenance planning problems.

Regarding future studies, scheduling and dynamic maintenance scheduling methods could also be investigated, and this is very promising for the industry. These methods could propose a more detailed schedule for maintenance resources and machines based on the last events as failures and updated maintenance tasks. However, regarding scheduling and dynamic scheduling problems, finding efficient solution methods could be studied. Spare parts replenishment constraints could also be envisaged in the problem. The emergency priority of maintenance activities is the other aspect that could be studied and integrated into scheduling models and methods.

Final remarks

More accessibility to real-time data via the IIoT implementation has allowed extensive investigation of predictive maintenance in a variety of applications. Most studies focus on the prediction of RUL, however, from an industrial point of view, the simultaneous decision-making for all maintenance activities is more important. Furthermore, in the literature, it is often neglected that all the equipment or components cannot be maintained by RUL and PdM. In this study, the general main steps, problems, implementation challenges of PdMMS, our contributions, and perspectives are developed in this thesis. In this way, various maintenance problems in different areas as well as their application in the use cases are presented in the relevant steps and chapters.

The results of these studies have provided significant insights and light for the further advancement of PdM strategy and methodology and integration into the current strategies of a maintenance system. The results also indicated that through the existence of interconnected information and a real-time data management system, and a constructive collaboration between maintenance, ICT, data scientists, and optimization experts, is needed to develop efficient DSS and/or smart/intelligent DSS the six mentioned steps in the PdMMS approach (Figure 39, and Figure 40). This DSS could readjust the initial solution and propose the appropriate maintenance decisions using the last data and information of machine/components and maintenance system. It is expected that these DSS types be capable to support the maintenance engineers and managers. Therefore, the challenges encountered in these steps such as connecting and accessing data, processing data, and developing analytical models, integrating experts' knowledge, human resources training and usage, need to be carefully considered.

Publications

Journal papers:

1. Behnam EINABADI, Mehdi Mahmoodjanloo, Armand BABOLI, Eva ROTHER, « Dynamic predictive and preventive maintenance planning with failure risk, and opportunistic grouping considerations: A case study in the automotive industry» - Journal of Manufacturing Systems (Second revision with minor changes submitted)
2. Mojtaba EBRAHIMI, Mehdi Mahmoodjanloo, Behnam EINABADI, Armand BABOLI, Eva ROTHER, « A mixed-model assembly line sequencing problem with parallel stations and walking workers: a case study in the automotive industry » - International Journal of Production Research (IJPR). <https://doi.org/10.1080/00207543.2021.2022801>

International published conference papers:

3. Behnam EINABADI, Armand BABOLI, Eva ROTHER « A new methodology for estimation of dynamic Remaining Useful Life: A case study of conveyor chains in the automotive industry » EDI4.0 2022 « The 5th International Conference on Emerging Data and Industry 4.0 (EDI40) » <https://doi.org/10.1016/j.procs.2022.03.060>
4. Behnam EINABADI, Maryam AMINI, Armand BABOLI, Eva ROTHER « Dashboard proposition for health monitoring of production system in the automotive industry » 17th IFAC Symposium on Information Control Problems in Manufacturing (INCOM 2021) <https://doi.org/10.1016/j.ifacol.2021.08.091>
5. Maryam Mohammad-Amini, Behnam Einabadi, Armand. Baboli, Reza Tavakkoli-Moghaddam « Determination of health key performance indicators and their visualization in the production system in the context of industry 4.0», IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA 2021) <https://doi.org/10.1109/ICIEA52957.2021.9436703>
6. Behnam Einabadi, Armand Baboli, M. Ebrahimi, « Dynamic Predictive Maintenance in industry 4.0 based on real time information: Case study in automotive industries », 9th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2019) <https://doi.org/10.1016/j.ifacol.2019.11.337>
7. Anthony CHEHAMI, Armand BABOLI, Behnam EINABADI, Mojtaba EBRAHIMI, Eva ROTHER « Determination and Prioritization of Flexibility Types in the Context of Industry 4.0: a Use Case in Automotive Industry» IEEM 2022 « The IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) » <https://doi.org/10.1109/IEEM55944.2022.9989757>

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Annex I

A. Fast fourier transform

Frequency variations of data are the hidden aspect of time-domain data that can be achieved by performing the Fast Fourier Transform (FFT) method.

