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ANDRÉ LUIZ ALCÂNTARA CASTILHO VENÂNCIO

# FEASIBILITY, CLASSIFICATION AND IMPLEMENTATION FRAMEWORK FOR MAINTENANCE LEGACY SYSTEMS IN INDUSTRY 4.0 SCENARIOS

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Advisor: Prof. Dr. Eduardo de Freitas Rocha Loures
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# TERMO DE APROVAÇÃO

## André Luiz Alcântara Castilho Venâncio

### FEASIBILITY, CLASSIFICATION AND IMPLEMENTATION FRAMEWORK FOR MAINTENANCE LEGACY SYSTEMS IN INDUSTRY 4.0 SCENARIOS.

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Presidente da Banca
Prof. Dr. Eduardo de Freitas Rocha Loures
(Orientador)

Prof. Dr. Fernando Deschamps
(Membro Interno)

Prof. Dr. Eduardo Alves Portela Santos
(Membro Interno)

Prof. Dr. Rui Francisco Martins Marçal
(Membro Externo / residente da ABEPRO)

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**ABSTRACT**

The Industry 4.0 (I4.0) – 4th Industrial Revolution – movement highlights the importance of communication and information technologies (ICT) in industry, as a result of advances in digitization and automation, in search of a more intelligent and sustainable manufacturing. These technologies enable the horizontal integration of the organization where suppliers, workers, machines, products and customers are constantly exchanging data between the different phases of the product life cycle in manufacturing. The I4.0 plant is suited to create intelligent products capable of collecting and using information from sensors and semantic technologies. In addition, intelligent manufacturing networks are able to control themselves autonomously in response to different situations, adapting based on data histories generated by several types of sensor applications. In this way, the concept of Industry 4.0 can be perceived as a strategy to make the industry more competitive. Specifically, in maintenance systems some of those concepts standout, such as real time analysis of historical data, characterizing the predictive maintenance. However, organizations trying to implement these concepts of new processes and technologies face a number of interoperability (the ability to communicate as transparently as possible) barriers across systems. This problem is intensified in legacy systems, those strongly coupled with the organization's processes and therefore cannot be changed drastically without a critical analysis. The present work proposes a digital transformation framework, aiming at the diagnosis and best strategy to upgrade maintenance legacy systems. Based on Multicriteria Decision Making/Analysis (MCDM/A) methods, it is sought trace a strategy to make those systems capable of interoperate with others, characteristics of I4.0. These legacy systems adapted to the new intelligent factory profile will be called *Smart Legacy Systems* (SLS). The results show that the conjunction of three aligned MCDM methods, if properly exploited their characteristics, can provide a tangible digital transformation project to be executed in maintenance legacy systems.

**Keywords:** Industry 4.0, Maintenance, Legacy Systems, MCDM, Interoperability.

# RESUMO

O movimento Indústria 4.0 (I4.0) - 4ª Revolução Industrial - destaca a importância das tecnologias de informação e comunicação (ICT) na indústria, como resultado dos avanços em digitalização e automação, em busca de uma manufatura mais inteligente e sustentável. Essas tecnologias permitem a integração horizontal da organização, onde fornecedores, funcionários, máquinas, produtos e clientes estão constantemente trocando dados entre as diferentes fases do ciclo de vida do produto na fabricação. A planta I4.0 é adequada para criar produtos inteligentes capazes de coletar e usar informações de sensores e tecnologias semânticas. Além disso, as redes inteligentes de manufatura são capazes de se controlar de maneira autônoma em resposta a diferentes situações, adaptando-se com base nos históricos de dados gerados por diversos tipos de aplicações de sensores. Desta forma, o conceito de Indústria 4.0 pode ser percebido como uma estratégia para tornar a indústria mais competitiva. Especificamente, em sistemas de manutenção destacam-se alguns desses conceitos, como a análise em tempo real de dados históricos, caracterizando a manutenção preditiva. No entanto, as organizações que tentam implementar esses conceitos de novos processos e tecnologias enfrentam uma série de barreiras de interoperabilidade (a capacidade de se comunicarem da forma mais transparente possível) entre sistemas. Esse problema é intensificado em sistemas legados, aqueles fortemente acoplados aos processos da organização e, portanto, não podem ser alterados drasticamente sem uma análise crítica. O presente trabalho propõe um framework de transformação digital, visando o diagnóstico e a melhor estratégia para atualização de sistemas legados de manutenção. Baseado nos Métodos Multicritério de Apoio à Tomada de Decisão/Análise (MCDM/A), busca-se traçar uma estratégia para tornar esses sistemas capazes de interoperar com outros, característicos da I4.0. Para esses sistemas legado adaptados para o novo perfil de fábrica inteligente serão chamados de *sistemas legado inteligentes* (SLS). Os resultados nos mostram que a conjunção de três métodos MCDM alinhados, se exploradas suas características corretamente, pode propiciar um projeto de transformação digital tangível para ser executado em sistemas legados de manutenção.



**Palavras-chave:** Indústria 4.0, Manutenção, Sistemas Legado, MCDM, Interoperabilidade.

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# 1. INTRODUCTION

Maintenance is a critical part of the organizations because it impacts all of its layers from processes to business. However, research on the future of manufacturing, revolutionized by Industry 4.0, reveals a gap of understanding regarding the specific changes that can be expected for maintenance systems.

According to Bokrantz, Skoogh, Berlin, & Stahre (2017) this revolution of manufacturing digitalization, started by the German initiative “Industrie 4.0”, builds upon ICTs to develop future manufacturing systems with: connectivity between system elements; intelligent information acquisition; and responsiveness to internal and external changes.

With this new scenario of information and communication technologies being applied in the industry, maintenance is getting a new perspective and a much more important view, as more sensors are installed at production systems to acquire data for production and maintenance optimization purposes (Biahmou, Emmer, Pfouga, & Stjepandić, 2016). In addition, machines and systems in the production area are increasing its digital networked capacity and power, and because of that, large datasets are generated. Therefore, data interpretation is one of the main challenges in applying Industry 4.0 concepts.

Sensors producing data, such as system-internal alarms and messages (produced during maintenance operation) can be used to optimize production processes and besides that, information can be extracted from raw data and used to develop new data-driven business models and services (Uhlmann, Laghmouchi, Geisert, & Hohwieler, 2017).

Predictive maintenance can easily be related, as an example, to the Industry 4.0 data-driven business because their concepts are supported by the same elements: intelligent information acquisition; connectivity between system elements; and responsiveness to internal and external changes, using current and prognostic machine tools information (Bokrantz et al., 2017). An example of that is explained by Shafiee (2015), as predictive maintenance is comprehended as a maintenance which includes “the use of modern measurement and signal processing methods to accurately predict and diagnose system condition during operation.” Regarding predictivity, it could be used in I4.0-maintenance to minimize (or in a certain level of prediction, eliminate) failures, time waste and resources.

In this 4th Industrial revolution, because data starts to flow in a more efficient digital-driven environment, the manufacture and also the enterprise business sector are impacted.

However, even while bringing significant improvements to the organization, according to Kaiser et al. (2005) adding capabilities to existing systems can be a major concern related to interoperability (i.e. smart-digital capabilities from the I4.0 context). The smart capabilities provided by I4.0 technologies brings a new paradigm of interoperability concerns, and this statement can be supported by Ullberg, Chen, & Johnson (2009), which explains that interoperability “concerns” are defined by the content of interoperation that may take place at various levels of the enterprise – data, service, process, business levels. Conclusively, the reference suggests that "concerns" are defined where the interoperability may occur whilst interoperability “barriers” are defined as incompatibilities between two systems.

For a more generalized understanding, according to Chen, Dassisti, & Elvesæter (2007) - “…interoperability is the ability or the aptitude of two systems that have to understand one another and to function together. The word ‘inter-operate’ implies that one system performs an operation for another system”.

Therefore, while the industry has been seeking optimization through the application of Industry 4.0 technologies Tedeschi, Rodrigues and Emmanouilidis, (2018) and Rosendahl et al. (2015), the assignment of these technologies to already operating systems within an organization can easily expose problems related to interoperability. In such a way that even if a system is operating with I4.0 capabilities, it must be able to fully interoperate with its other adjacent systems to exploit the true potential of existing acquired information.

With such interoperability perspectives being presented, legacy systems may be the most challenging to consider for an upgrade driven by these I4.0 technologies. Tedeschi et al. (2018) explains that legacy systems are typically a piece of manufacturing equipment natively lacking external communication capabilities and API which, among other things, could provide real-time machine data.

A legacy system is not just about software, but a wider concept, which includes the organization within which the hardware is situated, as well as its processes tools, machines and staff; could also be an old technology that still worked fine for its originally-intended purpose, but is hopeless when trying to communicate with others (i.e. lack of interoperability) (Ramage, 2000); it is a system which, taking account of its relationship to the organization's business, no longer meet the needs of its organizational environment (Brooke & Ramage, 2001). As it is understood in many different elements, it is coherent to interpret these systems from the point of view of interoperability.

Particularly, those legacy systems will be maintenance systems, as maintenance is a critical service in industry. In production lifecycle, maintenance is a core activity. Besides, the I4.0 maintenance sector is being based on a combination of visual, automatic and dynamic information monitoring, sensor technology, performance information and operational data analysis enabling to follow up on wear and repair, or corrective actions in order to obtain maximum performance through the machines lifetime (Bokrantz et al., 2017; D Mourtzis, Zogopoulos, & Vlachou, 2017; Dimitris Mourtzis, Vlachou, Milas, & Xanthopoulos, 2016; Sandengen, Estensen, Rødseth, & Schjølberg, 2016).

Is proposed in the present work a legacy system upgrade framework, composed by three steps, each one supported by a different multicriteria decision-making method (MCDM), characterizing a tool that optimizes legacy systems by preserving its functionalities of operation in the organization, and at the same time assigning capabilities of digital I4.0-driven systems to them.

The framework is called "Industry 4.0 maintenance feasibility, classification and implementation framework" (I4.0MFCI framework). It was originated by the necessity of support decision-making in industrial environments, searching for digital transformation towards maintenance legacy systems whom needs I4.0 capabilities to interoperate properly with others high-technological systems. The framework will support the organization decision-makers by validating (or not) the upgrade of a particular legacy system (from a maintenance process) in order to make it perform in an Industry 4.0 smart environment. Afterwards, the new digitalized system – which still have the legacy system requirements but now is embedded with I4.0 capabilities to interoperate and perform in a most digitalized manufacture context – will be called *Smart Legacy System* (SLS).

## 1.1. RESEARCH QUESTION

As understood in Tedeschi et al. (2018), the movement of Industry 4.0 has encouraged manufacturing organizations to update their systems and processes by implementing IoT technologies in legacy systems to provide new services such as autonomous condition monitoring and remote maintenance. The present work proposes to implement I4.0 technologies to improve gradually the maintenance legacy systems of organizations, that way, the main question is: "*How can an organization maintain a maintenance legacy system, improving its faculties and making it more competitive, with the implementation of I4.0 capabilities and without generate interoperability issues in this course?".*

## 1.2. OBJECTIVES

The ideal scenarios to apply this framework take as hypothesis that an organization already has decided to improve or it is open to improve its processes (i.e. through a digital transformation project). As premise, in the introduction section the specification of this scenario was built, explaining the contexts of: maintenance sector (i.e. not just as a fundamental manufacture process, but also, as a subject easily explorable and relatable to the I4.0 concepts); legacy system (i.e. which is a system important to the organization's business but lacks of technological capabilities); and how interoperability issues can emerge if a I4.0 and legacy systems interacts with each other.

Given the relevance of the maintenance sector to I4.0 in line with the importance of the legacy system, which has technical difficulties to interoperate with modern systems due to its lack of interoperability, it can be found an ideal problem space for the application of the I4.0MFCI framework.

Applying the framework consists in follow three steps: Step 1, suggesting the appliance of an assessment model through an *feasibility* analysis, to understand if it is relevant to upgrade the analyzed legacy system; Step 2, consisting of a *classification* model which intends to insight the most valuable I4.0 maintenance functions that could mostly improve the system; and finally, Step 3, representing a decisional model for *implementation*, pondering the I4.0

technologies that best suit the analyzed system without compromising the interoperability between it and others subjacent systems. Figure 1.1 presents an overview from the whole I4.0MFCI framework, and its main elements.

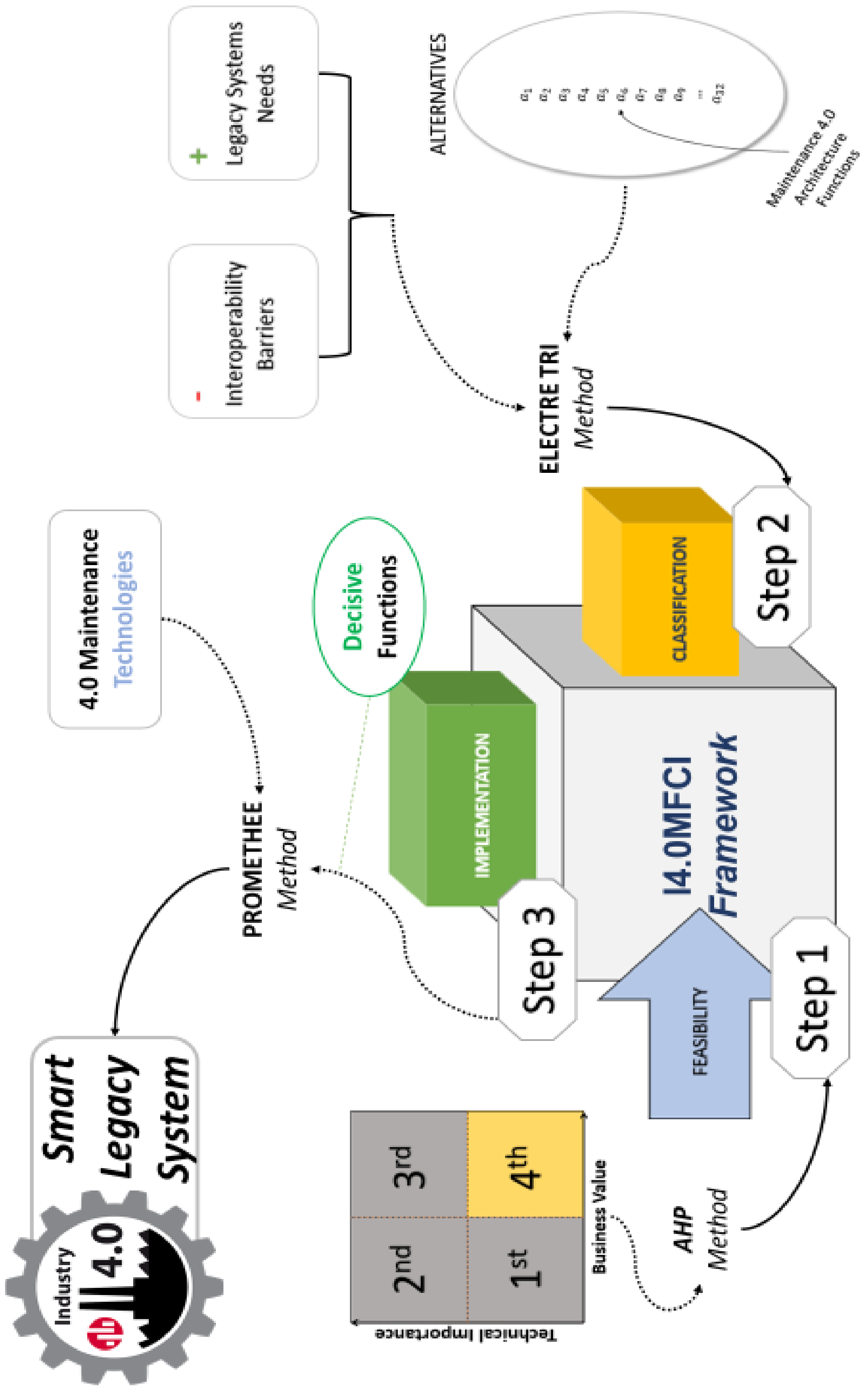


**Figure 1.1 I4.0MFCI Framework illustration.**

Also, the framework's name explicit references its steps: "Industry 4.0 maintenance *feasibility (Step 1)*, *classification (Step 2)* and *implementation (Step 3)* – I4.0MFCI – framework".

Following the main question, hypothesis, premise, the proposed scenarios and the framework's structure, this *research objective* is to: Propose a digital transformation project based on multicriteria methods, by diagnosing an upgradable (by SLS definition) maintenance legacy system and via an I4.0-maintenance architecture, proposing I4.0 technologies (supported by a literature review) to corroborate with this upgrade by an interoperability perspectives.

The research's *secondary objectives* are:

a) Understand the feasibility to upgrade a maintenance legacy system through the application of AHP method;
b) Classify the most beneficial functions, from a referential I4.0 maintenance architecture, to be implement in the legacy system through the application of ELECTRE TRI method;
c) Investigate the application of I4.0 technologies that better suit the maintenance functions for the legacy system under analysis through the application of PROMETHEE method;
d) Present final decisional analysis, exposing the critical technologies that will bring more differential to the analyzed maintenance legacy system, making it a SLS.

All steps have their own specific approach/model where each one is supported by a different MCDM method that better suits its problematic.

## 1.3. RESEARCH JUSTIFICATION

The new emergent technologies used to characterize I4.0 are bringing more reliability to the industry: Cyber-physical Systems, perceived as the pivotal enabler for a real-time internet-based communication Colombo, Karnouskos, Kaynak, Shi, & Yin (2017); Internet of Thing (IoT), as IoT-enabled manufacturing refers to an principle in which production resources are covered into smart manufacturing objects (SMOs) able to sense, interconnect and interact to automatically carry out manufacturing logic Zhong, Xu, Klotz, & Newman (2017); Cloud Computing, as cloud-enabled prognosis benefits from both advanced computing capability and information sharing for intelligent decision-making (Schmidt, Wang, & Galar, 2017).

Especially in the maintenance sector, I4.0 technologies have a significant impact e.g., motivated by adapting to the rapid changing business requirements and reducing maintenance costs, organizations are outsourcing their processes using Cloud Computing resources (Belghith, 2017).

Maintenance is a core activity of the production lifecycle, accounting for as much as 60 to 70% of its total costs (Dimitris Mourtzis et al., 2016). Although the cost of Maintenance is extremely high, the existing industrial maintenance solutions are used in isolation without considering the real condition of the machine and equipment. A typical maintenance issue is the downtime of production systems, which causes not only repair costs but also high failure follow-up costs because of the production interruption (Lee, Ardakani, Yang, & Bagheri, 2015). Machines failures easily lead to bottlenecks, damaging the subsequent value-added processes of the company due to the interlinked production systems.

Apply ICTs to those processes seems to be a good alternative, however, it can increase the use of complex highly automated and networked production systems, demanding that enterprises rethink their maintenance strategies. Developing scenarios for future maintenance is needed to define long-term strategies for the realization of digitalized manufacturing (Uhlmann et al., 2017).

In one hand, information and communication technologies will improve efficiency of the maintenance, reduce through-life cost of the product and continuous maintenance within this I4.0 context also highlight the role of IoT and cyber security (Roy, Stark, Tracht, Takata, & Mori, 2016). In the other hand, implementing these technologies is not a trivial task because of the risk of a lack of interoperability, generated between the organization systems (the one which is being upgraded and its adjacent ones). This problem intensifies when regarding legacy systems.

In contrast a legacy system is a system of which may include: software, people, expertise, hardware, data, approaches to maintenance and development (Brooke & Ramage, 2001). Most of all, legacy systems have a critical relationship to the organization's business process Cimitile, Fasolino, & Lanubile (2001), they may work with data acquired from years of operation, are highly coupled with the processes of the organization and even if they lack in technological capabilities, they still can generate a significant economic revenue.

The difficulties explored in this work relates those legacy systems (the ones that need to be kept operational) with the necessity of digital transformation responsible for integrate I4.0 technologies with already existing process.

## 1.4. DOCUMENT STRUCTURE

This work is organized in 5 sections. The Section 1 discusses the research universe, presents the problematics and the question, implying in the specific research objectives.

In Section 2, the literature review is presented, with the objective of consolidate concepts about Maintenance in an Industry 4.0 context, Legacy Systems, Interoperability and MCDM technics, along with the methodology approach.

Further, Section 3 presents the three steps I4.0MFCI (Industry 4.0 Maintenance – Feasibility, Classification and Implementation) Framework, objectifying: understand if it is feasible implement I4.0 faculties in a maintenance legacy system; classify the main maintenance functions from I4.0 in order to understand the most critical ones due to the legacy system performance optimization; and finally, deciding which technologies from I4.0 will suit better this system, without compromising the interoperability between it and other adjacent systems.

In Section 4, two case studies scenarios to apply the I4.0MFCI Framework methodological approach are presented, along with a discussion about the results obtained and participants perceptions over the methodology.

Conclusively Section 5 presents objectives, recommendation, perspectives and limitations about the research, along with possible future works related to the main topics addressed in this work.

## 2. LITERATURE REVIEW

In this section will be presented the literature review that is responsible for all the background information used in this work. It is understood that interoperability between systems is not only a question of removing barriers, but also the way these barriers are removed (Chen, 2006). This is key to understanding how to implement I4.0 technologies in legacy systems which might not prepared to receive them.

As the proposal of this work puts in perspective legacy systems working in Industry 4.0, it ended up revisiting old knowledge bases, as legacy systems and their evolution/upgrade is not a recent issue. That way, much of the legacy systems literature, cited in here, was conceived at latest 20th and early 21st.

Nowadays, legacy systems are receiving renovate attention (Batlajery, Khadka, Saeidi, Jansen, & Hage, 2014; Maeda, Sakurai, Tamaki, & Nonaka, 2017; Rosendahl et al., 2015; Tedeschi et al., 2018). The systems which operates before the I4.0 era, are in some sense "recent" legacy systems, as some of them aren't capable to operate in a digital CPS-driven environment. Also, the legacy system concept can be related to the current reality of systems that are unable to fully interoperate with recent I4.0 systems from the same enterprise.

Ullberg et al. (2009) identifies and categorizes a set of interoperability barriers, and according to them, barriers to interoperability are defined as incompatibility between two enterprise systems. Generally, the word "inter-operate" implies that one system performs an operation on behalf of another, but in a more punctual definition, interoperability is the ability to communicate with pier systems and access the functionality of the pier systems (Chen & Doumeingts, 2003). In the present work this concept was used to define this incompatibility between maintenance systems from the same organization i.e., a legacy system and a I4.0 capability enabled system.

As understood in a legacy system reference, Ransom, Sommerville, & Warren (1998) if for example, an application software is in a poor technical state, will be difficult to understand its lines of code and also will be expensive to maintain it. For a system with a long-required life, effort to make the system more responsive to digitalized technologies would be sensible. Nevertheless, some requirements need to be anticipated to determine whether a legacy system can satisfy the implementation of more flexible I4.0 features. A system’s lifetime is strongly dictated by factors such as serviceability of software and hardware. When a support hardware or software becomes obsolete, the useful life of the system is limited.

The solutions in this work are elaborated to implement I4.0 capabilities in to legacy systems, trying to reduce or allow to generate the least possible interoperability barriers (i.e. incompatibilities between systems or components of systems that are concerned by interoperations - exchange of information) using a set of MCDM methods.

For each step structured in the I4.0MFCI framework, a different multicriteria decision-making method is used, aiming to understand specific points such as: the feasibility to upgrade a maintenance legacy system to a smart I4.0-driven system, using the AHP method; classify the main I4.0 maintenance functions which will bring more improvements to the system, according to its specific characteristics, using the ELECTRE TRI method; and finding the best I4.0 technology to suit this system functions, due to interoperability, via PROMETHEE method.

## 2.1. BACKGROUND – MAINTENANCE CONTEXT

Maintenance expenditure can be viewed as the necessary investment to be paid for reliability insurance, then it follows that all maintenance activity should be directed towards improve that reliability, i.e. zero waste.

The role of maintenance can be described in the manufacture as the control, execution, management and quality of activities which will reasonably ensure that levels of availability and performance of assets are achieved in order to meet business objectives as proposed in “*Asset Maintenance Management – The Path toward Defect Elimination*” (Lifetime Reliability Solutions, 2012). However, usually the emphasis is on returning the machine to service as quickly as possible without any serious reliability differentiations.

Conclusively, maintenance can be described as a Risk Control activity: Risk = Consequence x Probability = Consequence x (Opportunity x Chance).

Further, Lifetime Reliability Solutions (2012) explains that the expenditure of maintenance on risk management (e.g. condition monitoring, process control, etc.) should be directly related to the probability and consequences of failure. Generally, in maintenance, decisions are made based on risk assessments outcomes. For that kind of assessment, maintenance activities are defined such as: repair costs; design and process; additional maintenance activities resulting from premature equipment failure, or rework; unexpected failures incurring costs as - diversion of planned maintenance resources, lost production or reputation (in that case generating penalties for late delivery), etc.

Nowadays, Industry 4.0 capabilities are regarded as competitivity value driver to manufacturing. McKinsey&Company, indicated that predictive maintenance can improve the asset utilization with 30 to 50% reduction of total machine downtime and increase the machine life by 20 to 40%, as exposed in "Industry 4.0 - How to navigate digitization of the manufacturing sector" (McKinsey & Company, 2015). The maintenance and performance measures, in the context driven by Industry 4.0, mostly ICTs, makes them even more impactful.

To better understand the importance of information and communication technologies in the industrial context, it is important to understand how changes along years have affected how industry's plants where been maintained. Preceding to the Second World War machines was rugged and relatively slow running, as instrumentation and control systems were very basic. Downtime was not usually a critical issue as the demands of production were not overly severe and maintenance was regarded repair work because there was no way to predict failures as machines operated until they broke down.

Even today it is possible to see examples of machines made in that period which have worked very hard and are still good in its essentials. For processes which these machines are still fundamental elements they could be referred as legacy systems (Ramage, 2000).

After the war, in the 1950's with the rebuilding of the industry particularly those of Japan and Germany, there developed a much more competitive marketplace; there was increasing intolerance of downtime. Following those particularities, cost of labor became increasingly significant leading to more and more mechanization and automation and, as consequence, machines became more lighter and faster. However, these machines began to wear out more easily and were seen as less reliable, which made the manufacture require better maintenance, which led to the Planned Preventive Maintenance.

From the 1980's plant and systems became increasingly complex and maintenance costs continued to rise, the demands of the greater reliability at a lower cost and intolerance of downtime increased came. New awareness of failure processes, improved management techniques and new technologies to allow an understanding of machine and component health emerged.

Historically, the study of Risk has become very important, aside with environmental and safety issues. Condition monitoring, just in time manufacturing, quality standards, expert systems, reliability centered maintenance, world class, CMMS (Computerized Maintenance Management System), CAD (Computer-aided design), TPM (Total Productive Maintenance), TQM (Total Quality Management) also have emerged as new concepts in maintenance. In the mid-1980's DuPont Corporation carried out a study of the effectiveness of the maintenance operations in their large number of plants. They identified the characteristics of these operations and found the pattern shown on Figure 2.1.

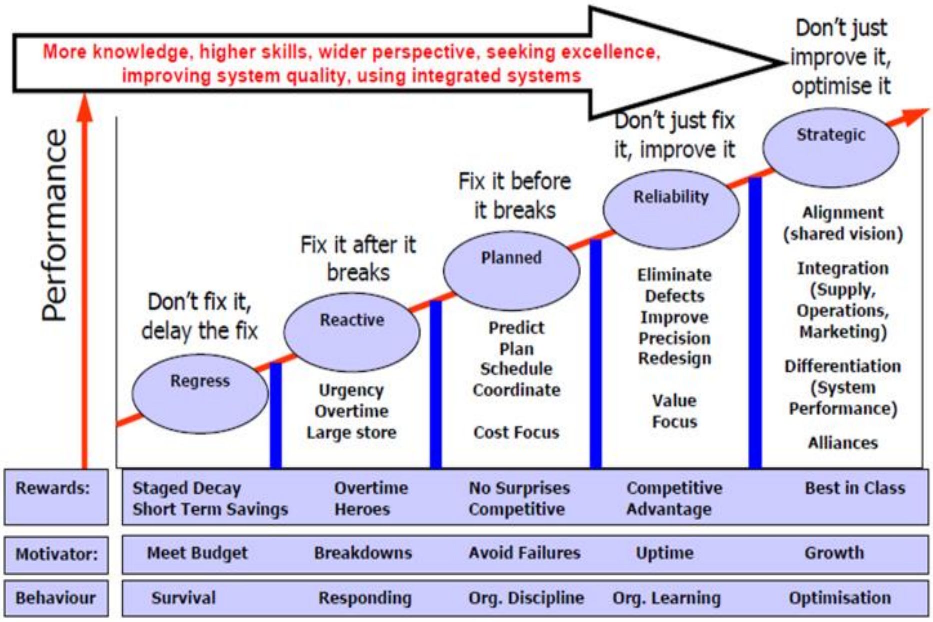


**Figure 2.1 DuPont stable domain model diagram (Lifetime Reliability Solutions, 2012).**

Lifetime Reliability Solutions (2012) analyzes this diagram "*…many organizations today are in, or coming into, the 'Planned' phase with some of the components of 'Reliability' either in use or being put into place, suggests. DuPont* *additionally found that in the move from 'Reactive' to 'Planned' the value gained when doing predictive and preventative maintenance is most successful in lifting reliability when they are planned and scheduled. In many organizations the Predictive or Condition Monitoring component are still not well integrated.*"

Correlate maintenance (and its concepts through the course of history) with new ICTs emerging in the industry is not trivial. Traditional manufacturing systems cannot adequately consume I4.0-requirements because of their inflexibility, i.e. difficulty of the deterministic decision-making in a stochastic environment and insufficient communication and exploitation of expertise in a collaborative environment. Technology has always been a key driver of change in industry, leading enterprises to adopt methods to improve maintenance decisions and striving for maintenance excellence (Vilarinho, Lopes and Oliveira, 2017).

To attain excellence in maintenance the balance of performance, risks, and costs must be considered in order to achieve good quality solutions. This includes developing tactics that maximize the benefits of maintenance strategies, which are usually classified in two major categories, corrective maintenance (CM) and preventive maintenance (PM). CM can originate high costs which also include loss of production incurred due to equipment downtime and, therefore, PM should be performed to reduce these costs whenever introduces the likelihood of the failure occurrence (Brezinski, Venâncio, Gorski, Deschamps, & Loures, 2018; Sandengen et al., 2016).

However, a too high frequency of preventive maintenance interventions can also result in high costs, once resources may be wasted without been necessary. There is also a tactic closely related to I4.0, the predictive maintenance, aiming to predict when equipment failure might occur as well as to prevent the occurrence of the failure by performing maintenance. The tendency in industry is that, with the advance of machines networking and manufacturing facilities driven by IoT, the predictive faculties encountered in the I4.0 manufacture environment stand out, lessen corrective and preventive maintenance approaches (Lee et al., 2015; Ruschel, Santos, & Loures, 2017).

As described in K. A. Kaiser & Gebraeel (2009), since then, novel principles for maintenance planning with a systems perspective are emerging, e.g. advancement of data analytics, education and training, stronger environmental legislation and standards. Those novel principles, today called I4.0 technologies, are enabled by technological-drivers like: sensors, which facilitate the easy monitoring of machine conditions (Lee, Kao, & Yang, 2014); cloud storage systems and data bases enable the long-time archiving (Sandengen et al., 2016); and computational excellence in analysis of machine data for diagnostic and maintenance purposes (Tiddens, Braaksma, & Tinga, 2015).

For a competitive and I4.0-driven maintenance process, the lack of technological upgrade in legacy systems leads to lack of standardization with new systems and process, which, in turn, implies loss of scale, the lock of projects and advanced technologies that could improve the performance of industrial processes. An example of Industry 4.0 technologies applied in maintenance context are wind power turbines. To process 200 gigabytes of data per day, Siemens wind power have a remote diagnostics center in Brande (Denmark) for advanced analytics and real-time human monitoring. This application of monitoring technology, comes from Industry 4.0 concepts of collecting data to improve process (data-driven process).

Bokrantz et al. (2017) explains – "*Those trends suggest that the industrialized world is facing a revolution through a digitalized manufacturing and in literature expectations include substantial gains in productivity, higher levels of automation, and improvements in resource efficiency"* and its references: Capgemini Consulting (2014), Cisco (2015), Deloitte (2015), PWC (2015), Roland Berger (2015) and The Boston Consulting Group (2015); which have also corroborated directly with the present work.

A literature review was made on the references exposed in this last paragraph, resulting in an analysis of trending technologies used in I4.0 maintenance sector. With this systematic analysis along with the main technologies and technics used in maintenance, it was concluded that, although the references diverged in their way of defining the Smart Industry, they were very similar ideologically, promoting that the ICTs linked to the digitization and high connectivity are strong trends already in use in the industry. This literature review will be commented in subsection 2.3.2 and detailed further in subsection 3.3.2.

The reports cited in the previous paragraph, along with other academic papers and world class industries (e.g., Bosch, Siemens) white paper's researches show that I4.0 is more than a set of concepts structured in frameworks, it has been gaining momentum since the appearance of the term in 2011 at the Hannover Messe "*Machine Automation concepts to enable innovation for digitalized manufacturing*" (OMRON, 2018).

Conclusively, Bokrantz et al. (2017) explains that the advancements of digitalized manufacturing will increase the associated need for maintenance management including: digitalized manufacturing such as e.g. autonomous navigation, robustness at every level, remote and real-time control, predictability, efficiency and safety. However, I4.0 is still a long way from its apex, which envisages in its limit a future of intelligent, autonomous, and highly sustainable production. In the universe of maintenance systems, this benefit of I4.0 capabilities point to the reduction of losses, seeking greater viability, performance and quality of products as processes, aiming a manufacture with *zero losses*.

### 2.1.1 INDUSTRY 4.0 (I4.0)

Industry 4.0 (also named as "Smart Factory") has been introduced to enable high-tech competitive advantage which means: (vertically) smart networking, mobility, flexibility of industrial operations; (horizontally) integration with customers, suppliers; and the adoption of innovative and sustainable business models (Man & Strandhagen, 2017).

In an organizational structure point of view, Industry 4.0 includes horizontal integration through networks in order to facilitate an internal cooperation, vertical integration of subsystems within the factory, in order to create a flexible and adaptable manufacturing systems and through-engineering integration, across the entire value chain, enabling an easy customization of products. This integration also facilitates the exchange of information (interoperability) for cross-company product development, as some products life cycle involves several stages that should be performed by different companies (Pereira & Romero, 2017).

During the last decade, the use of I4.0 driven technologies (ICTs) in industry have become unavoidable. The defining feature associated to the fourth industrial revolution is the intelligent networks based on cyber-physical systems.

Cyber-physical systems (CPS) can be defined as - the digitalization of the physical world. They are physical and engineered systems, whose operations can be monitored, coordinated, controlled and integrated by a computing and communication system (Sandengen et al., 2016).

CPS involves the interaction with the physical world and it is composed by a set of networked agents. Because of this data-physical integration, they are seen as digitized systems – i.e. reflecting physical means in virtualized interpretations. These network driven technologies include: sensors, actuators, control processing units, and communication devices. At the same criticality of CPS, the Industrial Internet of Things (IIoT) promoted new challenges in logistic domain, which might require technological changes such as: high need for transparency (supply chain visibility); integrity control (right products, at the right time, place, quantity condition and at the right cost) in the supply chains (Barreto, Amaral, & Pereira, 2017).

Industrial IoT has also affected the way CPS can interact, be monitored, be controlled and managed. Therefore, IoT technologies cooperate to the integration of processes and systems across sectors and to a better communication and cooperation with each other in a more intelligent way. It also collaborates with revolutionizing production, services provision, logistics and resource planning in a more effective way and cost-efficient manner (Tjahjono, Esplugues, Ares, & Pelaez, 2017).

In an IIoT context the logistics challenges might require something like: high need for transparency (supply chain visibility); integrity control (right products, at the right time, place, quantity, condition and at the right cost) of the supply chain; dynamic ‘reconfigurability’ of supply networks, specially by re-examining service-level agreements with upstream and contracted suppliers; supply network design, towards achieving lean, agile, resilient and green supply chains (Zhong et al., 2017).

Still according to Barreto, Amaral and Pereira (2017), the intensive use of the technological applications and the increase growth of wireless embedded sensors and actuators are contributing to the development of several new applications – in areas such as production processes, autonomous vehicles, health services, logistics services, transportation system, machine learning and smart structures. In consequence, they increase the technological improvements of existing applications – such as Supervisory Control and Data Acquisition (SCADA) systems.

Industry 4.0 world is digitalized and automated, sustainable business models exist but have not become mainstream. Man & Strandhagen (2017) describes opportunities for sustainable offerings exist by designing products for longevity, repair and recycling, such that sustainability is not only focusing on being more efficient, but also on using less raw materials and recycling more products. This changes the value proposition, supply chain, relation with the customer and financial justification of a business model.

Yet, the last reference suggests the question whether this will lead to a market shift to sustainable products depends on how well Industry 4.0 can support sustainable value propositions that lead to more sustainable supply chains. This technological evolvement is evidenced, for example, by shortened production cycles, incorporation of customer needs in real time, maintenance being largely carried out automatically, orders automatically filled in the right order, shipped and dispatched.

Industry 4.0 driven technologies strongly relates interoperability, as one of the objectives to reduce internal operating costs through digital end-to-end integration. That way systems will end up having more control and autonomy in relation with the whole process they perform, implying they “inter-operate” i.e. perform an operation on behalf of such process or less-autonomous systems (Chen & Doumeingts, 2003).

Regarding the supply chain, the digital transformation and the use of intelligent and cooperative systems will make it more transparent and more efficient in every stage (Deloitte, 2015). There will be a particular focus in new models which will be more closely to individual customer needs, promoting a significantly increase of the decision-making quality and become more flexible and efficient in the near future (Barreto, Amaral, & Pereira, 2017; Lee, Kao, et al., 2014). It is safe to say that the involvement of people will always be needed, controlling the processes and monitoring system failure, regardless of the level of autonomous decision taken by machines, be them operational, tactical and mainly strategic.

Challenges for business models do not only come forward from business and customer needs. While business has experienced unprecedented growth after the world-war era, it now faces major challenges in which there is a misbalance between available supply and expected demand; with a growth from 3 billion to over 7 billion people from 1960 to 2015, the purchasing power of each individual tripled. This has led to an enormous pressure on natural resources and climate, and will result in social instability (Man & Strandhagen, 2017).

### 2.1.2 LEGACY SYSTEMS

After three decades of legacy modernization research, it is admirably to find that legacy systems are still in operation nowadays. However, they are not naturally undesirable and its existence is inevitable, as a legacy system characterizes any system that significantly resists modification but are business critical, and hence, their failure can have serious impact on the enterprise (Batlajery et al., 2014).

According to Ramage (2000), legacy systems are: very big systems that only held together because people were continually patching them up or being employed to deal with exceptions that the system couldn't handle; old technology that (15 years later) still worked fine for its originally-intended purpose, but was hopeless when one tried to communicate with others; of technologies once regarded as state-of-the-art but now they are ancient and fail to respond to organizational needs. In general, a system becomes legacy when its underlying business process has changed.

Legacy systems refer to much more than the software, it is a wider system of which the software is merely a part. They are made of technical components and social factors, including: people, expertise, skills, hardware, data, business processes, approaches to software maintenance and development; which no longer meet the needs of the business environment (Brooke & Ramage, 2001). Understanding a legacy system requires taking account of its relationship to the business environment. All these things – and especially their interactions with each other – constitute a legacy system. Thus, legacy systems consist of much more complex consideration than just a technical dimension, they encompass issues of organizational structure, strategy, process, and workflow.

A macro impact level of legacy system example might include the millennium ‘bug’ or the introduction of the Euro. At a micro level, an event driven by a legacy system will vary from company to company. The key point is that the event may not be a one-off, and it could also result from internal organizational circumstances as well as external ones.

Other way to classify a legacy system is, when it is one which no longer meet the needs of its organizational environment. As Liu, Alderson, Sharp, Shah, & Dix (1998) have said: “*To remain competitive, businesses must continually change their processes, sometimes radically, though more often incrementally, to cope with their changing environment. As a result, IT systems become inadequate in reflecting business needs, either operationally or economically, and so become legacy systems.”*

However, the term ‘legacy’ is not necessarily negative in practice. Many organizations have a great amount of valuable data, functionality, encoding of processes and expertise bound up in their legacy systems. Sometimes, the organization may view the system as an organizational memory. According to Brooke & Ramage (2001) their objective is not necessarily to eradicate the legacy but to enable it to endure into the future. The meaning of the word ‘legacy’ in everyday speech also implies something that can be a value data for the future.

As explained by Zhou, Wang, & Norrie (1999), since the end of $20^{th}$, the manufacturing environment was already undergoing global and significant changes, due to the changing customer requirements. Because of that, much production started to following trends of small batches with higher variation as the market changes frequently and has shorter lead times. High variation of product and small batches are also characteristics even more expressive in I4.0.

To respond to market changes and shorter lead times, production facilities need to become reconfigurable and based on increasingly intelligent autonomous modules that dynamically interact with each other to achieve both local and global objectives; manufacturing equipment and process must be adaptable to assure the agility of the company; and shorter product life cycles and rapid reconfiguration will require control systems that are intelligent, flexible, extensible, fault-tolerant and re-usable (Wang, Balasubmramanian, & Norrie, 1998).

A literature review approach was taken to identify the main characteristics from legacy systems, putting in perspective the technologies encountered today in the industry. Eight prepositional main traits were discriminated in this research, showed in Table 2.1.

**Table 2.1 Legacy systems prepositional main industrial traits.**

| Main Traits |
|---|
| 1. Low IT capabilities |
| 2. High cost to maintain |
| 3. Not old, but defined by how the organization uses it |
| 4. Monolithic (i.e. not adaptable, hard to modify) |
| 5. Does not keep up with the organization business changes |
| 6. Lack of communication capabilities |
| 7. Its underlying processes were changed |
| 8. Heterogeneous, including: software, its processes tools, hardware, people, expertise, data, business processes, and approaches |

All of those traits are confirmed as they were encountered in a very close syntactical relation in more than one of the referential works. The follow Table 2.2 shows insights on what the term "Legacy System" means, found in the references.

**Table 2.2 Legacy systems, insights from a syntactic approach research.**

| Referential work | Insight | Description | Maintenance Context/ Example |
|---|---|---|---|
| Managing legacy system costs: A case study of a meta-assessment model to identify solutions in a large financial services company (Crotty & Horrocks, 2017) | 1 | "...are so costly to maintain and support." | A legacy software/machine will be needing adaptations and regular maintained, to keep up with the others organization processes, when they start to be modified and optimized, generating costs. Legacy staff and tools, are hard to find and costly to have. Ex(i): A maintainer whom understand a system which is the same for too long, will be requested to train new staff just to work with that system. Same goes for legacy tools, as replacing them will be more difficult along the years and the supplier may stops |
| | 2 | "(Bennet *et al.*) observed that research into legacy system assessment approached the subject as a technical issue rather than as a broader business problem." | |
| | 3 | "...contemporary architectural issues, in considerations such as extensibility and interoperability." | |
| | 4 | "...old information systems that remain in operation within an | |

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|---|---|---|---|
| | | organization (2001, Brooke and Ramage)." | manufacturing them; Ex(ii): A maintenance legacy system architecture may not communicate with the flexibility needed by a digitalized process. When processes that interact with the legacy one change/are optimized, it can generate interoperability barriers; Ex(iii): A maintenance software whom provides critical direct data to the business management fails, because of technological inability, and that impacts directly the organization finances. |
| | 5 | "...any business-critical software systems that significantly resist modification and their failure can have a significant impact on the business (2001, Brooke and Ramage)." | |
| | 6 | "...a legacy application or system may be based on outdated technologies, but is critical to day-to-day operations (2001, Brooke and Ramage)." | |
| An Approach to Autonomizing Legacy Systems (G. Kaiser, Gross, Kc, Parekh, & Valetto, 2011) | 7 | "...developed by different vendors, mixing and matching COTS and "open source" components." | A maintenance legacy system can have several components provided by different vendors. Ex(i): If a machine's tool breaks and its software need update, they can have different vendors, and its maintenance will be more expensive. |
| Method for Automatically Recognizing Various Operation Statuses of Legacy Machines (Maeda et al., 2017) | 8 | "...a lot of legacy machines, which are old and lack the capability of sending data on their operation status to networks, are still in use because the average useful life of machine tools is more than 20 years." | Some machines have a significant life-time. If its adjacent systems are optimized, to keep up with the processes, the machine needs to receive retrofit (i.e. upgrade). Ex(i): If a maintenance machine can't provide data due to lack of network incompatibility (once the process demands its systems to be network-connected), it is time to analyses retrofit possibilities to it; E(ii): Once a maintenance system is valuated to receive retrofit, it is important to analyses its interoperability impacts among adjacent systems. The more legacy is the system, more adaptations it might need. |
| | 9 | "...'legacy' equipment (with average serviceable lifetimes exceeding twenty years) that is incompatible with networks is still being used..." | |
| | 10 | "...retrofitting such legacy equipment to make it IoT compatible presents big problems." | |
| | 11 | "...takes the standpoint that legacy systems are obsolete | In today's competitive environment, companies must be |

| | | | |
|---|---|---|---|
| Industrial Perception of Legacy Software System and their Modernization (Batlajery et al., 2014) | | systems, yet they are crucial for an organization's operation..." | capable of manufacturing products of high quality and at low cost. Many companies have responded to these competitive demands by adopting new manufacturing technologies. Maintenance legacy systems can be less flexible to attend to those manufacturing needs. Ex(i): A legacy machine which is critical to day-to-day operations, e.g. an electric testing robot in a circuit boards manufacturing industry. This machine cannot stop because all the production depends on the test of the circuit boards to secure their quality; Ex(ii): A monitoring alarm system which provides inadequate data management are in need of upgrade if these data is business critical; Ex(iii): A maintenance legacy software system which does not upgrade in the way that keeps up with the sensor technology implemented in the monitoring, is making it difficult the production flexibility to innovate and optimize the process. |
| | 12 | "...practitioners value their legacy systems highly, the challenges they face are not just technical, but also include business and organizational aspects." | |
| | 13 | "A legacy system can be any software system that significantly resists modification but are business critical, and hence, their failure can have serious impact on the business." | |
| | 14 | "Brodie & Stonebraker in their book describe legacy systems as 'any systems that cannot be modified to adapt to constantly changing business requirements and their failure can have a serious impact on business'." | |
| | 15 | "Brodie & Stonebraker reported various characteristics of the legacy systems such as mission critical, hard to maintain, inflexible and brittle." | |
| | 16 | "...system that we don't know how to cope with but that are vital to our organization." | |
| | 17 | "...high maintenance cost, lack of resources, achieve flexibility." | |
| | 18 | "In contrast, a legacy system refers to much more than the software. It is a wider system of which the software is merely a part. Other components of the system might include: people, expertise, hardware, data, | A maintenance legacy system can be dedicated to a whole process and in that case, the staff, data, hardware, tools and specific approaches in which this system may perform are legacy too. Ex(i): One business-strategic costumer of an online service is the only one |

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|---|---|---|---|
| Organisational scenarios and legacy systems (Brooke & Ramage, 2001) | | business processes, and approaches to software maintenance and development... also requires taking account of its relationship to the business environment." | using its service in the version 1, because all the other costumers are using version 2. In that case the online service will have to keep at least one specialist to do the maintenance of that particular system and as the time goes by, that one specialist will become a legacy asset in this maintenance process. |
| | 19 | "...legacy systems consist of much more than just a technical dimension: they encompass issues of organizational structure, strategy, process, and workflow." | |
| | 20 | "A legacy system is one which no longer meet the needs of its organizational environment." | |
| | 21 | "(Liu *et al.* 1998) To remain competitive businesses must continually change their processes, sometimes radically, though more often incrementally, to cope with their changing environment. As a result, IT systems become inadequate in reflecting business needs, either operationally or economically, and so become legacy systems." | |
| Global perspectives on legacy systems (Ramage, 2000) | 22 | "It is important to distinguish between legacy software and legacy systems (a wider concept, which includes the organization within which the software is situated, as well as its processes and members)." | Maintenance legacy systems are not focused only in software. A monitoring system depends on hardware technology to extract data in the best way possible. Ex(i): If for business reasons, the quality of potato chips X needs to be better than its competitors, the X company may not be able to upgrade its sensors to choose between its potatoes, because its software monitoring system do not support this new sensor; E(ii): A shoes manufacturing industry which provides for two different companies, may upgrade the |
| | 23 | "'Legacyness' lies in the gap between the needs of the business and the capabilities of the technology." | |
| | 24 | "Legacy is what is left after a particular event happens: the | |

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|---|---|---|---|
| | | recognition of that event varies from place to place and from person to person." | machinery to produce new shoes for company A. At the same time the company B, which never changes its shoes pardon will need the same production systems. This way, every process which is business critical but cannot change can be acknowledge as legacy by its members. |
| | 25 | "Legacy systems contain much which is valuable (especially data): in fact, the term only makes sense in referring to systems which are important but hard to change." | |
| A Method for Assessing Legacy Systems for Evolution (Ransom et al., 1998) | 26 | "Legacy systems are usually critical to the business in which they operate, but the costs of running them are often not justifiable. Determining whether such systems are worth keeping requires an overall assessment of the system." | If the maintenance process of a product is necessary to guarantee the quality of it, but the cost to maintain this operation does not justify it, the system might need to be optimized or completely changed. Ex(i): A maintenance software which are developed in the early stages of an enterprise and needed several upgrades and modifications tend to grow in complexity and new employees could have difficulties to understand it; E(ii): If employees from a check-up process in an automotive factory can't keep up with the high standards needed for guarantee the competitiveness of the car parts, they might be representing unjustifiable expenses. |
| | 27 | "A legacy system is a system which was developed sometime in the past and which is critical to the business in which the system operates." | |
| | 28 | "… systems which are often difficult to understand and expensive to maintain." | |
| | 29 | "...but maintaining (legacy systems) incurs unjustifiable expense." | |
| | 30 | "A legacy system may evolve in a number of ways, depending on factors such as its technical condition..." | |
| | 31 | "... special attention is given to legacy systems that are not equipped with monitoring technology..." | Ex(i): Due to the condition base and predictive maintenance ensuring high quality, a maintenance system which does not monitor and/or make use of its data hardly will fit in a digital manufacture environment. Ex(ii): |
| | 32 | "Legacy systems are typically a piece of manufacturing | |

| | | | |
|---|---|---|---|
| A cost estimation approach for IoT modular architectures implementation in legacy systems (Tedeschi et al., 2018) | | equipment natively lacking external communication capabilities and API that could provide real-time machining data." | At the same time, if a machine does have a monitoring component but does not have ways to communicate its data towards the process, still it will not be a good option for a digital environment. Those two examples are in their order, one very hard and other hard to upgrade. The first one is harder to upgrade, because it lacks even the monitoring function, so the more complex the system is, the more apparent are its legacy characteristics. |
| | 33 | "For example, monitoring systems for legacy machine tools raise security aspects related to data sharing and data protection that are associated to both hardware and software threats." | |
| | 34 | " Legacy system - is characterized by the attribute cost of the machine tool and complexity of devices' implementation (e.g. the difficulty to equip the machine with external devices)." | |

### 2.1.3 SLS (SMART LEGACY SYSTEMS)

This work proposes to couple a "Sensorial Layer" to the legacy system which will, most of the time, requires a complex reengineering action (Extraordinary Adaptation) in order to add smart/digital characteristic (of maintenance real-time data analysis and transmitter) to it, making the system a "Smart Legacy System" (SLS). "Systems" are understood as the synergy between software and hardware delimited to a certain function in an organized way inside a process. "Sensory Layer" is understood as the implementation of sensors at the key points of industrial processes, producing a digital monitored reflection of the system that will be accessed by the organization's network (in that case, CPS).

The goal of this SLS upgrade is: to approach the organization of a digital transformation gradually, since a legacy system is a key system and, in most cases, cannot be changed drastically.

