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DECISION-MAKING MODELS FOR PREDICTIVE MAINTENANCE SERVICE SUPPORT SYSTEMS

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ABSTRACT

In the digital era, technology is continually evolving, with enormous advancements in automation enabling more efficient and cost-effective maintenance management. Digital technologies are converging and advancing in tandem with industries, resulting in significant progress in maintenance management. The traditionally human-managed preventive maintenance strategy is outclassed with predictive maintenance, something that represents a wonderful opportunity to significantly improve system maintenance planning, particularly for more complex systems with a significant monetary value. However, predictive maintenance methods face numerous substantial challenges in terms of their application, as they necessitate the use of contemporary tracking technologies, the development of robust data-gathering systems, and the execution of a variety of intricate procedures.

Considering the significance of maintenance management in industries, the primary motivation for this research work is to investigate existing practices and propose new methodologies capable of providing practical implications that may be useful in contributing to this field of study in terms of predicting failures, efficiency, and cost optimization. The present work is organized through three chapters, representing the main areas of study: 1) overview on maintenance management, 2) decision-making models supporting predictive maintenance, and 3) digital transformation in maintenance management. The objectives of research linked to the defined chapters are; 1) to study current practices of predictive maintenance and its applications in industry to identify its capability to predict and control equipment failures of complex systems; 2) to investigate various Multi-Criteria Decision-Making (MCDM) methods and their applications so as to develop an integrated predictive maintenance decision-making methodology for complex systems in industry 4.0; 3) to study the digital transformation of maintenance management and critical factors of digitalization, as well as uncertainty in the decision-making process for maintenance management in industry 4.0.

In achieving the objectives of this research, a mixed methodology, i.e., qualitative and quantitative research, is carried out on the basis of an extensive literature study. A literature review of predictive maintenance, its industrial applications along with its limitations is developed to identify the shortcomings in existing approaches. Various MCDM methodologies have been studied as well to investigate their effects on maintenance management and a plethora of real-world cases have been developed to offer practical managerial insights.

SOMMARIO

Nell'era digitale, la tecnologia è in continua evoluzione, con enormi progressi nell'automazione che consentono una gestione della manutenzione più efficiente ed economica. Le tecnologie digitali stanno convergendo e avanzando insieme alle industrie, determinando progressi significativi nella gestione della manutenzione. La tradizionale strategia di manutenzione preventiva gestita dall'uomo lascia progressivamente spazio alla manutenzione predittiva, che rappresenta un’ottima opportunità per migliorare significativamente la pianificazione della manutenzione del sistema, in particolare per i sistemi più complessi e dal significativo valore monetario. Tuttavia, l’implementazione di tecniche di manutenzione predittiva si trova ad affrontare una serie di sfide sostanziali, essendo richiesti l’utilizzo di tecnologie di tracciamento moderne, lo sviluppo di solidi sistemi di raccolta dati e l'esecuzione di una varietà di procedure complesse.

Considerando il ruolo chiave della gestione della manutenzione nelle industrie, la motivazione principale di questo lavoro di ricerca consiste nell’indagare le pratiche esistenti e proporre nuove metodologie in grado di fornire implicazioni pratiche che possono essere utili nel contribuire a questo campo di studio in termini di previsione dei guasti, efficienza e ottimizzazione dei costi. Il presente lavoro di tesi è organizzato in tre capitoli, che rappresentano le principali aree di studio: 1) panoramica sulla gestione della manutenzione, 2) modelli decisionali a supporto della manutenzione predittiva, 3) trasformazione digitale nella gestione della manutenzione. Gli obiettivi di ricerca relativi ai menzionati capitoli sono: 1) studiare le attuali pratiche di manutenzione predittiva e le sue applicazioni nell'industria per identificare la sua capacità di prevedere e controllare i guasti delle apparecchiature di sistemi complessi; 2) studiare vari metodi di decisione multi-criterio (MCDM) e le loro applicazioni in modo da sviluppare una metodologia decisionale di manutenzione predittiva integrata per sistemi complessi nell'industria 4.0; 3) studiare la trasformazione digitale della gestione della manutenzione e i fattori critici della digitalizzazione, nonché l'incertezza nel processo decisionale per la gestione della manutenzione nell'industria 4.0.

Questi obiettivi di ricerca vengono perseguiti attraverso una metodologia mista, ovvero sia qualitativa e sia quantitativa, basata su un ampio studio della letteratura. È stata sviluppata una revisione della letteratura sulla manutenzione predittiva e le sue applicazioni industriali insieme ai suoi limiti per identificare le carenze negli approcci esistenti. Sono state inoltre studiate varie metodologie MCDM per analizzarne gli effetti nella gestione della manutenzione ed è stata sviluppata una pletora di casi reali per offrire spunti gestionali pratici.

TABLE OF CONTENTS

ACRONYM LIST

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AI-ESTATE	AI Exchange and Service Tie to All Test Environment
ANN	Artificial Neural Network
ANP	Analytic Network Process
APM	Asset Performance Management
AR	Augmented Reality
BN	Bayesian Network
BWM	Best-Worst Method
CBM	Condition-Based Maintenance
CNC	Computer Numerical Control
CNN	Convolutional Neural Network
CM	Corrective Maintenance
CMMS	Computerised Maintenance Management Systems
CPS	Cyber Physical System
CSF	Critical Success Factor
DEMATEL	Decision Making Trial and Evaluation Laboratory
DL	Deep Learning
DTMC	Discrete Time Markov Chain
EMP	Emergency Maintenance Procedure
ELECTRE	ELimination Et Choix Traduisant la REalité
FAHP	Fuzzy Analytic Hierarchy Process
FBR	Faulty Behaviour Risk
FCM	Fuzzy Cognitive Map
FMEA	Failure Modes and Effects Analysis

FMECA	Failure Modes, Effects and Criticality Analysis
FTOPSIS	Fuzzy Technique for Order of Preference by Similarity to Ideal Solution
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
IIoT	Industrial Internet of Things
IPDSS	Intelligent Predictive Decision Support System
JIT	Just In Time
KPI	Key Performance Indicator
LOTO	Lock Out/Tag Out
MaaS	Maintenance as a Service
MCDM	Multi Criteria Decision-Making
ML	Machine Learning
MM	Maintenance Management
OEE	Overall Equipment Effectiveness
OM	Opportunistic Maintenance
OSA-CBM	Open System Architecture for Condition-Based Maintenance
PDM	Pre-Determined Maintenance
PM	Preventive Maintenance
PHM	Prognostics Health Management
PoF	Physics of Failures
PrdM	Predictive Maintenance
RAMI	Reference Architectural Model Industry
RCM	Reliability-Centred Maintenance
RIMFDS	Real-time Intelligent Multiple Fault Diagnostic System
RPN	Risk Priority Number
RUL	Remaining Useful Life
RTFM	Run-to-Failure Maintenance

SIMICA	Software Interface for Maintenance Information Collection and Analysis
SM	Scheduled Maintenance
SME	Small and Medium-size Enterprise
SOP	Standard Operating Procedure
SPC	Statistical Process Control
SVM	Support Vector Machine
TFNs	Triangular Fuzzy Numbers
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TPM	Total Productive Maintenance

SUMMARY OF FIGURES

SUMMARY OF TABLES

INTRODUCTION

Motivation

There is still a lot of ambiguity in maintenance management when it comes to the terminology used for different forms of maintenance in industries. Not just does this apply to operation and production management, but also to the related studies. Such a lack of standardization can represent a barrier to the establishment of a standard definition because of the wrong concepts or diffusion of the accepted labels for the different forms of maintenance, which are not necessarily well or completely described or understood, rather being assumed as local or specific habits. Neologisms are typically developed from foreign language translations, author definitions of specific names, and special circumstances. Even if definitions may vary, careful standardization is necessary to provide a clear notion supporting maintenance decision-makers towards the selection of the best type of maintenance for a component, equipment, or system. As a result, these definitions will have an impact on the economic elements of industrial organisations.

The evolution of maintenance concepts is linked to the approaches used to satisfy current maintenance demands and is based on the expectations of the industries. There are now such principles as keeping dependable and existing systems, shut down for maintenance, detecting and monitoring characteristics that suggest the optimal time to undertake maintenance for preventing problems, and so on. Other concepts, such as, for instance, initiatives to assure reliability and maintainability, are still in the design phase and serve as reinforcements to anticipate maintenance operations. Effective use of a maintenance approach is required for decision-making assertiveness. As a result, understanding the ideas of the most appropriate maintenance type to be implemented is required. Although the integration of various categories of maintenance must be theoretically understood, recognizing where a given application is completed and another one is initialised is critical for effectively planning and managing industrial maintenance.

In the current practice, new definitions for types of maintenance are continually being presented in literature and scientific publications, with little modification with respect to the existing notions, but potentially generating confusion due to the introduction of diverse terms [1]. As studied by Trojan and Marçal [1], maintenance may be categorized into generations, and the timeframe for each generation has been selected as shown in Figure 1.A. This evolution can be seen in the industrial demands of each generation, which emphasised the basic notions concerning maintenance classes and how they may be categorised. Splitting maintenance into generations resulted in the development of concepts for more efficient maintenance types that could be used in industry.

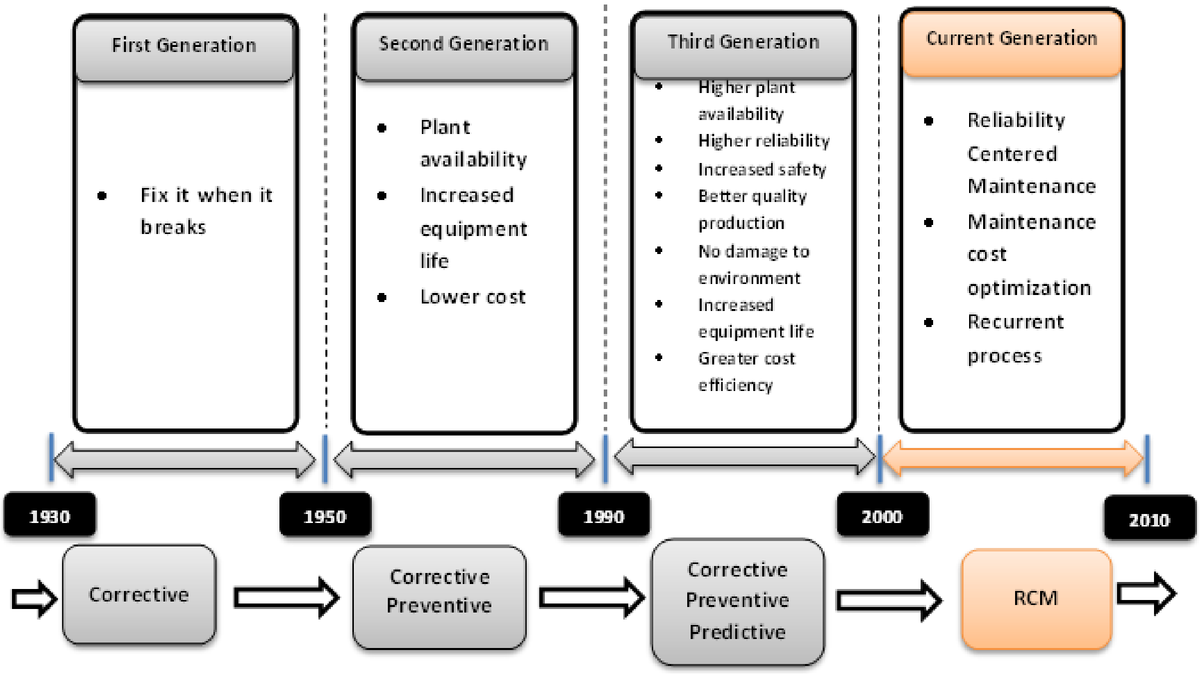

Figure 1.A. Maintenance evolution over time [1]

The first generation backed the development of corrective maintenance ideas including planned, unplanned, preventative, or repairing. The core idea of the first generation was corrective maintenance, which is until now "repair after damage". The second generation introduced conceptual ingredients towards preventive maintenance development, that is founded on planned repairs, operational process scheduling and control, and the progression of information technology. The evolution of condition monitoring tools as well as failure and risk analysis techniques provided the foundation for predictive maintenance in the third generation. Increasing maintenance demands fuelled the growth of these notions. These demands compelled the emergence of new innovations that may assist the manufacturing industry in ensuring quality and reliability, safety, availability of their assets and ultimately manufacturing operations. In such a context, reliability centred maintenance provided sophisticated methodologies connected to availability and reliability to the present generation, borrowed from the aerospace sector and commonly applied to industrial facilities [1].

Industrial assets and resources are maintained while controlling time and budget constraints, in order to provide optimal efficiency in the production process via the use of maintenance management. There was a time when maintenance management was seen as a merely time-consuming, labour-intensive, paper-based procedure. Nowadays, on the contrary, maintenance management is completely handled by Computerised Maintenance Management Systems (CMMSs).

While software plays an important role in maintaining equipment, the most effective methods, best practises, and properly qualified staff all come together to make up the whole of maintenance management. The types of maintenance carried out at a facility may be taken into consideration when designing a maintenance management system. Maintenance programmes should be calibrated according to the specific maintenance adopted and also by considering the function played by maintenance itself in the organisation of reference, independently on using a condition-based programme like predictive maintenance or a time-based programme like preventive maintenance. Any organisation with machine assets should strive to continually improve maintenance management, but there is no one-size-fits-all answer to this problem.

Assuring the long-term success of a maintenance programme relies on maintenance management, also involving such aspects as quality assurance, operational efficiency, and asset condition. Unplanned downtime is considerably reduced when industrial assets and resources are well-maintained. When there is unexpected downtime, the expenses associated with repairs (overtime personnel, replacement parts, and so on), delays in shipments, lost income, or full malfunctions of machinery, may quickly escalate. In addition to reducing operating expenses and increasing the quality and quantity of produced goods, maintenance management helps to increase the operational efficiency of plant facilities. Besides cost savings, additional advantages include greater workplace safety and productivity, and lower human errors [2].

The primary objective of equipment maintenance is to ensure that equipment continues to operate at peak performance levels. When a piece of equipment is properly maintained on a regular basis, its manufacturing output is maximized and its usable life is extended. If a maintenance department does not approach proactive equipment maintenance, then the frequency of failures may increase, potentially leading to shorter equipment life cycle, production delays, budget concerns, increase in overtime, inventory issues, safety accidents, and unsatisfied personnel throughout the factory floor. The actual cost of equipment downtime may be catastrophic when the above-mentioned list is not taken properly into account, as well as the possible damage to brand reputation [3].

Considering the significance of maintenance management in industries, the primary motivation for this dissertation work is to investigate existing practices and propose new methodologies capable of providing practical implications that may be useful in contributing to this field of study in terms of predicting failures before they occur, efficiency and cost optimization.

Research topics

The overall goal of maintenance management is to implement activities aimed at maximising productivity and identify the most effective methods and procedures in a particular field. In order to effectively manage expenses, efficiently plan projects, and reduce the likelihood of system failures, a CMMS report analyses constitute an excellent starting point. Generally, maintenance management's primary goals include the aspects detailed in the following.

Budgeting and cost control: maintenance management tools help managers to make informed decisions on how to spend company money. Cost management is a critical issue, since certain expenditures are more cost-effective than other ones. Decisions about which new component to be purchased for an equipment have to be made by considering cost, useful life and reliability.

Work scheduling and resources allocation: operational efficiency depends on scheduling work and allocating time and resources to maximize productivity. Maintaining thorough awareness of the phases of a process is helpful for maintenance managers to prioritize different tasks. As an example, maintaining a forklift is a task that may be prioritized by a maintenance manager in order to assure on-time delivery of products in the warehouse and onto the delivery vehicle.

Regulation and compliance: in order to comply with local, state, and federal requirements, enterprises use maintenance management software. A single operator may seem to be the most cost-effective solution, even if at least two people are required by law to be assigned to each asset for reasons of safety.

Reduced downtime/loss: to minimize downtime and losses due to failure, an effective maintenance management program establishes a maintenance schedule. In such a way, less income is wasted due to fewer production stoppages.

Increase life of asset: organizations use to invest a lot of money on equipment; therefore, they want to extend the related life cycle. Programs for equipment and infrastructure maintenance assist to keep them in excellent working order at all times. Indeed, machines, facilities, and other components last longer when properly maintained.

Equipment upgrade: maintenance management also aims to improve the current state of equipment by changes and expansions, or through the addition of new, low-cost products.

Training: Ensuring and maximizing the quality of the finished end product, maintenance management programs should involve educating employees in specialized maintenance skills as well as increasing operational safety and providing advice on equipment procurement, installation, and operation.

New trends in maintenance: latest technologies and computerized maintenance management strategies should be considered in achieving a comprehensive understanding of the day-to-day operations. Moreover, accessing historical data may reveal important information such as, for example, the reasons why a specific asset is continually underperforming [2], and so on.

An important part of maintenance management consists in dealing with assets aiming at guaranteeing their long-term functioning. However, a few fundamental differences have to be specified between the two disciplines of asset management and maintenance management.

1. *Asset management:* it is aimed at monitoring performance of industrial assets, and then acting on this data to increase production efficiency. Long-term success of organisations strictly depends on their asset management systems, being in tune with their entire business strategy. Organizations may use asset management techniques to determine whether their equipment are running as expected, operational expenses are being lowered, and their assets are yielding a greater return on investment.
2. *Maintenance management:* as previously discussed, CMMS software is often used to effectively track such company's resources as personnel, materials, and equipment. This kind of system provides analyst with relevant information about how to express judgments regarding building or enhancing maintenance processes. In order to reduce downtime and unplanned repairs, maintenance management ensures that company's equipment is kept in top functioning condition.

While asset management and maintenance management are technically defined as two diverse disciplines, they are typically combined and well complemented with each other. On the one hand, asset management examines the whole set of available data to identify and prioritize work that needs to be carried out on each asset. On the other hand, maintenance management focuses on the physical performance and upkeep of equipment [2]. CMMS eases the whole maintenance function, and the benefits of implementing a software platform which is capable to track all the relevant aspects for maintenance is clear. By maintaining a computer database of information on industrial maintenance activities, this type of system may provide progress reports as well as comprehensive records of the maintenance tasks. When data are reviewed, this will allow maintenance staff to perform their duties more efficiently and, at the same time, will enable the top management to make more effective decisions resource distribution and manage expenditures. Using CMMSs eliminates the need of manual data tracking and enables to monitor and synthetize numerous organisational aspects into a single digital location. CMMSs facilitate equipment information management, along with the management of preventive and predictive maintenance activities, the organization of work order systems, planning and scheduling, supplier management and inventory control. There are two types of CMMS systems: on premise (more conventional) and cloud-based (more current). On-premise servers are characterised by some limitations, including higher prices, complicated setup, and ongoing maintenance. Advantages are listed in the following.

Work order management: CMMSs with work order management features considerably streamline each stage of the maintenance work order process. Operators may submit service requests and maintenance managers can monitor work orders from their desktop or mobile device. It is possible to include preventative maintenance into the program by employing time, use, or condition-based events to automatically notify the software when a planned activity needs to be performed. Work orders may be scheduled automatically, and inventory can be alerted to guarantee that the essential components are in stock. All of the software's users, including technicians and managers, have access to real-time upgrades. Technicians have access to a dashboard where they can keep track of their day-to-day activities, mark tasks as completed, and bring assets online. Managers, meanwhile, are capable to monitor the status of tasks.

Reports on assets performance: the capability to gather and analyse information of every equipment is a huge benefit for maintenance managers, as it allows them to identify areas where performance and effectiveness may be quickly improved. Monitoring how company assets are being used and how they are functioning is an important aspect of maintenance management. Examining working hours and having the possibility of reading indicators based on time and distance are part of this. By using this data, CMMSs create asset profiles that contain information relevant to each asset, such as repair checklist, malfunction signals, safety precautions, and single-point lessons. A thorough picture of company's maintenance function can be obtained by building reports on such topics as asset unavailability and influence profiles of each asset on the inventory costs.

Inventory management: tracking extra components may be a complex task. Industries can have the right components on hand when they need them with the precise quantity. Various CMMS systems allow organizations to keep track of all inventory, including their location, time of procurement, way of use, and whether or not they are available across all of the organization sites. When carrying out activities of maintenance or repairs, professionals can locate the needed items and learn how to use them. Using CMMS also helps to keep track of inventory prices, order information, cycle counts, usage statistics and first-in/first-out details.

Audit capabilities: having a searchable record of each task makes prepares for audits processes. This enables the asset maintenance history to be audited by the maintenance management team. User profiles tracking certifications and renewal dates can be set up and standard training videos can be provided to people who need to renew and stay compliant with many CMMS systems. All of the work orders, task lists, and photos are saved for future reference, in case they will be needed to support the ISO certification application.

Mobile capabilities: recent cloud-based CMMS technology is almost always provided with the opportunity to be used from a smart device through remote access. This is essential as maintenance staff devote most of their period in the field, on the plant floor, and away from the office. The use of mobile technology enables maintenance professionals to document their work in real time. Taking images and asking for assistance on-site is also possible. Changes may be made even with no Wi-Fi connection thanks to a CMMS app with offline capability.

Integrating capabilities: modern CMMS technology has the capacity to interact with some different systems in any firm, which is one of the finest features. For example, integrating CMMSs with sales software offers the sales staff permissions to access to data they were unable to see before. With a wide range of integration options available from a reliable CMMS supplier, it is possible to create the perfect system for business organisations [2].

Firms often restrict access to their CMMSs to a small number of maintenance managers, something that has led to heated dispute about who should possess access authorizations. This can lead to a handful of issues over time. Most of the system's functions are placed on a small set of users, who must handle everything from tracking down work requests to evaluating and reporting on them. Another problem refers to the reduction of the collective influence of the entire team. Human resources are more likely to skip work, make poor judgments, and have poorer moral if they cannot understand the big perspective of maintenance operations.

Alternatively, having CMMSs accessible to a wider range of co-workers and departments may significantly benefit business by spreading the burden of maintenance management. This allows the maintenance staff to focus on other aspects of their work. Additionally, other departments may take data-driven choices based on information throughout the whole organization.

Some of the stakeholders that should have accessibility to the CMMS are listed below.

- *Maintenance manager:* human resources from the maintenance department, who are also system administrators, are obviously the most significant choice. The CMMS is under the direct control of the system administrators, who are also extensively engaged in the selection, implementation, and optimization of the CMMS itself. Maintenance managers are responsible for drafting, scheduling, and prioritizing work orders, as well as maintaining assets and providing reports on the status of those assets.
- *Facility manager/operator:* by granting the access to facility managers, they will be able to view data on various facilities, including maintenance schedules, measurements, and overall efficiency. Improved efficiency, budgeting, planning for audits and purchasing inventory can be extremely benefited from this information.
- *Reliability engineers:* engineers specialized on ensuring systems are reliable people who analyse CMMS reports and transform them into useful information. Providing reliability engineers with access to all of the CMMS's data enables them to produce effective reports and process enhancements with higher degree of accuracy.
- *Inventory managers:* the need of a CMMS in inventory management has been already discussed. Improved inventory management and buying helps to ensure that the maintenance crew gets the right components in the correct place whenever they require them. It also helps to keep better track of expenditures and data.
- *Health and Safety personnel:* maintaining regulatory compliance is easier when all the safety and health data are housed in a single system. This information is available to all the workers and can be accessed any time.
- *Technicians:* guaranteeing access to CMMS to technicians should be considered, since they use the system's capabilities more frequently. It is not necessary to grant all technicians administrative access, but they should be able to read work orders, get notifications and update asset profiles, and execute other duties related to repairs and inspections. Additionally, having all of this information available means that they will have the ability to log data in real-time and to consequently be more efficient and precise.
- *Production staff:* equipment workers and supervisors as well as other staff members who interact with the machinery on a regular basis fall into this category. CMMS enable

manufacturing workers to make proposals or add more information to work orders, enabling more effective repair procedures. CMMS can also be used by maintenance managers to allocate generic personnel or autonomous maintenance tasks, such as cleaning of equipment.

- *Vendors:* CMMS visitor permission should be granted to vendors and professionals who are not directly linked with the firm but conduct normal working activities. In such a way, work orders, task lists, and resources can be all readily visible. Furthermore, with the addition of mobile access, vendors would be able to keep in touch with maintenance personnel.
- *Executives:* the executive board and top management take data-driven choices using all the available facts. Accessibility to the CMMS is a simple approach to keep them informed regarding progress, successes, key performance metrics and more [2].

Objectives and methodologies

Given the importance of maintenance management in industrial contexts, the key purpose of the present work of thesis consists in investigating on current practices and in developing new approaches capable to offer practical insights that may be helpful to contribute to this field of research in terms of performance optimisation and cost reduction. Hence, the objectives of this research are:

1. To study current practices of Predictive Maintenance (PrdM) and its applications in industry to identify its capability to predict and control equipment failures of complex systems.
2. To investigate various Multi-Criteria Decision Making (MCDM) methods and their applications to develop an effective integrated PrdM and decision-making methodology for complex systems optimization in industry 4.0.
3. Study the digital transformation of maintenance management in industry 4.0, advantages and constraints of digitalization, critical factors of digitalization in maintenance management, and to determine what types of data should be gathered digitally to efficiently execute PrdM strategies.
4. Studying and addressing uncertainty in decision-making process for effective maintenance decision making of complex systems in industry 4.0.

In achieving the objectives of this thesis, a mix methodology i.e qualitative and quantitative research, and an extensive literature study is carried out. Literature review of PrdM and its applications in industry along with its limitations is conducted to identify the flaws in existing approaches. Various MCDM methodologies are studied as well to investigate the effects of applying MCDM in maintenance management. Mainly, Failure Modes Effects and Criticality Analysis (FMECA), ÉLimination Et Choix Traduisant la REalité (ELECTRE) TRI and Decision-Making Trail and Evaluation Laboratory (DEMATEL) approaches are analysed and a case study is conducted of a pump used in cleaning vehicle of a company operating in waste management sector. FMECA, ELECTRE TRI and DEMATEL techniques subjected to PrdM are integrated to identify failure mode and their criticality, sort failure into ordered classes and rank failures of a complex service system. Moreover, study discussed the digital transformation of maintenance management, identified critical factors and their interdependence by studying Fuzzy Cognitive Mapping (FCM). Additionally, dealing with uncertainty in decision making is also demonstrated in this study. Further, this research is extended to another real-case dealing with Fuzzy theory along with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), i.e FTOPSIS is utilized to investigate the most critical factor of maintenance management by converting linguistic variables, obtained from maintenance expert during various brainstorming sessions, into Fuzzy numbers, calculating the positive and negative distance from ideal solutions, and finding the closeness coefficient using TOPSIS method.

Thesis organisation

This thesis is formalized with a brief introduction on maintenance management along with objectives and methodologies, including three main chapters namely, overview on maintenance management, decision-making models supporting predictive maintenance, and digital transformation of maintenance management, respectively. The last part of the thesis includes the conclusion and future developments section. Moreover, appendices, abbreviations, references and list of publications are also provided in the thesis.

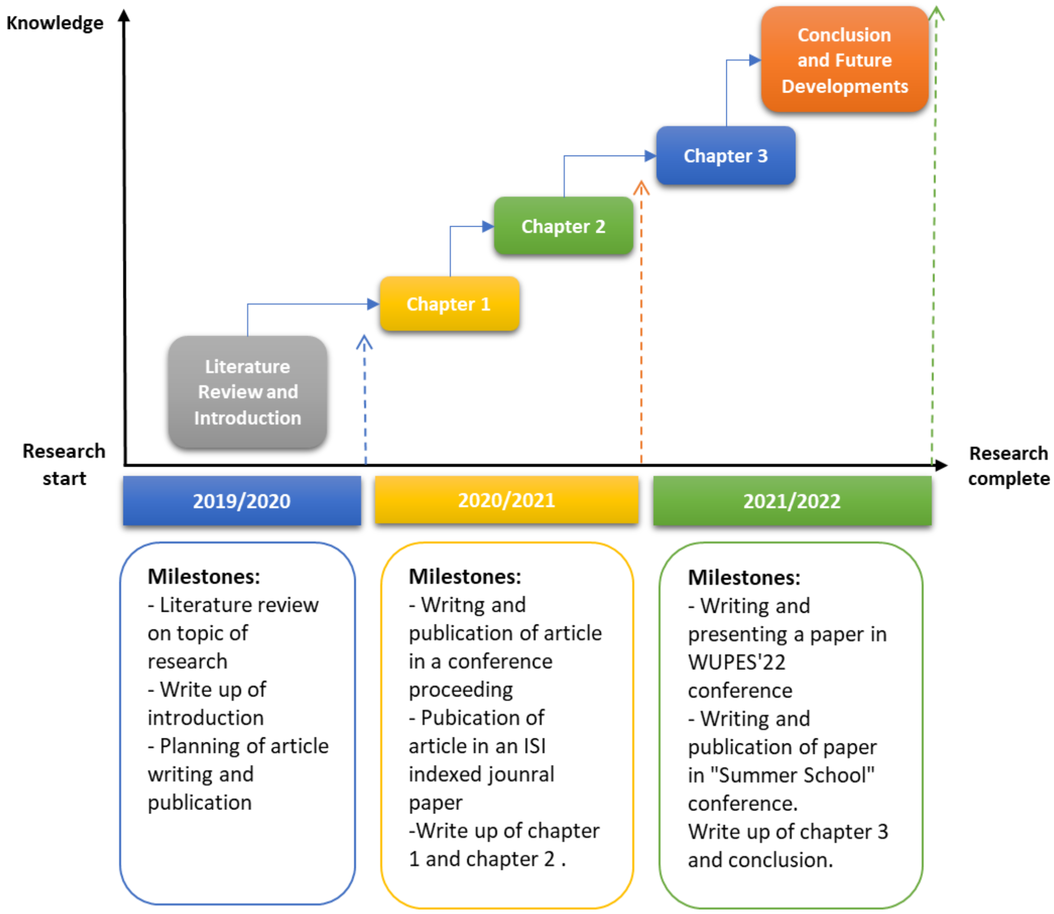

Figure 1.B. Thesis organization

Introduction section of this thesis includes the motivation that provides the idea and need of research on this topic. Further, various definitions, concepts and important factors of maintenance in industry are presented. Moreover, objectives of the research are formalized in this section and methodology used in this study is presented.

Chapter 1, “overview on maintenance management” elaborates the role of maintenance in industrial context, various maintenance policies, maintenance strategies and their classification, maintenance triggers and latest maintenance technologies are presented. Critical success factors of maintenance management in industry are also debated. Various literatures on Predictive maintenance (PrdM) and its role in industry 4.0 along with benefits and constraints is presented too in this chapter. Moreover, applications of PrdM in various industries, technical drivers of PrdM, role of technology in maintenance, and how to initiate a successful maintenance policy is discussed. At the end of the chapter, various analysed cases of PrdM in industry 4.0 are presented.

Chapter 2 titled as “decision-making models supporting predictive maintenance” discusses the decision-making approaches integrated with PrdM to achieve the maintenance objectives in the industry 4.0. In this chapter, FMECA, ELECRE TRI and DEMATEL methodologies are integrated and implemented for complex service system optimization. FMECA method is utilized to classify all likely failure modes of a system subjected to PrdM and risk matrices of relevance is utilized to assess the criticality of each failure mode. Critical failures are identified and categorized, as well as failures considered with high risk levels and conditions are highlighted using ELECTRE TRI method. Finally, DEMATEL is applied to find particular failures which are considerably dependent with other failures in the similar risk category than others within a class. An industrial case study is performed to observe the applicability of these integrated methodologies.

