POLITECNICO DI MILANO

Scuola di Ingegneria Industriale e dell'Informazione

Master of Science in
Management Engineering

Industrial IoT: a Cost-Benefit Analalyis of Predictive Maintenance Service

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Academic Year 2019 - 2020

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Abstract

The Industrial Internet of Things (Industrial IoT) is revolutionising the way of doing business in all industries connecting the industrial machinery with the surroundings. In this scenario, predictive maintenance seems to be one of the most promising uses. Indeed, the Industrial IoT allows a continuous stream of a massive amount of real-time data that are analysed and made available to all users, solving the problems related to this maintenance practice and improving its effectiveness. Thanks to this level of technological development, it is possible to deliver the maintenance that is necessary rather than possibly required. However, the spread of predictive maintenance is slowed by several factors, including a poor understanding of its benefits. In this regard, we developed a model to quantify the savings that arise, switching from a traditional maintenance approach (corrective and preventive) to a predictive maintenance solution with the help of the Industrial IoT. In particular, this thesis focus on a precise economic study about the feasibility of investment in Industrial IoT to implement this type of maintenance with a pay-per-performance agreement between the vendor, or a general OEM, and the manufacturer.

A sensitivity analysis was performed on the variable measuring the effectiveness of the prediction. A real case, together with a theoretical case, is performed too. The result is a model that can help both manufacturers to evaluate the NPV of the investment, and vendors to understand how to capture part of the benefits they generate for their customers.

Key words: Industrial IoT, Predictive Maintenance, Cost-Benefit Analysis, Pay-per-Performance.

Abstract

L’Industrial Internet of Things (Industrial IoT) sta rivoluzionando il modo di fare business in tutti i settori connettendo i macchinari industriali con l'ambiente circostante. In questo scenario, la manutenzione predittiva sembra essere uno degli usi più promettenti. Infatti, l'Industrial IoT permette un flusso continuo di un'enorme quantità di dati in tempo reale che vengono analizzati e resi disponibili a tutti gli utenti, risolvendo i problemi legati a questa pratica di manutenzione e migliorandone l'efficacia. Grazie a questo livello di sviluppo tecnologico, è possibile effettuare la manutenzione realmente necessaria. Tuttavia, la diffusione della manutenzione predittiva è rallentata da diversi fattori, tra cui una scarsa comprensione dei suoi benefici. A questo proposito, abbiamo sviluppato un modello per quantificare i risparmi che ne derivano, passando da un approccio di manutenzione tradizionale (correttiva e preventiva) ad una soluzione di manutenzione predittiva con l'aiuto dell'Industrial IoT. In particolare, questa tesi si concentra su un preciso studio economico sulla fattibilità di un investimento nell'Industrial IoT per implementare questo tipo di manutenzione con un accordo pay-per-performance tra il venditore, o un OEM generale, e il produttore.

È stata effettuata un'analisi di sensibilità sulla variabile che misura l'efficacia della previsione. È stato anche eseguito un caso reale, insieme ad un caso teorico. Il risultato è un modello che può aiutare sia i produttori a valutare il VAN dell'investimento, sia i venditori a capire come catturare parte dei benefici che generano per i loro clienti.

Parole chiave: Industrial IoT, Manutenzione Predittiva, Analisi Costi-Benefici, Pay-per-Performance.

Executive Summary

The Internet of Things (IoT) has the potential to transform the way we interact with our surroundings by making it smarter and more responsive. Thanks to the IoT, every physical object acquires its counterpart in the digital world, and thus allows monitoring and managing physical objects electronically. The merger of the two universes enables taking data-driven decision making to unprecedented levels - to optimise the performance of systems and processes, save time for people and companies and improve product quality. The data collected by the sensors in the factories, as well as the data relating to the status of the goods along the entire supply chain, can help companies obtain much more from their physical resources, improving the performance of the machines, extending their life and learning how they could be redesigned to do even more (McKinsey&Company, 2015).

As the Internet revolution has redefined business-to-consumer (B2C) industries such as media, retail and financial services, the IoT has the potential to subvert the manufacturing, energy, transportation and other industrial sectors that together account for about a third of the Gross Domestic Product (World Bank, 2018). The IoT applied to the industrial world is dubbed Industrial Internet of Things (Industrial IoT). It is defined as a system that includes intelligent objects, cyber-physical resources, and platforms that allow access, collection, analysis, real-time and autonomous exchange of information within the industrial environment. The collective belief is that this latest wave of technological change will bring unprecedented opportunities and new risks to businesses and society. However, although the Industrial IoT is starting to spread into the global industrial fabric, it is still in its early stage. The surveys conducted in collaboration with the 'Osservatorio Internet of Things' of the Politecnico di Milano confirm this aspect. Indeed, a study carried out on a global base, reports that most of the Industrial IoT projects started after 2015. At the Italian level, the Industrial IoT is even less widespread. A 2019 survey on large enterprises shows that almost the entire number of projects reported started after 2017 and underlines a limited knowledge of the topic by the managers of the companies interviewed. If, on the one hand, it is a common opinion that the Industrial IoT is truly transformative, on the other, by studying the Italian and world industrial sector carefully, we realise that many companies are still struggling to understand the implications of the Industrial IoT on their businesses and industries. For these organisations, the risks of moving too slowly are real.

Inside the factories, IoT systems can make production processes more efficient, guaranteeing hardware-software integration and supporting traditional production models with the vital support of objects with their own "intelligence". Industrial IoT also represents one of the six technologies behind the so-called Industry 4.0. According to this principle, digital technologies - IoT devices, but also sensors, cloud, machine learning, collaborative robotics, 3D printing - would be able to increase the efficiency and value of production by stimulating interconnection and cooperation between all resources, internal and external (Miragliotta G. , 2020).

In the world of Industrial IoT, there are dozens of new possibilities that are emerging. Predictive maintenance is expected to be one of the most promising uses of the Industrial IoT (Schallehn, Schorling, Bowen, & Straehle, 2019), and companies evaluate it as the area of major interest. The surveys carried out at the Italian level confirm this aspect, showing that 14% of the projects activated in recent years in the smart factory field regards predictive maintenance and 18% fall under the broader preventive maintenance hat. It is for this reason that we decided to focus our thesis on this area of Industrial IoT. It should be specified that predictive maintenance, i.e., the ability to collect and process data to obtain forecasts regarding the breakdown of parts of the machinery, is not a topic introduced with the Industrial IoT. However, it should be stressed that IoT technology makes this maintenance more effective and efficient, and it is for this reason that it has paid great attention in recent years from both the scientific and the business world.

The purpose of the research study

Among the many areas of analysis that can be pursued concerning predictive maintenance, this thesis focuses on a precise economic study about the feasibility of investment in Industrial IoT to implement this type of maintenance. Therefore, the thesis aims to create a model aimed at evaluating the benefits obtainable from this implementation in the manufacturing sector.