The first step in the current I4.0MFCI framework methodology concerns a decisional analysis of specific actions that must be taken, in order to analyze the feasibility of adapting a legacy system to the I4.0 requirements. If the result of the actions proposed by the method is an Extraordinary Adaptation or a Simplified Adaptation, the legacy system analyzed must undergo a gradual reengineering that meets the requirements of I4.0. Gradually, because these adaptations aim to *not impact in a negative way* the interoperability between others underlying systems and processes (i.e. not generating interoperability barriers).

For this, the adhesion of sensors (I4.0 base technology) on legacy systems linked to a high-performance industrial network with a strong computational intelligence, upgrade them to smart/intelligent legacy systems (SLS), keeping the useful legacy traits, but now, enabling them to digitally communicate, in a more autonomous and flexible way.

That digital transformation strategy, which supports the implementation of I4.0 digital information and communication faculties being embedded on legacy systems, can be confirmed in two reference works. With a focus on software, Kaiser et al. (2005) work addresses how to "autonomize" legacy systems, thus, the monitoring layer (sensors) can evaluate system performance based on data according to a broad variety of metric models, protocol and architecture, etc. With a focus on hardware, in the work of Tedeschi et al. (2018) it is understood that, to use these new intelligent systems (e.g. sensors, IoT technologies, etc.), manufacturers need to reconfigure the IT level to create the next generation of "smart legacy machines".

A Smart Legacy System is explained as: *“Legacy systems lacks on some technological-capabilities level, but because they are important to the organization business, I4.0 capabilities (i.e. ICTs) must be embedded on them. In that way they can be called Smart Legacy Systems, enabling them to be more digitally-interoperable, facilitating the synergy towards the processes which they participates”*.

## 2.2 INTEROPERABILITY

Interoperability is the relation between products or systems to communicate and exchange information with another product/system, in an organized an easy way (i.e. with minimum or any restriction). As referenced by

Ide & Pustejovsky (2010), "*Broadly speaking, interoperability can be defined as a measure of the degree to which diverse systems, organizations, and/or individuals are able to work together to achieve a common goal.*"

For this present work, interoperability is the root which intertwine all other topics. Precisely, the measurement of interoperability between systems exists so that the organization (or even systems between organizations) could be more efficient, aiming information/communication flexibility and speed with the less losses possible. This can be automatically transported to the context of industry 4.0, as in present days, information and communication technologies represents a major differential to the factory's flexibility and sustainability.

Having said that, the concept of interoperability is closely related to I4.0, as systems need to communicate in a high level of complexity to reach smart and predictive response toward the organization's layers. Chen (2006) addresses that enterprises interoperability barriers are incompatibilities which obstruct the sharing of information and prevent from exchanging services and developing interoperability means to develop knowledge and solutions to remove the incompatibilities.

Parallel to it, a concern about the importance for organizations and its immutable legacy systems, coupled with how they can be critical to the business but lacks in, again, information and communication technologies (e.g. lack of digital capability to transfer the right type of data, reduced speed to generate alarms, unable to rely on algorithmic insights for business and KPI needs, etc.) describes its necessities to engage I4.0 technologies to them. This can also be represented in context of interoperability, to ensure that the legacy system can be changed without compromising the information dynamics already imposed by the organization's processes.

This work supports the concept of interoperability based on Framework for Enterprise Interoperability (FEI) Chen (2006), Chen et al. (2007), ISO 11354-1 (2011) defined in The INTEROP Network of Excellence (INTEROP NoE) project. FEI describes three interoperability dimensions: interoperability aspects, barriers and approaches.

Interoperability aspects regards to different enterprise levels where interoperability can take place. Interoperability barriers are incompatibilities or mismatches (e.g. conceptual or technical) between the concerned systems.

Finally, the Interoperability approaches describes the solutions to be adopted for reducing or eliminating the identified barriers.

Further, Ullberg et al. (2009) presents a list of interoperability barriers which are also mapped to the FEI, consisting in a major input for the present work regarding specific examples of barriers categorized. The research work proposed by Leal, Guédria, & Panetto (2019), Leal (2019) was also considered as it represents an updated context from the domains of enterprise interoperability applied in an evaluation bias.

## 2.3 MAIN REFERENTIAL WORKS

The I4.0MFCI Framework steps to implement I4.0 faculties in maintenance legacy systems is an effort to combine and improve diagnostical and decisional approaches that covers those systems, in the view of interoperability.

In early researches regarding this work, aiming a diagnostical bias, the goal was to investigate the feasibility to upgrade a legacy system into a more digital-driven system prepared to work in a I4.0 environment (which in this work context is called *Smart Legacy Systems* – SLS). The argument behind this objective revolves around that the first stage for digital transformation in legacy systems is to understand whether some systems in the organization really need actions that involves their change. This is approached through a multicriteria analysis and decision-making support – using the AHP (Analytic Hierarchy Process) method.

Later on, envisioning the perspective of a more decisional bias, two key referential works were combined, one referring to “Reference Architectural Model Industrie 4.0 (RAMI4.0)” Plattform Industrie 4.0 (2016), and another, referring Interoperability barriers “Barriers to Enterprise Interoperability” (Ullberg et al., 2009). The objective of this merge was to propose an interoperability assessment of technologies that may collaborate in maintenance activities of a given production environment through the application of Industry 4.0-oriented technologies in legacy systems. This idea was firstly discussed in terms of another AHP model to represent the space problem of “interoperability x I4.0

layers", but as the researches proved the necessity to extend the complexity of the criteria used in this analogy, the ELECTRE method proved more suitable.

Finely, to present the decisional aspect of technologies that could better embed the analyzed legacy system, PROMETHEE method was applied, enriching the MCDM aspect of this work as the particularities of each method needed to be properly developed. MCDM will be addressed in subsection 2.4 and the reasons about why each method was used are approached in the sections that presents its application, Section 3, and detailed further in Section 4 in the context of the case studies.

Together, diagnostical and decisional approaches where combined in such way that they could relate legacy systems (focused in maintenance) and I4.0. Thus, in this work the assumption is that, to improve the organization maintenance processes in which legacy systems perform it is necessary to embed technologies, business contexts, and high interoperability performances, capacitating those systems to perform in a I4.0 environment.

### 2.3.1 DIAGNOSTIC APPROACH

As explained in the beginning of section 2, old problematics regarding legacy systems assessment and upgrade approaches are revisited in this work, as they are putted in perspective with the present context of digital technologies and I4.0. That being said, the first referential article, "*A Method for Assessing Legacy Systems for Evolution*" from Ransom et al. (1998), regards this present work's feasibility to upgrade a legacy system in a diagnostic approach.

The product of the evaluation model presented in the reference work seeks to understand the importance of the legacy system, from technical, commercial and organizational perspectives, providing an assessment basis from which a decision can be made contemplating four different strategies.

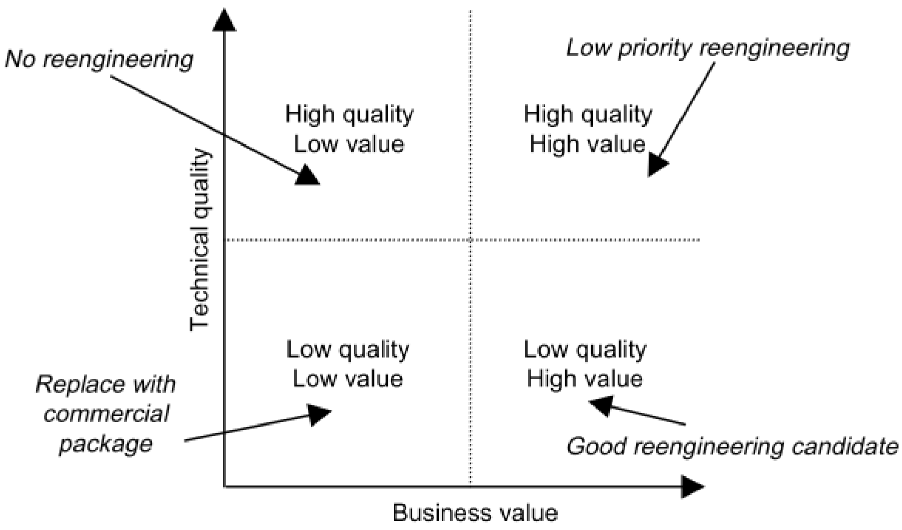



**Figure 2.2 Technical quality and business value (Ransom et al., 1998).**

A second diagnostical referential article is from Cimitile, Fasolino and Lanubile (2001), "*Legacy Systems Assessment to Support Decision Making*", which objectify to support the decision-making process of a systematic evaluation of legacy systems during the life cycle of their evolution. All systems go through a continuous evolution, alternating between four main phases and interpreted by four basic attributes.

| Attribute | Definition |
|---|---|
| Business Value | It expresses to what extent a software system is essential to the business of an organization |
| Decomposability | It expresses how easily the main components of a software system are identifiable and independent from each other |
| Obsolescence | It expresses the aging of a software system caused by the failure to meet changing needs |
| Deterioration | It expresses the aging of a software system as a result of continuing changes that are made |

**Figure 2.3 The four attributes to assess a legacy system in the reference life cycle (Cimitile, Fasolino and Lanubile, 2001).**

Notably, in this present work, as the definition of legacy systems is contemplated at its full notion (i.e., beyond the limits of software context), adaptations were explored and applied to include those attributes into a more extensive sight.

Conclusively, the current work was designed to provide a legacy systems assessment, seeking scientific requirements for application in industry, offering options that impact on investment decisions, aiming to make the system more competitive in the process of digital transformation promoted by the advent of Industry 4.0. That way, commercial and technical criteria have been presented as factors which impacts processes that have legacy systems. Those criteria are later analyzed in an AHP method to support decision making, as its result indicates whether it is feasible to apply digital transformation efforts to the system, and if so, the next approach indicates what and how I4.0 technologies should be used.

### 2.3.2 DECISIONAL APPROACH

The decisional-related part of this present work had the objective of identify Industry 4.0 technologies applied on maintenance activities. It starts searching through consulting and scientific groups which provide studies on those technologies in their respective frameworks: Industry 4.0 at McKinsey's model factories, McKinsey & Company (2016); Industrie 4.0 Maturity Index, Acatech (2017); Industry 4.0, The Boston Consulting Group (2015); Industry 4.0 - The Capgemini Consulting View, Capgemini Consulting (2014); Industry 4.0, Deloitte (2015); and Industry 4.0: Building the digital enterprise (PWC, 2016).

To collect data on the applicability of I4.0 technologies in maintenance systems a literature review was presented, constructing relations between I4.0 technologies and maintenance systems. Filtering the relevant references about Industry 4.0 technologies applied in the maintenance sector, this research aimed articles at the time period from 2014 to 2018 (researched year), considered adequate since the term appeared by 2011, resulting in 59 articles found. Notwithstanding, this research was complemented later by another cycle of articles, including some previous from 2010, in order to understand how some technologies already used in maintenance evolved in a more digitalized applicability. The detailed process pertinent to this research can be found in subsection 3.3.2.

This research proceeds by investigating interoperability barriers which might appeared by implement I4.0 technologies in maintenance legacy systems. In order to do so, two frameworks were considered: Framework Enterprise

Interoperability (FEI) from Chen et al. (2007) and Ullberg et al. (2009), and the RAMI 4.0 model (Plattform Industrie 4.0, 2016). The FEI emerges from a necessity of a wide investigation, more in an organizational than technological way, for existing interoperability models. It is presented in Figure 2.4.

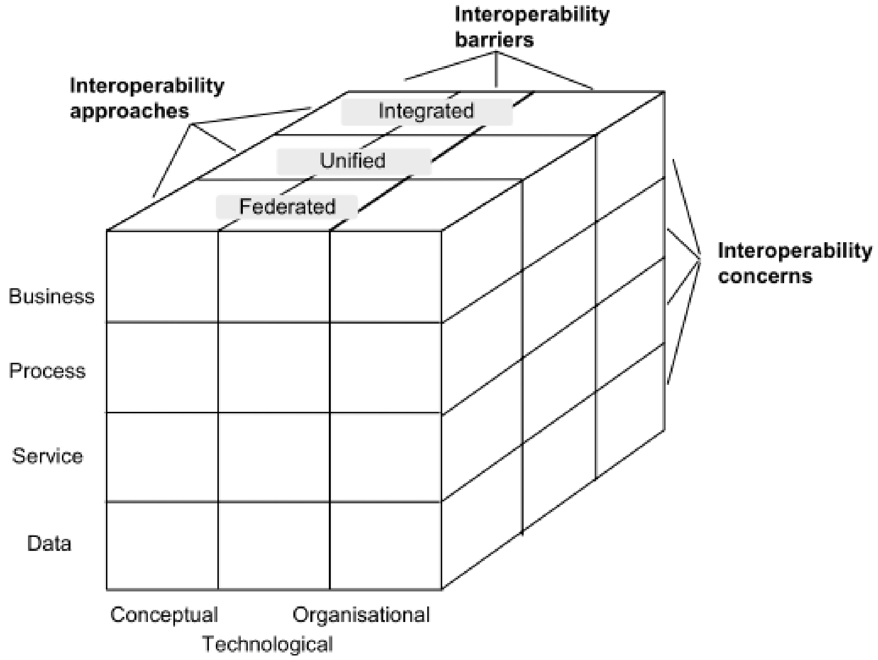



**Figure 2.4 Enterprise interoperability framework (Chen et al., 2007).**

Analogously to the FEI, which has a broad organizational view (not linked to Industry 4.0), the RAMI4.0, Figure 2.5, presents (in a vertical view comparison) layers perspective with a very close interpretation of FEI interoperability concerns, linking it with a I4.0 architectural model.

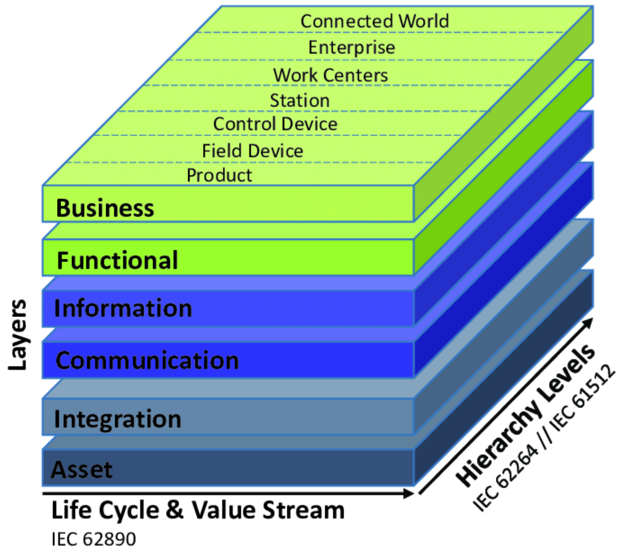



**Figure 2.5 RAMI 4.0 architecture - 3D Axis view.**

The layers perspective from RAMI4.0 model, related to the concerns from FEI, guide a relational analysis aiming to organize maintenance domain attributes into RAMI4.0 layers. This approach highlights the conceptual relationship between interoperability and industry 4.0, from RAMI4.0 structural reference, an interoperability diagnosis approach guiding I4.0 – oriented maintenance initiatives.

Above all, this present work refers to FEI merged with RAMI4.0 along its development, focusing in make the right decisions, supported by decision-making methods as tools to guide the implementation of I4.0 faculties to maintenance legacy systems.

## 2.4 MULTI-CRITERIA DECISION MAKING (MCDM)

MCDM is a branch of operational research dealing with finding optimal results in complex scenarios, including various indicators, conflicting objectives and criteria. It is considered as a complex decision making (DM) tool, involving both quantitative and qualitative factors, helpful to make decisions while considering all the criteria and objectives simultaneously, due to the flexibility it provides to the decision-makers. MCDM problems generally comprises of five components which are: goal, decision-maker's preferences, alternatives, criteria's and outcomes respectively (Kumar et al., 2017). This subsection objective is to review the applications and approaches of the MCDM techniques used in the I4.0MFCI three steps framework.

According to Xu & Yang (2001), multi-criteria decision making (MCDM) refers to making decisions in the presence of multiple, usually conflicting, criteria. MCDM problems are common in everyday life. In personal context, buying a car may be characterized in terms of price, size, style, safety, comfort, etc. In business context, MCDM problems are more complicated and usually of large scale. This is stated in Kumar et al. (2017), suggesting MCDM can be complex due to involvement of factors including technical, institutional, standards, social, economic and stakeholders. Thus, it involves both engineering and managerial level of analysis.

Xu & Yang (2001) also describes that MCDM discipline is closely related to the advancement of computer technology. The rapid development of computer technology in recent years has made it possible to conduct systematic analysis of complex MCDM problems. But at the same time, the widespread use of computers and information technology has generated a huge amount of information, which makes MCDM increasingly important and useful in supporting business decision making. In general, due to the different problem's settings two distinctive types of MCDM problems exists: one having a finite number of alternative solutions and the other an infinite number of solutions.

Normally in problems associated with selection and assessment, the number of alternative solutions is limited, which is the focus in this work. A MCDM problem generally is described using a decision matrix. Suppose there are $m$ alternatives to be assessed based on $n$ attributes, a decision matrix is a $m \times n$ matrix with each element $Yij$ being the *j-th* attribute value of the *i-th* alternative.

Although MCDM problems could be very different in context, they share the following common traits:

- Multiple attributes/criteria often form a hierarchy. An alternative, such as an action plan, or a product, can be evaluated on the basis of a criterion. A criterion is a property, quality or feature of alternatives in question. Some criterions may break down further into lower levels, called sub-criteria;
- MCDM itself can also be referred to as Multiple Attribute Decision Analysis (MADA) if there are a finite number of alternatives. Sometimes criteria are also referred to as attributes and used interchangeably in the MCDM context;
- Conflict among criteria. Multiple criteria usually conflict with one another;
- Hybrid nature model can be: 1) Incommensurable units. An attribute may have a different unit of measurement; 2) Mixture of qualitative and quantitative attributes. It is possible that some attributes can be measured numerically and other attributes can only be described subjectively; 3) Mixture of deterministic and probabilistic attribute;
- Uncertainty can exist in subjective judgments. Because it is common that decision-makers may not be 100% sure when making subjective judgments. Or Uncertainty due to lack of data or incomplete information;
- Large Scale. A MCDM problem may consist of hundreds of attributes;

- Assessment may not be conclusive. Due to lack of information, the conflict among criteria, the uncertainties in subjective judgment and different preferences among different decision-makers, the final assessment results may not be conclusive.

MCDM problems may not always have a unique or conclusive solution, therefore, different names are given to different solutions depending on the nature of the solutions (Tzeng & Was, 1981).

All criteria in a MCDM problem can be classified into two categories, criteria to be maximized (profit criteria) and criteria to be minimized (cost criteria). An ideal solution to a MCDM problem would maximize all profit criteria and minimize all cost criteria. However, hardly this solution is obtainable and then the problematic revolves around in trying to understand what would be a best solution for the decision-maker and how to obtain such a solution. A solution is satisfying depends on the level of the decision-maker's expectation. Because it is not easy to obtain an ideal solution, the decision-maker may look for "non-dominated" solutions, i.e. the most suitable in his/her opinion.

There are two types of MCDM methods. One is compensatory (organized in 4 groups) and the other is non-compensatory (credited for their simplicity) (Tzeng & Was, 1981). Non-compensatory methods do not permit tradeoffs between attributes. Analogously in compensatory methods a slight decline in one attribute is acceptable if it is compensated by some enhancement in one or more other attributes (Xu & Yang, 2001).

In this work an example of compensatory method is the AHP, which is a scoring method, used to select or evaluate an alternative according to its score (or utility), expressing the decision-maker's preference. However, compensatory methods exhibit a high dependency to the weights of some dominant criteria. In compensatory techniques, poor performances of a strategy in some criteria can be compensated by high performances in some other criteria; therefore, the aggregated performance of a strategy might not reveal its weakness areas (Banihabib, Hashemi-Madani, & Forghani, 2017).

This qualifies the AHP method being used in the Step 1, as the decision-makers are seeking for a highly weighted alternative, not worrying about granular discrepancies regarding details nor weakness areas. Thus, their decision is not going to affect the system directly, being strictly a decision about how the system's characteristics match with the feasibility to upgrade it.

By contrast, the other two methods are non-compensatory techniques, where each individual criterion can independently play a crucial role in aggregated performance of a strategy. ELECTRE TRI an PROMETHEE II are examples of this.

For the ELECTRE scenario, the criteria reflect various levels of an organization and how it deals with interoperability barriers (cost criteria) and systems necessities (profit criteria), which will vary from system to system. The PROMETHEE, Step 3 scenario, also represents a case that poor performances in some criteria cannot be compensated for even with very high performances in other criteria, as the criteria to be chosen in this method will be specific functions highly varying from system to system. Those necessities of decision analysis are some specificities which corroborated with the choice of methods.

The methods used in this dissertation are summarized next and detailed in the I4.0 FCI framework presentation, section 3, contextualizing with the decisional problematics involving this work.

### 2.4.1 AHP

The Analytic Hierarchy Process (AHP) is a general theory of measurement. It is used to derive ratio scales from both discrete and continuous paired comparisons (Saaty, 1987). These comparisons may be taken from actual measurements or from a fundamental scale which reflects the relative strength of preferences and feelings. T. L. Saaty developed the AHP in 1971-1975 while at the Wharton School (University of Pennsylvania, Philadelphia, Pa).

This MCDM has a special concern with departure from consistency, its measurement and on dependence within and between the groups of elements of its structure. AHP has found its widest applications in multicriteria decision making, planning and resource allocation and in conflict resolution. Saaty (1987) says that, in its general form the AHP is a nonlinear framework for carrying out both deductive and inductive thinking without use of the syllogism by taking several factors into consideration simultaneously and allowing for dependence and for feedback, and making numerical tradeoffs to arrive at a synthesis or conclusion.

AHP method is based on the innate human ability to make sound judgments about small problems. It facilitates decision-making by organizing perceptions, feelings, judgments and memories into a framework that exhibits the forces that influence a decision. There are three main stages in the AHP methodology:

First one is the stage of structuring the hierarchy. Group related components and arrange them into a hierarchical order that reflects functional dependence of one component or a group of components on another. The approach of the AHP involves the structuring of any complex problem into different hierarchy levels with a view to accomplishing the stated objective of a problem;

After that, the second stage is performed to paired comparisons between elements/decision alternatives. Construct a matrix of pairwise comparisons of elements where the entries indicate the strengths with which one element dominates another using a method for scaling of weights of the elements in each of the hierarchy levels with respect to an element of the next higher level. Use these values to determine the priorities of the elements of the hierarchy reflecting the relative importance among entities at the lowest levels of the hierarchy that enables the accomplishment of the problem's objective.

Finally, the third stage suggests synthesize the result priorities to obtain each alternative's overall priority and select the alternative with the highest priority. Those stages are detailed in (Bayazit, 2004).

One of the main advantages of Saaty's AHP is its simplicity compare to other decision support methods. It uses hierarchal way with goals, sub goals or factors and alternatives. The structure for comparing the criteria is translated into a series of questions of the general form, 'How important is criterion A relative to criterion B?'. The input to AHP models is the decision-maker's answers to a series of questions is then termed pairwise comparisons. Questions of this type may be used to establish, within AHP, both weights for criteria and performance scores for options on the different criteria.

It is assumed that a set of criteria has already been established based on AHP model. For each pair of criteria, the decision-maker is then required to respond to a pairwise comparison question asking the relative importance of the two. Responses are gathered in verbal form and subsequently codified on a nine-point intensity scale, as presented in Table 2.3.

**Table 2.3 AHP pairwise comparison values.**

| How important is *A* relative to *B*? | Comparison Value |
|---|---|
| Equally important | 1 |
| Weakly more important | 3 |
| Strongly more important | 5 |
| Very strongly more important | 7 |
| Absolutely more important | 9 |

The value in between such as 2,4,6,8 are intermediate values that can be used to represent shades of judgement between those five basic assessments. If the judgment is that *B* is more important than *A*, then the reciprocal of the relevant index value is assigned, for example if *B* is considered to be strongly more important (5) than *A* as a criterion for the decision than *A*, then the value 1/5 (or 0.2) would be assigned to *A* relative to *B*.

In some cases, judgments by the decision-maker are assumed to be consistent in making decision about any one pair of criteria and since all criteria will always rank equally when compared to themselves, it is only ever necessary to make $1/2n\ (n - 1)$ comparisons to establish the full set of pairwise judgments for n criteria. Then the results of all pairwise comparisons are stored in an input matrix $A = [aij]$ that is an $n \times n$ matrix.

The element $aij$ is the intensity of importance of criterion $ni$ compared to criterion $nj$. One should follow four simple steps below in order to apply AHP method for guiding decision-making process:

• Structure the problem into hierarchy;

• Comparing and obtaining the judgment matrix;

• Local weights and consistency of comparisons;

• Aggregation of weights across various levels to obtain the final weights of alternatives (Syamsuddin, 2009).

The following equation (1) shows a typical matrix for establishing the relative importance of three criteria:

$$\begin{pmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 7 \\ 1/5 & 1/7 & 1 \end{pmatrix} \tag{1}$$

Conclusively, the AHP is used in this work to weight the criteria used to analyze which action constitute the most feasible approach to the legacy system to be analyzed, explained with details in subsection 3.1, described as feasibility step.

### 2.4.2 ELECTRE TRI

The Elimination and Choice Translating Reality (ELECTRE) method considers the problem *β (P.β)*, which classifies the various alternatives for solving a problem by comparing each potential alternative with a stable reference.

ELECTRE TRI is an overclassification method and is one of the methods of the ELECTRE (Elimination and Choice Translating algorithm) family, which is composed of ELECTRE I, II, III, IV, IS and TRI methods. Overclassification methods, also called outranking methods, are based on the construction of an overclassification relationship that incorporates the preferences established by the decision-maker in face of the problems and available alternatives. According to Roy (1974), the overclassification relation *S* is a binary relation defined in *A* such that *aSb* if *a* is at least as good as *b*. This relationship does not require transitivity (Szajubok, Mota, & Almeida, 2006).

The ELECTRE TRI allocates alternatives in predefined categories. This allocation of an alternative *a* result from the comparison of *a* with defined profiles of the limits from the categories (Trojan & Morais, 2012). Given a set of criteria indices {*g1, . . ., gi, . . ., gm*} and a set of indices of profiles {*b1, . . ., bh, . . ., bp*} are defined *(p+1)* categories, where *bh* represents the upper class and the lower *Ch, Ch+1* category, with *h = 1, 2, . . ., p*, Figure 2.6.

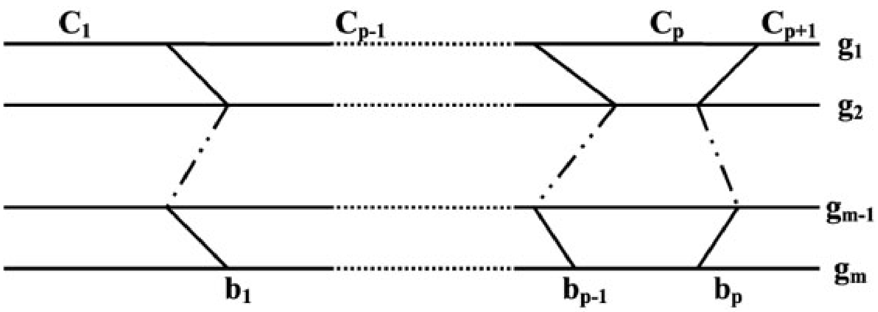



**Figure 2.6 Boundaries between categories (Mousseau & Slowinski, 1998).**

The preferences for each criterion are defined by pseudo criteria in which the preference thresholds and indifference *pj[g(bh)]* and *qj[g(bh)]* provide intra criteria information. Thus, *qj[g(bh)]* specifies the largest difference *gj(a)* − *gj(bh)*, which preserves *th* indifference between *a* and *bh* in the criteria *gj* and *pj[g(bh)]* representing the smallest difference *gj(a)* − *gj(bh)*, consistent with a preference for *a* in the criteria *gj*. The structure preferably with pseudo criteria – double threshold model with *pj[g(bh)]* and *qj[g(bh)]*, avoids an abrupt transition between indifference and strict preference, existing a zone of hesitation, represented by the weak preference.

ELECTRE TRI method constructs outranking relations *S*, it means, it validates or invalidates the assertion that *aSbh* and *(bh Sa)*, whose meaning is "*a* is at least as good as *bh*". Two conditions must be verified to validate the assertion *aSbh.* The Concordance condition presents that, for an outranking *aSbh* to be accepted, most of the criteria should be in favor of affirming *aSbh*; Non-discordance condition happens when in concordance condition is not satisfied, none of the criteria should be opposed to the assertion *aSbh*.

In the construction of *S*, it is used a set of veto thresholds *[v1(bh), v2(bh), . . ., vm(bh)]*, for the test of inconsistency *vj(bh)*, which represents the smallest difference *gj(bh)* − *gj(a)* inconsistent with the statement *aSbh*. The indexes of partial concordance *cj(a, b)*, concordance *c(a, b)* and partial discordance *dj(a, b)* are calculated by the equations (1), (2) and (3) below.

$$c_j(a,b) = \begin{cases} 0 \;\; if \;\; g_j(b_h) - \; g_j(a) \geq \; p_j(b_h) \\ 1 \;\; if \;\; g_j(b_h) - \; g_j(a) \leq \; q_j(b_h) \\ \frac{g_j(b_h) + g_j(a) - p_j(b_h)}{v_j(b_h) - p_j(b_h)}, otherwise \end{cases} \qquad (1)$$

$$c(a,b) = \frac{\sum_{j \in F} k_j c_j(a,b_h)}{\sum_{j \in F} k_j} \quad (2)$$

$$d_j(a,b) = \begin{cases} 0 \ if \ \ g_j(b_h) - g_j(a) \leq p_j(b_h) \\ 1 \ if \ \ g_j(b_h) - g_j(a) > v_j(b_h) \\ \frac{g_j(b_h) + g_j(a) - p_j(b_h)}{v_j(b_h) - p_j(b_h)}, otherwise \end{cases} \quad (3)$$

The ELECTRE TRI constructs an index *σ(a, bh) 2[0, 1] (σ(bh, a)*, respectively, which represents the degree of credibility of the assertion in which *aSbh*, *a 2 A*, *h 2 B*, expression (4). The statement *aSbh* is considered valid if *σ(a, bh)* ≥ *λ* · *λ* starts a cutoff level such that *λ 2 [0, 5, 1]* (Szajubok et al., 2006).

$$\sigma(a,b_h) = c(a,b_h) \cdot \prod_{j \in F} \frac{1 - d_j(a,b_h)}{1 - c(a,b_h)} \quad (4)$$

Where;

$$\bar{F} = \{ j \in F : d_j(a,b_h) > c_j(a,b_h) \} \quad (5)$$

After calculating the indices *ρ(k, bh)* and *ρ(bh, k)*, we use a cut off level *λ 2 [0.5, 1]* to determine the preferably relationship with the condition: *ρ(k, bh)* ≥ *λ ⇒ ak Sbh*. Thus, the higher the value of *λ*, the more severe are the subordination conditions of one alternative over the border.

So, with ELECTRE TRI, mainly used in alternative classification problems, it seeks to assign the performance of the alternatives in one of the of predefined performance classes.

Two assignment procedures can be evaluated: Pessimistic procedure and Optimistic procedure (Trojan & Morais, 2012). The pessimistic procedure compares successively with *bi,* to *i = p, p−1, . . ., 0, bh*, starting with the first profile such in which *aSbh* says to the category *Ch+1(a → Ch+1)*. The optimistic procedure compares successively with *bi,* to *i = 1, 2, . . ., p, bh*, starting with the first profile, such that "*bh* is preferable to *a*" says *Ch* for category *(a → Ch)*.

The *bh* is the first threshold value such in which *ak Sbh* assigns the alternative *ak* to class *Ch+1*. If the values of *bh* and *bh−1* are the lower and upper limits from class *Ch*, this procedure gives to *ak* the highest-class *Ch*, such in which *ak* makes the value *bh−1(ak Sbh−1)*. Moreover, the optimistic procedure compares the performance of *ak* successively to *bi, i = 1, 2, . . ., p*. Being *bh* the threshold value such in which *bh Pak*, must assign *ak* to the class *Ch*.

This procedure assigns to *ak* the class *Ch*, but lower, in which the upper limit *bh* is preferred to *ak(bh Pak)*. Following (Trojan & Morais, 2012), the description and understanding of the ELECTRE TRI sorting algorithm require an additional effort, especially by the fact that this method is based on recent concepts of fuzzy logic.

The ELECTRE TRI method is used in this work's second step, referring to the particularities to upgrade the system, that at this point, should be known as feasible to become a *Smart Legacy System*, described in subsection 3.2. It is chosen by its flexibility to filter (i.e. overclassify/outrank) a series of alternatives suiting them between criteria with not only profitable but also costly characteristics.

### 2.4.3 PROMETHEE

Among numerous methods of MCDM, outranking methods have a rapid progress because of their flexibility to the most real decision situations. Vinodh & Girubha (2012) states that PROMETHEE method is the most known and widely applied outranking methods for pair wise comparison of the alternatives in each separate criterion.

The PROMETHEE main features are simplicity, clearness and stability. According to Brans & Mareschal (1986), the notion of generalized criterion is used to construct a valued outranking relation. All the parameters to be defined have an economic signification, so that the decision-maker can easily fix them.

In PROMETHEE I, partial ranking is obtained by calculating the positive and the negative outranking and both the flows do not usually convey the same rankings. Since the decision-maker always wants to have full ranking, PROMETHEE II has been selected for the evaluation. This method starts with the formulation of alternatives and a set of criterions then it is formed as an *m x n* decision matrix. It suggests six types of preference functions to express how important the relative difference between alternatives for a certain criterion and weights to indicates the relative importance of the criterion (Vinodh & Girubha, 2012).

For each criterion, pair wise comparison of alternatives *a* and *b* is indicated by a preference indicator *Pj(a,b)*. *Pj(a,b)* are pooled over the set of all criteria using expression (1).

$$\pi(a,b) = \sum_{j=1}^{k} P_j(a,b)w_j, with\ w_j\ in\ [0,1] \qquad (1)$$

Where *wj* is the weight of criterion *j*.

Then the positive and negative outranking flows are calculated using the expressions (2) and (3).

$$\emptyset^{+}(a) = \frac{1}{n-1}\sum_{x \in A} \pi(a,b) \qquad (2)$$

$$\emptyset^{-}(a) = \frac{1}{n-1}\sum_{x \in A} \pi(x,a) \qquad (3)$$

The net dominance is calculated using equation (4).

$$\emptyset(a) = \emptyset^{+}(a) - \emptyset^{-}(a) \qquad (4)$$

The best alternative is the one with the highest net dominance.

This MCDM is detailed in the last decisional analysis of the proposed framework, which is Step 3 and describe how to apply the technologies inherited from I4.0-maintenance concepts, suiting the previous functions classified using the Step 2. PROMETHEE II uses a complete ranking method to compare all the alternatives, as they represent different ways to embed determined technology into a system function needed.

## 2.5 METHODOLOGY APPROACH

A methodology is the general research strategy that outlines the way in which research is to be carried out and provides the theoretical basis for understanding which method, set of methods or best practices can be applied to a specific case (Howell, 2013). These methods define the means or modes of data collection.

In the I4.0MFCI framework, each step uses a different MCDM method. That set of methods have each one a specific objective, aiming to provide the necessaire data to its subsequent step. In this work is expected to achieve the upgrade of a maintenance legacy system in a structured way. Figure 1.1 presents the I4.0MFCI Framework, a cube which can revolve in three steps.

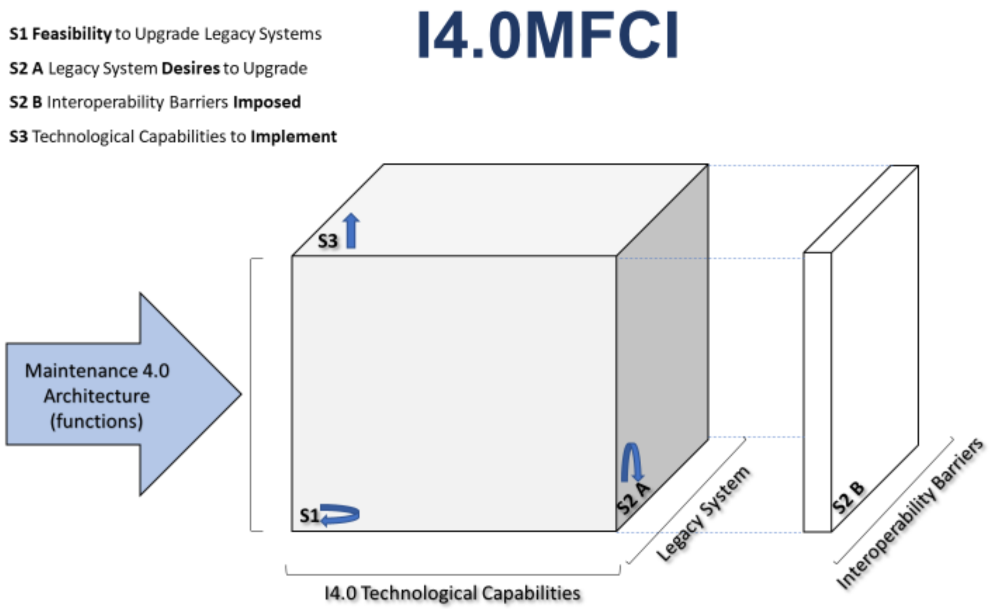



**Figure 2.7 Industry 4.0 maintenance feasibility, classification and implementation (I4.0MFCI) framework.**

The decision-making methods presents in steps 1, 2 and 3 are respectively the AHP, ELECTRE TRI and PROMETHEE II. The willingness to use those methods was described during the section 3, which corelates legacy systems, interoperability, feasibility to upgrade those legacy systems and how to integrate them in a I4.0 organization model.

I4.0MFCI framework represented by a cube is an abstract idea that can also be translated to a well stablished industrial notation. For that, the present work adopts the Integration Definition for Function Modeling – IDEF0 (Presley & Liles, 2015). IDEF0 is a subset of the Structured Analysis and Design Technique (SADT) developed by Douglas Ross in the late 60s and made available as a public domain by Softech Inc. at the request of the United States Department of Defense (Ross, 1977). It is applicable in: strategy modeling and automation of strategic plan development and implementation; to formally describe a process, to ensure a detailed, clear and precise result; when the process is complex, and other methods would result in a more complex diagram; when there is time to work on understanding and producing a complete and correct description of the process (Berre et al., 2004).

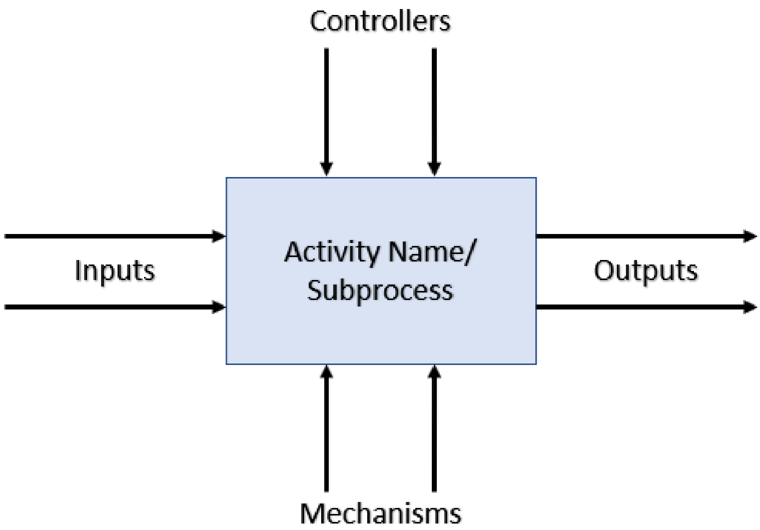



**Figure 2.8 IDEF0 structure.**

The modeling element of the diagram, Figure 2.8, uses only one rectangle to define each activity or process. Each new rectangle is a subprocess. The four arrows around the rectangle represents:

- Inputs, that raw material that is transformed during the activity/process;

- Controls, which influence or direct the activities, such as security rules, plans, specifications, norms, rules, etc.;

- Mechanisms, what is needed for the activity to occur, such as people, tools or machinery and equipment;

- Output, which are the result of the activity and are transmitted to another process or used by the process client. Each output line represents an information generated by the activity.

Figure 2.9 describes the IDEF0 process for this research (i.e. research strategy), synthesizing the cube steps flow, methods, tools used to apply the decisions analysis, and objectives. Section 3, which will explain how to properly approach each analysis in the framework steps will be representing the IDEF0 processes in Figure 2.9, focusing on the respective cube face being described.

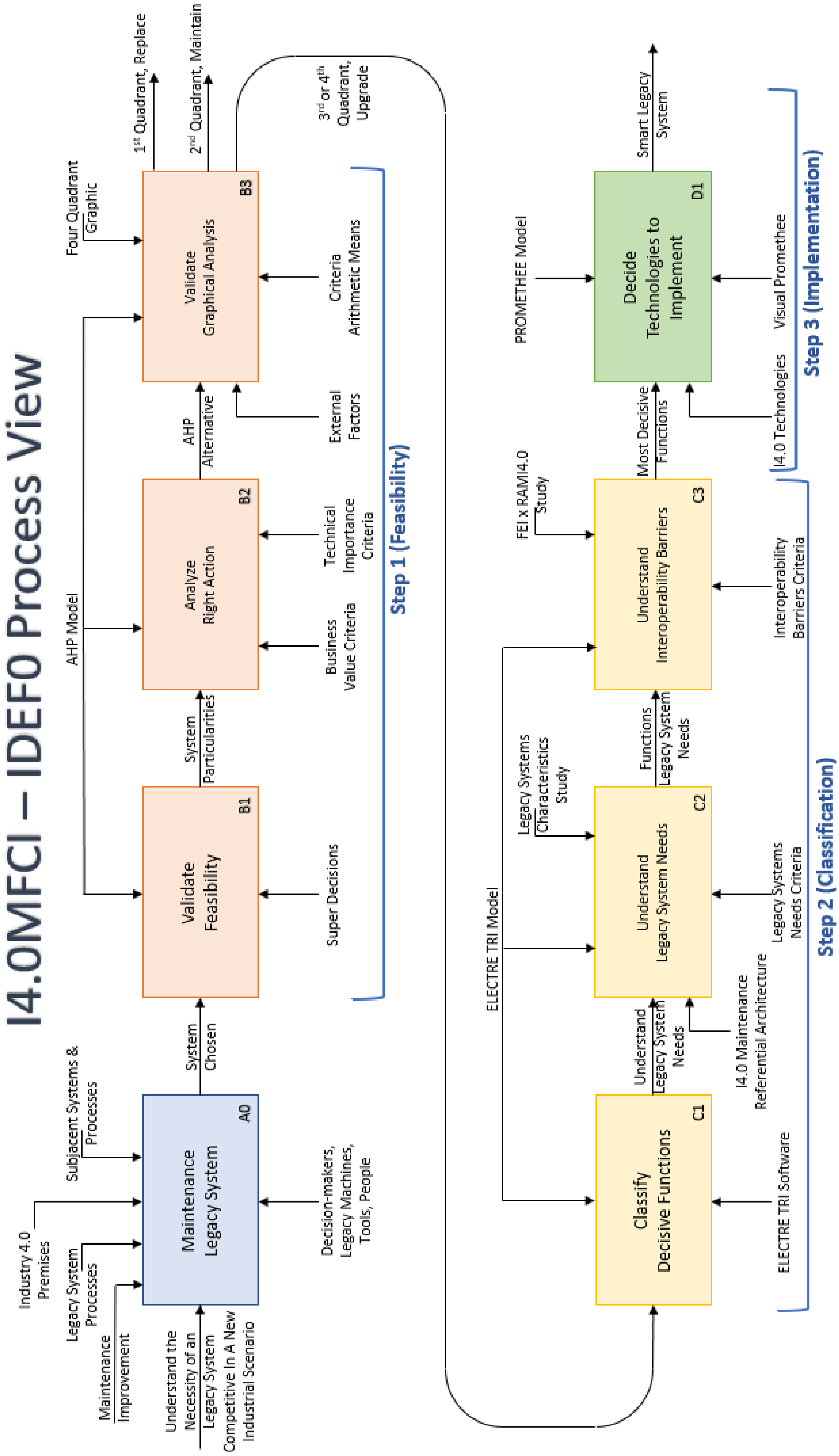



**Figure 2.9 I4.0MFCI framework in IDEF0 process view.**

In that way, it will be possible to cover each detail regarding inputs, outputs, mechanisms and controllers used in the whole I4.0MFCI framework.

The digital transformation process initiates with a blue activity representing the maintenance legacy system chosen to be upgraded. In it, is briefly discussed maintenance improvements that are expected, how is the processes regarding the system works, its subjacent systems/processes and whom will might be the organization's decision-makers involved in the deciding processes. The next activities describe the framework Step 1 in red, Step 2 in yellow, and finely Step 3 in green.

The three red activities represent the feasibility step, which intends to support a decision regarding if it is feasible to upgrade the system or not, and which strategic action will suit such answer. There the AHP method is applied.

Following the IDEF0 structure, in yellow are the activities which represent the classification step, where will be discriminated the system characteristics, what is needed for it to be upgraded to a I4.0-driven digital maintenance system. Also, here the barriers of interoperability to achieve the functions required to upgrade this system will be exposed. As demonstrated in Figure 2.9, this Step 2 only occurs if Step 1 Graphical Analysis gives the 3$^{rd}$ or 4$^{th}$ quadrants as answer.

Finely, there is the Step 3, represented by the green activity. The Implementation step intends to shows, by its specificities (i.e., barriers encountered and system's needs) provided by the decision-makers, which I4.0 technology, from a maintenance perspective, could suit better the requirements for the system to be considerate a *Smart Legacy System*. The intention of this Step 3 is to secure the best technology to be implemented in the system, aiming the best results regarding the process without compromise interoperability with adjacent systems, but more than that, improving it.

## 2.6 CONSIDERATIONS AND SECTION SYNTHESIS

This section starts presenting the background, explaining industry 4.0 and legacy systems in such way that demonstrate the importance of ICTs, bringing competitivity to a new digitally-oriented organization business model. Further, it presents the *Smart Legacy System* upgrade approach, as a strategy to combine I4.0 capabilities to legacy systems which are too critical to be stopped and so, need to receive those capabilities without compromising the current system (i.e. replacing or drastically changing it).

Also, the background section describes interoperability, corroborating the importance of advanced information and communication technologies (ICTs) actively in the industry, and how they can benefit interoperable processes. Proceeding that, concepts derived from base articles used to build the I4.0MFCI Framework methodology are presented. Intrinsically it is divided in diagnostic and decisional reference approaches, inherited from late researches. Conclusively, this section was structured in a way that could cover the theory base for this work, yet other details about methods and theory will be cover further.

Furthermore, the section explains three different multicriteria decision-making (MCDM) methods, where each one is used to support a different decision across the I4.0MFCI Framework methodological analysis.

Proceeding with this work, Section 3 will present the methodological structure from the I4.0MFCI Framework, what each step means, what to analyze in each and how to implement those analysis in a maintenance legacy system.

# 3. LEGACY SYSTEM ASSESSMENT FOR I4.0

The methodology presented in this work suggests a cube framework view (I4.0MFCI framework presented in Figure2.7, subsection 2.5), referencing each face by a sequential action that needed to be validated so that it is possible to achieve the digital transformation of a maintenance legacy system. Upgrade a legacy system to a *Smart Legacy System* (SLS) i.e. suitable for I4.0 – as it needs to interoperate with processes, business strategies and highly digital environment – is the main objective.

This framework fulfils its objective in three steps, embedding I4.0 faculties in legacy systems. Each step has a different approach, necessary in order to embed those faculties in a way that the system upgrade does not harm the organization processes and its adjacent systems. Those steps are responsible to address different MCDMs, as solutions to different decision that must be made.

In the course of this section an explanation of each step is presented, regarding the I4.0MFCI Framework, the motives related to the steps, the MCDM used in every step, why these decision-making methods matter to the step in which they are being applied, the synergy between the steps and how it contributes to the work's main frame.

## 3.1. SLS - FEASIBILITY (STEP 1)

This first step of the methodological approach operates as an evaluation model of legacy systems on digital transformation processes in industry 4.0. To that end, Step 1 proposes the combination of two diagnostic techniques that corroborate with decision-making for legacy systems, Ransom et al. (1998) and Cimitile, Fasolino and Lanubile (2001). With some effort, the methods and concepts applied in those reference works were extracted and made it possible to understand: whether maintenance legacy systems are (highly or not) prone to undergo re-engineering; if they should be ordinarily maintained; or if they can be replaced by other systems (without such change being detrimental to underlying processes). Figure 3.1 represents the framework face approached in Step 1.

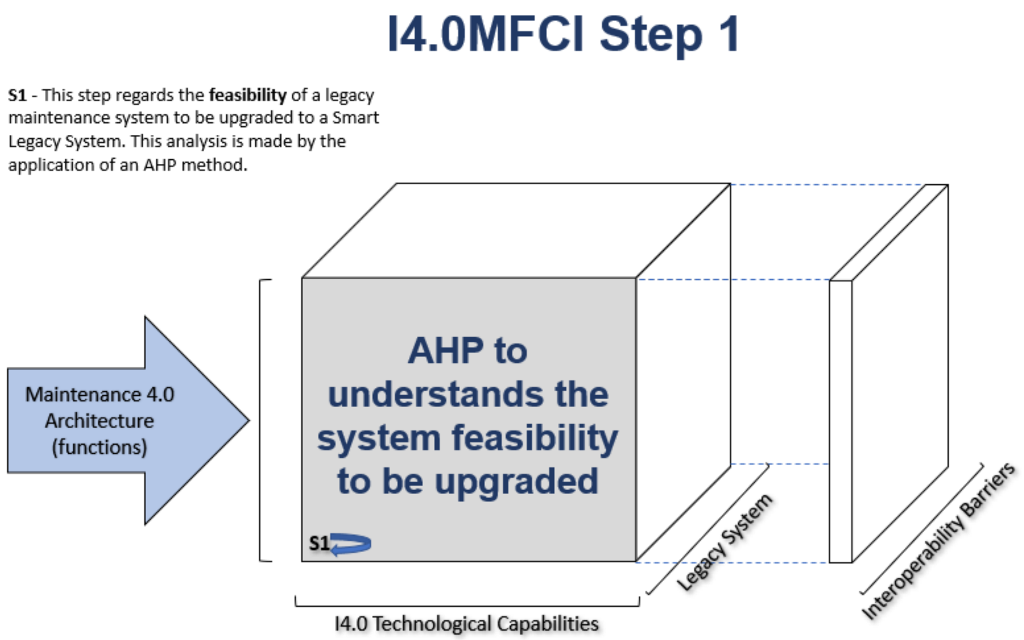



**Figure 3.1 I4.0MFCI Step 1 approach.**

The blue horizontal arrow represents the I4.0-maintenance architecture functions, waiting to the AHP analysis on the feasibility to upgrade the system, represented by the S1 face, if the system is not feasible to became a SLS the project does not continue. In this process, the criteria analyzed in the method represent the context of the maintenance legacy system within the physical and business processes of the factory. It is important to note that, for all three steps of I4.0MFCI framework, the organization's decision-makers must be chosen considering their know-how of the processes and their commitment to the whole analysis.

For this Step 1, the AHP method is applied to *weight* criteria involved in its model, with the objective to answer its main question: "It is *feasible* to upgrade the current maintenance legacy system?" To understand that, the analyzed criteria must involve questions that bring a more comprehensive view of the process (e.g., the time in which the system is in operation, how much life time it still has, what monetary gain the system brings to the organization, etc.). Thus, the feasibility to upgrade the current legacy system can be analyzed following the proposed model, separated by levels, in the Figure 3.2.