Chapter 3 is formalized with the title of “digital transformation of maintenance management”. This chapter discusses the relation between technology and maintenance, and digital transformation of maintenance management from traditional one. Chapter studied that what different types of data could be gathered digitally to efficiently execute predictive maintenance strategies. Chapter also discussed the critical factors of digitalization in maintenance management along with their advantages and limitations. Additionally, this chapter elaborated a decision-making model to support such strategies of maintenance management. Chapter presented that the expected outcome of the study would have the capability to assist maintenance management through the understanding of relations of influence bonding related critical factors with each other, by allowing to monitor equipment health, identify problems, predict and resolve issues long before they occur, and even enhance performance. Moreover, in this chapter, we assume a Multi-Criteria Decision-Making (MCDM) approach and, specifically, a method based on the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is applied to rank alternatives relevant to industry 4.0 for characterizing ambiguity in maintenance decision-making.

Last part of the thesis is conclusion and future development section. This section concludes the thesis and provides the future directions in the field of study. The presented research might be beneficial to facilitate organizations in making effective decisions and optimizing business. As a result, this study may have positive impacts on economic, social, and environmental factors, as well as maintenance policies implementation on the whole.

Chapter 1.

Overview on Maintenance Management

1.1. The role of maintenance in industrial contexts

The capability of business organisations to compete on the basis of minimum cost, excellent quality, and productivity is strongly impacted by the importance of maintenance as a core function in industries [4]. Maintenance costs and downtime due to machine and asset breakdown can be catastrophic in many sectors. Maintenance and reliability managers' primary goal is to assure the availability of systems and machines in organizations [5]. In the event of an unanticipated outage of machinery, equipment, or devices, the organization could be severely harmed with a consequent damage on reputation. As an example, when Amazon was offline for forty-nine minutes in the year 2013, this event cost $4 million in revenue to the corporation [4]. According to a study report carried out by Ponemon Institute, organisations on an average experience a loss of $138,000 per hour due to data centre outage. According to research, this is also believed to be between the 20% and 35% of the entire income earned by offshore wind turbines and between the 15% and 70% of the overall production expenses of oil and gas industries. As a result, it is crucial for organizations to apply a well-executed and effective maintenance planning to counter unexpected interruptions, enhance overall reliability, and minimize operating cost [4]. Maintaining an effective strategy for preventive maintenance may indeed lower operational risk and boost efficiency. Even if there are tried-and-true methods for growing plants, there is not a single approach that works for all of them. What works for one industry may not work for another. It all depends on company's resources available, and on company's long-term objectives [6].

Maintenance management is described in EN 13306:2010 as a set of all the "activities that determine the maintenance objectives, strategies, and responsibilities, and implement them through such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics". Objectives are established for the management approach based on such factors as costs and availability, safety and dependability. It is important for maintenance management to determine the approach based on the liability it bears, by taking into consideration equipment availability, human safety, environmental impact, and any other important requirement that may be connected with it, as well as the item's reliability and final product quality with relation to both cost and environment. The maintenance strategy is constructed to take into account processes, actions, resources, and duration. The European Standard EN 15341:2007 contains the most important indications. The aims of the main aspects are: assessing condition, comparing (internal and external benchmarks), diagnosing (analysing threats and opportunities), creating objectives and establishing the targets to be met, planning improvement activities, and constantly measuring changes over time. Financial, technological, and organisational factors are the three main categories. Elements from within and outside the organisation (culture, industry, product life cycle, criticality) must be taken into account while determining these parameters [7].

Repairing the equipment is not often worthy once it has malfunctioned, since problems must be forecasted and managed beforehand they occur by recognising associated root causes. Omshi, et al. [8] investigated on the different maintenance and repair approaches which have been presented until now, varying from basic life-based to condition-based maintenance. Lundgren, et al. [9] examined various models of maintenance and discovered that their applicability in industry is restricted to measure the effect of maintenance. Industry needs regular maintenance to ensure and keep equipment, components and assets, and for guaranteeing correct operational work. Lack of equipment to fulfil specified functions results in downtime, cost, and hazards for workers, and all of these factors are progressively worsened by each failure. In current business practices, high levels of competition do not allow companies to fail. With the advancement of technology and information systems, industries have been forced to adopt advanced monitoring technologies. In order to format, preserve, and evaluate the information on a descriptive and analytical level, they also involve complex analytics.

Implementing proper maintenance activity is necessary to limit the risk of breakdown. As presented by the British Standard BS EN-13306:2017, maintenance is a set of "management operations during the life cycle of an object designed to keep or restore it to a state in which it can perform the appropriate function”. Inspection, monitoring, testing, diagnosis, prognosis as well as such active maintenance measures as repair and refurbishing are examples of technical maintenance. Maintenance backed occurs when an organization receives support for its responsibilities [10].

Integrating cyber physical systems with the advancement of computing infrastructures, like big data, Artificial Intelligence (AI), data analytics, Internet of Things (IoT), cloud computing platform, and so on, is enabling smart manufacturing, in other terms Industry 4.0. Integrating systems through the use of digitalization promotes the creation of systems responding on a real-time basis to changing circumstances in the manufacturing facility, logistics system, and demands from clients. During the course of a manufacturing process, a vast amount of data is gathered and aggregated from many elements such as, for instance, human, tangible and intangible resources. Pre-trained AI algorithms may be used to rule computing infrastructures based on data available from manufacturing systems [10].

It is common to apply AI-based tools in order to obtain valuable knowledge from industrial data. The methods leverage past training and experience to integrate knowledge into the systems, allowing them to automatically learn and perceive to new environments. It is also shown that the approaches may be used in the manufacturing business because of their capability of managing large amounts of data, decreasing complexity, enhancing current knowledge, and uncovering key process relationships. These skills permit to predict the subject of interest of the company in order to ideally minimize the variance in their manufacturing line and increase efficiency and product quality. AI algorithms may be used to predict how production systems will behave in the future, and so this information can be used to make better decisions [10].

Optimising decision-making processes with the help of data-based useful information can aid the industrial transition to more environmentally friendly practises (e.g. reduction in wastage, increase in energy and resource efficiency, and predictive maintenance). An effective way to promote industrial sustainability while using intelligent manufacturing platforms consists in establishing proper communication tools between equipment and reliability/maintenance experts with the aim of optimising machinery maintenance activities. Also, manufacturing plants need effective maintenance plans to maintain system dependability, save costs, eliminate downtime, and optimize the usable life of equipment. Unforeseen events induced by ineffective maintenance approaches diminishes the overall economic output of a plant up to 20% and costs roughly $50 billion annually [10].

The first maintenance technique is the so-called run-to-failure, which means that no maintenance is performed until a breakdown occurs. Unforeseen events are inevitable in this case, even if the usage of a machine part is enhanced to some level. To avoid any unwanted breakdowns, preventative maintenance is the most common practice in industry, something that involves inspecting and maintaining parts periodically. A large suspension period and significant maintenance costs may be associated with routine inspections and maintenance. For these reasons, maintenance engineers frequently face a compromise scenario: they must choose between increasing the useful life (unplanned maintenance) and increasing uptime (preventive maintenance) [10].

Various kinds of maintenance strategies are described in literature. A comprehensive descriptive overview is reported in the following sections.

1.1.1. Maintenance policies

Several maintenance policies currently exist, but the three main commonly used approaches to keep machine and equipment operational are reactive, preventive, and predictive maintenance [6, 7, 11, 12]. The terminology of types of maintenance may differ from organization to organization, making it difficult to distinguish between concepts like preventive and predictive maintenance [13]. Historically in Europe, maintenance is organized and executed according to scheduled regular plans, and it is referred to as preventive maintenance or corrective maintenance if a failure has occurred. In preventive maintenance, actions involve performing repairs or changing out the parts to avoid equipment failure while, in corrective maintenance, repair is done only after the equipment or component has failed. This last approach makes it possible to get the most out of the machine's complete lifespan. However, as it can be expected, sudden breakdown can lead to costly repairs and potentially catastrophic circumstances. Alternatively, in predictive maintenance, machine or equipment failure is predicted before breakdown, considering the condition monitoring data predictions [1, 11]. Millions of dollars are yearly spent in industry because of unexpected shutdown and bad equipment conditions. In their never-ending effort to address these events, companies apply various maintenance methods, usually integrating two or more policies [13]. Based on the significance of the system, certain maintenance should be promptly undertaken, while other interventions could be rescheduled/postponed [1, 11]. Different types of maintenance are herein presented.

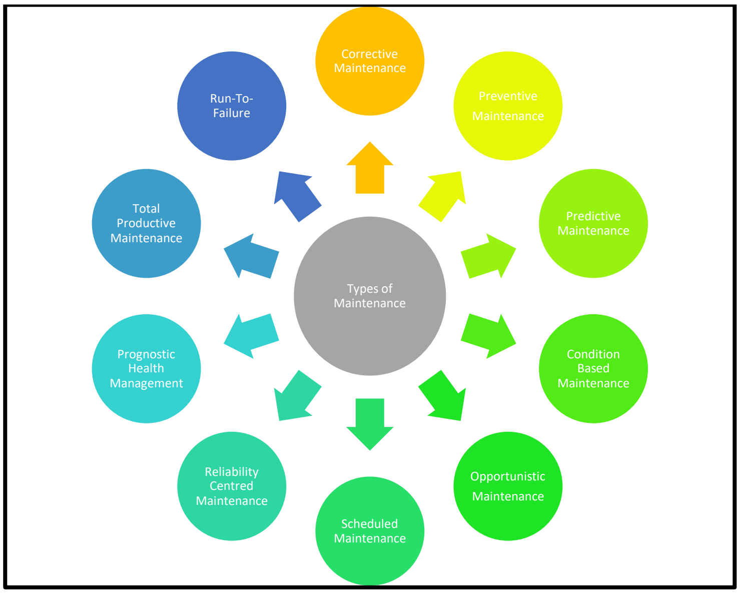

Figure 1.1. Maintenance policies

Corrective Maintenance (CM)

Corrective maintenance seems to be the most prevalent form of maintenance and is concerned with finding, isolating, and correcting a problem. Restoring a machine or component back up and running is ideal. However, corrective maintenance is completed after failure occurrence, which may be both costly and dangerous [1, 6, 7, 13]. If the intervention is postponed, this refers to as deferred corrective maintenance, while if the intervention is completed immediately, this refers to as immediate corrective maintenance [1, 7], since maintenance crew is primarily focused on restoring the equipment to the original operational status. Specifically, corrective maintenance could be deliberated as a run-to-failure maintenance approach, that is defined as "maintenance until the system fails." Condition-based maintenance could be beneficial and represent a cost-effective strategy relying on the maintenance team being observant enough to see how to maximize advantages of corrective maintenance by integrating condition-based, reliability-centred maintenance or other approaches [13, 14].

Preventive Maintenance (PM)

Preventing breakdown and malfunctioning is the primary goal of preventive maintenance. Failure occurrence is herein prevented, even if this is more commonly accomplished on the basis of a specific amount of time. Missing failures not occurring within a predetermined period of time may be extremely expensive [6]. Preventive maintenance is performed by analysing such data as operating hours or duration from the previous intervention, which results in periodic maintenance operations that do not take into account the actual state of the equipment. In most cases, there is still a reasonable amount of useful life remaining at the point of maintenance, but there is a concern of extra maintenance, for example, extensive lubrication of moving components [1, 11]. Preventive maintenance is carried out at programmed schedules or based on predetermined conditions in order to decrease the likelihood of breakdowns [7]. Specific procedures are generated for examining equipment on a regular basis, identifying minor faults and implement corrections before they become serious. Preventive maintenance aims to minimise the downtime risk. Several strategies are used to such an aim, including increasing the productive life of equipment, reducing the number of key equipment failures, and minimising productivity loss caused by equipment failure [3, 13]. The term "preventive maintenance" refers to a range of different forms of maintenance. The following ones are two examples:

1) *usage-based maintenance*, which employs triggers depending on how each item is really used and maintenance managers are expected to organise a preventative maintenance schedule based on predefined criteria by tracking asset utilization with equipment monitors;

2) *prescriptive maintenance*, which mirrors preventive maintenance in application, but making use of such machine-learning technologies as AI and IoT to support plan preventive maintenance actions [13].

Pros and Cons of Preventive Maintenance

PROS	CONS
Improves asset lifespan and reliability	Can take a while to implement fully
Reduction in unscheduled downtime	Doesn't take asset wear into account, meaning you might be doing excessive maintenance on some assets
Production improvement by keeping machines running at peak conditions	More complex to operate than reactive maintenance
Reduces overtime costs	
Gives a large amount of ana-lytical data when used with a CMMS	

Figure 1.2. Pros and Cons of preventive maintenance adopted from [13]

<u>Predictive Maintenance (PrdM)</u>

The primary goal of predictive maintenance consists in identifying possible problems before their occurrence, which opens a longer window of opportunity to address them [1, 6, 12]. Maintenance actions are performed in accordance with the machines projected condition to prevent a breakdown [7]. Condition monitoring, system efficiency, and other indicators are combined in predictive maintenance in order to forecast breakdowns or efficiency loss. Equipment conditions are continuously monitored, and any change in that state corresponds to prompt measures, something that extends the system lifespan. Predictive maintenance is the preferred technique when it comes to maintain supply grids in the most cost-effective, labour and environmentally-friendly way. A sophisticated algorithm is needed to establish effective and risk-free methods. Such AI-based techniques as expert systems and machine learning can also be utilized to develop these algorithms. PrdM currently represents one of the most popular use of AI in industry [3, 11]. This policy keeps track of the progress and status of equipment under normal operating situations in order to predict equipment failure. It is similar to preventive maintenance, being even defined as a type of preventive maintenance. A recent survey led by Reliable Plant found that many firms implement either predictive and preventive maintenance, but there are some differences between these two policies. Preventive maintenance does not use condition monitoring, which is required by predictive maintenance, implying the integration of such condition-based techniques as acoustic monitoring, infrared thermography, oil analysis, and vibration analysis. The fact that preventative maintenance entails the examination and execution of maintenance on equipment independently on the actual need of maintenance is another significant distinction, being the schedule based on a trigger.

Pros and Cons of Predictive Maintenance	
PROS	**CONS**
Cost savings by minimizing unscheduled downtime and maximizing uptime	Requires condition monitoring equipment/software
Offers real-time statistics of your asset's current condition	Requires specialized training to interpret and analyze condition-monitoring data
Ensures minimal productivity disruptions	Higher upfront costs
Optimizes the use of spare parts	
Optimizes the time spent performing maintenance tasks	

Figure 1.3. Pros and Cons of predictive maintenance adopted from [13]

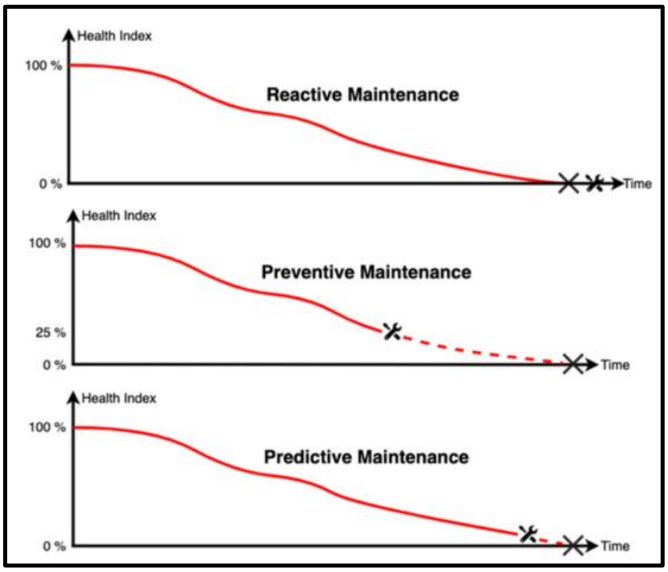

Figure 1.4. Example of maintenance strategies adopted from [11]

It can be extremely useful to have a thorough grasp of each of the maintenance policies previously described to have the possibility to include all of them into the general maintenance plan as much as possible. Predictive maintenance strategies can assist decrease unplanned downtime and outages, but they have also some flaws and limitations. Even if these strategies can assist in reducing human error, they cannot totally eradicate it [6]. Moreover, literature has been identifying other types of maintenance as discussed further.

Condition-Based Maintenance (CBM)

CBM denotes to predictive type of maintenance [14] which can be executed through the use of complex algorithms describing the failure progression. Indeed, the predicted form of the component as it declines to complete failure form is different from the actual condition of the component. On the one hand, as a complementary action, detection systems or any associated hardware device(s), which are critical to the accuracy required to monitor significant changes at the most fundamental physical level, might too become integral to the implementation of effective high-end CBM methodology for critical or complex systems as a whole. On the other hand, many CBM interventions do not necessitate such sophistication [3, 13]. This is the reason why the type of maintenance activity to be undertaken to prevent an approaching failure should have to be determined on the basis of the relevant trends of the failing state [14]. More in detail, predictive maintenance can be considered as one of the alternative form that have emerged from CBM: a preventive part which concerns the identification of the underlying causes of failures and a predictive side that concerns the identification of the significant symptoms and defects leading to failures [13]. A component's Remaining Useful Life (RUL) may be predicted by using CBM, which is based on the capability of being able to anticipate the RUL. This can be obtained by examining and measuring the physical features of the component at its most fundamental physical level as it progresses through its failure process until the data necessary to enable this predictive technology can be gathered. Such advanced procedures as the Highly Accelerated Life Test (HALT) and the Highly Accelerated Stress Test, are used to evaluate and expedite the experience of failure.

Prognostics Health Management (PHM)

PHM implies the existence of a dependence on decision-making based on CBM, even if not all the prognostics approaches are developed to be autonomously controlled and implemented as integrated components of the PHM process. Prognostics may comprise the development of a health management system and the use of specific devices to determine the physics of failure characteristics of essential parts aboard an automobile or system, among others. More straightforward implementations of prognostics-informed diagnostics may include the employment of a indicator, simple visible gauge, or other procedure that will provide an alarm beforehand with respect to failure occurrence, which can be considered to serve the role of a prognostic capacity. It goes without saying that minimizing the chance of encountering any failure is beneficial, but this gain is usually associated with a cost [14].

Reliability-Centred Maintenance (RCM)

RCM is among the most conventional type of preventive maintenance. It is Based on the application of reliability-based engineering principles into the planning and scheduling activities for replacing parts before they fail. Particularly, such a technique is used to reduce the likelihood of component failure. Accordingly, systems are likely to fail independently and in line with the particular individual reliability engineering forecasted breakdown features that are associated with them [1]. This assumption is utilized to justify the planning of maintenance schedules and the associated operations under a maintenance policy where the main goal consists in the possibility of preventing the occurrence of more severe failures [14]. The procedure of recognizing expected failures with company’s assets and identifying what are the specific needs to ensure that those systems last to operate at highest capability is known as RCM. In other words, breakdown is examined in order to determine optimal maintenance procedures and specific maintenance plans for each particular asset. Preventive maintenance and RCM are sometimes interchanged, even if there is still a significant distinction between these two policies: preventive maintenance is not selected like RCM, resulting in being lesser effective. Since RCM examines every component on an individual basis, inadequacy is minimized by allocating maintenance activities that are specific to each component of the system. When it comes to reliability-centred maintenance, a standard four-step workflow is used: asset selection, asset assessment, maintenance policy identification, and process repetition [13, 14]**.**

Scheduled Maintenance (SM)

Parts or components could be changed carefully to their predicted failure when using scheduled maintenance in order to exploit more usage of the equipment at the chance of them failing just before they are replaced. Furthermore, the scheduled maintenance program may promote more cautious approaches in which parts are substituted more in advance of the expected failure, that might put the system at danger of some kind of early change of parts. This might naturally increase the cost of opportunity while minimizing the possibility of operational accomplishment [14].

Opportunistic Maintenance (OM)

Maintenance activities performed as a part of a preventive or corrective maintenance program may necessitate the utilization of OM, aiming at replacing parts in ahead of time depending on the factor of convenience. In such a way, their probability of breakdown or becoming deteriorated avoid to compromise operational success when undertaking an associated maintenance task. Another reason for implementing this procedure would be to improve the system's availability, productivity of organizations, and safety as well as to reduce or increase the cost of ownership. This is a predictive process relying on elements of both RCM and CBM occurrences. OM is a type of individual technique that allows decision-makers to take into account interrelations among parts, systems, and variable costs connected with any changes or repairing operation while taking decisions about replacement or repair. It is possible to completely vet any component, structure, or design since the interrelationships of the parts, systems, and models have already been defined. Because of this, a high-end diagnostic assessment tool may be used to assess the possibility of an efficient opportunistic maintenance plan for a given design with respect to any model where the interrelated operational and failure features have been properly described and documented. This will provide the benefit of being capable to evaluate the effect of this type of preventive maintenance plan in conjunction with other combination of concepts, methods, systems, or economic aspects. When designing the implementation of any maintenance paradigm, opportunistic maintenance solutions can be efficiently utilized by involving production, manufacturing, and industrial sustainment decision-making [14].

Total Productive Maintenance (TPM)

In the manufacturing industry, the TPM policy refers to the process of employing machines, equipment, and workers as well as supporting processes capable to sustain and enhance the consistency of manufacturing along with system quality. In this context, TPM programs build small, interdisciplinary teams to target such fundamental areas as preventive and autonomous maintenance by simultaneously educating machine operator and standardising work procedures. Total productive maintenance refers to all of the departments within a business organization, and it is concerned with ensuring that the means of production are efficiently and effectively used. Instead of being considered as a strategy, total productive maintenance is regarded more as a process that helps to enhance activities. Also, TPM is not a fast cure, since it takes years to fully collect the benefits of a high-quality process. However, related gains are quite relevant [1, 3, 13].

<u>Run-to-Failure Maintenance (RTFM)</u>

RTFM is an unscheduled and repair-after-fail style of maintenance, typically implemented as a conscious effort to save expenses. For items such as disposable assets (i.e. equipment with disposable components that are intended to be changed out instead of to be fixed), items which are not critical such as tools, durable components (i.e. items which are not subjected to break or do not expected to be failed during normal operational situations), and systems that shows haphazard failure signs which are impossible to be predicted, organisations can choose to implement an RTFM plan [13]. Maintenance is approached in a reactive manner, actively intending to continue to use a piece of equipment until it breaks down or malfunctions. RTFM policy is appropriate for equipment with modest repair costs and when a breakdown would not imply significant operating concerns (as for instance production delays). It is possible to implement this policy for important equipment that need to be replaced after the next failure [3].

The following figure provides a quick overview of the many existing maintenance policies, as well as the sorts of activities that are involved, the goal of each work, and the methods by which the interval between two consecutive tasks is established. A maintenance plan that is efficient and successful will include a combination of all of these distinct forms of maintenance [15].

Comparison of Maintenance Types

Maintenance Type	Preventive Maintenance					Corrective Maintenance	
	Time Based Maintenance	Failure Finding Maintenance	Condition Based Maintenance	Predictive Maintenance	Risk Based Maintenance	Deferred Maintenance	Emergency Maintenance
Task Type	Scheduled Overhaul / Replacement	Functional Test	Measurement of condition	Calculation and extrapolation of	Inspection or Test	Repair / Replace	Repair / Replace
Objective	Restore or replace regardless of condition	Determine if hidden failure has occurred	Restore or replace based on a measured condition compared to a defined standard		Determine condition and conduct risk assessment to determine when next inspection, test or intervention is required.	Restore or replace following failure. Result of a Run to Failure Strategy or an unplanned failure.	Restore or replace following unplanned failure.
Interval	Fixed time or usage interval e.g. 1 month, 1,000hrs or 10,000 km	Fixed time interval (can be set based on risk assessment e.g. SIL)	Fixed time interval for condition measurements / inspections		Time based interval between tasks and scope of task is based on risk assessment	Not applicable, but intervention is deferred to allow for proper planning & scheduling.	Immediate intervention required.

Figure 1.5. Comparison of maintenance policies adopted from [15]

1.1.2. Selecting strategies and classifications

Predictive maintenance initially appears as the most cost-effective policy. On its turn, PrdM may be expensive, seldom representing a good investment, especially if employed for relatively inexpensive piece of equipment. Actually, the most effective strategy is frequently a mix of several approaches. Most firms begin with preventive maintenance and then gradually introduce more advanced solutions such as CBM and PrdM as people become more competent and confident in adopting a proactive attitude towards maintenance [3]. The figure below provides insights to adopt the best maintenance strategy.

	Reactive maintenance	Preventive maintenance	Condition-based maintenance (CBM)	Predictive maintenance (PdM)	Total productive maintenance (TPM)
PROS	cheap and easy to implement	fairly easy to implement	increases asset reliability and lifespan	increases asset reliability and lifespan	increases asset reliability and lifespan
	takes minimum training to run	doesn't require that much training to run successfuly	reduces the number of unexpected equipment breakdowns	gives insight into real-time condition of the asset	trains machine operators to take over simple maintenance tasks
		increases asset reliability and lifespan	gives insight into real-time condition of the asset	eliminates excessive maintenance	maintenance tech can be focused on compley tasks
		reduces the number of unexpected equipment breakdowns	reduces excessive maintenance	help you optimize maintenance schedule and spare parts inventory	improves team cohesion
		reduces waste and energy consumption		maximizes asset uptime	tries to eliminate waste a maximizes productivity
CONS	high posibility of equipment breakdowns	takes some time to get everyone on board and in the right mindset	requires the implementation of condition monitoring sensors	high upfront implementation costs	it can take years to fully implement
	often results in a lot of overtime work	it can lead to excessive maintenance	can have high implementation costs	requires specialized hardware and software to run	requires commitment and effort from the whole organization
	lock of tracking provides no insight into maintenance data	takes some training to fully implement and run	requires some training to implement and run	requires specialized set of skills to analyze sensor data	requires a strong commitment to continuous improvement
	can create unsafe working environment	requires consistency to prove its worth		can take some time to fully implement	takes a lot of training and oversight in the early days
	often leads to operational issues (like production delays)			requires a decent amount of training to run properyl	
	results in compunding negative impacts on your bottom line				
BEST USED FOR	Equipment that is cheap and easy to repair/replace. Equipment you plan to replace after next failure.	All assets that can cause operational problems if they are not working properly.	Critical assets that are expensive to repair/replace and which failure causes big operational issues.	Critical assets that are expensive to repair and which failure causes big operational issues.	Business in the manufacturing industry. Represents a maintenance philosophy that can be combined with any proactive maintenance strategy.

Figure 1.6. Summary of maintenance strategies adopted from [3]

Maintenance has been understood and categorised in many ways across the world. As already discussed, the European Standard EN 13306 divides preventative maintenance between two types: CBM and pre-determined maintenance (PDM) [1].

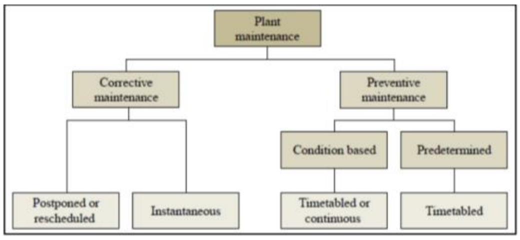

Figure 1.7. Maintenance types by CEN (2001) [1]

A particular standard in Germany, termed DIN 31051, states that “all steps for maintaining and restoring the goal condition, as well as evaluating and analysing the actual condition of the technical equipment in a system" are handled by a division referred to as Plant Maintenance”. Preventive maintenance, inspection, and repairs are the three categories of maintenance that are classified by DIN 2003. The following figure depicts this classification [1].

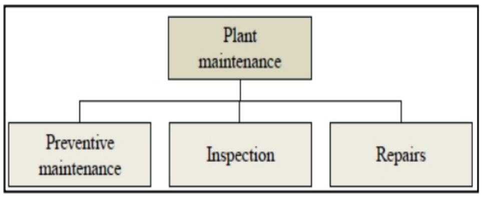

Figure 1.8. Maintenance types by DIN (2003) [1]

In the United States, the US Department of Energy (US DOE) requires that historical and present maintenance procedures have to be carried out once a system has failed. This definition emphasizes the actual interpretation of maintenance as “the work of keeping something in proper working order”, something that should consist in activities performed to save a system or asset from breakdown, as well as measures implemented to fix regular machine degradation during the function of the system, to retain its appropriate functioning state. With this understanding, there are four main kinds of maintenance: reactive, preventive, predictive, and RCM. This classification is depicted below [1].

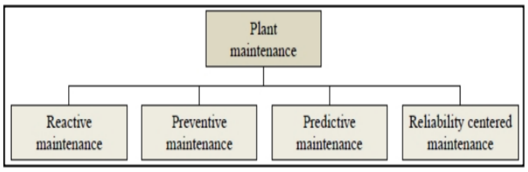

Figure 1.9. Maintenance types by US DOE (2004) [1]

Trojan and Marçal [1] presented a categorization system based on the strategies that were considered to be associated with conventional maintenance considerations. The authors provide two major methods in equipment maintenance, namely reactive and preventive strategies, as well as the numerous tactics associated with the maintenance ideas, as indicated in the following tables. The authors come to the conclusion that each of these approaches can be undoubtedly implemented through the use of a variety of methods, strategies, and technologies.

Table 1.1. Reactive tactics in maintenance [1]

Abbreviation	Brief description
IRM	Immediate reactive maintenance
SRM	Scheduled reactive maintenance
DRM	Deferred reactive maintenance
FBM	Failure-based maintenance
OTF	Operate to failure

Table 1.2. Preventive tactics in maintenance [1]

Abbreviation	Brief description
AGM	Age-based maintenance
BBM	Block-based maintenance
CIM	Constant interval maintenance
FTM	Fixed time maintenance
IBM	Inspection-based maintenance
LBM	Life-based maintenance
PPM	Planned preventive maintenance
TBM	Time-based maintenance
UBM	Use-based maintenance

s

Table 1.3. Proactive tactics in maintenance [1]

Abbreviation	Brief description
ACM	Availability centered maintenance
BCM	Business centered maintenance
DOM	Design-out maintenance
RBM	Risk-based maintenance
RCM	Reliability-centered maintenance
TPM	Total productive maintenance

Some writers from Latin America, notably Brazil, where the research was conducted, offer maintenance categorization in the same way as European and North American categories are presented, resulting in a miscellaneous classification [1]. The Brazilian standard ABNT, NBR 5462 (1994), categorises the different kinds of maintenance into the following categories:

precautionary maintenance, remedial maintenance, measured maintenance or predictive maintenance, scheduled and non-scheduled maintenance, On-site and off-site maintenance, distant maintenance, programmed maintenance, delayed maintenance, and planned maintenance [1].

As presented by French standards AFNOR NF X60-010 and NF X60-011, maintenance could be characterised as follows: corrective maintenance, preventive maintenance, and other maintenance. It is also possible to investigate preventive maintenance in the form of Preventive Systematic and Preventive Conditional approaches. Corrective maintenance was separated into two branches by Monchy (1989), in addition to the definitions provided by the AFNOR standards: Curative Corrective Maintenance and Palliative Corrective Maintenance [1].

According to Trojan and Marçal [1], the categorization developed by the United Nations includes an intriguing aspect on the forms of maintenance that are preventative and corrective in nature. Planned maintenance was the name given to the group of tasks that were assigned together. Accordingly, the United Nations categorization analyses remedial maintenance with approximate degree of scheduling, and maintenance measures are accounted when the machine is working, while it is not operating, or until the machine fails completely (repair by fatigue). The idea of operating following a failure is addressed in this categorization by maintaining a breakdown or performing unexpected maintenance [1]. As studied by Trojan and Marçal [1], a classification distinguishing between preventive maintenance and corrective maintenance was developed, however it also involves PrdM inside the preventive category, assuming it to be a form of prevention based on the situation of the equipment. In this aspect, the notion of "repair after failure" was introduced by corrective maintenance, and the concept was further developed to include improvements in the application of corrective maintenance practises. The authors' concepts include the planning criterion as an implicit part of their overall design. Summing up, fundamental conditions for establishing effective maintenance strategies are the following: 1) the equipment, system, or installation must be capable of some form of monitoring; 2) the equipment, system, or installation must be capable to make decision on which the maintenance type to be used is supported by the associated expenses; 3) breakdowns necessarily initiate from root causes which could be analysed and their progression must also be managed [1].