The first step taken to define the research field was the analysis of the existing literature. We first analysed the papers to study how the IoT improves predictive maintenance and creates value for the different actors of the value chain. Then we have deepened the theme to fully understand its characteristics, the IoT structure necessary for the installation, the technical and economic advantages, the barriers and all the new business models that could arise from the implementation of this technology. The study revealed that there are some gaps in the literature and explicit requests of future researches in the creation of a cost model for the estimation of the economic benefits of predictive maintenance. Moreover, we found out that among the major barriers to adoption, there is a poor understanding of the benefits of predictive maintenance and the consequent economic return on the investment. The articles on the subject report the benefits only of a qualitative nature and without providing in-depth analysis. They are generally used as evidence to support the thesis. On the other hand, those who venture into the creation of a model only estimate the costs rather than provide an estimation of the total benefits obtainable. For this reason, our thesis work tries to fill this gap, creating a tool to quantify these benefits and to calculate the return on investment.

Furthermore, recognising the importance that partnerships have to achieve the objectives of the industry, we wanted to include this aspect in the model. We asked ourselves how to incentivise the vendor to invest in IoT technology for predictive maintenance. The price surplus and the competitive advantage are certainly two aspects not to be underestimated, but the new business models to which the Industrial IoT permits to access are the real treasure.

Our primary research question and a sub-question arose from these analyses:

- Q1: Does an investment in Industrial IoT for predictive maintenance generate value for the company?
- Sub. Q1: How can the vendor benefit from the value generated to the manufacturer?

Several approaches have been carried out to answer to the presented research questions:

- *Literature:* The literature was extensively revised to find out the existing gaps and where to concentrate the work, as well as to go deeper into predictive maintenance theme (57 papers were analysed).
- *Interview:* To validate the notions collected with secondary sources and to collect data regarding real situations, we carried out some interviews. The total meetings with industrialists were three.
- *Secondary sources:* Secondary sources were also used as a first step together with the literature to deepen the theme of Industrial IoT. Similarly, they were used at a later stage to fill some literature deficiencies, as well as a secondary benefits verification, therefore the variables to consider in the model.
- *Analytical model:* An analytical model has been formalised to answer the research question concretely. The model allows evaluating the economic feasibility of investment in Industrial IoT for predictive maintenance. The model, developed in Excel, represents the core of this dissertation because it enables to concrete answer the research questions.

Model definition

For the evaluation of potential benefits obtainable with predictive maintenance using the Internet of Things, an innovative approach has been developed. Starting from input variables that characterise the state of the machinery and the type of maintenance that is used, an analytical model has been constructed to quantify the benefits and provides the Net Present Value of the investment.

Hypotheses

Some hypotheses are necessary to make the model work better:

- H0: Since several companies today use corrective or preventive maintenance (or a combination of the two), we have considered these two situations as two possible initial stages.
- H1: To incentivise the manufacturer to purchase the predictive analysis solution, the vendor must be as transparent as possible about the installation costs. We hypothesised that the machinery supplier would install the complete solution. By limiting the applicability to a single machine, it is assumed that different faults can be monitored using the same architecture, improving the multipurpose and interoperability characteristics of an industrial IoT solution, no longer closed in a silo perspective.
- H2: Apart from corrective actions that are unscheduled by nature, preventive and predictive maintenance has a margin of error. Therefore, the planned interventions are accompanied by unscheduled interventions. It follows that the formalisation of costs per intervention lies in the division into two types, unplanned and planned intervention costs, estimated on an annual basis.
- H3: To limit uncertainty, we hypothesised that the intervention restores the initial conditions of the machinery, allowing the system to function until the project life.

Model Structure

Once the hypotheses to let the model work are set, it is necessary to specify the type of variable that compose the model. The idea is to quantify the obtainable benefits passing from a standard maintenance situation to a predictive in a Pay-per-Performance solution. The benefits are used into the numerator of the NPV formula as differential cash flow, and they are discounted for the useful life of the machine analysed.

$$NPV = -Inv_0 + \sum_{i=1}^{n} \frac{Sav_{PdM,i} - DiffMSC_i}{(1 + WACC)^i}$$

Once the machine on which perform the analysis is chosen, the first important step is to define the cost of the as-is situation. According to H0, the two as-is maintenance can be corrective or preventive. Both solutions are composed by a variable part, which varies according to the number of interventions, and fixed annually based components. The structure of the intervention cost is the same in the case of scheduled intervention and unscheduled, although some values may vary accordingly. The machine is analysed, and the pieces with similar characteristics (such as, type of maintenance, mean time to repair) are grouped in clusters.

The variable part, also called intervention cost, is composed of three main values:

$$IC = DTC + SpC + Pnlt$$

1. Downtime cost (DTC): This cost measures the loss of revenue that would not have occurred if the machine had worked correctly and all products had been sold. It is calculated multiplying the Mean Time To Repair of a specific type of products (cluster) by the sum of the gross profit contribution of every single piece.
2. Spare parts costs (SpC): This value considers the costs of spare parts technicians have to change after the breakdown occurs (or when they perform preventive interventions) to fix the machine. It takes into account also the change of other pieces that breakdown because of the main breakage.

3. Penalties ($Pnlt$): This variable considers a financial outlay caused by a delay in delivering the goods to the customer because of a machine stop caused by a breakdown.

Another essential aspect to consider is the failure rate λ. Failures are unavoidable consequences of using a machine. All the pieces, especially those that have to endure more significant stress, break. Different patterns have been identified to describe their degradation (linear, two-, three-, multi-stage) so their reliability, in this way it is possible to define the statistical distribution of the behaviour of the pieces and determine the right breaking moment. The proposed model requires a unique value and could be estimated by summing the failure rate of the specific cluster.

Once the failure rates are set for each cluster, the initial cost of the two as-is solutions can be computed. The total cost of the corrective intervention is simply the multiplication of the unscheduled intervention cost by the failure rate since the intervention is performed every time, and only after, a failure occurs. To this variable part, a fixed annual charge is added (EXC_{CrM}). This value is considered to take into account the cost of the service and the warehouse costs.

$$Charge_{CrM} = IC_{un} \cdot \lambda + EXC_{CrM}$$

The preventive maintenance cost is a bit more intricate. It is calculated multiplying the schedule intervention cost by the number of preventive intervention that has been performed. However, since the preventive maintenance is not perfect unscheduled interventions may be required. Therefore, the previous value is summed with the unplanned intervention cost multiplied by an estimation of the error of the preventive maintenance. Besides, the value obtained is added to a fixed annual part that considers the cost of the service: internal or external.

$$Charge_{PvM} = IC_{un} \cdot B + IC_{sc} \cdot S + EXC_{PvM}$$

In the end, the differential cost between both the as-is solutions and the predictive maintenance is calculated. The predictive maintenance, as well as the preventive, is composed of a scheduled intervention cost and an unscheduled one when the prediction is wrong. Unlike preventive maintenance, the number of planned interventions is calculated based on the accuracy of the prediction algorithm that is evaluated using the confusion matrix. The savings formulas that arise are the following:

$$Sav_{PdM-CrM} = IC_{un} \cdot TP - IC_{sc} \cdot (FP + TP) + EXC_{CrM}$$

$$Sav_{PdM-PvM} = IC_{un} \cdot (B - FN) + \ IC_{sc} \cdot (S - FP - TP) + EXC_{PvM}$$

Not always, a shift to predictive maintenance is advantageous. Therefore, the model only considers the positive savings from the different clusters.

The last step to determine the numerator is to define the value of the subscription for a pay-per-performance solution. It is calculated multiplying a fee entrusted by the vendor, by the actual working hours of the machine.