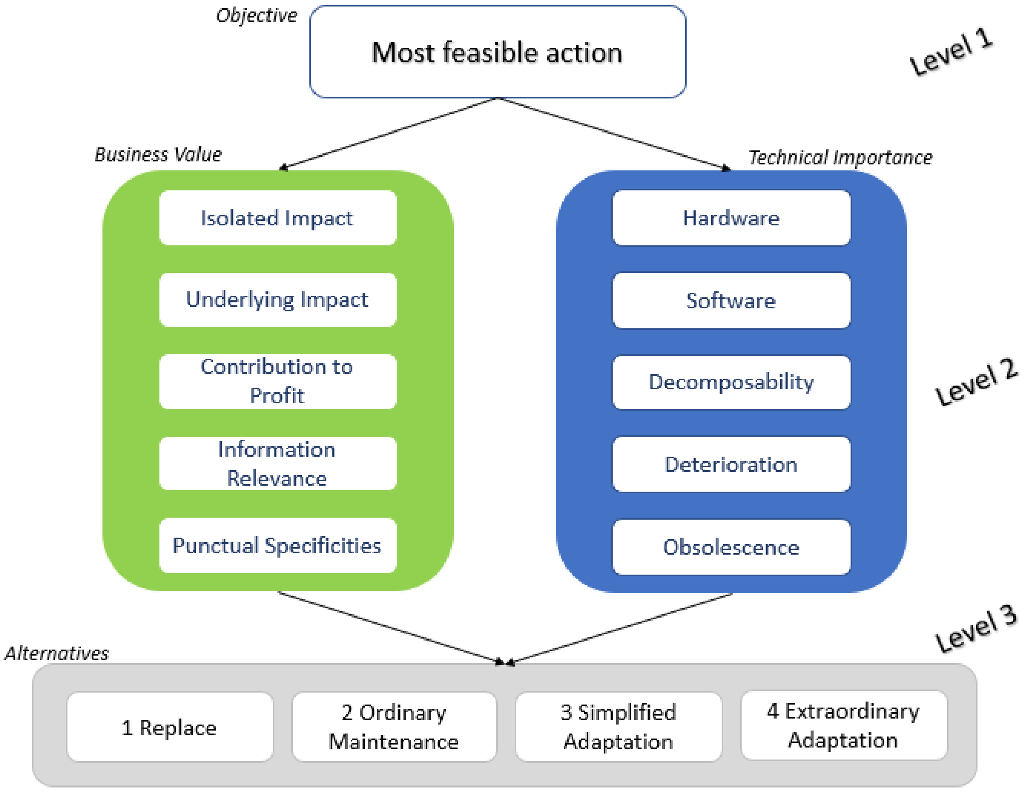



**Figure 3.2 AHP model to feasibility analysis.**

Following the AHP modelling structure the next subsections contemplates what is expected at each level.

### 3.1.1 AHP MODEL'S LEVEL 1

In the first level of this model the objective is defined and Because this decision-making method deals with a hierarchical structure, the *objective* cluster is called "*Most feasible action*", as a reference to the main objective of this step. However, this first AHP level objectifies only to understand specific details related to the legacy system.

Therefore, evaluators from within the organization must be chosen (e.g., managers, directors, IT and infrastructure specialists). At this initial level their action, as decision-makers, is to ponder in a subjective discussion (not considering the method yet), whether or not the system should be evaluated according to its:

a) Criticality for the organization - if a given system is not essential for the continuous operation of the business, initially it is not necessary to apply digital transformation actions in it;
b) Business objective - evaluators must understand the business objectives of the legacy system within the organization;
c) Current system life - factors such as the capability to maintain software and hardware operational. An example to it is, when support software becomes obsolete, the life of the system is limited making it a strong candidate for digital transformation;
d) Projection of evolution - a projection of how the system should operate after digital transformation, predicting that the digital transformation of the system supports the main elements of the business process for a considerable time;
e) Interoperability - for example, if the underlying systems are evolving to standards in which the evaluated legacy system cannot interoperate.

All of this initial analysis should be in conformity among the evaluators. However, it is necessary to reaffirm that this prior analysis is not yet present in the AHP decision method, having only the role of promoting the debate about the need to upgrade the legacy system. This can be perceived as a good practice to engage the decision-makers with what will be expected to understand applying the method. The follow paragraphs will proceed by explaining how the actual AHP method is executed after this first overview.

The term *action* (i.e. most feasible action) presented in this Step 1 objective is also called *alternative*. This happens because in the AHP method, alternatives are part of a choices cluster which the decision-makers have to make, meaning, each *alternative* is also one *action* cited before.

### 3.1.2 AHP MODEL’S LEVEL 2

Moving on in the AHP structure, the second level of the model is where the *clusters* (i.e. criteria pools) stands and they are responsible to promote the legacy system feasibility analysis. The “*Business Value*” (BV) and “*Technical Importance*” (TI) will be the *clusters* which will serve to understand the diagnostic support response of the model, at the end of the analysis. Notably the current AHP model presents a peculiarity, which uses those two clusters to positioning a final chart analysis response into quadrants, presented by the alternatives in the model's level 3, explained further.

From the *clusters* will be extracted scores (i.e. *weights*), provided by the AHP method. This happen in an analysis made by each of the decision-makers chosen at the previous model's level. Such analysis occurs by comparing five sub-criteria one by one in each *cluster*, following the pairwise comparison attributed by the AHP method. Next, each of the two *clusters* are presented following by their criteria.

*Business Value cluster* - When it comes to business value, it is understood: the importance of the system within monetary issues in the organization. In many cases, changes in the underlying business process mean that the legacy system has none or few impacts to others, that is, low value. In other cases, systems are critical to business and must be kept in operation, validating the time and effort invested in modifying or constantly maintaining such systems. The following detailed criteria correspond to *Business Value cluster* analysis:

a) *Isolated Impact* - the impact that the system causes, not directly on other systems, but individually to the processes of the organization;
b) *Underlying Impact* - represents the impact that the system has on other systems. Legacy systems can be, by definition, key processes of the organization and so, possibly, others depend on them;
c) *Contribution to Profit* - this criterion represents the weight of the system for the profit of the organization. Efforts are needed to understand how the isolated system generates profit and expenditure;
d) *Information Relevance* - understands the process data, if that data is accessible only through the legacy system, then its commercial value is critical;
e) *Punctual Specificities* - legacy system-specific functions, for example, office automation functions, can be easily replaced by commercially available products, while highly specialized and strategic domain functions cannot.

*Technical Importance cluster* - The technical environment understanding of a legacy system is the union of hardware, applied software (unique to the system), interactive subsystem software tools, and technical activities related to the process in which it participates. This measures the technical importance of the system to the organization. The criteria that correspond to the *cluster* analysis of *Technical Importance* are detailed below:

a) *Hardware* - suppliers, maintenance cost, failure rate and ability to perform function are some of the points that should be considered in this criterion. The quality of the hardware is determined by the total maintenance costs and if it is still supported. Typical hardware components found in legacy systems include mainframe, disk drives, terminals, printers, and network devices;

b) *Software* - the application software is system dependent, operating directly on the factory machine computer. In turn, a system's support software comprises components that require regular maintenance in the form of updates. Usually, there are many interdependencies between application software components, for example, some specific hardware type. Examples of supporting software components include operating systems, databases, compilers, office computing tools, network software;

c) *Decomposability* - ease with which the main components of a system are independent of each other. In an architecture where decomposability is high, applications and data management services can be considered as distinct components with well-defined interfaces. An architecture where decomposability is low consists of components that are not separable;

d) *Deterioration* - expresses the aging of a system as a result of continuous changes made, and therefore more often reaches software systems. Common maintenance is usually accomplished without respecting a system's "conceptual integrity." Deterioration is also considered when maintainers do not update documentation. It is expressed by the loss of reliability in performance, due to new errors introduced as a side effect of past changes occurred in the system;

e) *Obsolescence* - expresses the aging of a system and represents its failure to meet changing needs. The continuous progress of hardware/software platforms, programming languages and development practices makes the system outdated in a short time. This criterion represents an indirect cost, not taking the opportunity to reduce maintenance expenses, but rather to gain a foothold in the business market.

### 3.1.3 AHP MODEL'S LEVEL 3

Finally, at the third level of the AHP model a *cluster* called *alternatives* suggest the decision that best fits the score in the analysis of the previous level.

According to Figure 3.3, four quadrants are representing the decisions suggested by the AHP method and aims to assist a graphical, qualitative analysis. Whereas, if the decision score is highly uncertain nearest to the periphery of another quadrant is the answer, perceived in the graphic.

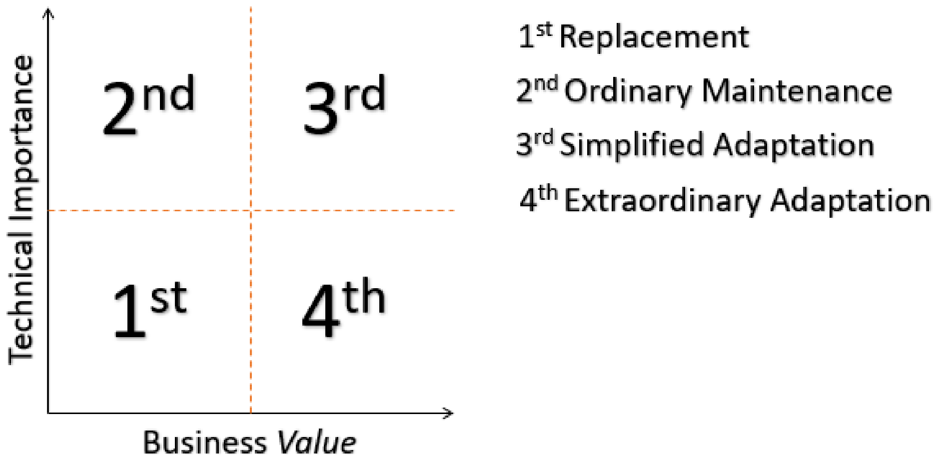



**Figure 3.3 I4.0MFCI Step 1 graphical view.**

The best action course which answers the feasibility to upgrade the system is reflected in the chart axes, that directly participate in the outcome of this decision and which were weighted at the second level of the AHP model, suggesting the following decisions that can be applied described below:

a) *Replacement* - during the replacement, the existing system is no longer maintained. For the software, this action implies the purchase of a new commercial tool. For the hardware, this replacement happens, when the machine no longer holds the technology necessary to remain operating or competitive;

b) *Ordinary Maintenance* - this quadrant represents that the best action is not to alter, but ordinarily continue to maintain the legacy system;

c) *Simplified Adaptation* - reduce system size to be maintained by eliminating dead code and removing unused functions, data, cables, antennas and peripherals;

d) *Extraordinary Adaptation* - expressed by major changes in all of the legacy system components and the way they operate.

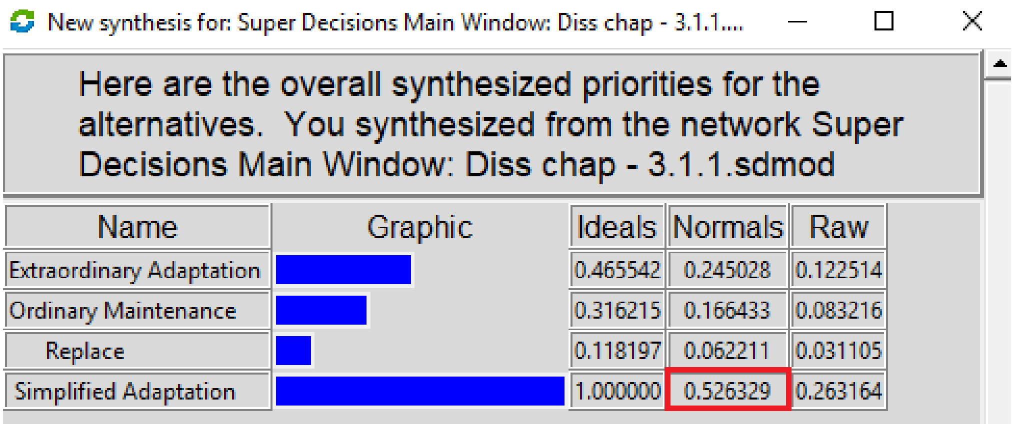
With the graphical representation it is possible to visualize how close the current action/alternative is from the others.

For actions c) and d) (3rd and 4th quadrants), it is proposed a strategy widely supported in academic researches and strongly used in the industrial environment, which implies in upgrade legacy systems gradually, providing I4.0 capabilities to it without replacing the entire system and referred in this work as: the upgrade to *Smart Legacy Systems*. Therefore, the necessary conditions to moving up to the next two steps proposed in the I4.0MFCI framework is that the Step 1 best action decided in the AHP method analysis, is permuted within the limits of the 3rd and 4th quadrants.

### 3.1.4 FEASIBILITY TO UPGRADE THE SYSTEM

Step 1 chart analysis is composed of four quadrants that represents the actions from the *alternatives* cluster. Those actions are: *Replacement*, *Ordinary Maintenance*, *Simplified Adaptation*, *Extraordinary Adaptation*; and only one of them will represent the best alternative for the legacy system, proposed by the decision-makers choices applied in the AHP method.

An AHP method experimental example was developed in the *Super Decisions* software. The analysis result expressed that the best decision to be made is the alternative that represents the 3rd quadrant, *Simplified Adaptation*, with 53% preference by Saaty’s scale used in the method, showed at Figure 3.4.




| Name | Graphic | Ideals | Normals | Raw |
|---|---|---|---|---|
| Extraordinary Adaptation | | 0.465542 | 0.245028 | 0.122514 |
| Ordinary Maintenance | | 0.316215 | 0.166433 | 0.083216 |
| Replace | | 0.118197 | 0.062211 | 0.031105 |
| Simplified Adaptation | | 1.000000 | 0.526329 | 0.263164 |

**Figure 3.4 Alternatives ranking according to the AHP method.**

After recognizing the best choice by the AHP method, a graphical analysis can be represented to help the decision-makers better understand how the chosen alternative will impact the next steps and how far it is from others.

Another key thing to remember is that, the higher the specialist's knowledge the more consistent the response tends to be. It is a concept that also can be applied for the methods in Step 2 and 3. An ideal scenario using the I4.0MFCI framework would be if the same group of specialists could participate in all three steps (i.e., operating the AHP analyzes in Step 1, ELECTRE TRI and PROMETHEE in Step 2 and 3 respectively), taking in count that they understand how the legacy system operates within the organization. Exceptionally, it will be explained further in the subsection 3.3, that the Step 3 don't necessarily require a decision-maker because it is a decision that have to be made by a digital transformation/Industry 4.0 specialist, in that case if none of the decision-makers are, the specialist applying the framework will execute Step 3 alone.

The chart analysis is also a tool that helps decision-makers to make adjusts in the final decision. An *external factor* can be considerate and validated by the decision-makers. This *external factor* acts like a criterion outside from criteria which the conventional AHP model proposes in the I4.0MFCI. A real scenario could assume a criterion, e.g. "cost of project", as an *external factor*, and this could enable the *alternative* (one of the four quadrants supported by the AHP method analysis) to be moved in the chart, if the decision-makers decides that this is convenient for the organization, demonstrated in Figure 3.5 example.

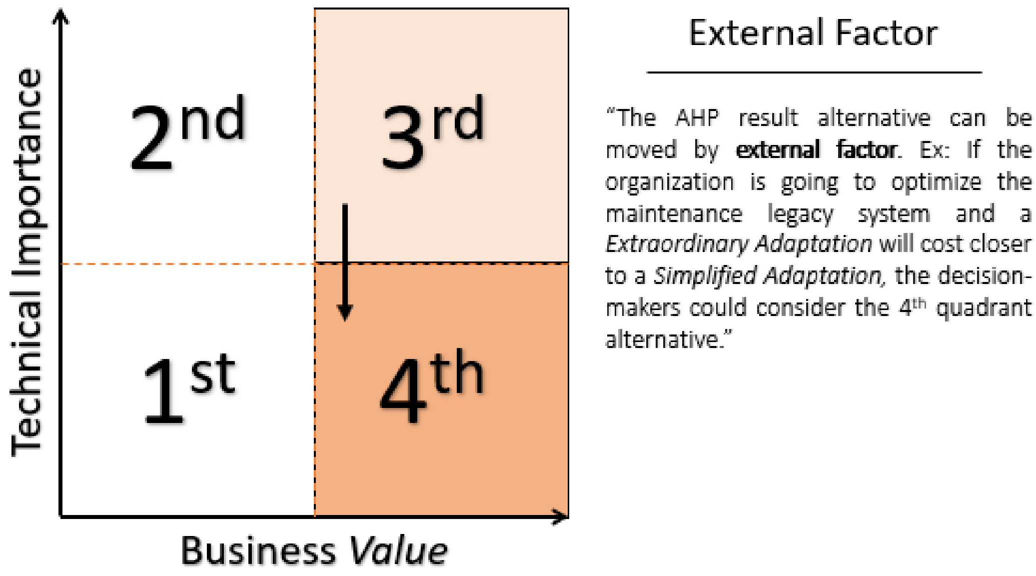



**Figure 3.5 External factor can change the final alternative.**

In the given example, "Cost of project" can be easily related to the criterion on the BV cluster, *Contribution to Profit*. However, after this criterion is considered in the AHP model's analysis, the decision-makers could interpret that: "Because alternatives *Simplified Adaptation* (3rd quadrant) and *Extraordinary Adaptation* (4th quadrant) have similar values in the AHP response, even if the best decision is *Simplified Adaptation* we still could implement an *Extraordinary Adaptation,* if the 'Cost of project' (i.e. external factor of the proposed model) is still in our budget". If even the decision of *Simplified Adaptation* is dominant, it can be changed including other pertinent *external factors* imposed by the decision-makers, specific for a particular strategy.

Conclusively, an *external factor* it is not a *criterion*. Its function is to consider any factor that can be relevant enough to change the alternative proposed by the application of the AHP method, it is a future subjective perception that have to be accepted by all the decision-makers. The "Cost of Project" supposition, considerate in the AHP model example, reflect the cost of the project at the end of all the application of the framework, as if the decision-makers are already presuming the cost of a *Simplified Adaptation* at the end of all 3 steps of the framework.

### 3.1.5 AXES INTERPRETATION AND OPTIMAL SOLUTION

*Business Value* (BV) is a strong motivator for the implementation of digital transformation in a maintenance legacy system (i.e. upgrade to SLS). Figure 3.6 represents the understanding of BV.

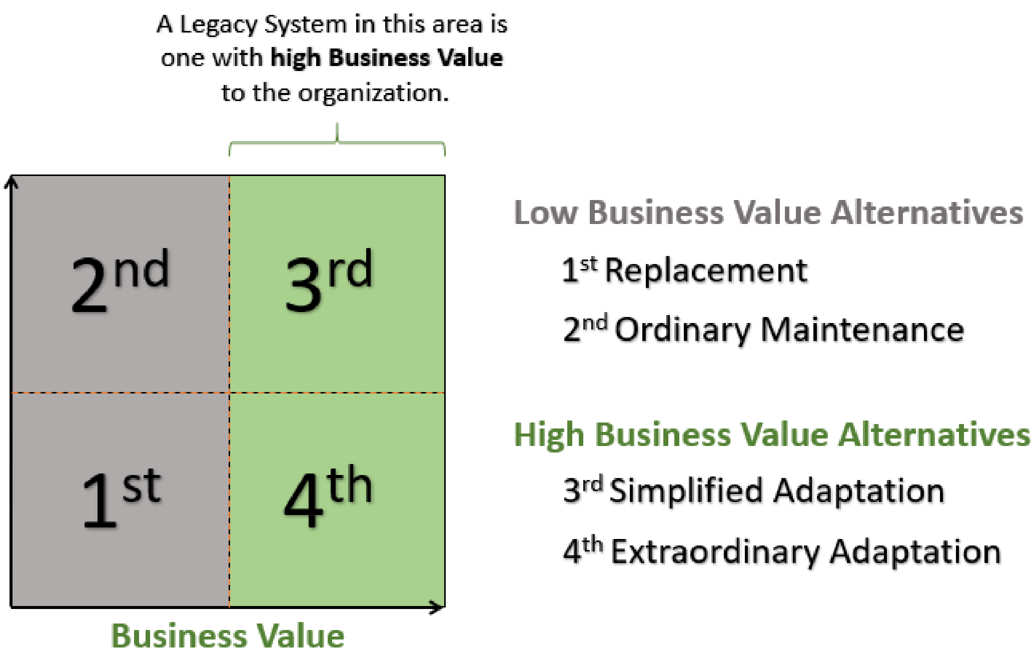



**Figure 3.6 Business Value driven alternatives.**

The previous argument is valid firstly because I4.0 capabilities will presumably bring growth and efficiency for the organization's business goals, in relation to the efficiency those capabilities could bring. Secondly because systems with great BV are strategically important to the organization, in a way that stopping them or replacing them is highly impracticable.

*Technical Importance* (TI) measures if the legacy system is highly accessible by adjacent systems, and so, stopping it would negatively impact the organization. In contrast, the legacy systems with less TI need to become highly accessible, as they could be more optimized, in a sense that those systems could be more integrated with the digital aspects existing in I4.0. Analogously to Figure 3.6, Figure 3.7 represents the understanding of TI to this Step 1 analysis.

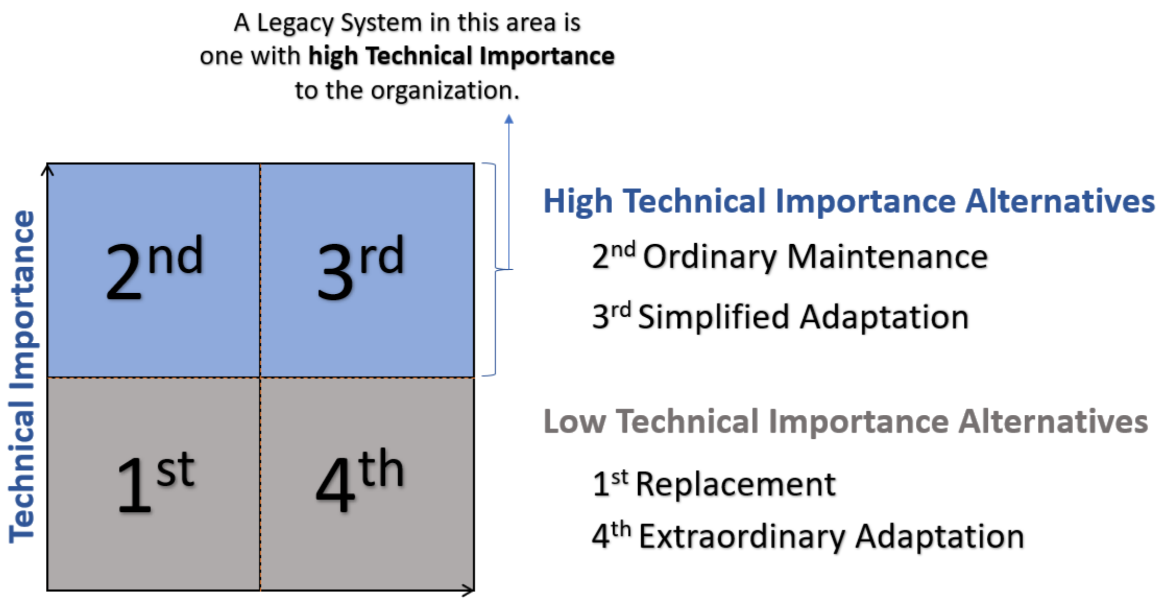



**Figure 3.7 Technical Importance driven alternatives.**

In case that the result of the AHP analysis express the 1st or 2nd quadrant as best action to apply in the maintenance legacy system, the main understanding is that the system doesn't need to be upgraded to a SLS. In parts because, if it is on the 1st quadrant, the system can be totally changed without all its legacy characteristics as it is not impactful for the organization's business; if it is on the 2nd quadrant, the system already accomplishes its needs within the processes without being changed, and also, they do not have much impact on the organization's business to justify its upgrade.

The optimal alternative to upgrade a legacy system into a *Smart Legacy System* is if it is on the 4th quadrant. Technologies inherited from I4.0 will bring more *Technical Importance* to a legacy system which already have high *Business Value* to its organization. Figure 3.8 represents the optimal alternative scenario.

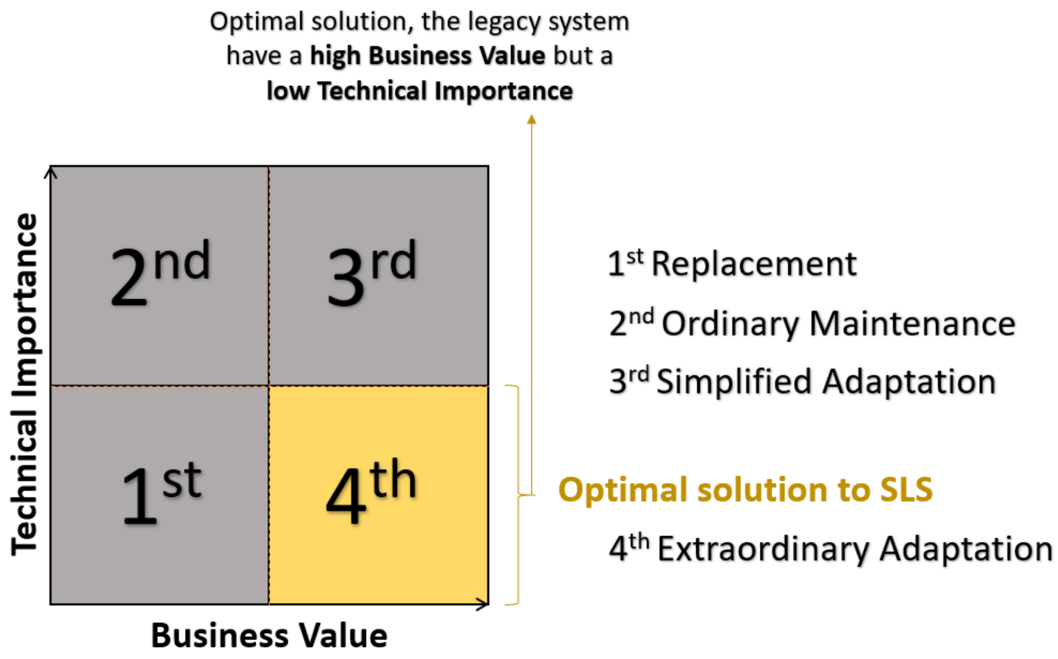



**Figure 3.8 AHP best alternative to upgrade a legacy system.**

All of those analysis will be better argued in the follow subsections. To be more specific, subsection 3.1.6 will discuss when the maintenance legacy system is not a good candidate to be upgraded to a SLS, follow by subsection 3.1.7 which intends to clarify how a system can be classified as a good candidate them, moreover, subsection 3.1.8 finely make explicit when the system analyzed is a good candidate.

### 3.1.6 ANALYSIS RESPONCE TO NOT UPGRADE TO SLS

To perform in an I4.0 environment the system must be able to communicate/trade data with the adjacent systems which are part of the process they are impacting. However, legacy systems that do not have a significant impact on the organization's BV, do not need any improvement (in order to perform in the I4.0 environment) so urgently, even in the case of the 2$^{nd}$ quadrant where the TI of the legacy system is consider high. This subsection comminutes those analysis when the action to be taken does not imply in upgrade the legacy system to an SLS, in other words, when the AHP analysis suggests the 1$^{st}$ or 2$^{nd}$ quadrants as best alternative.

If the best alternative analysis results in *Replacement*, 1st quadrant, means that the BV and the TI of the legacy system analyzed is so unimportant that even if the whole system stops and gets changed, the adjacent systems will not be harm. Yet, it is important to understand that at some point, to become a fully data driven environment, all the organization's systems must be able to interoperate in an I4.0 level of digitalization. Assuming a *Replacement* strategy implied by the AHP method, it is underattended that: "Is feasible to replace this entire particular legacy system, without upgrading it to a SLS".

That way the best course of action is to change the maintenance legacy system to perform at a I4.0 level. Because systems must be able to make quick tactical decisions, communicate and change data with each other to fully reach those faculties benefited by the I4.0, all systems in some point must be at this highly digitalized level of interoperability. But at the same time, another course of action for the 1st quadrant alternative is that, if the system by itself will not impact much the BV of the organization, it can be maintained as it is and be upgraded later on. Figure 3.9 represents the 1st quadrant as best action.

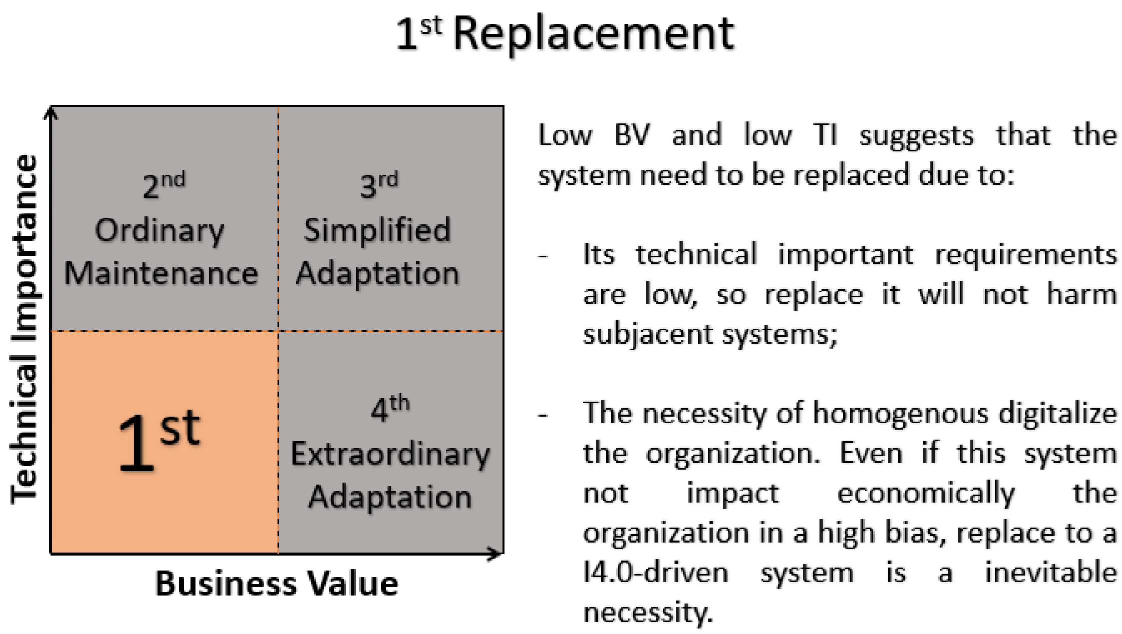



**Figure 3.9 Alternative Replacement analysis.**

Regarding the *external factors* (mentioned in subsection 3.1.4), by the graphical analysis, if the result (value) is too closer to 2nd quadrant the system can be left as it is without upgrade; if it is closer to the 4th quadrant it might be better upgrade the system by adapting I4.0 faculties in it.

In a conclusive analysis, this 1st quadrant indicates that if the digital transformation is not applied to the legacy system, at the present time, the organization will not suffer any harm. But for the sake of the homogeneity and interoperability, the system replacement to a digital I4.0 system is relevant and will not impact much its adjacent systems either.

Following the same principle, if the best action analysis supported by the AHP method results in *Ordinary Maintenance*, 2nd quadrant, it means that the legacy system analyzed will not have a significant impact to the organization, regarding *Business Value* specifications. But, different for the 1st quadrant analysis response, the *Technical Importance* of the legacy system is more impactful to the organization for a system that stands in the 2nd quadrant. This means that, this system is not so relevant to the BV of the organization but is considerate drastic to a technical point of view.

If the system stops working to be upgraded, and stands on the 2nd quadrant, subjacent systems and processes which depends on it may suffer a negative impact. In this case, the course of action will be to ordinarily maintain the system as it is.

This happens because the system can accomplish its purpose (by doing what it does, the way it does) despite the lack of technological capabilities/resources. It also means that the system can still ordinarily interoperate with other subjacent systems, and so, change its core faculties to perform in an I4.0 scenario will not bring imminent or significant impact to the organization’s BV.

Thus, still in the 2nd quadrant, if this AHP response value is closer to the 3rd quadrant value, the action can be interpreted as: “A system which is almost valuable enough in terms of business specificities, however, its technical importance will be critical, and so, until the system becomes important enough to the BV of the organization (by future analysis), it will be ordinarily maintained”. Figure 3.10 represents this analysis.

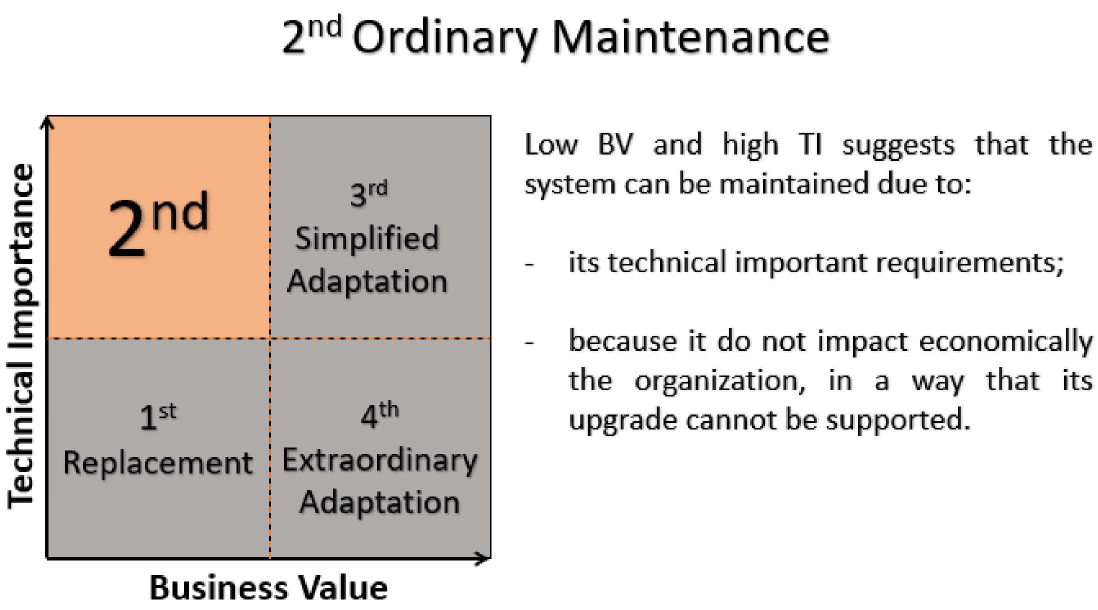



**Figure 3.10 Alternative Ordinary Maintenance analysis.**

Conclusively, for this 2nd quadrant the *Technical Importance* is such that the legacy system needs to be constantly in operation, but its impact on the organization's *Business Value* is so minimal that at the present time its upgrade is not justifiable.

The next subsection regards how to identify a good candidate to become a SLS, which is essential to understand subsection 3.1.8, that will present the analysis responses (3rd and 4th quadrants) to actually upgrade a legacy system.

### 3.1.7 IDENTIFYING A SMART LEGACY SYSTEM CANDIDATE

For a legacy system to be improved (receiving I4.0 faculties), it must be at a high level of BV for its organization. Different from the 1st quadrant response analysis, total *Replacement*, which imply that a system can be changed completely to receive I4.0 capabilities (without critically harm adjacent systems/processes), the response analysis of the 3rd and 4th quadrants propose a strategy of gradually implement features to digitalize the maintenance legacy system, upgrading it to a *Smart Legacy System*.

A general analysis of each one of the quadrants so far, implies that, the quadrants 1 and 2 are chosen by technical parameters. The 1st quadrant analysis says that the system is so irrelevant in a technical perspective that if it is changed, the adjacent processes will not be harmed, so the system can be replaced by a I4.0 system, benefiting even if in some lesser degree, both BV and TI. Looking to the 2nd quadrant, it is understandable that the system's TI is high, and because of that, may not be wise to upgrade the system at the moment, to not compromise its adjacent systems.

The quadrants perspective changes when it comes to the *Business Value*, which is, when the AHP method response suggest one of the alternatives that crosses de middle of *x-axis*, represented Figure 3.6 (subsection 3.1.5). In other words, when the analysis response of the AHP method indicates the 3rd or 4th quadrant as best alternatives. For those cases, it will be feasible for the organization to apply the proposed SLS upgrade.

SLS upgrade means to *gradually* implement sensors, data collection, advanced analysis, IoT, mobile, predictivity, or autonomous capabilities to the legacy system. *Gradually* in the sense that, the maintenance legacy system will continue to operate, while making gradual (tangible) actions of implementing digital transformation in that system, without bringing harm to its underlying/adjacent systems that are operating and may be critical to the organization.

Therefore, I4.0MFCI framework suggests that, upgrade to *Smart Legacy System* means to *gradually* implement I4.0 capabilities (digital transformation) into a maintenance legacy system, making it more efficient and bringing growth to the organization. At the same time, that will not compromise, but contrariwise, will bring more interoperability between the organization's systems and processes adjacent to the legacy system analyzed. Based on the analysis made, the next subsection deals with the cases where the analysis agrees with the upgrade action of the legacy system for an SLS.

### 3.1.8 ANALYSIS RESPONCE TO UPGRADE TO SLS

The concept of SLS upgrade is important to totally understand the other two alternatives suggested by the AHP method. Those are the ones driver by their importance in *Business Value*, quadrants 3 and 4.

When the Step 1 AHP analysis suggests the 3rd quadrant as best alternative, it is feasible but not urgent, to upgrade a maintenance legacy system to a maintenance SLS. The alternative of *Simplified Adaptation* represents a legacy system that has high TI and BV to the organization. However, as explained in a previous subchapter, high BV is a strong motivator for the implementation of digital transformation, whereas high TI makes this implementation less attractive, due to its present interoperability criticality with its subjacent systems. Figure 3.11 shows the 3rd quadrant analysis.

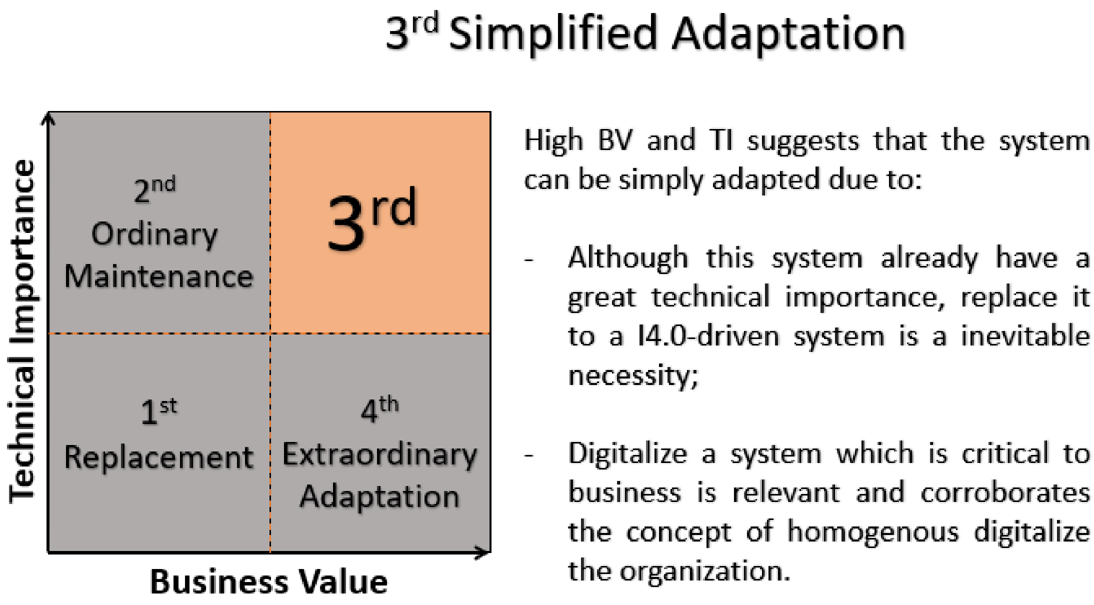



**Figure 3.11 Alternative Simplified Adaptation analyses.**

Reinforcing that analysis, upgrade a legacy system which is monolithic and highly accessible by other systems, i.e. high TI, need to be a “gradual” process. If not, changes in protocols, machines and tools can compromise subjacent systems/processes. Besides that, the implementation of I4.0 capabilities might not bring as many changes to the legacy system that already have good TI.

However, if the AHP method suggests the 4th quadrant as best alternative, means the legacy system is not valuable enough in a technical point of view, i.e. low TI. Figure 3.7 in subsection 3.1.5 already exemplifies this analysis.

I4.0MFCI framework suggest that: “The need to implement I4.0 capabilities in legacy systems – upgrading them to *Smart Legacy Systems* – it is, briefly, a need to bring more *Technical Importance* (TI), to a system which has highly *Business Value* (BV). So, the best course of action (alternative) to implement the SLS upgrade for a maintenance legacy system is considered when the response of the Step 1 AHP's analysis is represented in the 4th quadrant." Figure 3.12 detailed it.

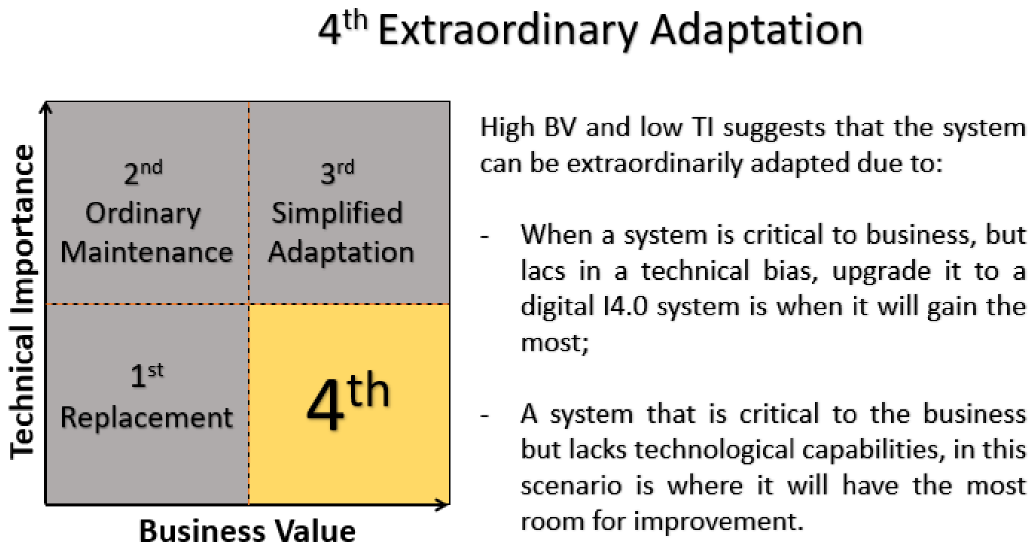



**Figure 3.12 alternative Extraordinary Adaptation analysis.**

The chart analysis was developed in this work as a tool to make final decision adjustments, under external factors decided by the decision-maker, in the case a second-best decision is closer to the method best decision supported. As an example: "If in the AHP final response says the 4th quadrant is chosen, but the second-best answer (close to it) is the 3rd quadrant, it means that the system's TI is almost critical enough to consider a *Simple Adaptation*. So, like may happen in the others graphical analysis, *external factors* can be imposed by the decision-makers, which could slightly change the alternative suggested by the AHP method".

Similarly, still in the 4th quadrant (looking to the left of it) if the second-best value points to the 1st quadrant, it means that the BV of the system to the organization may be not so critical, in some sense that, it is almost preferably to *Replace* the legacy system to an entire new I4.0 smart system, regarding again *external factors*.

Those *external factors* cases are cited to put on perspective how they can contribute to the final course of action of a feasibility evaluation submitted by the AHP method response, as the MCDM method's role could be seen more as supportive than definitive. Conclusively, when a legacy system has a high BV but a low TI, to the organization, the best scenario is to apply the SLS strategy, implicit in the alternative of *Extraordinary Adaptation*.

In this whole Step 1 the evaluators can understand by a set of pairwise comparisons (AHP method), in two different *clusters* (TI and BV), if it is feasible to upgrade their maintenance legacy system. If this answer is "no" (2nd quadrant), them the system should be maintained as it is. Otherwise, with a "yes" answer, they should interpret the results that will suggest: if it is better replace the entire system (1st quadrant alternative); or apply the SLS upgrade (3rd quadrant simple adaptation or 4th quadrant extraordinary adaptation), in such way that the new smart-maintenance legacy system will bring better efficiency towards less losses.

## 3.2. SLS - PARTICULARITIES TO UPGRADE (STEP 2)

The I4.0MFCI Framework's Step 2 methodology is structured to understand which functions, of a referential I4.0 maintenance architecture, are the most *decisive* to be implemented in the maintenance legacy system analyzed on the previous step. Those architecture functions will be considered *alternatives* that will be chosen, in a new decision-making method, relating *interoperability barriers* (representing negative-impact traits, representing criteria to be minimized – cost criteria) and *legacy system necessities* (representing positive-impact traits, representing criteria to be maximized – profit criteria).

Thus, working with a MCDM method named ELECTRE TRI, decision-makers will make their decisions in a way that such method will classify the I4.0 maintenance functions in four groups, by how decisive the referential architecture functions are to the enterprise's legacy system. *Decisive* functions comprehend all of the best classified ones, meaning: (1) those whom better suit the legacy system *needs*; (2) but also those whom *can* be implemented, even if they generate interoperability barriers. Figure 3.13 represents the I4.0MFCI framework Step 2 (i.e. a view after its first rotation).

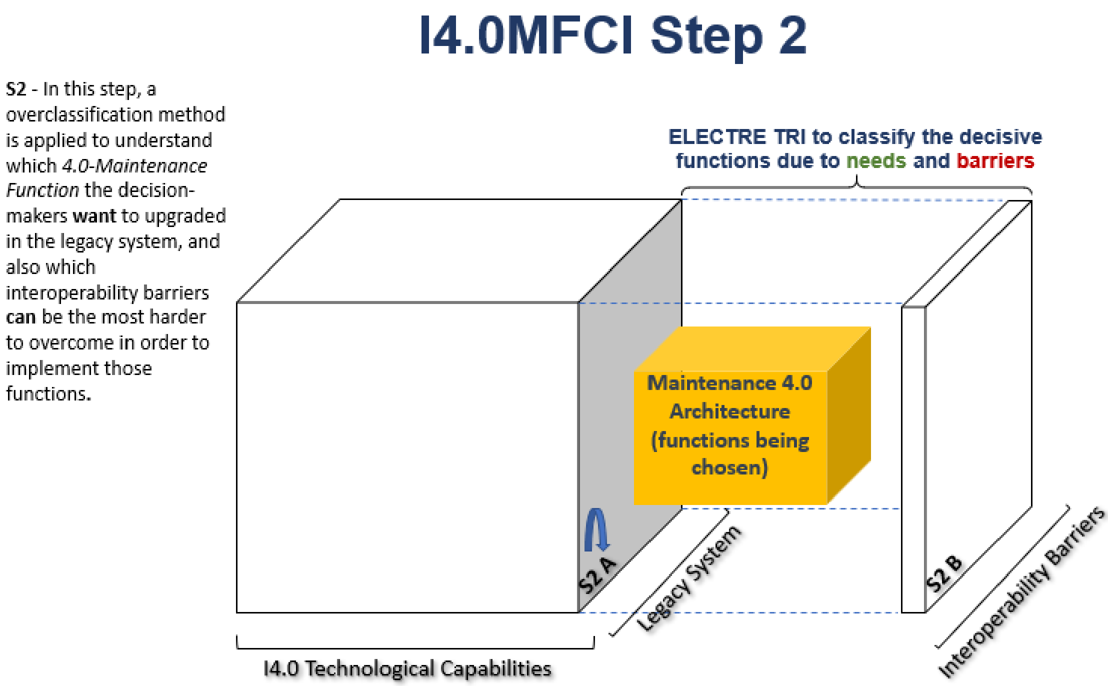



**Figure 3.13 I4.0MFCI Step 2 approach.**

It can be noticed that the horizontal arrow in the Step 1 approach has being consumed by the cube, representing that once the feasibility to upgrade the system is guaranteed, the I4.0 maintenance architecture is applied to the analysis. Now, in this step, the architecture functions must be chosen regarding the legacy system needs to became a SLS and its interoperability barriers (opposing to it). Therefore, the parallel white rectangle represents the interoperability barriers delimitating the amount of space (i.e. necessities) the architecture functions can cover.

Step 1 explained why it is feasible to a maintenance legacy system receive I4.0 faculties without being changed completely. If the answer permutes in somewhere between the 3$^{rd}$ & 4$^{th}$ quadrant, it means that the legacy system is important to the organization business and had proved its validity to receive, gradually, I4.0 capabilities without replacing the system. In the case of the 4$^{th}$ quadrant alternative, the *Extraordinary Adaptation* strategy, the pertinence to implement I4.0 capabilities are even higher, because there is more space for improvement in relation to the technical aspects that the system could provide for the organization i.e., higher growth differential to the system's *Technical Importance*.

The MCDM used in this Step 2 is the ELECTRE TRI, envisaged by Bernard Roy "… *overcome some deficiencies of popularly used MCDM tools to deal with ordinal attributes without the need for transforming them into cardinal values*." (Chatterjee, Mondal, & Chakraborty, 2014). This method requires another one to *weight* the criteria evaluations for the alternatives, which will be the MUDGE method, explained further. The decision matrix, representing the *criteria* versus *alternative*, may include preference information expressed as weights, thresholds, and other (subjective) parameters.

There are different variations of THE ELECTRE family, and the one used in this work is the ELECTRE TRI, a multi-criterion sorting method which "*assigns alternatives to some predefined categories*" (Mousseau, Slowinski, & Zielniewicz, 2000). As described in Rangel, Gomes, & Moreira (2009), the preference model is an outranking relation and parameters involved are *criteria weights* and various thresholds on each of the *criteria*. The assignment of any *alternative* results from the comparison with the profiles defining the limits of the categories/classes. Figure 3.14 shows a sketch of ELECTRE TRI method model.

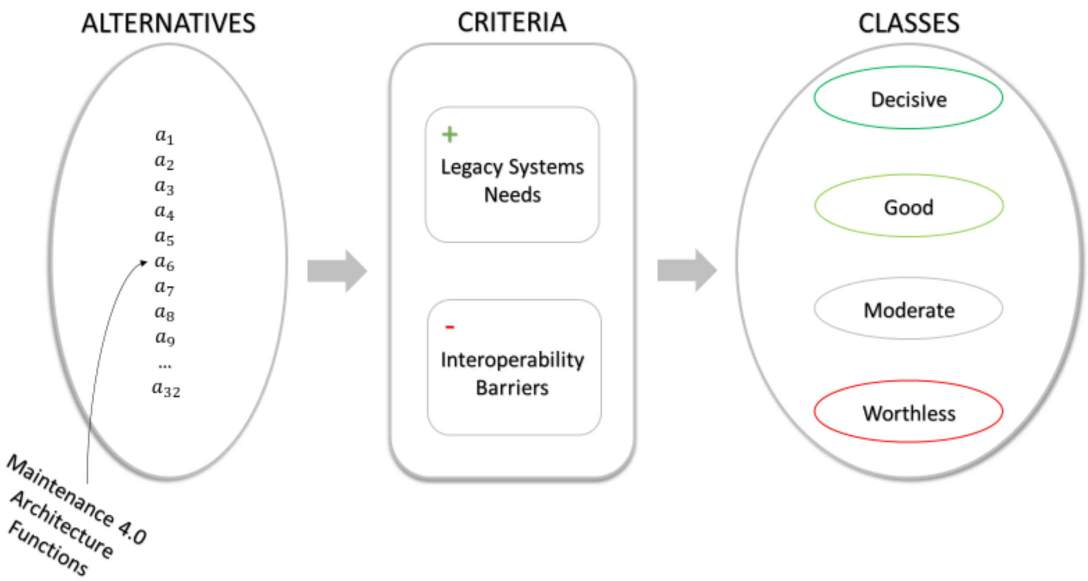



**Figure 3.14 ELECTRE TRI model to classify the most decisive functions for a legacy system.**

To make this step more comprehensible, each stage of the decision-making method used will be expressed in three distinct *research contexts* (*alternatives*, *criteria* and *classes*) that polarized themselves, relating that Step 2 problematics into the ELECTRE TRI model utilized.