A more comprehensive approach adopted by The Brazilian Association of Maintenance, aiming at satisfying the dependability and maintainability objectives of the third revolution of industrial maintenance. Corrective, preventive, and predictive maintenance are the three primary branches. Other nomenclatures are used to comprehend some of the changes that have been occurring in each of these subgroups [1].

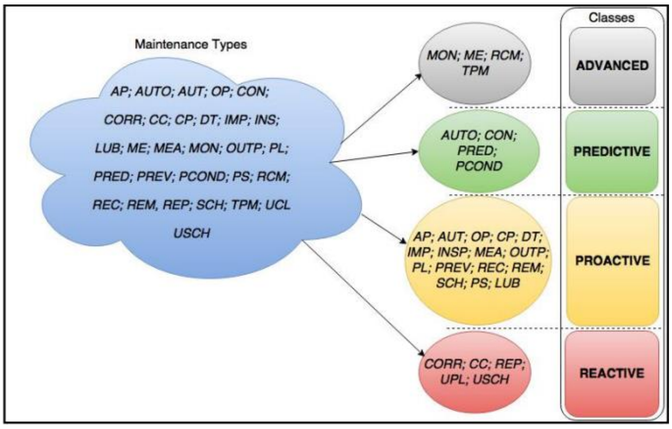

Figure1.10. Classification of maintenance strategies proposed by [1]

1.1.3. Maintenance triggers

Maintenance triggers may be created and utilized in anticipation of a variety of different sorts of maintenance projects. Breakdown triggers are employed in conjunction either RTF or corrective maintenance schedules. PrdM employs techniques such as time-based triggers in the shape of warnings in order to attempt to control a breakdown from happening. In addition to event-based triggers, usage-based triggers, and condition-based triggers will be explored [13].

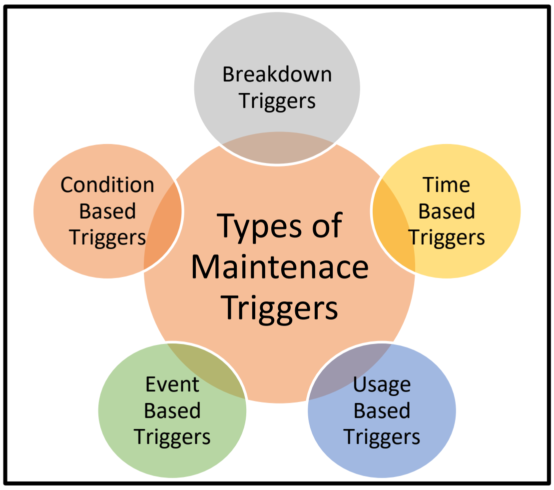

Figure 1.11. Types of Maintenance Triggers

- *Breakdown triggers:* as earlier indicated, breakdown triggers are employed in conjunction with RTF or reactive maintenance plans. In the event that an asset ceases to function, an alert is generated, which prompts the creation of a maintenance activity request aimed at repairing the system and returning it to its previous functioning state. In case, an industry is operating a collection of less-expensive, replaceable equipment and has inventory of replaceable components and units with them that may be switched out quickly and cheaply, stoppage is minimized to the greatest extent feasible and breakdown triggers are often not beneficial. There is no need to organize interventions with a great advance and this helps to keep maintenance budget as low as possible. However, it is also necessary to have replacement components and equipment accessible at any times, as well as qualified employees to handle problems. Keeping stock in this manner goes in contradiction of lean concepts such as Just in Time (JIT), which are intended to reduce the amount of retained inventory [13].
- *Time-based triggers:* these are among the most popular types of maintenance trigger. A computerized maintenance management system or other maintenance planning software is linked to these devices, which warn when a certain time period is exceeded. The use of time-based triggers in prognostic and precautionary maintenance plans is common for basic activities such as oiling components or organizing examination appointments. For instance, when a system's operating time reaches the period of fourteen days, an alert is sent to the appropriate party to have it serviced. As a practical example, a time-based trigger outside of the industrial environment would be changing the air filters in Heating, Ventilation, and Air Conditioning (HVAC) quarterly [13].
- *Usage-based triggers:* usage-based triggers are same as the time-based triggers since they depend on an already determined metric subjected to the utilization of the asset under analysis, irrespective of the duration during which the metric is measured. Usage-based triggers, as opposed to time-based triggers, ensure that an asset receives maintenance only after it has performed a particular amount of service. This is in contrast to time-based triggers, which are carried out on a regular basis regardless of the machine state. Any equipment that conducts period or amount-limited activities may be created along with a usage-based trigger in the same way that, for instance, an automobile receives changing of oil in each 5,000 miles. Meter readings can be entered into a computerized maintenance management system and utilized to trigger indications when a specified amount or reading is attained. Usage-based triggers are an excellent method of keeping machines operational

that operates on an irregular schedule, and they are most frequently used in combination with predictive or preventive maintenance approaches [13].

- *Event-based triggers:* a fire or a flood are examples of events that can be triggered, and event triggers may be utilized to act and inspect system or asset one the incident has happened. As an example, the requirement of planning and executing checks on the electric system and structure following a flood may be operated by a computerized maintenance management software capable to notify the maintenance team. Despite the fact that event-based triggers occur once an incident has occurred, they might also indirectly relate to the incident that triggered them. In most cases, event-based triggers serve as investigating activities after an incident has occurred [13].
- *Condition-based triggers:* depending on the conditions of a certain asset, condition-based triggers are used to activate this asset. The evaluation is used to decide if the asset can be acceptably allowed to continue operating or whether maintenance is required on the asset under consideration. Maintenance employees must get a comprehensive understanding of how the asset works so as to make a reliable conclusion regarding its state under this option, which is a more in-depth choice. The conditions of the equipment can also be assessed remotely. It is possible to employ condition-triggered alerts in conjunction with sensors installed on a system to observe characteristics such as noise, temperature, and vibration. An alarm may be generated to schedule an inspection if, for instance, a sensing device detects a rise in temperature which exceeds a predefined limit [13].

1.1.4. Latest maintenance technologies

One of the most important factors in achieving excellence in operations and maintenance for manufacturers is to have the benefits of the data offered by latest smart technologies. In order to accomplish this objective, a new maintenance solution is almost certainly necessary for keeping assets, workers, and procedures organized and running smoothly. The most significant technological advancements have occurred in the field of condition-based monitoring, which is used to perform preventive and predictive maintenance. Techniques such as thermography, vibration analysis, oil analysis, and motor current analysis may be used in conjunction with these types of maintenance to better decide on underlying reasons and failure triggers, search for advantages such as enhancement of machine’s lifespan and prior problem identification, and reduction in the frequency and effect of faults. With current technology advancements, manufacturers are seeing fewer mistakes and defects, as well as increased productivity while decreasing labour expenses. The use of automated sensors that can continually monitor machines is one of the most significant advancements. Not only can they be used in a variety of different forms of maintenance, but also they can provide a large quantity of data to be examined and utilized to enhance the efficiency of the maintenance process. Maintainability management system solutions can assist in harnessing all of these data and integrating them with four critical components for latest maintenance technology policy: utilizing PrdM, quality data and IoT, inventory management, and enhancing rounds for continuous improvement [13].

1. *Using predictive maintenance:* Although preventive maintenance is an excellent practice for avoiding shutdowns and decreasing stoppage, the subsequent phase is to adopt PrdM in order to effectively acquire and analyse the information generated by equipment.
2. *Quality data and IoT:* CMMSs capable of handling the huge quantity of data generated across facilities represent an ideal solution. The information from ordinary already connected sensing devices to implanted devices and all other in between will need to be included into the system. It is common a CMMS to be integrated with an IoT-based approach to not be dependent on specific types of gear. Data collected from assets on the plant floor are wirelessly integrated into the CMMS systems used by the company, thanks to IoT technology. This will need as a basis the configuration of the previously stated triggers and indications in order to automatically create work orders without personnel intervention.
3. *Managing inventory:* according to a recent Plant Services' study, approximately the 29% of respondents reported a backlog of maintenance activities that lasted three to four weeks. Adopting a reactive maintenance strategy all of the time simply leads to a growing backlog, which means that assets are not receiving the proper repair as they would require. Tracking backlogged jobs in a CMMS aids in the identification of problems, their causes, and their remedies, as well as the adoption of added positive culture in order to minimize accumulation.
4. *Improving cycles:* using information from a smart factory system and connected them with a CMMS allow to improve the maintenance cycle by sustaining savings and globally increasing efficiency [13].

Current maintenance technology trends are mentioned and briefly discussed in the following.

- *The Industrial Internet of Things (IIoT):* IIoT is a new technology based on the automated collection of data by making utilization of a system of cordless sensing devices. Affordable, multi-purpose sensing devices are now quite easily accessible than they have ever been.

These sensors may be integrated into a variety of industrial assets, and they can be used to collect maintenance data in an automated and reliable way. This removes the need for manual data entry, which is both expensive and time-consuming, as well as open to the occurrence of human mistakes.

- *Augmented Reality (AR):* as a result of the capability to provide remote instructions, AR is being used in remote maintenance and training, among other applications. This is a personalized method which enables maintenance duties to be tailored to the understanding and ability level of each individual employee who performs them. Augmented reality can be used to assist training delivered through an equipment merchant or senior maintenance employees through the use of a virtual presentation that demonstrates how a task has to be performed. While still a new trend, the use of AR for training is growing in fame as the complication of industrial system continues to rise. When it comes to continue with the variances in new system, especially the technically enhanced abilities that come with every system, augmented reality may release the stress on the involved maintenance employees. In the current market, some vendors supply large-scale AR services for maintenance, as well as IIoT organizations who offer AR as compliment of a packaged solution.
- *Maintenance as a Service (MaaS):* this is a relatively novel concept in the realm of maintenance. Essentially, it entails to provide maintenance facilities and, instead of charging a fixed service amount, plant operators can be charged with respect to the equipment maintenance services truly used. Vendors accomplish this by gathering and analysing data, processing data in the online data management system i.e. cloud, and planning jobs. Providers of services include those that predict the remaining life of an equipment or provide understanding into optimum maintenance intervals, those that provide service instructions and recordings, as well as virtual reality and AR communicating services, those that configure information technology and additional plant systems in accordance with investigative results, and those offering thorough data and information on system [13].

1.1.5. Critical success factors for maintenance management

Organizations must pay close attention to the critical success factors (CSFs) for maintenance management (MM) systems. Bakri, et al. [16] identify and synthesis nine CSF components having the most significant influence on MM implementation on the basis of the examination of prior research. A summary of the CSF components generated from prior investigations is depicted in the figure below. The past study conducted by earlier researchers served as the foundation for the development of the maintenance management framework. Based on the cause-effect diagram, the nine CSF components were integrated to form a final product. The MM framework built on this foundation illustrates the critical role played by senior management towards the solution of problems involving human and operational contextual variables throughout the MM program implementation.

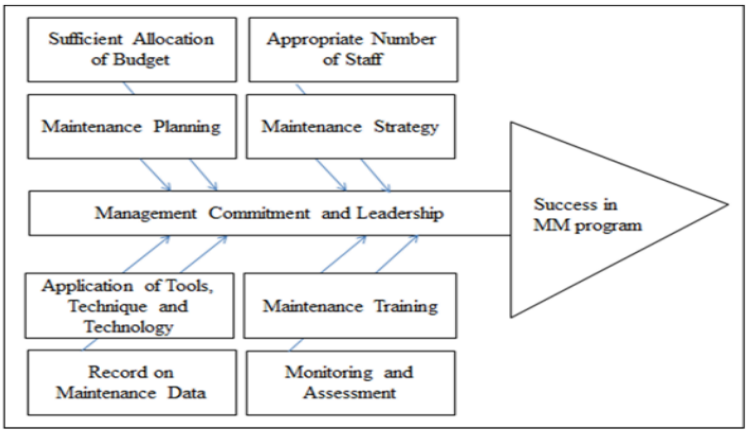

Figure 1.12. CSFs for MM adapted from [16]

Workers have to necessarily adjust their mind-sets and working culture for progress and improvement of the program. All of these challenges represent a significant element that must be carefully considered by senior management prior to the launch of a mass migration initiative. Top management should have a dominant role in setting maintenance policies, procedures, resource allocation, and aligning them with the company's commercial objectives.

The emphasis on training and instruction would instil in employees a desire to alter their mind-sets and be eager to take control of their equipment. Training on MM is indeed one of the most important factors defining success. Effective training programs would increase the competence of employees in the use of maintenance management approaches, according to the report. Emphasising the operational contextual variables would be the next step to be taken into account upon the human contextual aspects.

Bakri, et al. [16] lastly highlight that, in order to assure successful maintenance management, the strategy should be practical, complemented with strategic planning and disciplined execution methods in place. The integration of the maintenance management program with appropriate tools, methodologies, and technology will assure the long-term viability of the endeavour. The use of a computerised system would aid the corporation in its examination of the maintenance data for its machinery. Maintenance management would be able to improve if appropriate performance monitoring and evaluation on its progress are regularly carried out. This would allow management to examine its accomplishment while also addressing shortcomings in the implementation [16].

1.2. Literature review on predictive maintenance

Over the past years, the concept of maintenance has evolved from a reactive maintenance activity to a proactive process [17], with a focus on preventive maintenance. Maintenance that is reactive, such as corrective maintenance, only rectifies failures after they have occurred, tending to result in unplanned downtime. Preventive maintenance instead aims to replace components or machines that may still have significant productive operating time, leading to higher overall repair costs. Alternatively, predictive maintenance has the potential to forecast breakdowns in advance, minimising unexpected downtime and prolonging life of equipment, thereby decreasing maintenance costs while enhancing system dependability [18].

Through the growth of advanced methods, e.g. those based on IoT, sensor systems, intelligent systems, among others, there has been a transition in maintenance approaches through CM to PM and finally to PrdM. As already widely discussed, CM is only performed to restore the working condition of the equipment after a problem arises, tending to create significant latency and leading to important reactive maintenance costs. To prevent breakdowns, PM is led with respect to a predetermined plan depending on time or procedure repetitions. As a result, PM may undertake needless interventions, resulting in excessive preventive maintenance costs. PrdM is conducted based on online assessments of the equipment state of health, in achieving the finest transaction between the two needs of, on the one hand, exploiting as much as possible the useful life of systems and, on the other hand, to minimise the number of maintenance interventions and avoid the related expenses [4].

PrdM has become an important concept both in industry and academia [17]. Since it can be considered as a condition-based method forecasting equipment failures in ahead of time (on the basis of past data like inspection, condition monitoring data from previous failures as well as maintenance and other kinds of data), not only is a PrdM-based strategy cost-effective, but also it significantly increases the useful life of equipment [18]. Engineers and researchers have been continuously developing new methods for predicting problem and system degradation throughout the period of a system useful life, based on historical data, modelling, simulation, and failure probability calculations. In general, the useful lifespan of equipment is determined by the amount of data that is available and reachable. However, there are certain unanticipated scenarios difficult to be forecasted, such as for example shock damage and unwanted sudden equipment degeneration. Researchers are currently trying to figure out what is causing these issues and how they are affecting PrdM [17].

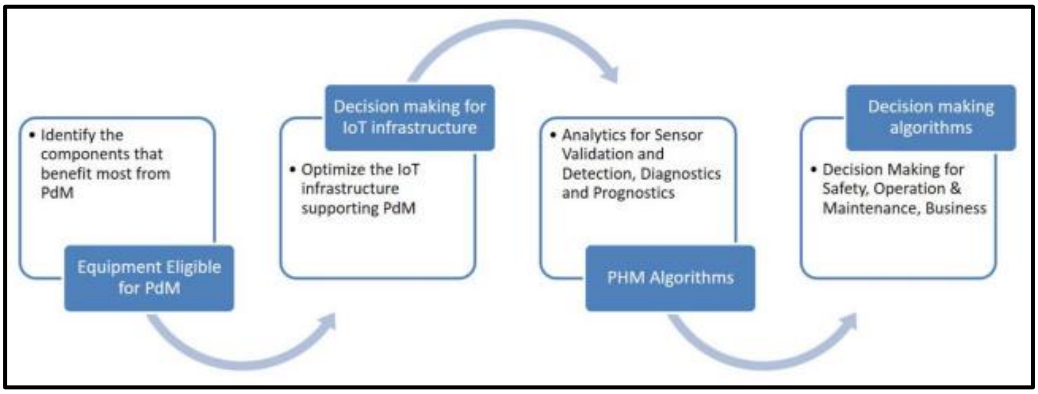

Figure 1.13. PrdM development activities adopted from [19]

By encouraging a more proactive maintenance approach, it is possible to reduce the need for regular and preventive maintenance interventions. A great deal of study has been developed on PrdM till date. Cheng, et al. [20] demonstrate that reactive maintenance is not able to avoid breakdowns and that preventive maintenance is unable to forecast the impending state in advance, allowing equipment to be restored early and therefore extending their life. As a result, companies are using the PrdM strategy in conjunction with new technology in order to bypass such constraints. AI, Machine Learning (ML), Statistical Process Control (SPC), Deep Learning (DL), IoT, Big Data, the Cyber Physical System (CPS), and the cloud architecture have all been used to make advancements, and they have provided significant avenues for future study. These strategies are mainly based on data collection from multiple resources, enabling to accurately predict failures of various nature.

While both unscheduled and preventive maintenance are subjected to the need of matching the previously discussed trade-off scenario, PrdM is a reliable strategy which has the ability to bridge the gap by optimizing availability. It is intended to observe the health of running system and to forecast when the system will fail in order to maximize uptime. In other words, it is possible to predict the future behaviour and condition of systems, which will aid to overall optimise maintenance activities. It is feasible to considerably minimise machine outage and maintenance costs by decreasing the occurrence of maintenance, while at the same time increasing the performance of the equipment [10].

The field of predictive maintenance has gained significant attention during the past couple of years for a wide number of reasons. Determining which method is the most appropriate, robust, and accurate in terms of fault detection still remains a challenge for industries, since detecting faults as early and as accurately as possible is an extremely critical issue as well as an important aspect of predictive maintenance. The main difficulty originates from that fact that, in manufacturing contexts, it is often essential to design models in the absence of a consistent amount of historical data. In such situations, unsupervised learning would be a preferable method for model construction [21].

Many sectors have benefited from the positive contributions of PrdM, demonstrating that it can be a crucial part of asset management both at the organizational and operational levels. Being the life cycle data of assets made of several measures resulting in huge amounts of data, data-driven algorithms are often used to effectively support Asset Performance Management (APM). As already expressed, current PrdM technologies are becoming more reliant on ML technologies, as data-driving technology progressively matures and becomes more widely used and accepted. However, despite the fact that ML algorithms have shown to be high-tech in terms of increasing diagnostics and condition monitoring abilities, these are not entirely exempt from flaws. Indeed, data types or structures utilized to train and verify algorithms may have a negative effect on their global performance. These constraints may result in greater calculation complexity, longer computational times, and worse accuracy, making PrdM solutions useless in terms of creating real-time estimates of assets future status as well as correct findings. A standard of practise for how data should be formatted per type of PrdM analysis depending on ML does not exist at this time due to the lack of suitable architectures or frameworks. Data-driven PrdM algorithms, as a result, may be restricted in their capacity to offer accurate and up-to-date information, depending on the ML-based analytical method that is used [22]. It still seems that failures have to be preferably corrected by firefighting rather than by identifying and solving the root causes [23]. It is possible to infer that methodologies capable to anticipate failures and identify associated reasons for pursuing core systems optimization continue to be developed and refined. Particularly, aiming at avoiding to experience possible critical failures, the foremost objective of PrdM is to provide opportunities to perform either an autonomous remedial maintenance along with the most desireable maintenance actions to mitigate the impacts triggered by undergoing incipient failures [14].

1.2.1. Predictive maintenance in industry 4.0: benefits and constraints

While the immediate goal is to establish a predictive maintenance capacity, there are several costs and aspects that must be addressed in achieving desired objectives. The greatest portion of the cost and predictive capabilities may indeed affect the implementation of maintenance strategies and, consequently, their efficacy, aspect that can be observed only after the investment has been shouldered [14].

Many predictive techniques need knowledge that is both expensive and unlikely to be easily accessible when the system is deployed, at least not at a fair cost. Consequently, except the knowledge is held internally and not ready to be transferred to another program, studying predictive tactics above and beyond the low-hanging fruit may result in cost savings for the system integrator or client. Finally, PHM designers must take into account the limitations of the own knowledge and experience. Most of the time, this is the case when knowledge is not shared for a single piece of design that the expert produces and implements. As a consequence, such information is not easily transferable to others. Thus, all of the potential options have to be carefully evaluated before committing to a maintenance strategy assuming the prediction of failures as the best solution in every situation. PrdM should first analyse live conditions of the systen and find if the anticipated RUL of important equipment is adequately more, by defining the so-called "Failure Horizon". This will increase the probability that the equipment is going to be appropriately used in the future. It is possible that the equipment depends on the accomplishment of a specific job or operation. This aspect leads to the view that PrdM seems among the exclusively desirable technique to maximise the operating capability of the component or comlex system [14].

During the previous years, there has been increasing attention on tools and methodologies for engaging in the concepts of predictive maintenance activities is developed. Maintenance can be planned by observing mechanical conditions of critical assets employing such parameters and predictors as temperature distribution, vibration trends, and acoustic features with the support of numerous condition monitoring systems. This allows the scheduling of maintenance when actually necessary. The study of Physics of Failures (PoF) patterns has received significant attention over the past fifteen years, raising the possibility that, sometime, almost any failure may be stopped or forecasted by thoroughly evaluating related PoF trends and developing suitable sensors to accurately notice and assess the progress of the indications to the failure as capability prognostics. In this context, PrdM actions may be planned in anticipation of a breakdown on the basis of the condition of the detected components, which is finally characterised as CBM [14].

Fourth industrial revolution (Industry 4.0), has been driven by the technological transformation which has turned manufacturing into smart manufacturing via evolvement and development of intelligent systems [24]. Almost every aspect of our life has been affected by the expansion of intelligent systems and other forms of information technology, by means of which the industrial world has undergone a huge evolution process. Since its inception in 2011, the notion of

"Industry 4.0" has ushered in significant transformations, particularly in manufacturing. Smart machines, big data, cloud computing, and CPS are just a few examples of notions that have emerged within the context of 4.0, which is a broader paradigm including a wide range of technologies. With Industry 4.0 technology, manufacturing costs are reduced and performance is boosted, resulting in a more efficient processes and techniques. In addition, Industry 4.0 made it simpler to detect and correct system faults [25].

The IoT technology as well as cloud computing methods are key components of Industry 4.0. As technology advances, such a concept is spreading. Industry 4.0 aims to build latest generation software and hardware to enhance productivity while simultaneously minimising expenses. Some of the most significant concepts of Industry 4.0 refer to interoperability, virtualization, autonomous management, real-time competence, service orientation, and modularity. Interoperability enables CPS to connect with humans and intelligent systems via the IoT technology. Sensor data utilized in the created system are connected to a virtual space and simulation models via virtualisation. It is evident as condition monitoring and problem diagnostics can be considerably simplified in systems through Industry 4.0 technologies. Another advantage consists in the possibility to consistently reduce costs and build new business along with innovative service models. The primary goal of Industry 4.0 is to create a network of connected devices that can interact with each other, monitor their surroundings using sensors, and analyse the collected data for leading relevant analyses [25].

From the reactive to the preventive to the predictive approach, it is clear as maintenance has been hugely evolving over time. Predictive maintenance does not represent the end of the road though, since new technology-driven advances are continuously in progress. The optimal use of industrial resources requires plants iterating and refining their core procedures on a regular basis. Strengths derived from diverse policies should be preferably combined in order to design a comprehensive plan for maintenance and to be prepared to face the occurrence of failures in the most effective way [6].

Since available resources are limited, it is important to consider that inaccuracies and restrictions will inevitably occur. There is a direct correlation between the time and money needed to fix or replace a piece of equipment or a system, as well as how much productivity is lost as a result of the reaction time required by workers who are obliged to manage failures or outages, e.g. corrective vs preventive vs predictive maintenance. Maintenance plans may be improved via reflection and implementation, which will lead to operational excellence [6].

Predictive maintenance has several advantages, one of which is the possibility of implementing the intervention only when it is really necessary, in general immediately prior to equipment breakdown. In other words, predictive maintenance allows to save money until the very last minute, before any significant harm occurs and without resulting in business shut-down and mechanism breakdown. It has been calculated as, thanks to the support of PrdM, return on investment may be enhanced while exponentially reducing downtime by up to 70-75% and 35-45%, respectively [12]. The following graph shows how a typical operational breakdown progresses over time. Failure is depicted in the form of an orange arrow. The time period reported in the top-right corner begins when the failure first begins to show signs of physical degeneration and process may last at a reduced level. With time advancing, the approaching failure moves across its predicted failure prospect, culminating in actual failure at the orange line uppermost point.

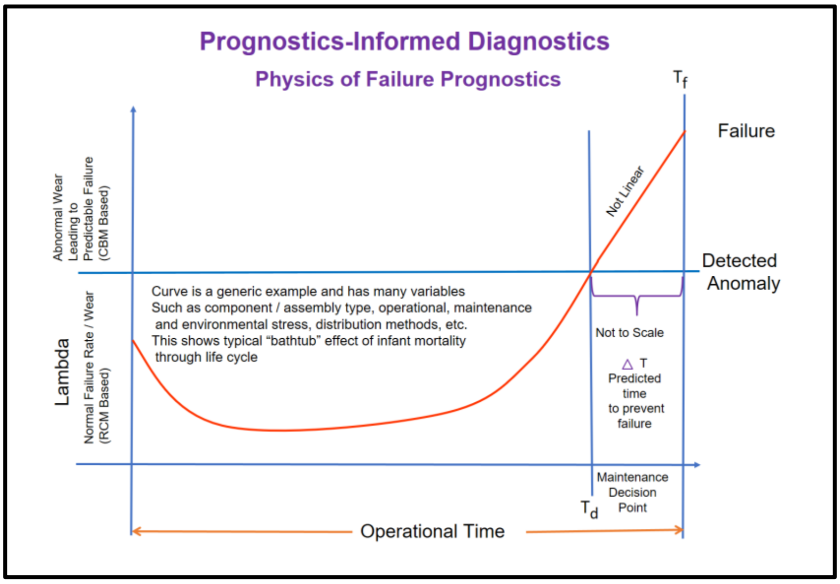

Figure 1.14. Progression of failure over time adopted from [14]

When examining the course of failure, scientists make use of cutting-edge sensors and algorithms derived from in-depth research into the underlying physics of the process. In order to accomplish this task, which is highly specialized and often expensive, researchers must first gather enough data from a variety of sources, including measurements and sensors that can only be obtained by studying determined physical characteristics.

However, we are more interested in enhancing the investigative model and sustaining capabilities of an item by fulling use any inclusion of this kind of technology. There are factors that must be taken into consideration while developing a predictive or prognostic system for a deployed asset, such as location, coverage, diagnostic validation, and so on [14]. PrdM has also a number of disadvantages, the most significant being the high initial investment. High degree of technology is indeed required for the implementation, as well as workers that can correctly analyse data from condition monitoring sensors. This may require part-time employees capable to read and disseminate information. This is the reason why making decision on PrdM implementation has to follow a thorough budget analysis.

1.2.2. Applications of predictive maintenance in relevant industries

There are several businesses contexts whose operations are heavily relying on predictive maintenance. These industries often feature important equipment that can be anticipated with regular monitoring. Food production, oil and gas, manufacturing, electricity and energy plants, and information technology are examples of industries falling within this description. Let us think, for example, to industrial ovens that are critical components of food processing plants and whose capability to remain viable may depend on PrdM. In such a case, placing a sensor monitoring heating and shaking would allow workers to make actual improvements or modifications on under-performing devices [14]. Since the 1990s, PrdM has been used in industrial settings. ISO published a series of condition-based maintenance standards in 2003. As a part of the ISO 13374, MIMOSA implemented the Open System Architecture for Condition-Based Maintenance (OSA-CBM), which represents criteria and techniques for exchanging, providing, and showing pertinent statistics and facts. OSA-CBM began with seven common layers, but now only six functional blocks are considered [4].

- Data sensors can be accessed and collected using the data acquisition module.
- Single or multi channel signals can be transformed by particular feature extraction techniques used to acquire data.
- Condition monitoring is carried out by comparing characteristics to predicted values or operating limitations and returning indications and/or alerts.
- Health of systems is assessed by monitoring operation condition and maintenance history.
- An assessment of future usage patterns is carried out as a prognostics assessment to predict the existing health status of the machines into the future.
- Considering the operating history, existing and prospective mission profiles and resources, the Advisory Generation suggests maintenance operations and modifications to systems.

Table 1.4. Benefits, challenges and applications adopted from [4]

	Benefits	Challenges	Suitable applications	Unsuitable applications
RM	• Maximum utilization and production value • Lower prevention cost	• Unplanned downtime • High spare parts inventory cost • Potential further damage for the equipment • Higher repair cost	• Redundant, or non-critical equipment • Repairing equipment with low cost after breakdown	• Equipment failure creates a safety risk • 24/7 equipment availability is necessary
PM	• Lower repair cost • Less equipment malfunction and unplanned downtime	• Need for inventory • Increased planned downtime • Maintenance on seemingly perfect equipment	• Have a likelihood of failure that increases with time or use	• Have random failures that are unrelated to maintenance
PdM	• A holistic view of equipment health • Improved analytics options • Avoid running to failure • Avoid replacing a component with useful life	• Increased upfront infrastructure cost and setup (e.g., sensors) • More complex system	• Have failure modes that can be cost-effectively predicted with regular monitoring	• Do not have a failure mode that can be cost-effectively predicted

Table 1.5. Summary of international standards related to PrdM [4]

Organizations or Countries	Standards No.	Year	Subject
IEEE	IEEE P1856	2017	IEEE Draft standard framework for prognostics and health management of electronic systems
	IEEE 3007.2	2010	IEEE recommended practice for the maintenance of industrial and commercial power systems
	IEEE 1232	2010	Artificial intelligence exchange and service tie to all test environment (AI-ESTATE)
	IEEE 1636	2009	Software interface for maintenance information collection and analysis (SIMICA)
ISO	ISO 13373-2	2016	Condition monitoring and diagnostics of machines – Vibration condition monitoring – Part 2: Processing, analysis and presentation of vibration data
	ISO 13381-1	2015	Condition monitoring and diagnostics of machines – Prognostics – Part 1: General guidelines
	ISO 13372	2012	Condition monitoring and diagnostics of machines – Vocabulary
	ISO 2041	2009	Mechanical vibration, shock and condition monitoring – Vocabulary
	ISO 13374-1	2003	Condition monitoring and diagnostics of machines – Data processing, communication and presentation – Part 1: General guidelines
	ISO 13373-1	2002	Condition monitoring and diagnostics of machines – Vibration condition monitoring – Part 1. General procedures
IEC	IEC 62890	2016	Life-cycle management for systems and products used in industrial-process measurement, control and automation
	IEC 60706-2	2006	Maintainability of equipment – Part 2: Maintainability requirements and studies during the design and development phase
	IEC 60812	2006	Analysis techniques for system reliability – Procedure for failure mode and effects analysis (FMEA)
	IEC 60300-3-14	2004	Dependability management – Part 3-14: Application guide – Maintenance and maintenance support
German	NE 107	2017	NAMUR-recommendation self-monitoring and diagnosis of field devices
	VDI/VDE 2651	2017	Part 1: Plant asset management (PAM) in the process industry – Definition, model, task, benefit
	VDI 2896	2013	Controlling of maintenance within plant management
	VDI 2895	2012	Organization of maintenance – Maintenance as a task of management
	VDI 2893	2006	Selection and formation of indicators for maintenance
	VDI 2885	2003	Standardized data for maintenance planning and determination of maintenance costs – Data and data determination
China	GB/T 22393	2015	Condition monitoring and diagnostics of machinesGeneral guidelines
	GB/T 25742.2	2014	Condition monitoring and diagnostics of machines – Data processing, communication and presentation – Part 2: Data processing
	GB/T 25742.1	2010	Condition monitoring and diagnostics of machines – Data processing, communication and presentation – Part 1: General guidelines
	GB/T 26221	2010	Condition - based maintenance system architecture
	GB/T 23713.1	2009	Condition monitoring and diagnostics of machines – Prognostics – Part 1: General guidelines

As reported in the above Table, OSA-CBM is not the only standard currently existing in the field of PrdM. For the need of comprehensiveness, it is important to mention the IEEE Standards developing regulations primarily focused on the generic definition of examining and finding the information, e.g. the AI Exchange and Service Tie to All Test Environment (AI-ESTATE), within IEEE 1232, and the Software Interface for Maintenance Information Collection and Analysis (SIMICA), within IEEE 1636. Moreover, such published standards as ISO 2041, ISO 13372, ISO 13373-1, and ISO 13381-1 refer to condition monitoring in a methodical way. It is possible to observe as PrdM has widely been the focus of many other organizations and nations. Based on all of these considerations, we may conclude that the PrdM framework is still an open issue. The substance of standards created by various organizations and governments overlaps and, lastly, developing technologies have not yet been included in the standards into the backdrop of smart operations and Industry 4.0 [4].