Model Application

In this chapter, applications of the model are presented. In particular, a theoretical case and a real case are introduced to investigate and understand the impact of the different variables.

The theoretical model has been introduced to create a complete scenario that uses all the variables and shows the computations behind the model gradually. It also presents a sensitivity analysis conducted on the two variables that define the efficiency of the prognostic algorithm to show the considerable fluctuation that depends on it.

ConBio case study

ConBio is a vegan ready meal producer belonging to Granarolo Spa group. The vast majority of the products are produced starting from vegan protein like tofu and seitan that are produced internally. The tofu production has been investigated, and the model applied to a unique and essential machine to which only corrective maintenance is performed. Since this raw material is used in the production of several different products, the impact of downtime is considerable. Two clusters have been identified: one characterised by a long $MTTR$ but a low failure rate, the second by a relatively short $MTTR$ and a high failure rate. The model shows positive values for both clusters generating an overall NPV of 458,008 € with a payback shorter than a year.

Conclusions

The model quantifies in monetary terms the downtime, spare parts, penalties and other variables associated with the breakdown of a machine by calculating the overall cost of the as-is maintenance solution and a predictive maintenance solution with a subscription pay-per-performance. The difference between these costs represents the cash flows at numerator in the VAN formula, which provides the user with a specific cost-benefit analysis for a specific machinery. This innovative model allows manufacturers to make more informed choices; it also represents a useful support tool for vendors to understand how much their customer's earnings are and to share the benefits with them.

However, the model has room for future improvements and, among others, considering other possible types of maintenance interventions is one of the main ones. The calculation can be extended and adapted to include all maintenance strategies and create a model that evaluates the optimal solution to be undertaken for each specific case. Another improvement step could be achieved by understanding more in detail possible present and future risks that the implementation of an Industrial IoT service may involve. Finally, it is possible to integrate other considerations in the model which we have not taken into account, such as increasing the useful life of the machinery which is declared as one of the benefits of predictive maintenance.

The model, the analysis and the validations performed, allow answering the formulated research questions.

1. Q1: Does an investment in Industrial IoT for predictive maintenance generate value for the company?

   Savings achievable using an Industrial IoT system for predictive maintenance depend on the characteristics of the as-is situation. In general, they have a highly positive NPV in the case of corrective maintenance in the as-is, with a high return on the investment on the whole useful life and a payback lower than two years. In the case of preventive maintenance as the starting situation, the positivity of the NPV depends much more on the prediction algorithm effectiveness. Therefore, it is not possible to generalise the conclusion, but it is necessary to adapt the model to each specific case.
2. Sub. Q1: How can the vendor benefit from the value generated to the manufacturer?

   Selling smart machines able to interact with the surrounding and stream a massive amount of valuable data provide the vendor with a considerable competitive advantage. Moreover, these data can be used directly from the vendor to provide the predictive maintenance service in a pay-per-performance agreement that generates additional revenues and better customer relationships.

The results obtained from this thesis and the future developments that could derive from it to overcome current limitations and explore new areas can lead to very interesting and more accurate results. All stakeholders would greatly benefit from this, and the research for more efficient sensors and more precise algorithms will be boosted by the increased interest and investments on the subject.

Introduction

Fifty years ago, we delivered a message from a computer in the University College of Los Angeles 3,000 miles away to a computer in Boston. It was the first time two computers could communicate using a system different from the telephone lines. In the following years, many other networks came online, but only ten years later, we start the creation of one common network, a "network of network". It was the origin of what we call today the Internet (Computer History Museum). The same years the concept of the smart device was first discussed. Coca-Cola created a connected vending machine able to report its inventory and whether newly loaded drinks were cold or not and peoples around the world started to craft bizarre smart devices (Gupta & Simmons, 2010)

In less than fifty years we evolved from connecting two computers to connecting everything surround us, from the connected refrigerators that can purchase more milk and eggs online before they run out, to machines that tell the operator how to optimise productivity or detect a failure before it occurs: it is the time of the Internet of Things Revolution.

The term Internet of Things (IoT) is nowadays gaining more and more popularity. People are familiarising with it dealing with the purchase of a new refrigerator, reading about new solutions to save our planet or discovering new ideas aimed to solve the problem of traffic congestion or to create more reliable public transportation. For decades sci-fi movies presented futuristic scenarios dominated by technologies able to interact with humans, enabling revolutionary skills and creating unimaginable tools that made the viewer dreams about the future. Today, technology makes some of these things possible.

Internet of Things is a much wider theme than what we think or watch on the screen, and it ranges from the futuristic technologies we dream, to much more concrete and less astonishing solutions. The term 'things' is specifically used to refer to everything around us, from the smallest particle to the biggest machine, from what we have to what we cannot even imagine. The things we refer to are all the smart objects able to interact with the environment surrounding them. The IoT challenge seeks to make smart more things possible, bridging the gap between the physical and the virtual world enabling advanced services and other applications[1].

Much of the hype of these recent years centres on consumer applications, such as digital assistants, who leads the scene between 2017 and 2018 in the smart fashion industry (Reply), connected cars and consumer wearables like smart glasses. However, the real revolution stands on the industry side of the market. According to a forecast of Oxford Economics, the IoT's industrial applications, also called Industrial Internet, will transform many industries, including manufacturing, oil and gas, agriculture, mining, transportation and healthcare that account nearly two-third of the world economy (Oxford Economics). The Industrial Internet may ultimately dwarf the consumer side in potential business and socioeconomic impact. The integrated digital-human workforce will redefine the job market, creating new working positions and reshaping the very nature of work (World Economic Forum, 2015).

Given the great importance the Industrial Internet covers, this work focuses exclusively on it. In particular, the aim of Chapter 1 is to introduce the importance of manufacturing and the new trends. Chapter 2 is focused on the definitions of Industrial Internet of Things, its boundaries and the future dimension of the phenomenon. The industrial IoT theme is then analysed through surveys at the Italian and world level in Chapter 3 to figure out the current level of diffusion. Chapter 4 analyses the literature presenting the most studied areas and discovering the least, concluding with recommendations for further studies. Chapter 5 presents the methodology followed in conducting the thesis and the research questions formulated from the existing gaps in the literature. To answer these questions, a specific model has been developed, and it is presented in chapter 6. In Chapter 7, the model is applied to a theoretical and a real case to show its functioning and validate the results. Conclusions are reported in Chapter 8.

[1] See Appendix A for an in-depth analysis of IoT.

Chapter 1

Manufacturing

In this first chapter, the changes in manufacturing will be deepened, presenting all the smart technologies that are transforming this sector. These innovative technologies available in the market are revolutionising the way of doing business and the related operational processes around the world. A final focus on maintenance will highlight the gaining of its strategic relevance in many sectors.