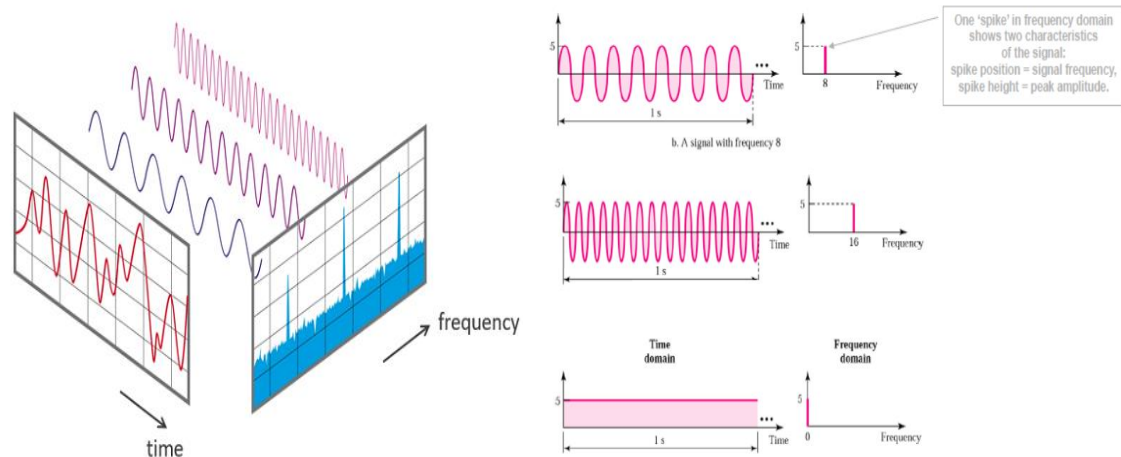


Figure 89. Time-domain and frequency-domain data (*Fast Fourier Transformation FFT - Basics*, 2017)

B. Feature extraction methods based on signal processing

Table 17. Signal processing-based methods in diagnostic and health monitoring

<p>Time-domain methods</p>	<p>RMS (N. Li et al., 2015)</p> <p>Kurtosis (Lei et al., 2016)</p> <p>Peak Value (Malhi et al., 2011)</p> <p>Correlation Coefficient</p> <p>Signal Residual Error (Lin et al., 2004)</p> <p>Energy Ratio (R. Li et al., 2012)</p> <p>Autoregressive (AR) (Al-Bugharbee & Trendafilova, 2016)</p> <p>Autoregressive Moving Average (ARMA)</p> <p>Pseudo-Phase Portrait (W. J. Wang & Lin, 2003)</p> <p>Correlation Dimension (Koizumi et al., 2000)</p>
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Frequency domain methods	Wavelet transform (Devendiran & Manivannan, 2015))
	Spectral flatness (Loutas et al., 2013)
	Hilbert–Huang Transform (Soualhi et al., 2015)
	moving-average wear degradation index (D. Wang & Tse, 2015)
Time-Frequency domain methods	Short-Time Fourier Transform (L. H. Wang et al., 2017)
	Wigner–Ville Distribution (Singru et al., 2018)

C. Wavelet transform in signal processing

Wavelet transform is one of the regularly used methods in signal analysis. This method can be used in the time domain and frequency domain analysis of non-stationary vibration signals. Here, the authors have used wavelet transform in order to decompose the vibration signals into 10 levels. One of the vibration decomposition graphs for the normal state can be seen in Figure 90. They have registered the vibration signals in four different conditions as normal, faulty, etc. based on the signal decomposition, statistical time domain, and frequency domain features have been considered as the health indicator for the diagnosis application. These HIs are Kurtosis, Skewness, Variance, Standard deviation (SD), and RMS. These HIs are further used for perdition purposes.