1.3. Technical drivers for predictive maintenance management

The high level of complexity characterising modern industrial systems along with required automation and adaptability make PrdM an appealing strategy for reducing machine downtime, enhancing overall system dependability, and lowering operating costs. The following three critical issues have to be taken into account when evaluating PrdM.

1) Architectures of PrdM systems: as a output of the urgency of Industry 4.0, such smart techniques as enhanced sensing methods and cloud computing have been incorporated into industrial systems. This allows to create compatibility with diverse industry standards in developing effective, correct, and generalized maintenance models by adopting evolving approaches. As long as the essential needs of PrdM are met (e.g. data collection, problem identification and prediction), it will be viable to maintain this integration.

2) Objectives of PrdM: objectives have to be thoroughly analysed and specified with relation to the specific system subjected to PrdM. Multi-component systems, for example, may suffer from excessive dependability, with consequent unacceptable availability rates corresponding to minimum maintenance costs. It is then important to comprehensively characterise systems and constraints before considering PrdM.

3) Diagnostic and prognostic methods: some of the most popular methods differ in terms of used algorithms, e.g. model-based algorithms, auto encoder, Support Vector Machine (SVM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and others. PrdM may face problems varying according to the specific industrial context. Fault diagnostic and prognosis methodologies supporting PrdM must be developed for particular issues [4].

1.3.1. Use of technology in maintenance

Technological solutions, particularly predictive maintenance tools, should be considered as integrant part of maintenance plans. In the case of systems requiring more frequent monitoring than set point alarms, industries have the following options.

1. All of the equipment can be monitored on a rotational basis, something that enables the plant to check on the status of all of the equipment on a regular basis.

2. Core and critical equipment can be continuously monitored so that the likelihood of severe failure occurrence can be reduced, with consequent beneficial influence on the overall safety and production level of performance related to a given plant.

Resources and time are constraints on what a facility can observe, but technology can assist in overcoming these constraints. If predictive maintenance technology automatically tracked all of the equipment in real time, sending alerts to the plant when a piece of equipment needs to be repaired or replaced, this would be more effective. Besides predictive maintenance solutions, there are a variety of technologies available for enhancing the maintenance function [6].

Strategy is crucial, but even the finest strategy is worthless if not integrated with effective methods. The first step to accomplish this integration aims to assess current skills as well as specific goals. Using machine learning to forecast maintenance, for example, will require high-quality data. Moreover, training and information exchange are two important steps that are commonly overlooked. Implementing maintenance strategies requires resources in terms of time and money to achieve and maintain effectiveness. In this context, developing suitable training plans as well as strategies for information exchange is fundamental to involve human resources as actual parts of the process by nurturing their awareness.

It is also important to highlight as predictive maintenance services are available in a variety of price ranges and complexity levels, ranging from economical to expensive and from simple to sophisticated. They do not have to be simultaneously implemented, even if considering potential areas for service integration can support towards the development of maintenance plan and methods, something that is not a one-time endeavour [6].

1.3.2. Initiating a successful maintenance program

Maintenance personnel is often under pressure to deliver appropriate outcomes while working with restricted budget constraints. This occasionally leads to the purchase of the cheapest assets just because they are more easily accessible. However, this is clearly a short-sighted decision, since this kind of assets tend to breakdown more frequently, apart from using a greater proportion of maintenance resources over time. What are potential solutions? The quantity of equipment maintenance required corresponds to the quality of the assets purchased. The necessity to find a balance between maintenance expenses and investments is something that maintenance departments must take into account on a daily basis. Independently on the quality of the equipment, some amount of maintenance will always be necessary. Let us consider how to draw up a preventative maintenance schedule for equipment. This subsection will proceed under the premise that an organisation has previously implemented a CMMS since, as already stressed, running an efficient maintenance program without a centralised maintenance system and the capabilities that come with it is nearly impossible.

1) Making a list of all of the equipment. CMMSs should manage information about every piece of equipment that will be subjected to predictive maintenance schedules. There are two primary causes for this. The first point to mention is that establishing a work order for a specific piece of equipment is much easier if the equipment is already registered in the CMMS database. The second point to mention refers to the asset history, since a major advantage of computerized maintenance management systems over paper records is that they automatically store asset history, which can be accessed from any location with an internet connection.

2) Deciding which maintenance method will be used on which piece of equipment and when. The maintenance schedule should be created once the whole list of the equipment needing to be serviced on a regular basis has been compiled. However, before doing that, it is necessary to determine which maintenance procedures would be most appropriate for the specific situation. A comprehensive predictive maintenance policy will be implemented by the vast majority of enterprises at the outset. Of course, embedding critical pieces of equipment with suitable sensors may represents a great advantage.

3) Establishing maintenance programs for equipment. Equipment maintenance schedule is the focal focus of every equipment maintenance program, regardless of its size. It determines which maintenance actions should be performed, when they should be performed, and by whom. Therefore, the maintenance schedule should offer a comprehensive picture of all incoming and ongoing maintenance tasks. To go along with that, it should provide a simple way to swiftly plan normal operations, simply reschedule any maintenance task, and easily adjust task priority with a few clicks. When constructing an initial preventive maintenance plan, original equipment manufacturer manuals have to be carefully analysed by following the guidelines included. Also, it is necessary to have a brainstorming with maintenance specialists to understand whether any specific asset may have any long-standing concerns that need to be taken into consideration. If a company is using CBM or PrdM, then a portion of its maintenance plan should be based on data collected from sensors or predictive algorithms, respectively, to be part of the maintenance schedule. Independently on the specific techniques and strategies adopted by the organisation, a set of routine maintenance chores must be scheduled and carried out on a continuous basis.

4) Developing checklists and processes for preventative maintenance. Maintenance management involves a huge amount of repetitive operations that must be performed on a regular, weekly, or monthly timeframe. In such a context, establishing best practices and standardising processes represent substantial benefits. In particular, organisations should define:

- Standard Operating Procedures (SOPs);
- Emergency Maintenance Procedures (EMPs);
- Lock Out/Tag Out procedures (LOTO);
- Predictive maintenance checklists;
- All-purpose safety precautions instructions.

These listed items must be disclosed to the individuals who will be required to utilize these, and who may also be connected to particular work orders, and should be determined or required.

5) Maintenance personnel training. Technicians should be able to read and understand maintenance plans, apart from having the professional skills required to carry out the maintenance operations stated in the plan. These stakeholders must also be familiar with the implemented CMMS as well as with any other digital solution adopted by the company. It may be necessary to conduct a number of maintenance skills training sessions in order to bring everyone up to the needed level. When making the transition from reactive to proactive maintenance services, the organisation should invest special efforts to ensure that the entire maintenance staff is on board together with the direction of the company. The first few months may be the most critical period for ensuring that technicians are following new processes, recording every significant information within the equipment maintenance log, and making proper use of the CMMS features that have been implemented successfully. This is done in order to modify undesirable habits before they become established in the individuals.

6) Evaluating and improving. Being overconfident and expecting things to operate smoothly on the first try would be a mistake. It is vital to conduct a regular evaluation of maintenance performance metrics and monitor other indicators in order to identify and eliminate inefficiencies and faults in the maintenance plan at its current state. The equipment maintenance software that is being employed should be able to provide analysts with enough information to properly optimise a successful equipment maintenance program over time [3].

1.4. Analysed industrial cases

Various research has been conducted in literature on the predictive maintenance field, and a wide variety of models and procedures has been established in the context of the Industry 4.0. Hashim, et al. [23] propose a modified PrdM approach in order to reduce the upkeep costs of centrifugal pumps in chemical plants. Miller and Dubrawski [26] analyse the work on PrdM from a system perspective, as well as distinct failure risk prediction and condition estimating capabilities, which are currently employed for basic components but which are required to solve important assets. Gohel, et al. [27] develop a machine learning method to conduct PrdM of nuclear facilities. Daniyan, et al. [28] apply artificial intelligence to PrdM and develop training elements to teach maintenance staffs how to observe and investigate information collected from the IoT technology and certain alternate source materials in predicting the status and possible breakdown of a rail-car wheel bearing. Hsu, et al. [29] employ statistical process control (SPC) and machine learning to identify defects in wind turbines and estimate when maintenance should be performed. Jimenez-Cortadi, et al. [30] review several maintenance techniques and describe the procedure that should be followed for the deployment of data driven PrdM in machine decision-making, and data collecting and processing. Fernandes, et al. [31] offer a failure detection system for boilers that makes it possible to predict defects and mistakes in advance of their occurring. In addition, their research includes preliminary PrdM strategies utilizing the data they obtained. Namuduri, et al. [32] provide an overview of the deep learning methods utilized for PrdM and give a real-case of the prediction of engine failure. In addition, their paper analyses the existing usage of sensors in the industry as well as the potential for electrochemical sensors in PrdM in the future. Peters, et al. [33] investigate a number of standard machine learning approaches to develop a unique one. Using the example of Industry 4.0, Sang, et al. [34] investigate how to effectively support PrdM. A distinctive feature of the Reference Architectural Model Industry (RAMI) 4.0 is to support PrdM through the use of the FIWARE framework.

We have been widely described PrdM techniques as capable to assist in failure detection for essential equipment that has a variety of failure modes that occur on a regular basis. With this recognition, the study of failure physics should be preferably combined with real-time gathering of the appropriate metrics utilising IoT technology, as well as the use of ML techniques to anticipate and categorise the condition of healthy and defective equipment. Furthermore, the transition of conventional maintenance into PrdM must be accompanied by an financial study to demonstrate the viability and effectiveness of the shifting process. Performing a real case scenario in a local hospital in the United Arab Emirates (UAE), it was demonstrated that the Vitros-Immunoassay analyser, which was chosen on grounds of maintenance activities and criticality analysis as an ideal applicant for changing maintenance from CM to PrdM, could be applied in a variety of situations [35]. Using information from the medium's yearly temperature and annual sunshine information, a complex fuzzy system was constructed in this research study. In this case, the proposed predictive maintenance strategy for rail systems is based on periodic influences such as seasonal weather and daylight availability. Therefore, the complex fuzzy system outperforms the classic fuzzy system when it comes to precision of results. Complex fuzzy membership functions were generated on the complex plane in this article, and the phase interval was restricted to a value of 2 in the complex plane. According to the investigations in the literature, both the rail line and the pantograph condition monitoring have made a contribution to the suggested approach, which includes the proposed technique [25].

Lee, et al. [10] chose two essential machine tool system parts to be monitored using artificial intelligence algorithms: the cutting tool and the spindle motor, respectively. The algorithms are taught to forecast the occurrences of failure events in the systems. A number of predictive modelling approaches is described and then applied to industrial data in investigating their effectiveness. The results of the model are displayed using the confusion matrix, which displays both the accuracy and the inaccuracy of the prediction together. The study discusses the progress that has been made in the water business in the direction of digitalisation. It has been specifically detailed how the progress, authentication, and field testing of a live edge device as part of a condition monitoring/predictive maintenance system for implementation on large-scale pumping system for use in the water sector was carried out [36]. Specifically, in this study is presented the construction of a live prediction system which can aid information technology teams in the maintenance of large-scale storage systems by sending alerts when a drive failure is approaching. In addition, it is provided a framework for the predictive monitoring of hard disc drives failure relying on machine log files rather than traditional statistical prediction methods [18]. As an example of unsupervised learning algorithms, the authors have selected a normal vibration data set gathered from an exhaust fan and fitted with multiple untrained learning algorithms, in order to evaluate precision, efficiency, and applicability. An approach for comparing multiple algorithms and selecting the appropriate model [21] is provided. According to this study, all of the areas of condition monitoring for medium voltage switchgear are now at the cutting edge of technology. It also proposes a strategy for developing a PrdM system that is composed of innovative devices and ML techniques. Another study demonstrates how the current medium voltage grid infrastructure may be adapted to meet these additional requirements on a cost-effective basis [11]. As part of the Industrial 4.0 framework, a big data environment is offered for the application of problem identification and diagnosis in predictive maintenance utilising actual industrial big data collected directly from large-scale global manufacturing facilities. The objective is to provide a comprehensive framework for commercial IoT-based smart factory. Multifaceted challenges, such as big data absorption and incorporation, conversion, and storing in a real-time setting are addressed by the proposed architecture. It makes use of various technologies and methods capable to solve data and network security challenges. A distributed model based on the Map-Reduce framework is being developed for fault identification and diagnosis [24]. An overall context for developing a digital twin is discussed in conjunction with industrial IoT technologies in increasing the autonomy of aircraft platforms. The use of data fusion techniques, in particular, is critical in the development of the digital twin architecture. Sensor-to-sensor, sensor-to-model, and model-to-model integration are the mechanisms that push the transfer of data from raw information to meaningful decision-making. Further discussion and identification of the function of data integration in the digital twin architecture for aviation PrdM are presented and discussed in [37]. The goal of this project is to construct prediction models making use of current data from a railway agency and produce outcomes that are easy to understand. To forecast the need for maintenance, the kind of activity, and the state of the triggers on railway switches, we propose to use tree-based categorization approaches in machine learning in conjunction with other methodologies. Predictive models on grounds of the decision tree, random forest, and gradient boosted trees are constructed based on data from a real-world business process [38]. A systematic methodology is employed to evaluate the advantages and disadvantages of available open-source programs for big data and stream processing in order to determine their suitability for use in Industry 4.0 applications. Among the selected PrdM utilized cases in the areas of rail carriage and wind energy, they developed a set of demands that were then tested against each other. They performed the first-ever comprehensive mapping of PrdM utilized case needs to the capabilities of big data streaming technologies, with a particular focus on open-source tools [39]. Condition monitoring, in conjunction with predictive maintenance, of electric motors and some other machines used by the industrial sector helps to prevent serious economic losses caused by unforeseen motor failures and to enhance system dependability by a significant margin. This work provides a ML architecture for PrdM, which is based on the Random Forest technique and is described in detail elsewhere. In order to test the system on a real-world industrial example, researchers developed a method for data collecting and analysis, used a ML methodology, and compared the results to those obtained from a simulation tool [40]. Using readily available data, this work proposes a novel technique to predicting rail and geometry flaws that blends prediction with inspection and maintenance scheduling operations. The underestimate of faults is controlled in the suggested strategy by the new application of risk-averse and hybrid prediction methodologies. Then, using these predictions, a discounted Markov decision process model is used to generate the best inspection and maintenance scheduling rules [41]. This study focuses on the topic of PrdM for a metallurgical firm, and it reports the findings of primary data investigation and characteristics selection that was done on a sample of the data that had been obtained in the course of the research. Using the knowledge gathered from the data, researchers would construct adaptive learning models capable to process complicated information to be implemented to a complete system of industrial machine. In addition, multiple rules were derived from the associations discovered throughout the data investigation procedure, and these rules were aggregated into a rule-based model for further consideration. A rule-based system would be built around these principles, to be used to supplement the predictive model that will be developed in the future [42]. A method for integrating the practical application of Industry 4.0 in a small bottling plant is proposed in [43], which focuses on early fault detection and threat detection in conveyor motors, as well as the generation of a predictive maintenance schedule in response to these early faults or threats. Hoffmann, et al. [11] use PrdM and ML in medium voltage switchgear. PrdM was adopted in the steel sector by Ruiz-Sarmiento, et al. [43], while deployed in wind turbines by Wang, et al. [44]. Lee and Pan [45] describe an interconnected PrdM strategy for complex systems that incorporates the Discrete Time Markov Chain (DTMC) and Bayesian Network (BN) methods, while Verhagen and De Boer [46] describes a PrdM approach for aeroplane components that incorporates the proportional hazard model technique. Further application and examples of PrdM applicability to critical systems can be seen more in detail in [22, 47-55].

Chapter 2.

Decision-making models supporting predictive maintenance

2.1. Decision-making models for failure classification

Organizations nowadays must be agile, adaptable, and robust, as well as exhibit dynamic skills, to strive in the economical world. Due to the advancement of powerful digital technology, industries have now the ability to radically reinvent themselves. High-intelligence maintenance systems have grown increasingly popular as a result of the development of smart devices. Large-scale advances are being made in the realm of operation management as intelligent systems converge and advance with industries. As already underlined, the emergence of different information technology breakthroughs has resulted in a considerable disruption of industrial techniques. Preventive maintenance approach that was previously handled by humans are now being changed into predictive maintenance. Large amounts of data from manufacturing operations are gathered, evaluated, and triggered in order to enable effective decision - making in real time basis [47, 56]. In predictive maintenance, decision-making refers to create practical suggestions regarding maintenance activities and initiatives that remove or minimise the effects of the expected breakdown or failures. Industry 4.0 has caused in a extensive utilization of sensing devices for health monitoring of machines, that enables timely taking of decision. The P-F interval, defined as the interval of time among the emergence of a possible problem and its progression into a system failure, can be considered as an indication window throughout which decision-making algorithms can suggest steps aimed at avoiding or mitigating the predicted functional failure.

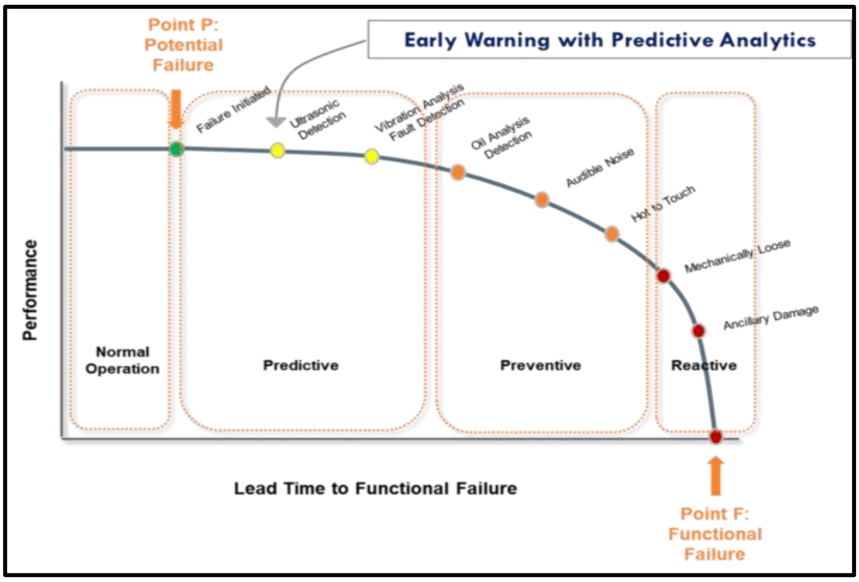

Figure 2.1. Predictive maintenance in a P-F curve adopted from [6]

Most PrdM decision-making strategies focus on algorithms-based diagnostic models instead of data-driven models. As a result of the limitation of data analytics competences, the accompanying decision-making methodologies and strategies are mostly knowledge-based. For predictive maintenance, the degradation process is unpredictable, something that makes the decision-making approach extremely difficult. The use of simulation models or iterative solution processes is hence widespread in present decision-making systems. Simple models are often engaged in finding exact answers. Furthermore, simulation is often integrated with robust optimization strategies (for example: simulated annealing, genetic algorithms, and others) to minimize the computational efforts and obtain useful results [47].

The applications of Multi Criteria Decision-Making (MCDM) methods in the maintenance planning domain is extremely beneficial since they combine both subjective and quantitative aspects in a highly effective manner. A wide variety of MCDM approaches already been proposed in the field of study in the past decade to choose the alternatives that reflect the most effective results as per a set of assessment standards, and it is found among the most widely implemented decision-making approaches in a variety of domains such as manufacturing, materials, safety and risk, supply chain, reliability, quality and technological innovation. Mardani, et al. [57] give a number of studies that demonstrate the relevance of the technique as well as numerous approaches that have been presented in the literature. In this context, ELimination Et Choix Traduisant la REalité (ELECTRE) TRI is a multi-channel data management technique that is frequently utilized. ELECTRE TRI has evolved after the ELECTRE group of techniques, which comprises a number of iterations, such as ELECTRE I, II, III, IV, and IS, among others. There are two versions of this approach [58, 59]. The first one is a multi-criteria aggregating and decision assisting process applied to cope with the ordinary sorting issues, while the second one distributes choices to specified categories. ELECTRE TRI applications in a variety of fields and organisations have been documented in the literature. Fontana and Cavalcante [60] employ the ELECTRE TRI technique to solve the problem of storage site assignment. Norese and Carbone [61] utilise it to analyse and allocate every airport to a sequential class based on the results of their evaluations in Italian Airports. Becker [62] extends the method to information and communications technology (ICT) in businesses. This approach is used by Trojan and Morais [63] for the minimization of losses in water distribution system, the maintenance of electricity supply plant [64], and the maintenance of water supply system among other things [65]. Certa, et al. [66] employed ELECTRE TRI in the realm of project risk management. In addition, Brito, et al. [67] used this technique to estimate the hazards associated with natural gas pipelines. Furthermore, Trojan and Marçal [68], Trojan and

Marçal [68] make use of the ELECTRE TRI technique for aggregating maintenance types by multi-criteria analysis in order to explain maintenance ideas in operations and production management. Almeida-Filho, et al. [69] constructed a decision support system for an electrical power distribution firm to help in maintenance scheduling, while, de Almeida, et al. [70] proposed MCDM strategy to categorise and distribute maintenance priority for reliable maintenance scheduling. Based on the existing literature, it is feasible to deduce that multiple evidence of implementations of the ELECTRE TRI technique have been associated with the topic of maintenance. However, because of the limited number of applications of this approach in PrdM, the above-mentioned methodology has been herein used for complex systems that are exposed to PrdM interventions. The primary goal is to provide analysts with a tool potentiating failure control procedures without having to pairwise compare all of the parts of the study, hence decreasing mistakes and simplifying computations for complex systems. ELECTRE TRI involved two sequential steps. The first step uses concordance and discordance indices to construct outranking connections among pairs of alternatives and reference profiles to identify which options are better for concordance. This stage entails assigning options to categories based on their evaluation of the performance relationships that were developed during the previous phase. For this task, it is necessary to have previously defined ordered classes in which there is no crossing among the linked reference profiles, in addition to having collected the subsequent input data:

- Set of evaluation criteria B_j, (j = 1, …, J) and weights w_j indicating their relative importance.
- Set of reference profiles b_k, (k = 1, …, K) for each criterion, being $b_0^{(j)} < \ldots < b_{K+1}^{(j)}$.
- Set of classes C_h, (h = 1, …, K+1) specified by the K reference profiles.
- Set of alternatives A_i, (i = 1, …, I) and associated evaluations $g_j(A_i)$ under each criterion.
- Cutting value $\lambda \in]0.5, 1]$, need to conclude the initial stage of the ELECTRE TRI method.
- Indifference, solid preference, and veto thresholds, respectively q_j, p_j, and v_j.

An in-depth description of the procedure [71] will be provided later, specifically in subsection 2.4.1.2. A real-case of a complex service systems whose key elements are exposed to PrdM is reported in the next section. Particularly, the ELECTRE TRI, has been applied to categorize failure modes of components into ordered risk groups, as opposed to the traditional way of classification. The adoption of such a strategy allows for the identification of failures that are connected with greater risk circumstances, hence necessitating interventions to be prioritised more aggressively. This is accomplished by optimising the monitoring for the entire system.

2.2. Complex maintenance service systems optimisation

This section presents a case study that demonstrates the applicability of the ELECTRE TRI technique to a real-world complicated system that is exposed to preventative maintenance interventions. This case study has been published within a conference paper [72], then extended as a journal paper [73]. In particular, the complex system refers to the vehicle studied in [74] deputed to provide street cleaning service and embedded with a network of sensors for predictive maintenance. The dependability diagram of the system, along with the associated block map defining the system assembly, were both developed in [75] and [76], respectively. This most recent study [76] particularly highlights a group of three important parts that should be considered with importance in order to lead to proactive maintenance actions. These identified components are three hydraulic pumps, which are critical in ensuring the proper operation of the most significant sweeping parts, as well as the loading and emptying systems, among other things. In order to detect the wear state of pumps, an appropriate network of sensors was created to monitor acceleration as a metric connected to wear condition. This study will look at these hydraulic pumps in more detail. Table 2.1 contains a list of probable breakdowns and underlying reasons affecting these components, as well as a diagram illustrating the potential consequences of failures on the overall system's operation and performance.

As per the obtained results of the investigation of Table 2.1, identified two categories of probable faults which are discovered for pumps I (deployed to the sweeping system), II (deployed to the loading system), and III (deployed to the emptying system). Despite the fact that failures are caused by the same underlying reasons, they might have drastically varied consequences depending on how the three pumps are distributed throughout the system in various locations. To such an aim, the present application is aimed at sorting failures into priority classes upon identifying the particular root causes of problems for which a high level of urgency is necessary. Accordingly, the six failures (i.e., options of the MCDM problem) are categorised into the three different ordered risk classes as follows: C_1, low priority; C_2, medium priority; and C_3, high priority (see below). According to three key assessment criteria, the assignment method is carried out: B_1, execution time; B_2, execution mode; and B_3, frequency of occurrence. The first two criteria are concerned with the execution of maintenance interventions, whilst the third criterion is concerned with the incidence of failures in the system. Each criterion has been reviewed by a panel of decision-makers, and the results obtained (Table 2.2) have been converted, in turn, into numerical values (Table 2.3) ranging between [1, 5].

Table 2.1. Failures, root causes and criteria evaluation

ID	Failure	Causes	Effects
A_1	Pump I: fault distribution system	Power outage; fluid properties; valve or other equipment failure	Hydraulic circuit and hydraulic actuators are not operating properly; work position is not taken; and brush and roller rotation is not permitted.
A_2	Pump I: mechanical fault	Components wear (journal boxes, bearings, etc.) and sealing elements undergo wear.	Hydraulic circuit and hydraulic actuators are not operating properly; work position is not taken; and brush and roller rotation is not permitted.
A_3	Pump II: fault distribution system	Power outage; fluid properties; valve or other equipment failure	The loading and unloading mechanism is not working properly; a work position is not being taken; trash is not being loaded; tank is not being emptied.
A_4	Pump II: mechanical fault	Components wear (journal boxes, bearings, etc.) and sealing elements undergo wear.	The loading and unloading mechanism is not working properly; a work position is not being taken; trash is not being loaded; tank is not being emptied.
A_5	Pump III: fault distribution system	Power outage; fluid properties; valve or other equipment failure	Elevator plant functioning has been compromised; interaction between the elevator plant and the collecting tank has been challenging; waste loading in the tank has not been completed; elevator plant was shut off.
A_6	Pump III: mechanical fault	Components wear (journal boxes, bearings, etc.) and sealing elements undergo wear.	Elevator plant functioning has been compromised; interaction between the elevator plant and the collecting tank has been challenging; waste loading in the tank has not been completed; elevator plant was shut off.

Table 2.2. Evaluation of alternatives under criteria

ID	B_1	B_2	B_3
A_1	4.00	3.00	3.00
A_2	4.00	3.00	3.00
A_3	2.00	3.00	2.00
A_4	3.00	3.00	2.00
A_5	2.00	3.00	2.00
A_6	3.00	3.00	2.00

Table 2.3. Evaluation scale

Criteria	**Evaluation**	**Value**
B_1, B_2	Low	1.00
	Medium-Low	2.00
	Medium-high	3.00
	High	4.00
B_3	Remote	1.00
	Occasional	2.00
	Probable	3.00
	Frequent	4.00

The preference and indifference limits were supposed to be half and one-fourth of the width of the categories, while the disapproval barrier was considered to be similar to the width of the categories, respectively. Table 2.4 shows the outcomes obtained from both the pessimistic and the optimistic approaches to the problem. The pessimistic method starts with higher-valued, restricting reference profiles and designating classes as a starting point for the operation. When the condition that the alternative A_i is at slightest excellent as profile P_h is tested, it allocates the option A_i to class Ch+1 if the requirement that Ai is at least as excellent as profile P_h is satisfied. The optimistic procedure begins with smaller value restricting reference profiles that define classes and works its way up. Assigning alternative A_i to class C_h is accomplished by verifying the condition that P_h is preferred to A_i in the class C_h where the alternative Ai has been determined to be preferable to P_h. Readers are encouraged to visit [77] for further information on this subject and [78] for more details about the application. Because there is no difference between the two approaches, we may conclude that there are no incompatibility relations between the items in the set of elements that have been examined. The allocation of every failure to the established classes was accomplished considering the principle of equal weightage conditions and by establishing three different values for the cutting level: 0.60, 0.70, and 0.80 (see Figure 2.2). Results were double-checked and confirmed using the J-Electre-v2.0 programme for multi-criteria decision assistance (https://sourceforge.net/projects/j-electre/files/) [79].

Table 2.4. Assignment of alternatives to classes

ID	$\lambda = 0.60$	$\lambda = 0.70$	$\lambda = 0.80$
A_1	C_3	C_3	C_3
A_2	C_3	C_3	C_3
A_3	C_2	C_2	C_2
A_4	C_2	C_2	C_2
A_5	C_2	C_2	C_2
A_6	C_2	C_2	C_2

By examining the findings acquired through the implementing the ELECTRE TRI process, it is possible to derive various practical insights. All of the three pumps under consideration are regarded to be key components of the complex system under investigation. Failures that may have included pump I, on the other hand, have been allocated to the high priority class, and failures that may have involved pumps II and III have been rated a moderate priority status. This result is critical for planning maintenance interventions on the system, since it identifies the needed maximum priority using a systematic MCDM assistance, which is useful for system organisation. As seen in Figure 2.2, a block diagram describing the subsystems of the vehicle that are directly dependent on the operation of pump I is reported.