1.1 Introduction to Manufacturing

Manufacturing is the cornerstone of the overall economy. In every developed and developing country, we witnessed political proclamations regarding its relevance (Trump, 2018). In Italy[2], Carlo Calenda, Minister for Economic Development from 2016 to 2018, referred to manufacturing as following: «Our manufacturing companies are the engine of economic growth and development with their ability to produce prosperity and employment, feed the supply chain and service activities, contribute to financial, economic and social stability.»[3] (Calenda, 2017). Three points of view can be considered to provide a general overview of manufacturing:

- Economic: the economic impact of manufacturing in developed-developing countries is vast. In Italy represents approximately 15.1% of the GDP (World Bank, 2018), not considering the part of the service-related that multiplicate the former value of 2/3 times. Another interesting data regarding the Italian landscape is about the export of this value: almost 40%; manufacturing represents a key and strategic point in the competitiveness of Italy in the world.
- Social: employment from manufacturing is crucial in developing countries as in developed ones. In Italy, we counted 3.9mln directly employed workers, and 6.5mln workers related to manufacturing business service (comparing to an Italian population of 60mln). Every new job in manufacturing generates two jobs in services, referred to as a "pull" effect (Semeraro, 2012).

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[2] Although we adopted a worldwide viewpoint, this paragraph reports some more specific references on Italy. This choice was taken to better introduce the surveys presented in the third chapter focused on that country.

[3] «Le nostre imprese manifatturiere rappresentano il motore della crescita e dello sviluppo economico con la loro capacità di produrre ricchezza e occupazione, alimentare l'indotto e le attività dei servizi, contribuire alla stabilità finanziaria, economica e sociale.» (Calenda, 2017)

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- Environmental: in Italy, energy consumption regarding industry accounts for 19.5% of the total primary source. Manufacturing has a strong lever to reduce its carbon footprint, packaging waste, water usage and overall effect on the environment. A strategy characterised by the new trend in sustainability (e.g. the circular economy) will be key in the next years.

Manufacturing is part of a complex and highly competitive global economic system that has witnessed different evolving business needs with their connected tech requirements. Globalisation, decentralisation and fragmentation require more and more visibility, business integration, decision support considering multiple products and sites. The competition has different dimensions: competing on time requires the need for fast decision making, simulations to promise reliable data; competing on product variety with shorter lifetime involves the ability to manage uncertainty and complexity; competing on service ask for connected products and extracting knowledge from data.

Industrial IoT promises to deal with these business needs representing the new source of competitive advantage. Governments play an essential role in contributing to the development of this new field. Germany activated "Industrie 4.0", the German industrial plan in 2011. Italy needed five more years to activate "Piano Nazionale Industria 4.0" (2016)[4], following UK (2011), Netherland (2014), Sweden (2014), France (2015).

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[4] The Italian industrial plan is divided into a first part related to contribute for Innovation and a second one about contribute for competitiveness. Regarding the former, the instruments that the government has introduced are:

The government incentives combine with the organic growth saw a considerable evolution of the Italian Industrial IoT market: the investments related grew by 40% between 2018 and 2019, from 1,35mld€ to 1,9mld€ respectively (Osservatorio Industria 4.0 - Politecnico di Milano, 2019).

Apart from the individual national industrial plans of European countries, it is vital to report the concepts inside "2030 Vision for Industrie 4.0". The vision, jointly developed by experts from Platform Industrie 4.0 (Germany), underlines as international cooperation is indispensable for many industry 4.0 issues. It states that "skills for the digital age or IT security are fields that are better addressed together. Standardisation and regulatory challenges require cooperation with other countries or supranational institutions" (2030 Vision for Industrie 4.0, 2019). The success of the Industrial IoT system is connected with the success of European cooperation, and as a result, Europe union will be more connected with Industrial IoT innovation.

- Iper e super ammortamento: the value of depreciation for investment in new tangible assets, purchased or leased devices and technologies (enabling the transformation into a 4.0 perspective) has been increased to 250% of the original one. Regarding investments in intangible capital goods (software and IT systems), it is possible to have access to the amortization of 140% of investments.
- Nuova Sabatini: Contribution to partially cover the interest paid by the company on bank loans.
- Credito d'imposta R&S: 50% of incremental R&D expenses will be considered as a tax credit.
- Patent box: Optional taxation regime facilitated on derived income from the use of intangible assets: industrial patents, trademarks registered, designs and models industrialists, know-how.

1.2 Smart Technologies

The Industrial IoT is the enabling and core element of industry 4.0 (Osservatorio Industria 4.0 - Politecnico di Milano, 2019). The connection between the physical and the digital world is central, and it can likewise be seen in the convergence of IT/OT Smart Technologies. We presented the six smart technologies identified by the digital innovation observatories of Politecnico di Milano, due to the importance that together they will have in the manufacturing and the inter-correlation between them. It is significant to underline two aspects: (1) a strong correlation between the ability to adopt "traditional" technologies successfully (e.g. MES systems, PLM, traditional automation) and the probability of success to approach Industry 4.0; (2) the Smart Technologies represent the foundation of Industry 4.0, and not an endpoint. This transformation will have to redesign processes and organisational models in the problematic balance between operational management, continuous improvement and radical innovation.

1.2.1 Cloud Manufacturing

For understanding naturally what cloud manufacturing is, we have to move through cloud computing, the prior enabling technology. Through the internet, cloud computing enables widespread, easy and on-demand access to a virtualised, shared and configurable set of resources to support production processes and supply chain management. Resources can range from infrastructure layer, IaaS (e.g. virtual machines, storage), through the platform layer, PaaS (e.g. offering environments already equipped with development applications, database management system, web server), till the application layer, SaaS, where applications and data are also hosted online on virtualised resources. Cloud computing has well-known benefits from high reliability to scalability and availability in a distributed environment. Three significant results obtained:

1. The democratisation of engineering analysis, this result was reached thanks to the possibility to request flexible-high computational power; this lets small enterprises have access to practice like computational fluid dynamics (CFD), virtual manufacturing and integrated planned that require considerable computational power.
2. Industrial IoT platforms, they will be analysed with the next sub-chapter due to the strict connection with Industrial IoT technologies.
3. Value chain collaboration, the visibility gained thanks to data shared in cloud and managed collectively; this result represents the state-of-the-art of Information System (Miragliotta, 2019)

In this area, Cloud Manufacturing paradigm is emerging: what does it happen if the dynamically scalable and virtualised resource is not a hardware infrastructure, a platform or a software application, but manufacturing? All the benefits related to cloud computing will remain, scalability, high performance, real-time quoting, pay-per-use, with the possibility to add services ranging from product design, testing, management, and all other stages of a product life cycle. In cloud manufacturing, distributed resources are encapsulated into cloud services and managed in a centralised way (Xu X. , 2012). The type of manufacturing that seems more suitable to move to the cloud is represented by additive manufacturing (Wu. D., Rosen D. W., Wang L., Schaefer D., 2014).

1.2.2 Industrial Internet of Things

The fundamentals of Industrial IoT are the smart objects (i.e., capable of identification, location, status diagnosis, data acquisition, processing, implementation and communication) and the smart networks (independent, standard and multifunctional). It represents the connection between the physical and the digital world in an industrial environment[5]. Industrial IoT platform can be defined as cloud

[5] In the second chapter, a structure definition of the Industrial IoT will be defined.

or edge environments for device management, data management, data analytics, automation & data security functionality. The platforms also represent the point of separation between the hardware state (sensors and actuation) and the software layer (applications), making the progressive shift towards the software component evident. The latter is often represented by Industrial Business Apps, i.e. vertical applications dedicated to decision support in specific areas (such as optimising the life of cutting tools, or maintenance). The big players in the Industrial IoT platform world also differ in the strategies they use to develop this application layer. Three different approaches are reported:

1. Offer applications natively available on the platform, developed directly or through strongly supported communities;
2. Show a greater openness towards spin-offs, public and private accelerators, as a source from which to attract developers;
3. Work on the accessibility of data, the availability of versatile and well documented development tools, more distant from the application development layer. In this way, they focus on application self-development by the manufacturing company itself, through its own IT Function or consultants or connected SW houses (Miragliotta, Macchi, & Terzi, 2019).