### 3.2.1 ALTERNATIVES RESEARCH CONTEXT

The *alternatives* to be chosen by the MCDM approach of this Step 2 are I4.0 maintenance architecture functions. This architecture is aligned to PPGEPS (Programa de Pós-graduação em Engenharia de Produção e Sistemas – at PUCPR university) researches regarding maintenance systems and the application of industry 4.0 concepts to improve their requirements. One of the researchers, Guiherme L. Brezinski, proposes in his dissertation – (PROPOSTA DE CRIAÇÃO DE UM FRAMEWORK DE ARQUITETURA ORGANIZACIONAL PARA IMPLEMENTAÇÃO DOS CONCEITOS DA INDÚSTRIA 4.0 NO SETOR DE MANUTENÇÃO INDUSTRIAL) – an architecture that contemplates how I4.0-maintenance architectures are organized. Conclusively, this architecture is a work that underlines I4.0-maintenance aspects/functions, business roles, actors, services, and events. Thus, the Step 2 from this present work glimpses to embed I4.0 capabilities to maintenance legacy systems, based on maintenance functions from a referential architecture, proposed by Brezinski.

The architecture from M4.0EAF (Maintenance 4.0 Enterprise Architecture Framework) put in perspective six main *courses of action*, based on TPM (Total Productive Maintenance), which are guided by main functions. Thus, these functions can access some I4.0 maintenance systems actions, that are only capable to operate in their full potential when a system is embedded to a high digital-driven environment, i.e. when the system is a *cyber physical system*. In that way, the primary goal of these functions is to drive organization maintenance processes to *zero waste*.

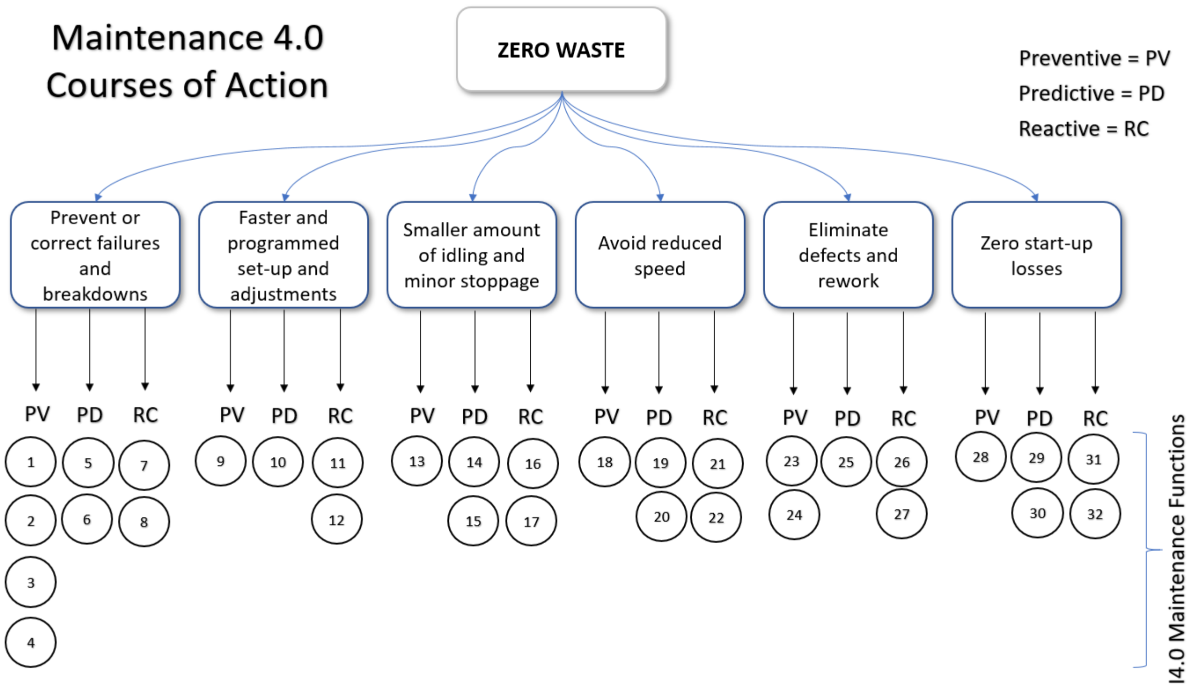



**Figure 3.15 M4.0EAF six courses of action.**

In the Figure 3.15 the six courses of action, represented in the architecture are the follow: Prevent or correct failures and breakdowns; Fast and programmed set up and adjustment; Smaller amount of idling and minor stoppage; Avoid reduce speed; Eliminate defects and reworks; Zero startup losses. Those courses of action are based on the six big losses from TPM (total productive maintenance). Also, this referential architecture separates each course of action into three approaches: *predictive*, *preventive*, and *reactive* approaches; where every one of them is responsible for determined set of maintenance functions.

Firstly, when preventive maintenance fail, it is necessary reactive countermeasures approaches. Reactivity is related by *corrective maintenance*, and exists in manufacturing sectors as well as services. An example of corrective maintenance activities can be the fix of a robot (suddenly broken), by an outsourced maintainer, characterizing a typical corrective approach for a none-predicted break. Projections from maintenance in the I4.0 supports that reactive approaches will gradually be replaced by predictive approaches, which intend to predict maintenance actions before the problem could cause damage to the system's process/machine. Eventually, corrective maintenance will always be necessary in some point. Even if future technologies can predict punctual actions to counteract something harmful or undesirable in the system, there could be uncertain factors that will justify corrective (unpredicted) measures.

*Preventive* approaches are today, the most applied in the maintenance context. Preventive maintenance is regularly performed on equipment to reduce the likelihood of failure. In terms of future trends, preventive maintenance can also lose some space to predictive maintenance, because trying to prevent the break of a machine is an approach less assertive than actually predict that the machine will break.

The *predictive* approaches in maintenance shares data-driven principles that are also essential I4.0 characteristics. Predictivity is aligned with the purposes of information and communication technologies digitalization. Means that, exchange data in the fastest way possible on an algorithmically smart environment enables predictivity occurs in its ideal conceptual biases. Predictive maintenance enables new perspectives of manufacture, more reliability and less loses.

For every courses of action regarding the referential architecture, there will be a *reactive*, *preventive* and *predictive* approach which assigns the maintenance functions in more granular specificities, as can be seen in Figure 3.15. These functions will be consumed by the ELECTRE TRI method, and used as *alternatives*. This means that, the method intent to classify the most decisive functions to be implemented in the maintenance legacy system. The I4.0 maintenance architecture functions, represented by the ELECTRI TRI *alternatives*, are showed in Table 3.3.

**Table 3.1 ELECTRE TRI alternatives (i.e. I4.0 maintenance functions).**

| M4.0EAF Courses of Action | Approach | Alternative ID | Maintenance Function |
|---|---|---|---|
| Prevent or correct failures and breakdowns | Preventive | a1 | Equipment upgrade to prevent failures |
| | | a2 | Improvement due to education and training |
| | | a3 | Preventive decision making to prevent failures and breakdowns |
| | | a4 | Inspection routine to prevent or correct failures |

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| | | | |
| | Predictive | a5 | Predictive maintenance due to predictive plan |
| | | a6 | Predictive decision making to prevent failures and breakdowns |
| | Reactive | a7 | Corrective maintenance to correct failures due to service execution |
| | | a8 | Corrective decision making to correct failures due to analysis |
| Faster and programmed set-up and adjustments | Preventive | a9 | Preventive decision making due to schedule |
| | Predictive | a10 | Predictive decision making due to setting time |
| | Reactive | a11 | Corrective adjustment due to a faster and programmed set-up |
| | | a12 | Corrective decision making to a faster set-up due to analysis |
| Smaller amount of idling and minor stoppages | Preventive | a13 | Preventive decision making for smaller amount of idling |
| | Predictive | a14 | Machine to machine communication due to report management |
| | | a15 | Predictive decision making to smaller amount of idling |
| | Reactive | a16 | Corrective maintenance to less stoppage service |
| | | a17 | Corrective decision making to a smaller amount of idling due to analysis |
| Avoid reduced speed | Preventive | a18 | Preventive decision making to avoid reduce speed due to KPIs |

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|---|---|---|---|
| | Predictive | a19 | Facility alignment to avoid reduce speed |
| | | a20 | Predictive decision making to avoid reduce speed |
| | Reactive | a21 | Corrective maintenance to avoid reduce speed due to service execution |
| | | a22 | Corrective decision making to avoid reduce speed due to analysis |
| Eliminate defects and rework | Preventive | a23 | Cost optimization to eliminate defects and rework |
| | | a24 | Preventive decision making to eliminate rework |
| | Predictive | a25 | Predictive decision making due to quality monitoring to eliminate defects |
| | Reactive | a26 | Corrective maintenance to eliminate rework |
| | | a27 | Corrective decision making to eliminate defects due to analysis |
| Zero start-up losses | Preventive | a28 | Preventive decision making to less start-up losses due to system integration |
| | Predictive | a29 | Startup planning to zero losses due to validation test |
| | | a30 | Predictive decision making to zero start-up losses due to acquired data |
| | Reactive | a31 | Corrective maintenance to less start-up losses |
| | | a32 | Corrective decision making to zero start-up losses due to analysis |

### 3.2.2 CRITERIA RESEARCH CONTEXT

Legacy systems and interoperability are both part of the second research context representing the ELECTRE TRI *criteria* which will be used to weight the *alternatives* to the framework's Step 2. Thus, the I4.0 maintenance architecture functions will be chosen by their *decisiveness*, meaning: (1) those most needed functions that the decision-makers *want* to implement in the legacy system; (2) but also those functions that *can be* implemented, generating less interoperability barriers possible.

Decision-makers will, for the Step 2, make their decisions regarding the relation between two tied contexts, what is *wanted* against what *can* be implemented in the legacy system analyzed. At first hand, "what is *wanted* to implement" represents positive traits, so the decision score in these criterion pool, i.e. *cluster* (1), will classify the maintenance function as *more critically decisive*. In the other hand, "what the system *can* implement" represents negative traits and the decision score, regarded as *cluster* (2), classifying the maintenance function as *less critically decisive*. These contexts are specified in sequence with more detail.

#### 3.2.2.1 WHAT DECISION-MAKERS WANT TO IMPLEMENT

*Cluster* (1) – "Expresses what is *wanted* to implement in the maintenance legacy system". All 32 functions represented in the reference architecture would be essentials for a maintenance system operates in a fully I4.0 manufacture environment. However, the objective of the SLS implementing strategy is to embedded I4.0 capabilities gradually, without stop or replace the system. In that case the decision-makers would focus in choose the most relevant functions to be implemented in the maintenance legacy system. Other case will be if a relevant function is already contemplated in the legacy system, it would still carry the characteristic of legacy but contemplating some I4.0 capability.

Another motive to choose exceptionally the most relevant functions regards cost e.g., if the organization can only spend a determined amount of capital in the maintenance system, certainly not all 32 maintenance functions suggested by the reference architecture can be embedded in that system.

The criteria from the *cluster* (1) where conceived after a legacy systems bibliography review. Firstly, among articles, books and white papers researched about legacy systems, eight prepositional main traits were described earlier, in section 2.1.2. Secondly, from those eight main traits, in order to perform in the I4.0 environment, were proposed "necessities" that legacy systems have. Also, these necessities are leveled by their capabilities. Table 3.4 presents those legacy system necessities and also, their description by capability level.

**Table 3.2 Legacy system necessities level.**

| Criteria (Legacy System Necessity) | Necessity Level | Description |
|---|---|---|
| Trait 1 - Expenses optimization | Level 1 | No optimization. |
| | Level 2 | Optimization driven by simple database feedback. |
| | Level 3 | Expenses optimization are integrated with data gained. |
| | Level 4 | Some degree of predictability based on gained data. |
| | Level 5 | Predictivity to expenses optimization based on gained data, driven by intelligent algorithms. |
| Trait 2 - Business alignment | Level 1 | No service related to IT; selling standardized products. |
| | Level 2 | Online portals; Sales/consulting regarding production. |
| | Level 3 | Service execution directly via product; Sales, consulting and adaptation meeting customers specification. |
| | Level 4 | Independently performed services; Additional sale of product-related service. |
| | Level 5 | Complete integration into infrastructure of IT services; Sale of production functions. |
| Trait 3 - Communication potential | Level 1 | No communication interfaces. |
| | Level 2 | System sends or receives I/O signals; Systems have field bus interfaces. |
| | Level 3 | System has industrial ethernet interfaces. |
| | Level 4 | System has access to the internet. |
| | Level 5 | System has access to internet without oscillations or losses. |

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|---|---|---|
| Trait 4 - Standard formalization | Level 1 | No standard definition. |
| | Level 2 | Defining basic information protocols; Mail and telecommunication. |
| | Level 3 | Uniform data and protocols formats and rules for data exchange. |
| | Level 4 | Uniform data and protocols formats and interdivisional linked data servers. |
| | Level 5 | Fully formalized data and protocols; Inter-divisional, fully networked IT solutions. |
| Trait 5 - Risk management control | Level 1 | No monitoring. |
| | Level 2 | Maintainer monitoring. |
| | Level 3 | Recording of operating condition for diagnostic purposes. |
| | Level 4 | Prognostic of its own functional condition. |
| | Level 5 | Independently adopted control measures. |
| Trait 6 - Flexibility | Level 1 | No communication interface; Rigid production. |
| | Level 2 | Field bus interfaces; Flexible production and identical parts. |
| | Level 3 | Industrial Ethernet; Modular designs for the products. |
| | Level 4 | Machines have access to internet; Component-driven flexible production (within the company). |
| | Level 5 | Web services independent machine; Component-driven flexible production in value-adding networks. |
| Trait 7 - Technological capability | Level 1 | Manual actions in the system's process; No use of sensors/actuators. |
| | Level 2 | Production line and electronic tools; Sensors, actuators integrated and local user interface. |
| | Level 3 | Automated technological capabilities and mobile tools; Sensor reading are processed by the system and decentralized monitoring/control. |
| | Level 4 | Digitalization capabilities and mobile tools; Data evaluated for analyses be the system via intelligent data-driven algorithms. |
| | Level 5 | Autonomous decision-making and AI capabilities; System |

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|---|---|---|
| | | independently responds based on the gained data and augmented assisted reality. |
| Trait 8 – Towards-the-system data-integration | Level 1 | No processing of data. |
| | Level 2 | Storage of data for documentation; Individual identification. |
| | Level 3 | Analyzing data for process monitoring; Product has a passive data storage. |
| | Level 4 | Evaluation for process planning and control; Product with autonomous information Exchange. |
| | Level 5 | Data enabling automatic process planning and control; Data and information exchange as integral part. |

A preposition admits that, because the legacy system analyzed must be known by the decision-makers, they are also aware of the system necessities regarding the main traits. Following that preposition and as Table 3.4 suggests, the criteria chosen to classify the most decisive maintenance functions to be implemented in the legacy system are, in that case, the system necessities due to: *Expenses optimization level*; *Technological capability level*; *Flexibility level*; *Standard formalization level*; *Business alignment level*; *Risk management control level*; *Towards-the-system data-integration level*; *Communication potential level*. The syntactic interpretation from each criterion in *cluster* (1) are follow explained.

Expenses optimization level – This criterion measures the potential of cost reduce the legacy system needs to provide;

Business alignment level – Measure how much infrastructure the legacy system needs, in order to obtain business alignment;

Communication potential level – How much communication accuracy with other processes and systems the legacy system needs to improve;

Standards formalization level – Measure how much protocols and data formalization the legacy system needs in order to communicate towards its adjacent systems/process;

Risk management control level – Interpreted as the measure of monitoring and control a legacy system needs to perform digitalized duties;

Flexibility level – Express how much independent a legacy system needs, to operates along with the digital production or service in which it operates;

Technological capability level – This criterion measure how digitalized, autonomous, sensor-driven and the level of tools complexity a legacy system needs;

Towards-the-system data-integration level – This last criterion measures the degree of data information a legacy system need exchange between processes, other systems or products.

It is perceived that this *cluster* (1) have a subjective measure scale to each one of its *criteria*. The motive of that is because the *alternatives* which are trying to be measured are "*maintenance functions*". Thus, those functions needed to be chosen in relation to the differential they will bring for the organization's maintenance legacy system, by a comparison between them over a levels-based magnitude measure. Jahedi & Méndez (2014) examine the performance of subjective measures relative to objective ones and by doing that, it was distinguished between two types of subjective measures: *specific* and *general* (the second characterizing the *criteria* used in the current work). Still according to Jahedi & Méndez (2014) – "*Specific subjective measures* are derived from survey questions that ask about well-defined concepts that can be observed in principle such as – the amount of money paid in bribes (i.e. the specific amount). *General subjective measures* are derived from questions that ask about broad concepts, such as – the level of corruption (i.e. scale measure levels)".

Therefore, for this Step 2, in order to measure those *alternatives* (32 referenced maintenance I4.0-architecture functions), the decision-makers will have to choose the most decisive functions in relation of *subjective* criteria (8 main traits needed to make legacy systems operable in I4.0 environment). Jahedi & Méndez (2014) work support subjective criteria, indicating that – "…*general subjective* measures can effectively capture changes in both the explicit and the implicit components of the variable being measured and, therefore, that they can be better suited for the study of broadly defined concepts than objective measures".

Conclusively, for the ELECTRE TRI method applied in this Step 2, the *criteria* will be characterized by *general subjective* measures. That way, its broadly defined concepts can reach the necessary understand to compare maintenance functions between them.

#### 3.2.2.2 WHAT DECISION-MAKERS CAN IMPLEMENT

*Cluster* (2) – “Expresses what *can* be implemented in the maintenance legacy system”. If in one hand, there are *criteria* that decision-makers should choose in order to classify maintenance functions that they *want* to implement in the legacy system, on the other hand, not all functions *can* be easily implemented without generating interoperability barriers for the system. This problem relates that "*not everything that decision-makers want, they can*". Thus, the second research context addresses legacy systems interoperability to represent the criteria *cluster* (2), used in the ELECTRE TRI method. Those *criteria* related to interoperability will classify the maintenance function (i.e., ELECTRE TRI alternatives) as *less critically decisive*.

FEI (Framework Enterprise Interoperability), extracted from Ullberg et al. (2009) work, conjecture that:

a) Enterprises are not interoperable because there are barriers to interoperability that obstruct exchange of information and services;
b) Barriers are incompatibilities of various kinds and can be found at various levels and domains of an enterprise;
c) Whenever there is heterogeneity in two related systems, there is a risk of interoperability problems;
d) There exist generic barriers which are common in all situations of non-interoperability.

This framework relates conceptual, technological and organizational barriers linked between the enterprise layers, that could be generated by two systems from different enterprises trying to communicate. Modifications were made to represent that problem, but from the perspective of this current work. Was assumed that these barriers between systems are actually inside the same enterprise, where one is a legacy system and the other is an adjacent system/process, sharing communication-dependence.

*Conceptual barriers* are concerned with syntactic and semantic incompatibilities of information to be exchanged. For the current work, these incompatibilities are referenced due to interoperability between a maintenance legacy system and other systems/processes adjacent to it. These barriers needed to be analyzed in a high level of abstraction and information.

*Technological barriers* are concerned with the use of computer or ICT (Information and Communication Technology) to communicate and exchange information. Barriers in the technological domain are encountered e.g., when it is impossible to exchange data files between two systems because they do not share an exchange format.

*Organizational barriers* are concerned with the incompatibilities of organization structure and management techniques from maintenance legacy systems implementing I4.0 capabilities and its subjacent systems. From the interoperability point of view, different ways of defining and assigning responsibility and authority e.g., by the introduction of a new communication technology; may result in different organization rules which could raise problems due to information needed to be exchanged.

From Ullberg et al. (2009), each three barriers are identified in four enterprise layer (business, process, service and data) and for all the twelve combinations there are descriptions regarding how a barrier impacts on an enterprise layer.

The layers described in this FEI are easily contextualized with the architecture layers from Reference Architectural Model Industrie 4.0 (RAMI 4.0). This RAMI4.0 model describes that enterprise layers from I4.0 as business, functional, informational, communication, integration and asset. A semantic analysis over these two works suggests that the four first layers described in RAMI4.0 model can be related to FEI model in such way that: the business layer are represented with the same name and have the same level of comprehension in both; RAMI4.0's layers, function, information and communication, in that order. Figure 3.16 represents the two frameworks relation.

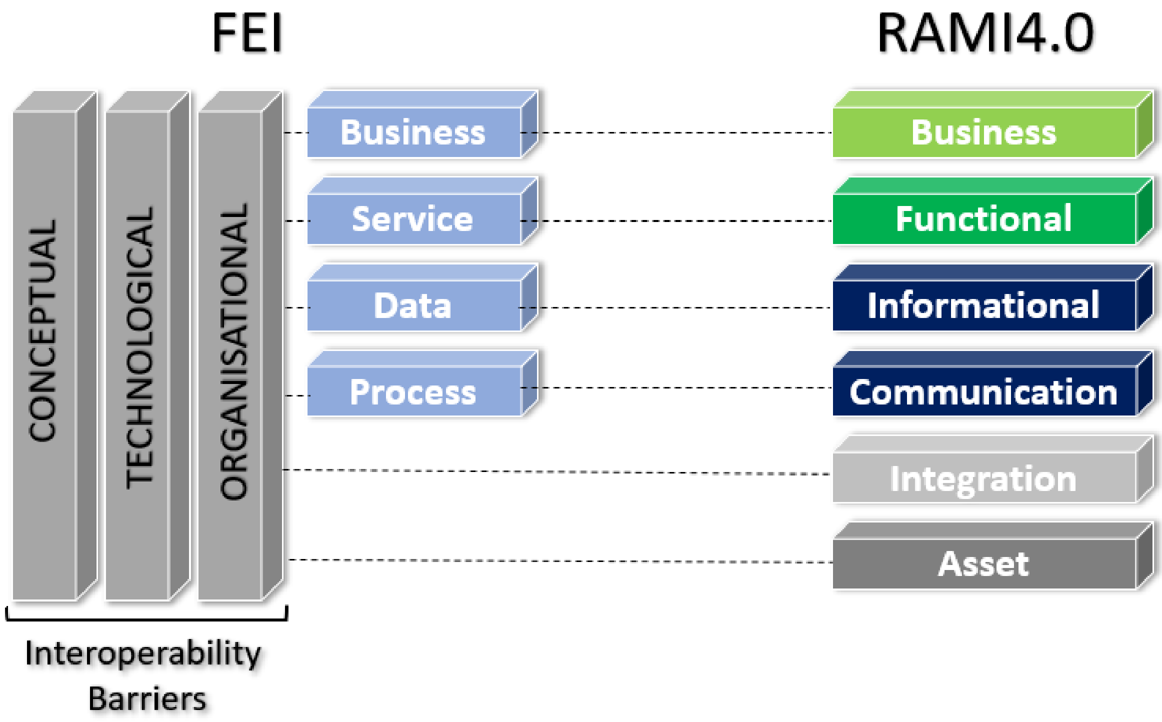


**Figure 3.16 (FEI barriers) x (RAMI4.0 layers) composed frameworks.**

By doing this analogy, only the integration and asset layers from RAMI4.0 could not be related with FEI interoperability concerns (blue layers), and needed to be explored in literature for suit this work. By doing that, even without direct all layer relationships, those interoperability barriers could be applied to all the RAMI4.0 framework.

For the same reason of *cluster* (1), which deals with legacy system needs, the *cluster* (2) uses *general subjective* criteria to be chosen by the decision-makers. Even if the legacy system that is being analyzed deals with punctual data, KPI, time and other objective metrics, consider the importance of implementing a *function* to this system is a subjective problem, as many variables exists to be considered.

Because of the current context, two arguments about the subjectivity of the alternatives stand out. First, the *alternatives* (maintenance 4.0 functions) to be compared are aligned by their perspective of *zero waste*, and compare: alternative – Inspection routine to prevent or correct failures; with alternative – Preventive decision making to less start-up losses due to system integration; is a subjective bias. Second, the *criteria* regarding *cluster* (1) (systems traits that needs to be implemented) and *cluster* (2) (interoperability barriers) are defined mostly as a subjective understanding on the part of system's decision-makers.

Continuing the interpretation of *cluster* (2), the current work references the barriers of interoperability from FEI, with the I4.0 enterprise layers from RAMI4.0 architecture, combining (three barriers) x (six layers), which results in eighteen definitions. The following Table 3.5 represents: I4.0 layers definition; definition of barriers, imposing those layers due to interoperability; and general aspect of interoperability barrier in each layer.

**Table 3.3 I4.0 - enterprise layers and interoperability barriers interpretations.**

| RAMI4.0 Architecture Layers | Layer Interpretation | General Interoperability Barriers Interpretation |
|---|---|---|
| Business | Business strategy, environment, goals; Advertises; Price model; Manufacture; Cost analysis; etc. | Business terms and expressions, data service and legislative requirements. |
| Functional | Production rules, actions, processes; System control; Cloud-like services (e.g. store, back up); Coordination of system components (e.g. system power on/off, alert lights, touch screen, snapshot). | Content, language and syntax and services definitions, interface system problems and allocation of resources. |
| Informational | Hold data in an organized way; Total number of sales information; Purchase order information; Suppliers information; Customer information and feedback; Location, production, manufacture maintenance, machines, components, files, application data information; Software troubleshooting. | Data representation, heterogeneous protocols format and structure available to exchange information (aligned with data rights). |
| Communicational | Standardized communication between Information and Integration layers; Transmit and receive data (TCP/IP, HTTP/FTP, | Process grammar with meanings and graphical representations, organized by computerized |

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|---|---|---|
| | LAN, WAN, BLUETOOTH, Wi-Fi and devices). | process aligned with business rules. |
| Integration | Process the information; Link between physical and digital; System drivers; HDMI devices; Bridges; Wires; Switches; Hubs; Sensor readers. | Standard communication protocols, data integrators and geographically organized operations and devices. |
| Asset | Machines, documents, motors, spread parts, software applications, customers, system users, suppliers, service providers, mobile devices, smartphones, PCs. | Machines, devices and tools accessible for staff and suppliers, customers, people training, aligned with manufacture processes. |

*General interoperability barrier interpretation* column, from Table 3.5, represents the semantic on the *criteria*. For the ELECTRE TRI method, too many subjective *criteria* could represent noisy answers in the choice of the best *alternatives*. For that motive, all interoperability barriers definitions were grouped in each RAMI4.0 architecture layer, meaning that, the conceptual, technological, organizational barriers where merge in one broad concept regarding the layer they are considered. This also represents that, because the barriers are being considered together in each level of the organization, the one most *heavily weighted* architecture level will be the one in which the legacy system interoperates whit the most difficulty.

#### 3.2.2.3 ELECTRE TRI – CRITERIA OVERVIEW

Figure 3.17 shows the entire *criteria* utilized in the ELECTRE TRI method, the ones from *cluster* (1) representing traits wanted for the legacy system (i.e. profit criteria), and *cluster* (2) representing interoperability barriers that will be imposed by changes that may occur on the legacy system (i.e. cost criteria).

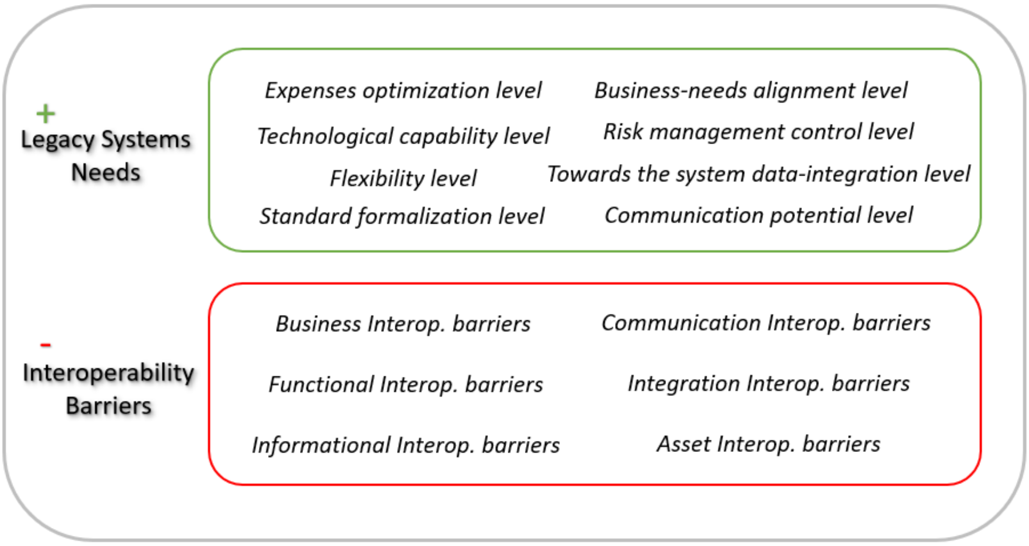



**Figure 3.17 ELECTRE TRI total criteria.**

A final study over the feasibility of all *criteria* was needed, to confirm the validity of its subjective measures meaning. The paper – Selecting Attributes to Measure the Achievement of Objectives, Keeney & Gregory (2004) – is one of the latest to approach the problem of poor attribute choice, and presents theory and guidelines for identifying appropriate attributes. Five attribute properties were defined: *unambiguous*, *comprehensive*, *direct*, *operational*, and *understandable*.

1- *Unambiguous* attributes are those whom are neither vague nor imprecise but express a clear relationship between consequences and descriptions of consequences in their use. When the decision-makers know what the consequence is or will be, they know how to describe it using the attribute, and when the description of a consequence in terms of the attribute level is also known, it is known what the corresponding consequence is or will be.

2- *Comprehensive* attributes are those which their measure levels cover the full range of possible consequences and if any implicit value judgments that are part of the attribute are appropriate for the decision problem being addressed. Attributes cannot be comprehensive because experts want to rely on a narrower set of measures than is appropriate, and whenever an attribute involves counting, there is the assumption that each of the items counted is equivalent. To be comprehensive requires that one consider the appropriateness of value judgments embedded in attributes.

3- *Direct* attributes directly describe in its levels the consequence for the fundamental objective of interest. Not direct attributes are sometimes intentionally selected when decision-makers seeks to distort the results of a decision process, because of their desire to hide controversial implications of their choices or to present potentially troubling information.

4- *Operational* attribute concerns how easy it is to obtain the information describing consequences. Tradeoffs are always necessary between how practical it is to do an analysis (operational property) and the additional insight that would be provided if the analysis were done more thoroughly (comprehensive property). Yet, tradeoffs are necessary to balance the various pros and cons of alternatives.

5- *Understandable* attribute, should be the ones understandable to anyone interested in the analysis e.g., those doing the analysis, decision-makers who will interpret the analysis, and stakeholders who will be informed by the analysis. The standard on understandability is that an individual understands the consequences if they are given the attribute levels.

The *criteria* in the two clusters were validated using those five properties, naturally some of those properties were more strongly supported than others.

As described in section 3.2, the ELECTRE TRI method requires another to *weight* the *criteria*, classifying its importance for the decision-makers analysis. For that, to each one of the criteria, the MUDGE method will be applied. "*The Mudge diagram is a tool that allows the comparison of criteria two by two, with the purpose of ordering them by relevance. This comparison is usually done by enumerating the criteria as 1,2,3 ... n, where n is the number of criteria, then values are assigned for the comparisons*" (Schuster, Schuster, & Oliveira, 2014). The *criteria* used in the ELECTRE TRI was *weighted* in Figure 3.18, by the application of the MUDGE method.

**Syntax (***comparison, line x column***)** = Criteria n; N times more Important

**Criteria (n)**

| | |
|---|---|
| c1 | Standard formalization level |
| c2 | Business-needs alignment level |
| c3 | Communication potential level |
| c4 | Towards the system data-integration level |
| c5 | Expenses optimization level |
| c6 | Flexibility level |
| c7 | Technological capability level |
| c8 | Risk management control level |
| c9 | *Business Interop. barriers* |
| c10 | *Functional Interop. barriers* |
| c11 | *Informational Interop. barriers* |
| c12 | *Communication Interop. barriers* |
| c13 | *Integration Interop. barriers* |
| c14 | *Asset Interop. barriers* |

| | c2 | c3 | c4 | c5 | c6 | c7 | c8 | c9 | c10 | c11 | c12 | c13 | c14 | SUM | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| c1 | c1;3 | c1;2 | c1;1 | c1;4 | c1;3 | c1;1 | c8;4 | c1;4 | c1;2 | c1;1 | c1;1 | c1;4 | c1;5 | **31** | 12.7 |
| | c2 | c3;4 | c4;3 | c5;1 | c6;2 | c7;2 | c8;5 | c2;1 | c10;3 | c11;4 | c12;4 | c13;1 | c2;2 | **3** | 1.2 |
| | | c3 | c3;2 | c3;4 | c3;2 | c3;1 | c8;3 | c3;4 | c3;1 | c11;1 | c12;1 | c3;4 | c3;5 | **27** | 11.1 |
| | | | c4 | c4;2 | c4;1 | c7;1 | c8;4 | c4;4 | c10;2 | c11;3 | c12;4 | c4;2 | c4;3 | **15** | 6.1 |
| | | | | c5 | c6;1 | c7;2 | c8;5 | c5;1 | c10;3 | c11;4 | c12;4 | c13;1 | c5;1 | **3** | 1.2 |
| | | | | | c6 | c7;1 | c8;3 | c6;2 | c10;3 | c11;4 | c12;4 | c6;2 | c6;2 | **9** | 3.7 |
| | | | | | | c7 | c8;3 | c7;3 | c10;1 | c11;2 | c12;2 | c7;3 | c7;4 | **16** | 6.5 |
| | | | | | | | c8 | c8;5 | c8;4 | c8;3 | c8;2 | c8;4 | c8;5 | **50** | 20.5 |
| | | | | | | | | c9 | c10;3 | c11;3 | c12;4 | c13;1 | c9;1 | **1** | 0.4 |
| | | | | | | | | | c10 | c11;1 | c12;2 | c10;2 | c10;3 | **20** | 8.2 |
| | | | | | | | | | | c11 | c12;1 | c11;3 | c11;4 | **29** | 11.9 |
| | | | | | | | | | | | c12 | c12;4 | c12;5 | **35** | 14.3 |
| | | | | | | | | | | | | c13 | c13;2 | **5** | 2 |
| | | | | | | | | | | | | | c14 | **0** | 0 |
| | | | | | | | | | | | | | **T** | **224** | **100** |

**Importance Levels (N)**

| | |
|---|---|
| 5 | Totally more important |
| 4 | Much more important |
| 3 | More important |
| 2 | Reasonably more important |
| 1 | Little more important |

**Figure 3.18 Mudge diagram.**

This tool is necessary to understand, in the understanding of the decision-makers, which criterion is heavier i.e., most impact the *alternatives* they are measuring, where *criteria cluster* (1) will classify them as *more critically decisive*, and *cluster* (2) will classify them as *less critically decisive*.

### 3.2.3 CLASSES RESEARCH CONTEXT

Lastly, the third research context expressed in this Step 2 represents the classification process occurred in the ELECTRE TRI method. After the *alternatives* (I4.0 Maintenance Architecture functions) being weighted using a series of *criteria* (legacy system's needs – representing positive traits, and interoperability barriers – representing negative traits), they are classified in four levels by their decisiveness. A decisive aspect is semantically understood as: crucial; able to decide, to resolve. For this current work's perspective, the decisiveness of a function represents how much differential it will bring to the maintenance legacy system in question, i.e. how close to *zero waste* the I4.0 maintenance function will bring to the legacy system while allowing to generate the least number of possible interoperability barriers between its adjacent systems/processes. Figure 3.19 represents the four classes in which the reference architecture functions will be categorized.


**Figure 3.19 ELECTRE TRI classes.**

Some considerations have to be made in order to better understand this classification process results. To proceed with the I4.0MFCI framework Step 3, the functions classified as *Decisive* will be the ones to be implemented in the maintenance legacy system.

If the method's classification proposes too few functions, two approaches are proposed. The first suggests that some functions classified as *Good*, the nearest ones in the limit to be considerate *Decisive*, can also assume the position of being implemented.

A second approach is to attribute the responsibility to the decision-makers, guided by the specialist applying the framework, to decide a more judicious threshold to filter the I4.0-maintenance functions. Following this idea, if too many functions (e.g. supposing it is 20) became classified by the ELECTRE TRI method to be on the *Decisive* class. This is another feature that corroborates with the use of this method, as its indifference and preference thresholds can be adjustable, constituting the intra-criterion preferential information. That way the specialist can modify the thresholds in the Step 2 model to make it more critic in the process of support the choices. Figure 3.20 exemplifies that.

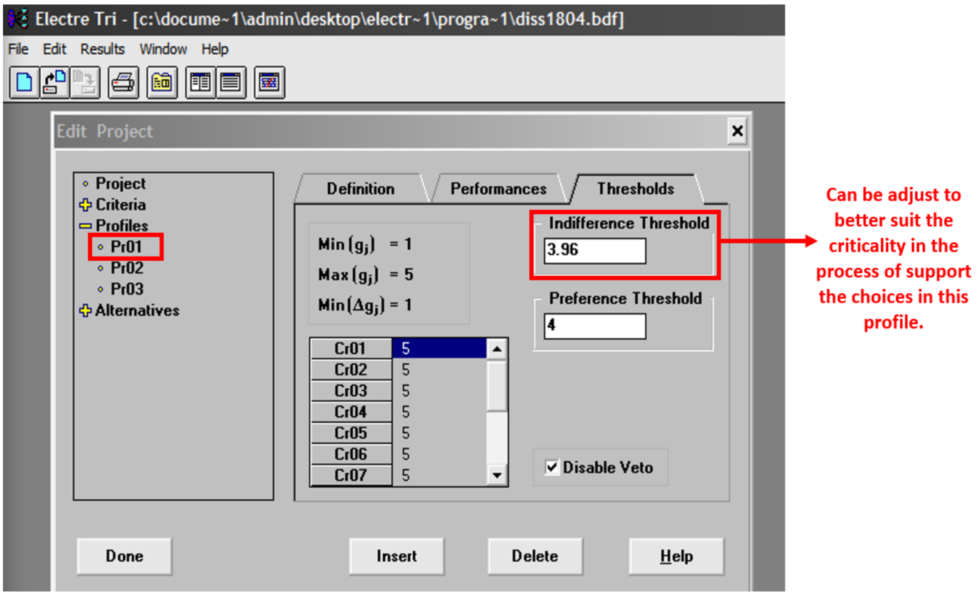



**Figure 3.20 ELECTRE TRI threshold adjust.**

In this case, the *profile* represents the intervals between the categories, Decisive, Good, Moderate and Worthless. That is to say, if the model has four *categories*, it will automatically have three intervals (i.e. *profiles*) limiting and delegating the alternatives into the correct class, regarding the decision-makers choices. The following table shows the *degrees of credibility* for decisive functions (i.e. a global concordance index from a valued outranking relation, representing the alternative's tendency to belong in a class), resulted from a testing experiment, also related to the Step 1 example.

**Table 3.4 Rank of Decisive function (degree of credibility).**

| Function | Degree of Credibility (limits) | | |
|---|---|---|---|
| Code – Name | Decisive/ Good | Good/ Moderate | Moderate/ Worthless |
| **A04** - Inspection routine to prevent or correct failures | **0.910** | 0.910 | 0.914 |
| **A10** - Predictive decision making due to setting time | **0.833** | 0.837 | 0.837 |
| **A12** - Corrective decision making to a faster set-up due to analysis | **0.768** | 0.820 | 0.820 |
| **A15** - Predictive decision making to smaller amount of idling | **0.828** | 0.906 | 0.906 |
| **A21** - Corrective maintenance to avoid reduce speed due to service execution | **0.772** | 0.910 | 0.910 |
| **A22** - Corrective decision making to avoid reduce speed due to analysis | **0.863** | 1.000 | 1.000 |
| **A26** - Corrective maintenance to eliminate rework | **0.820** | 0.854 | 0.854 |
| **A31** - Corrective maintenance to less start-up losses | **0.772** | 0.777 | 0.777 |

Those functions represent the most decisive ones and can be classified according to its credibility to exists in the *limits* of the classes *Decisive* to *Good*. Thus, to fully comprehend this Step 2, it is important to clarify the way the method make its choices. ELECTRE TRI needs limit *profiles*, that will serve as filters to establish in which *category* the alternative (I4.0-maintenance function) will be allocated.

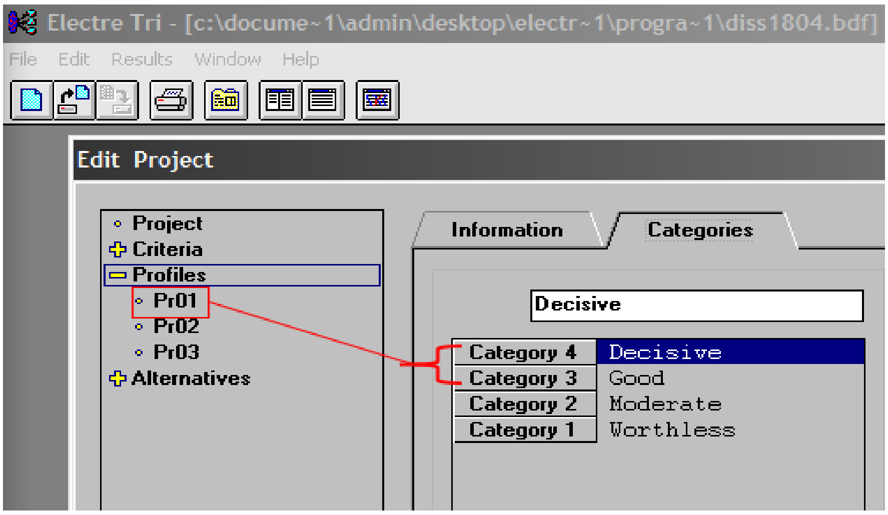



**Figure 3.21 ELECTRE TRI difference between profile and category.**

Conclusively, for the I4.0MFCI framework, the ELECTRE TRI's *category* represents the importance of a function for the legacy system, classifying them as Decisive, Good, Moderate or Worthless; while the *degree of credibility* delimitates the categories acceptance limits, Profile 01 – Decisive to Good, Profile 02 – Good to Moderate and Profile 03 – Moderate to Worthless (i.e. limit values for the I4.0-maintenance function to exist in one of the four classes).

## 3.3 SLS - TECHNOLOGY APLICATION (STEP 3)

The Figure 3.22 shows the I4.0MFCI framework after being rotated for the second time, contrasting technologies with maintenance functions, representing the best upgrade options to incorporate into a given legacy maintenance system.

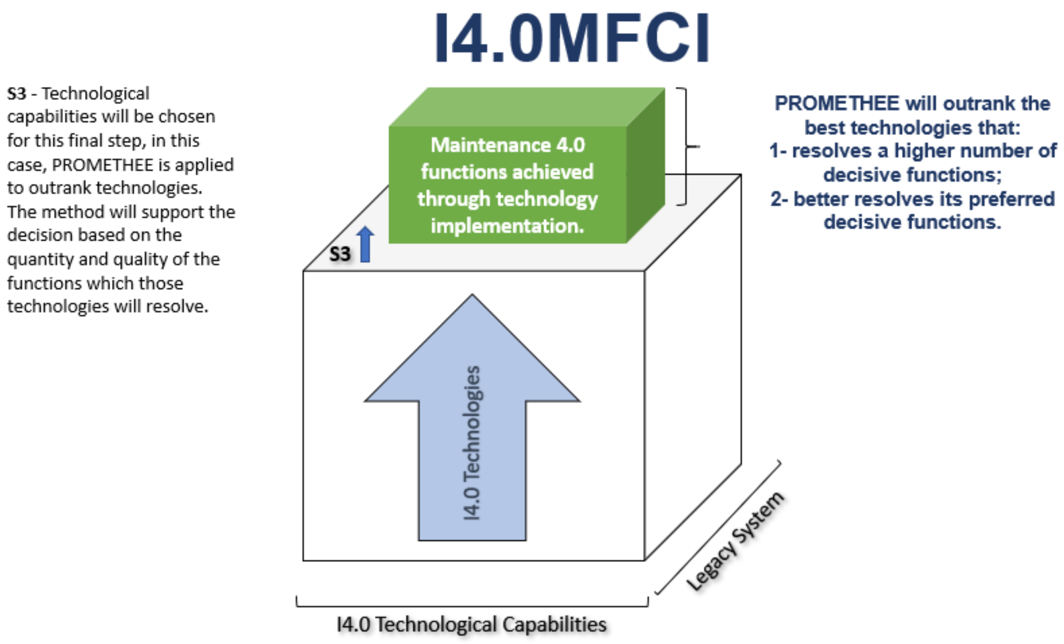



**Figure 3.22 I4.0MFCI Step 3 approach.**

Once the most decisive functions are discriminated by the last step, regarding interoperability barriers, this final rotation represents the technologies inherited from I4.0-maintenance being chosen. The green rectangle represents the most decisive functions being enabled by the technologies, which are represented by the ascending blue arrow.

For this third and last step, the PROMETHEE II method will be applied. It objectifies to compare which technology prominent from I4.0 will make the system perform better. Recalling that the premise in the context of this research is that, those I4.0-driven technologies will digitalize the process in which the legacy system is performing, bringing more flexibility, better data acquisition and autonomy for intelligent algorithms, intrinsic to it, to make decisions through the process in which they find themselves.

A MCDM process will typically requires to define objectives, chooses the criteria to measure the objectives, specifies alternatives, transforms the criterion scales into commensurable units, assigns weights to the criteria that reflect their relative importance, selects, and applies a mathematical algorithm for ranking and choosing an alternative (Qu, Wan, Yang, & Lee, 2018). With this statement taken into account, Step 3 PROMETHEE II model will consist in I4.0-maintenance technologies prominent from a literature review as *alternatives.* These alternatives will be compared by *criteria*, representing decisive maintenance functions chosen in the last step (i.e. those that will bring the best performance for the system and its process without compromising its interoperability).

Now, it will first be explained how the criteria will be represented in this model, and then the alternatives and how they were searched in the literature.

### 3.3.1 CRITERION PARAMETERS

Because the *criteria* part of this Step 3 consists in the *alternatives* of Step 2, in other words, most decisive I4.0-maintenance functions, they do not need introduction. However, some caveats should be made as how the criteria are evaluated. PROMETHEE II method make use of some preference parameters to better adjust its criteria. This work focuses in two most used parameters:

i) *Weigh*, which will come from the previous ELETRIC TRI method (i.e. *degree of credibility* rank), indicating the relative importance of the criterion;

ii) *Preference functions* (not related with the referential architecture's I4.0-maintenance functions described so far), as stated before in (Vinodh and Girubha, 2012), the PROMETHEE II method suggests six types of preference functions to express the relative difference between *alternatives* for a certain *criterion*.

Assuming that the most decisive functions from the Step 2 was those showed in Table 3.6 example, reorder them from the ones which have better credibility to enter in the *Decisive* class (by the threshold adjusted for the Decisive/Good limits, Step 2) would result in the following table with its respective weights.

**Table 3.5 Rank of most decisive functions.**

| Function (code – name) | Weight |
|---|---|
| A04 - Inspection routine to prevent or correct failures | 0.910 |
| A22 - Corrective decision making to avoid reduce speed due to analysis | 0.863 |
| A10 - Predictive decision making due to setting time | 0.833 |
| A15 - Predictive decision making to smaller amount of idling | 0.828 |
| A26 - Corrective maintenance to eliminate rework | 0.820 |
| A31 - Corrective maintenance to less start-up losses | 0.772 |
| A21 - Corrective maintenance to avoid reduce speed due to service execution | 0.772 |
| A12 - Corrective decision making to a faster set-up due to analysis | 0.768 |

This last table organize by weight the most decisive functions to be implemented in the maintenance legacy system, from the test example already covered in the last subsection.

The second parameter used to measure the criteria in this PROMETHEE II model is the *preference functions*, which consists in the decision-makers preferences for each criterion using six predefined functions (Mladineo, Jajac, & Rogulj, 2016). Those functions cover a variety of situations:

- *Usual criterion* – It is a basic type without any threshold. No parameter to be determined;
- *Quasi criterion* – It is always used for qualitative criteria and it uses a single indifference threshold and it should be fixed;
- *V-shape linear criterion* – Criterion with linear preference up to a preference threshold and it is to be determined;
- *Level criterion* – It is always used for quantitative criteria and it uses additional indifference. The indifference and a preference threshold which must be fixed; between the two, preference is average;
- *V-shape indifference criterion* – Criterion with indifference and linear preference. Both should be fixed; between the two, preference increases;

- *Gaussian criterion* – It is seldom used. Preference increases and it follows normal distribution, the standard deviation of which must be fixed.

This list was based on (Vinodh and Girubha, 2012). To represent the criteria from Step 3 the *Quasi Criterion* was chosen, as the model's criteria are subjective in its totality. Also, using the "Help me…" guide on the PROMETHEE II software, the U-shape function (i.e. which express the *Quasi Criterion*) are indicated as best function to be used, validating this setup in the model.

### 3.3.2 ALTERNATIVES – I4.0 MAINTENANCE TECHNOLOGIES

This subsection will introduce how a literature review was conducted under three research rounds. To that end, will be possible to understand how and why the alternatives for this last step's MCDM, PROMETHEE method, was chosen. In subsection 2.3.2 a literature review was presented, accounting some references cited in Bokrantz et al. (2017) and coupled with some cited as follow.

**Table 3.6 Consulting companies and their reports about Industry 4.0.**

| Consulting Companies | Report |
|---|---|
| (Capgemini Consulting, 2014) | Industry 4.0 - The Capgemini Consulting View |
| (Deloitte, 2015) | Industry 4.0: Challenges and solutions for the digital transformation and use of exponential technologies |
| (PWC, 2016) | Industry 4.0: Building the digital enterprise |
| (PWC, 2015) | The Smart Manufacturing Industry |
| (Cisco, 2015) | The Digital Manufacturer Resolving the Service Dilemma |
| (McKinsey & Company, 2016) | Industry 4.0 at McKinsey's model factories |
| (The Boston Consulting Group, 2015) | Industry 4.0 |
| (Acatech, 2017) | Industrie 4.0 Maturity Index |
| (Roland Berger, 2014) | The Digital Transformation of Industry |
| (Plattform Industrie 4.0, 2016) | Plattform Industrie 4.0 |
| (The Warwick Manufacturing Group, 2017) | An Industry 4 readiness assessment tool |

These references are frameworks developed by professional technology consulting companies, which discuss the Industry 4.0 and how it will be presented in a near future (not to mention that some factories already perform in that context, at least in some level of autonomy and flexible data acquisition/ utilization). That was the first-round of the literature review and helped to find the common terms and the most characteristic ICTs presented in the Industry 4.0 panorama.

Regarding the reports this review was based on, two of them were considered the most, (Capgemini Consulting, 2014; Acatech, 2017). Those two reports also couple with each other, the first predicting with strong arguments the technologies trending and the second confirming it (indirectly) with a maturity assessment on those technologies, proven by their apart dates. The extractions in this research lead to the follow key technologies existing in the smart digital manufacture: Artificial Intelligence & Machine learning; Augmented Reality; Big data & Analytics; Cloud; Energy Consumption; Human-machine Interface; Machine-to-machine; Open innovation platforms; RFID. The technologies were chosen by the accounting of times they were mentioned in the reports database.

3D printing and Mobile technologies were categorized in Open Innovation and Human-machine Interface, in that order. Further, all of those technologies were revaluated and recategorized in the final research round.