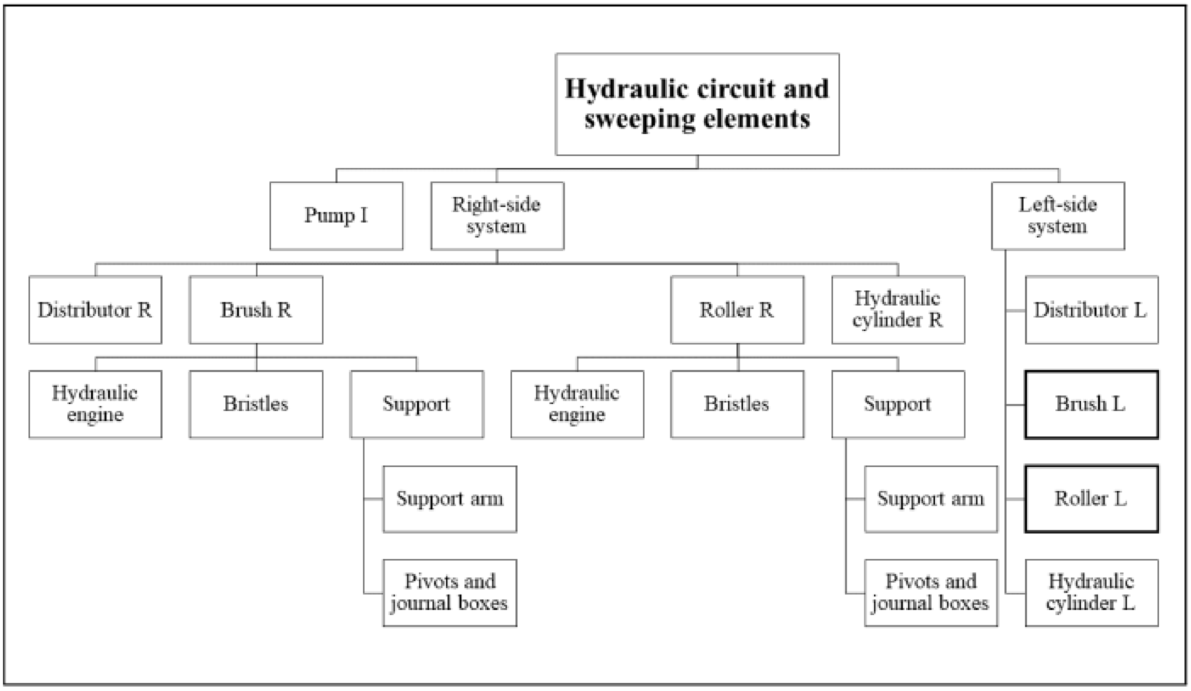

Figure 2.2. Block diagram of subsystems impacted by pump I

Optimisation of the hydraulic circuit, actuators, as well as sweeping elements such as brush and roller, will be achievable after minimising the root causes associated with the likely occurrence of failures A_1 and A_2. Furthermore, because a system of sensors is accessible to inspect pumps I, II, and III, the existing application can even recommend a more desirable assignment of sensors, given that underlying causes of failure connected with pump I require greater priority than those associated with the other pumps. Finally, the results are confirmed to be robust because no differences can be observed when the cutting level is varied (Table 2.4).
Main goal of this application is to adopt a MCDM viewpoint for MM of service systems in order to better understand and manage maintenance. The implementation of the ELECTRE TRI approach, in particular, is proposed for sorting failures that might possibly include fundamental components of systems that are exposed to predictive maintenance and the underlying causes of those failures. The primary goal of allocating failures to ordered priority classes is to draw attention to which underlying reasons of failure must be eliminated with the highest level of priority. This application can be beneficial in assisting with predictive maintenance management by ensuring timely responses and operational preparedness in a variety of situations. On a real-world service system, we employed the suggested technique to sort common failures involving its key components, and in particular, to classify common issues composed of its key elements.

The implementation has been guided by the consideration of various cutting level values in order to get an understanding of the probable differences in outcomes. It is a benefit of the suggested technique that failed categorization may be performed without the need to elicit preference between pairs of alternatives, because items are only compared pairwise with reference profiles that define classes. This is unquestionably a more successful technique as the number of basic items to be considered rises, since it promotes effective management of complexity and the elimination of the possibility of transitive comparisons. As expansions of this study, the suggested approach has been integrated with another MCDM (this will be reported and discussed in the next sections). The issue of reliance among criteria and alternatives may be the subject of future applications if the possibility of the presence of no transitive preference relations is taken into consideration once again. In order to improve predictive maintenance management on a global scale, it is critical to examine the possibility of dependence relationships between the various aspects of the analysis, as described in the next section.

2.3. Evaluation of interdependence among critical failures

2.3.1. Open challenges

As widely discussed throughout the present work of thesis, corrective maintenance may have a negative impact on industrial operations and results in severe economic, social, and environmental losses [80]. In the great majority of circumstances, fixing equipment after it has failed is not convenient, mainly because of the fact that failures should be avoided whenever possible by identifying significant underlying reasons prior to their occurrence. Various methods of maintenance and replacement have been proposed to date [8]. Traditionally, industrial maintenance policies have focused on PM, by scheduling maintenance activities on the basis of the revision of historical failure data and system conditions. Because PM does not take into account the existing health status of systems, this technique is not totally successful in preventing unanticipated system breakdowns, which may result in extra expenditures associated with the execution of some unneeded actions. However, by deploying an architecture of sensors across the system, these concerns can be alleviated.

In observing and inspecting systems, installed sensors, operational data, process data, and systems and previous failure data are all utilised to anticipate failures. PrdM discourages routine and preventative maintenance interventions while encouraging a more proactive approach to maintenance. It is a sort of technique in which staff may dynamically watch performance, productivity, and other relevant elements in predicting the optimum period for performing maintenance on a certain system. The individual characteristics of systems, as well as the distinctive wear behaviour of the most crucial components, are taken into consideration, rather than just relying on statistical data to make this determination. When PrdM is effectively applied, the cost of maintenance is significantly decreased and, with this perspective, highlighting interdependence among critical failures may be strategic.

Both PM and PrdM strategies are designed to avoid system failures by maintaining the running condition of the system until the breakdown occurs. As previously specified, most major difference between the two methodologies may be discovered in the analysis stage, where The assessment granularity that contributes to the maintenance process is the most significant distinction. The maintenance planning process does actually concentrate on groups of systems that have common characteristics and aim to identify metrics that may be used to enhance maintenance planning. The PrdM method, on the other hand, treats each individual system as if it were a single element, seeking to extract the parameters that describe the present condition-of-health of assets in predicting the timeframe until failure [81]. PrdM, as a whole, contributes to the minimization of issues by forecasting the state of systems [80]. Despite the fact that various attempts have recently been made to migrate to PrdM, incorporating reactive maintenance techniques is helpful and is predicted to continue to be required for effective management. The value of reactive maintenance can be seen in the fact that certain systems will still fail suddenly, and the value of proactive maintenance can be seen in the fact that it serves as a form of safety net if the actions necessary for PrdM are not available [81]. Nevertheless, on the one hand, reactive maintenance is unquestionably ineffective at preventing failures and, on the other hand, PM is incapable of predicting future situations and of assisting in the early restoration of equipment in extending their useful lives [20]. The use of PrdM is a more successful way for reducing the degree of PM, as well as the occurrence of failures that contribute to reactive maintenance, thus improving run-time and decreasing overall maintenance expenses [81]. Furthermore, by implementing PrdM, equipment and systems may be extra readily safeguarded against failure, while also ensuring that the scheduled activities may be performed during their lifespan. Moreover, its efforts to maximise performance by minimising the significant expenses associated with PM.

Previous study has discovered that, whenever PrdM is utilised intelligently, the asset's average dependability, availability, and maintenance operational expenditure are the minimum level of any of its competitors. The evolution from corrective to predictive maintenance significantly enhances equipment maintenance scheduling, especially for complex assets with higher economic value [82]. However, PrdM strategies have significant practical obstacles since they need the development of new tracking technology, the construction of robust data gathering systems, and the deployment of complicated supervision and prognostic structures [83]. As widely discussed in the previous chapter, some problems of the use of PrdM for complex assets are now impeding its effectiveness in some situations. Individual businesses would be put under a significant amount of financial and technological stress if they were required to monitor and analyse all probable failure modes for the complicated equipment under consideration. Furthermore, it is difficult to categorise each probable failure mode associated with a single asset, and a independent set of data concerning failures is always inadequate, resulting in low forecast accuracy. Therefore, reliable and timely maintenance schedule information is required. In order to do this, it is required to improve the flexibility of PrdM decision-making in complex manufacturing settings [84].

Since they automate prognostics and can effectively monitor complex systems in real-time, system models have become popular. They also give early warning indications of impending problems. As with any field, there are several methods to PrdM, each with its own set of strengths and weaknesses [85]. For utilizing PrdM, it is essential to have online access to information about the system conditions, that is now feasible owing to the adoption of appropriate monitoring sensors. Many studies have been conducted to date on estimating a system's remaining usable lifespan, whether it is a single component or the entire equipment, using deterministic reliability models. There is a lot of research on PrdM for complex systems that can be found in the literature and has already been presented in chapter 1 under section 1.4.

2.3.2. Overview on FMECA strengths and weaknesses

Failure Modes, Effects and Criticality Analysis (FMECA) was one of the first failure analysis methodologies to be developed. It is a technique that uses inductive logic to monitor the safety and health of system [82] and to methodically investigate potential component failure mechanisms of a method or product. In order to enhance the constancy of critical systems or component, it is necessary to identify and evaluate the risks connected with various failure modes, as well as the related impacts on equipment operations [82, 86, 87]. Notable cases of complex systems having a wide range of subsystems and components are ships and other transport facilities, power plants, chemical industries, and the oil and gas industry [88]. The FMECA approach can help to carry out in-depth analyses by focussing on the criticality of systems. Although this approach is helpful to detect all of the required components, it does not guarantee that all of them have been recognised [89]. FMECA is used in combination with CM to determine the criticality of a system [86]. There are several applications for this technique, including the identification of system components and the definition of system elements in identifying the most relevant aspects to be examined and observed and also to effectively implement a PrdM strategy [90]. Even though a PrdM-based method appears to be a desired approach for a provided complex system, it is possible that it will not be feasible with all of the elements of that specific equipment in some circumstances. To categorise acceptable components, the FMECA method may be used. Traditional FMECA-based procedures, on the other hand, may become more thorough and time-consuming when used at the component level for essential assets. In these instances, it would be advantageous to investigate options that might reduce the amount of effort necessary for maintenance [89].

For complex systems, FMECA applications integrated with PrdM have been demonstrated in a number of case studies, including maritime systems [83], aircraft and manufacturing [91], Computer Numerical Control (CNC) lathe machines [90], dynamical evolving systems [83], super thermal power plants [86], wind turbine assembling plants [92], and so on. Furthermore, as can be seen in [87], there are several studies justifying the use of FMECA for complex systems. Despite the fact that FMECA is a very adaptable tool, it has a number of drawbacks and boundaries in terms of application, cause and effect presentation, risk investigation, and resolving issues [93]. A few benefits of FMECA are mentioned here.

- It facilitates the detection of failure's root causes and the development of corrective actions.
- It assists in the identification of failure modes that may jeopardise the safety of operations, as well as the detection of failures that may have unwanted or significant effects for the functioning of the system.
- By intervening at the beginning of the development process, it aids in the recognition of the requirement for profitable design strategies for reliability improvement, likewise product selection and redundancy.
- It provides a method for analysing the possibility of system failures as well as a method for doing criticality analysis.
- Demonstrating that anticipated hazards have been identified can assist in the resolution of protection and system accountability concerns, also the resolution of supervisory non-compliance.
- It assists in categorising and rating failures according to their Risk Priority Number (RPN).
- In addition to assisting in the installation of a cost-effective quality monitoring and management as well as controlling the production process, it assists in the selection of a maintenance strategy by giving a foundation for planning maintenance.
- It is particularly exhaustive and responsive to different techniques of equipment analysis, and it may enhance design, component selection, and system dependability. It is also effective for identifying individual failure areas in a system [94].

Despite its many advantages, FMECA has a number of important flaws that must be addressed.

- It considers just the effects of single failures, being unsuccessful when required in providing a gauge of system dependability, despite being an important component of decision-making.
- It is useless when attempting to depict links between distinct failure modes since it is predicated on the independence of failure modes as a core premise.
- As a result of the numerous failure scenarios that must be addressed, dealing with complex assets may be exceedingly difficult and time-consuming [94]. Furthermore, the quantity of unique system information that must be researched is enormous, particularly when dealing with a wide range of different operating modes, repairs, and maintenance procedures.

- It is fundamentally a reductionist strategy, and the implications of simultaneous problems are not taken into consideration in the correct way. Variations in the surrounding environment may have an impact on the assumed dependability of components. More to the point, human errors and hostile conditions are frequently overlooked, and system flaws are nearly hard to remedy in most cases [94].
- It's only useful during the design phase, and it solely considers failure modes, with no consideration given to their interrelationships. Due to the fact that failure rates vary from one element to another and that numerous integration of many components result in the similar RPN index, there is replication or deceptive assessments as well [95].

2.3.3 Review on MCDM approaches in the field

The integration of classical failure analysis for complex systems with MCDM techniques can be crucial in overcoming the limitations that have been identified. In this aspect, MCDM incorporates both subjective and quantitative factors, and is thought to be a very helpful approach. A wide number of MCDM strategies have been proposed and advocated in the literature in previous decade to help decision makers in selecting the alternatives that reflect the optimal compromise under a variety of assessment criteria. Various methods have been widely utilized in different fields, as presented by [57]. Mardani, et al. [57] provide a number of research that demonstrated the relevance of the MCDM approach, as well as a number of methods that had been offered in the literature. The ELECTRE TRI approach is among most extensively selected MCDM approaches [96]. In order to counter with ordinary classification failures and assign options to specified classes, the ELECTRE TRI approach is utilized [58-60]. This MCDM approach has been selected for implementing the methodological tactic proposed in the present work of thesis because of its flexibility for addressing diverse types of problems. As previously reported, there are numerous real-world scenarios of the ELECTRE TRI technique in the maintenance area that may be studied in the literature. Considering PrdM, a basic problem is undoubtedly presented by the dependency bounding critical failure modes with each other.

At the end, the DEcision-MAking Trial and Evaluation Laboratory (DEMATEL) strategy is a successful MCDM method, being capable to illustrate the structure of complex causal relationships through the use of appropriate matrices and graphical charts. A popular theme in the area of industrial engineering at the moment is the DEMATEL method, which is used to discover significant parts in complex systems by combining many techniques in one. As previously said, an extensive study of dependent relations is very crucial for achieving exhaustive findings in our specific field of application, and this is particularly true in this specific area of application. It is still difficult to have an objective viewpoint on things, despite the reality that multiple work has been put into improving this element [97].

For the first several years of its existence, DEMATEL was intended and utilised to resolve complex and interconnected cluster components or systems [98-101]. It is a systematic structural modelling strategy for developing and analysing cause-and-effect linkages (dependency) between system elements. When investigating and solving challenging and linked situations, DEMATEL may aid in the process by proving dependency between pieces and assisting in the construction of a diagram to represent relevant relationships inside components. By identifying causal aspects that may be prioritised in order to achieve rapid and effective resolution of major problems, it assists in the identification of cause-and-effect variables [98-102]. Not only does the DEMATEL technique turn interdependency relationships into cause and effect clusters by utilising matrices, but it does so in a more comprehensive manner. It also makes use of an effect-relation flow chart to discover the characteristics of complex systems that are relevant to their operation. Due to the advantages and diversity of application of this approach, it has attracted a better deal of consideration over the last decade, and other academicians have utilised it to tackle complex system difficulties in a range of sectors. As a result, DEMATEL has been developed to improve decision-making in a variety of settings as various complex systems consist erroneous and ambiguous dataset [100]. The majority of decision-making techniques that have been developed are based on idealistic beliefs, such as the risk contributing component in a complex system and the factor independence. The risk variables and the information sources used in the decision-making method do, in fact, have a strong relationship with one another. It is still necessary to develop a decision-making approach that takes into account the interaction between risk factors and data sources [103]. The literature has several DEMATEL applications, and a few of them are discussed in this section. Rolita, et al. [99] proposed integrating DEMATEL with the Analytic Hierarchy Process (AHP) in improving the efficiency of the airport safety management system. Using related analysis, the authors look at contributing relationships between the linked conditions for successful decision-making in order to make more informed decisions. Maduekwe and Oke [104] applied the DEMATEL approach in the food processing sector to analyse and rank key performance indicators (KPIs) for the maintenance system. Karuppiah, et al. [105] used a combination of DEMATEL and Fuzzy AHP (FAHP) to identify, explore, and assess a group of Faulty Behaviour Risks (FBRs) that were likely responsible for factory accidents and injuries.

Karuppiah, et al. [80] used a combination of Interpretive Structural Modelling (ISM) and the DEMATEL approach to develop a sustainable PrdM implementation strategy. As an example, in [102], an integrated model for photovoltaic cell manufacturing industry based on Failure Modes and Effects Analysis (FMEA) and the DEMATEL strategy is proposed, and an combination of DEMATEL with the Best-Worst Method (BWM) and the Bayesian Network (BN) for safety management in the highly digitized industry was carried out in [103]. DEMATEL implementation include a structural DEMATEL method for critical equipment [106], a combination between DEMATEL and Analytic Network Process (ANP) as a risk assessment model in oil and gas building projects [107], an integrated dynamic quantitative risk assessment method for oil and gas leaks on offshore platforms [108], and a DEMATEL-ANP risk assessment model in oil and gas exploration and production developments. The DEMATEL has been widely used in its fuzzy form to treat with a variety of problems, such as home appliance assembly [109] and supply chain management in the automobile sector [110]. Furthermore, fuzzy DEMATEL has been used in conjunction with other approaches, such as the TOPSIS technique, to evaluate risks of a hydrogen production unit [111], as well as with cloud models [112], and FMEA analyses applied to turning machines [113].

FMECA	ELECTRE TRI	DEMATEL
• Determine appropriate research limits by determining the crucial elements and key components of the complex system susceptible to predictive maintenance. • Applying FMECA to gain a thorough understanding of the system by establishing a list of failure mechanisms as options to the MCDM concern.	• Employing ELECTRE TRI to arrange modes of failure among risk categories by assigning varied weighting to FMECA variables, which are criterion of the MCDM problem. • The treatment is carried out in two parts. • First step: establishing an outranking connection by evaluating each option to the class limits, or referenced items. • Second step: assigning options to groups using pessimistic and optimistic approaches.	• Implementing DEMATEL for the study of dependency connections between classes and highlighting particular faults needing a prioritised maintenance update. The following is a summary of the technique. • Obtaining the total relation matrix, which collects the complete connection between elements, by manipulation of the input matrix. • Determining significance and relationship, ordering elements on their declining significance value, and constructing the related impact chart.

Figure 2.3. Diagram exemplifying the proposed procedure for complex systems

Table 2.5. Synthesis of the literature analysed

Technique	Description	References
FMECA	Articles describing the extensive use of FMECA to a variety of engineering disciplines. The importance of this method for optimising complex systems is highlighted in context of component criticality assessment.	[82] [87] [88] [89]
	Studies suggesting the actual implementation of FMECA to equipment undergoing proactive maintenance, highlighting the efficacy of this type of combination.	[83] [86] [88] [90] [91] [92]
	Publications detailing the primary benefits and drawbacks of the FMECA approach, emphasising that, amidst its adaptability, FMECA must be used caution.	[93] [94] [95] [114]
ELECTRE TRI	Studies demonstrating the methodology's applicability for tackling a wide variety of classification issues relative to certain other current MCDM methodologies.	[58-60] [77]
	Efforts establishing the practical applicability of ELECTRE TRI to address challenges in several management domains, revealing a deficiency in the arena of PrdM.	[61] [78] [63] [64] [65] [115] [68] [72]
DEMATEL	Articles illustrating the application of DEMATEL for assessing the presence of cause-and-effect linkages among a variety of decision-making factors.	[97] [98]
	Papers detailing integrations of DEMATEL with certain other methodologies, such as risk assessment, other MCDM techniques, probability-based strategies, structural modelling, etc.	[80] [99] [102-108]
	Works expanding DEMATEL's fuzzy variant to handle unclear data input.	[109-113]

2.4. Proposed integrated approach

2.4.1. Objectives and methodological details

Based on an examination of the shortcomings and strengths of each approach, as well as their common applications, we propose to use the integration of these three strategies that optimises the management of system breakdowns exposed to predictive maintenance. Such an integrated approach has been published as a journal paper [73] by extending the previous conference paper [72]. The following are the formalised justifications for which the combination of these three particular methodologies is being suggested to the area of the study.

1. All possible failure modes in systems subjected to PrdM are identified using FMECA and the criticalness of failure modes is evaluated using risk metrics of relevance.
2. ELECTRE TRI is used to identify and categorise the high-risk failures, as well as highlight those failures that have been related with greater risk levels and situations.
3. DEMATEL is used to identify specific failures that are more interdependent with other failures in the same risk category than others within a class.

The proposed integrated framework may support business realities in making effective decisions and implementing successful risk management actions. Identifying the failure modes that have the greatest influence on systems and the incidence of additional failures is the ultimate aim for each risk class. However, it is also important to control the other dependent failure scenarios as well. Maintenance and risk management processes, as well as system functionality, might be improved as a result of this approach.

2.4.1.1. FMECA for quantitative failure assessment

CEI EN 60812 specifies FMECA as a method for organising the analysis of systems in order to identify probable failure modes, pinpoint reasons, and assess the impact on system capability of those findings. By extending the FMEA methodology, FMECA makes it possible to rank and highlight failure modes in connection to their importance. Severity (S), Occurrence (O), and Detection (D) are the three risk metrics utilized to assess the criticality of any failure scenario. S is an estimation of the degree of impact the breakdown could cause to the system, O is the ratio of frequency of any failure mode within a certain timespan, and D is the probability of detecting the fault. Equation 1 reports the RPN calculation:

$$RPN = S \cdot O \cdot D \tag{1}$$

A number between [0, 10] is commonly used to represent each risk factor. FMECA begins with a description of the recognised system and the creation of a logical framework. To acquire a complete picture of the examined system, it is needed to gather enough data on the dependability connection between the system's primary components and to characterise them in terms of their rank and placement. It is strongly suggested that components of the study be omitted since they will not be evaluated or taken into account throughout the analysis. A system block diagram depicts the practical relationships between components. It is also critical to detail all possible failure modes for each element, classify the reasons, and describe fully the consequences of each. According to Mzougui, et al. [116], it is important to consolidate and record all the results in appropriate spreadsheets that aid in establishing risk assessment in particular, calculating RPN against each failure scenario [116].

2.4.1.2. ELECTRE TRI for sorting failures into risk priority classes

As already discussed at the beginning of this chapter, ELECTRE TRI is a decision-making problem-sorting and categorization technique centred on outranking. In the ELECTRE TRI method, an outranking relation indicates circumstances that exist between groups of options or, more specifically, between options and reference items. Concordance and discordance rules are at the heart of this kind of relationship since they validate the consistency amongst criterion indicating a certain solution is superior to other choices (or reference items) and the confliction among elements that this statement may not be accepted. Occasions of disinterest, preferences, or incomparability can be highlighted by having a common relationship with someone. Alternatives consistently outperform reference items in the first scenario; in the second, alternatives consistently outperform reference items but not in the reverse; and in the third, alternatives and reference items have such a wide disparity between them that they cannot be compared. Setting the right numerical thresholds can lead to these kinds of scenarios.

For ELECTRE TRI, determining threshold values is crucial since it has a direct impact on the classification of results. Cut-off values must be defined by the analyst in order to adjust the technique based on the unique problem being investigated, as stated in [77]. In order to simulate larger thresholds, it is important to begin with a variety of different methodologies and then continually adjust such parameters till every criterion determines that they are satisfactory.

Ordered classes must be specified, and they must not overlap with any of the related reference items, as required by ELECTRE TRI. At the same time, every referenced element displays the higher and lower referenced elements for a given class simultaneously. An individual or a team of decision-makers might identify the reference item directly, or by using specific elicitation processes that allow for indirect preference information. A typical example of this is shown in Figure 2.4, which shows four ordered classes defined by three reference profiles and four generic criteria. In order to proceed with the application and address these fundamental issues regarding ELECTRE TRI, the same input data as the ones recalled in section 2.1 are necessary.

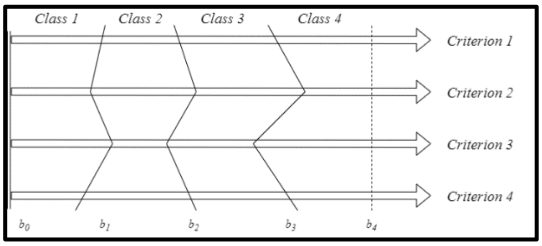

Figure 2.4. Classes and reference profiles representation for each criterion [77]

The first and second stage to be implemented to carry out the technique are specified next.

1. First stage: The first step is to build an outranking relation (herein denoted as X) by comparing each option to the reference profiles. This level has four intermediate steps.

1.1 Computing each criterion's correlation index. Each option A_i must be evaluated bilaterally with each of the specific reference elements b_k, and correlation indexes, $C_j(A_i, b_k)$, must be calculated for each criteria g_j utilizing the given equations:

$$C_j(A_i, b_k) = \begin{cases} 1 & \text{if } g_j(b_k) - g_j(A_i) \leq q_j \\ \frac{g_j(A_i) - g_j(b_k) + p_j}{p_j - q_j} & \text{if } q_j < g_j(b_k) - g_j(A_i) < p_j. \\ 0 & \text{if } g_j(b_k) - g_j(A_i) \geq p_j \end{cases} \tag{2}$$

The aggregated concordance index $C(A_i, b_k)$ going to be calculated by utilising the previously computed correlation values for every criteria and collecting and weighting the indexes as a function of follows:

$$C(A_i, b_k) = \frac{\sum_{j=1}^{J} w_j \cdot C_j(A_i, b_k)}{\sum_{j=1}^{J} w_j}. \tag{3}$$

1.2 Compute the discordance indexes for each criteria using the equation given hereunder:

$$D_j(A_i, b_k) = \begin{cases} 1 & \text{if } g_j(b_k) - g_j(A_i) > v_j \\ \frac{g_j(b_k) - g_j(A_i) - p_j}{v_j - p_j} & \text{if } p_j < g_j(b_k) - g_j(A_i) \leq v_j. \\ 0 & \text{if } g_j(b_k) - g_j(A_i) \leq p_j \end{cases} \tag{4}$$

1.3 Calculate the relative importance index utilising formula provided here.

$$\sigma(A_i, b_k) = \prod_{j \in F} \frac{1 - D_j(A_i, b_k)}{1 - C(A_i, b_k)}, \quad (5)$$

where $F = [j: D_j(A_i, b_k) > C(A_i, b_k)]s$; $\sigma(A_i, b_k) = C(A_i, b_k)$ otherwise. In the absence of a defined rejection limit for every criteria, the confidence value $\sigma(A_i, b_k)$ equates the aggregate correlations score, $C(A_i, b_k)$. A fuzzy outranking connection based on parameters must be transformed into a crisp relationship after computing.

1.4 The significance level, which often resides in the range [0.5, 1], provides the limit value for $\sigma(A_i, b_k)$ to back up the theory that A_i outranks b_k, and is utilized to characterise the sort of pairwise connection. The preferred connection between $\sigma(A_i, b_k)$, $\sigma(b_k, A_i)$ and λ is determined by the values of A_i and b_k:

- $\sigma(A_i, b_k) \geq \lambda$ and $\sigma(b_k, A_i) \geq \lambda \Rightarrow A_i$ S b_k and b_k X $A_i \Rightarrow A_i$ I b_k;
- $\sigma(A_i, b_k) \geq \lambda$ and $\sigma(b_k, A_i) < \lambda \Rightarrow A_i$ S b_k and not b_k X $A_i \Rightarrow A_i$ P b_k;
- $\sigma(A_i, b_k) < \lambda$ and $\sigma(b_k, A_i) \geq \lambda \Rightarrow$ not A_i S b_k and b_k X $A_i \Rightarrow b_k$ P A_i;
- $\sigma(A_i, b_k) < \lambda$ and $\sigma(b_k, A_i) < \lambda \Rightarrow$ not A_i S b_k and not b_k X $A_i \Rightarrow A_i$ R b_k;

Here X stands for the outranking relationship (e.g., A_i X b_k) means that option i is at least as beneficial as reference profile k) and I, P, and R stand for irrelevance, solid choice, and superiority, respectively.

2. Second stage: The second stage is aimed at allocating possibilities to categories based on two different procedures that are the pessimistic and optimistic procedures.

2.1 The process known as a pessimistic (or conjunctive) procedure assigns an alternative A_i to the class C_k for which the condition A_i X b_k is verified, meaning that this alternate profile A_i is at minimum as excellent as characteristic k. The pessimistic process begins with the highest value limiting reference profile creating classes, then goes through the next two steps.

- Progressively analysing each option to the class borders, that is, A_i is gradually equated to profiles defining classes until the earlier stated criteria is verified.
- Class $C_{(k+1)}$ has been assigned to alternative A_i.

2.2 Positive (or disjunctive) method: Option A_i is allocated to the class C_k for which the criteria b_k P A_i is satisfied, meaning that reference profile k should be chosen over alternative A_i in an optimistic (or disjunctive) method. The optimistic method initiates with the minimum score constraining reference profiles and forming classes, and it proceeds from there:

- Comparing each alternative to the class limits. In order to verify alternative A_i, the profiles describing classes are compared progressively until the criterion b_k P A_i is met.
- Class C_k has been assigned to alternative A_i.

2.4.1.3. DEMATEL for analysing dependence within each class

It is discussed in this subsection how to determine the effect connection between the important components of a complex system using a technique called impact analysis. It is necessary to take into account the existence of mutual reliance among the key parts when making decisions about complex systems, and the DEMATEL approach may be used to achieve this task quickly and efficiently. As a result, when dependency relationships are not thoroughly explored, the consequences of decision-making are more than likely to be adversely influenced. In present research, the DEMATEL method is utilised to assess the influence of the effects of relations between components on the decision-making of a complex system, and the results are presented. In order to obtain this goal, the DEMATEL strategy needs the cooperation of an expert or a team of specialists in the subject matter in order to get a more in-depth understanding of the problem under investigation. The essential steps involved in putting the method into action are detailed in further below [117].

- Collecting the positive input parameters, X, whose cells shows the relation of effect X_{ij} of one element, i, over other one, j, utilizing the following descriptive evaluation scale: 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence), and 4 (very high influence). In order to avoid the possibility of components having an influence on oneself, the major diagonal is filled with zeroes.

- The earlier step is accomplished by engaging a decision-making team, each expert is asked to create their individual input data matrix, with the objective of processing the entire collection of input variables as equitably and consistently as feasible. All created matrices are then integrated into a single matrix, which is referred to as the direct relation matrix, abbreviated as A (input of the subsequent phase of the process). If only single specialist is involved, the matrix X will match with the matrix A,

- Computing the normalised direct connection matrix N as:

$$N = sA, \tag{6}$$

s denotes a non-negative numeral somewhat lesser than:

$$\min\left[\frac{1}{\max\limits_{1\leq i\leq n}\sum_{j=1}^{n}x_{ij}},\frac{1}{\max\limits_{1\leq j\leq n}\sum_{i=1}^{n}x_{ij}}\right]. \tag{7}$$

Matrix N represents the preliminary influence that elements produce on one another as well as the effect that they receive from one another. Getting a continual reduction in non-direct effects between variables in relation of successive powers of N is the goal of the subsequent stage.

- Gaining the whole connection matrix T, that gathers all of the interrelationships between components, together with both direct and indirect influences. This matrix is computed by summing the powers of the standardised direct connection matrix N, and given by the following equation:

$$T = N(I - N)^{-1}, \tag{8}$$

Since I is the identity matrix. One has to consider as $\lim\limits_{n\to\infty} N^n = 0$, as the spectral range of N is lesser than 1 and is limited by the sum of extreme row and column. The power sequence of the standardised direct relation matrix meets to $(I - N)^{-1}$. Importantly, it must be observed that the major diagonal of matrix N is filled with zeroes, as described earlier, an item has no direct influence on itself. Simultaneously, the key diagonal of the overall relation matrix T aggregates all of the indirect affects connected with the corresponding elements.