The availability of data in a platform environment opens up the connection to environments like digital control room applications (allowing 360° monitoring of production resources) and real-time scheduling applications (one of the historical limitations of which was the lack of real-time feedback with the status of the shop floor).

1.2.3 Industrial Analytics

With Industrial analytics, we indicated methodologies and tools for the treatment and processing of big data coming from Industrial IoT systems or from the exchange of data between IT systems to support the planning and synchronisation of production and logistic flows. There are included the applications of new techniques and tools for business intelligence, visualisation, simulation and forecasting, data analytics.

The challenge of big data management is representing by the expansion of three dimensions: volume refers to the amount of data, variety refers to the number of types of data, and velocity refers to the speed of data processing (Laney, 2001).

It is useful to present the distinction between the types of data analytics. For this purpose, an everyday explanation has been used: the question answered by the descriptive analysis is: 'what happened?' – the diagnostic analysis: 'why did it happen?' – the predictive analysis: 'what future? – the prescriptive analysis: 'how to react to events?' – the pre-emptive analysis: 'how to avoid events?'

1.2.4 Advanced Human-Machine Interface

We referred to recent technological developments in the field of wearable devices and new human/machine interfaces for the acquisition or transmission of information in voice, visual and tactile formats. These devices include established systems, such as touch displays or 3D scanners for the acquisition of gestural motion. At the same time, more innovative and bidirectional solutions are being developed, such as augmented reality viewers (both superimposed and peripheral vision) to support operational activities and operator training.

Advanced Human-Machine Interfaces are enabling news ways to acquire or deliver information to the operator, using voice, vision, touch and vibration, and to empower human-centred operations. They range from consolidated solutions (e.g., touch displays) to more innovative solutions (e.g., visors, wearables). The salient fields are represented by visual management, remote maintenance, training, and warehouse operations (Osservatorio Industria 4.0 - Politecnico di Milano, 2019).

1.2.5 Advanced Automation

Reference is made to the latest developments in automated production systems, which are enriched with solutions characterised by high cognitive capacity, context adaptation, self-learning and reconfigurability. The distinctive features of advanced automation are different: the ability to interact with the environment, self-learning and automatic driving; the use of vision and pattern recognition techniques (handling systems, quality control); and finally the ability to interact with operators, thanks to robots designed to operate in and alongside operators, rather than rigidly separated from them. The development of these skills has taken place progressively over time in the research and development laboratories of universities and manufacturers, and now advanced automation becomes a concrete option in the design of a production system (Osservatorio Industria 4.0 - Politecnico di Milano, 2019).

1.2.6 Additive Manufacturing

It is defined as a game-changing technology with exceptional capabilities and able to substitute and reinvented historical processes. More commonly known as 3D printing, this technology it leads to the creation of an object through "printing" layer by layer, and it represents a revolution respects to the historically available production processes (removal or plastic deformation of material) (Osservatorio Industria 4.0 - Politecnico di Milano, 2019). The beginnings of this technology date back to the first half of the '80s. In the last years, it has had an overwhelming development, expanding the number of basic technological processes (selective laser sintering, electron beam melting, fused deposition modelling and stereolithography) and the number of treatable materials (both plastics and metals) with good finishing performance and mechanical resistance. From the application point of view, additive manufacturing finds application in 4 specific areas: 1- Rapid Prototyping; 2- Rapid Manufacturing; 3- Rapid Maintenance & Repair; 4- Rapid tooling.

1.3 Predictive Maintenance

In a manufacturing plant, maintenance has always been perceived as an expensive activity and an obstacle to the pursuit of the economic goal. Only recently, this widespread idea begun to be eradicated from the collective ideal and an unheard-of awareness of its centrality has begun to spread. Smart Technologies, in particular Industrial IoT, is playing a central role in this process, re-evaluating underutilised maintenance techniques that suffered from large investments and poor returns in the past: it is the case of predictive maintenance.

The concept of predictive maintenance was first introduced by the American company Rio Grande Western Railroads back in 1940 and spread to other industries throughout the 1950s, 1960s, and early 1970s. "Automotive, aerospace, military, and manufacturing are the main industries where predictive maintenance has been embraced and have shown several benefits in both efficiencies and cost savings". (Prajapati, Bechtel, & Ganesan, 2012). Although the idea of detecting early signs of fault or failure to initiate maintenance procedures at the right time appeared in the second part of the 20th century, "its rudimentary version, dates further back" (Selcuk, 2015). From its definition onwards, better ways of collecting, transmitting and processing data have been sought. In the beginning, the prediction was based on the skills of an expert maintenance person who used his senses of seeing, hearing, smelling and touching to detect a sign of a problem. Over time, sensors have been created for these tasks. The maintenance technician's experience has changed from the use of the senses to detect these signs to the use of intellect to interpret them. Today, Industrial IoT permits to collect unprecedented amounts of data and transmit them in real-time to all users who have the access. The system is able to collect and evaluate data, decide the right time to intervene, activate and conduct the necessary maintenance procedures such as the mobilisation of personnel and the order of spare parts (Selcuk, 2015). Thanks to the current level of technological development, it is possible to deliver the maintenance that is necessary rather than possibly required.

Given these premises, we can define predictive maintenance as "measurements that detect the onset of system degradation (lower functional state), thereby allowing causal stressors to be eliminated or controlled prior to any significant deterioration in the component physical state. Results indicate current and future functional capability." (U.S Department of Energy, 2010).

As we have highlighted, although visual inspection and human senses still provide valuable information relating to the state of the system to be maintained, predictive maintenance relies heavily on sensors for collection, on Industrial IoT for transmission and processing. Consequently, the reduction in the cost of sensors typical of recent years and the possibilities created by the Industrial IoT allowed this technology to acquire credit in the industrial world. Therefore, it can be said that predictive maintenance, as we know today, was born only in recent years following the introduction of the Industrial IoT. This growing interest is also confirmed by the relevant literature. Searching on Scopus "Predictive maintenance" as a key word it turns out that the first papers published on the subject date back to 1970 but only after 2000 the number begins to rise above 100 to jump in the five years between 2015 and today.