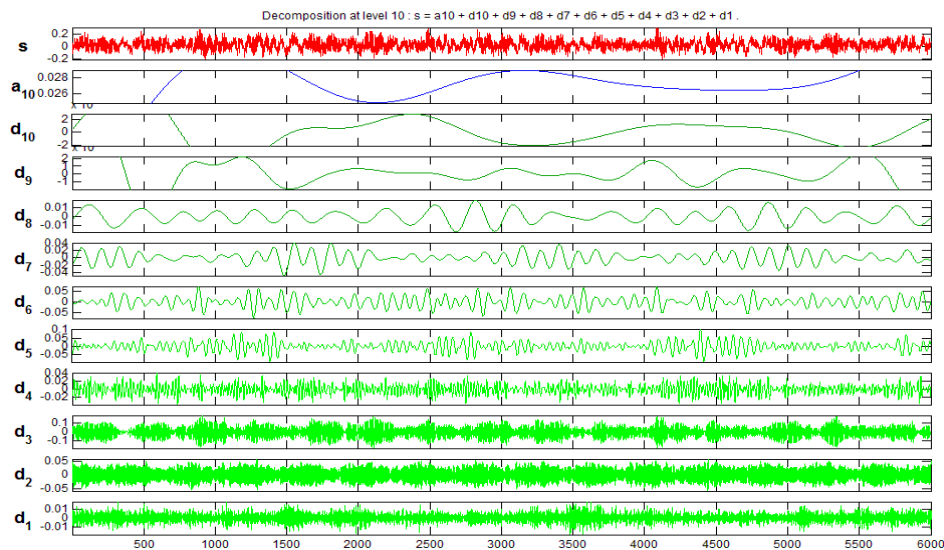


Figure 90. Wavelet transform for decomposition of vibration signal in a laboratory gear (Devendiran & Manivannan, 2015)

FOLIO ADMINISTRATIF

THESE DE L'INSA LYON, MEMBRE DE L'UNIVERSITE DE LYON

NOM : EINABADI (avec précision du nom de jeune fille, le cas échéant)		DATE de SOUTENANCE : 21/07/2023
Prénoms : Behnam		
TITRE : Nouvelles méthodes d'aide à la décision pour la maintenance prédictive dynamique basée sur la science des données et l'optimisation multi objectifs		
NATURE : Doctorat		Numéro d'ordre : 2023ISAL0053
Ecole doctorale : ED 512 Info-Maths		
Spécialité : Informatique et applications		
RESUME :		
<p>La maintenance prédictive (PdM) est devenue un sujet de recherche majeur dans l'industrie et dans le monde académique. L'objectif est d'utiliser des données en temps réel pour surveiller l'état de santé des équipements et prédire leur durée de vie restante (RUL). La plupart des études se concentrent sur la prédiction des défaillances, tandis que la prescription de décisions pour les activités de maintenance est beaucoup moins abordée. L'objectif de cette thèse est d'explorer les nouvelles méthodes et approches de PdM et de maintenance préventive (PvM) grâce à la science des données et aux méthodes d'optimisation mathématique. Notre étude vise à répondre à plusieurs questions telles que la possibilité d'estimer l'état de santé et/ou la RUL des équipements et de proposer une planification intégrale des activités de maintenance. Pour cela, une approche globale est proposée, qui couvre l'ensemble des stratégies de maintenance, et intègre l'analyse de la criticité de l'équipement, l'identification de la stratégie de maintenance, l'acquisition de données et d'informations, la surveillance de l'état de santé des équipements, la surveillance du système de maintenance, l'estimation de la RUL et la planification. Pour la mise en œuvre de cette approche, plusieurs outils, algorithmes et méthodes appropriés ont été développés et expérimentés sur quelques cas d'utilisation à l'usine Fiat Powertrain Technologies Bourbon-Lancy. Les résultats ont permis de démontrer la faisabilité de l'estimation de la RUL en se basant sur des données en temps réel, ainsi que l'efficacité engendrée. Par la suite, une méthode d'optimisation de planification des activités PdM et PvM a été développée et appliquée sur un cas réel en prenant en compte la RUL, le groupement opportuniste des activités et le risque de défaillance. Enfin, les perspectives managériales et les défis de la mise en œuvre de l'approche globale proposée dans d'autres entreprises ont été discutés.</p>		
MOTS-CLÉS : Maintenance prédictif, Estimation RUL, Planification de la maintenance, Données du temps réel, Data analytiques, Optimisation mathématique, Industrie 4.0.		
Laboratoire (s) de recherche : LIRIS		
Directeur de thèse :		
Armand Baboli	Maitre de Conférences HDR - -INSA de Lyon	Directeur de thèse
Président de jury :		
PETIT Jean-Marc	Professeur - INSA de Lyon- LIRIS	Président de jury
Composition du jury :		
MACCHI Marco	Professeur - Politecnico di Milano	Rapporteur
SIADAT Ali	Professeur - Arts et Métiers Metz- LCFC	Rapporteur
PETIT Jean-Marc	Professeur - INSA de Lyon- LIRIS	Examinateur
SCUTURICI Marian	Professeur - INSA de Lyon - LIRIS	Examinateur
Fouzia OUNNAR	Maitre de Conférences - Aix Marseille Université	Examinatrice
ROTHER Eva	Directrice industriel - Comeca Group-Chatenoy le Royal	Examinatrice
BABOLI Armand	Maitre de Conférences HDR - -INSA de Lyon	Directeur de thèse