- It is necessary to describe the two vectors $\mathbf{r} = (r_i)$ and $\mathbf{c} = (c_j)$, which denote the $n \times 1$ and $1 \times n$ vectors of sums of the rows and the columns respectively in the total relation matrix T. Considering these two vectors, the prominence may be computed as the sum $r_i + c_i$, which indicates the overall influence of element i on all the other elements, and the relation can be computed as the difference $r_i - c_i$, which assists in classifying the elements as cause (if positive) or effect (if negative), based on these two vectors.

- When necessary, constructing the impact chart prominence-relationship and calculating the final ranking of components based on their diminishing importance value.

2.4.2. Case study: a complex service system subjected to PrdM

When applied to a key subsystem of a complex service system that has been exposed to PrdM, the presented real-case is intended to illustrate the practical utility of integrating the FMECA method with the suggested integrated MCDM technique, published as a journal paper [73]. The ELECTRE TRI is used as an alternate method to regular RPN, with the goal of eliminating few of its disadvantages. As an alternative of just sorting alternatives based on their RPN score, ELECTRE TRI is used to classify failures between risk preference categories, which is then be ranked accordingly.

Those failures that are in urgent need of repair will be quickly identified and highlighted in accordance with their respective classifications. By simplifying the implementation of maintenance activities, this strategy will help to improve the efficiency of maintenance management. The described technique will also allow for different levels of relevance to be assigned to the FMECA risk factors. For determining the allocation of failures to classes, the DEMATEL approach will rely on views offered by the specialist in charge of maintenance regarding the relation that connect pairs of failed failures. The goal is to draw attention to those failures within each class that are linked with a greater extent of dependency with the other failures and whose direct management can work together to reduce the likelihood of the occurrence of other dependent failures.

As a result, the fundamental benefits of the suggested technique is that it can identify, for all preference class, the failure reasons that are distinguished by their greater importance. Direct involvements on these particular failure modes help to the overall improvement of system conditions as well as the optimization of maintenance in accordance with the PrdM strategy that has been implemented for the system in question. The complex system under consideration is again the vehicle studied in [118]. Two factors, the interconnected power take-off (PTO) and the oil storage, as well as three core subsystems, make up the system. 3) system for movement, 4) system for cleaning and funnelling, and 5) system for loading and dumping, make up the vehicle's basic construction. Table 2.6 contains an in-depth functional description of the system components. Because the failure of any one of these five basic aspects would result in the breakdown of the entire system, reliability networks are adopted as in sequence.

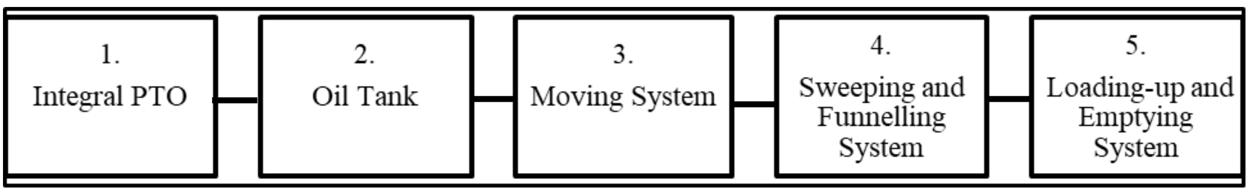

Figure 2.5. Series of components and subsystems

Table 2.6. Components and subsystems functional description

Component/ Subsystem	Description
1. Integral PTO	Component 1: Through the employment of a suitable power take-off system, Component 1 enables the linkage of the hydraulic pumps to the main engine, hence enabling the functioning of the complete system. The normal functioning status of the whole system is directly reliant on the performance of this element, with the pumps functioning as the key key parts by which vehicle's mobility is assured and all of the different stages of sweeping are executed.
2. Oil Tank	Component 2: It is the initial part in the whole hydraulic circuit, and its major role is to promote the loss of heat generated during regular vehicle functioning. This design decision results in the oil tank being partially integrated into the water tank and linked to it through an outside flange. Tracking of the oil level and temperature is essential, and this may be achieved with the aid of an appropriate level gauge and temperature sensor.
3. Moving System	Subsystem 3 includes the beginning pump (3.1), start-up engine (3.2), and electronically controlled system. It is accountable for the vehicle's progress throughout operational stage (3.3). The varying start-up pump controls the operation of the hydraulic traction engine. It is crucial to note that by modifying the pump dislocation, it is possible to vary the rotor velocity of the hydraulic motor and, subsequently, the vehicle's motion. The hydraulic transmission enables the vehicle to be driven more slowly for sweeping operations (vehicle speed is determined by the flow of oil from the pump). The electronics control regulates each part of system, such as the connected PTO and hydrostatic transmission.
4. Sweeping and Funnelling System	Subsystem 4: It is accountable for coordinating the sweeping activity with the garbage transfer to the garbage loading system. There are numerous parts, such as a sprinkler system (4.1), a hydraulic system, and sweeping elements (4.2). The spraying system consists of a water tank, water pump, and spray nozzles and is placed upstream of the cleaning and transporting operations. Subsystem 4.1 is primarily responsible for spraying water over powders to compact them and keep them from spreading into the air, hence enhancing the performance of the side brushes and side rollers. There is a pump I in subsystem 4.2 that is accountable for the movement of the circuit's sweeping sections, which have been separated into two systems based on their location: the right-side system and the left-side system.
5. Loading-up and Emptying System	Subsystem 5: It organises and supervises garbage loading and tank dumping processes. It consists of three parts: pump II (5.1), loading system (5.2), and dumping system (5.3). Pump II controls a hydraulic engine that powers the rear roller, as well as cylinders that act on the roller framework and cylinders accountable for the tank overturning. Pump II also regulates the elevator plant's releasing cylinder. The loading-up system, which is governed by pump III and fully accountable for garbage pickup until the collection tank is full, includes a back roller and connected elevator plant. First, waste is transmitted from the rear roller to the elevator plant, and then from the elevator plant to the storage tanks. After the release of the elevator plant by the suitable cylinders, the tank is emptied by inverting it via the support system, enabling the cleaner to reinstate cleaning operations.

In previous studies [75, 76], comprehensive block drawings depicting the entire set of components as well as the overall layout of the system were developed. As discussed in the case study reported in section 2.2 [72], Aiello, et al. [76] particularly highlighted three important components that must be monitored by sensors in order to lead to treatments for PrdM. Pump I, pump II, and pump III are three hydraulic pumps that are required to ensure the proper operation of the most critical sweeping elements, as well as the loading and emptying systems, among other things. Speed has been identified as the characteristic associated with the wear condition of pumps, and it will be monitored by a network of sensors in the right configuration. The research conducted in [72] revealed that failures possibly affecting pump I are related with a higher degree of intervention priority as compared to failures potentially involving pumps II and III. As a consequence of this finding, the current real-case considers on the central subsystem that is directly influenced by the operation of pump I, namely subsystem 4.2 (hydraulic circuit and sweeping parts), whose process structure is depicted in Figure 2.5 (this is the version of the figure 2.2, updated with ID codes for each component/subsystem). Fig. 2.6 depicts the reliability diagram of the "Right-side system" [74]. It is noticeable as subsystem 4.2 is critically important for avoiding any unintended service termination.

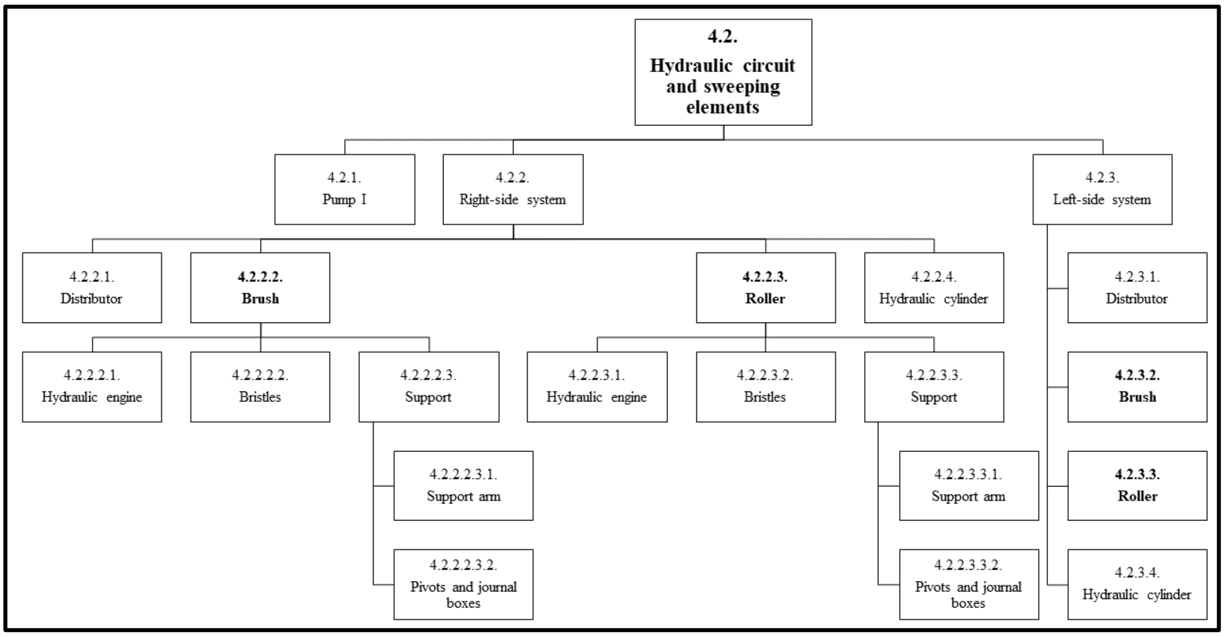

Figure 2.6. Hierarchical structure of the subsystem ruled by pump I [118]

The FMECA analysis will be performed first, followed by the use of the integrated MCDM technique to address the list of failure modes and their assessments in the next paragraph.

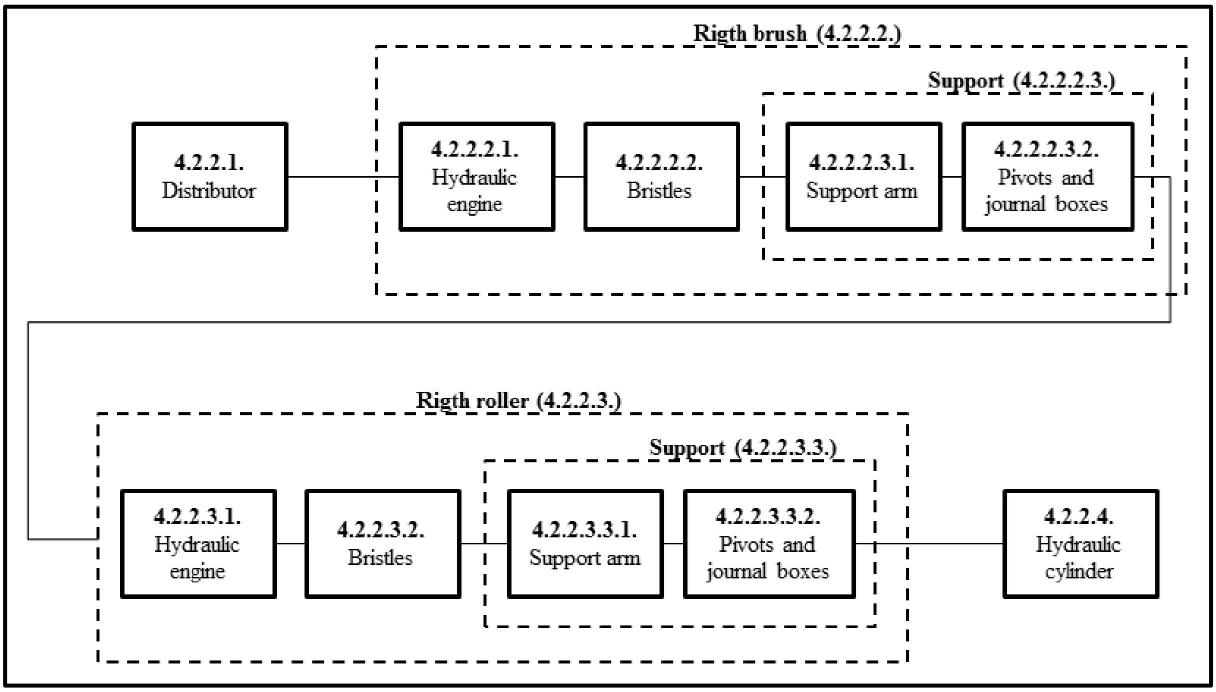

Figure 2.7. Detailed reliability diagram of the “right-side system” [118]

2.4.3. Data collection and application

After all of the components have been identified to the greatest extent possible, Table 2.7 examines the failure of the parts that are placed at the lowest levels of the structure of the subsystem under consideration. It has been determined what the various failure modes are for each component, as well as what the failure causes and effects are for each component, with the last two relating to both single components and the entire system. The quantitative evaluation of three FMECA variables, which were established within the discrete range of values [1-3] with the assistance of the technician responsible for vehicle maintenance, is presented in Table 2.8. To be specific, the During one-on-one sessions with the relevant decision-making experts, who was personally questioned about the quantitative assessments to be connected with the three FMECA variables for each failure mode, the input data collecting stage was organised, as well as through questionnaires. As part of this collaboration, the expert has agreed to regard the interval [1-3] as appropriate for representing the subject under investigation in its entirety, and he has also agreed on the definition of the scale of values. Because he is responsible of vehicle maintenance, the specialist who was questioned is familiar with the most common problems that affect the system and its basic components, as well as the most important factors relating to operator safety and security.

Table 2.7. Analysis of failure modes, causes and effects

ID	Component	Failure Modes	Failure Causes	Failure Effects
4.2.1.	Pump I	Fault distribution system	Power outage; fluid characteristics; Valves or other elements failure.	The hydraulic circuit and hydraulic actuators are not operating properly; The work position is not taken; The spinning of the brush and rollers is not permitted.
		Mechanical fault	breakdown of elements (bearings, journal boxes, etc.); breakdown sealing elements.	Faulty hydraulic circuit and hydraulic actuators; Unoccupied work location; Prohibited brush and roller spinning.
4.2.2.1./ 4.2.3.1.	Distributor	Sweeping elements not lubricated	No supply of oil; mechanical malfunction; contact element deterioration	Not permitted to rotate brushes or rollers; Garbage not conveyed.
4.2.2.2.1./ 4.2.2.3.1./ 4.2.3.2.1./ 4.2.3.3.1.	Hydraulic engine	Stopped start-up engine	Pump I failure; Oil overheating.	Brushes stopped; lateral rollers halted; trash not transported
		Mechanical fault	Bearing wear.	Increased vibrations.
4.2.2.4./ 4.2.3.4.	Hydraulic cylinders	Stopped hydraulic cylinders	Pump I and / or pump II failure; high friction; hydraulic circuit failure.	Translation of brushes/rollers was not executed (elements not adherent to the ground when working or not lifted during transportation).
		Mechanical fault	The deterioration of the sealing components.	Inconsistent interpretation and oil wastage
4.2.2.2.3.1. 4.2.2.3.3.1. 4.2.3.2.3.1. 4.2.3.3.3.1.	Support arms	Broken arms	Deformation caused by collisions with huge trash or sidewalks.	Impaired performance of brushes and side rollers
		Stopped arms	Hydraulic system problem.	Failing to open or close side arms; Alterations in action range of transportation system.
4.2.2.2.3.2. 4.2.2.3.3.2. 4.2.3.2.3.2. 4.2.3.3.3.2.	Pivots and journal boxes	Slackened pivots	Due to vibrations, incorrect assembly/ strain has occurred.	Excessive vibration; Possibility of brush or roller removal from the holder.
		Worn journal boxes	Incorrect assembly/ activity of pins included inside the journal boxes	Improper connection between the arms and the brushes or rollers.
4.2.2.2.2./ 4.2.2.3.2/ 4.2.3.2.2./ 4.2.3.3.2/	Bristles	Damaged brush or roller	Mechanical interaction between garbage and the road surface.	Waste collection inefficiency; Bristles that attach poorly to the ground

Table 2.8. List of failure modes for subsystem 4.2 and factors evaluation

FAILURE MODES		ID	S	O	D
4.2.1. Pump I	Fault distribution system in Pump I	PI_1	2	2	2
	Mechanical fault in Pump I	PI_2	2	1	2
4.2.2. Right-side system	Sweeping elements not lubricated by right-side distributor	RSS_1	2	3	2
	Stopped right-side hydraulic cylinders	RSS_2	1	2	2
	Mechanical fault of right-side hydraulic cylinders	RSS_3	1	2	2
	Stopped start-up engine of right-side brush	RSS_4	1	2	1
	Mechanical fault of start-up engine of right-side brush	RSS_5	3	1	1
	Broken support arms of right-side brush	RSS_6	2	1	1
	Stopped support arms of right-side brush	RSS_7	2	1	1
	Slackened pivots of right-side brush	RSS_8	1	2	3
	Worn journal boxes of right-side brush	RSS_9	2	2	3
	Damaged bristles of right-side brush	RSS_10	1	3	2
	Stopped start-up engine of right-side roller	RSS_11	1	2	1
	Mechanical fault of start-up engine of right-side roller	RSS_12	3	1	1
	Broken support arms of right-side roller	RSS_13	2	1	1
	Stopped support arms of right-side roller	RSS_14	2	1	1
	Slackened pivots of right-side roller	RSS_15	1	2	3
	Worn journal boxes of right-side roller	RSS_16	2	2	3
	Damaged bristles of right-side roller	RSS_17	1	3	2
4.2.3. Left-side system	Sweeping elements not lubricated by left-side distributor	LSS_1	2	3	2
	Stopped left-side hydraulic cylinders	LSS_2	1	2	2
	Mechanical fault of left-side hydraulic cylinders	LSS_3	1	2	2
	Stopped start-up engine of left-side brush	LSS_4	1	2	1
	Mechanical fault of start-up engine of left-side brush	LSS_5	3	1	1
	Broken support arms of left-side brush	LSS_6	2	1	1
	Stopped support arms of left-side brush	LSS_7	2	1	1
	Slackened pivots of left-side brush	LSS_8	1	2	3
	Worn journal boxes of left-side brush	LSS_9	2	2	3
	Damaged bristles of left-side brush	LSS_10	1	3	2
	Stopped start-up engine of left-side roller	LSS_11	1	2	1
	Mechanical fault of start-up engine of left-side roller	LSS_12	3	1	1
	Broken support arms of left-side roller	LSS_13	2	1	1
	Stopped support arms of left-side roller	LSS_14	2	1	1
	Slackened pivots of left-side roller	LSS_15	1	2	3
	Worn journal boxes of left-side roller	LSS_16	2	2	3
	Damaged bristles of left-side roller	LSS_17	1	3	2

The collection of possibilities for the hybrid MCDM application is based on thirty-six failure scenarios, with the three FMECA risk factors serving as the foundation presumed to be the assessment criteria in this study. For the interest of completeness, we would like to point out that the ELECTRE TRI application described below may be carried out by altering or increasing the set of criteria, for example, by considering features relating to human factors and/or economic considerations, among other things. We will go into further depth regarding the parameters' assessments in the next sections. Insignificant failures, defined as those that cause just a partial deterioration of specific functionalities without having a significant impact on the system or individuals, have been assigned severity values equal to 1. The severity values of 2 have been assumed for marginal failures, which are failures that may cause a decline in efficiency or even the complete loss of some functionalities, but do not cause significant damage to the system or to the individuals who are affected by them. In the case of catastrophic failures, severity values equivalent to 3 have been assumed, which means that they can substantially impair major working roles and reason significant harm to the system and its surroundings, with possible consequences for human safety. The probability of occurrence has been assigned a value of 1 for remote failures, 2 for occasional failures, and 3 for probable failures. Finally, detection has been rated from 3 to 1, with 3 reflecting failures that are difficult to detect (hence concomitant with greater risk conditions) and 1 representing failures that are easy to detect (thus concomitant with lower risk situations). For the ELECTRE TRI application, three classifications of risk with equal width, designated by two reference profiles ($b_1 = 1$ and $b_2 = 2$ for each criteria), have been taken into consideration: low (class C), medium (class B), and high risk (class A). With the use of the J-Electre-v2.0 software for multi-criteria decision assistance established by Pereira [79], the results of the ELECTRE TRI method have been double-checked to ensure they are accurate.

The ELECTRE TRI outcomes are detailed in Appendix A. Tables A1 (pessimistic process) and A2 (optimistic procedure) display the assignment based on varying values of the cut-off level λ and cases with varying risk factor weights. In specifically, scenario 1 assigns 50% weight to the severity component, with the remaining 50% weight divided evenly between occurrence (25%) and detection (25%). Likewise, cases 2 and 3 provide 50% weight to occurrence and detection, and 25% weight to each of the remaining criteria. The values of the limits have been determined by guiding several phases of application until they were deemed suitable for the case study under consideration. The indifference threshold q_j has been assumed to be equivalent to 0.5 and the severe preference limit p_j has been set to 1, but the rejection limit v_j

has not been considered for this application. It is possible to note as results obtained through the optimistic procedure should be preferred because, as demonstrated in [77], it has a tendency to allocate solutions to classes associated with higher ratings, which can make risk appraisal and action management more effective. Accordingly, the output of the optimistic method (Table A2) has been deemed a body of input data for the DEMATEL application, which will be used to carry out the application. Failure modes have been classified into two groups, designated as A and B, which reflect high and medium risk circumstances, respectively. According to the evaluations presented, no failure has been classified as being of low-risk class C. In order to find the most affecting failure(s), which might have a negative influence on all of the others, two independent phases of DEMATEL were carried out, one for each class.

Table 2.9. DEMATEL results

Class A: HIGH RISK				**Class B: MEDIUM RISK**			
ID	$r_i + c_i$	$r_i - c_i$	**Ranking position**	**ID**	$r_i + c_i$	$r_i - c_i$	**Ranking position**
PI_1	6.8649	-0.5896	1st	PI_2	5.0521	0.6556	1st
RSS_1	6.5265	0.9876	3rd	RSS_2	3.5946	-0.0669	5th
RSS_5	6.5564	-1.1123	2nd	RSS_3	4.4026	0.4313	2nd
RSS_8	5.6600	0.0889	7th	RSS_4	3.6040	0.0098	4th
RSS_9	5.7838	-0.0397	5th	RSS_6	3.3846	0.3366	8th
RSS_10	5.5247	-0.1170	8th	RSS_7	3.5146	-0.6614	6th
RSS_12	5.9712	-0.3207	4th	RSS_11	4.0056	0.1520	3rd
RSS_15	5.1112	0.7988	9th	RSS_13	3.3186	-0.1777	9th
RSS_16	5.7361	0.1284	6th	RSS_14	3.4807	-0.3515	7th
RSS_17	5.0962	-0.1193	10th	LSS_2	3.5946	-0.0669	5th
LSS_1	6.5265	0.9876	3rd	LSS_3	4.4026	0.4313	2nd
LSS_5	6.5564	-1.1123	2nd	LSS_4	3.6040	0.0098	4th
LSS_8	5.6600	0.0889	7th	LSS_6	3.3846	0.3366	8th
LSS_9	5.7838	-0.0397	5th	LSS_7	3.5146	-0.6614	6th
LSS_10	5.5247	-0.1170	8th	LSS_11	4.0056	0.1520	3rd
LSS_12	5.9712	-0.3207	4th	LSS_13	3.3186	-0.1777	9th
LSS_15	5.1112	0.7988	9th	LSS_14	3.4807	-0.3515	7th
LSS_16	5.7361	0.1284	6th				
LSS_17	5.0962	-0.1193	10th				

DEMATEL input data have been organised throughout Appendix B. As a starting point, the first step has been guided by gathering pairwise influence assessments (Table B1) from the involved specialists on the set of nineteen failure modes that have been categorised into class A. The second stage has been focused on the remaining seventeen failure possibilities, which have been categorised into class B (Table B2). According to their diminishing levels of prominence ($r_i + c_i$), failures within each risk class are finally ranked in Table 2.9 according to their ultimate ranking. Additionally, the values of the relationship ($r_i - c_i$) are presented in order to differentiate between causes and effects. Specifically, the DEMATEL charts relevant to the two steps of the application, i.e. inside each class, are shown in Figures 2.8 and 2.9.

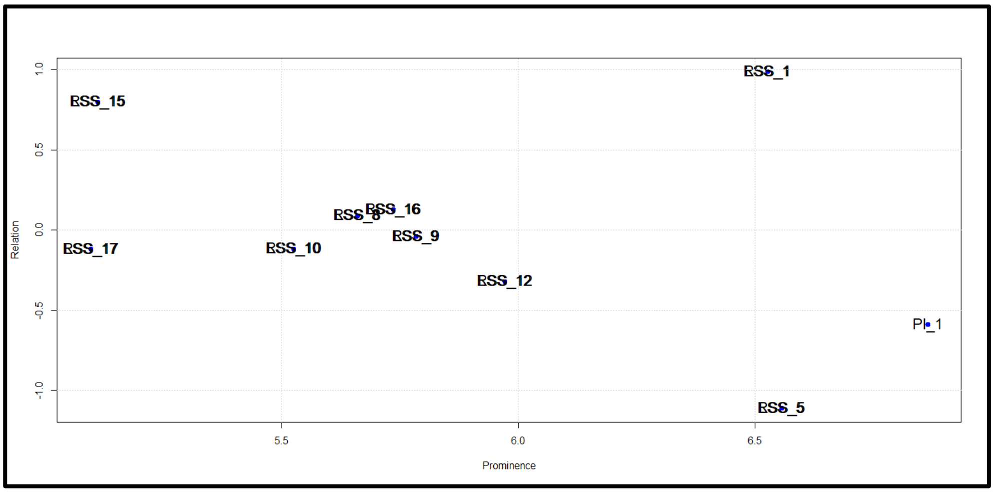

Figure 2.8. DEMATEL chart with failure modes of class A (high risk)

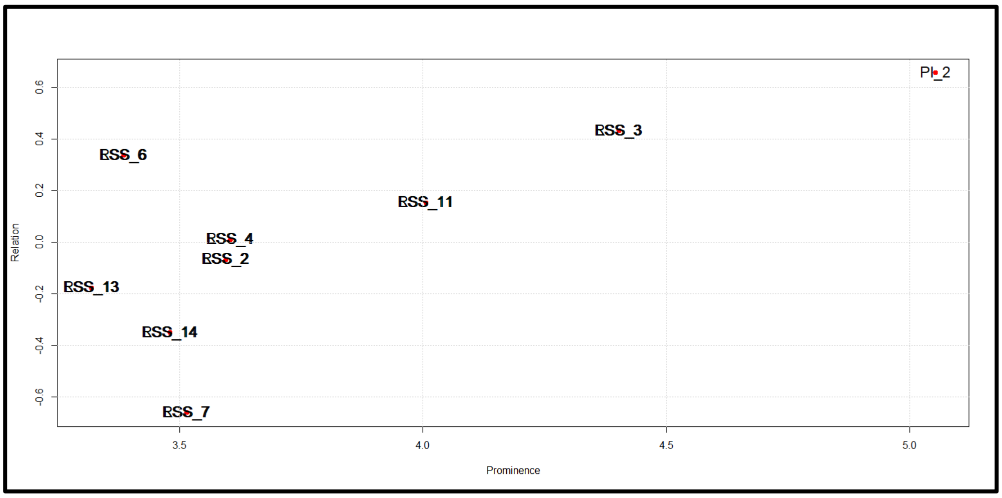

Figure 2.9. DEMATEL chart with failure modes of class B (medium risk)

2.4.4. Discussion of results and managerial implications

The achieved outcome is intriguing from the standpoint of actual management application, and numerous valuable thoughts may be drawn from them. Using FMECA, which is a significant technique of safety and risk analysis performed by safety and risk engineers [118], appropriate assessments have been conducted on the service system under consideration. With the FMECA application, it is possible to perform an exhaustive system analysis by synthesising reliability relations and characterising possible failure modes in a complex system with three critically important pumps that are monitored by sensors and subjected to PrdM.

Due to the higher criticality of pump I identified in a previous conference paper [72], we chose to concentrate on the part of the system that is directly dependent on this component's performance. FMECA was utilised to identify thirty-six failure modes (i.e., alternatives to the decision-making issue), and the hybrid MCDM was implemented to further optimise maintenance management. The ELECTRE TRI method was utilised to categorise the thirty-six failure scenarios into two risk groups suggesting a high and a medium intervention priority, respectively. In addition to making it easier for decision-makers to access failure modes [114], moreover, classifying failure modes into ordered classes has been shown to be a more effective approach than the usual ranking method of merely arranging RPN values. It is true that categorising failures can provide useful information, allowing risk managers to see which failure modes need to be prioritised when it comes to risk mitigation and management. A total of 19 failures have been classified as high-risk classes A and B, respectively, while 17 failures have been classified as low-risk classes A and B. (medium risk). According to the evaluations offered by the included maintenance professional, the method evaluated a additional class C (low risk class), but no failure mode was sorted there according to the results of the method. This implies that all of the failure modes obtained by FMECA are critical in some way to the system's operation. To put it another way, the quantitative assessments assigned to FMECA parameters do not support the notion of associating a low level of risk with any of the failure modes that have been found. Following a further discussion with specialist, he stated that this is a very prudential supposition, as it is always important to keep in mind the worst-case scenario when it comes to the risk assessment of the particular component under consideration. Study assume that this finding may be confirmed as a universal rule, because it might lower the likelihood of underestimating the probable incidence of particular failures by seeing them as unimportant than they actually are. Indeed, even when it appears that this is the case, buried issues might every time conspire to raise the overall risk estimate at the system level. After considering the foregoing, we can infer that maintenance actions targeted at mitigating the risks associated with the detected failures must be taken with a high or medium-high priority, and that no action should be suspended indefinitely.

A sensitivity analysis was conducted by adjusting the cutting level as well as the weights of risk variables (i.e. criteria of the decision-making issue), which revealed no changes in the final results and subsequently confirmed the reliability of the findings. Again, in contrast to typical FMECA, one of the advantages of our method is the ability to take into account varying degrees of relevance for severity, incidence, and detection. In addition, different criterion might be included to the investigation. In order to visualise causal linkages [118] and determine which options are highly important within every class of failures, the DEMATEL process was employed after the failures had been categorised. It is necessary to manage these failures to reduce the likelihood of further failures occurring within the class of reference, and this involves minimising global risk.

Class A (high risk) failures include those characterised by PI I (fault distribution system in Pump I), RSS 5 (mechanical fault of start-up engine on right side brush), LSS 5 (mechanical fault of start-up engine on left side brush), RSS 1 (sweeping elements not lubricated through right-side distributor), and LSS 1 (sweeping elements not lubricated through left-side distributor), all of which must be addressed immediately. In addition, it is feasible to see that, among the failures listed, RSS 1 and LSS 1 may be regarded as causes, while the rest failures can be regarded as consequences.

By addressing these issues as soon as possible, it would be possible to reduce the likelihood of the occurrence of associated breakdowns like RSS 12, which is a mechanical problem of the start-up engine of the right-side roller; LSS 12, which is a mechanical failure of the start-up engine of the left-side roller; RSS 9, which is worn journal boxes of the right-side brush; and LSS 9, which is worn journal boxes of the left-side brush. This might also have a good impact on pump I, which was exposed to PrdM, by increasing the status of its operation and lowering the associated maintenance costs. Moreover, similar to this, the technique specifies that when leading initiatives for controlling failures associated with class B (moderate risk), such as PI 2 (mechanical fault in pump I), RSS 3 (mechanical fault of right-side hydraulic cylinders), LSS 3 (mechanical fault of left-side hydraulic cylinders), RSS 11 (stopped start-up engine of right-side roller), and LSS 11 (stopped start-up engine of left-side roller), needs priority treatment. According to the positive values of prominence (ri-ci), the technique shows that these failures might be considered as sources of the observed phenomena.