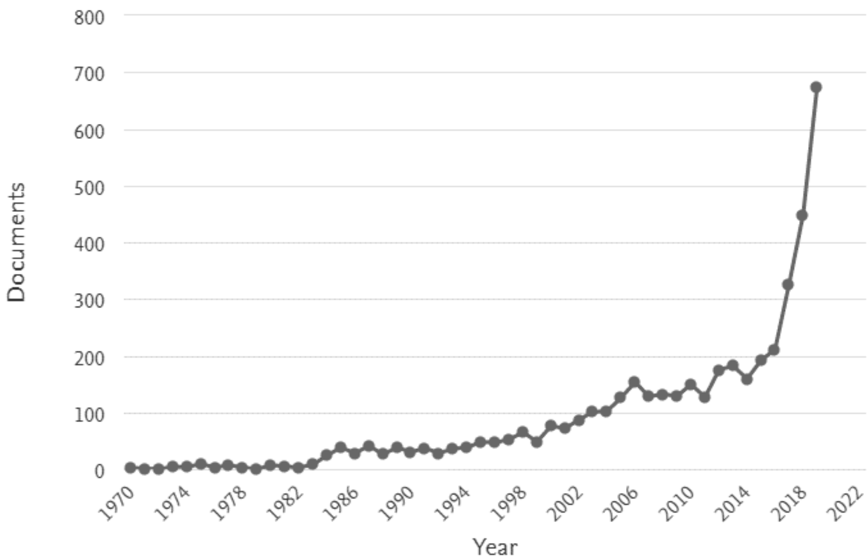

Figure 1.1: Trend of academic papers per year

According to the energy department of the United States of America (2010), the benefits obtainable by implementing predictive maintenance are manifold. In particular:

- Return on investment: 10 times
- Reduction in maintenance costs: 25% to 30%
- Elimination of breakdowns: 70% to 75%
- Reduction in downtime: 35% to 45%
- Increase in production: 20% to 25%.

However, even if its benefits are known for ten years, there is not a clear understanding of what they mean for a company in economic terms since they can widely vary from case to case. This uncertainty, together with the difficulties to extract valuable insights from data, explain why predictive maintenance has failed to take off as broadly as expected (Schallehn, Schorling, Bowen, & Straehle, 2019). Although it is still far behind its potential level of adoption, the long-term predictions remain positive, and there is the certainty that takes hold in the following years and vastly improves efficiency.

Chapter 2

Industrial Internet of Things

An operational definition of Industrial IoT is provided together with the architecture and an overview of the different connectivity typologies. The Industrial IoT is compared to the three main revolutions on history, and a taxonomy of all these revolutions has been performed better to understand this phenomenon, its implications and its size. Finally, catalyst, precursors and risks are deeply analysed too to figure out the reasons and the barriers behind the affirmation of this new technology.

2.1 Definition

It is tough to find a unique definition of "Industrial Internet of Things". Indeed, there is not unanimity in literature, neither there is common consensus between firms, international conferences and governments. Each of them has its view of this revolution, with different definitions and different boundaries.

Some scholars define the Industrial Internet of Things (Industrial IoT) as one of the "Smart Technologies" enabling the digital transformation in manufacturing, the so-called Industry 4.0. According to this view, the Industry 4.0 lays its foundations in two macro-categories: the first one, closed to the Information Technology (IT) area embed Industrial Internet of Things, Industrial Analytics and Cloud Manufacturing; the second one, closer to the Operational Technology (OT), include Advanced Automation, Advanced Human-Machine Interface and Additive Manufacturing (Miragliotta, Macchi, & Terzi, 2019). This classification presents the environment the Industrial IoT belongs and the engines that propel the Industry 4.0 transformation. However, it is a bit too vague and does not provide insights on the technology itself.

In order to create a precise definition of Industrial IoT that fit in the boundaries presented above, we need something that embeds: (a) the kinds of technologies that are used in an Industrial IoT settings and (b) the distinctive implication that it allows. Therefore, we can compose the following. The Industrial IoT is a technology that enables the connection between the physical and the digital world in an industrial environment through a three-level architecture. Sensors and nodes compose the first level, gateways and repeaters that allow this connection the second, platforms where data are stored and managed the third (Miragliotta G.). Although this definition limits the Industrial IoT to the generation, transmission and storage of a large volume of data, there is still an evolution compared to the traditional solutions. Indeed, the industrial IoT empower flexibility (each machine that before communicate only within its system, can now talk to every-'thing' connected, generating a large amount of data) and accessibility (the platform: i. Allows these data to be stored; ii. Acts as a general skeleton where all the other smart technologies can access and operate; iii. Is a universal link for all type of business applications).

So far, we created a definition that perfectly fits into the industry 4.0 framework and satisfies (a) and (b), however, it is too narrow and technology centred for our purpose. To compose a satisfying definition, we must abandon this rigid and theoretical framework and pay our attention to the real-world applications of the Smart Technologies. From this perspective, emerge a deep integration among them that thins their boundaries and reveals intersections. This suggests looking to the Industrial IoT in a much broader acceptation, including in its definition also the distinctive aims and purposes to which those technologies are put.

A different approach is presented in the report of the World Economic Forum in 2015. To define the Industrial IoT, they start from its roots, the Internet of Things. They define the IoT as "a network of physical objects that contain embedded technology to communicate and sense or interact with their internal states or the external environment". Based on this definition, they simply say that the Industrial IoT is "a short-hand for the industrial applications of IoT, also known as the Industrial Internet of Things, or IIoT" (World Economic Forum, 2015). Similarly, Thames and Schaefer in their paper regarding Cloud Manufacturing define the IoT as "a collection of physical artefacts that contain embedded systems of electrical, mechanical, computing, and communication mechanisms that enable Internet-based communication and data exchange. The Industrial IoT follows the same core definition of the IoT, but the things and goals of the Industrial IoT are usually different" (Thames & Schaefer, 2016).

Even if this conception provides a template for a definition of the Industrial IoT and a primary criterion to distinguish IoT devices from Industrial IoT devices, it is too simple and not enough detail for our purpose.

In the attempt to formulate an improved conception of Industrial IoT, we searched further in the contemporary academic and industry-driven literature looking for more informative definitions than those already mentioned. We found a few that improved the basic one presented above. "Industrial Internet or Industrial Internet of Things (IIoT) is built for bigger 'things' than smartphones and wireless devices. It aims at connecting industrial assets, like engines, power grids and sensor to cloud over a network" (Helmiö, 2017). A second definition states that "The Industrial Internet of Things (Industrial IoT) is made up of a multitude of devices connected by communications software. The resulting systems, and even the individual devices that comprise it, can monitor, collect, exchange, analyse, and instantly act on information to intelligently change their behaviour or their environment – all without human intervention" (Real Time Innovations Inc, 2015). The first definition introduces the presence of a connection and tells us a little about the nature of this: that the relevant assets are connected to a cloud, beyond a network. The second one omits the specifics about the connection. However, it makes it clear what the functions of the Industrial IoT devices are: to monitor, collect, analyse information to take useful insight to manage the behaviour of the assets without human intervention. Two words of this latter are significant for our purpose: to analyse and to act. Indeed, the Industrial IoT is the bridge between the physical and digital world that make the Industry 4.0 revolution possible. It is the system where the other Smart Technologies exist and the place where they can operate. For this reason, as several definitions do, we eliminated the rigid boundaries of the industry 4.0 framework, generalised the concept and embraced in the definition of Industrial IoT also some other Smart Technologies.

Thus far, we presented a general framework for Industry 4.0 and scrutinised how Industrial IoT is part of it. We gave this Smart Technology a restricted definition, and we put forward reasons why it is reasonable to consider the Industrial IoT in a broader acceptation. Finally, we presented several different definitions found in the literature that gradually add details to a first more simplistic. Now we can provide a complete definition.