With a more critical view, a second-round review was based primarily on academic articles. It aimed to understand which of these first set of technologies were used in the maintenance context the most. This was key to filter the understanding of their applicability. It was conducted as follow: (i) search the relation between *technology* AND *maintenance* (e.g., Cloud AND Maintenance; or, Augmented Reality AND Maintenance); (ii) only open access articles were searched; (iii) time period from 2014 to 2017 was considered adequate since the term “Industry 4.0” appeared by 2011. The platforms used to research were: ScienceDirect, ResearchGate and Archive Ouverte HAL.

At the end, 59 articles were found. It is worth mentioning that even researching for a specific technology, eventually, it was found examples of contextualization with other technologies. Likewise, those researches contributed and were validated as well for the I4.0-maintenance referential architecture.

**Table 3.7 Industry 4.0 technologies hits in articles database.**

| I4.0 Technology | Hits in the database |
|---|---|
| A.I. & Machine learning | 3 |
| Augmented Reality | 3 |
| Cloud | 17 |
| Energy Consumption | 12 |
| Human-machine-interface | 16 |
| M2M | 25 |
| Open Innovation Platforms | 3 |
| RFID | 2 |

While the I4.0MFCI framework was under development, middle of 2018, another research complemented the present set of articles and reports. This third-round research was conducted as the previous one, but also aiming articles that dated 2010 and before, intending to better understand how some of the technologies already in use by industry maintenance systems/processes was being applied, before the term I4.0 arrived. Couple with that, a reevaluation of the late research was made, in a more mature view, intending to comprehend more tangible examples of I4.0 technologies being applied for maintenance.

Then again, it was possible to understand different levels of maintenance technologies applicability, supporting the Step 3 decision, on which technology could better suit the *most decisive functions* in need to implement, independent on the legacy system in view. Merging the database from the previous set of consulting companies reports (first-round), the first set of articles (second-round) and the second one (third-round), the whole literature database ended with 87 articles and reports. After this review, eight main ICTs were pondered to be used, as they demonstrate characteristics accessed for a digitalized I4.0-maintenance context.

Primarily, those eight technologies were allocated in two subgroups, *cyber-physical* and *application*. The technologies allocated in the *cyber-physical* subgroup were those whom represents the digitalization of the process, as they only had impact in the cybernetic world, they are: Big Data, Analytics, Artificial Intelligence and Cloud Computing. Allocated in the *application* subgroup were technologies responsible for transmit (or respond) the digitalized data to the physical world: Advanced Machines, Advanced Materials, Flexible Connection

Devices and Digital-to-Real Representation. However, this subgroup division does not interfere directly on this work, but more precisely, was used to classify each of those eight technology groups for possible scenarios regarding I4.0 maintenance contexts, explained in the next subsection.

Despite the technologies being allocated in the *cyber-physical* and *application* subgroup a midway technology needed to be discriminated. Sensors technology was considerate as such, classified for not just transport the data perceived in the physical world to the digitalized one, but also to make the other way back, transporting information from the cyber-physical world to the real one. All things considered, the alternatives for the Step 3 PROMETHEE method are the eight technologies plus sensor.

The technologies, others similar they contain as a group, the characteristics and applicability that are considered in each one of them will be better explained in the next subsection.

#### 3.3.2.1 I4.0 TECHNOLOGIES REVIEWED IN MAINTENANCE

In the referential architecture (M4.0EAF), presented in Figure 3.15, subsection 3.2.1, a level above the functions, stands six courses of actions (i.e. groups that categorizes the 32 maintenance functions, based on the six main production losses: equipment failure, setup and adjustments, idling and minor stops, reduce speed, process defects, reduce yield). It is particularly relevant that the specialist applying the framework understands how each technology will impact those architecture aspects, for two main reasons.

The first is that, because some of the functions acts in similar ways but are applied for different courses of action. An example of that is function 7 – "*corrective maintenance to correct failures due to service execution*" (course of action for Prevent or correct failures and breakdowns) and function 16 – "*corrective maintenance to less stoppage service*" (course of action for Smaller amount of idling and minor stoppages). Both have corrective maintenance aspects, but applied in different course of action (i.e. applied in different context of losses).

The second reason is, because any of the 32 functions can be chosen as *Decisive* by the ELECTRE TRI method in Step 2, the specialist needs to be prepared to contextualize all of the possible alternatives while choosing the best technologies to access those decisive maintenance functions.

A more detailed classification of each technology chosen in the end of the three-round literature review stands next. Firstly, it will be explained the technologies classification (which may contain other technologies that function with similar principles).

*Analytics*: Insightful data interpretation techniques/processes. Every data acquisition must be analyzed to provide insights to the maintenance system and depending on the level of the analysis it could generate high or low impact insights. Optimization of prediction, data processing, historical data analysis, troubleshooting, increasing the effectiveness of operational planning, performance forecast, quantum computing and knowledge support system actions are some of the syntactical representations of this class;

*Artificial Intelligence*: Algorithms able to learning and/or enable devices, assistants and machines autonomously respond to tasks and learn in an unsupervised way. This is the last level of the data utilization in the smart factory, after being gathered and treated the artificial intelligence can optimize processes, training, tasks and autonomously make decisions. Machine learning, auto optimization, automatically learn, interaction with physical environment, predict regarding prognostic decision-making, enabling maintenance-aware and automation of production process, interpolation and extrapolation of human actions are some of the representations of this class;

*Big Data*: Data gathering methods and storage. When data is gathered it is not totally (merely) analyzed to be used in processes, that is to say, this class referee to storage of large amount of data, the techniques for that data retrieving and its quality measurements 5V (volume, velocity, value, variability, veracity value). Data warehousing, data mining (referring to the data base), dataset, vibration/temperature data, condition/state data, data-driven model, life-cycle data, control systems data repositories, data-driven algorithm, statistical process control (SPC) data and raw historical data are some of the representations of this class;

*Cloud Computing*: This class represent two main concepts. One is the industrial internet accessible geographical location (i.e. the area in which the factory internet/data is accessible). Two, the place were all factory components/assets have a digital representation. Network connection extension, remote operable software, platform between customers and suppliers, data exchange area, heterogeneous network devices, CMMS may be an add-on or an integrated part, data supply chain and sensor networks are some of the representations of this class;

*Advanced Machines*: High performance machines, machine tools, equipment, robots, drones, cars. Also, those cited agents when they are able to perform decision-making tasks in some degree of autonomy. Environment whereby smart machines that can communicate with one another (m2m communication), human-machine-interaction, self-healing equipment, high-performance laser beam, autonomous robots, A.I. applied in machines, collaborative and proactive machines, machines interaction with physical objects, connectivity with the factory, real-time feedback/communication are some of the representations of this class;

*Advanced Materials*: Materials which can provide a wide range of applicability for the factory, making it more flexible to build components, use in extreme conditions and monitor its health. Examples of that are data monitored components towards nanotechnology and self-healing materials. Replaceable component, resistant to external ambient/influences and ageing, spread part production, cleaning components, nanotechnologies, self-repairing materials are some of the representations of this class;

*Flexible Connection Devices*: Devices that provide connection with the factory robots, components, collaborators and value chain representatives. Then again, these devices can also monitor, control and access data, making the device user interact with the factory in a more flexible way. Smart phones, real-time transmission of analyzed object status, machine status input, check products status and track them, human-machine interaction and CMMS control are some of the representations of this class;

*Digital-to-Real Representation*: Technologies that provide control, monitoring, training and assistance for maintenance tasks. Augmented reality and virtual reality training systems are the main technologies to represent this class, providing interface with digital feedback and control systems. AR googles, assistance with localization and diagnostics of faults in the system, remote maintenance/inspection, visualization of prototypes and operator training are some of the representations of this class;

*Sensors*: Data gathering/transmitting components. Sensors can be represented inside other technology classes (i.e. every smart device have sensors) and also be represented individually (e.g. a sensor can be installed in a production line to retrieve data). Equipment containing RFID tag, condition monitoring processes, real-world scanning, vision/sound/temperature sensitivity, wireless sensors, alert on equipment maintenance need, remote detection are some of the representations of this class.

Importantly, the third-round literature review served as data consulting for Step 3. This review is compiled in the form of nine different tables, one for each technology group, presented in the appendix section. Those tables give an illustration about the main I4.0-maintenance ICTs contextualized with some possible maintenance scenarios (i.e. functionalities and applications). Also, the articles/reports names used as references, are cited along with the maintenance scenarios. It can be noticed that not all consulting companies' reports were used in those final tables, mostly the ones used in the first-round research. This happened as an effort to suggest only examples prevenient from article and new reports (not used for the first-round validation), ensuring that other fonts could confirm the research process.

### 3.3.3 PROMETHEE MODEL EXAMPLE

This subsection presents an example of Step 3 method model. Different from Step 1 (AHP method) and Step 2 (ELECTRE TRI method), the PROMETHEE II method from Step 3 will not be the same applied under different circumstances (i.e. applied in different legacy systems). This is trivial in a sense that independent the system, the first two steps are modeled to resolve singular problems: feasibility to upgrade a legacy system (Step 1); and which I4.0 maintenance functions are the most needed (and generate less barriers) when being applied for upgrade (Step 2). Regarding that, Step 3 consists in answer a question based on the Step 2 response, which depending on the system will require different needs and generate different barriers, so because of that, it means this is a variable model.

Figure 3.23 shows a PROMETHEE II model, from the same testing experiment used so far, presenting its elements: the *criteria* (I4.0-maintenance functions to be implemented from the previews step, described in table 3.7); the *alternatives* (nine I4.0-maintenance technologies), as well as its weights (*degree of credibility* from the Step 2 method) and *preference functions* (i.e. to express the relative difference between *alternatives* for a certain *criterion*) using *Quasi-criterion* (for qualitative criteria).

Visual PROMETHEE Academic - STEP 03 - PROMETHEE Testing.vpg (saved)

File Edit Model Control PROMETHEE-GAIA GDSS GIS Custom Assistants Snapshots Options Help

| Scenario1 | Preventive d... | Predictive m... | Predictive de... | Corrective d... | Machine to ... | Corrective m... | Corrective d... | Corrective m... |
|---|---|---|---|---|---|---|---|---|
| Unit | unit | unit | unit | unit | unit | unit | unit | unit |
| Cluster/Group | | | | | | | | |
| **Preferences** | | | | | | | | |
| Min/Max | max | max | max | max | max | max | max | max |
| Weight | 0,91 | 0,83 | 0,77 | 0,83 | 0,77 | 0,86 | 0,82 | 0,77 |
| Preference Fn. | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape |
| Thresholds | absolute | absolute | absolute | absolute | absolute | absolute | absolute | absolute |
| - Q: Indifference | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |
| - P: Preference | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| - S: Gaussian | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| **Statistics** | | | | | | | | |
| Minimum | 3,00 | 2,00 | 3,00 | 2,00 | 4,00 | 4,00 | 4,00 | 4,00 |
| Maximum | 8,00 | 8,00 | 7,00 | 8,00 | 7,00 | 8,00 | 8,00 | 7,00 |
| Average | 5,22 | 5,56 | 5,11 | 5,22 | 5,22 | 5,89 | 5,56 | 5,44 |
| Standard Dev. | 1,81 | 1,77 | 1,45 | 1,87 | 0,92 | 1,20 | 1,57 | 1,07 |
| **Evaluations** | | | | | | | | |
| Big Data | 7,00 | 7,00 | 7,00 | 6,00 | 4,00 | 6,00 | 4,00 | 4,00 |
| Analytics | 6,00 | 8,00 | 7,00 | 5,00 | 4,00 | 5,00 | 5,00 | 5,00 |
| A. Intelligence | 3,00 | 6,00 | 6,00 | 7,00 | 6,00 | 7,00 | 4,00 | 4,00 |
| Cloud Computing | 3,00 | 6,00 | 4,00 | 8,00 | 6,00 | 4,00 | 5,00 | 5,00 |
| F. C. Devices | 8,00 | 6,00 | 5,00 | 5,00 | 7,00 | 8,00 | 4,00 | 6,00 |
| Adv. Machines | 5,00 | 7,00 | 3,00 | 7,00 | 5,00 | 6,00 | 5,00 | 5,00 |
| DtR Representat... | 7,00 | 4,00 | 6,00 | 4,00 | 5,00 | 5,00 | 7,00 | 7,00 |
| Adv. Materials | 3,00 | 2,00 | 3,00 | 2,00 | 5,00 | 5,00 | 8,00 | 7,00 |
| Sensors | 5,00 | 4,00 | 5,00 | 3,00 | 5,00 | 7,00 | 8,00 | 6,00 |

**Figure 3.23 example PROMETHEE II model.**

As can be seen in the last figure, the technologies are leveled from 1 to 9 points (Evaluations matrix) representing the necessity of each technology to the decisive function to be implemented. Table 3.10 indicate those levels.

**Table 3.8 Technologies levels of necessity.**

| Level | Syntactical Representation |
|---|---|
| 9 | Extremely important to implement |
| 8 | Strongly important to implement |
| 7 | Very important to implement |
| 6 | Important to implement |
| 5 | Good differential if implemented |
| 4 | Some differential if implemented |
| 3 | Low differential if implemented |
| 2 | Some necessity to implement |
| 1 | Minimal necessity to implement |

Another key thing to remember is that this step does not need to be accessed by the decision-makers, fundamental actors so far. In one hand, this is stated because not all decision-makers are digital transformation nor I4.0 specialists, on the other hand, if they are, they can be eligible to participate in the third step. In some sense, the market in present days is contemplating more professionals in the area of I4.0 and digital transformation, then again, this kind of professional is well suitable to be designated as decision-maker in Step 3.

As stated in subsection 3.3.2.1, it is particularly relevant that the specialists applying the framework understands how each technology will impact the system. The digital transformation specialist will be the one whom have the knowledge to interpret the results in the previews steps and must propose, in a decisional way, which technologies will fill the necessity from determined maintenance function required to upgrade the legacy system analyzed into a SLS.

## 3.4 CONSIDERATIONS AND SECTION SYNTHESIS

In this section the I4.0MFCI framework was described. The dynamic on how to use it, regarding its three steps, was presented and applied in test examples. By contrast, each step consists in the application of a different multicriteria decision-making method, modeled to attend a necessity to upgrade determined maintenance legacy system, premise which is the focus of the project.

The first two steps are considerate not variable, because their multicriteria decision model is always the same, the first, responsible to present de decision about the feasibility to upgrade the legacy system, and the second, responsible to expose the I4.0-characteristics needed to upgrade de system, without generating interoperability barriers on its adjacent systems/processes. Then again, Step 3 it is a MCDM model that will vary its structure, from a project to another, because it depends on the previous step answer to be modelled. That is to say, its alternatives will be classified and outranked regarding the maintenance legacy system functions to be embedded in it.

To explain this section, it was decided to merely present in an intrinsically way, the software tools used, not explaining nor merely citing them. In other words, it was preferable to not detailed the MCDM tools, in order to understand how the framework function as a digital transformation project, rather than a sequence of tools applied. Next section will clarify how those tools were used, to that end, demonstrating two different case studies in which the framework was applied.

# 4. I4.0MFCI FRAMEWORK – APPLICATION CASES

This section is reserved to describe how the framework was applied in two case studies, as well as its data collected, insights from the decision-makers and from the specialist, whom acted as the digital transformation specialist. It was expected to measure the necessity of maintenance legacy systems to become *Smart Legacy Systems* in the first step, followed by its necessities/barriers to be upgraded in the second steps; the tools used for that were fully software based; and the interviews were conceived one by presential meeting (case one) and the other by video chat (case two). After that, the third step, which support the specialist decision to implement the right technology/method to the system, was conducted only by the specialist (the author).

For testing the dynamic of the I4.0MFCI three steps framework, the tools base were MCDMs software programs: Superdecision (AHP modeler) in Step 1; Lamsade ELECTRE TRI 2.0 (ELECTRE TRI modeler) in Step 2; and Visual PROMETHEE (PROMETHEE II modeler) in Step 3.

Other software tools used for modelling the decision strategies and collect the data were: VirtualBox, necessary to simulate a Windows XP OS environment, aiming better performance for running the ELECTRE TRI 2.0; Microsoft Excel, used to create a metamodel for Step 2 in order to better guide the decision-makers with the decision process, and to build the Mudge decision diagram in a subprocess needed to weigh the Step 2 criteria.

The time invested for the interviews was about three hours each case, were Step 1 and Step 2 took an average of one hour each, plus one hour for the assessment introduction and the Mudge method application. The Step 1 was applied direct in the Superdecisions software, but for Step 2, the input for the ELECTRE TRI matrix was via Excel metamodel. After that, for each case, two more hours were consumed by the specialist to transport the Step 2 data from the metamodel to the ELECTRE TRI 2.0 tool, and to build the Step 3 (based in the previous step conclusions). To propose a coherent decisional view, the analysis in Step 3 made by the specialist for about four hour each case.

The follow subsections will be divided into 4.1 (case study general understanding), 4.1.1 (Step 1), 4.1.2 (Step 2) and 4.1.3 (Step 3), presenting the first case. Subsection 4.2 will be describing the second case study in the same structure.

## 4.1 CASE ONE – AUTOMOTIVE ASSEMBLY LINE

This case study refers to a multinational automotive organization and its maintenance area directly responsible for the welding robots that assemble the side and bottom of the cars, arranged in the production line, without human presence. This is the system proposed to be analyzed by the first decision-maker. Those robots have soldering points and when their electrode gets worn it performs preventive maintenance autonomously by milling the tip of the electrode, thus allowing the robot to continue pinching its points. This is done so that there is no wear of the tool, which causes damage to the car. When the electrode cycle ends completely, the robot also switches it autonomously.

In addition, every 200 to 300 operations, the robot checks its own system autonomously. There is no human interaction in the production line, except when it stops, for some specific corrective maintenance.

When human maintenance is necessary, a robot report is transmitted on the external computer for error checking. This way the robots can be monitored by: its oil flow; the electric current and pressure that is arriving at it; if the tools added to it are all working. This characterizes a preventive (non-reactive) autonomous maintenance. In case of failure warning the robot continues to act until its stop is programmed by the maintainer.

An example of procedure is when the current of the robot is too high, the welding process causes a solder splash, inferring marks in the car that later the maintenance team has to lynch (characterizing rework). This occurs in a space of one hour for the maintainer to correct, while this event that is continually accused by the robot in this time period, until the fault is corrected. The maintainer corrects it via software in the external computer.

The maintainer may need to access the robot in case of oil leakage in the pneumatic system or water leakage in the cooling system. The robot must be stopped so it can be accessed. This is a preventative process that must be corrected at some point, it does not have to be on time, as long as within the space of one hour. This stop is usually made in the exchange of models produced. When the maintainer decides to correct the fault in the robot after the accuse of the error, he has by default a time interval of 5 minutes to carry out the procedure.

A reactive maintenance occurs when the robot stops working. The entire line must be stopped so that the location can be accessed and the maintainer has one hour to solve this error. In theory, reactive maintenance only occurs if preventative one fails. In this case the maintenance sector is responsible for the downtime in which the factory stops producing cars. An example is when a robot needs to be fully replaced, it is not often that but when this happens the backup-robots are stored logistically far from this process.

In the specialist's analysis, the system presents some elements that utilizes digitalized information but it is heavily dependent on human resource if the robot breaks. The time variable is critical in the case of performing a corrective maintenance but even so, the production line depend on strategic stops. That way, in an initial overview, it seems that the preventive actions can be improved since it is already embedded to the process. Predictivity is a solution that, if implemented, could bring a differential to the process, further reducing the need for corrective stops.

This process is characterized as legacy because it is extremely important to the organization business value, but also, it does not necessarily lack on technological capabilities, rather it lacks on a more accurate digital monitoring. This could minimize the human corrective necessity, which is irreplaceable for the system.

### 4.1.1 FEASIBILITY STEP

The AHP method is consider hierarchical because, to support the proposed alternatives (Replacement, Ordinary Maintenance. Simplified Adaptation and Extraordinary Adaptation) it will first compare the criteria with each other. That is to say, first the decision-maker have to choose between the criteria of the *Business Value* cluster, pondering its weights, and then do the same with *Technical Importance* cluster. After having made that first set of choices he had to compare each of the criteria among the proposed alternatives. This sequence of first comparing the criteria between themselves and then the alternatives (for each of these criteria) is what characterizes the method as hierarchical.

During the evaluation, in the *Business Value* cluster, the *Underlaying Impact* criterion was considered of high relevance, together with *Punctual Specificities* and *Contribution to Profit*. The first because the decision-maker interpreted that the *Punctual Specificities* in the system described were related to the security of the maintainers in the system. Apparently in this system the safety characterizes the moment in which the maintainers come in direct contact with the machines. The second most important criterion, *Contribution to Profit*, is considered critical precisely because the company's culture aims for simple and low-cost solutions, even if this will jeopardize the process or leave it less reliable.

*Underlaying Impact* is an important criterion because as the factory is arranged in a production line, this maintenance system can strongly impact other processes. Figure 4.1 shows how the decisions are compared and Figure 4.2 the decision-maker choices for the *Business Value* cluster, in the AHP software.

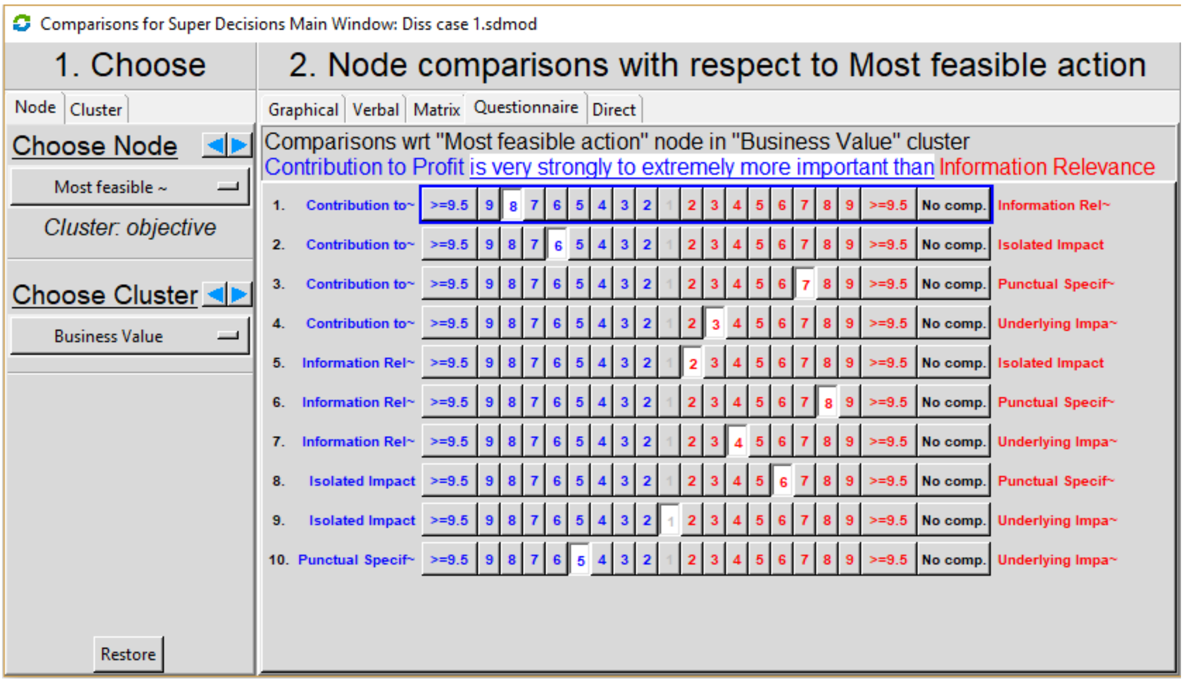



**Figure 4.1 Step 1 decision process (Business Value cluster).**

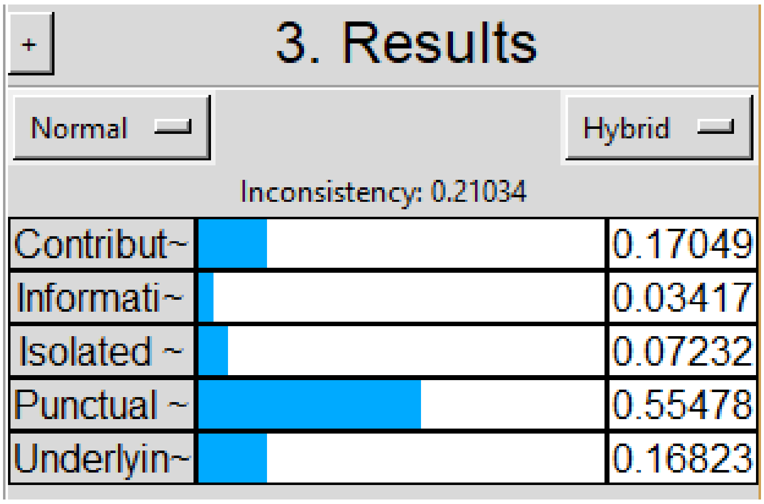



**Figure 4.2 Business Value cluster results, case1.**

Regarding the cluster of *Technical Importance*, the *Decomposability* criterion is the most critical. This indicates the relevance in which components/assets of the system are independent of one another. The decision-maker stressed that what is needed for software and hardware implementation (being within the company's costs) will be easily supplied for adaptation and exchange. To that end, *Hardware* and *Software* criteria are considered important, but not critical. Figure 4.3 present this cluster's comparisons.

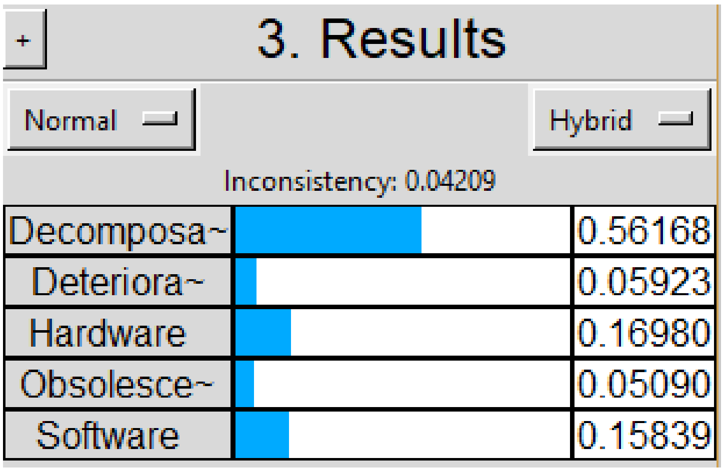



**Figure 4.3 Technical Importance cluster results, case 1.**

After that, all criteria in *BV* and *TI* clusters are pondered by its four alternatives (*Extraordinary Adaptation, Simplified Adaptation, Ordinary Maintenance and Replacement*). The *Isolated Impact* criterion comparison example is showed in Figure 4.4. Likewise, all other criteria are compared the same way.

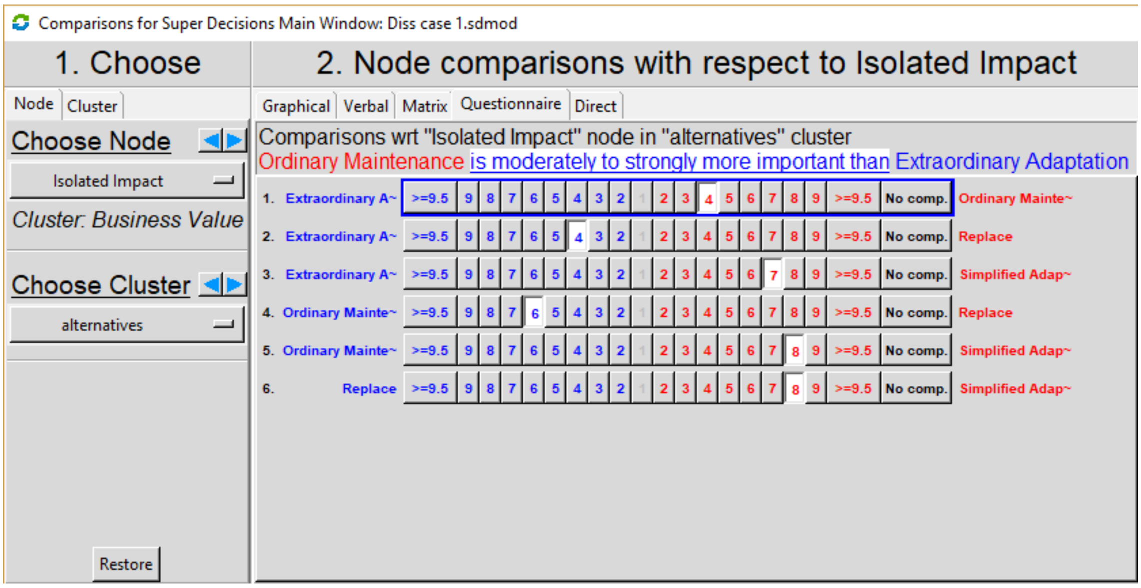



**Figure 4.4 Alternative level comparison (Isolated Impact criterion).**

Then again, this comparison is made for all ten criteria (five each cluster). At the end of this first step, the alternative supported by the AHP method was considerate the one in the third quadrant of the graphical analysis, *Simplified Adaptation*. This agreed with the organization's culture, which is to support the simplest scenario to consider changes. The results can be seen in the Figure 4.5.

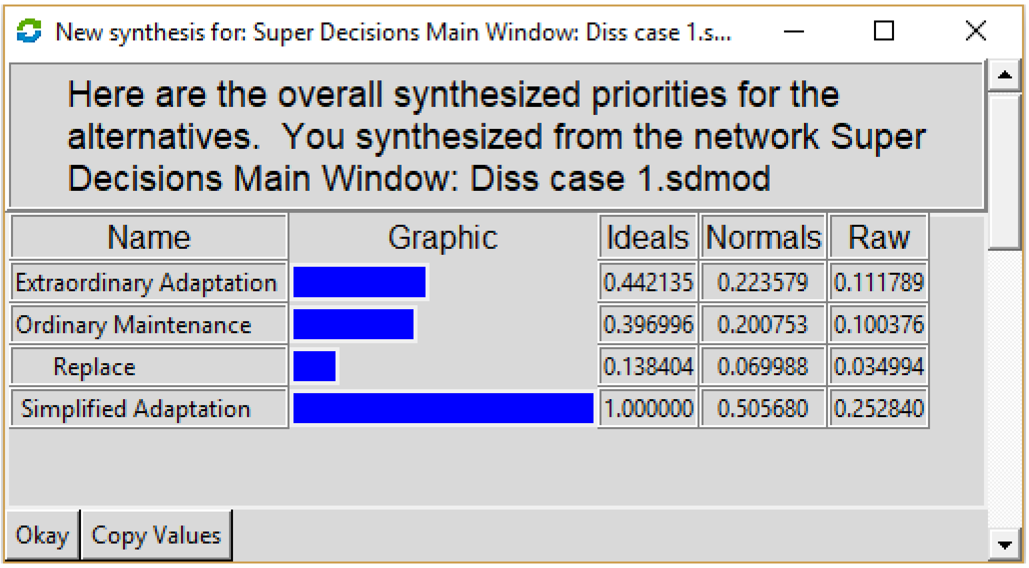



**Figure 4.5 Best alternative supported by the AHP method, case 1.**

Other insights are exposed as the result is showed for the decision-maker: Most maintenance processes have to occur within 50 seconds; Adding or removing process is difficult and causes problems (interoperability barriers); The organization often keep damaged machines, because the decision-making to repair them revolves around monetary aspects. In this way the organization keeps the machine (or code) until it results in an unsustainable problem; In many processes of this system, it is preferable to apply rework than to change the process so that the problem does not occur. This is proven by the splash example given in the case's introduction, even if the 6mm electrode allows less solder splash in the cars, it is more convenient to keep the 4mm electrode (larger splash) and execute rework, than to change it.

### 4.1.2 CLASSIFICATION STEP

This step analyzes, through the *Simplified Adaptation* previous decision, which functions/requirements of a given 4.0-maintenance architecture are most needed to be implemented to the system, while generating the least amount of interoperability barriers. However, before applying Step 2, the Mudge method should be applied. As described at the end of subsection 3.2.2.3, this process occurs to define weights for the criteria to be compared among the alternatives of the ELECTRE TRI method. Unlike the AHP method of Step 1, the ELECTRE TRI method requires another process so that the weights of its criteria are discriminated.

In the application of the Mudge method, the decision-maker compares the criteria of Step 2 with each other (similarly to the AHP method). In this comparison, a criterion may not score (weight 0). The non-scored criteria were considered the same as the lowest score criteria. In this case study, the Mudge method applied by the decision-maker ended up having two scoreless criteria. This way they assumed the value of the criterion decided as less valuable besides zero which was 0,013514 (*relevance points*).

The application of the ELECTRE TRI method is given through a meta-model built in Microsoft Excel. This was necessary to facilitate its understanding and data input to the participants of both cases. This case study's Mudge diagram is showed in Figure 4.6 and after that, the ELECTRE TRI meta-model scored can be seen in Figure 4.7.

| | |
|---|---|
| **Much** more important | 5 |
| **More** important | 3 |
| **Little** more important | 1 |
| **Same** importance | 0 |

| | | | | A | B | C | D | E | F | G | H | I | J | K | L | M | N | Value | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | Expenses optimization | A | 1 | X | 2a | 2a | 1d | 3a | a1 | 1a | 3a | 4a | 2a | 3a | 4a | 2a | 3a | 30 | 0,2027 |
| C2 | Business alignment | B | 2 | | X | 0 | 2d | 1b | 2f | 1g | 1b | 2b | 0 | 1b | 2b | b1 | 1b | 9 | 0,06081 |
| C3 | Communication potential | C | 3 | | | X | 2d | 1c | 2f | 1g | 1c | 2c | 1c | 1c | 2c | 0 | 1c | 9 | 0,06081 |
| C4 | Standard formalization | D | 4 | | | | X | 3d | 1d | 1d | 3d | 4d | 2d | 3d | 4d | 2d | 3d | 31 | 0,20946 |
| C5 | Risk management control | E | 5 | | | | | X | 3f | 2g | 0 | 2e | 1j | k1 | 1e | 1m | 0 | 3 | 0,02027 |
| C6 | Flexibility | F | 6 | | | | | | X | 1f | 3f | 4f | 2f | 3f | 4f | 2f | 3f | 29 | 0,19595 |
| C7 | Technological capability | G | 7 | | | | | | | X | 2g | 3g | 0 | 1g | 2g | g1 | 1g | 14 | 0,09459 |
| C8 | Towards-the-system data-integration | H | 8 | | | | | | | | X | 1h | 1j | 0 | 1h | 1m | 0 | 2 | 0,01351 |
| C9 | Business | I | 9 | | | | | | | | | X | 2j | 1k | 0 | 2m | 1n | **0** | **0** |
| C10 | Functional | J | 10 | | | | | | | | | | X | 1j | 2j | 0 | 1j | 8 | 0,05405 |
| C11 | Informational | K | 11 | | | | | | | | | | | X | 1k | 1m | 0 | 3 | 0,02027 |
| C12 | Comunication | L | 12 | | | | | | | | | | | | X | 2m | 1n | **0** | **0** |
| C13 | Integration | M | 13 | | | | | | | | | | | | | X | 1m | 8 | 0,05405 |
| C14 | Assets | N | 14 | | | | | | | | | | | | | | X | 2 | 0,01351 |
| | | | | | | | | | | | | | | | | | | 148 | **TOTAL** |

**Figure 4.6 Mudge comparison, case 1.**

**Legacy System Needs**

Function **a** will bring **which level of** benefit to the necessity **C** ?

| | |
|---|---|
| C1 | Expenses optimization |
| C2 | Business alignment |
| C3 | Communication potential |
| C4 | Standard formalization |
| C5 | Risk management control |
| C6 | Flexibility |
| C7 | Technological capability |
| C8 | Towards-the-system data-integration |

**Interoperability Barriers**

Function **a** will bring **which level of** barriers for the layer **C**?

| | |
|---|---|
| C9 | Business |
| C10 | Functional |
| C11 | Informational |
| C12 | Comunication |
| C13 | Integration |
| C14 | Assets |

| | Action courses for the six major TPM losses | VALUES FROM 1 to 5 | c1 | c2 | c3 | c4 | c5 | c6 | c7 | c8 | c9 | c10 | c11 | c12 | c13 | c14 | SUM | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equipment upgrade to prevent failures | Prevent or correct failures and breakdowns | a1 | 5 | 1 | 5 | 5 | 5 | 2 | 3 | 3 | 2 | 5 | 1 | 1 | 3 | 5 | 46 | 0,05686 |
| Improvement due to education and training | | a2 | 5 | 3 | 2 | 4 | 1 | 1 | 4 | 4 | 1 | 5 | 5 | 2 | 4 | 1 | 42 | 0,051916 |
| Preventive decision making to prevent failures and breakdowns | | a3 | 5 | 3 | 4 | 4 | 4 | 4 | 5 | 1 | 1 | 4 | 4 | 2 | 1 | 1 | 43 | 0,053152 |
| Inspection routine to prevent or correct failures | | a4 | 5 | 1 | 3 | 5 | 5 | 1 | 5 | 4 | 1 | 4 | 1 | 1 | 1 | 1 | 38 | 0,046972 |
| Predictive maintenance due to predictive plan | | a5 | 4 | 1 | 1 | 3 | 1 | 4 | 4 | 2 | 1 | 3 | 2 | 2 | 1 | 1 | 30 | 0,037083 |
| Predictive decision making to prevent failures and breakdowns | | a6 | 3 | 1 | 1 | 5 | 2 | 5 | 5 | 1 | 1 | 3 | 3 | 2 | 1 | 1 | 34 | 0,042027 |
| Corrective maintenance to correct failures due to service execution | | a7 | 1 | 1 | 1 | 4 | 1 | 1 | 5 | 1 | 1 | 1 | 4 | 1 | 1 | 1 | 24 | 0,029666 |
| Corrective decision making to correct failures due to analysis | | a8 | 1 | 1 | 1 | 3 | 1 | 4 | 2 | 1 | 1 | 3 | 1 | 1 | 4 | 2 | 26 | 0,032138 |
| Preventive decision making due to schedule | Faster and programmed set-up and adjustments | a9 | 5 | 2 | 3 | 4 | 2 | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 30 | 0,037083 |
| Predictive decision making due to setting time | | a10 | 5 | 4 | 1 | 4 | 1 | 5 | 2 | 1 | 5 | 1 | 2 | 1 | 3 | 5 | 40 | 0,049444 |
| Corrective adjustment due to a faster and programmed set-up | | a11 | 4 | 1 | 2 | 2 | 3 | 4 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 1 | 27 | 0,033375 |
| Corrective decision making to a faster set-up due to analysis | | a12 | 4 | 3 | 1 | 3 | 2 | 4 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 1 | 28 | 0,034611 |
| Preventive decision making for smaller amount of idling | Smaller amount of idling and minor stoppages | a13 | 2 | 2 | 3 | 3 | 1 | 3 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 23 | 0,02843 |
| Machine to machine communication due to report management | | a14 | 4 | 5 | 4 | 4 | 4 | 4 | 1 | 2 | 4 | 1 | 1 | 1 | 5 | 4 | 44 | 0,054388 |
| Predictive decision making to smaller amount of idling | | a15 | 1 | 1 | 1 | 1 | 1 | 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 17 | 0,021014 |
| Corrective maintenance to less stoppage service | | a16 | 4 | 3 | 4 | 3 | 1 | 4 | 2 | 5 | 1 | 1 | 1 | 1 | 3 | 1 | 34 | 0,042027 |
| Corrective decision making to a smaller amount of idling due to analysis | | a17 | 4 | 4 | 4 | 5 | 1 | 5 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 32 | 0,039555 |
| Preventive decision making to avoid reduce speed due to KPIs | Avoid reduced speed | a18 | 4 | 1 | 2 | 3 | 1 | 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 23 | 0,02843 |
| Facility alignment to avoid reduce speed | | a19 | 4 | 4 | 4 | 1 | 1 | 4 | 4 | 4 | 3 | 2 | 1 | 1 | 1 | 4 | 38 | 0,046972 |
| Predictive decision making to avoid reduce speed | | a20 | 3 | 2 | 2 | 2 | 1 | 3 | 2 | 2 | 2 | 2 | 1 | 1 | 2 | 1 | 26 | 0,032138 |
| Corrective maintenance to avoid reduce speed due to service execution | | a21 | 4 | 3 | 2 | 4 | 1 | 3 | 2 | 1 | 1 | 2 | 1 | 1 | 2 | 2 | 29 | 0,035847 |
| Corrective decision making to avoid reduce speed due to analysis | | a22 | 4 | 1 | 1 | 3 | 1 | 3 | 2 | 1 | 1 | 2 | 1 | 1 | 3 | 2 | 26 | 0,032138 |
| Cost optimization to eliminate defects and rework | Eliminate defects and rework | a23 | 1 | 2 | 3 | 3 | 1 | 3 | 2 | 1 | 2 | 2 | 1 | 1 | 3 | 2 | 27 | 0,033375 |
| Preventive decision making to eliminate rework | | a24 | 1 | 2 | 2 | 2 | 1 | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 20 | 0,024722 |
| Predictive decision making due to quality monitoring to eliminate defects | | a25 | 1 | 2 | 3 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 20 | 0,024722 |
| Corrective maintenance to eliminate rework | | a26 | 1 | 2 | 2 | 1 | 1 | 1 | 5 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 21 | 0,025958 |
| Corrective decision making to eliminate defects due to analysis | | a27 | 1 | 2 | 1 | 5 | 1 | 1 | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 21 | 0,025958 |
| Preventive decision making to less start-up losses due to system integratio | Zero start-up losses | a28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Startup planning to zero losses due to validation test | | a29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Predictive decision making to zero start-up losses due to acquired data | | a30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Corrective maintenance to less start-up losses | | a31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Corrective decision making to zero start-up losses due to analysis | | a32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | 86 | 58 | 63 | 87 | 46 | 83 | 71 | 47 | 39 | 54 | 42 | 33 | 54 | 46 | 809 | TOTAL |

**Figure 4.7 ELECTRE TRI meta-model scores, case 1.**

During the decision-maker’s comparisons, it was noticed that the criterion c1 (Expenses optimization) was shown to be inverse to the criterion c9 (Business interoperability barrier) in the sense that, when the company decided to optimize its expenses accepting and encouraging more simple solutions, it can be said that many interoperability barriers are not encountered by the organization's management layer, easily accepting those cheaper and simple solutions.

It could also be note in this case that *Zero Start-up Losses* is a course of action (criteria c28, c29, c30, c31 and c32 – see Table 3.3 ELECTRE TRI alternatives, page 70) that does not need to be considered in the opinion of the decision-maker. This is because the system should already be with the setup prepared at the beginning of the activities in the factory. The decision-maker understands that this system has complete control in this type of action and decided not to evaluate the set of criteria pertinent to this course of action.

Because only three functions were considered decisive in this case, the indifference thresholds for the *Decisive* category were adjusted (in 1.0 point), request by the decision-maker, extending the category to lower scores than the initial setup adopted by the specialist. Figure 4.8 shows the adjustment.

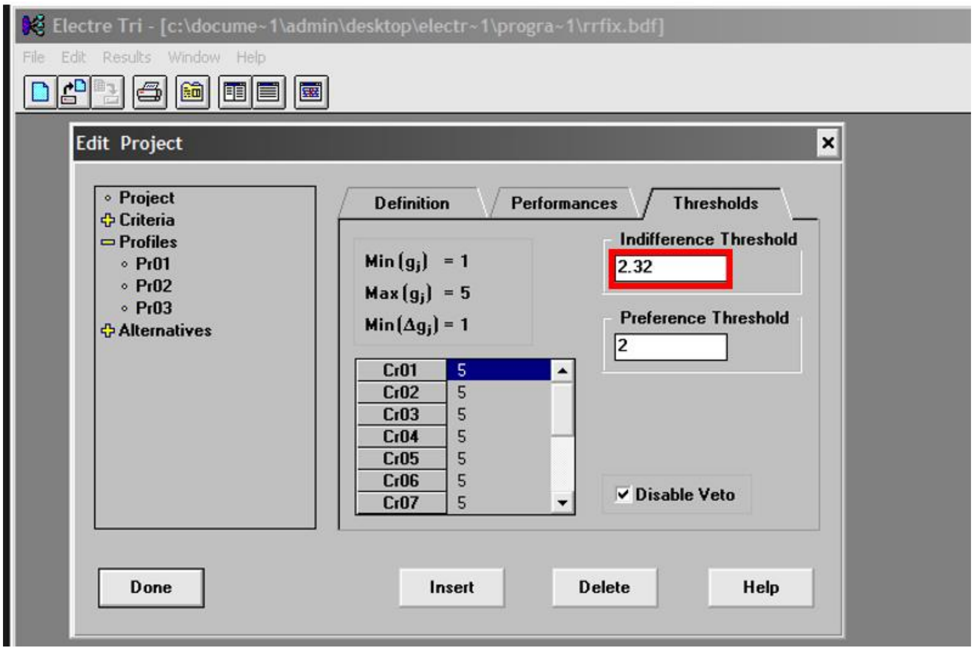



**Figure 4.8 Threshold adjusted.**

As default, the specialist adopted an indifference threshold of 1,32 for the Decisive/Good profile, 2,64 for the Good/Moderate profile, and 3,96 for the Moderate/Worthless (see subchapter 3.2.3 for the difference of *profiles* and *classes*). Firstly, this value was adopted after several trials, taking into account the subjective score of the criteria, from 1 to 5 points, divided in three categories, representing a value closer to 1,67. Secondly, couple with the previous argument, 1,32 characterizes that, the acceptance of the most decisive profile is more rigorous, as the other increase the easiness to enter their classes. Also, for the *legacy system needs* (criteria c1 to c8), 5 is the highest value, for the *interoperability barriers* (criteria c9 to c14) the score is reversed because they are unwanted.

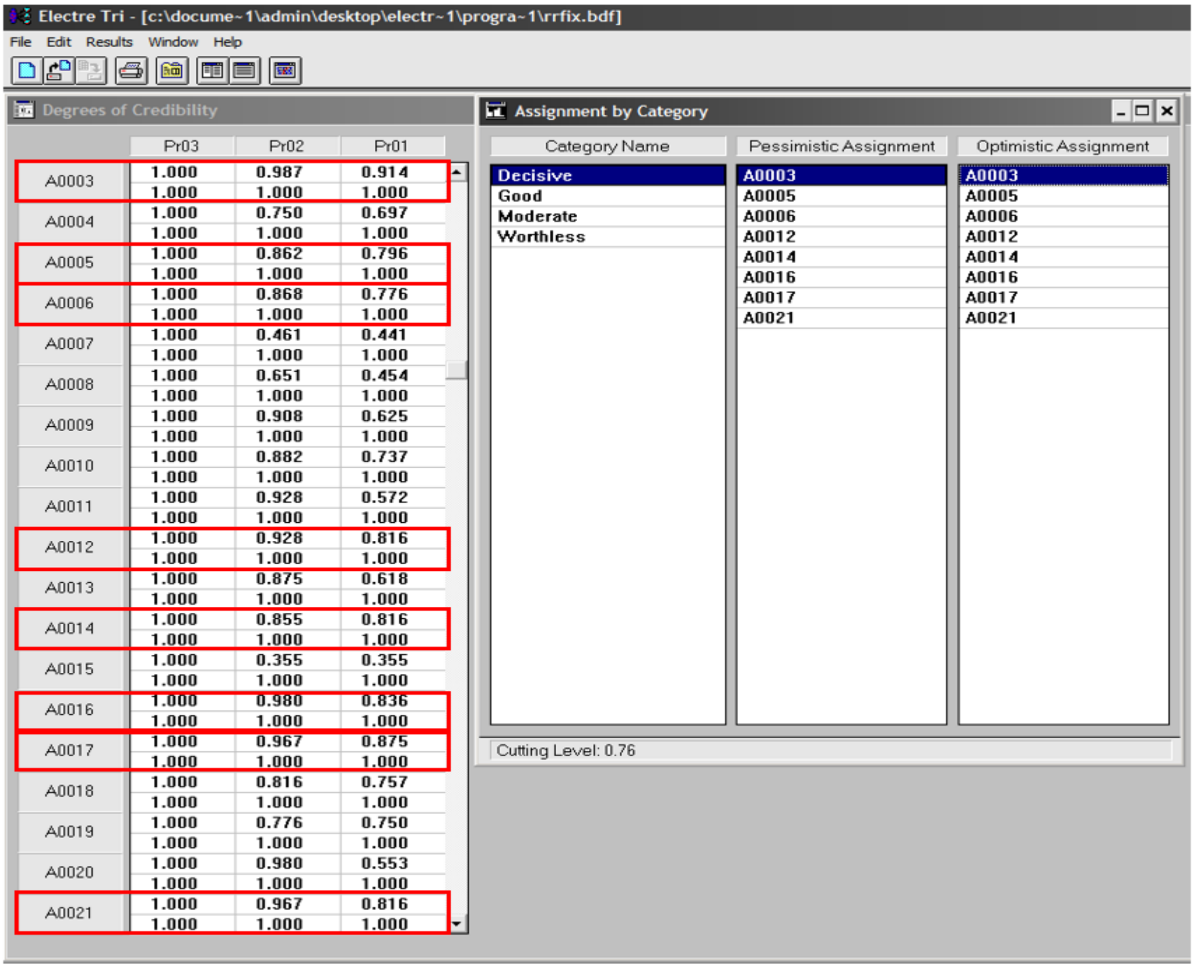



**Figure 4.9 Decision supported by ELECTRE TRI method, case 1.**

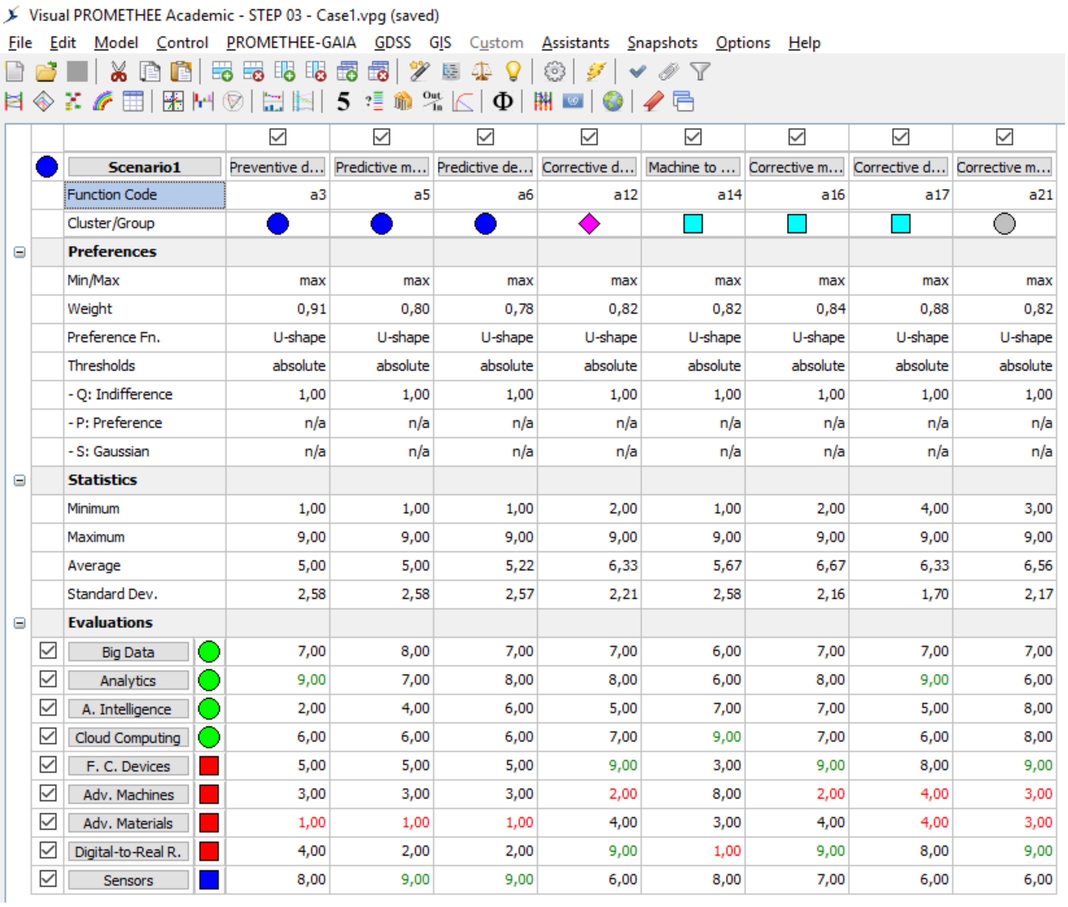
Finely, the decision supported by the method with the indifference threshold adjust can be seen in the Figure 4.9.