To summarise, it has been demonstrated that initiatives that are aimed at enhancing pump I, a vital part that is subjected to PdM, in addition to the engines that rule the sweeping components and their oil changes, are essential for keeping the complex system that is being investigated in an appropriate functional state and for optimising its level of efficiency over the course of its lifecycle. It is claimed that concentrating on these specific failures will result in a reduction in the likelihood of the recurrence of further failures in the similar class as the ones being targeted. The failures that have been identified as the utmost serious are, in fact, the ones whose existence is most probable to have an influence on the occurrence of all other failure.

Chapter 3.

Digital transformation in maintenance management

3.1. Industry 4.0 technologies

Technology growth has dramatically changed the entire industry in the previous few years, and all manufacturing industries are therefore forced to a shift in the technological paradigm. Industry 4.0 is the distinguishing aspect that has emerged as an enabling factor of industrial functions (maintenance, operations, production, etc.) which are streamlined and become more productive via the huge adoption of advanced digital technologies. Industry 4.0 is a technological revolution that aims to create a worldwide impact by revealing the true possibilities of a sustainable society and permitting sustainable production. Implementing the industry 4.0 concept entails converting the industries into a completely networked facility where actions could be taken swiftly using comprehensive, clear, and factual data. It can be said that adaptability, integration, automation, collaboration, consistency, information-sharing, interconnectivity, modularity, condition monitoring, service quality, improvement, technical support, and remote visualization are some of its core features [119].

Industry 4.0 technologies have a significant influence on industries' maintenance, operational processes, security, and economics [119]. As a result, the entire process inferred significant benefits because of the incorporation of different industry 4.0 aspects that foster true predictive maintenance, allow data analysis and collection, enhance collaboration across multiple maintenance activities, assist monitoring via virtual technologies, and, ultimately, enhance efficiency and productivity, minimize accidental breakdowns, and, hence, decrease maintenance expenses [120]. Maintenance management in industries is one of the driving factors of Industry 4.0, and it has led to the emergence of new industrial difficulties [121]. In regards to effective interconnectivity, the incorporation of various industry 4.0 technologies, namely AI, ML, CPS, IoT, Big Data, AR, Cloud Computing, and so on, has substantially changed the maintenance management of traditional production systems of industries [120]. Particularly, PrdM has made substantial advancements, offering numerous promising benefits including increased output, particularly by enhancing both quality and availability and lowering expenses through digitalization for manufacturing real-time tracking, early diagnosis of breakdowns, reduced idle time, and asset life forecasting [121]. Industry 4.0 permits PrdM to intervene prior to actual failures or breakdowns emerge, ensuring the uninterrupted functioning of manufacturing processes. Once potential equipment abnormalities have been recognized or anticipated, a diagnostic process can be initiated to determine the underlying causes of the failures. In such a manner, maintenance activities like machine user interference are recommended to prevent assembly line failure [122].

The notion of Industry 4.0 is centered on technological advancements, and this study has outlined technologies that represent Industry 4.0, such as Cyber-Physical Systems (CPSs) [119, 120], Cognitive Computing [119], Cybersecurity [119, 123], Cloud Computing [119, 120, 123], Mobile Technologies [119], Machine-to-Machine (M2M) [119], Additive Manufacturing (AM) [119, 123], Autonomous Robotics [119, 123], Big Data and Analytics [119, 120, 123], Internet of Things (IoT) [119, 120, 123], Augmented Reality (AR) [119, 123], Simulation [119, 120, 123], and Artificial Intelligence (AI) [120] as shown in Figure 3.1. These technologies have been extensively studied and reported in the literature, among few references are [119, 120, 123-125]. Furthermore, readers are encouraged to see [119] for a detailed list of industry 4.0 technologies where authors identified and listed "100 Industry 4.0 technologies for world class manufacturing" which can be adopted and utilized in various domains of industries, such as for PrdM [119]. Moreover, study has found interoperability, interconnectivity, decentralization, and integration as the important features of industry 4.0 [120, 123].

3.2. digitalization in maintenance management

Technology and maintenance are mutually advantageous since the constant evolution of technology leads to substantial breakthroughs in the maintenance industry [126, 127]. Digitalization has been recognised as one of the fundamental trends altering society and industry [128], and it plays a crucial role in efficiently modernizing maintenance management. Innovation in technology does lay the foundation for the industry's long-term success. Digitalization is continually transforming organisations by allowing them to collect data automatically via the application of suitable technology. Different kinds of equipment and components are now capable of collecting long-term operating data, which, when digitalized, may yield an abundance of insightful information [126].

However, to ensure accurate failure prediction, maintenance management requires a number of smart technologies with wider digitalization solutions, such as AI, big data, IoT, digital twins, novel sensor technologies, information gathering and distribution from different smart sensors, and the investigation of huge amounts of information employing machine/deep learning [129, 130]. Lamdasni and Okar [131], determined that the concepts of digitization and Industry 4.0 could be implemented to maintenance, which is a crucial industry practice. Failure prediction, maintenance diagnostics, and decision-making can benefit from data collection and intelligent systems [131]. Pech, et al. [132] investigated and enumerated many kinds of smart sensors that allow the gathering of a huge amount of information that can be effectively analysed to optimize the maintenance management of complex systems and decision-making. Digitization has emerged as one of the most prominent trends over the past decade, not just in the manufacturing industry but also in other facets of industrial operations, including maintenance. The digital revolution has been compared to the industrial revolution in terms of its impact. The growing complexity of products, the progress of engineering fields, and the constant implementation of technologically intelligent solutions are all factors that have contributed to the unprecedented increase in global competitiveness, where the application of totally new notions in manufacturing and process advancement represents a significant dilemma [128, 131].

Figure 3.1. Technologies connected to Industry 4.0 [133]

This study herein presented mainly aims to evaluate which kind of data should be collected digitally in order to effectively perform predictive maintenance methods. This may be discovered by developing a literature analysis and examining the most recent digitalization trends in maintenance management. This research will also examine the key factors of digitization in maintenance management, as well as their benefits and drawbacks. Additionally, a decision-making model will be proposed in order to enable such maintenance management strategies. The anticipated outcome of the research would be able to support maintenance management through the understanding of influence relationships between related critical factors, enabling the monitoring of equipment health, identification of problems, prediction and resolution of issues well in advance of their occurrence, and improvement of performance. Consequently, this study may have good effects on economic, social, and environmental concerns, as well as the execution of maintenance policies in general.

Numerous researchers have studied the term Industry 4.0, which involves the present era and may be defined as the "fourth industrial revolution" thanks to the introduction of smart factories that are defined by their capacity to connect with each other. To achieve a level of production that is at the same time soft, dynamic and smart, the physical and virtual applications are blended in the fourth industrial revolution by utilizing interconnected systems, cutting-edge manufacturing equipment, and embedded technology. Numerous experts believe that the world has reached four important milestones on the road to the fourth industrial revolution. Specifically, the term “Industry 4.0” arose in 2011 as a synthesis for the global industrial aims of the German economy. There are three interconnected motivations for the development and implementation of Industry 4.0. Through digitization, we must move away from fundamental technical-economic ties and toward complex networks. Utilizing digital technologies enhances the quality of processes in terms of both products and services. As a third reason, new market models must be created. This industrial digital revolution encompasses the integration of every digital technology used in our daily life, including smartphones, tablets, and computers.

As industrial processes and communications technologies constantly improve, and as new analytic concepts are brought to the industry, maintenance management has attained a high degree of accuracy and an outstanding level of dependability in the huge quantity of data acquired from sensors and robots. In recent years, evolving notions such as CPS, IoT, and big data have altered how manufacturing industries are viewed, and have prompted researchers and practitioners to discover different research insights that will unquestionably influence top management perspectives by opening new avenues for innovation and information capitalization. As previously stated, digitization has had a huge influence on industrial maintenance tasks. Lamdasni and Okar [131] laid out four phases of maintenance digitization strategies. In the first reactive stage, the use of technologies is restricted in order to decreased maintenance response time. During the second phase, digital technologies contribute to the optimal implementation of the maintenance preventive programme. At the level of predictive maintenance, intelligent technologies employ historical data to anticipate conditions, and monitoring current state problems at their onset has become practicable due to the easy access of real-time data. In addition, proactive maintenance is a maintenance plan in which digital transformation guarantees criticality investigation and aids in making critical decisions like equipment death or investment decisions. Several intelligent maintenance systems have been developed in the past to help the digitization of maintenance. Among the models researched and reported by [131] include the Real-time Intelligent Multiple Fault Diagnostic System (RIMFDS), a system with ability to process numerous failure analyses as presented by smart sensors, the Intelligent Predictive Decision Support System (IPDSS), among others.

Johansson, et al. [134] studied the effects of implementing digital maintenance, including greater information on uncertain situations, increased capacity, enhanced maintenance, decreased costs, and increased sustainability. All of these factors illustrate a variety of economic, environmental, and social benefits. Digitalization is a compelling approach for value generation that encompasses all automated operations that are combined with communication and information technologies. Several advantages and high potentials of digitalization have been noted in the literature, such as rapid coordination, increased manufacturing process flexibility, and cost reduction [131]. Figure 3.2 depicts the maturity model of industry 4.0 concerning digitalization.

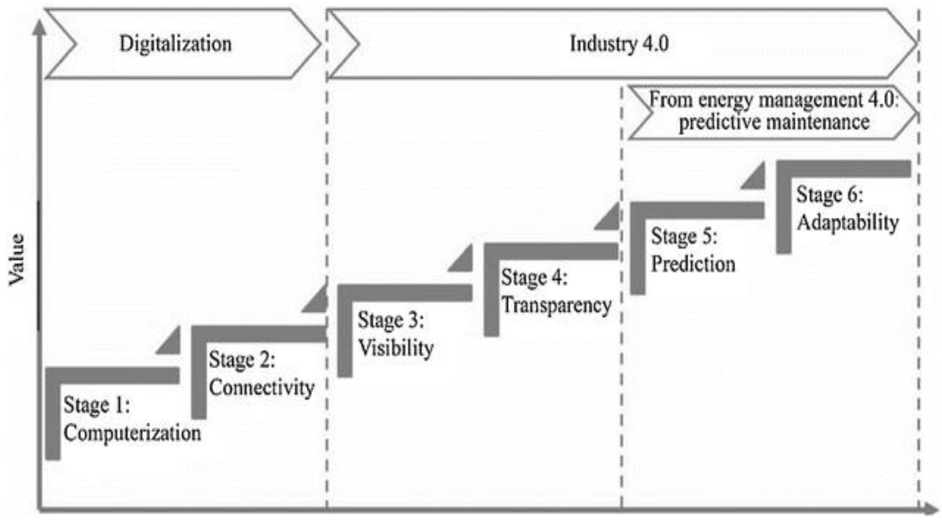

Figure 3.2. Industry 4.0 maturity model concerning digitalization adopted from [135]

3.2.1. Digital data collection

As we are living the 4th industrial revolution, empowered by Industry 4.0 developments such as ML, big data analytics, and virtual reality, we usually have access to a significant amount of data to aid in decision-making and the direct connection of assets via technologies such as embedded devices, also known as the IoT. In recent years, the greatest difficulty has shifted from collecting data to determining whether the information is practically helpful. The significance of having sufficient data in the maintenance decision-making process is contingent on our ability to use this data and predictive analysis to propose and take smarter decisions. As a result of this growth, new opportunities for data-driven techniques like as predictive analytics, AI, and ML have emerged, with the ability of higher productivity gains. [136].

Digital collection of data for maintenance management is a method that employs IoT technology to incorporate maintenance equipment, enabling distant data gathering, data transfer, investigation, and prospective efficiency and productivity enhancements, in addition to the scheduling of maintenance activities. For data collection, sensors convert machine-emitted physical processes such as temperature and vibration into digital signals. Machine data alone is insufficient for maintenance decision-making; a dependable IoT architecture is necessary to enable widespread sensor data collection and the connection of maintenance equipment to data sources [137]. Various types of data are being collected digitally, some of the examples are listed in Table 3.1.

It is usual for the data gathered by inspection devices to provide information regarding the status of plant components, as opposed to normal maintenance chores such as cleaning, lubrication, and component replacement. Physical phenomena can be monitored across time and space to provide diagnostic and prognostic information regarding the equipment's state. In addition, a list of sensor applications for each type of equipment and other details on maintenance digitalization may be found in a variety of research publications, as indicated by the authors [138].

Table 3.1. Examples of digital data collection

Types of Data	**Device/Sensors**
Vibration Data	Accelerometers or Piezoelectric sensors
Imaging of abnormally hot regions	Thermography
Subsurface inspection data	Ultrasonics
Materials integrity data	Resistance
Viscosity and impurity levels data	Oil analysis
Pipe thickness data	Radiography

3.2.2. Critical factors for digitalization

Maintenance management techniques have been profoundly affected by the digital revolution of industries. It is essential to determine which organizational competencies are required, as well as how organizations should evaluate their eagerness to initiate a digitalization transfer for maintenance management. Lamdasni and Okar [Lamdasni and Okar [131]] carried out research and outlined various critical factors for the successful digitization of maintenance management, which are categorized under five key notions as management of information and communication technology, resources for digitalization, organizational development, formation of maintenance programs, and progression of corporate culture, as depicted in Figure 3.3. Additionally, Johansson, et al. [134] analysed others aspects, such as smart technology development, organizational growth, change in working practices, regulatory compliance, and data privacy and security, that are beneficial for the effective implementation of digital maintenance. Moreover, Singh and Gupta [139] analysed and investigated fourteen maintenance management aspects using a literature study, interviews with maintenance professionals and specialists, the nominal group method, and brainstorming. In contrast to critical factors, three major obstacles to the adoption of maintenance techniques in the industry have emerged: insufficient management collaboration, lack of overall equipment effectiveness (OEE) evaluation, and lack of strategic planning and execution measures [140].

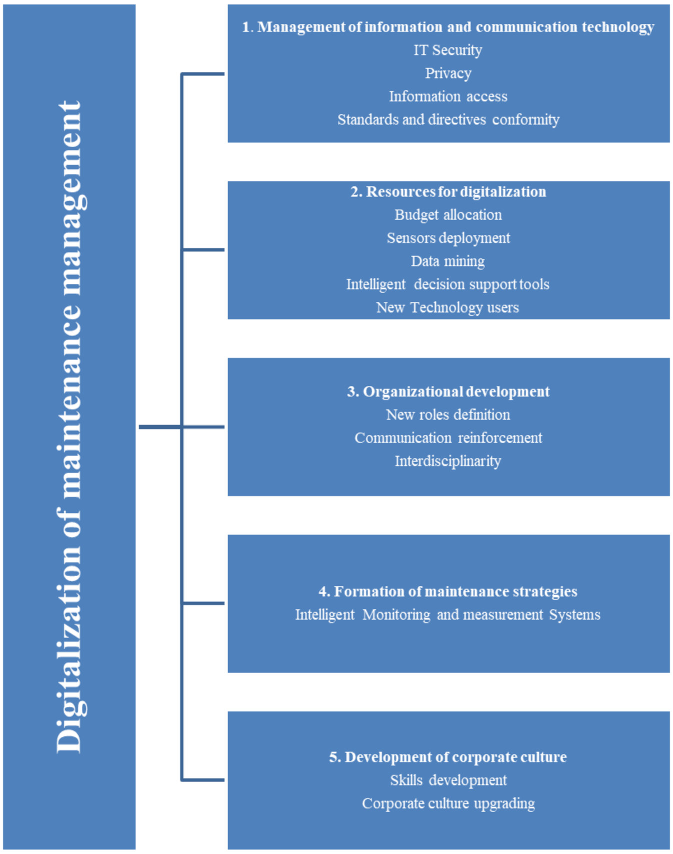

Figure 3.3. Critical factors for digitalization of maintenance management

3.2.3 Advantages and limitations of digitalization

Digital maintenance promotes the development, refining, and implementation of contemporary technologies, hence enhancing their efficacy. Integrating vast volumes of past and real-time data with analytical skills has created the foundation of digitized maintenance services. As a result of the positive technical effect, maintenance skills such as tracking, detecting, troubleshooting, predicting, and optimising are all contribute to the technological sustainability of these developments. By digitizing maintenance and employing the necessary tools and technology, only mandatory, adequate, and proper maintenance can be conducted through real-time predictions and diagnostics. This lowers waste and energy utilization, saves time, and eventually has a positive influence on the environment. Digital maintenance decreases failures dramatically by predicting, diagnosing, and eliminating breakdowns digitally and in advance. This promotes a culture of safety, enables employees to behave safely, and maintains a safe and healthy work environment. This ensures that digital maintenance has a healthy effect on the environment and society. Karki and Porras [126] outlined the numerous economic, environmental, social, technological, and administrative benefits of digitization in maintenance management.

Despite the potential benefits, the digitalization of maintenance brings several disadvantages. Not all industries possess the requisite level of abilities to digitalize their maintenance services, mostly owing to their inability to grasp effective implementation approaches and best practices. This is one of the fundamental obstacles. Indeed, it may be rather difficult to identify value-creation possibilities and shift the emphasis from technology to strategic thinking. The most crucial problem is the absence of the essential right mindset to transform the typical run-to-failure mentality into one that can perceive and integrate maintenance services into the system that permits digitalization. Rapid cost reduction is exceedingly challenging and may not initially appeal to all clients. When running expenses are restricted, operational issues and technological limits are unavoidable. Consequently, digital capabilities are limited, including the inability to automate maintenance procedures, the inability to utilize massive data sets, and poor remote monitoring. While it is evident that the digitalization of maintenance has an impact on sustainability in a number of ways, identifying the precise degree of this impact and how it appears is a big issue that needs considerable and in-depth research [126].

2.4 Decision-making models dealing with uncertainty

Everyday life is characterized by constant decision-making, and every decision brings with it the possibility of uncertainty and risk [136]. Various MCDM strategies and procedures have been proposed in the literature over the decade in order to choose the alternative that represent the optimal solution based on a number of distinct analysis criterion. Similar programs have been widely implemented in numerous domains, like manufacturing, industry, power management, economics, environment, sustainability, supply chain management, hospitality, production operations, materials, risk and safety, operations research, reliability, and quality [72, 73]. Multiple MCDM strategies have been developed and implemented in maintenance management. Among them, for instance, TOPSIS is a widely used traditional MCDM methodology with the following benefits: clarity, logically understood beliefs, increased operational efficiency, and the ability to express the efficiency of each alternative using a simple mathematical form. As a result, TOPSIS has been used in a variety of sectors [141-143]. Behzadian, et al. [144] evaluated and contrasted several MCDM strategies with TOPSIS and recognized it as an effective tool for categorizing maintenance decision-making. Singh, et al. [140] utilised TOPSIS to determine the most significant maintenance management obstacles in their investigation. Moreover, Alshraideh, et al. [145] in instances involving complicated decision-making, the proportions of the variables or factors are sometimes contradictory, which might present analytical challenges. Extending standard models with fuzzy logic has been effectively utilized in a variety of industrial applications to alleviate this issue [146]. In the context of the present study, an examination of the interdependencies between the identified essential elements may help to identify those that are most significant for the optimization of the entire maintenance management procedure. As demonstrated in recent studies (Carpitella and Izquierdo [147], Carpitella, et al. [148]), both pertaining to the subject of risk management, this objective may be efficiently attained by developing a decision-making model using Fuzzy Cognitive Maps (FCMs).

3.3.1. Critical factors of maintenance management

In this chapter, the research identified the critical elements required for the digitalization of maintenance management, among which are the management of information and communication technology, resources, organizational growth, smart technology development, formation of maintenance strategy, corporate culture, transition in working practices, regulatory compliance, data privacy, and security, etc., as detailed in Table 3.2. In this study, digital data collecting via intelligent technologies are also explored. In addition, the study identified possible benefits and constraints throughout the transformation to maintenance management digitalization. Consequently, it has been determined that the digitization of maintenance management is advantageous for performing timely maintenance and preventing breakdowns in advance. Moreover, the research explored certain decision-making methodologies frequently employed in the area of maintenance management in an effort to enable maintenance employees to make proper judgments and prioritize maintenance operations.

Table 3.2. Critical factors of maintenance management

No.	Critical factors of maintenance management	Ref
CF_1	*Management commitment and support*	[139]
CF_2	*Smart technology development*	[134]
CF_3	*Organizational growth*	[131, 134]
CF_4	*Development of skilled and empowered workforce*	[139]
CF_5	*Resources required for digitalization*	[131]
CF_6	*Maintenance strategy development*	[131, 139]
CF_7	*Corporate culture*	[131]
CF_8	*Change in working practices*	[134]
CF_9	*Effective and efficient maintenance system*	[139]
CF_10	*Regulatory compliance*	[134]
CF_11	*Safety and health awareness*	[139]
CF_12	*Data privacy and security*	[134]
CF_13	*Sustainable performance improvement*	[139]

3.3.2. FCM to identify relations of influence among factors

As indicated in the preceding section, the essential components of maintenance management formalized in Table 3.2 are further analysed to find the most significant factors based on influence connections. The relationships in Table 3.3 were gathered through many brainstorming activities with a specialist in the digitalization process and maintenance management. Judgments have been formulated as linguistic variables, that was gradually translated into fuzzy numbers in order to construct the FCM shown in Figure 3.4. The map was created using the software Mental Modeler. For more information, readers are referred to the previously cited studies (Carpitella and Izquierdo [147], [Carpitella, et al. [148]]), in which the FCM tool was proposed for use in different engineering fields, and whose findings led to the development of pertinent management processes.

Observable in Table 3.3 are the indirect effects (IE) and total effects (TE) connected with each critical factor based on the influence relationships between pairs of factors. Linguistic evaluations have been attributed as very low (VL), low (L), medium (M), high (H), very high (VH). The assessment process is very adaptable, as evaluations may be tailored to the specific business context of interest. Factors with higher TE values indicate conditions of significant influence; in other words, their proper management might have a favourable impact on all other elements considered.

Table 3.3. Connection Matrix

	CF_1	**CF_2**	**CF_3**	**CF_4**	**CF_5**	**CF_6**	**CF_7**	**CF_8**	**CF_9**	**CF_10**	**CF_11**	**CF_12**	**CF_13**	**IE**	**TE**
CF_1	0	VH	H	VH	M	H	H	VH	VH	M	VH	H	H	M	M
CF_2	0	0	VH	VH	H	H	L	VH	VH	0	H	M	H	L	L
CF_3	M	VH	0	H	H	H	H	H	H	0	H	M	H	M	M
CF_4	H	0	L	0	0	M	VL	H	H	0	VH	0	H	VL	M
CF_5	VH	H	L	M	0	VH	L	H	VH	0	0	M	H	L	L
CF_6	H	M	M	M	0	0	H	VH	VH	0	H	0	VH	M	M
CF_7	H	L	H	H	L	H	0	H	H	0	H	H	H	L	L
CF_8	0	M	H	H	0	L	M	0	M	0	VH	0	H	L	M
CF_9	0	L	H	H	H	VH	M	H	0	0	H	0	VH	L	M
CF_10	VL	VH	H	0	M	H	H	M	H	0	VH	VH	VH	VL	M
CF_11	VH	H	H	VH	0	H	H	VH	H	M	0	M	VH	M	H
CF_12	0	M	M	0	M	0	M	M	M	0	0	0	0	M	M
CF_13	VL	0	H	0	H	VH	H	H	VH	M	VH	0	0	VL	H
IE	VL	L	L	M	L	L	VL	M	M	M	H	M	H		

Figure 3.4 of 1FCM depicts 125 connections among 13 elements or around 9.6 connections per element. The critical elements CF_11 and CF_13 are connected with total effects indicating very influential linguistic assessments. This means that "safety and health awareness" and "sustainable performance improvement" are crucial factors to consider when planning and executing digital transformation initiatives for maintenance management operations. Other factors have associated moderate total impacts, but, according to the judgments of the questioned expert, critical factors CF_2, CF_5, and CF_7 are the least influential, having associated lower total effects. Smart technology development, digitalization, required resources, and company culture are unquestionably crucial challenges in the field of analysis. However, in terms of prioritising relevant features, the FCM tool proposes that we place greater emphasis on other components, which may have a favourable effect on less influential factors. This is evident, as the deployment and optimization of effective and efficient maintenance systems (CF_9) unquestionably contribute to the formulation of innovative smart developments (CF_2) for the whole maintenance function, and so on.

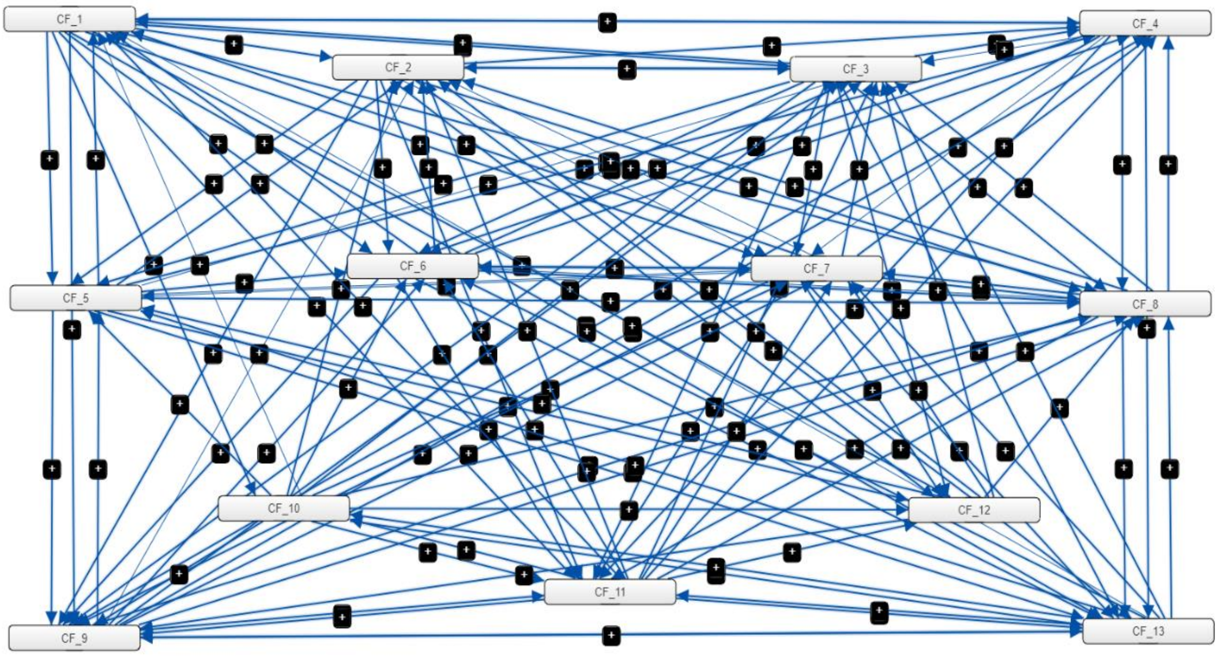

Figure 3.4. FCM displaying relationships among critical factors

3.3.3. Uncertainty in decision-making models

Everyday life is characterised by continuous decision-making, and all of these decisions has the possibility of risk and uncertainty [136], which might have a significant impact on maintenance practises. Various factors contribute to uncertainty, some of which are quite substantial while others may be insignificant, influencing the system's performance in a positive, neutral, or negative manner [149]. Overall, two distinct types of uncertainty may be differentiated: qualitative, which relies on heuristic estimations generated from expert judgements, supplier needs, and equipment accuracy, and quantitative, which relies on observable statistical data. The first group, on the one hand, has been studied extensively and can be easily quantified using the data set's standard deviation. Conversely, the second category is notoriously difficult to classify. In addition, there are epistemic and aleatory types of uncertainty. The first is associated with the precision of the models and data used, which is influenced by the available data and may be improved on or even minimised. The other category refers to statistical variables that are in a constant state of change and hence cannot be reduced [149]. The lack of understanding of engineering phenomena is the leading cause of uncertainty among the many factors that contribute to it. Actually, decision-making methods are influenced by many types of ambiguity, each of which has its own origins. Uncertainty expresses itself on several levels in diagnostic difficulties, especially with regards to information and/or system flaws. Fuzziness and randomness are the two fundamental elements of uncertainty that pertain to the information utilised to assist decision-making challenges. Depending on the system's characteristics and the decision-priorities, maker's the optimal decision-making techniques in uncertain scenarios for achieving the maintenance aim differ [150]. Currently, decisions on industrial maintenance are generally dependent on two types of data: recorded information and subjective specialist's opinions. The gathered data comprises factual information which are subjected to a quantitatively measurable level of uncertainty represented by the standard deviation of the data under consideration. Subjective specialist's comments attribute qualitative ambiguity to persons based on the attributes that classify them as experts and the basis for their perspective in order to demonstrate its validity. Rarely are the accuracy of the utilised system and the skill of the maintenance acknowledged as contributing to total uncertainty in data gathering procedures.

A combination of empirical facts and subjective perspectives should be incorporated to generate trustworthy judgements that lead to efficient maintenance outcomes. Certain situations require more abilities, while others require more data. The question is having a complete view of these uncertainties might aid in enhancing decision-making and mitigating both through life costs and unexpected failures [149].

It is essential for maintenance managers to review and adjust maintenance plans to the numerous options accessible in systems or facilities. Particularly when many contradictory criteria and methodologies are considered, it is challenging to implement effective maintenance plans. Using many criteria for evaluation and taking into account actual maintenance circumstances are key to minimising evaluation uncertainty are the fundamental challenges [151, 152]. In this study, study assumed a MCDM paradigm and, specifically, implement a method based on FTOPSIS to rank related alternatives connected to industry 4.0 in characterising uncertainty in maintenance decision-making. The presented research might help organizations in making decisions that optimise their overall company outcomes.

3.3.4. Treating uncertainty with fuzzy-based MCDM techniques

Numerous fields, including engineering, supply chain management, economics, social sciences, and medicine, make substantial use of MCDM methodologies. Despite its diversity, the MCDM perspectives has numerous objectives and criteria that can contradict. In recent decades, MCDM methods have gained prominence in fields such as operations research [153], and their adoption is generally regarded as a reliable scientific strategy for making reliable and beneficial decisions in complex maintenance aspects [154] such as those associated with industry 4.0. Diverse specialists in a variety of academic fields have extensively employed MCDM approaches [146]. Some of these strategies are outlined by Aruldoss, et al. [155], as shown in Figure 3.5, and can be utilised in either their conventional or fuzzy forms.

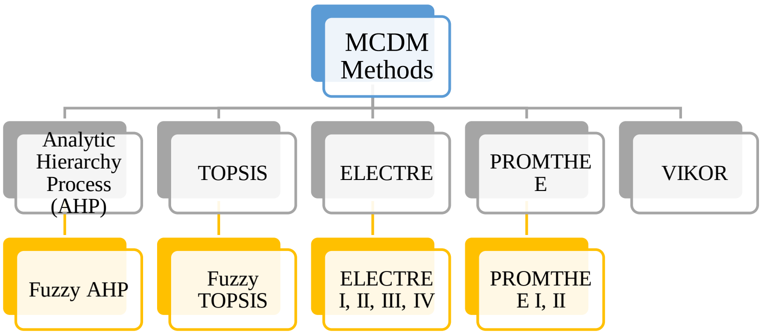

Figure 3.5. MCDM techniques and versions [155]

In the first scenario, decision-making components (e.g., criteria, sub-criteria, alternatives) are assessed, scored, and/or weighted based on numerical evaluations. Alternately, in the second situation, linguistic variables are transformed into fuzzy integers to better control uncertainty and the lack of accuracy and clarity impacting input assessments [156]. Study has utilized the TOPSIS and its fuzzy extension FTOPSIS among the MCDM approaches available in the literature. This decision is supported by the reality that these methodologies permit exceptional flexibility in ranking aspects, which looks to be particularly effective in maintenance environments that have been profoundly influenced by digital transformation.