"Industrial Internet of Things: A system comprising networked smart objects, cyber-physical assets, associated generic information technologies and optional cloud or edge computing platforms, which enable real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information, within the industrial environment, so as to optimise overall production value. This value may include; improving product or service delivery, boosting productivity, reducing labour costs, reducing energy consumption, and reducing the build-to-order cycle" (Boyes, Hallaq, Cunningham, & Watson, 2018).

As well as the first definition we gave of Industrial IoT related to the Industry 4.0 framework, this includes (a) the kinds of technologies that are used in an Industrial

IoT settings and (b) the distinctive implications that it allow. However, as requested by our purpose, this definition expands the boundaries previously set. It states that the Industrial IoT system comprises "generic information technologies", the same Smart Technologies that we consider as separate entities in the first acceptation. Indeed, the implication is not only the mere connection between the physical and virtual world as before, but also the functionalities it enables: real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and service information. Moreover, it also emphasises the clear distinction between the consumers and the industrial applications specifying that the system operates in the industrial environment. From now on, this will be our working definition of Industrial IoT, and we will refer to all these functions as typical of this system.

2.1.1 Architecture

A reference architecture is a description of the Industrial IoT system at a higher level of abstraction that helps identify problems and challenges for different application scenarios. The design of an Industrial IoT architecture must highlight extensibility, scalability, modularity and interoperability between heterogeneous devices that use different technologies (Sisinni, Saifullah, Han, Jennehag, & Gidlund, 2018). In this part, we will present a quick overview of the several reference frameworks of industrial IoT architectures originated in the past. Then we will define and scrutinise what we intend to take as a reference (Weyrich & Ebert, 2016).

Generally, the Industrial IoT architecture models have a multilayer structure with a specific function in each level depending on the business needs and technical requirements. For example, the International Telecommunication Union has designed an architecture consisting of five levels: detection, access, network, middleware and application levels. Some academics have suggested instead, an architecture on three levels: perception level (or detection), network level and service level (or application) (Jia, Feng, Fan, & Lei, 2012); (Atzori, Iera, & Morabito, 2010). Others else have proposed a four-tier architecture, which includes the detection layer, the network layer, the service layer and the interface layer (Xu, He, & Li, 2014). The Reference Architectural

Model Industrie 4.0 (RAMI) is a three-dimensional map showing all the crucial aspects of Industrie 4.0 in a structured manner. Its axes identify the hierarchy levels that represent the different functionalities within factories or facilities; the life cycle & value stream of facilities and products; and the layers (Hankel & Rexroth, 2015).

The Industrial Internet Consortium published in 2019 an updated version of the "Reference Architecture" document to continue the work of finishing and advancing the 'Industrial Internet Reference Architecture' (IIRA). In particular, among those presented we will adopt in this paper the widely accepted three-level model which includes the edge, the platform and the enterprise levels.

1. The edge tier collects data from the edge nodes, using the proximity network.
2. The platform tier receives, processes and forwards data from the edge level to the enterprise level and the control commands in the opposite direction. This level has multiple functions: it consolidates processes and analyses data flows from different levels; provides management functions for devices and resources; and offers non-domain specific services such as data query and analytics.
3. The enterprise tier implements domain-specific applications, decision support systems and provides interfaces to end-users (Industrial Internet Consortium, 2019).

2.1.2 Connectivity

In this subchapter, we will make a brief excursus of the connection technologies of the Internet of Things paradigm in general and not only applied to the industrial world. In the analysis of the 'Osservatorio Internet of Things' of the Politecnico di Milano, they have created eight clusters of the main IoT connection technologies available internationally based on their architectural, functional and operational characteristics (Osservatorio IoT Politecnico di Milano, 2018).

- Passive RFID (Radio Frequency Identification): it is the most straightforward technology with which an object can be integrated into the Internet of Things. It groups all the radio frequency automatic identification standards that do not require the presence of a battery onboard the object;
- Active RFID (Radio Frequency Identification): provides additional functionality compared to passive RFI thanks to the use of a battery, which improves communication performance (reading distance) and enables autonomous operation. They have included in this cluster only the protocols with simple functionalities, mainly oriented to the point-to-point communication of the object identification code, while the most advanced protocols are included in the cluster of the Low Power Mesh Networks;
- Personal Communication: it group's standards for communication in short-range networks (PAN - Personal Area Network) designed for consumer applications and characterised by very narrow communication bands (such as Bluetooth low-energy, ANT, NFC). The diffusion of these technologies has received a significant boost thanks to their integration with most of the latest generation mobile devices (smartphones, tablets);
- Wireless Bus: these standards (which include for example Wireless M-Bus, KNX, X10) are a "wireless" alternative to wired solutions that have already been used in the industrial world for some time. The Wireless M-Bus, a protocol that supports, among others, the 169 MHz frequency band, represents the most widespread technology. The technologies belonging to this cluster do not allow sophisticated communication architectures;
- WiFi: These protocols allow wireless access to local broadband networks. Developed for multimedia applications, which require the transmission of a large amount of data, they have high energy consumption, which entails severe limitations of applicability in the IoT field;
- Mesh Low-Power Networks (RMLP): networks formed by low-power nodes and characterised by complex, self-configuring network architectures, capable of supporting dynamic data routing and optimised for low energy consumption (such as ZigBee, WHart). There is currently a great ferment on

these technologies, considered one of the cornerstones of the development of the IoT, and much work is being done on the standardisation of protocols;

- Cellular networks: these are the usual cellular communication technologies, i.e. GPRS, GSM (2G), HSPA (3G), LTE (4G). Due to the high energy consumption, they are mainly applied in the cases in which they can be powered, as well as in combination with RMLP and Wireless Bus for communication between second-level devices and control centres;
- PLC (Power Line Communication): the transmission of information takes place by modulating the electrical signal used for the power supply. There are both protocols designed for the residential world and for the medium and high voltage network: the main difference concerns the maximum communication distance and the supported data rate.

2.2 Taxonomy of Revolutions

Humankind is facing the edge of a new wave of innovation, a wave of the same stormy sea that shaped the world we observe today. Only the companies capable of riding this wave will survive and prosper, becoming the leaders of tomorrow. To fully understand this disruptive phenomenon and his implications we must explore the main events that reveal how we got here and how past innovations formed this wave that we are calling "Industrial IoT" (Evans & Annunziata, 2012).

In this historical journey, we will analyse the main events that defined today's businesses, following the path that led us from pre-industrial manufacturing facilities to today's large multinationals. Taking the industrial perspective, we will investigate the main technological innovations and the productivity growth, to depict the whole picture of opportunities and benefits that the Industrial IoT can create to the businesses.

2.2.1 Industrial Revolution

In the middle of the eighteenth century, the world experienced an unprecedented change. For the very first time, the humankind was able to generate a continuous and powerful flow of inventions and innovations in a few decades (Romagnoli, 2008). The magnitude of this change was so powerful that it had a profound impact on the society, the economy and the culture of the world. According to the GE Industrial Internet paper, we dubbed "Industrial Revolution" the period between 1750 and 1900[6]. During these 150 years, innovations in technology applied to manufacturing, energy production, transportation and agriculture started a sustained period of economic growth and transformation.