Some final statements for this step are: The organization invests in a skill school designed to teach employees how to use different tools and methods (contributing to c2 - Improvement due to education and training); An observation made by the decision-maker was that the organization does not measure efforts for in its Informational and Communicational layers;

### 4.1.3 APLICATION STEP

Step 3 regards the specialist’s insight on how much a I4.0-maintenance technology can enable determined decisive function for the legacy system analyzed and PROMETHEE II decision-making method is applied to support this choosing process. Now in the role of decision-maker, the specialist indicate levels for each alternative (I4.0 technology) to the criteria (which in this method’s case are represented by the *decisive functions*). The alternatives are leveled from 1 to 9, and a syntactical representation can be reviewed in Table 3.10.

Firstly, the following figure will present the Visual PROMETHEE software with the specialist's analysis regarding this case study, then the weighting of each technology will be discussed and finely, the results will be presented in a last figure, followed by an analysis on the alternatives ranking.




| Scenario1 | Preventive d... | Predictive m... | Predictive de... | Corrective d... | Machine to ... | Corrective m... | Corrective d... | Corrective m... |
|---|---|---|---|---|---|---|---|---|
| Function Code | a3 | a5 | a6 | a12 | a14 | a16 | a17 | a21 |
| Cluster/Group | | | | | | | | |
| **Preferences** | | | | | | | | |
| Min/Max | max | max | max | max | max | max | max | max |
| Weight | 0,91 | 0,80 | 0,78 | 0,82 | 0,82 | 0,84 | 0,88 | 0,82 |
| Preference Fn. | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape |
| Thresholds | absolute | absolute | absolute | absolute | absolute | absolute | absolute | absolute |
| - Q: Indifference | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |
| - P: Preference | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| - S: Gaussian | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| **Statistics** | | | | | | | | |
| Minimum | 1,00 | 1,00 | 1,00 | 2,00 | 1,00 | 2,00 | 4,00 | 3,00 |
| Maximum | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 |
| Average | 5,00 | 5,00 | 5,22 | 6,33 | 5,67 | 6,67 | 6,33 | 6,56 |
| Standard Dev. | 2,58 | 2,58 | 2,57 | 2,21 | 2,58 | 2,16 | 1,70 | 2,17 |
| **Evaluations** | | | | | | | | |
| Big Data | 7,00 | 8,00 | 7,00 | 7,00 | 6,00 | 7,00 | 7,00 | 7,00 |
| Analytics | 9,00 | 7,00 | 8,00 | 8,00 | 6,00 | 8,00 | 9,00 | 6,00 |
| A. Intelligence | 2,00 | 4,00 | 6,00 | 5,00 | 7,00 | 7,00 | 5,00 | 8,00 |
| Cloud Computing | 6,00 | 6,00 | 6,00 | 7,00 | 9,00 | 7,00 | 6,00 | 8,00 |
| F. C. Devices | 5,00 | 5,00 | 5,00 | 9,00 | 3,00 | 9,00 | 8,00 | 9,00 |
| Adv. Machines | 3,00 | 3,00 | 3,00 | 2,00 | 8,00 | 2,00 | 4,00 | 3,00 |
| Adv. Materials | 1,00 | 1,00 | 1,00 | 4,00 | 3,00 | 4,00 | 4,00 | 3,00 |
| Digital-to-Real R. | 4,00 | 2,00 | 2,00 | 9,00 | 1,00 | 9,00 | 8,00 | 9,00 |
| Sensors | 8,00 | 9,00 | 9,00 | 6,00 | 8,00 | 7,00 | 6,00 | 6,00 |

**Figure 4.10 PROMETHEE analysis, case 1.**

Function a3 – Preventive decision-making to prevent failures and breakdowns: Analytics was considerate the best technology, regarding that the system strongly relies on preventive decisions. It does not necessarily need more sensors, but the analysis of data could be optimized to cope with better preventive decision making, from both maintainer and machines. For that same function, Advanced Materials need to be in a high level to support preventive decision, so it was considerate the less relevant technology.

Function a5 – Predictive maintenance due to predictive plan: Sensors was considerate the best alternative to this function, because more reliable data is necessary to build a better predictive plan, as well-prepared data storage (Big Data). Again, Advanced Materials technologies would not impact so much this function.

Function a6 – Predictive decision-making to prevent failures and breakdowns: Failures and breakdowns are the production funnel which this system take part, so an Analytics technology to predictive decision-making is relevant. Although this system does not have sufficient Sensors to perform such analysis, so this is also considerate another relevant technology to be implemented.

Function a12 – Corrective decision-making to a faster set-up due to analysis: Because it is responsibility of the maintainers to execute corrective maintenance, Flexible Connection Devices are important to monitoring. Digital-to-Real Representation technologies also could assist, but on a guided corrective task. Analytics is considerate a high necessity, as this function suggests that the decision-making is due to analysis. But in this case, the tasks execution is more important that the ways the system's data is treated. Artificial Intelligence could provide an advantage, but as the factory does not have that kind of assistant already configured, that technology is not so relevant for this function. Advanced machines would be the less relevant upgrade for this function, as the corrective decisions are performed by human workforce only.

Function a14 – Machine to machine communication due to report management: To enable a more flexible communication the factory would need a better connection and Cloud Computing technology could suit this function better. Followed by Sensors and Advanced Machines technologies, the first one would enable the second to perform with more autonomous decisions. Digital-to-

Real Representation is a technology class that could not be addressed to this function in this particular system.

Function a16 – Corrective maintenance to less stoppage service: Again, because stoppage is a critical issue for this system and corrective actions are totally addressed by the maintainers, Digital-to-Real Representation and Flexible Communication Devices could bring a differential to the process. It is a close relate to function a12 analysis.

Function a17 – Corrective decision-making to a smaller amount of idling due to analysis: This time the corrective decision-making is addressed to the analysis importance. That way, Analytics is the most relevant technology for this function. Besides the technologies that would help to performed the corrective actions (by DtR representation and F.C. Devices), Big Data is important to provide the analysis needed.

Function a21 – Corrective maintenance to avoid reduce speed due to service execution: This function discriminates the importance of DtR Representation and Flexible Connection Devices. Because the critical task of a maintainer, in this system, is to perform corrective maintenance in the fast way possible, technologies which intend to guide the workers to this end can be decisive. For this to happen, a great supporting guide could be implemented (A.I.), along with a reliable connection (Cloud Computing). Advanced Machines could not help in corrective tasks regarding they are executed by maintainers and Advanced Materials could only be used to spread parts that are not so necessary to this system.

PROMETHEE Flow Table

| Rank | action | Phi | Phi+ | Phi- |
|---|---|---|---|---|
| 1 | Analytics | 0,4285 | 0,5510 | 0,1225 |
| 2 | Sensors | 0,3241 | 0,5125 | 0,1884 |
| 3 | F. C. Devices | 0,2689 | 0,5012 | 0,2323 |
| 4 | Big Data | 0,2505 | 0,4377 | 0,1872 |
| 5 | Cloud Computing | 0,2313 | 0,4363 | 0,2050 |
| 6 | Digital-to-Real R. | 0,0110 | 0,3800 | 0,3689 |
| 7 | A. Intelligence | -0,1533 | 0,2281 | 0,3814 |
| 8 | Adv. Machines | -0,5798 | 0,1235 | 0,7033 |
| 9 | Adv. Materials | -0,7814 | 0,0465 | 0,8278 |

**Figure 4.11 PROMETHEE rank, case 1.**

After analyzing the evaluation matrix, the Visual PROMETHEE software indicates the rank of technologies that could bring most differential to this system.

In conclusion, the presented legacy system could be upgraded firstly aiming better analytics technologies. A dedicated analytic team/method, could be implemented without many barriers to the processes. To retrieve the necessary data, more sensors could be implemented (e.g. to the line robots or even direct on the production line) and if this analysis and real time data could be delivered to the maintainers by smart devices, the critical corrective actions would be performed faster and even guided. To sustain the connection of those technologies and reevaluation of the factory wireless internet is recommended.

This analysis concludes the first case study. More details will be mentioned in the conclusion section. Subsections 4.2 present the second case study.

## 4.2 CASE TWO – WORKSTATIONS/MACHINES ASSEMBLY & SETUP

The second case refers to a multinational company active in the engineering and technology sectors, with core operating areas spread across business sectors like: mobility (hardware and software); consumer goods (including household appliances and power tools); industrial technology (including drive and control); and energy and building technology. This interview was conducted by video chat and to input the data, the specialist remotely shared his screen with the participant. In the workstation building/testing system proposed by the decision-maker, which is one of the organization's project engineer, every time a workstation is set up the maintainers must test those stations and machines that will be part of it. This assembly may be required by the company itself or for customers (other industries) and at the end of this service the stations/machines must be delivered fully functional.

The system consists of following certain actions like, designing the line for it to function, testing and fixing problems. Specifically, the system is in charge of assembling the workstations and machines participating in the required process, test them and put them to work. The project cannot be delivered without its required functionalities, however, the station will fail during its first setup/assembly test, characterizing the possibility of error as *certain*, where in the words of the decision-maker: "*There is no machine that is being assembled and does not show at least some fault*".

Primarily, what characterizes this process as a maintenance system is the debugging (i.e. testing) of the stations and their machines. The chance of problems to occur in assembling production lines is guaranteed. That way, these issues must be resolved before delivery to customers.

It is important to acknowledge that the system also have to be characterized as legacy, and to that end, it has to be extremely important to the organization's business value. To illustrate that, the decision-maker describes that the process impact drastically the speed in which the stations are delivered, but historically fails to treat some errors, always accusing the same set of problems each time the workstations are build.

Yet, the parts used to assemble the stations/machines are new, unique each time this process is executed. This reaffirms the fact that systems can be legacy not because of old components. In fact, this particular system proves to be legacy not necessarily by lacking on technological capabilities, rather it lacks on execution, monitoring and flexibility, while is still important for the organization’s business value bias.

In general, this is not a trivial understanding of a legacy system, but it is perfectly consistent as proven by this research and its references (see subsection 2.1.2). When the workstation's setup problems arise a maintenance process is called, addressed by the engineer as "process debugging" (which characterizes a term used for code programming, however in this case it is being implicated as a reactive maintenance due system setup). For this scenario, the system rules out a preventive maintenance process. In the specialist view, the pertinence of possible preventive and predictive actions will be discussed later.

### 4.2.1 FEASIBILITY STEP

During the analysis of Step 1, some insights were raised by the participant. For *Business Value* criteria, according to the decision-maker: "*For an isolated impact that you do not have, there are three underlying impacts you prevent*." An example of this has been described, indicating that if the workstation does not turn on, at least three tests must be done - in relation to the electrical part, the software part and in relation to the assembly of parts; this indicates the importance of the *Isolated Impact* criterion. This can change depending on the project and how it will impact the process in which it will be installed.

However, *Contribution to Profit* is also a critical criterion in this analysis, because the profit in this process only happens in the delivery of the workstations. Having said that, the most important criterion in this cluster was consider the *Isolated Impact*. In the decision-maker view, the system is extremely important by itself, independent from the contribution to the organizations profit and the underlying impact on other systems, the process that occurs isolated (e.g. monitoring and arranging the machines and workstations) is more critical.

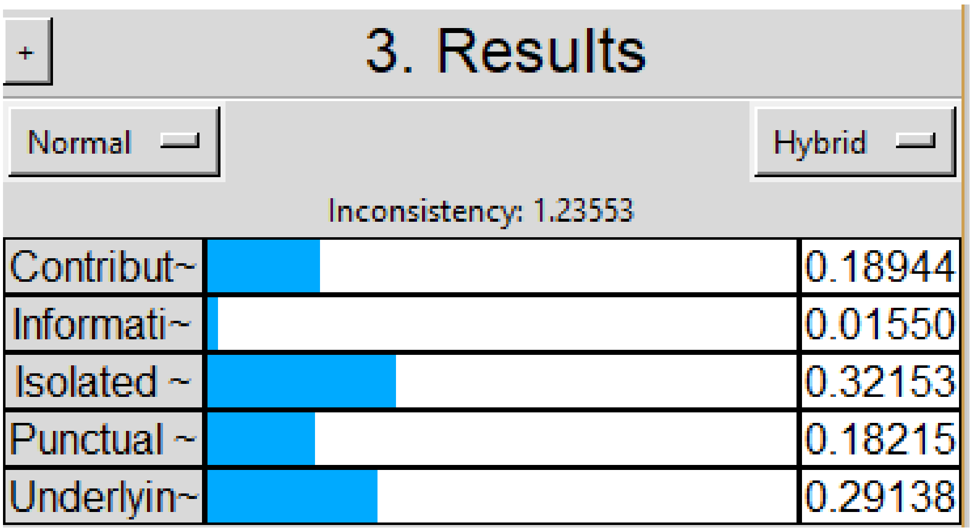



**Figure 4.12 Business Value cluster results, case2.**

In this case study, *Punctual Specificities* was considered by the participant to be a fault monitoring characteristic. Despite this, the system allows to review much of what is wrong in the design, mechanical, electrical, software and assembly. In the process of putting the workstation to work it is possible to discriminate the error in each of the sectors involved. Because of this, the process can be considered as monitoring. This aspect proves to be relevant in helping the specialist insight in the last step, explained further.

For the analysis of *Technical Importance*, the *Software* and *Hardware* criteria were characterized as important. However, the *Software* criterion received more relevance because the hardware is repeated several times. For instance, many equipment available for the assembly of workstations and machines are the same and independent the case, the problems they generate by their setup are similar. However, the code applied to the program and behavior of these workstations may vary more intensely. In short, software programming can hardly be the same as another, but the hardware parts/components used to assemble those stations will repeat themselves.

Also, as described in this last paragraph, it is easy to understand that *Obsolescence* and Deterioration were considered as weak criteria, since all hardware and software used for the assembly of the stations is composed of new parts.

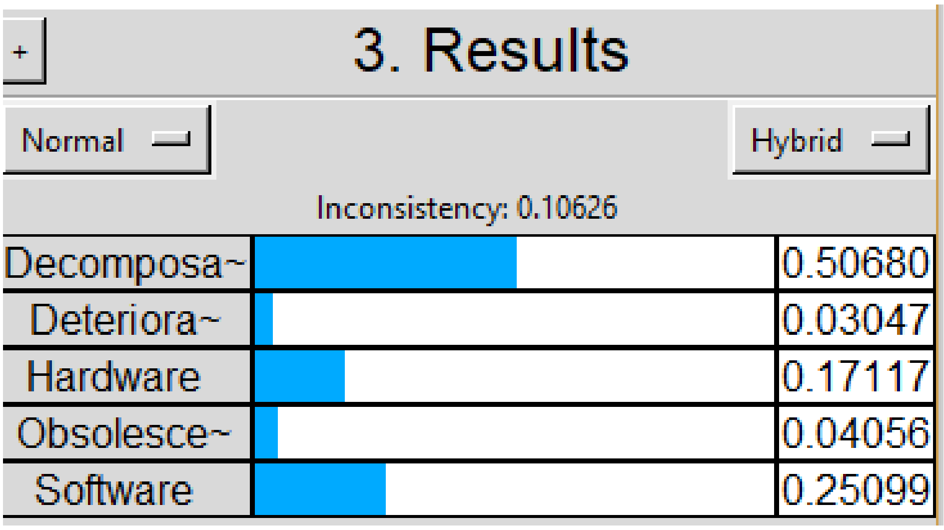



**Figure 4.13 Technical Importance cluster results, case 2.**

As can be seen in Figure 4.13, *Decomposability* is the most relevant criterion in the decision-maker opinion for this system. The fact that the system is modular and the ease which its main components are independent of each other characterizes it as *highly* decomposable. This allows the specialist to focus on digital integration aspects for the decisional analysis.

Figure 4.14 shows the most feasible alternative proposed by the AHP method, after each of the ten criteria (the same way as demonstrated by figure 4.4) has been compared by the participant.

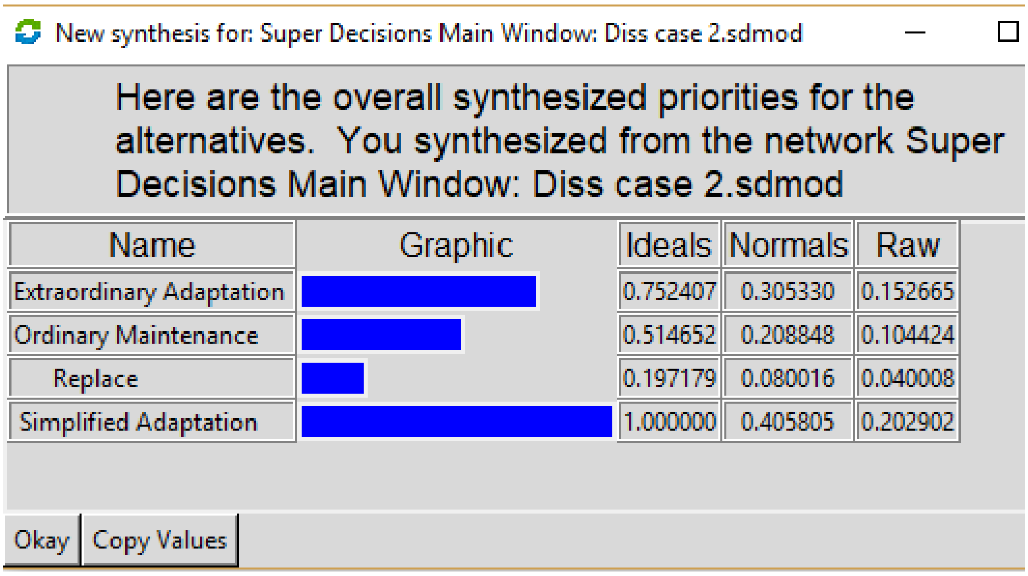



**Figure 4.14 Best alternative supported by the AHP method, case 2.**

Similar as the first case, the alternative supported by the AHP method once again was considerate the *Simplified Adaptation*. For the case study is relevant to acknowledge this result emphasizes that, despite the system is considered important to the organization, its *Technical Importance* is already well resolved and do not need an extraordinary adaptation. Nevertheless, the *Extraordinary Adaptation* was a close second place, and the alternative could be graphically analyzed to support a change, although the decision-maker had agreed to proceed with the method's first proposed choice.

The decision-maker finalize this first step analysis reframing that: The problems are usually the same, nevertheless, the parameterization of the machines and the arrangement of the processes may be different; The process does not usually reuse hardware and hardly software.

### 4.2.2 CLASSIFICATION STEP

After the *Simplified Adaptation* decision supported by the late AHP model, the functions needed to upgrade the legacy system to a SLS, as well as the barriers they will generate, are analyzed next. As described in the last case study, the Mudge method is applied to discriminate the criteria weight. In this case, only one criterion did not score (c10 – Functional layer interoperability barriers), and so, it received the score of the criterion with less importance (c14 – Assets layer interoperability barriers).

After the Mudge diagram, the ELECTRE TRI metamodel was applied. In this process, ten functions were classified as *Decisive*, sufficient number in the decision-maker’s view. The evaluation showed that even the participant scoring high levels for the *Prevent or correct failures and breakdowns* course of action, regarding the *Legacy System Needs* (positive criteria), he also scored high to its *Interoperability Barriers* (negative criteria), canceling out all the functions of this course of action to enter in the *Decisive* class, reported further.

Next figures show the Mudge diagram and its criteria weight process, follow by the ELECTRE TRI metamodel scored by the decision-maker.

| | |
|---|---|
| **Much** more important | **5** |
| **More** important | **3** |
| **Little** more important | **1** |
| **Same** importance | **0** |

| | | | | A | B | C | D | E | F | G | H | I | J | K | L | M | N | Value | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | Expenses optimization | A | 1 | X | 0 | 3c | 3d | 2e | 0 | 0 | 3h | 1i | 1a | 0 | 3l | 1m | 1a | 2 | 0,01183 |
| C2 | Business alignment | B | 2 | | X | 3c | 3d | 2e | 0 | 1b | 3h | 1i | 1b | 0 | 3l | 1m | 1b | 3 | 0,01775 |
| C3 | Communication potential | C | 3 | | | X | 1c | 1c | 3c | 3c | 1h | 2c | 4c | 3c | 1c | 2c | 4c | 28 | 0,16568 |
| C4 | Standard formalization | D | 4 | | | | X | 1d | 3d | 4d | 1h | 2d | 4d | 4d | 1d | 2d | 4d | 31 | 0,18343 |
| C5 | Risk management control | E | 5 | | | | | X | 2e | 2e | 2h | 1e | 3e | 2e | 1l | 1e | 3e | 18 | 0,10651 |
| C6 | Flexibility | F | 6 | | | | | | X | 0 | 3h | 1i | 1f | 1f | 3l | 1m | 1f | 3 | 0,01775 |
| C7 | Technological capability | G | 7 | | | | | | | X | 3h | 1i | 1g | 0 | 3l | 1m | 1g | 2 | 0,01183 |
| C8 | Towards-the-system data-integration | H | 8 | | | | | | | | X | 2h | 4h | 3h | 1h | 2h | 4h | 32 | 0,18935 |
| C9 | Business | I | 9 | | | | | | | | | X | 2i | 1i | 2l | 0 | 2i | 9 | 0,05325 |
| C10 | Functional | J | 10 | | | | | | | | | | X | 1k | 4l | 2m | 1n | **0** | **0** |
| C11 | Informational | K | 11 | | | | | | | | | | | X | 3l | 1m | 2k | 3 | 0,01775 |
| C12 | Comunication | L | 12 | | | | | | | | | | | | X | 2l | 4l | 28 | 0,16568 |
| C13 | Integration | M | 13 | | | | | | | | | | | | | X | 2m | 9 | 0,05325 |
| C14 | Assets | N | 14 | | | | | | | | | | | | | | X | 1 | 0,00592 |
| | | | | | | | | | | | | | | | | | | 169 | **TOTAL** |

**Figure 4.15 Mudge comparison, case 2.**

**Legacy System Needs**

Function **a** will bring **which level of** benefit to the necessity **C** ?

- C1 Expenses optimization
- C2 Business alignment
- C3 Communication potential
- C4 Standard formalization
- C5 Risk management control
- C6 Flexibility
- C7 Technological capability
- C8 Towards-the-system data-integration

**Interoperability Barriers**

Function **a** will bring **which level of** barriers for the layer **C**?

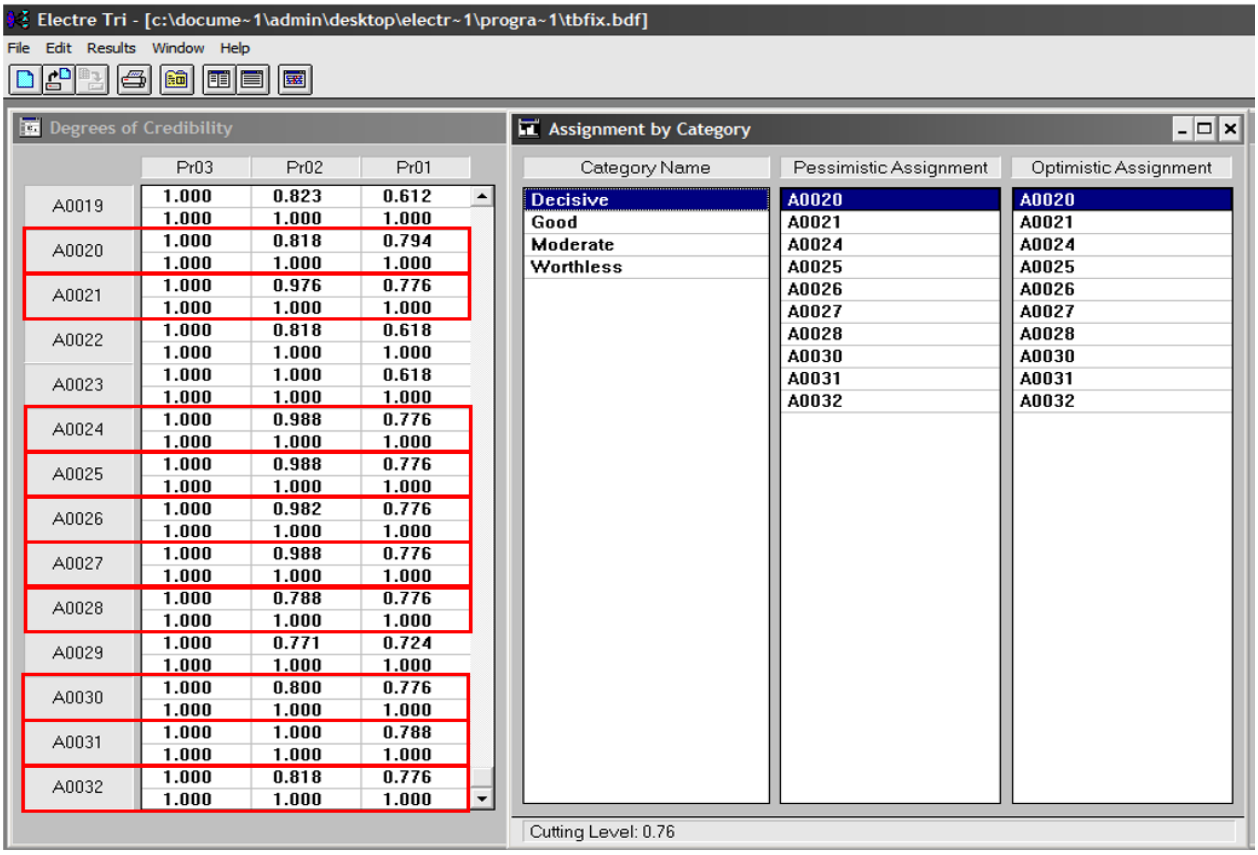
- C9 Business
- C10 Functional
- C11 Informational
- C12 Comunication
- C13 Integration
- C14 Assets

| | Action courses for the six major TPM losses | VALUES FROM 1 to 5 | c1 | c2 | c3 | c4 | c5 | c6 | c7 | c8 | c9 | c10 | c11 | c12 | c13 | c14 | SUM | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equipment upgrade to prevent failures | Prevent or correct failures and breakdowns | a1 | 4 | 4 | 4 | 3 | 2 | 1 | 5 | 4 | 1 | 2 | 4 | 5 | 5 | 3 | 47 | 0,03769 |
| Improvement due to education and training | | a2 | 5 | 1 | 4 | 5 | 2 | 2 | 4 | 4 | 1 | 1 | 4 | 5 | 4 | 3 | 45 | 0,036087 |
| Preventive decision making to prevent failures and breakdowns | | a3 | 2 | 1 | 5 | 4 | 4 | 2 | 3 | 4 | 1 | 3 | 4 | 4 | 4 | 1 | 42 | 0,033681 |
| Inspection routine to prevent or correct failures | | a4 | 4 | 1 | 4 | 4 | 4 | 3 | 1 | 5 | 3 | 3 | 5 | 4 | 5 | 3 | 49 | 0,039294 |
| Predictive maintenance due to predictive plan | | a5 | 2 | 2 | 4 | 4 | 3 | 2 | 4 | 4 | 1 | 1 | 4 | 5 | 5 | 1 | 42 | 0,033681 |
| Predictive decision making to prevent failures and breakdowns | | a6 | 3 | 1 | 4 | 5 | 3 | 3 | 2 | 5 | 1 | 1 | 5 | 5 | 4 | 1 | 43 | 0,034483 |
| Corrective maintenance to correct failures due to service execution | | a7 | 2 | 1 | 5 | 5 | 4 | 2 | 4 | 5 | 2 | 1 | 4 | 4 | 5 | 3 | 47 | 0,03769 |
| Corrective decision making to correct failures due to analysis | | a8 | 2 | 2 | 5 | 4 | 3 | 2 | 3 | 5 | 1 | 1 | 4 | 4 | 4 | 1 | 41 | 0,032879 |
| Preventive decision making due to schedule | Faster and programmed set-up and adjustments | a9 | 1 | 1 | 3 | 4 | 3 | 1 | 1 | 3 | 4 | 1 | 3 | 4 | 3 | 1 | 33 | 0,026464 |
| Predictive decision making due to setting time | | a10 | 1 | 1 | 4 | 5 | 4 | 2 | 1 | 4 | 4 | 1 | 1 | 4 | 3 | 2 | 37 | 0,029671 |
| Corrective adjustment due to a faster and programmed set-up | | a11 | 1 | 1 | 4 | 5 | 3 | 1 | 1 | 3 | 4 | 1 | 2 | 5 | 2 | 2 | 35 | 0,028067 |
| Corrective decision making to a faster set-up due to analysis | | a12 | 1 | 1 | 4 | 4 | 3 | 2 | 1 | 5 | 3 | 1 | 1 | 4 | 3 | 1 | 34 | 0,027265 |
| Preventive decision making for smaller amount of idling | Smaller amount of idling and minor stoppages | a13 | 2 | 2 | 4 | 4 | 3 | 2 | 3 | 4 | 3 | 1 | 2 | 4 | 2 | 1 | 37 | 0,029671 |
| Machine to machine communication due to report management | | a14 | 1 | 1 | 5 | 4 | 2 | 2 | 3 | 4 | 3 | 1 | 1 | 4 | 3 | 2 | 36 | 0,028869 |
| Predictive decision making to smaller amount of idling | | a15 | 1 | 2 | 5 | 5 | 4 | 2 | 2 | 5 | 4 | 1 | 2 | 5 | 3 | 2 | 43 | 0,034483 |
| Corrective maintenance to less stoppage service | | a16 | 1 | 2 | 5 | 4 | 4 | 2 | 3 | 4 | 4 | 2 | 1 | 4 | 2 | 1 | 39 | 0,031275 |
| Corrective decision making to a smaller amount of idling due to analysis | | a17 | 1 | 2 | 5 | 5 | 5 | 2 | 2 | 5 | 3 | 1 | 1 | 3 | 2 | 1 | 38 | 0,030473 |
| Preventive decision making to avoid reduce speed due to KPIs | Avoid reduced speed | a18 | 1 | 2 | 5 | 4 | 3 | 2 | 1 | 4 | 3 | 1 | 2 | 3 | 3 | 2 | 36 | 0,028869 |
| Facility alignment to avoid reduce speed | | a19 | 2 | 2 | 5 | 4 | 2 | 2 | 1 | 4 | 3 | 3 | 2 | 5 | 1 | 2 | 38 | 0,030473 |
| Predictive decision making to avoid reduce speed | | a20 | 2 | 4 | 4 | 5 | 4 | 1 | 2 | 4 | 2 | 2 | 1 | 5 | 2 | 1 | 39 | 0,031275 |
| Corrective maintenance to avoid reduce speed due to service execution | | a21 | 1 | 3 | 4 | 4 | 4 | 2 | 1 | 5 | 2 | 1 | 1 | 4 | 1 | 1 | 34 | 0,027265 |
| Corrective decision making to avoid reduce speed due to analysis | | a22 | 2 | 2 | 5 | 5 | 3 | 1 | 2 | 4 | 3 | 1 | 1 | 5 | 1 | 1 | 36 | 0,028869 |
| Cost optimization to eliminate defects and rework | Eliminate defects and rework | a23 | 4 | 4 | 4 | 3 | 4 | 2 | 2 | 4 | 2 | 3 | 1 | 3 | 1 | 1 | 38 | 0,030473 |
| Preventive decision making to eliminate rework | | a24 | 2 | 2 | 5 | 5 | 5 | 2 | 1 | 5 | 2 | 1 | 1 | 4 | 1 | 1 | 37 | 0,029671 |
| Predictive decision making due to quality monitoring to eliminate defects | | a25 | 3 | 2 | 4 | 4 | 5 | 2 | 1 | 5 | 2 | 1 | 1 | 4 | 1 | 1 | 36 | 0,028869 |
| Corrective maintenance to eliminate rework | | a26 | 2 | 2 | 4 | 5 | 4 | 1 | 2 | 4 | 1 | 1 | 2 | 4 | 2 | 2 | 36 | 0,028869 |
| Corrective decision making to eliminate defects due to analysis | | a27 | 3 | 2 | 5 | 4 | 5 | 2 | 1 | 5 | 1 | 1 | 1 | 3 | 1 | 1 | 35 | 0,028067 |
| reventive decision making to less start-up losses due to system integratio | Zero start-up losses | a28 | 2 | 1 | 4 | 4 | 4 | 1 | 1 | 5 | 2 | 1 | 1 | 5 | 1 | 1 | 33 | 0,026464 |
| Startup planning to zero losses due to validation test | | a29 | 3 | 3 | 4 | 4 | 4 | 2 | 1 | 5 | 5 | 1 | 2 | 5 | 2 | 1 | 42 | 0,033681 |
| Predictive decision making to zero start-up losses due to acquired data | | a30 | 3 | 1 | 5 | 5 | 5 | 1 | 2 | 5 | 2 | 1 | 2 | 5 | 2 | 1 | 40 | 0,032077 |
| Corrective maintenance to less start-up losses | | a31 | 2 | 3 | 4 | 4 | 5 | 3 | 4 | 4 | 2 | 1 | 1 | 4 | 1 | 2 | 40 | 0,032077 |
| Corrective decision making to zero start-up losses due to analysis | | a32 | 3 | 1 | 4 | 5 | 5 | 3 | 2 | 5 | 2 | 1 | 1 | 5 | 1 | 1 | 39 | 0,031275 |
| | | | 69 | 60 | 140 | 139 | 118 | 60 | 67 | 141 | 77 | 43 | 68 | 137 | 80 | 48 | 1247 | TOTAL |

Figure 4.16 ELECTRE TRI meta-model scores, case 2.

Interoperability barriers at the communication layer were highly scored by the decision-maker, not because of the organization's culture itself, but most because of the country's culture in which the system in question performs. Then again, because of this cultural characteristic, barriers are also found in the information layer. Maintainers choose to perform tasks in a none standardized way, committing the same mistakes due to electrical, mechanical and testing planning. Some machines have certain standards, but many maintainers assemble all those machines from scratch, without following standard nor any criteria to maintain the standardization of the assemblies. Backup is not standard procedure for process setup and workstation assembly.

The ELECTRE TRI supported alternatives for the decisive I4.0-maintenance functions to be implemented in the legacy system is given in the follow figure, together with the *Degrees of Credibility* of the alternatives.




| | Pr03 | Pr02 | Pr01 |
|---|---|---|---|
| A0019 | 1.000 | 0.823 | 0.612 |
| | 1.000 | 1.000 | 1.000 |
| A0020 | 1.000 | 0.818 | 0.794 |
| | 1.000 | 1.000 | 1.000 |
| A0021 | 1.000 | 0.976 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0022 | 1.000 | 0.818 | 0.618 |
| | 1.000 | 1.000 | 1.000 |
| A0023 | 1.000 | 1.000 | 0.618 |
| | 1.000 | 1.000 | 1.000 |
| A0024 | 1.000 | 0.988 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0025 | 1.000 | 0.988 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0026 | 1.000 | 0.982 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0027 | 1.000 | 0.988 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0028 | 1.000 | 0.788 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0029 | 1.000 | 0.771 | 0.724 |
| | 1.000 | 1.000 | 1.000 |
| A0030 | 1.000 | 0.800 | 0.776 |
| | 1.000 | 1.000 | 1.000 |
| A0031 | 1.000 | 1.000 | 0.788 |
| | 1.000 | 1.000 | 1.000 |
| A0032 | 1.000 | 0.818 | 0.776 |
| | 1.000 | 1.000 | 1.000 |

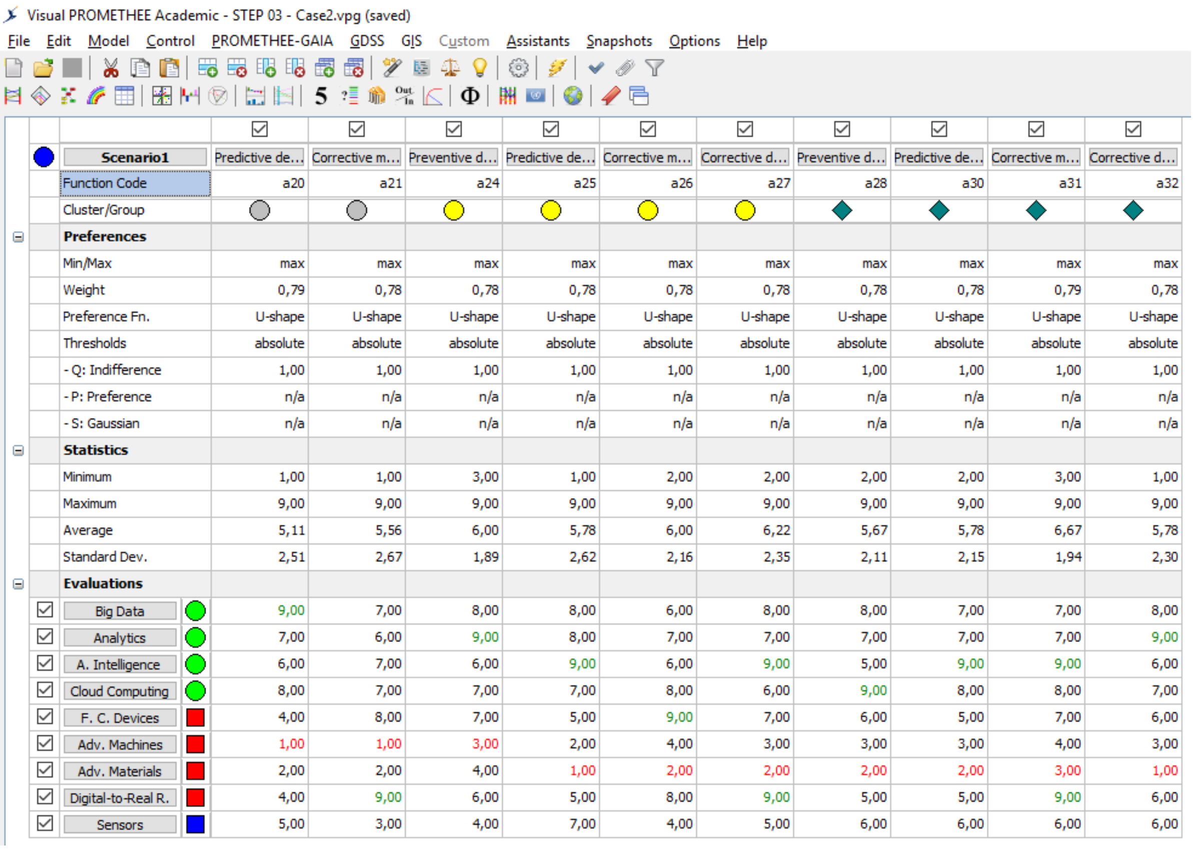
| Category Name | Pessimistic Assignment | Optimistic Assignment |
|---|---|---|
| Decisive | A0020 | A0020 |
| Good | A0021 | A0021 |
| Moderate | A0024 | A0024 |
| Worthless | A0025 | A0025 |
| | A0026 | A0026 |
| | A0027 | A0027 |
| | A0028 | A0028 |
| | A0030 | A0030 |
| | A0031 | A0031 |
| | A0032 | A0032 |

**Figure 4.17 Decision supported by ELECTRE TRI method, case 2.**

In this case, the indifference threshold of 1,32 was maintained. Ten functions were selected to enter the *Decisive* category. As commented before, much of the first functions (a1 to a19) were not selected because its interoperability barriers also were scored with high values, as can be seen in Figure 4.16. In general, no function that entered in the *Decisive* class scored more than 0,7 in its *Degree of Credibility* weight. To put in another way, in this class none of the functions is much more valuable as the other. This will impact in the next analysis, because the technology that will be chosen have to, in a general way, resolve all the functions (i.e. the most generic technology that can resolve all the functions will probably be the best one).

### 4.2.3 APLICATION STEP

For this second case study the PROMETHEE method is applied for ten decisive functions chosen in the previous step. As already mentioned in subsection 4.1.3, Step 3 regards the specialist's insight on how much a I4.0-maintenance technology can enable those ten functions for the legacy system presented. Again, the specialist indicates levels for each alternative (I4.0 technology). In the PROMETHEE method the alternatives are actually called *actions*.




| Scenario1 | Predictive de... | Corrective m... | Preventive d... | Predictive de... | Corrective m... | Corrective d... | Preventive d... | Predictive de... | Corrective m... | Corrective d... |
|---|---|---|---|---|---|---|---|---|---|---|
| Function Code | a20 | a21 | a24 | a25 | a26 | a27 | a28 | a30 | a31 | a32 |
| Cluster/Group | | | | | | | | | | |
| **Preferences** | | | | | | | | | | |
| Min/Max | max | max | max | max | max | max | max | max | max | max |
| Weight | 0,79 | 0,78 | 0,78 | 0,78 | 0,78 | 0,78 | 0,78 | 0,78 | 0,79 | 0,78 |
| Preference Fn. | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape | U-shape |
| Thresholds | absolute | absolute | absolute | absolute | absolute | absolute | absolute | absolute | absolute | absolute |
| - Q: Indifference | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |
| - P: Preference | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| - S: Gaussian | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| **Statistics** | | | | | | | | | | |
| Minimum | 1,00 | 1,00 | 3,00 | 1,00 | 2,00 | 2,00 | 2,00 | 2,00 | 3,00 | 1,00 |
| Maximum | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 | 9,00 |
| Average | 5,11 | 5,56 | 6,00 | 5,78 | 6,00 | 6,22 | 5,67 | 5,78 | 6,67 | 5,78 |
| Standard Dev. | 2,51 | 2,67 | 1,89 | 2,62 | 2,16 | 2,35 | 2,11 | 2,15 | 1,94 | 2,30 |
| **Evaluations** | | | | | | | | | | |
| Big Data | 9,00 | 7,00 | 8,00 | 8,00 | 6,00 | 8,00 | 8,00 | 7,00 | 7,00 | 8,00 |
| Analytics | 7,00 | 6,00 | 9,00 | 8,00 | 7,00 | 7,00 | 7,00 | 7,00 | 7,00 | 9,00 |
| A. Intelligence | 6,00 | 7,00 | 6,00 | 9,00 | 6,00 | 9,00 | 5,00 | 9,00 | 9,00 | 6,00 |
| Cloud Computing | 8,00 | 7,00 | 7,00 | 7,00 | 8,00 | 6,00 | 9,00 | 8,00 | 8,00 | 7,00 |
| F. C. Devices | 4,00 | 8,00 | 7,00 | 5,00 | 9,00 | 7,00 | 6,00 | 5,00 | 7,00 | 6,00 |
| Adv. Machines | 1,00 | 1,00 | 3,00 | 2,00 | 4,00 | 3,00 | 3,00 | 3,00 | 4,00 | 3,00 |
| Adv. Materials | 2,00 | 2,00 | 4,00 | 1,00 | 2,00 | 2,00 | 2,00 | 2,00 | 3,00 | 1,00 |
| Digital-to-Real R. | 4,00 | 9,00 | 6,00 | 5,00 | 8,00 | 9,00 | 5,00 | 5,00 | 9,00 | 6,00 |
| Sensors | 5,00 | 3,00 | 4,00 | 7,00 | 4,00 | 5,00 | 6,00 | 6,00 | 6,00 | 6,00 |

**Figure 4.18 PROMETHEE analysis, case 2.**

Figure 4.18 presents the Visual PROMETHEE software with the technologies pondered regarding the specialist's strategy to upgrade the legacy system. Now the most relevant analyzes will be described, followed by the actions rank and an overview of this step.

Function a20 – Predictive decision-making to avoid reduce speed: For the system being able to support predictive decisions, a data retrieving from each build-up/testing workstation could be performed. In that way, Big Data is an important technology that could be used to retain data from previous failures. However, this data input cannot rely on maintainers, as culturally they tend to not follow basic procedures. This data could be received via software debugging. For the software to be responsible for the factory, Cloud Computing technologies can be the applied. Advanced Machines are not the case of upgrading in this situation because the hardware used for the workstation assemble is new.

Function a21 – Corrective maintenance to avoid reduce speed due to service execution: To avoid reduce speed in the service execution a guiding technology could be used by the maintainers. If guided, maybe the collaborators could execute the workstation assemble and resolve maintenance issues faster. To that end, Digital-to-real Representation technologies are a best choice, followed by Flexible Connection Devices that can also provide feedback to the user. For those technologies to be accurate, a cloud connection (Cloud C.) can connect them to the database (Big Data), where a troubleshoot guide (A.I. based) could help the maintainers perform their tasks. Again, machines already wave great technological response and do not need to be improved.

Function a24 – Preventive decision-making to eliminate rework: Rework can be reduced, as stated by the organization's engineer, by assemble examples that might be similar to previous projects. That way Analytics could be used to manage different scenarios where those reworks occur. Couple with that, Big Data technologies are important to retain those feedbacks. To present the preventive solution, Flexible Connected Devices might present previous workstations set-ups. This whole process needed to be ensured by a high-performance cloud network (Cloud C.).

Function a25 – Predictive decision-making due to quality monitoring to eliminate defects: To predict decisions, a historical data need to be stored and analyzed. That way Big Data technology and Analytics are important but predictive measures are better translated by Artificial Intelligence algorithms. Data relying on system debugging feedback require a high-performance Cloud technology (as the workstation can be assemble outside the organizations area) and some Sensors with easy setup. There are no needs on Advanced Materials for this function.

Function 26 – Corrective maintenance to eliminate rework: Corrective measures that needed to be executed one single time (no rework). For that to occur in this system, the maintenance needs to be executed by an experienced maintainer or a well reliable troubleshooting/intelligent guide. The first solution is easier to achieve, Flexible Connected Devices are important to transmit the expert maintainer feedback to corrective measure, followed by a Digital-to-Real Representation guide that could be representing this expert’s on-the-go feedback. Cloud Computing technology is important to transmit this feedback that could also be supported by Analytics applied on historical data stored.

Function a27 – Corrective decision-making to eliminate defects due to analysis: This function is closely related to the last one. As this function specify analysis as a measure to approach corrective work, it can be perceived as corrective decision guided by a well reliable troubleshooting/intelligence. In that case, Analytics and Digital-to-Real Representation technologies can be implemented. Although, for that to occur, a historical data needs to be explored (Big Data), followed by Analytical insights.

Function 28a – Preventive decision-making to less start-up losses due to system integration: For the system to be integrated and transmit preventive decisions, Cloud Computing is the most feasible technology. When the connection between the system tools are secured, Big Data technology is important to retain data for later work on preventive actions. Sensors and maintainers using Flexible Connection Devises also could be used to data gathering.

Function a30 – Predictive decision-making to zero start-up losses due to acquired data: Predictivity stands for the need of prognostic approaches and for that to be acquired the system need derivative Artificial Intelligence methods. Analytic and Big Data technologies are also important but, because the function describe the decision due to acquired data, Cloud Computing technology is more important, because most of the data will come directly from the system software.

Function a31 – Corrective maintenance to less start-up losses: To ensure zero star-up losses, the corrective approach could rely on Digital-to-Real Representation and Flexible Connection Devices technologies, if executed by maintainers. If done by the system itself, automated methods (A.I. technologies) could help the process. Those technologies are enabled by Big Data storage, Analytics and Cloud Computing networked system.

Function a32 – Corrective decision-making to zero start-up losses due to analysis: Similar to the last function, this one particularly addresses to decision making due to analysis. This case puts in perspective the syntax of the functions chosen to implement in the legacy systems. Because the corrective maintenance occurs in a decisional process a due to analysis, Analytics technologies are more relevant for this function, as well as its Big Data storage. Autonomous algorithm (A.I. technologies) could be useful in this case, but secure the connectivity of the system is more relevant.

PROMETHEE Flow Table

| Rank | action | Phi | Phi+ | Phi- |
|---|---|---|---|---|
| 1 | Big Data | 0,4627 | 0,5503 | 0,0875 |
| 2 | Cloud Computing | 0,4132 | 0,5004 | 0,0872 |
| 3 | Analytics | 0,3996 | 0,5248 | 0,1252 |
| 4 | A. Intelligence | 0,3628 | 0,5253 | 0,1625 |
| 5 | Digital-to-Real R. | 0,2123 | 0,4625 | 0,2502 |
| 6 | F. C. Devices | 0,0741 | 0,3496 | 0,2755 |
| 7 | Sensors | -0,2246 | 0,2251 | 0,4497 |
| 8 | Adv. Machines | -0,8252 | 0,0249 | 0,8501 |
| 9 | Adv. Materials | -0,8750 | 0,0000 | 0,8750 |

**Figure 4.19 PROMETHEE rank, case 2.**

Because this system uses new mechanical parts to assemble its workstations, as stated in the case presentation, it does not need Advanced Machines technologies. Advanced Materials are not used for this workstation assembling/testing system.

Using the engineer's insights, the mapping of this system needs was based on technologies that could provide a great amount of data, connection and insights without having to rely on maintainers, exception to tasks evolving corrective maintenance/machine-assemble. The data for analysis and insights have to be mostly inputted by the system itself, in its debugging feedback. Analysis and guided devices could support decisions, helping maintainers that tends to assemble the workstations modules without considering old historical problems.

## 4.3 RESULTS OVERVIEW

At the start of the both analysis it becomes clear to see that those are systems that have aspects to be upgraded, but neither have a major lack of technological capabilities issue. They do have good part of their processes depending one human resources, much more regarding the second case. A conclusion for that insight refers to human tasks and how to optimize them in this context of *Smart Legacy System* proposal. The premise was to conduct the legacy systems to a more autonomous execution of tasks, but once the systems relies on human task execution, the idea of change the operation to a more automated context is difficult and requires *Extraordinary Adaptation* (e.g. substitute that human task by a robot).

Although, neither cases were chosen by the Step 1 method for extraordinary but to *Simplified Adaptation*. That is to say, world class organizations that already have a strong defined culture and consolidated work standards do not crave to change their processes/systems drastically. In other words, proofs in both scenarios suggests that, to be upgraded, the systems needed to be adapted to their human workforce, rather than its machinery/sensors. For those cases Big Data and Analytics technology classes where highly consider, because they provide ways to insight better practices and conduct more precise data analysis to the procedures. Those technologies classes can resolve well both autonomous and human decision-making. Cloud Computing, considerate to embrace all aspects of internet in the factories, is another top 5 technologies to be implemented in both cases, notably because it makes Big data and Analytics easily accessible.

Another key thing to notice is that the culture of the organization can affects how the work is being executed, and above that, even the country in which this organization is stablished can also affect the ways the work is being executed. This is clearly discriminated in the Step 2 when the ELECTRE TRI method was applied, in the first case it was cited that the organization’s culture is directed to optimize process by cutting all possible costs, easily reducing some interoperability barriers. Emphasized by the decision-maker, this is perceived as part of the organizations culture, revolving in solve problems aiming lower costs (i.e., it is not sufficiently concerned if any lower cost alternative might somehow place the maintainer at some degree of risk).

In the other hand, in the second case, still perceived in Step 2 and reinforced by the respective decision-maker, the country’s culture and how its maintainers tend to execute its tasks may affect the upgrade in the system. This was cited in the case study that, culturally, the operators tend to execute tasks neglecting their past mistakes (i.e., not questioning and just executing the work) and because of that, some of the same assemble errors regarding the workstations are made in each project.

Finely, the framework proved to be an insightful tool for even systems well resolved in technical quality aspects. Both cases needed only a Simplified Adaptation, which suggests they were not ideal scenarios for upgrade (*Extraordinary Adaptation*). Also, the two decision-makers did not made use of any *external factor* in Step 1, even the decision on case two being close to an *Extraordinary Adaptation*, which could provide a clear scenario on how to change an alternative’s approximate value decision. Notwithstanding, the graphical view was used to bring awareness to the decision-makers about the outcome of their decisions and for where their strategies were being targeted.