With great majority of actual-world situations, because of the uncertainty of human preference behaviour, decision-makers are frequently unable to provide adequately meaningful numerical assessments for distinguishing between the principal aspects of a complicated problem. Multiple MCDM strategies have been proposed and implemented in past decade, and amongst, TOPSIS is found to be the most prevalent strategies presented in the literature to resolve complex decision-making issues [141, 146, 157-159], with the key objective of getting a systematic ranking of choices [158, 160] based on assessment criteria, appropriately weighted. TOPSIS was established on the notion that the selected alternative(s) should have the shortest distance to a Positive Ideal Solution (PIS) and the longest distance to a Negative Ideal Solution (NIS) [141, 156, 158, 159, 161]. The output is then determined by calculating the positive and negative distances for each alternative [162]. To this end, an accommodating aggregation approach may give weights to each criterion to perform a preliminary evaluation of a group of alternatives [146]. Nevertheless, utilising real precise numbers to evaluate the options under consideration may constrain the ability to handle ambiguity [157]. In any event, TOPSIS features a straightforward and adaptable calculating method that may simultaneously take into account many criteria with different units [158]. TOPSIS is a well-known MCDM technique utilised by several academics in a vast array of fields [144, 162].] owing to its high application versatility. In addition, it has been frequently incorporated with a variety of other MCDM approaches as an effective means of prioritising maintenance decision-making (see Singh, et al. [140]; Ighravwe and Oke [163], among others). TOPSIS is thought to be significantly more adjustable, understandable, and uncomplicated than the majority of other MCDM techniques [164]. TOPSIS' strengths include clarity, intuitively understood concepts, enhanced productivity level, and the ability to analyse the effectiveness of every option in a easy numerical form, which has caused in the widespread admittance and comprehension of this method across a variety of organizations [141]. The primary advantage of using TOPSIS is that it needs limited data from experts, like criterion score and linguistic inputs of options [160]. It welcomes suggestions in the shape of any conceivable collection of criteria and attributes. As a result of the concept of dissociation from perfect patterns, it truly has physical importance. It is especially useful in situations in which maintenance managers, based on their specialised expertise, think that technical issues may be ranked from most important to least important factors. The aforementioned characteristics of TOPSIS make it a potential option for dealing with prioritising problems [163], especially when taking into consideration the ability to concurrently examine optimum and crucial solutions using a straightforward mathematical programming technique [165]. In its conventional version, TOPSIS has significant drawbacks despite its extensive usage, as it fails to provide exact information when situations are highly vague and poorly articulated [162]. In addition, the subjective nature of human cognition is typically not captured by the use of objective values to evaluate alternatives. This may cause the approach to fail to accurately reflect the priorities of decision makers in real-world circumstances [164]. In multi-criteria scenarios, changing proportions are typically inconsistent, creating significant evaluation issues. In addition, TOPSIS's shortcomings may result in the following deficiencies: 1) its use may yield inaccurate results due to its simplicity; 2) its deterministic approach may not assist completely when addressing uncertainty [154].

Consequently, traditional TOPSIS can only partly support ambiguous or unclear expert input. Numerous research papers have incorporated fuzzy logic concepts into MCDM methodologies to overcome all of the aforementioned flaws. In this regard, Chen's [166] FTOPSIS technique is offered as a mix of fuzzy set theory and classical TOPSIS, wherein fuzzy numbers are utilised to generate preference ratings by specialists [146, 157, 160, 164].

In complex and challenging maintenance management decision-making situations in industry 4.0, understanding the numerous variables and elements may be a difficult process. Extending classical approach to fuzzy logic, as we have already discussed, can considerably aid in mitigating this issue, as has been effectively proved in several industrial applications [146]. Taking into consideration human ambiguity and subjectivity, Zadeh invented the notion of fuzzy sets in 1965 to stimulate spontaneous thinking by including human ambiguity. As the basic objective of fuzzy logic is to quantify the imprecision of human thought [141, 162], linguistic variables can be expressed by fuzzy integers with an associated degree of membership $\mu(x)$, ranging from 0 to 1. Many scholars have been examining the feasibility of applying fuzzy sets theory to address complicated uncertain decision-making challenges. In addition, Gau and Buehrer proposed the idea of ambiguous sets in 1993, emphasising that a single value cannot attest to a set's actuality [141]. FTOPSIS is very effective in addressing uncertainty and ambiguity in collected data resulting from human perception and judgement. Given the uncertainty and absence of understanding in MCDM, linguistic concepts utilised in FTOPSIS could be used to express erroneous data in order to cope with ambiguous information more effectively [146, 157]. In fact, the usage of fuzzy numbers for evaluating criteria accelerates the entire analysis process by making it easier for decision-makers to communicate their personal ideas regarding qualitative criteria. Consequently, FTOPSIS is a straightforward, practical strategy for anticipating and compensating prospective alternatives based on hard cut-offs [159, 161]. Nevertheless, it is essential to note that the majority of the data collected and utilised in FTOPSIS is developed on human perception, which makes assessment of values vital and reliant on the amount of data, which must be "reliable, dependable, consistent, definite, genuine, true and credible." Despite the drawbacks, FTOPSIS is a suitable approach for analysing values and ranking key decision-making factors based on linguistic variables and fuzzy numbers [162]. Numerous research on FTOPSIS and its integrations have been published. Using Design Structure Matrix (DSM) and FTOPSIS techniques, Hwang, et al. [167] analysed maintenance requirements for train electrical facility systems based on the subjective assessment information of decision-makers. Alshraideh, et al. [145] employed an FTOPSIS model to assess the quality of offers in order to determine the best suitable maintenance contractor under uncertain situations. Momeni, et al. [168]] suggested the FTOPSIS as a tool for choosing maintenance schedules by transforming the decision makers' uncertain and imprecise judgement into fuzzy numbers. Selim, et al. [169] developed a maintenance scheduling framework that integrates the FTOPSIS and Failure Mode and Effect Analysis (FMEA) techniques for evaluating the maitnenance urgencies of machines in reducing and sustain maintenance costs. Chen, et al. [170] utilised the FTOPSIS approach to rank and prioritise pathways to smart waste management solution implementation in Ghana, taking into consideration the subjectivity of decision-maker priorities. FTOPSIS have been designed to address any kind of issue; examples include evaluating and selecting solutions for the long-time adoption of renewable energy technology in Pakistan Solangi, et al. [162]; considering several options based on subjective criteria and weighing each component for robot selection Chu and Lin [171]; assessing vendors in the oil and gas sector based on Health Safety and Environment (HSE) criteria to select maintenance and operations contracts Haddad, et al. [164]; and so on. According to Kutlu and Ekmekçioğlu [158], FTOPSIS has also been applied to the following issues: Method and site selection for the disposal of municipal solid waste, selection of the most effective energy technology alternatives, modelling the processes involved in the acceptance of new consumer products, and selection of plant locations and suppliers are all examples of important decisions.

3.4 Proposed methodological procedure

3.4.1 Methodological overview

As indicated in previous studies [Carpitella, et al. [75], Brentan, et al. [142]], the most prevalent form of fuzzy numbers are Triangular Fuzzy Numbers (TFNs), herein $\tilde{n}$,which may be represented as follows [172]:

$$\tilde{n} = (a, b, c); \tag{9}$$

where a ≤ b ≤ c. It is simple to execute standard algebraic operations with one or more fuzzy integers. For instance, the following equations can be written:

$$\tilde{n}_1 \oplus \tilde{n}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2); \tag{10}$$

$$\tilde{n}_1 \odot \tilde{n}_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2); \tag{11}$$

$${\tilde{n}_1}^{-1} = (\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}); \tag{12}$$

Next, we will discuss the procedures required to execute the FTOPSIS methodology based on these preliminaries. [173-175].

• Defining the fuzzy decision matrix $\tilde{X}$ collecting the whole set of input data:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix}. \tag{13}$$

The generic TFN $\tilde{x}_{ij}$ of matrix $\tilde{X}$ corresponds to the rating of alternative *i* under criterion *j*:

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}); \tag{14}$$

• We generate matrix $\widetilde{U}$ by applying various weighting and normalisation criteria to matrix $\tilde{X}$, and its elements are computed as follows:

$$\tilde{u}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right) \times w_{ij,}\ j \in I'; \tag{15}$$

$$\tilde{u}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right) \times w_{ij,}\ j \in I''; \tag{16}$$

I' is the subset of criteria that has to be maximized, I'' is the subset of criteria that needs to be minimized, $w_{j,}$ is the weight of criterion j and c_j^* and a_j^- are determined by using the formulas below:

$$c_j^* = \max_i c_{ij} \quad if \quad j \in I'; \tag{17}$$

$$a_j^- = \min_i a_{ij} \quad if \quad j \in I''; \tag{18}$$

• Computing distances between each alternative and the fuzzy ideal solutions A^* and A^-:

$$A^* = (\tilde{u}_1^*, \tilde{u}_2^* \; . \; . \; . \; , \tilde{u}_n^*); \tag{19}$$

$$A^- = (\tilde{u}_1^-, \tilde{u}_2^- \; . \; . \; . \; , \tilde{u}_n^-); \tag{20}$$

Where $\tilde{u}_j^* = (1, 1, 1)$ and $\tilde{u}_j^- = (0, 0, 0)$, j = 1. . . n. The vertex approach allows for the calculation of distances between each feasible option and these ideal spots Chen [166], for which the distance $d(\tilde{m}\,, \tilde{n})$ between two TFNs $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ corresponds to the crisp value:

$$d(\tilde{m}\,, \tilde{n}) = \sqrt{\frac{1}{3}\,[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{21}$$

Then, aggregating based on the total set of criteria, the distances between each possibility *i* from A^* and A^- are, respectively:

$$d_i^* = \sum_{j=1}^{n} d(\tilde{u}_{ij}\,, \tilde{u}_j^*) \quad i = 1, \ldots, n; \tag{22}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{u}_{ij}\,, \tilde{u}_j^-) \;\; i = 1, \ldots, n; \tag{23}$$

• Calculating the closeness coefficient CC_i:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{24}$$

To determine the final rank of alternatives, it is important to order the closeness coefficient values for each option in descending order.

3.4.2 Application and discussion

The present case study utilised the FTOPSIS method to analyse a set of thirteen maintenance criteria essential to industry 4.0, as identified and published by [Ahmed, et al. [176]]. The researched elements propose to investigate the role of digitization in maintenance, and their resultant evaluation reveals the concerns that should be considered most when formulating industrial strategies in the face of evaluation uncertainty.

Alternatives have been examined based on three primary criteria: safety & security (C1), process quality (C2), and cost efficiency (C3), all of which must be optimised and are equally weighted in the current application. The linguistic assessments in Table 3.4 pertain to a real organisation that is involved in the waste management activities; has been assigned, in partnership with the human resources responsible for the maintenance function, and is accountable for the safety and security system.

The following is a list of the utilised linguistic variables and the accompanying TFNs: VL (1,1,3), very low impact; L (1,3,5), low impact; M (3,5,7), medium impact; H (5,7,9), high impact; VH (7,9,9), very high impact. The findings of the FTOPSIS process and the final ranking of maintenance factors are summarised in Table 3.4.

Table 3.4. Evaluation of maintenance factors relevant to industry 4.0

ID	**Maintenance Factors**	C_1	C_2	C_3	d_i^*	d_i^-	CC_i	**Rank. pos.**
MF_1	Management commitment and support	M	M	M	0.5844	2.4512	0.1925	9^{th}
MF_2	Smart technology development	M	H	M	0.6558	2.3773	0.2162	7^{th}
MF_3	Organizational growth	M	M	H	0.6558	2.3773	0.2162	7^{th}
MF_4	Development of skilled workforce	VH	VH	H	0.8874	2.1277	0.2943	1^{st}
MF_5	Resources required for digitalization	VH	VH	M	0.8160	2.2015	0.2704	3^{rd}
MF_6	Maintenance strategy development	H	H	VH	0.8431	2.1787	0.2790	2^{nd}
MF_7	Corporate culture	M	M	L	0.5161	2.5251	0.1697	10^{th}
MF_8	Change in working practices	M	M	M	0.5161	2.5251	0.1697	10^{th}
MF_9	Effective maintenance system	H	H	H	0.7987	2.2296	0.2637	4^{th}
MF_{10}	Regulatory compliance	M	H	L	0.5875	2.4512	0.1933	8^{th}
MF_{11}	Safety and health awareness	VH	H	M	0.7716	2.2525	0.2552	5^{th}
MF_{12}	Data privacy and security	L	M	M	0.5161	2.5251	0.1697	10^{th}
MF_{13}	Sustainable performance improvement	M	H	H	0.7273	2.3035	0.2400	6^{th}

Considering Table 3.4, factor MF4, which is "development of skilled workforce," has, in the opinion of the engaged experts, the greatest impact on optimising all of the assessed criteria. MF6 ("maintenance strategy development") and MF5 ("resources required for digitalization") are also viewed as important factors. In contrast, factors MF7, MF8, and MF12, which are, respectively, "corporate culture," "change in working practice," and "data privacy and security," are ranked at the bottom of the list due to their weaker influence relative to the other maintenance factors.

Some of the factors, such as MF2 and MF3, occupy the same place in the ranking due to the fact that factors have been assigned the similar weightage. If weightage fluctuated, so will position in the rankings. In the case of MF2 and MF3, for instance, if a high weightage was assigned to the quality criteria and a low weightage to the cost-effectiveness criterion, MF2 would hold a higher place in the final ranking than MF3, which had a lower assessment under C2.

CONCLUSIONS AND FUTURE DEVELOPMENTS

Conclusions

As we are living in the digital era, technology is continually evolving, with enormous advancements in automation enabling more efficient and cost-effective maintenance management. The contemporary digital era, empowered by industry 4.0 technologies like ML, big data, and AR, is often characterized by a plethora of data access to help in decision-making. Systems may be simply and instantly integrated through architecture of compatible sensing devices, sometimes known as the IoT. The major issue has moved from gathering data to creating informed judgments based on that data. The entire maintenance management is based on these data sets, also to use data and predictive analytics to support decision-making. As a result, more opportunities for data-driven methodologies like as predictive maintenance, AI, and ML have evolved, having the potential for substantial productivity improvements.

To compete in today's global market, organizations must be nimble, flexible, and resilient, as well as have dynamic talents. As a result of the growth of advanced digitalized technology, industries are now able to undergo significant transformations. As smart devices have become more prevalent, the demand for maintenance systems with a high level of intelligence has arisen. Intelligent systems are converging and advancing in tandem with industries, resulting in significant progress in operation management. As has been previously stated, the introduction of various information technology innovations has caused a significant upheaval in industrial practices. The traditionally human-managed preventive maintenance strategy is being replaced with predictive maintenance. Massive volumes of data from industrial activities are collected, analysed, and triggered in real-time to allow effective decision-making. In predictive maintenance, decision-making refers to the generation of hands-on endorsements for maintenance functions and initiatives that remove or control the effects of anticipated breakdowns or failures.

In complex systems' condition monitoring and inspection, on-board sensors, lifecycle data, process data, systems, and historical failure data are all used to predict failures. PrdM rejects routine and preventive maintenance activities instead of a more proactive maintenance strategy. It is a methodology in which one function monitors a system's performance, productivity, and other important factors to determine the real time to do maintenance. Instead of depending solely on statistical information, this analysis takes into account the exclusive features of machines and the particular deterioration behaviour of the critical components. When PrdM is utilized properly, the maintenance expenditure is greatly reduced; hence, it may be beneficial to emphasize the dependency between major failures.

Previous research discovered that the system's average dependability, availability, and operational expenditure for maintenance are lower than those of its rivals when PrdM is used intelligently. Switching from reactive maintenance to proactive maintenance is a wonderful way to significantly improve system maintenance planning, particularly for more complicated systems that have a significant monetary value. PrdM methods do, however, face a number of substantial challenges in terms of their application, as they necessitate the use of contemporary tracking technologies, the development of robust data gathering systems, and the execution of a variety of intricate procedures. As was extensively covered in the preceding chapter, various issues with the usage of PrdM for complex assets are inhibiting its efficacy in some circumstances. If organizations were expected to monitor and assess all probable failure modes for the complex system under consideration, they would experience substantial economic and technological pressure. In addition, it is impossible to classify each potential failure mode associated with a single asset, and a single failure dataset is always inadequate, resulting in poor prediction accuracy. Therefore, accurate and timely information regarding the maintenance schedule is necessary. To achieve this, it is vital to increase the flexibility of PrdM decision-making in contexts of complex industrial environments.

System models have gained popularity since they can successfully observe complicated systems in real time and automate prognostics at the same time. In addition, they provide early warning signals of future failures. As with any discipline, multiple PrdM approaches exist, each with its advantages and disadvantages. PrdM requires online access to information about the system's conditions, which is now possible due to the development of suitable detection systems. Using deterministic reliability models, several studies have been undertaken to estimate the remaining useable lifespan of a system, whether it be a single component or the complete system.

Considerable research on PrdM for complex systems are available in the literature and have been reviewed earlier in section 1.4 of chapter 1. This study also examined the FMECA and several MCDM methodologies. Specifically, the ELECTRE TRI and DEMATEL approaches, as well as their strengths and drawbacks, are analysed, and potential applications in industries for the enhancement of complex systems for decision-making are evaluated. Based on an analysis of the strengths and disadvantages of each strategy, as well as their typical applications, this work presented the implementation of integration of these three approaches to optimise the maintenance management of failures in systems subject to predictive maintenance. Employing FMECA, all potential failure modes in systems subjected to PrdM are recognized, and the severity of failure modes is assessed using risk metrics of relevance. ELECTRE TRI is applied to recognize and categorize high-risk failures, as well as to expose failures associated with higher risk levels and scenarios. DEMATEL is utilized to detect particular failures that are more reliant on other failures within the same risk category than other failures within the same class. The suggested integrated approach may assist organisations in making good decisions and conducting effective risk management strategies. The end goal for each risk class is to determine the failure modes that have the significant impact on systems and the frequency of further failures. Nonetheless, it is equally essential to manage the other dependent failure possibilities. As a result of this strategy, maintenance and risk assessment practices, as well as system functioning, may be enhanced.

Industry 4.0 has resulted in extensive usage of smart devices for condition monitoring, enabling quicker decisions. So, the significance of digitalization in maintenance management in the industry is emphasized in this study and possible benefits of digitalization such as monitoring, diagnosing, forecasting, troubleshooting, and optimizing maintenance capacities. Digitalization facilitates remote maintenance tasks, resulting in lower maintenance costs and time savings for all stakeholders. The utilization of technology and data aids in promptly detecting and preventing failures. Maintenance services are now based on the assessment of massive amount of previous and current data, as well as the use of sophisticated analytics tools. Novel and effective technologies have emerged to facilitate maintenance activities such as monitoring, diagnosing, troubleshooting, forecasting, and optimizing. This is the outcome of successful technical impact, and in exchange, these improvements promote secure and dependable data transfer, efficient and quick maintenance operations, lower operating costs, and so on. Maintaining current equipment procedures and data provides for more accurate diagnosis, troubleshooting, prediction, and optimization

This research also studied ways to cope with uncertainty in decision-making methods, with a focus on maintenance management in industry 4.0. After conducting a thorough analysis of the MCDM approaches utilised in the issue in question, we highlight the significant aid provided by the inclusion of tools such as fuzzy set theory for addressing complex real-world problems with uncertain human views. We analysed the TOPSIS and FTOPSIS techniques based on their unique characteristics, significant methodological flexibility, formalizing both approaches' limitations and advantages. As illustrated by various applications, FTOPSIS is particularly beneficial for dealing with uncertainty. Following a description of the methodology, this study performed an actual case study with the goal of offering useful insights for maintenance managers in the complicated world of digitalization.

Overall, by decreasing unexpected downtime and keeping equipment in excellent condition, greater availability and performance capabilities may be achieved. This boosts client’s trust in the company's ability to compete internationally. Only the required, adequate, and correct forms of maintenance may be conducted with the use of the proper technologies and instruments, allowing for real-time prediction and diagnostics. Consequently, waste may be decreased, energy consumption can be lowered, and time can be saved. Digitalization in maintenance contributes significantly to failure reduction by forecasting, diagnosing, and preventing breakdowns as early as possible. Establishing a safety culture and encouraging safe behavior results in a safe and healthy workplace for everyone. Risks are minimized when confidence in an improved maintenance capability is established. Moreover, advanced equipment and technologies guarantee information and communication security, which is currently recognized as a fundamental social need. This ensures that digital maintenance has a positive environmental and social impact. With digitalization, maintenance activities become more reliable, safe, and effective, enabling for optimal equipment performance. It helps to reduce slowdowns and enhance availability, as well as reduce overall expenses and increase profitability, which strengthens the company's decision-making and strategic planning. All of this eventually adds to positive environmental benefits and the development of profitable, sustainable enterprises.

Future developments

Future research directions may involve the incorporation of other MCDM approaches providing a more exact computation of criterion weights as well as valuable mathematical tools, such as probability theory. Further, expansions of the current study include expanding the application to the entire system excluding the core components and merging the suggested method with an additional MCDM methodology for calculating the weights of criteria. This will be done to account for the likelihood that the major parts of analysis may have varying mutual effects on the final outcome. The element of interdependence between criteria and alternatives may be the subject of additional applications by reconsidering the possibility of the absence of transitive preference connections. Analysing the potential presence of dependence relationships between the primary aspects of analysis will be a crucial signal for enhancing global predictive maintenance management.

Moreover, future areas of research may also involve the usage of Bayesian Networks that may be used to describe and portray conditional dependency and, consequently, causation by edges in a directed graph. This approach may incorporate human factors as primary aspects of analysis, taking into account the knowledge of human resources in conducting their jobs as well as the risk of human errors.

A future area of study may refer to the development of real-case studies on the use of Collaborative Robots (Cobots) to improve industrial maintenance techniques. Collaborative robots have a great influence on how systems and processes are streamlined, especially in the manufacturing industry. Interacting with humans to improve productivity and efficiency of operations, these highly-sophisticated machines need to be monitored to prevent safety issues. This topic is gaining more and more importance in modern industries, but many realities struggle to integrate such systems within their contexts at a practical level. Some of these realities may be deeply analysed and a decision-making model may be implemented with the goal of supporting the introduction of Cobots towards the optimization of some of the core manufacturing processes with a specific focus on maintenance management. This first stage would take into account such criteria as economic aspects, difficulty of practical implementation, as well as the achievable level of performance. A second stage would refer to the capability of the decision-support system to organize monitoring activities and continuously improve the safe relation between human workers and Cobots.

APPENDIXES

Appendix A

Table A1. ELECTRE TRI results – pessimistic procedure

	Scenario 1			*Scenario 2*			*Scenario 3*		
Failure ID	**λ=0.70**	**λ=0.80**	**λ=0.90**	**λ=0.70**	**λ=0.80**	**λ=0.90**	**λ=0.70**	**λ=0.80**	**λ=0.90**
PI_1	A	A	A	A	A	A	A	A	A
PI_2	B	B	B	B	B	B	B	B	B
RSS_1	A	A	A	A	A	A	A	A	A
RSS_2	B	B	B	B	B	B	B	B	B
RSS_3	B	B	B	B	B	B	B	B	B
RSS_4	B	B	B	B	B	B	B	B	B
RSS_5	B	B	B	B	B	B	B	B	B
RSS_6	B	B	B	B	B	B	B	B	B
RSS_7	B	B	B	B	B	B	B	B	B
RSS_8	B	B	B	B	B	B	B	B	B
RSS_9	A	A	A	A	A	A	A	A	A
RSS_10	B	B	B	B	B	B	B	B	B
RSS_11	B	B	B	B	B	B	B	B	B
RSS_12	B	B	B	B	B	B	B	B	B
RSS_13	B	B	B	B	B	B	B	B	B
RSS_14	B	B	B	B	B	B	B	B	B
RSS_15	B	B	B	B	B	B	B	B	B
RSS_16	A	A	A	A	A	A	A	A	A
RSS_17	B	B	B	B	B	B	B	B	B
LSS_1	A	A	A	A	A	A	A	A	A
LSS_2	B	B	B	B	B	B	B	B	B
LSS_3	B	B	B	B	B	B	B	B	B
LSS_4	B	B	B	B	B	B	B	B	B
LSS_5	B	B	B	B	B	B	B	B	B
LSS_6	B	B	B	B	B	B	B	B	B
LSS_7	B	B	B	B	B	B	B	B	B
LSS_8	B	B	B	B	B	B	B	B	B
LSS_9	A	A	A	A	A	A	A	A	A
LSS_10	B	B	B	B	B	B	B	B	B
LSS_11	B	B	B	B	B	B	B	B	B
LSS_12	B	B	B	B	B	B	B	B	B
LSS_13	B	B	B	B	B	B	B	B	B
LSS_14	B	B	B	B	B	B	B	B	B
LSS_15	B	B	B	B	B	B	B	B	B
LSS_16	A	A	A	A	A	A	A	A	A
LSS_17	B	B	B	B	B	B	B	B	B

Table A2. ELECTRE TRI results – optimistic procedure

	Scenario 1			*Scenario 2*			*Scenario 3*		
Failure ID	**λ=0.70**	**λ=0.80**	**λ=0.90**	**λ=0.70**	**λ=0.80**	**λ=0.90**	**λ=0.70**	**λ=0.80**	**λ=0.90**
PI_1	A	A	A	A	A	A	A	A	A
PI_2	B	B	B	B	B	B	B	B	B
RSS_1	A	A	A	A	A	A	A	A	A
RSS_2	B	B	B	B	B	B	B	B	B
RSS_3	B	B	B	B	B	B	B	B	B
RSS_4	B	B	B	B	B	B	B	B	B
RSS_5	A	A	A	A	A	A	A	A	A
RSS_6	B	B	B	B	B	B	B	B	B
RSS_7	B	B	B	B	B	B	B	B	B
RSS_8	A	A	A	A	A	A	A	A	A
RSS_9	A	A	A	A	A	A	A	A	A
RSS_10	A	A	A	A	A	A	A	A	A
RSS_11	B	B	B	B	B	B	B	B	B
RSS_12	A	A	A	A	A	A	A	A	A
RSS_13	B	B	B	B	B	B	B	B	B
RSS_14	B	B	B	B	B	B	B	B	B
RSS_15	A	A	A	A	A	A	A	A	A
RSS_16	A	A	A	A	A	A	A	A	A
RSS_17	A	A	A	A	A	A	A	A	A
LSS_1	A	A	A	A	A	A	A	A	A
LSS_2	B	B	B	B	B	B	B	B	B
LSS_3	B	B	B	B	B	B	B	B	B
LSS_4	B	B	B	B	B	B	B	B	B
LSS_5	A	A	A	A	A	A	A	A	A
LSS_6	B	B	B	B	B	B	B	B	B
LSS_7	B	B	B	B	B	B	B	B	B
LSS_8	A	A	A	A	A	A	A	A	A
LSS_9	A	A	A	A	A	A	A	A	A
LSS_10	A	A	A	A	A	A	A	A	A
LSS_11	B	B	B	B	B	B	B	B	B
LSS_12	A	A	A	A	A	A	A	A	A
LSS_13	B	B	B	B	B	B	B	B	B
LSS_14	B	B	B	B	B	B	B	B	B
LSS_15	A	A	A	A	A	A	A	A	A
LSS_16	A	A	A	A	A	A	A	A	A
LSS_17	A	A	A	A	A	A	A	A	A

Appendix B

Table B1. DEMATEL input matrix for high risk class A

X	PI_1	RSS_1	RSS_5	RSS_8	RSS_9	RSS_10	RSS_12	RSS_15	RSS_16	RSS_17	LSS_1	LSS_5	LSS_8	LSS_9	LSS_10	LSS_12	LSS_15	LSS_16	LSS_17
PI_1	0	3	3	1	1	0	3	1	1	0	3	3	1	1	0	3	1	1	0
RSS_1	1	0	3	3	3	3	3	2	2	2	1	2	2	2	2	2	1	1	1
RSS_5	3	2	0	2	2	2	1	1	1	1	2	1	1	1	1	0	0	0	0
RSS_8	2	1	3	0	3	3	1	1	1	1	1	2	1	2	2	0	0	0	0
RSS_9	2	1	3	2	0	3	2	1	1	1	1	2	1	1	2	1	0	0	0
RSS_10	1	1	3	2	3	0	2	1	1	1	0	2	1	2	1	1	0	0	0
RSS_12	3	1	1	2	1	1	0	0	3	3	2	0	1	0	0	1	0	2	2
RSS_15	2	1	2	1	1	1	3	0	3	2	1	2	0	0	0	2	1	2	1
RSS_16	2	1	2	1	1	1	3	2	0	3	1	2	0	0	0	2	1	1	2
RSS_17	1	1	2	1	1	1	1	2	3	0	0	2	0	0	0	0	1	2	1
LSS_1	1	1	2	2	2	2	2	1	1	1	0	3	3	3	3	3	2	2	2
LSS_5	3	2	1	1	1	1	0	0	0	0	2	0	2	2	2	1	1	1	1
LSS_8	2	1	2	1	2	2	0	0	0	0	1	3	0	3	3	1	1	1	1
LSS_9	2	1	2	1	1	2	1	0	0	0	1	3	2	0	3	2	1	1	1
LSS_10	1	0	2	1	2	1	1	0	0	0	1	3	2	3	0	2	1	1	1
LSS_12	3	2	0	1	0	0	1	0	2	2	1	1	2	1	1	0	0	3	3
LSS_15	2	1	2	0	0	0	2	1	2	1	1	2	1	1	1	3	0	3	2
LSS_16	2	1	2	0	0	0	2	1	1	2	1	2	1	1	1	3	2	0	3
LSS_17	1	0	2	0	0	0	0	1	2	1	1	2	1	1	1	1	2	3	0

Table B2. DEMATEL input matrix for medium risk class B

X	PI_2	RSS_2	RSS_3	RSS_4	RSS_6	RSS_7	RSS_11	RSS_13	RSS_14	LSS_2	LSS_3	LSS_4	LSS_6	LSS_7	LSS_11	LSS_13	LSS_14
PI_2	0	4	4	3	1	3	3	1	3	4	4	3	1	3	3	1	3
RSS_2	2	0	2	2	1	3	2	0	0	0	1	1	0	2	1	0	0
RSS_3	2	3	0	3	2	3	3	3	3	2	0	2	1	2	2	2	2
RSS_4	2	2	1	0	2	3	2	1	1	1	0	0	1	2	1	0	0
RSS_6	1	2	2	1	0	3	3	1	1	1	1	0	0	2	2	0	0
RSS_7	2	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0
RSS_11	2	2	3	2	1	1	0	3	3	1	2	1	0	0	0	2	2
RSS_13	1	0	2	1	1	1	1	0	3	0	1	0	0	0	0	0	2
RSS_14	2	0	2	1	1	1	1	2	0	0	1	0	0	0	0	1	0
LSS_2	2	0	1	1	0	2	1	0	0	0	2	2	1	3	2	0	0
LSS_3	2	2	0	2	1	2	2	2	2	3	0	3	2	3	3	3	3
LSS_4	2	1	0	0	1	2	1	0	0	2	1	0	2	3	2	1	1
LSS_6	1	1	1	0	0	2	2	0	0	2	2	1	0	3	3	1	1
LSS_7	2	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1
LSS_11	2	1	2	1	0	0	0	2	2	2	3	2	1	1	0	3	3
LSS_13	1	0	1	0	0	0	0	0	2	0	2	1	1	1	1	0	3
LSS_14	2	0	1	0	0	0	0	1	0	0	2	1	1	1	1	2	0

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