Above all, the fact that those organizations already have well developed systems made the specialist’s decisional process, of chose the technologies to be implemented, a challenge overcome by the wide literature research on 4.0-maintenance main technologies and applications, presented in the appendix tables.

# 5. CONCLUSIONS

This section is organized to better understand the results provided by this research project, whether due to data collected, applicability, literature reviews and reflections.

In contrast, this dissertation is based on the premise that a digital transformation project is required for a legacy maintenance system, not only for optimization, following the digitization of all the organization's processes, but also for the reduction of losses. That is to say, this work aims to provide a tool, in order to embed maintenance legacy systems with I4.0-digital capabilities. To that end, this tool consists in a three-step framework integrated with multicriteria decision making methods. The subsection that follows are: Research objectives; Research perspectives and limitations; Recommendation;

## 5.1 RESEARCH OBJECTIVES

Accomplishments provided by this dissertation work are summarized at this subsection.

This research revolved around a main question: "How can an organization maintain a maintenance legacy system, improving its faculties and making it more competitive, with the implementation of I4.0 capabilities and without generate interoperability issues in this course?". That argument was supported by the importance of legacy systems and the damage caused if they are changed/discarded without analysis. Couple with that, this type of system also lacks capabilities when interoperating with I4.0 digital-based systems, which are gaining momentum in the industry. Despite this, a I4.0 system can represent a high growth in product and asset quality, reliability and also provide many real time data gathering and feedback for predictive actions.

That said, this work served to manipulate a digital transformation in maintenance legacy systems, upgrading them to *Smart Legacy Systems*, i.e. embedding them with I4.0 characteristics in a structural way.

In order to better understand how to answer this main question, objective-steps were mapped and structured as a processual framework. The three steps were executed by a series of analysis in two different case study. These two cases were conducted by the author, in the role of digital transformation specialist, responsible for applying the framework and its decision-making methods correspondent to each step. The other actor was the decision-maker, one in each case, both engineers, representatives from their respective organizations, which intends to optimize one of its maintenance legacy system.

Following the framework steps, firstly, was proposed to understand the feasibility to upgrade the maintenance legacy system. This is particularly important in a sense that, before any attempt to be upgraded, it might be necessary to understand how much business value and technical quality this system already brings to the organization. This can be measured by the use of the AHP method, characterizing the system into one of four alternative quadrants.

Both cases were considered to be adequate to be upgraded, but not in the *most feasible* scenario proposed by the analysis. A hypothesis about that fact suggests that those systems did not needed much adaptation because they already had much technological capabilities. To put in another way, those systems were legacy not because lack of technology but they had barriers to collect and utilize resourceful data analysis as beneficiary part of the process.

By the second step, it was necessary to understand the systems characteristics (regarding its needs and interoperability barriers). A parallel dissertation project from the PPGEPS (Graduate Program in Production and Systems Engineering, body part of PUCPR university) was used as a referential I4.0-maintenance architecture (the M4.0EAF). The architecture guided the decision-makers, whom chosen how their respective legacy system should be improved. The decision-making method applied here was the ELECTRE TRI. Insights in this step were provided early in the method application, as the participants struggled to correlate each of the 32 functions to be chosen with the 14 criteria (i.e. regarding the systems needs and barriers, which they might encounter in order to implement those functions). Despite this, after the participants had understood the functions syntaxes and how the subjective criteria would measure their relevance, many characteristics could be seen.

In the first example it became clear that the enterprise did not measured efforts to communication and information data to flow without many barriers. For the second case, the high-scored system's needs challenged the equally high-scored barriers, which canceled those alternatives to entered in the class of most decisive functions to be implemented.

Notably, for those steps the importance of the decision-makers was crucial, as they represent their organizations and understand their system's aspects. Yet, the final step (Step 3) did not require their interaction because none of them were considered I4.0 nor digital transformation specialists, in that case, it was a decisional part of the project conducted only by the specialist.

That said, finally, in a decisional analysis, it was investigated how to implement those decisive functions to the systems. Using the PROMETHEE II method the specialist related, in a critical analysis supported by a literature review, the main I4.0-maintenance technologies and their impact to each decisive function. Clues on which technology could better support the legacy systems was envisioned early, before the first step, on the introductory part of each interview. By the time that the first two steps were conducted, a preliminary idea of how each technology would benefits the most each of those systems already had been formulated.

Notably, the last step served to organize, already carved technology-implementation strategies, into more specific application bias, limited by the functions.

## 5.2 RESEARCH PERSPECTIVES AND LIMITATIONS

This section discusses the research rights, as well as some covered limitations encountered along with the author's reflections. As conducted in this whole document, the discussions start in the first step of the proposed framework.

The AHP method together with its model were easily comprehended by the decision-makers and the Superdecisions software was intuitive enough to be used directly with them. Also, the criteria chosen to measure the feasibility to upgrade the system seems to be intuitive, except for some confusions in the Technical Importance cluster, precisely between criteria Decomposability, Deterioration and Obsolescence.

Nonetheless, the graphical analysis, proposed as a measure to confirm the method's supported decision (and retrieved from one of the author's articles), did not needed to utilize the *external factor* proposed, which seems to be an over-explained specific measure. Still, acknowledging the efforts to structure this idea, it was used to explain how to analyze the four alternatives proposed by the method in a visual concept for the course of action supported, indicating by the values in the AHP, which action is more representative. This promoted insights like, e.g.: "If the AHP supports the 3rd quadrant action (*Simplified Adaptation*), and the second (and closest) value is 2nd quadrant action (*Ordinary Maintenance*), it means that the legacy system's *Business Value* almost invalid the system for an upgrade.", and in this case, if more decision-makers could have been part of the comparison and analysis process, the most feasible decision could be different.

Following the framework process the second step, ELECTRE TRI model, proved to be the most challenging part of this research. Express a combine idea of maintenance, interoperability and Industry 4.0 architecture was not an easy task. Understand how the referential architecture could beneficiate the legacy system regarding its needs versus its interoperability barriers was key to, posteriorly, structure the ELECTRE TRI model.

Notably, the results from choosing this method could be seen early, when Step 2 was being applied. The fact that the ELECTRI TRI method is structured in a comparison matrix, coupled with the positive (system's needs) and negative criteria (interoperability barriers) gave the decision-makers a complete representation of what they were measuring, in relation with the functions they intended to implement. The ELECTRE TRI sorting feature served as a flexible measure to filtering the quantity of functions that could be implemented, providing the decision-makers more strategic representativity and decision power. Likewise, the dynamics from the Mudge diagram was easily adhered to this method.

Finely, in the Step 3 the PROMETHEE II method was the most intuitive to implement. Already knowing that a pool of decisive functions was going to be chosen by the early step, the idea of use the best I4.0-maintenance technology to support those functions was always present. The most laborious part of this step and regarding the whole work, was the literature review on the main used modern technologies in maintenance. It consisted in a research started for the author's early articles, progressing into three major research-rounds. In resume, the first-round intended to discover the most feasible technologies applied for the whole I4.0 panorama, the second-round intended to filter those technologies to the maintenance context and the third-round aimed to refine those findings and list them in tables, along with application examples.

A limitation is still about the notion of impact that technologies have on the current industrial plant, the scenario is still new, regarding the application of concepts purely inherited from Industry 4.0. PROMETHEE helps quantify this mathematically, but as more research applications and databases grow, this impact perception will become more significant and may even make use of mechanisms such as Machine Learning for better weight stowage and impact perception (technologies vs. criteria).

In conclusion, this literature review supported the PROMETHEE II analysis with a table that could contextualize the specialist’s decisions on the best technology to be implemented regarding the decisive functions the legacy system was in need.

A difficulty was to find the decision-makers to validate the framework application, which as explained in section 4, demanded a significant time invested to be executed. This is a compelling argument since the whole framework represents a digital transformation project, which by premise, demands great amount of time invested to understand its dynamics, analyze and execute its steps.

## 5.3 RESEARCH RECOMMENDATIONS

One of the ELECTRE TRI method features was not explored, the pessimistic and optimistic limits to classify the alternatives. That said, a combination of AHP third and fourth quadrant alternatives (Simplified and Extraordinary adaptations) relating the optimistic and pessimistic ELECTRE TRI scenarios is a late insight, which could add more synergy to both Step 1 and 2 methods purposes. Exemplifying, the idea was to, still consider the AHP final response (even if it changes with the *external factor*), as long as presented the *Simplified* or *Extraordinary Adaptations* (i.e. premises to continue the framework application). Then in Step 2, independent of the adaptations supported by the

AHP method, both of them would be represented in the ELECTRE TRI method, *Simplified Adaptation* in the optimistic scenario and *Extraordinary Adaptation* in the pessimistic, contributing with the idea that a simple adaptation is a “easier to upgrade” scenario, reciprocal equivalent for a pessimistic scenario.

Because the ELECTRE TRI method presents pessimistic and optimistic scenarios by default in its answer, even if Step 1 AHP method proposes the *Simplified Adaptation* (which in this insight represents Step 2 optimistic ELECTRE scenario), both scenarios would be presented, available to analysis. Yet, this was not applied in this work, because of the parameters used for the thresholds, made the pessimistic and optimistic scenarios in the ELECTRE TRI method very similar (in several cases the same) in all experiments tested.

Regarding the last step, the Visual PROMETHEE software enables the final results to a sensitivity analysis. To that end, it would be possible to describe how the uncertainty in the output (i.e. I4.0 technologies as alternatives) of this step model can be divided and allocated to different sources of uncertainty in its inputs (i.e. I4.0 maintenance architecture functions). That is to say, it could be measured how the implementation of one technology would affect the functions which they were trying to enable in the system. Although this approach has been considered, the handling of a sensitivity analysis would impact further detail of this work, which had already converged to its expected final response (i.e. measuring the potential of a technology to solve a given function). Thus, it was proposed that this type of analysis could be included in future work.

It was envisioned the development of articles derivate from this work. One entering in further details on how the industry could beneficiate from a *Smart Legacy System*, further exploring the idea of a legacy system becoming and Industry 4.0-digital system while still carrying important legacy aspects, and how this can be important rather than replace that system entirely. Another article could regard why I4.0 technologies are not enough to, only by themselves, “smartize” systems/processes. In this second example, the research could be enriched by Machine Learning mechanisms inferring on the weights of the criteria or performance of the alternatives on the criteria in the application of the step referring to PROMETHEE. This base could be supported by the extensive research on I4.0-maintenance technologies.

Finely, it was always an idea to have the possibility to adjust this framework for other areas. While the first step consists in a premise for the project to be properly analyzed further and the third step explains in a more top view of how the I4.0-maintenance technologies can affect different/specific areas of a system, the Step 2 can provide a more granular analysis, independent of the area linked to the system. That way, for further possible applications by replacing the maintenance elements, i.e. referential maintenance architecture in Step 2 (and maintenance-specific technologies guide table in Step 3, which does not have a direct relation with the framework itself), any other digital transformation project, regarding the improvement of an existing legacy systems, could be adapted to this framework.

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# APPENDIX

**Table A.0.1 I4.0-Maintenance main technologies and applications (Analytics).**

| Analytics | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Life expectancy | | (OMRON, 2018) |
| 2 | Data processing | | (Rosendahl et al., 2015) |
| 3 | Control function forecast | | |
| 4 | Effectiveness | | (Colombo et al., 2017) |
| 5 | Analyze | | |
| 6 | Improve capabilities | | |
| 7 | Scalability | | |
| 8 | Performance | | |
| 9 | Analysis of large datasets | | (Romero & Vernadat, 2016) |
| 10 | Real-time analysis | | |
| 11 | Various forms of acquisition | | |
| 12 | Creation of useful information | | |
| 13 | It presents a barrier of complexity | | |
| 14 | Analyze | | (Biahmou et al., 2016) |
| 15 | Optimization of predictions | | |
| 16 | Intelligent | | |
| 17 | Penetrating | | |
| 18 | Reduced error rate | | |
| 19 | Computational analysis | | |
| 20 | Accessibility forecast | | |
| 21 | Statistical techniques | | |
| 22 | Advanced Analysis | | |

| | | | |
|---|---|---|---|
| 23 | Knowledge work | | (McKinsey & Company, 2015) |
| 24 | Advanced Robotics | | |
| 25 | Collection of relevant information | | |
| 26 | Get Insights data | | |
| 27 | Modeling capability | | |
| 28 | Analysis of historical data | | |
| 29 | Recommended data analysis | | |
| 30 | Based on actual measurements | | |
| 31 | Provides equipment coding | | |
| 32 | Actions based on accurate data | | |
| 33 | Real-time troubleshooting | | |
| 34 | Data driven by Design lever | | |
| 35 | Real-time optimization | | |
| 36 | Dynamic programming | | |
| 37 | Decentralized intelligence | | |
| 38 | Optimizing production flow | | |
| 39 | Interaction with complex systems | | |
| 40 | Use of data | | |
| 41 | Data analysis | | (Bokrantz et al., 2017) |
| 42 | Prediction | | |
| 43 | Prognostics | | |
| 44 | Pattern Detection | | |
| 45 | Identification and analysis of correct data | | |
| 46 | Analysis of methods | | |
| 47 | Best practices for maintenance | | |
| 48 | Predictive analysis | | |
| 49 | Optimization | | |
| 50 | View Profile | | |

| | | | |
|---|---|---|---|
| 51 | Collaboration for digital networks | | |
| 52 | Analysis together detecting patterns | | |
| 53 | Automatic analysis | | |
| 54 | Management of different information systems | | |
| 55 | Emphasis on identification and analysis | | |
| 56 | Ensure competence | | |
| 57 | Relevant classification and analysis of data | | |
| 58 | Decisional support in maintenance | | |
| 59 | Maintenance management | | |
| 60 | Decisions based on facts | | |
| 61 | Predictive and prescriptive data analysis | | |
| 62 | Development of greater automation | | |
| 63 | Development of greater interoperability of signals | | |
| 64 | Development of better methods of analysis | | |
| 65 | Disruption and fault prediction | | |
| 66 | Reduces maintenance response times | | |
| 67 | Reduces repair time | | |
| 68 | Optimize production system performance | | |
| 69 | Reliability and Availability-Driven Maintenance | | |
| 70 | Sustainable Maintenance | | |
| 71 | Contributes to sustainable manufacturing | | |
| 72 | Increases resource efficiency and product life | | |
| 73 | Logging information for project optimization | | (Qin, Liu, & Grosvenor, 2016) |

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| 74 | Record information for predictive maintenance | | |
| 75 | Standardization | Integration of business value networks and the product chain | |
| 76 | Flexibility | | |
| 77 | Reliability in real-time analysis | | |
| 78 | Discovery of knowledge | | (Knoll, Prüglmeier, & Reinhart, 2016) |
| 79 | Understanding data | | |
| 80 | Multi-functionality | | |
| 81 | Troubleshooting | | |
| 82 | Engineering project | Selection of components (bearings) | |
| 83 | Budget Forecast | | |
| 84 | Use of case examples | | |
| 85 | Limited learning of task types | | |
| 86 | Identification of the best logistics processes | Storage capacity | |
| 87 | Automated approaches to maintenance | | (Dimitris Mourtzis et al., 2016) |
| 88 | Calculation of process time from the input of the operator together with the sensory system | Calculation of the actual tool-machining time | |
| 89 | Monitoring data processing | | |
| 90 | Autonomous | | (Pereira & Romero, 2017) |
| 91 | Provides information throughout the product life cycle | | |
| 92 | Facilitator for adaptive production control | | (Vallhagen & Almgren, 2017) |
| 93 | Providing guidelines for execution of processes based on statistics | Individual heat treatment recipes specific to each product | |
| 94 | High processing speed | | |
| 95 | Efficient exploration of methodology and efficiency in model maintenance | | |
| 96 | Maintenance planning | Intelligent maintenance and repair solutions replace current procedures | (Man & Strandhagen, 2017) |
| 97 | Extending life expectancy | | |

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| 98 | Evidence of product status and energy efficiency | Monitoring, maintenance and recycling services | |
| 99 | Raising the level of automation | | (D Mourtzis et al., 2017) |
| 100 | Remote fault diagnosis | Operator can record malfunction by writing explanatory text | |
| 101 | Notifications of new inputs | | |
| 102 | Notifications of new crash reports | | |
| 103 | Algorithm of automation of the creation of scenes of procedures | | |
| 104 | Creating sequential procedures | | |
| 105 | Availability | | |
| 106 | Performance Monitoring | Shipbuilding Industry | (Zaman, Pazouki, Norman, Younessi, & Coleman, 2017) |
| 107 | Performance forecasting | | |
| 108 | Decision Support | Predictive analysis of vessel performance | |
| 109 | Need to maintain data veracity | | |
| 110 | Process management | | |
| 111 | Data storage | | |
| 112 | Data analysis | | |
| 113 | Impact on a wide range of industries | | |
| 114 | Dependent on reliable and appropriate methods of data collection | | |
| 115 | Data Lifecycle Management | Frequency that the data is re-stored or discarded | |
| 116 | Essential in process management | Shipbuilding | |
| 117 | Increasing the effectiveness of operational planning | Maintenance, navigation and communication managed by integrated data analysis connected to onboard and onshore decision support systems | |
| 118 | Provision of up-to-date information | | |
| 119 | Process planning | operators or charters may implement trip planning after analyzing the route | |
| 120 | Data management | Intelligent traffic management systems will be introduced as data-driven applications in the navigation industry. | |

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| 121 | Performance forecast based on current data | Ship operators will gain the ability to predict vessel performance | |
| 122 | Maintenance decision making help | | |
| 123 | Energy management | Navigation is moving towards flexible and alternative energy systems | |
| 124 | Monitoring and optimizing performance | Automation expands the capacity of optimization control of machines and vessels | |
| 125 | Combination of historical and current data | The optimization and efficiency of the vessel will be measured by the combined analysis | |
| 126 | Determination of routes of movement | The safety and protection of vessels will be increased with the aid of maneuvers and minimization of collisions | |
| 127 | Detects the need for maintenance to avoid failures | | |
| 128 | Determination of type of maintenance | | |
| 129 | Auto-regression models | Dynamic degradation modelling for bearings is developed | (Roy et al., 2016) |
| 130 | Kalman filter | Used to track the model to predict the mechanical degradation of the bearing | |
| 131 | Composite parts repair process | Assess the damage more accurately (moving from qualitative assessment to quantitative assessment) using advanced techniques like active thermography and laser ultrasonic | |
| 132 | Analysing the positional error and vibration energy | Sensor-less monitoring of machine health by analysing the positional error and vibration energy in a drive system | |
| 133 | Stochastic technique | Based on Weibull Cumulative Damage Model and multiple service-related stress profiles (e.g., mechanical, thermal and humidity stresses) to predict the remaining useful life of the component | |
| 134 | A Bayesian learning based prognostics | Reduce the maintenance cost | |
| 135 | Decision support | Decision support is essential for an integrated maintenance planning capability | |
| 136 | Non-destructive evaluation (NDE) for degradation assessment | | |

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| 137 | Degradation assessment | Techniques used for the degradation assessment include: visual inspection, dye penetrant inspection, magnetic particle inspection, ultrasonic testing, eddy current inspection, X-radiography, photoluminescence piezo-spectroscopy and thermography; Thermography is becoming popular in recent years for their ease of use and affordability, it can reflect a change in temperature or in the material's thermophysical properties, either of which can be exploited to seek assessment of the in-service degradation | |
| 138 | Functional/dysfunctional analysis | allowing a link to be made between the component level and the system one through the flows exchanged between the different functions at different levels together with the propagation of the component degradations at each level | |
| 139 | Predict the energy consumption and environmental impact | In order to support environmental and economic sustainability through maintenance services, recently prognostics techniques developed for health prediction are also used to predict the energy consumption and environmental impact | |
| 140 | Quantum computing | Potential for reduction of computation time. Shortened computation time can enable data analyses algorithm to evaluate data in real-time without the need for several hours of computing | |
| 141 | Support human analytical thinking | Visual analytics, synthesize multi-dimensional information and knowledge from complex and dynamic data in order to support assessment, planning and forecasting | |
| 142 | Visual analytics (VA) tools | VA tools should: provide multi user access to the data, support intuitive communication, support multiple and linked displays and track information flows between the users. The early design phase visualization could assist in the design evaluation and creativity through exploration of alternative future scenarios with associated uncertainties. | |
| 143 | Real time data capture | Real time data capture, analysis and modelling of the 'big data' from the products in use within a 'highly connected' manufacturing and use environment so that the maintenance efficiency can be improved | |
| 144 | Cross-sector research and technology development | A cross-sector (e.g. manufacturing, construction, health care and IT) approach to research and technology development will allow mutual learning and reduce the R&D costs required to support continuous maintenance of high value products in the future | |
| 145 | Economic control methodologies (fuzzy control) | Sophisticated technological schemes concerning economic control methodologies are now being developed for large scale buildings, based on various control theories like predictive control (fuzzy), which maintain thermal comfort while minimizing the operational energy consumption | (Darure, 2017) |

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| 146 | Reliable analysis from internal and external sensors | System-internal alarms and messages produced during the operation, can be used to optimize production and maintenance processes. Furthermore, information and knowledge can be extracted from raw data and used to develop data-driven business models and services, e.g. offer new availability contracts for production systems | (Uhlmann et al., 2017) |
| 147 | Data management system analysis | Sensor network is connected to the cloud, where data analysis results can be stored and managed using a data management system | |
| 148 | Predictive analytics for transformation of data to information to knowledge | Capability of implementing big data predictive analytics for transformation of data to information to knowledge to action through a CPS structure | (Lee et al., 2015) |
| 149 | Big data predictive analytics platforms | Pipeline of data to action has the potential to create value in different sections of a business chain. For example, valuable information regarding the hidden degradation or inefficiency patterns within machines or manufacturing processes can lead to informed and effective maintenance decisions which can avoid costly failures and unplanned downtime. From business perspective, such platform can effectively be used for customer relation management, supply chain management, execution branch and enterprise resource planning | |
| 150 | Integration of cloud services with knowledge management | In a platform that is able to provide enterprise services such as intelligent design and manufacturing, production modeling and simulation, and logistics and supply-chain management. | (Zhong et al., 2017) |
| 151 | Information retrieved on-demand | Flexibility and interoperability, in the development of automated systems, it is possible to select the best offer from a large number of suppliers' components, modules and services. For example, the operations diagnosis can be carried out partly by the user, through access to the information retrieved on-demand, intelligently used and linked | (Barreto, Amaral, Santana, et al., 2017) |
| 152 | Work orders (WO) analysis | Machine/unit/component on which maintenance action was performed; type of maintenance action (corrective, preventive); descriptions (symptoms, comments on performed actions); list of acquired spare parts for WO. | (Schmidt et al., 2017) |
| 153 | Control-centric optimization and intelligence | Greater intelligence can be achieved by interacting with different surrounding systems that have a direct impact to machine performance | (Lee, Kao, et al., 2014) |
| 154 | Smart decision support system | Proactive maintenance scheduling: with connected machines and awareness of machine condition across the fleet, tasks and maintenance plans will be scheduled and optimized from the fleet level | |
| 155 | Smart products | Provided with algorithms that can optimize operations, their utilization and maintenance | (Nunes, Pereira, & Alves, 2017) |

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| 156 | Lifetime predictions | Progresses in prognostic maintenance technologies offer opportunities to aid the asset owner in optimal maintenance and life cycle decision making, ensuring just-in-time maintenance. Identification of the correct parameters to measure, the translation of the gathered data into useful maintenance decision support and the need for guidance in prognostic technology route determination | (Tiddens et al., 2015) |
| 157 | Prognostic systems | Prognostic systems can be validated and improved during their lifetime because more and more data, for example failure or costing data, is collected during its utilization. Especially knowledge-based models should be updated since they require a high degree of completeness and exactness to be useful | |
| 158 | Advanced analytics in predictive maintenance programs | Manufacturing companies can avoid machine failures on the factory floor and cut downtime by an estimated 50% and increase production by 20% | (Fernández-Miranda, Marcos, Peralta, & Aguayo, 2017) |
| 159 | Statistical process control (SPC) | Predictive maintenance, smart energy consumption, and remote monitoring and control | (Karre, Hammer, Kleindienst, & Ramsauer, 2017) |
| 160 | Monitoring the vibration of rotating machinery | Predictive maintenance monitoring the vibration to detect incipient problems and to prevent catastrophic failure | (Sandengen et al., 2016) |
| 161 | Processing long distance analysis | A remote diagnostics center for advanced analytics and real-time human monitoring to convert this data into insights. This application of monitoring technology, which comes from Industry 4.0 concepts for collecting data for a process upgrade | (Venâncio, Brezinski, Gorski, Loures, & Deschamps, 2018) |
| 162 | Context-aware intelligent service systems | Manufacturing shop-floor | (Sipsas, Alexopoulos, Xanthakis, & Chryssolouris, 2016) |
| 163 | Collaborative system that provides decision support for team leaders | | |
| 164 | Knowledge support system | Analyses these data by grouping them into data structures that relate sensors with stoppage events and causes/resolutions and finally, persists the output on its internal database. When a line stoppage is identified, the knowledge support service looks up the sensor that caused the current stoppage, retrieves a specific sensor's stoppages data and finally, ranks the results according to by the frequency of the stoppages in order to provide the end user with information as to what would be the most possible cause/resolution to the stoppage | |
| 165 | Algorithm has to be established to track the changes of a machine status | Interconnection between machine health analytics through a machine–cyber interface (CPI) at the cyber level, which is conceptually similar to social networks | (Lee, Bagheri, & Kao, 2014) |
| 166 | Just-in-time maintenance strategy in manufacturing plant | Predicting remaining useful life of assets helps to maintain just-in-time maintenance strategy in manufacturing plant | |

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| 167 | Information Technology to converted into important information | Intelligent systems, processes and machines is rising, which also brings new challenges associated to Information Technology (IT). This aspect is of high impact for factories that will be increasingly intelligent with the ability to collect, analyse and distribute data, converted into important information for monitoring and maintenance services | (Tedeschi et al., 2018) |
| 168 | Data through an exploratory phase | Assessing the meaning of the features and to which degree they are redundant | (Fernandes et al., 2018) |
| 169 | Machine Learning and Data Mining techniques | Can be used to draw insights from the data and accurately predict outcomes to support decision-making and help organizations improve their operations and competitiveness | |
| 170 | Knowledge acquired by analysing | Knowledge acquired by analysing the data reaches the right people at the right time. The company's collaborators will be able to visualize information that is pertinent to their specific functions and responsibilities, such as short-term alarms and notifications for machine operators and key-performance indicators for upper management employees | |
| 171 | An operational pattern analysis | Incorporates the collected data from industrial systems | (Nikolakis, Papavasileiou, Dimoulas, Bourmpouchakis, & Makris, 2018) |
| 172 | Analyzing the machine data towards evaluating its condition | Regarding the automotive industry use case, after the identification of the maintenance need, the scheduling problem consists of identifying time slots for the maintenance activities to take place. Maintenance provider which can also be the equipment provider. The condition of the equipment is evaluated in terms of Remaining Useful Life (RUL) of the equipment | |
| 173 | Enable predictive analytics in cyber physical systems | Data management and processing to enable predictive analytics in cyber physical systems, holds the promise of creating insight into the underlying processes, discovering criticalities and predicting imminent problems | (Bowden et al., 2019) |
| 174 | Detecting and analyzing underlying data trends | Allow anomalies to be discovered | |
| 175 | Predictive maintenance neural network approach | Maintenance system for textile machine | (Ierace, Pinto, & Cavalieri, 2007) |
| 176 | Condition monitoring maintenance carried out according to need | Decision making strategy where the decision to perform maintenance is reached by observing the condition of the system and/or its components | |
| 177 | Computing techniques | Ability in resembling the human mind reasoning in dealing with contexts affected by heavy uncertainty and fuzziness. Eliminate unexpected breakdowns, thus increasing machine availability | |
| 178 | Maintainability for software engineering | Maintainability attempts to measure the effort required to diagnose, analyze, and apply a change to specific application software | (April & Abran, 2009) |

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| 179 | Automated analysis and manual modifications | Upgraded the programs to the new database version using several automatic tools, and performed an automated analysis supporting further manual modifications by the system experts | (Veerman, 2006) |
| 180 | Numerical analysis | Availability of the system can be improved considerably by controlling deterioration of the system using proper maintenance planning and scheduling. Following the above findings and the results of numerical analysis carried out in the study in different field conditions, the management can derive cost cutting plans and increased productivity | (Garg, Singh, & Singh, 2010) |
| 181 | Analysis of the optimal production control | Analysis of the optimal production control and corrective maintenance planning problem for a failure prone manufacturing system consisting of several identical machines | (Kenne, Boukas, & Gharbi, 2003) |
| 182 | Analytical approach | Applying an analytical approach, such as in, the structure of a feedback control policy is derived and is considered as an input of the relevant simulation | (Kenne, Boukas, & Gharbi, 2003) |
| 183 | SCADA registers data for diagnostic analysis | SCADA works online and registers data for further diagnostic analysis. Further integrate the signal analysis, establishing a network from data acquisition to diagnostic assessment | (Ma, Han, Wang, & Fu, 2007) |
| 184 | Condition Based Maintenance (CBM) program | Inspections are performed to obtain proper information about the degradation state of the system | (Ghasemi, Yacout, & Ouali, 2008) |
| 185 | Heuristic algorithm | Finding the near-optimal solution for large-sized problems. The objective was to minimize the maximum tardiness subject to periodic maintenance and non-resumable constraint | (Low, Ji, Hsu, & Su, 2010) |
| 186 | Intelligent prognostic technologies | Platform Watchdog AgentTM developed within the IMS project (Intelligent Maintenance Systems) | (Tucci, Rapaccini, De Carlo, & Borgia, 2010) |
| 187 | Machine capable of ensuring security in emergency conditions | | (Tucci, Rapaccini, De Carlo, & Borgia, 2010) |

**Table A.0.2 I4.0-Maintenance main technologies and applications (Artificial Intelligence).**

| Artificial Intelligence | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Enables predictive and preventive maintenance | | (OMRON, 2018) |
| 2 | Real-time high-volume data processing | | |
| 3 | Facilitators of use | | |
| 4 | Control | | (Colombo et al., 2017) |
| 5 | Built-in intelligence | | (Romero & Vernadat, 2016) |
| 6 | Robotic and Machine Algorithms | | |
| 7 | Fast decision making | | (Biahmou et al., 2016) |
| 8 | Self employed | | |
| 9 | Artificial | | |
| 10 | Self employed | | (McKinsey & Company, 2015) |
| 11 | New communication protocols | | |
| 12 | Development of machine learning | | |
| 13 | Status Quo Optimization | | |
| 14 | Change of operative parameters | | |
| 15 | Flexibility | | |
| 16 | Delegates processes | | |
| 17 | Assigns rules | | |
| 18 | Smart equipment | | |
| 19 | Decision-making capacity | | (Bokrantz et al., 2017) |
| 20 | Self-diagnosis | | |
| 21 | Self-monitoring | | |
| 22 | Auto optimization | | |
| 23 | Self-maintenance | | |
| 24 | Assertive Decision Making | | |
| 25 | Performance optimization | | |

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| 26 | Decision Support Systems in Maintenance | | |
| 27 | Turns BigData into decision support | | |
| 28 | Predictive maintenance suggests more appropriate counteraction | | |
| 29 | Early-aware | | (Qin et al., 2016) |
| 30 | Consciousness | Integration of business value networks and the product chain | |
| 31 | Predictive Maintenance | | |
| 32 | Decision aid | | |
| 33 | Understanding of consciousness | | |
| 34 | Reliable environment | | |
| 35 | Intelligent artificial functions | | |
| 36 | Evaluation and implementation | | (Knoll et al., 2016) |
| 37 | Automatically learn programs from data | | |
| 38 | Unsupervised learning | | |
| 39 | Data organization | | |
| 40 | Identification of interdependencies | | |
| 41 | Limitation of planning due to frequent changes of information | | |
| 42 | Realization of intelligent resources | | (Dimitris Mourtzis et al., 2016) |
| 43 | High degree of autonomy | | (Pereira & Romero, 2017) |
| 44 | Interaction with the physical environment | | |
| 45 | Limited space for manual verification and inspection | | (Vallhagen & Almgren, 2017) |
| 46 | Maintenance and recycling planning | | (Man & Strandhagen, 2017) |

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| 47 | Solving problems through the emulation of biological processes | Prediction of purchase, speech recognition or smart home devices | (Mata et al., 2018) |
| 48 | Learning and decision making with special emphasis on human cognitive processes | | |
| 49 | Control of optical networks | First amplitude search for routing and linear and mixed linear programming formulations for network planning | |
| 50 | Storage of knowledge about the environment and the impacts of its actions | | |
| 51 | Network Diagnostics | | |
| 52 | Simultaneous identification of cumulative nonlinearity | | |
| 53 | It is based on prior knowledge of a particular set of signals | | |
| 54 | Process automation is a key enabler to reduce operating costs | | |
| 55 | Removes human intelligence from repetitive tasks | | |
| 56 | Ability to analyze information efficiently | | |
| 57 | Targeting Scale Problems | | |
| 58 | User Integration Platforms | Chatbots, voice command devices | |
| 59 | Workflow automation | | |
| 60 | Demand-based resource optimization | | |
| 61 | Forecasting and traffic classification | | |
| 62 | Facilitates efficient joint operation of network and computing devices | | |
| 63 | Distribution of virtual network functions | | |
| 64 | Allocation of tasks | | |
| 65 | Predictive cache | | |

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| 66 | Interpolation and extrapolation of human actions | | |
| 67 | Intelligence of conveyors | Shipbuilding industry | (Zaman et al., 2017) |
| 68 | Operating Mode Detection | Using the automatic mode detection system, the crew would not need to update the mode every time the ship changed its operational state | |
| 69 | Assistance in compliance with current environmental legislation | This system will help ship operators comply with the EU MRV Regulation by monitoring fuel consumption and emissions for different modes of vessel. | |
| 70 | Automate the repair process as well to improve efficiency and reduce human error | | (Roy et al., 2016) |
| 71 | Automating the continuous maintenance | Continuous maintenance of machines can lead to significant reduction in through-life cost | |
| 72 | Self-healing and self-repairing | Hardware and software level using self-healing and self-repairing technologies. Self-repair is a top-down approach, where the system is able to maintain or repair itself | |
| 73 | Prognostic repair technologies | Embedded prognostics and self-repair capability could also support more resilient systems | |
| 74 | Generic prognostics patterns | Which could be applied at different abstraction levels | |
| 75 | Dynamic Bayesian Network (DBN) and to combine it with an event model | Creating a set of ‘‘event’’ DBN variables that correspond to the degradation (a) and maintenance (b) events, in order to adjust the parameters given a priori with the real value of the parameters | |
| 76 | Advanced stochastic optimization | machine diagnostics and algorithms can gain their full potential when combining with big data | |
| 77 | Real time data capture | Real time data capture, analysis and modelling of the ‘big data’ from the products in use within a ‘highly connected’ manufacturing and use environment so that the maintenance efficiency can be improved | |
| 78 | Autonomy for maintenance efficiency | | |
| 79 | Maintenance-aware Economic Model Predictive Control | Sophisticated technological schemes concerning economic control methodologies are now being developed for large scale buildings, based on various control theories like predictive control (fuzzy), which maintain thermal comfort while minimizing the operational energy consumption | (Darure, 2017) |
| 80 | Machines and systems for predictive maintenance | | (Uhlmann et al., 2017) |
| 81 | Interaction with surrounding systems | Turns regular machines into self-aware and self-learning machines, and consequently improves overall performance and maintenance management | |

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| 82 | Self-aware and self-maintained machine system | A system that can self-assess its own health and degradation, and further use similar information from other peers for smart maintenance decisions to avoid potential issues | (Lee, Kao, et al., 2014)t |
| 83 | Smart analytics | Intelligence will be used at the individual machine and fleet levels. Condition of the real-time machine can be fed back to the machine controller for adaptive control and machine managers for in-time maintenance | |
| 84 | Smart decision support system | Mitigation of production uncertainties to reduce unscheduled downtime and increase operational efficiency, and the efficient utilization of the finite resources on the critical sections of the system by detecting its bottleneck components | |
| 85 | Smart and connect products | Characterized by a high degree of autonomy, being able to be autonomously operated, self-coordinated and self-diagnosed | (Nunes et al., 2017) |
| 86 | Enable the automation of production lines | Analyze and understand a certain level of production issues and, with minimal human involvement, to solve them | (Tjahjono et al., 2017) |
| 87 | Enable customization, flexibility and rapid manufacturing | Artificial Intelligence (AI) automated systems | |
| 88 | Support from Cyber level with “digital advices” | Support from Cyber level with “digital advices” for updating the maintenance plan. | (Sandengen et al., 2016) |
| 89 | Intelligent services provision, logistics and resource planning | Shortened production cycles, incorporation of customer needs in real time, maintenance is largely carried out automatically, orders are automatically filled in the right order, shipped and dispatched | (Barreto, Amaral, & Pereira, 2017) |
| 90 | Autonomous condition monitoring | Implementing Internet of Things (IoT) technology in legacy systems to provide new services such as autonomous condition monitoring and remote maintenance | (Tedeschi et al., 2018) |
| 91 | Predictive maintenance Artificial Intelligence (AI) algorithm | Incorporates input data, as the outcome of a predictive maintenance Artificial Intelligence (AI) algorithm, adjusting the execution of maintenance operations according to the existing production schedule as well as to the availability of maintenance resources. Maintenance operations are fitted to the production schedule according to the maintenance plan of the maintenance provider. As a result, the service cost for the provider can be reduced by improving the management of its maintenance resources through adequate planning and scheduling | (Nikolakis et al., 2018) |
| 92 | Detecting autonomously the condition of the component | Further developments of this study can be followed in order to: create an on-line mechanism for detecting autonomously the condition of the component and autonomously planning the necessity of lubrication intervention; | (Ierace et al., 2007) |
| 93 | Tools for diagnostics and prognostics | Tools for “intelligent” support to maintenance decision making, i.e. These tools can be based, e.g., on artificial intelligence (AI) techniques, such as the Artificial Neural Networks (ANNs), fuzzy logic systems, fuzzy–neural networks (FNNs) | (Ma et al., 2007) |

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| 94 | Decision support systems | Using decision support systems based on methods and techniques from e.g. artificial intelligence, knowledge discovery and case-based reasoning | (Funk & Jackson, 2005) |
| 95 | Condition Based Maintenance (CBM) technology | Takes condition monitoring results to account and then plans the maintenance action. The purpose of CBM is to eliminate breakdowns and prolong the preventive maintenance intervals | |
| 96 | Methods and techniques with focus on information | Artificial Intelligence (AI) methods and techniques are being continuously developed with more focus on information and knowledge handling from the customers point of view | |
| 97 | Condition monitoring systems interacting with artificial intelligence | In this way you get the control and supervision of installations by an expert system. One advantage of this choice is the ability to manage the maintenance of the system from a remote location, thanks to the potential offered by current systems of communication (GSM - GPRS - EDGE - UMTS - HSDPA) | (Tucci et al., 2010) |
| 98 | Historical events which have marked the plant life | Instead of the installation of a large volume of sensors, it is considered more appropriate and suitable to develop an expert system able to translate into artificial intelligence the knowledge of the experts, maintenance and process, and the succession of historical events which have marked the plant life | |
| 99 | Carry out a learning process | System should be able to carry out a learning process from past events and their resolutions. It is necessary to award the operators performance guiding a process of continuous improvement | |

**Table A.0.3 I4.0-Maintenance main technologies and applications (Big Data).**

| Big Data | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Autonomous processing | | (OMRON, 2018) |
| 2 | Intelligent data production | | |
| 3 | Affects plant functions | | (Rosendahl et al., 2015) |
| 4 | Cyclical Acquisition | | |
| 5 | Digitization of data | | (Colombo et al., 2017) |
| 6 | Ability to access | | (Romero & Vernadat, 2016) |
| 7 | High metadata creation capacity | | |
| 8 | Data integration | | |
| 9 | Digital data | | (Biahmou et al., 2016) |
| 10 | Massive scanning of data | | |
| 11 | Data | | (McKinsey & Company, 2015) |
| 12 | Computational power | | |
| 13 | Connectivity | | |
| 14 | High volume data production | | |
| 15 | Availability of data | | |
| 16 | Identify opportunities | | |
| 17 | Weather data | | |
| 18 | In real time | | |
| 19 | Collects and reports data | | |
| 20 | Identification of products | | |
| 21 | Capture information | | |
| 22 | Collect | | |
| 23 | Data Orientation | | (Bokrantz et al., 2017) |
| 24 | Connectivity for interaction with other technologies | | |
| 25 | Data warehousing | | |
| 26 | Huge amounts of data generated | | |
| 27 | Based on data | | |

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| 28 | Sharing Information | | |
| 29 | Aggregate value | | |
| 30 | Data security | | |
| 31 | Diversity of data | | |
| 32 | Archiving | | |
| 33 | Smart work | | |
| 34 | Insight-based maintenance planning | | |
| 35 | Maintenance planning with a systemic perspective | | |
| 36 | Informative | | (Qin et al., 2016) |
| 37 | Collection of raw data | | |
| 38 | Data Mining | Web search, spam filters, fraud detection, drug projects | (Knoll et al., 2016) |
| 39 | Multi-functionality | | |
| 40 | Based on historical | | |
| 41 | Enables machine learning | | |
| 42 | Requires space and data quality | | |
| 43 | Template training | | |
| 44 | Sharing knowledge within the production network | Storage capacity | |
| 45 | Activation of KPI-based frameworks | | |
| 46 | Data processing | | (Dimitris Mourtzis et al., 2016) |
| 47 | Limitation of data usage for predictive maintenance actions | | |
| 48 | Gathers data from multisensory systems | | |
| 49 | Storage and use of data | | (Pereira & Romero, 2017) |
| 50 | Based on data provides production and maintenance information | | |
| 51 | Demand Data Logging | | (Vallhagen & Almgren, 2017) |
| 52 | Stores data for AI | Elaboration of action plans | (Mata et al., 2018) |

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| 53 | Limitations of multilocation and authenticity of the resource location | | (D Mourtzis et al., 2017) |
| 54 | Ubiquitous data access | | |
| 55 | Service Report | Operator can record malfunction by writing explanatory text | |
| 56 | Sensor data storage | | |
| 57 | Storing descriptions for troubleshooting | | |
| 58 | Discovery of correlations between different parameters to determine patterns | Naval industry | (Zaman et al., 2017) |
| 59 | Increased component interdependence | | |
| 60 | Processing large volumes of complex data | | |
| 61 | Data storage in various formats | They do not require previously structured data | |
| 62 | High data volume | | |
| 63 | High speed | | |
| 64 | High variety | | |
| 65 | Dependent on data quality | | |
| 66 | Facilitator of meaningful interpretation | | |
| 67 | Supports any type of dataset | | |
| 68 | Data filtering for volume reduction | | |
| 69 | Enables the deployment of digital technology and automation | | |
| 70 | Ability to process large volumes of data | The shipping industry produced a large amount of data | |
| 71 | Operations and maintenance | | |
| 72 | Autonomous data collation through networks and remote sensors | | |
| 73 | Provision of data for meteorological analysis | Calculation of appropriate maritime routes for the fleet of ships | |

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| 74 | Operational predictability | The vessel's operational performance can be monitored in real time by analyzing the vessel's data. | |
| 75 | Need to access historical data | | |
| 76 | Data logging during operation | | |
| 77 | Registration of data from various processes | It will reduce the cost of asset failures and minimize unplanned downtime. | |
| 78 | Reporting | Onboard and shore crew members could use this information to measure vessel operational performance and KPIs. | |
| 79 | Vibration data | Analysing signals which are available in machines (e.g. position, speed and drive current consumption) | (Roy et al., 2016) |
| 80 | Temperature data | | |
| 81 | Data-driven and model-based | Sampled data on the speed in case of a rotating machine is eliminated through the integration of complex wavelet transform-based envelope extraction of speed-varying vibration signals with computed order tracking | |
| 82 | Identified the product data model | Maintenance planning is a major capability to perform continuous maintenance. To support a model-based maintenance planning | |
| 83 | Life cycle data | | |
| 84 | Historical signals or indicators | Used to extrapolate the current trajectory of the component observed. It could be done by working on a mono-dimensional health index or multi-dimensional health index. The focus is on the performances/services expected at the system level and represented by the evolution of the properties of each flow (ex. product, energies) produced by the system | |
| 85 | Product design data | Besides IT-solutions product design data and technical documentation are important for functional understanding, repair and overhaul | |
| 86 | Data for continuous maintenance decision making | Defined to be high volume, high-velocity information assets, that comprises unstructured text, audio and video files | |
| 87 | Fast-changing Big Data | From continuous health monitoring across a number of assets within an enterprise | |
| 88 | Support human analytical thinking | Visualisation of the large volume of data is essential to support human analytical thinking and decision making for the continuous maintenance | |
| 89 | Real time data capture | Real time data capture, analysis and modelling of the ‘big data’ from the products in use within a ‘highly connected’ manufacturing and use environment so that the maintenance efficiency can be improved | |
| 90 | Control Systems Data Repositories | Designed control tool is validated on the existing non-residential buildings in the different Europe locations with different climates. These demonstration sites consist of four buildings with different topologies including an airport, offices and test labs, a commercial and office building, and a hotel. Finally, the building energy management systems are controlled automatically and remotely for the given demonstration sites. This serves as proof of concept of the Energy IN TIME solution | (Darure, 2017) |

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| 91 | Large datasets | Due to the increased digital networking of machines and systems in the production area | (Uhlmann et al., 2017) |
| 92 | Big data predictive analytics platforms | Enabling the collection and intelligent analysis of massive amount of data gathered from numerous sources including market trends, economical factors, current and future demands and enterprise resources | (Lee et al., 2015) |
| 93 | RFID-enabled real-time data | To integrate the manufacturing execution system and the enterprise resource-planning system | (Zhong et al., 2017) |
| 94 | Optimizing production or maintenance processes | An increasing number of manufacturing firms are committed to optimizing production or maintenance processes in a big data environment; Reducing after-sale maintenance cost; Optimizing the service contracts and maintenance intervals for industrial products | (Zhong et al., 2017) |
| 95 | Knowledge-driven models | data-based and services will be largely adopted for intelligent manufacturing | (Zhong et al., 2017) |
| 96 | Flexibility and interoperability from Big Data | Important inputs, in the automation operation, and in the maintenance, diagnosis and development | (Barreto, Amaral, Santana, et al., 2017) |
| 97 | Cloud Industrial environment | To improve diagnostics and prognostics for better maintenance decision making, there is a need to better correlate process and inspection data with machine condition to differentiate between process and machine degradation | (Schmidt et al., 2017) |
| 98 | Asset related data | Information about machine tools across factory – type of machines and their location; hierarchical structure – division into units, subunits, components, spare parts | (Schmidt et al., 2017) |
| 99 | Data-driven algorithm | Health assessment can be performed by using a data-driven algorithm to analyze data/information collected from the given machine | (Lee, Kao, et al., 2014) |
| 100 | Connection for smart products | Computation, data storage, communication and interaction with their environment | (Nunes et al., 2017) |
| 101 | Data monitoring | Essential quantities can be missing and non-relevant parameters been monitored. This is often discovered when the data is interpreted after a certain period of data collection | (Tiddens et al., 2015) |
| 102 | Statistical process control (SPC) | Predictive maintenance, smart energy consumption, and remote monitoring and control | (Karre et al., 2017) |
| 103 | Through-life engineering support | Support across the entire value chain: Innovation and technical improvements in engineering are present in the design, development and manufacturing processes. These enable the creation of new products and production systems utilizing a large amount of information (big-data) | (Tjahjono et al., 2017) |
| 104 | Long distance | Wind power illustrates the importance of Industry 4.0 technologies applied in maintenance context. About 300 sensors within each turbine transmit more than 200 gigabytes of data per day | (Venâncio et al., 2018) |
| 105 | Service Oriented Architecture (SOA) based system | Integrates several sub-systems, such as sensor data fusion, context modelling and contextual data information provision has been developed | (Sipsas et al., 2016) |
| 106 | Raw historical data | Data source, for the knowledge-based support, is the raw historical data lying under the legacy system that reports the stoppages | (Sipsas et al., 2016) |

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| 107 | Historical time machine records | Life prediction along with historical time machine records can be used to improve the asset utilization efficiency based on its current health status | (Lee, Bagheri, et al., 2014) |
| 108 | Equipment generating extensive amounts of data | continuous monitorization of industrial equipment | (Fernandes et al., 2018) |
| 109 | Operational data available or can be acquired with relative ease | This can be done by interfacing with legacy systems and sensor networks and applying principles of IoT and Cyber Physical Systems. Performing Predictive Maintenance requires the system to monitor the manufacturing machines and obtain vast amounts of operating data | |
| 110 | Data acquisition layer | collects data from the machines and from the production management software | |
| 111 | Data management and processing | Data management and processing to enable predictive analytics in cyber physical systems, holds the promise of creating insight into the underlying processes, discovering criticalities and predicting imminent problems | (Bowden et al., 2019) |
| 112 | Raw data collected from sensors | Prognostics and diagnostics applied to raw data collected from sensors aim to determine the health of the monitored system or equipment | |
| 113 | Smart data block | The smart data block derives relevant static features from the raw data (in many cases raw data are time series), supporting the predictive maintenance goal. Smart data represents the key characteristics of the raw data, as well as context information about how the data was collected and the operating conditions of the equipment it was collected from | |
| 114 | Maintaining and developing software products | Data come from CSC and relate to its outsourcing activities maintaining and developing software products on behalf of client organizations. Thus, the projects span different products from different sources | (Kitchenham, Pfleeger, McColl, & Eagan, 2002) |
| 115 | Maintenance via data | Short-term consulting assignments, where the user requests reports such as data or usage summaries. Development projects involve creating a new application or replacing an existing one | |
| 116 | Tools database supplied | The tool has not been calibrated with the past history of the corporate projects; estimates are made based on the database supplied with the tool. The estimate is expressed both in hours and in function points. The input questions vary according to whether the project is client/server, object-oriented, real-time, information engineering, maintenance or generic | |
| 117 | Manual data gathering | Data are collected, as needed, by maintainers at the operational level, and then incorporated into organizational repositories where they can be used to develop measurement models for maintenance purposes | (April & Abran, 2009) |
| 118 | Database system was accessed by the portfolio | Experience report on automated mass maintenance of a large Cobol software portfolio | (Veerman, 2006) |
| 119 | Web-enabled platforms for data optimization | Web-enabled platforms for data optimization and synchronization with Supply Chain systems. This technological component identifies any kind of platform used in order to integrate the data collection and data management, from shop floor level to business level of Supply Chain Management | (Ma et al., 2007) |

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| 120 | Data related to CMMS | Excel based database only for some particular activities, without a specific standard. CMMS implementation to enhance planning and scheduling of maintenance activities and create an historical database to perform maintenance analysis | |
| 121 | Data acquisition performed by traditional cable at PLC level | PROFIBUS (Process Field Bus) transmission and SCADA systems work through Ethernet on Optical fiber | |
| 122 | Data mining | Storing large amounts of data for data mining purposes. Now the increasing use of the Internet and information overload puts a great demand for managing the intelligent information skillfully and efficiently | (Funk & Jackson, 2005) |
| 123 | Condition Based Maintenance (CBM) | Condition Based Maintenance (CBM) of a system when the information obtained from the gathered data does not reveal the system's exact degradation state | (Ghasemi et al., 2008) |

**Table A.0.4 I4.0-Maintenance main technologies and applications (Cloud Computing).**

| Cloud Computing | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Production traceability | | (OMRON, 2018) |
| 2 | Efficient and fully integrated lines | | |
| 3 | Machine Enabler | | |
| 4 | Accessibility | | (Rosendahl et al., 2015) |
| 5 | Large-scale use | | (Colombo et al., 2017) |
| 6 | Operation in industrial environment | | |
| 7 | Hosting miscellaneous services | | |
| 8 | accommodation | | |
| 9 | Anything-as-a-Service | | (Romero & Vernadat, 2016) |
| 10 | Broadband Wireless Networks | | |
| 11 | Auto Acquisition | | (Biahmou et al., 2016) |
| 12 | Facilitates network in the value chain | | |
| 13 | Cloud Technology | | (McKinsey & Company, 2015) |
| 14 | Complete coverage of the production process | | |
| 15 | Specific data collection | | |
| 16 | Forecast Capability | | |
| 17 | Control and Stabilization | | |
| 18 | Connection | | |
| 19 | Online configurator | | |
| 20 | Online Community | | |
| 21 | Secure and remote connection | | |
| 22 | Base for I4.0 | | |
| 23 | Needs sensors and actuators | | |
| 24 | Spatial dissociation | | |
| 25 | Connectivity | | |

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| 26 | Integration of maintenance with other areas | | (Bokrantz et al., 2017) |
| 27 | Remote | | |
| 28 | Connectivity | | |
| 29 | Standardization for integration | | |
| 30 | Decision on decentralized maintenance | | |
| 31 | Online | | |
| 32 | Remote Orientation | | |
| 33 | Maintenance simulation | | |
| 34 | Sharing data | | |
| 35 | Platform between customers and suppliers | | |
| 36 | Diverse sources | | |
| 37 | Combined Sources | | |
| 38 | Integrated data | | |
| 39 | Analysis of maintenance data | | |
| 40 | High quality in maintenance | | |
| 41 | Fact-Based Planning | | |
| 42 | Remote Maintenance | | |
| 43 | Flexibility | | |
| 44 | Communicable | | (Qin et al., 2016) |
| 45 | Interoperability | Integration of business value networks and the product chain | |
| 46 | Communication | | |
| 47 | Vanguard in the use of networks | | |
| 48 | Web technologies in manufacturing | | (Dimitris Mourtzis et al., 2016) |
| 49 | Automatic notifications | | |
| 50 | Data exchange facilitator | | |
| 51 | Scalability of size and needs | | |
| 52 | omnipresent network access | | |
| 53 | Control of production processes | | (Pereira & Romero, 2017) |

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| 54 | Continuous access to data | | (Vallhagen & Almgren, 2017) |
| 55 | Products modularized | Intelligent maintenance and repair solutions replace current procedures | (Man & Strandhagen, 2017) |
| 56 | Remote Updates | | |
| 57 | Heterogeneous network devices | | (Mata et al., 2018) |
| 58 | Cloud manufacturing | Product Lifecycle Maintenance Planning | (D Mourtzis et al., 2017) |
| 59 | Design Anywhere Manufacture Anywhere | | |
| 60 | Ubiquitous network | | |
| 61 | Scalability | | |
| 62 | Facilitates the supervisory mechanism | | |
| 63 | Scanned report rich in detail | Operator can record malfunction by writing explanatory text | |
| 64 | Remote Maintenance | | |
| 65 | Maintenance job storage | | |
| 66 | Organization of stored data | | |
| 67 | Operational efficiency | Shipbuilding | (Zaman et al., 2017) |
| 68 | Different speeds of data creation and movement | | |
| 69 | Accessibility of data | | |
| 70 | Connects a dataset | Access from a single user to a multiple data set | |
| 71 | Requires data confidentiality | | |
| 72 | High rate of data transmission | | |
| 73 | Integration of data for analysis | | |
| 74 | Robust wireless network | Shipbuilding | |
| 75 | High transmission capacity | | |
| 76 | Real-time data acquisition | | |
| 77 | Increased security of physical processes | Information that will be useful for crew safety | |
| 78 | Automation could from inherent resilience | A system or a component or could be assisted using external agents, such as robots | (Roy et al., 2016) |
| 79 | Maintenance-planning platform | Integrated maintenance-planning platform, that connects different parts of an enterprise to support the maintenance planning | |

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| 80 | Managing life cycle data across the enterprise | The functional integration of maintenance within the product life cycle, based on experience obtained from work. Integration of the maintenance at the production planning stage for developing opportunistic maintenance task keeping conjointly the product/production/equipment performance | |
| 81 | Remote maintenance | Successful remote maintenance would require data communication across the Extended Enterprise | |
| 82 | Computerised maintenance management systems (CMMS) | In case Enterprise resource planning systems are used, CMMS may be an add-on or an integrated part | |
| 83 | Cloud-based management services | Integrated chipsets communicating with cloud-based management services | |
| 84 | Cloud-enabled prognosis for manufacturing and maintenance | Maintenance services in line with CPS through the ''Smart Maintenance Initiative'' advocated for Railway applications. An integrated maintenance platform will capture track irregularity and material condition data frequently by trains in operation and perform maintenance decision-making based on the condition of the individual track | |
| 85 | Well-governed data supply chain | With the emphasis on using more and more life cycle data, secure data communication across the Extended Enterprise is essential for the maintenance to work in practice. The Extended Enterprise will also require a well-governed data supply chain | |
| 86 | Cloud Control Systems | Designed control tool is validated on the existing non-residential buildings in the different Europe locations with different climates. These demonstration sites consist of four buildings with different topologies including an airport, offices and test labs, a commercial and office building, and a hotel. Finally, the building energy management systems are controlled automatically and remotely for the given demonstration sites. This serves as proof of concept of the Energy IN TIME solution | (Darure, 2017) |
| 87 | Energy Equipment | Energy optimization and the maintenance of the thermal comfort can be handled on the hierarchical level or in a single control layer | |
| 88 | Maintenance planner | Different services based on the data analysis in the cloud can be provided for various stakeholders involved in the production | (Uhlmann et al., 2017) |
| 89 | Decentralized data analysis in the production environment | Based on single-board computers and MEMS vibration sensors. This solution can act as a sensor network and can be used for condition monitoring application at production machines to enable them for predictive maintenance | |
| 90 | Cloud connected sensor network | Sensor network is connected to the cloud, where data analysis results can be stored and managed using a data management system | |
| 91 | Services for condition monitoring | Cloud services for condition monitoring, maintenance planning and apps for trend analysis, report generation of the current system condition can be carried out using mobile smart devices | |

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| 92 | Data management platform | Tether-free and connected data management platform with real-time streaming and processing capabilities; Pipeline of data to action has the potential to create value in different sections of a business chain. For example, valuable information regarding the hidden degradation or inefficiency patterns within machines or manufacturing processes can lead to informed and effective maintenance decisions which can avoid costly failures and unplanned downtime | (Lee et al., 2015) |
| 93 | Manufacturing Cloud | Advanced manufacturing model under the support of cloud computing. It covers the extended whole life cycle of a product, from its design, simulation, manufacturing, testing, and maintenance, and is therefore usually regarded as a parallel, networked, and intelligent manufacturing system (the "manufacturing cloud") where production resources and capacities can be intelligently managed | (Zhong et al., 2017) |
| 94 | Integration of cloud services with knowledge management | In a platform that is able to provide enterprise services such as intelligent design and manufacturing, production modeling and simulation, and logistics and supply-chain management. | |
| 95 | Internet-based diagnosis | Integration of cyber-technologies turns products and services as internet-enabled, which facilitates the integration of processes and systems across sectors and technologies and thus contributes to a better communication and cooperation with each other in a new intelligent way, revolutionizing production, services provision, logistics and resource planning in a more effective way and cost-efficient manner | (Barreto, Amaral, Santana, et al., 2017) |
| 96 | Smart networking | Mobility and flexibility of industrial operations and their interoperability, integration of customers and innovative business models | |
| 97 | Real-time end-to-end system-base applications | Mobility allows, using cloud-based platforms to use system-based applications, real-time end-to-end planning and horizontal collaboration. With these systems, companies can become more efficiently integrated with horizontal value chain partners, including suppliers and key customers, and also significantly improve efficiencies and reduce inventories | |
| 98 | Cloud Industrial environment | Effective maintenance policy improves quality, efficiency, and effectiveness of manufacturing operation and could influence the productivity and profitability of a manufacturing process. Generally, diagnostics and prognostics models require significant amounts of historical condition monitoring and event data, as the uncertainty of these models decreases when data become more extensive | (Schmidt et al., 2017) |
| 99 | Connection for smart products | Computation, data storage, communication and interaction with their environment | (Nunes et al., 2017) |
| 100 | On-demand sharing and accessing computing resources | Using configurable process models enables Cloud providers to deliver a customizable process according to tenants needs. Motivated by adapting to the rapid changing business requirements and reducing maintenance costs, organizations are outsourcing their processes using Cloud resources | (Belghith, 2017) |
| 101 | Interconnected by wireless communication | In order to utilize data systems as ERP (Enterprise Resource Planning) and PLM (engineering systems), they must be integrated with business systems | (Sandengen et al., 2016) |

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| 102 | Long distance dada access | A remote diagnostics center for advanced analytics and real-time human monitoring to convert this data into insights. This application of monitoring technology, which comes from Industry 4.0 concepts for collecting data for a process upgrade | (Venâncio et al., 2018) |
| 103 | peer-to-peer connections | | (Lee, Bagheri, et al., 2014) |
| 104 | Internet protocols to allow communication | Internet protocols to allow communication between machines, devices, objects and sensors anywhere on the network | (Tedeschi et al., 2018) |
| 105 | Control capability | Control refers to the capability of remotely controlled objects with internet technology | |
| 106 | Virtualized and cloud-based services | Context of manufacturing systems | (Bowden et al., 2019) |
| 107 | Wireless Technologies | Technologies that allow the communication in a restricted space (e.g. Zigbee, Bluetooth) or between long distance devices (e.g. GSM, UMTS) | (Ma et al., 2007) |
| 108 | Internet-based technologies | Technologies (e.g. XML, SOAP) enabling the communication through Internet or Enterprise Intranets: this technological component is considered in the research in order to assess whether the maintenance development will be web-based or not | |
| 109 | Computer Maintenance Management Systems | A CMMS is a software package that maintains a database of information about maintenance operations | |
| 110 | Web-enabled | Platforms for data optimization and synchronization with Supply Chain systems | |
| 111 | Web-enabled platforms for data optimization | Web-enabled platforms for data optimization and synchronization with Supply Chain systems. This technological component identifies any kind of platform used in order to integrate the data collection and data management, from shop floor level to business level of Supply Chain Management | |
| 112 | Local data acquisition | Bluetooth for “walk-around” inspections. Other wireless technologies (e.g. Wi-fi) for condition monitoring with sensor networks | |
| 113 | Condition based maintenance in old plants | An approach to achieve a condition-based maintenance in old plants, without peculiar exceptions for the technology involved, maintained through a collaborative network of enterprises | (Tucci et al., 2010) |
| 114 | Collaborative network of maintenance partners | | |

**Table A.0.5 I4.0-Maintenance main technologies and applications (Advanced Machines).**

| Advanced Machines | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Interaction between components of different complexities | | (OMRON, 2018) |
| 2 | Machine protection | | |
| 3 | Ability to connect machines | | |
| 4 | Robotic Technologies | | |
| 5 | Interaction with CPS | | (Colombo et al., 2017) |
| 6 | Advanced IT application cooperation | | (Romero & Vernadat, 2016) |
| 7 | Physical objects | | (McKinsey & Company, 2015) |
| 8 | Machines connected to each other | | |
| 9 | Interaction | | |
| 10 | Advanced Robotics | | |
| 11 | Collaborative Robot | | |
| 12 | Simultaneous operation with humans | | |
| 13 | MRO digital | | (Bokrantz et al., 2017) |
| 14 | Connection between machines | | |
| 15 | Remote Inspection and Repair | | |
| 16 | Auto-configuration | | (Qin et al., 2016) |
| 17 | Self-optimization | Integration of business value networks and the product chain | |
| 18 | Sustainability practices in manufacturing | Robotic handling (robotic handling, palletizing and molding), robotic welding, robotic assembly (press-fit, insertion and disassembly), robotic distribution (painting, gluing and spraying), robotic processing (waterjet and laser cutting) | (Ogbemhe, Mpofu, & Tlale, 2017) |
| 19 | Versatility | | |
| 20 | Reductions in time compared to manual methods | | |
| 21 | Collaborative | | |
| 22 | 24/7 operation | | |
| 23 | Performing various operations | | |
| 24 | Accuracy of movement | | |

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| 25 | Equipment Availability Information | | (Vallhagen & Almgren, 2017) |
| 26 | Adhesive systems for self-maintenance | | (D Mourtzis et al., 2017) |
| 27 | Automation and Robotics | | (Zaman et al., 2017) |
| 28 | Using robots to support maintenance tasks | Maintenance efficiency could be improved by using automation. maintenance is often irregular, non-uniform, non-deterministic and non-standardised. Building blocks of maintenance tasks and automated the tasks using a standard robot. Effective automation of maintenance tasks would require further co-ordination between robots and advances in autonomous robotics. | (Roy et al., 2016) |
| 29 | Coating technologies | So-called ‘‘patch processes’’ have been established for the repair of engine and turbine components. Damaged component areas are identified and replacements are attached. Subsequently, the contour is re-established with mechanical procedures. Laser metal deposition as an example is a technology to create a metallurgical bonded material deposition on a substrate. It can be used to repair worn surfaces or to produce a hard-facing layer. A laser beam is used to melt the surface of a specimen and a powdery filler material is injected in the molten pool. The low metallurgical impact is particularly important for preservation of material’s microstructure (e.g., high-strength steels). For proper use knowledge about process parameters and their influence on weld bead geometry is necessary. | |
| 30 | Self-healing | Electronic components | |
| 31 | Self-healing robotics | Is often achieved through reconfigurability, modularity, redundancy and adaptive behavior. Reconfiguration or self-repair by replacing a failed module with another functionally homogeneous module is the most common approach. A number of self-configuring robots already exist | |
| 32 | Remote Maintenance | The existing remote maintenance technologies work best when the environment is very structured and the state of a machine is less uncertain. In an effort to explore use of robots for autonomous maintenance, novel task classification for automation and collaborative robot application are being proposed. | |
| 33 | Real time data capture | Real time data capture, analysis and modelling of the ‘big data’ from the products in use within a ‘highly connected’ manufacturing and use environment so that the maintenance efficiency can be improved | |

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| 34 | CPS for machine tools | Machining processes in the manufacturing industry represent a highly dynamic and complex situation for condition-based maintenance (CBM) and PHM. A CNC machine can usually handle a wide range of materials with different hardness and geometric shapes and consequently requires different combinations of machine tool and cutting parameters to operate. The developed CPS for machine tools can be used to process and analyse machining data, evaluate the health condition of critical components (e.g. tool cutter) and further improves the overall equipment efficiency and reliability by predicting upcoming failures, scheduling maintenance beforehand and adaptive control | (Lee et al., 2015) |
| 35 | Machines-devices connection | Cloud-based system for connecting machines and devices from a variety of companies, facilitating transactions, operations and logistics, and collecting and analyzing data | (Barreto, Amaral, Santana, et al., 2017) |
| 36 | Mechanical systems self-awareness | Being able to assess the current or past condition of a machine, and react to the assessment output. Such health assessment can be performed by using a data-driven algorithm to analyze data/information collected from the given machine and its ambient environment | (Lee, Kao, et al., 2014) |
| 37 | Passively listen | Listen to the operators' commands and react, even when the assigned task is not optimal for its current condition | |
| 38 | Smarter machine system | Should be able to actively suggest task arrangements and adjust operational parameters to maximize productivity and product quality | |
| 39 | Connected proactive machines | Proactive maintenance scheduling: with connected machines and awareness of machine condition across the fleet, tasks and maintenance plans will be scheduled and optimized from the fleet level. By balancing and compensating the work load and stress for each machine according to their individual health condition, production and machine performance can be maximized | |
| 40 | Smart products | Moreover, smart products are able to perceive and interact with their physical environment without any human intervention | (Nunes et al., 2017) |
| 41 | Collaborative robotics | Human-robot interactions | (Karre et al., 2017) |
| 42 | Mobile workshops | Experiment with machine flexibility | |
| 43 | Enable the automation of production lines | Environment whereby smart machines can communicate with one another | (Tjahjono et al., 2017) |
| 44 | Enable customization, flexibility and rapid manufacturing | Robots, drones | |
| 45 | Sensor-based computer technology | In order to utilize data systems as ERP (Enterprise Resource Planning) and PLM (engineering systems), they must be integrated with business systems | (Sandengen et al., 2016) |
| 46 | Cyberlevel infrastructure | Machines can register into the network and exchange information through cyber-interfaces | (Lee, Bagheri, et al., 2014) |

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| 47 | Internet protocols to allow communication between machines | | (Tedeschi et al., 2018) |
| 48 | Smart legacy machines | New smart applications (e.g. smart sensors, IoT technology, etc.) the manufacturers need to reconfigure the IT level to create the new generation of "smart legacy machines". Monitoring systems for legacy machine tools raise security aspects related to data sharing and data protection that are associated to both hardware and software threats. These threats can cause machines breakdowns and data compromise that may represent drop in productivity and competitiveness, which in turn represent higher costs to the organisation and loss of profitability | |

**Table A.0.6 I4.0-Maintenance main technologies and applications (Advanced Materials).**

| Advanced Materials | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Decreasing costs | | (McKinsey & Company, 2015) |
| 2 | Variety of materials | | |
| 3 | Precision | | |
| 4 | Quality | | |
| 5 | Experimentation | | |
| 6 | Prototyping | | |
| 7 | Replacement of complete modules | | (Bokrantz et al., 2017) |
| 8 | Spare parts | | |
| 9 | Modularization of items with replaceable components | Upgradable control units | (Man & Strandhagen, 2017) |
| 10 | Advanced Materials | | (Zaman et al., 2017) |
| 11 | Replacement or repair of components and systems | Modern machines and components are exposed to changing environmental influences and material ageing effects. This results in damages or degradations that needs to be taken care of by using adequate repair and maintenance technologies | (Roy et al., 2016) |
| 12 | Products that have less degradation | By developing products that have less degradation the profitability to the manufacturer would increase. This would also mean longer mean time to failure (MTTF) | |
| 13 | Versatile repair mechanisms | Prevalent principles are separating, joining, coating and cleaning technologies for mechanical products | |
| 14 | Spare part production | A potential future technology for spare part production is Additive Layer Manufacturing that allows producing directly from 3D scan data | |
| 15 | Self-healing | Self-healing is a bottom-up approach, where the components of a system heal the damage internally. Can be achieved in materials | |
| 16 | Repair and overhaul strategies | Starting from single repair events that can be handled by replacement with spare parts up to complete overhaul strategies combined with facelifts and modernisation of machines. Furthermore, it is necessary to significantly reduce the production stoppage. This correlates with the productivity of machines and the costs of repair processes | |
| 17 | Cleaning technologies | As a preventive measure to maintain functionality, the application of flexible and eco-efficient cleaning processes has taken on greater significance. In addition, newly developed and adjusted cleaning technologies are able to reduce downtimes, because they can be either used during machine operation or need short time compared to other repair technologies | |

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| 18 | Dry ice | Dry-cleaning technology that causes no residues. Dry ice pellets are used as an abrasive for blasting processes. They are solid at ambient conditions with a temperature of -78.5C and change directly into the gaseous state during blasting. Due to its low hardness, it is suitable for gentle cleaning and processing of sensitive surfaces. Unfortunately, the low hardness makes the pellets sensitive to external impacts or friction. Dry ice blasting is predominantly used to clean easily accessible surfaces. For areas with limited accessibility, different blasting nozzles are available | |
| 19 | Ultrasound wet cleaning | | |
| 20 | Thermal cleaning principles | | |
| 21 | To reduce adverse environmental effect | For printed circuit boards principles without electrostatic effect can be used such as ultra-clean water, compressed carbon dioxide, blowing, suction or brushing; the major challenge is to reduce adverse environmental effect | |
| 22 | Selective Laser Melting (SLM) | Additive manufacturing and rapid prototyping principles | |
| 23 | Stereo-lithography (SL) | | |
| 24 | Fused Deposition Modelling (FDM) | | |
| 25 | Wire and Arc Additive Manufacturing (WAAM) | | |
| 26 | Laminated Object Manufacturing (LOM) | | |
| 27 | CAD parts in a database | Automated building of assembly models | |
| 28 | New advanced materials | Repair technologies for new materials (e.g. composite repair) for resource utilisation and life extension and an integrated approach to obsolescence management. Advanced materials are also important and are building on the advances in cleaning technologies, coating technologies and additive manufacturing. Self-healing technologies are still at its infancy and at the component level | |
| 29 | Ongoing 3D printing research | | (Karre et al., 2017) |
| 30 | Enable customization, flexibility and rapid manufacturing | Nanotechnologies | (Tjahjono et al., 2017) |
| 31 | Self-repairing materials | Aerospace industry, given the potential value for self-repairing airplanes and spacecraft | (Gould, 2003) |

**Table A.0.7 I4.0-Maintenance main technologies and applications (Flexible Connection Devices).**

| Flexible Connection Devices | | | |
|---|---|---|---|
| Appearances | Functionality / Features | | Article/Report Reference |
| 1 | Continuous communication between factory levels | | (OMRON, 2018) |
| 2 | Machine control platform | | |
| 3 | Efficient management | | (Colombo et al., 2017) |
| 4 | Life cycle management | | |
| 5 | Small devices | | (Romero & Vernadat, 2016) |
| 6 | Sharing | | (Biahmou et al., 2016) |
| 7 | Direct access | | |
| 8 | Digital integration | | |
| 9 | Human-Machine Integration | | (McKinsey & Company, 2015) |
| 10 | Personal devices | | |
| 11 | Capture information | | |
| 12 | Process Conduction | | |
| 13 | Remote Sensors | | |
| 14 | Robot-Human Collaboration | | |
| 15 | Remote Maintenance | | |
| 16 | Solutions by applications / software | | |
| 17 | Remote diagnostic capability | | |
| 18 | Remote monitoring | | |
| 19 | Knowledge control | | |
| 20 | Agility | | |
| 21 | Flexibility | | |
| 22 | Fast response time | | |
| 23 | Visual Interface Devices | | |
| 24 | Functionality of complex equipment through APP's | | |
| 25 | Facilitating the entry of new players | | |
| 26 | Remote | | |

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| 27 | Remote diagnostics | | (Bokrantz et al., 2017) |
| 28 | Maintenance | | |
| 29 | Simple Actions | | |
| 30 | High accessibility | | |
| 31 | Systems: CMMS, MONTH, PLM | | |
| 32 | Monitoring | | |
| 33 | Internal Benchmarking | | |
| 34 | Remote Maintenance | | |
| 35 | Real-time monitoring | | |
| 36 | personal data | | |
| 37 | Planning based on monitoring and forecasting | | |
| 38 | Provides information to employees | | |
| 39 | Real-time maintenance | | |
| 40 | Continuous monitoring of equipment performance and status | | |
| 41 | Meets environmental requirements | | |
| 42 | Transmission of functional orientations to customers | Check the status of products and track them | (Qin et al., 2016) |
| 43 | Provides feedback to the manufacturing system | | |
| 44 | Controllable | | |
| 45 | Remote Preventive Maintenance | | (Dimitris Mourtzis et al., 2016) |
| 46 | Multi-user access | | |
| 47 | Building real-time monitoring capabilities | | |
| 48 | System operates in collaboration with operators | Machine status input (available, busy, inactive) | |
| 49 | Integration to the entire value chain | | (Pereira & Romero, 2017) |
| 50 | Connection between the physical and virtual world | | |

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| 51 | Interaction with the environment | | |
| 52 | Accessibility to equipment status and maintenance requirements | Checking the state of heat treatment furnaces | (Vallhagen & Almgren, 2017) |
| 53 | Manual insertion of data | | |
| 54 | Low frequency of compilation of statistical data | Reducing the risk of inserting incorrect data in the optimizer and reducing the amount of work performed by the planner | |
| 55 | Remote monitoring | | (Man & Strandhagen, 2017) |
| 56 | Systems monitoring | | |
| 57 | New manufacturing potential risks arising from data integrity | Cyber-attack, malware, spyware, loss of data integrity or problems with availability of information | (Tupa, Simota, & Steiner, 2017) |
| 58 | Machine Monitoring | Limit machine downtime | (D Mourtzis et al., 2017) |
| 59 | Portable Devices | | |
| 60 | Mobile devices | Operator can record malfunction by writing explanatory text | |
| 61 | Transmission of images and audio recordings | | |
| 62 | Creating step-by-step instructions | | |
| 63 | Allows real-time monitoring and control of systems and processes | Shipbuilding | (Zaman et al., 2017) |
| 64 | Real-time transmission of analyzed object status | Loading information and personnel will be transferred to port authorities to improve cargo handling performance. | |
| 65 | Monitoring of gas emissions | Analysis of environmental impact caused by the operation of ships' combustion engines | |
| 66 | Performance Monitoring | | |
| 67 | Health Monitoring | Monitoring of machines to check their state of degradation due to use or health parameters. Sensor based monitoring example is a Health Usage and Monitoring System (HUMS), first used in helicopters | (Roy et al., 2016) |
| 68 | Remote monitoring and maintenance system for machine tools | Where a simple mobile phone-based communication is established to connect 8000 machine tools for the remote maintenance | |
| 69 | Remote maintenance | To cover all repair cases a flexible and robust process chain consisting of inspection, repair and remanufacturing technologies as well as quality control is needed. Mobile technologies offer advantages compared to stationary technologies, because there is no need for disassembling and transportation of damaged parts. The remote maintenance is mostly at the level of accessing the health parameters of a machine remotely and perform software-based repair and upgrade tasks. | |

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| 70 | Mobile laser metal deposition solutions | | |
| 71 | Self-healing MEMS | MEMS devices can be very cheap on its own, but can have significant impact on the overall availability of the system where it is used. There is a strong motivation to improve robustness of the MEMS for more resilient systems. There are two principal ways to develop the self-healing capability, one by using redundancy and the other protecting the MEMS device from damage using surface lubrication. Self-healing MEMS accelerometer has redundant gauging finger modules. With a built-in-self-repair strategy, when one module becomes damaged a circuit connection control mechanism replaces the damaged module by a redundant one, as a result improving the robustness of the MEMS device | |
| 72 | Tablets and smartphones weight and great wireless connection | Physical limitation of the Head mounted device (e.g., weight, lack of complete wireless connection) and its impact on prolonged use by the maintenance technicians is highlighted as a major challenge at the time. This basic issue about the HMD still exists and as a result more mobile and handheld technologies such as tablets and smartphones are gaining popularity in industry | |
| 73 | Energy Equipment | Control and Monitoring for the economic building operability within the user defined performance requirements. Maintenance by enabling the early detection of equipment malfunctions and defective system behavior followed by the appropriate corrective action to continue the normal building operability. Energy optimization and the maintenance of the thermal comfort can be handled on the hierarchical level or in a single control layer | (Darure, 2017) |
| 74 | Services can be reached from anywhere | Different services based on the data analysis in the cloud can be provided for various stakeholders involved in the production and via smart mobile devices these services can be reached from anywhere; Condition monitoring application at production machines can be enabled for predictive maintenance | (Uhlmann et al., 2017) |
| 75 | Maintenance planning and apps for trend analysis | Cloud services for condition monitoring, maintenance planning and apps for trend analysis, report generation of the current system condition can be carried out using mobile smart devices | |
| 76 | Real-time streaming and processing capabilities data management | Tether-free and connected data management platform with real-time streaming and processing capabilities | (Lee et al., 2015) |
| 77 | Real-time object visibility | RFID technology provided automatic and accurate object data to enable real-time object visibility and traceability. More cases are available from the mold and die industry, automotive part and accessory manufacturing alliances, product life-cycle management, and aerospace maintenance operations | (Zhong et al., 2017) |

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| 78 | Smart Monitoring | Smart monitoring is an important aspect for the operations, maintenance, and optimal scheduling of Industry 4.0 manufacturing systems. The widespread deployment of various types of sensors makes it possible to achieve smart monitoring | |
| 79 | Smart controls for maintenance, operations, mobility | Enhances the development of new business models, operating concepts and smart controls, mainly focusing on the user needs | (Barreto, Amaral, Santana, et al., 2017) |
| 80 | Spatially independent access to processes and services | Mobility, Smartphones and tablets providing a temporally and spatially independent access to processes and services of the automated systems, introducing efficient mechanisms in the diagnostics, maintenance and operation of systems | |
| 81 | Device-to-Device (D2D) communications | Used to track-and-trace devices on products allowing a better inventory performance and reduced logistics cost | |
| 82 | Integration of diverse organizational systems promoting their interoperability, | Machine, devices, sensors and people are connected and can communicate with each other | |
| 83 | Smart and connect products capabilities | A set of new capabilities are offered by smart and connect products, such as the ability of monitoring and reporting relevant information in real-time about themselves and their environment, as well as the possibility of being remotely controlled | (Nunes et al., 2017) |
| 84 | Smart shop floor board | Installation of a smart shop floor board as the basis for digital performance management; Setup of extended human-machine-interfaces (HMIs) including gesture control | (Karre et al., 2017) |
| 85 | Dynamic information monitoring | Predictive maintenance is based on a combination of visual, automatic and dynamic information monitoring | (Sandengen et al., 2016) |
| 86 | Information and operational data analysis | Performance information and operational data analysis it is possible to follow up on wear and repair | |
| 87 | Visualization with dashboard through control room and tablet technology | Local computers near the machines runs algorithms. Establishment of a mobile agent. This will enable a cloud of predictive maintenance where a collaborative engineering team supports in prognosis and diagnosis of the machines, as well as predictive maintenance planning | |

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| 88 | Provision of information services | Mobile solutions can be used for the provision of information services to shop-floor personnel according to customer situation | (Sipsas et al., 2016) |
| 89 | Context-aware apps | Context-aware apps that support the collaborating users to address maintenance issues | |
| 90 | Remote maintenance | Implementing Internet of Things (IoT) technology in legacy systems to provide new services such as autonomous condition monitoring and remote maintenance | (Tedeschi et al., 2018) |
| 91 | Internet protocols to allow communication between devices | | |
| 92 | Monitoring capability | Monitoring is the capability of the object to behave as a sensor or to be able to produce information about itself or the encompassing environment | |
| 93 | Control capability | Control refers to the capability of remotely controlled objects with internet technology | |
| 94 | Monitorization of equipment | Predictive maintenance techniques can be implemented through the monitorization of equipment combined with intelligent decision methods | (Fernandes et al., 2018) |
| 95 | Performing Predictive Maintenance | Performing Predictive Maintenance requires the system to monitor the manufacturing machines and obtain vast amounts of operating data | |
| 96 | Able to visualize information | The company's collaborators will be able to visualize information that is pertinent to their specific functions and responsibilities, such as short-term alarms and notifications for machine operators and key-performance indicators for upper management employees | |
| 97 | High-end computing devices | Their constantly increasing interconnection hold the promise of increased automation reducing production costs and time | (Nikolakis et al., 2018) |
| 98 | Efficiently determining the health status of a monitored device | | (Bowden et al., 2019) |
| 99 | Manage situation in a remote application | Further developments of this study can be followed in order to: create a structure able to manage this situation in a remote application; in this context this technique could be included in a web-based toolbox whose output would be, as an instance, the time before next planned maintenance; | (Ierace et al., 2007) |

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| 100 | Digital devices for personal data exchange | Technological components enabling data retrievals from the equipment and data exchanges with the informative system. Examples given are PDAs and Smart Phones | (Ma et al., 2007) |
| 101 | Tools for integrated signal processing | Tools for integrated signal processing are any kind of system capable to make integrated data acquisition and processing. An example of such a tool is a SCADA (Supervisory Control and Data Acquisition) | |
| 102 | SCADA monitoring | Automatic control is performed on 50% of equipment and everything is registered through programmable logic controller (PLC) and SCADA systems (Supervisory Control and Data Acquisition systems) | |
| 103 | Integrated Condition Assessment System | PROTEUS platform, aiming at integrating applications in the domain of remote maintenance of industrial installations, watchdog capabilities into product and systems for closed looped design and lifecycle management | (Tucci et al., 2010) |
| 104 | Optimisation function enables to reorganize the maintenance task | Maintenance impact on the fleet availability. Validate the scenarios proposed according to the possible failure scenarios. Eventually, the monitoring function aims to store and to manage the maintenance and flight data | (Djeridi & Cauvin, 2009) |

**Table A.0.8 I4.0-Maintenance main technologies and applications (Digital-to-Real Representation).**

| Digital-to-Real Representation | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Monitoring | | (Colombo et al., 2017) |
| 2 | Real time | | (Bokrantz et al., 2017) |
| 3 | Collaborative | | |
| 4 | Maintenance assistance | | |
| 5 | Training and maintenance planning | | |
| 6 | Remote Inspection & Repair | | |
| 7 | Digital tools | | |
| 8 | Virtual specialists | | |
| 9 | Real World Supplementation | Head-Mounted Display, Hand-Held Display and Space Displays | (Dini & Mura, 2015) |
| 10 | Enhancing the perception of reality | | |
| 11 | Enrichment of reality | | |
| 12 | High human-machine interaction | | |
| 13 | Real-world information overlap | | |
| 14 | Immersive system | | |
| 15 | Ease of user understanding | Maintenance, Repair and Inspection Tasks | |
| 16 | Transmission of knowledge | Perform an operation on an electrical transformer, where the system uses CAD models of the parts and visual cues to retrieve their names and illustrate to the user the steps of maintenance | |
| 17 | Systems integration | | |
| 18 | Asset management | | |
| 19 | Condition Monitoring | | |
| 20 | Sturdy and accurate detection | Helping aircraft technicians handle complex procedures for their maintenance tasks and minimize operational errors | |
| 21 | Robust software algorithms | | |
| 22 | Processing a huge amount of data | | |
| 23 | Intelligent Augmented Reality | | |
| 24 | Intuitive interface | Recognize markers placed on aircraft components | |
| 25 | CAD-based tracking system | | |
| 26 | Wireless Transmission | | |

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| 27 | Apps for smartphones | Support people in normal car maintenance | |
| 28 | 3D vision tracking | Perform simple maintenance operations | |
| 29 | GPS and inertial unit applications | Maintenance of underground infrastructures | |
| 30 | Remote Maintenance | Assist the exchange of collimator remote in a particle accelerator of energy | |
| 31 | Virtual co-location based on RA | Remotely support maintenance during space missions using an HMD | |
| 32 | Quality control | The MiRA (Mixed Reality Application) system overlaps digital simulation with reality with a tactile tablet as hardware. | |
| 33 | Diagnostic Tasks | | |
| 34 | The user may experience eye strain after long periods of | | |
| 35 | Transparent optical screens depend on favorable lighting conditions | | |
| 36 | Limited field of view | | |
| 37 | Limited peripheral visibility | | |
| 38 | High preparation, programming and configuration time | | |
| 39 | Handles maintenance procedures | | (D Mourtzis et al., 2017) |
| 40 | Voice commands, gestures, menus hosted by devices | Support for maintenance tasks in large manufacturing companies | |
| 41 | Telemaintenance | | |
| 42 | Synchronous and asynchronous information exchange | | |
| 43 | Current projection of observed object status | | |
| 44 | Constant monitoring | | |
| 45 | Prototyping and corporate design | Quick, free creation of visual prototypes that can be manipulated by more than one user | |
| 46 | Task Execution Training | | |
| 47 | Asynchronous remote maintenance support | Unexpected stops, where the contribution of external experts in fault detection and sequence of service may be necessary | |

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| 48 | Product / service support during its life cycle | | |
| 49 | Increased Machine Availability | | |
| 50 | Flexibility of services | | |
| 51 | Malfunction Report Composition | | |
| 52 | Diagnosis and generation of maintenance instruction | | |
| 53 | Maintenance and evaluation | | |
| 54 | Identification of causes of malfunction | | |
| 55 | Generation of instructions for maintenance procedures | | |
| 56 | Improved fault reporting | | |
| 57 | Manufacturer support in short time | | |
| 58 | Unusual failures require more time to be detected | In order to provide the end user with a high-quality visual result that also allows him to maintain eye contact with the potentially dangerous environment and not to occupy his hands, a set of AR goggles was used | |
| 59 | Visualization of the repair sequence | | |
| 60 | Reuse of knowledge | | |
| 61 | User Interfaces | | |
| 62 | Recurrent uses throughout the equipment life cycle | | |
| 63 | Increase efficiency in maintenance tasks | | |
| 64 | Reduction in machine downtime | | |
| 65 | Access to database | | |
| 66 | Mobility to the user | | |
| 67 | Digital maintenance-repair overhaul (MRO) | | (Roy et al., 2016) |
| 68 | Visualisation of maintenance tasks | Use of adaptive augmented reality in maintenance support will allow customised help and improve safety (i.e. less human error) and efficiency of the maintenance tasks | |
| 69 | Planning and training | | |

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|---|---|---|---|
| 70 | Automated repair associated with the manual process | A major trend to avoid human errors, robot guided reworking of functional areas and rapid manufacturing of spare parts is becoming popular | |
| 71 | Remote Maintenance | Another approach for remote maintenance is to use remotely controlled robots to perform maintenance tasks within uncertain environments. Use of remote-controlled robots for maintenance is widely used in Nuclear, space and any hazardous industries. Researchers have used Virtual Reality based training systems for the remote maintenance operator training | |
| 72 | Repair & Overhaul (MRO) | Virtual technologies for MRO optimisation in practice | |
| 73 | Virtual Reality | Visualise product changes compared to CAD design | |
| 74 | AR technology for maintenance support | Overlaying and integrating virtual information on physical objects. Optical combination, video mixing and image projection. Tools are used in conjunction with a head mounted device (HMD) or a portable hand held device or a spatial display unit and a tracking system; Augmented reality on the shop floor deals with legibility of text that is projected on surfaces. When information projected on surface in the shop floor is legible, it can assist the maintenance worker by providing valuable information about the maintenance task; Industrial applications of AR will also depend on the ease of AR content creation, especially related to the context of the real life object in focus, and adaptation of the AR response based on the object context. The offline content creation and adaptation of the AR response is very important for continuous maintenance as the AR service could adapt based on the technician expertise. There is a need to extend the offline authoring to an interactive input interface to capture the technician feedback and reasoning for a maintenance decision on a physical object (e.g., repairing a hydraulic valve) | |
| 75 | Simulation-based control for Energy Efficient building operation and maintenance | Maintain building operability within the user-specific performance requirements which includes the thermal comfort of occupants under economic building operation. Enable efficient detection, localization and diagnostics of faults in the operation of Building system. Reconfigurable control layer to adapt the control system parameters and objective despite of the presence of faults or performance deviation within its specified energy and comfort performance requirements | (Darure, 2017) |
| 76 | Manufacturing Cloud enabling virtualization | IoT, virtualization, and service-oriented technologies, which transforms manufacturing resources into services that can be comprehensively shared and circulated | (Zhong et al., 2017) |
| 77 | Integration of diverse organizational systems promoting their interoperability, | Machine, devices, sensors and people are connected and can communicate with each other | (Barreto, Amaral, Santana, et al., 2017) |

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| 78 | Smart glasses | Context specific standard operating procedures (SOPs) | (Karre et al., 2017) |
| 79 | Wear and repair | Corrective actions in order to obtain maximum performance through the machines lifetime. Predictive maintenance is closely connected to performance measurements, widely recognized as the industrial standard for Overall Equipment Effectiveness (OEE) | (Sandengen et al., 2016) |
| 80 | Wear with “digital advices” | Support from Cyber level with “digital advices” for updating the maintenance plan | |
| 81 | Manufacturing shop-floor maintenance | Detailed maintenance instructions should be provided to the maintenance personnel, according to their level of expertise | (Sipsas et al., 2016) |
| 82 | System for context-aware AR maintenance applications | Use of AR goggles, coupled with other mobile devices for the communication of people, working on the shop-floor and in the engineering offices | |
| 83 | internet protocols to allow communication between objects | | (Tedeschi et al., 2018) |
| 84 | Monitoring capability | Monitoring is the capability of the object to behave as a sensor or to be able to produce information about itself or the encompassing environment | |
| 85 | Control capability | Control refers to the capability of remotely controlled objects with internet technology | |
| 86 | Monitoring of the processed data from different temporal perspectives | It will also be possible to view comparative analysis of similar equipment and conduct analytical monitoring of the processed data from different temporal perspectives. Furthermore, the proposed system will be integrated with the company’s production and management software to aid the manufacturer improve their processes and reduce costs and maintenance times | (Fernandes et al., 2018) |

**Table A.0.9 I4.0-Maintenance main technologies and applications (Sensors).**

| Sensor | | | |
|---|---|---|---|
| Appearances | Functionality / Features | Application | Article/Report Reference |
| 1 | Detection capability | | (OMRON, 2018) |
| 2 | Power management and management | | |
| 3 | Acquisition of information | | (Rosendahl et al., 2015) |
| 4 | Collect | | (Colombo et al., 2017) |
| 5 | Lightweight devices | | |
| 6 | Variety of devices | | (Romero & Vernadat, 2016) |
| 7 | Embedded in physical objects | | (McKinsey & Company, 2015) |
| 8 | Feel the environment | | |
| 9 | Interoperability | | |
| 10 | Machine Vision | | |
| 11 | Individual data collection | | |
| 12 | Parameter capture through cameras | | |
| 13 | Application flexibility | | |
| 14 | Conditional monitoring | | |
| 15 | Predictive | | (Bokrantz et al., 2017) |
| 16 | Predictive Tools | | |
| 17 | Application in various equipment | | |
| 18 | Different sources | | |
| 19 | Equipment | | |
| 20 | Real time | | |
| 21 | Maintenance services | | |
| 22 | Resources | | |
| 23 | Enables interoperability through scanning | Integration of business value networks and the product chain | (Qin et al., 2016) |
| 24 | Smart Technologies | | |
| 25 | Cheap hardware | | (Knoll et al., 2016) |
| 26 | Boosts performance boost | Barcodes and RFID | |

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| 27 | Induces the electronic maintenance approach | | (Dimitris Mourtzis et al., 2016) |
| 28 | Monitoring hardware | Monitor motor drive currents and RPM | |
| 29 | Real-Time Acquisition | Product status on the production line | (Vallhagen & Almgren, 2017) |
| 30 | Getting Parameters Feeds Databases | | |
| 31 | Feed scheduling algorithms | Reducing the risk of inserting incorrect data in the optimizer and reducing the amount of work performed by the planner | |
| 32 | Side dish | Intelligent maintenance and repair solutions replace current procedures | (Man & Strandhagen, 2017) |
| 33 | Interface with AR for environment monitoring | | (Dini & Mura, 2015) |
| 34 | Acquisition of physical parameters of optical signals | | (Mata et al., 2018) |
| 35 | Rapid development of sensor technology | | (Zaman et al., 2017) |
| 36 | Large volume of data created in real time | | |
| 37 | Rates of data flows increase rapidly | | |
| 38 | Proper presentation and formatting of data | | |
| 39 | Different types of sensors | | |
| 40 | Real-world scanning | | |
| 41 | Transformation of data into value | | |
| 42 | Remote Detection | Vessels will be monitored continuously from remote locations | |
| 43 | Wireless Sensors | Security and Protection of Vessels | |
| 44 | Real-time condition monitoring | | |
| 45 | Alert on equipment maintenance need | | |
| 46 | Vibration data from sensors | The system records vibration measurements taken at different critical components using different sensors and stores in a removable memory for further diagnostics | (Roy et al., 2016) |
| 47 | Temperature data from sensors | Electronic components and systems are often replaced rather than repaired due to low cost of replacement and efficient turnaround | |
| 48 | Operating life of components | A dynamic optimisation of preventive maintenance schedule | |

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| 49 | Thermography | Thermography is a rapid, large area inspection, low-cost and non-destructive evaluation technique that is performed by directing an infrared camera at a target (i.e., a component with in-service degradation) and recording a heat map image (also known as a thermogram) of the specimen in order to detect variations in temperature emitted by the component or transmitted from behind it | |
| 50 | Sensing technologies | Often used to predict system failure. The sensing technologies cover component and system level feedback and support the evolution of the system level information | |
| 51 | Self-healing | Fault tolerant sensor systems that are relevant for continuous maintenance | |
| 52 | Passive wireless sensor network | Self-healing materials, identifying any damage to the structure, monitoring the self-healing process and raising an alert for major damages for human expert intervention. Verification and validation of the sensor network robustness is still a major challenge. | |
| 53 | Modern 3D scanning | Modern 3D scanning technologies deliver 3D models of actual product geometry and allow deviation and tolerance analyses in case of available reference models. However, optical limitations and difficult part disassembly make 3D digitisation still a laborious task which is followed by a high effort in data post-processing | |
| 54 | RFID | Solution approaches for overall reduction of through-life cost Products can become intelligent cyber physical systems by RFIDs | |
| 55 | Real time data capture | Real time data capture, analysis and modelling of the ‘big data’ from the products in use within a ‘highly connected’ manufacturing and use environment so that the maintenance efficiency can be improved | |
| 56 | Control Systems Sensors | Designed control tool is validated on the existing non-residential buildings in the different Europe locations with different climates. These demonstration sites consist of four buildings with different topologies including an airport, offices and test labs, a commercial and office building, and a hotel. Finally, the building energy management systems are controlled automatically and remotely for the given demonstration sites. This serves as proof of concept of the Energy IN TIME solution | (Darure, 2017) |
| 57 | Maintenance optimization purposes | External sensors are installed at production systems to acquire data for production and maintenance optimization purposes | (Uhlmann et al., 2017) |
| 58 | Sensor network for a monitoring application in the production environment | | |
| 59 | Wireless sensor networks | Distributed data analysis can be implemented that can be used for monitoring applications in different industrial fields | |

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| 60 | CPS enabling interaction | “Industrial Internet of Things” (IIoT) has also affected the way CPS can interact, be monitored, be controlled and managed. Therefore, facilitate the integration of processes and systems across sectors and technologies and contributing to a better communication and cooperation with each other in a new intelligent way, revolutionizing production, services provision, logistics and resource planning in a more effective way and cost-efficient manner | (Barreto, Amaral, & Pereira, 2017) |
| 61 | RFID-enabled shop-floor manufacturing solution | Automotive part manufacturer. Engine valve manufacturer uses an RFID-enabled shop-floor manufacturing solution across whole operations; Various types of sensors makes it possible to achieve smart monitoring. For example, data and information on various manufacturing factors such as temperature, electricity consumption, and vibrations and speed can be obtained in real time | (Zhong et al., 2017) |
| 62 | Real time maintenance and production cycles monitoring | New benefits for customers, as it is evidenced by shortened production cycles, incorporation of customer needs in real time, maintenance is largely carried out automatically, orders are automatically filled in the right order, shipped and dispatched. | (Barreto, Amaral, Santana, et al., 2017) |
| 63 | Integration of diverse organizational systems promoting their interoperability, | Machine, devices, sensors and people are connected and can communicate with each other | |
| 64 | Acquisition parameters and operational condition | Conditions that affect health state estimation, and condition that affects degradation processes at measurement time | (Schmidt et al., 2017) |
| 65 | Querying for components | Querying for components of the same type and associated condition monitoring data can increase the number of available datasets that can be used to train the diagnostics and prognostics models; Taking into consideration the type of performed maintenance work (corrective or preventive) involved in the replacement, obtained trends can be differentiated to ones related to actual lifetime, and to ones related to censored lifetime | |
| 66 | Smart products | Products are able to identify themselves and provide information about their progress throughout their value chain, storing information about the previous process steps and providing information about further process steps regarding production and maintenance | (Nunes et al., 2017) |
| 67 | Sensor health for data gathering | Data collected from multiple sensors are not necessarily in a readily usable form due to issues such as missing data, redundant data, noise or even sensor degradation problems | (Tiddens et al., 2015) |
| 68 | Production data acquisition system | RFID to enable the digital thread, intelligent lots, batch size 1, and quick product changeovers | (Karre et al., 2017) |
| 69 | Digitalized and connected devices and products | Allows the vendors to communicate with their own products while they are used by the customers and to provide new "digital" customer services such as predictive maintenance | (Sandengen et al., 2016) |

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| 70 | Real-time data acquisition | Real-time data acquisition from sensors in machines and RFID from spare parts. In addition, the data is transferred through wireless connection to local servers | |
| 71 | Detect developing problems | Monitoring the infrared image of electrical switchgear, motors, and other electrical equipment | |
| 72 | Overall effectiveness (OEE) in manufacturing plants | Predictive maintenance means improving productivity, product quality, and overall effectiveness (OEE) in manufacturing plants. Predictive maintenance uses vibration monitoring, thermal imaging, lubricating oil analysis or nondestructive testing techniques | |
| 73 | Facilitate the integration of processes and systems | Processes and systems across sectors and technologies and contributing to a better communication and cooperation with each other in a new intelligent way, revolutionizing production, services provision, logistics and resource planning in a more effective way and cost-efficient manner | (Barreto, Amaral, & Pereira, 2017) |
| 74 | Sensors offshore and onshore | Wind power technology. Sensors in its offshore and onshore wind turbines, with a database that increases daily with collected data from more than 10,000 turbines worldwide | (Venâncio et al., 2018) |
| 75 | Monitoring long distance analysis | A remote diagnostics center for advanced analytics and real-time human monitoring to convert this data into insights. This application of monitoring technology, which comes from Industry 4.0 concepts for collecting data for a process upgrade | |
| 76 | Advanced context information collection and management technologies | Near Field Communication (NFC) and Service Oriented Architecture (SOA) technologies, in the shop floor, provide opportunities for the development of such context-aware information systems, in aid of the maintenance operators and engineers | (Sipsas et al., 2016) |
| 77 | Description of the resolution handled on-the-go | Sensor that caused the stoppage and a quick description of the resolution if handled solely by the line operators without requiring the maintenance personnel | |
| 78 | Autonomous condition monitoring | Implementing Internet of Things (IoT) technology in legacy systems to provide new services such as autonomous condition monitoring and remote maintenance | (Tedeschi et al., 2018) |
| 79 | Internet protocols to allow communication between sensors | | |
| 80 | Monitoring capability | Monitoring is the capability of the object to behave as a sensor or to be able to produce information about itself or the encompassing environment | |
| 81 | Solution to improve legacy systems | in order to achieve higher productivity and reduce machines breakdowns. This technology covers for example the installation of smart sensors able to analyse the machine performance in terms of machine status, energy usage and others machining parameters using power signals analysis, which allow optimising the machine usage and maintenance actions | |

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| 82 | Enhanced sensing and communication capabilities | | (Nikolakis et al., 2018) |
| 83 | Sensor-based degradation models | For identifying the frequency of unexpected failures was used | |
| 84 | Advanced Internet of Things | Allow linking physical manufacturing facilities and machines | (Bowden et al., 2019) |
| 85 | Conventional Condition-Based Maintenance (CBM) | Development of complex and sophisticated equipment makes necessary to enhance modern maintenance management systems. Conventional Condition-Based Maintenance (CBM) reduces the uncertainty of maintenance according to the needs indicated by the equipment condition | (Ierace et al., 2007) |
| 86 | Tools for integrated signal processing | | |
| 87 | Smart sensors | Sensors that are able to play more functions than the representation of a physical quantity solely | |
| 88 | Digital devices for local data exchange | Technological components that can be used in order to support data exchange in local area and data storage. Examples given are the well-known RFID based devices | (Ma et al., 2007) |
| 89 | Local data acquisition | Local data acquisition and condition monitoring (e.g., from sensor networks installed in the plant | |
| 90 | Sensors networks | Condition monitoring are already installed in some parts of the plant: in particular, a critical equipment, i.e. the continuous rolling mill for tubes, is equipped with sensors networks | |
| 91 | Condition monitoring | Installing sensors on board of the machine which can collect information on the functioning of the asset. We unfortunately faced the current tendency to mount an excessive number of sensors, simultaneously losing the sight of the robustness of the installed system itself. This is often synonymous of an excess of information that saturate the system, hiding the useful information and ultimately making it unusable. In this regard, a major aid may come from the use of smart sensors capable of performing themselves a first processing of data, significatively reducing the amount of information to manage | (Tucci et al., 2010) |