Started in 1750 in Northern Europe, the most advanced economy at that time, the First Industrial Revolution spread later in the United States, where railways played a crucial role in accelerating the economic development (Evans & Annunziata, 2012). This radical change hinges on the steam engine that began the irreversible transition process from the exploitation to the creation of energy with the adoption of a new energy paradigm (Romagnoli, 2008). The Second Industrial Revolution came later in 1870. While the First Industrial Revolution led to the growth of industries, such as coal, iron, railways and textiles, the Second Industrial Revolution witnessed the mass production, the emergence of electricity and synthetic chemistry, giving rise to an even more powerful boost. Many other features characterised these 150 years (Freeman & Louçã, 2010). The rise of large industrial enterprises created significant economies of scale that led to a reduction in costs and prices resulting in an increase of volume traded. The investments in dedicated plants and equipment have grown dramatically. Innovation began to be thought of systematically; science became central to technological development. Enterprises started to invest in research and development (R&D) and work to exploit new inventions to create and profit from new markets.

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[6] As specified in the introduction, the aim of our paper is not to provide a detailed taxonomy of the revolution rather present the main aspects useful to understand better the change we are living today with the Industrial IoT. For further analysis of this period look (Romagnoli, 2008); (Van Zanden, 2009); (Freeman & Louçã, 2010).

Despite the considerable gains in the economy and society, the industrial revolution also had downsides. Two aspects in particular need to be highlighted: the high exploitation of natural resources, with the consequent impact on the external environment and the poor working conditions. It is also important to mention for our analysis that much of the research and incremental innovations after the Industrial Revolution has been focused on improving efficiency, reducing waste and improving the working environment (Evans & Annunziata, 2012).

2.2.2 Internet Revolution

The invention of the transistor in 1950 changed the world yet again (Evans & Annunziata, 2012). It allowed all types of devices (electric motors, calculating machines and operators in general) not only to run multiple programs simultaneously at a very high operating speed but also to decrease its size. These characteristics have given impetus to process innovations in all industries (changes in the plants and the organisation of production) that resulted in huge gains of efficiency. The timeframe of the Internet Revolution is much shorter than the 150 years of the Industrial Revolution. It starts in the 1950s with the creation of the first large mainframe computer and the invention of the concept of "packet switching"[7] in the mid-1960s'. After the first message sent in 1969, the technology continued to grow for all the '70s. Hundreds of protocols were developed. Only in 1983, researchers began to assemble all these protocols to create the "network of network" that became the modern internet (Andrews, 2019). However, the invention the helped popularise the internet among the public was the creation of the World Wide Web in 1990 (World Wide Web Foundation); (CERN).

In a much faster and more connected world, and thanks to this powerful engine based on openness and flexibility, the network diffusion was tremendous and the speed of adoption breathtaking. In 1981, less than 300 computers were connected to

[7] "Packet switching" is a method for effectively transmitting electronic data that would later become one of the major building blocks of the internet (Andrews, 2019).

the Internet. Fifteen years later the number had increased up to 19 million. Today the number is in billions. As well as the number of connections, the speed and volume of information transmitted has grown dramatically. The speed of the best modems in 1985 was of 9.6 kilobits per second (Kbps) (Evans & Annunziata, 2012). Today the fastest router transmits information 1 million times faster at a speed of 7.2 gigabits per second (Gbps). Besides, the new 5G standard will guarantee a speed up to 10Gbps enabling faster wireless internet that has the potential to benefit everything from entertainment and gaming to education and public safety (T-Mobile). New platforms for commerce and social exchange arose, scaling down the costs of commercial transactions and social interactions. Companies started to appear on the network creating their website and new efficient markets for exchanges.

The Internet Revolution resulted in several different transformations. It changed the way of think about the production systems permitting deeper integration and more flexible operations. It enabled concurrent innovation, transforming the orderly linear approach to research and development and, thanks to the rapid exchange of information and decentralise decision-making, it has spawned more collaborative work environments unconstrained by geography. As a result, old models of centralised internal innovation have given way to start-ups and more open innovation models that take advantage of a more abundant knowledge environment. In conclusion, we can affirm that the Internet Revolution was very different from the Industrial one. While the Industrial Revolution was resource-intensive, the Internet Revolution has been information and knowledge-intensive. It has highlighted the value of networks and the creation of platforms. It has created new means to cut back environmental footprints and produce more eco-friendly goods and services (Evans & Annunziata, 2012).

2.2.3 Industrial IoT[8]

Today, in the twenty-first century, the rise of the Industrial Internet of Things paradigm promises to change the world yet again. The Industrial Revolution brought the tools and the machinery into the factories; the Internet Revolution linked them eliminating the geographical constraints, now, the Industrial IoT enables to open up new frontiers to accelerate productivity, reduce inefficiency and waste and improve the experience of human work (Evans & Annunziata, 2012).

Back in 2012, General Electric, in his paper on industrial IoT, stated, "the Industrial Internet Revolution is already underway. […] However, we currently stand far below the possibility frontier: the full potential of Internet-based digital technology has yet to be fully realised across the global industry system." (Evans & Annunziata,

[8] Today's rate of innovation is so high that it is not anymore possible to make a clear distinction between the revolutions as it was in the past. At least a hundred of years passed between the invention of the steam engine that defines the beginning of the First Industrial Revolution and the electricity, that we can declare one of the main innovations of the Second. With such a large period of time between the two, it is easy to say what belongs to one and what to the other. Today there are so many innovations every year that it is even difficult to be updated. There are several debates regarding what is the Fourth Industrial Revolution, what are its boundaries and also if there are the conditions for defining these innovations the Fourth or considering them an extension of the third. We do not want to go into the discussion that generalizes too much our topic. We believe that, from an industrial point of view, the potential benefits that the Industrial IoT can generate are comparable to the one of the Internet or Industrial Revolution. Therefore, the Industrial IoT for us is itself a Revolution.

2012). From that moment on, the Industrial IoT projects have taken off. Our survey[9] underlines that more than 80% of the projects undertaken worldwide have started after 2012. This data are confirmed by another survey of 2019 based on an Italian sample, which shows that these last years have been the most thriving in terms of Industrial IoT investments. Before 2017, only 16% of the Italian firms started an Industrial IoT project while in the following three years, more than 60% invested in IoT. Moreover, the number of Industrial IoT platforms has increased dramatically from 2015. Many companies supplying software for logistics or production management have included IoT solutions in their offer, which has turned from a differentiating element to a must-have. Indeed, 74% of firms of our worldwide sample actively collaborate with these companies to implement IoT solutions. However, the GE consideration regarding the potentiality of the Industrial IoT is still valid: "we currently stand far below the possibility frontier" (Evans & Annunziata, 2012). Our Italian survey underlines that only 66% of the companies are aware of the Industrial IoT[10] and the average knowledge of the theme is just sufficient (6.4/10). In particular, we must underline the huge gap between large and small and medium-sized enterprises (SMEs). According to a survey from 'Osservatorio Internet of Things' of the Politecnico di Milano on an Italian sample, in large companies, 97% of the respondents heard about Industrial IoT. In comparison, the value in the SMEs drops to 39% (Tumino, 2020).

[9] Together with the 'Osservatorio IoT' of the Politecnico di Milano we have conducted two surveys and analysis. All the details regarding the methodologies and further analysis are disclosed in Appendix B.

[10] To assess whether people are aware on the Industrial IoT theme or not, we assumed that only those respondents who marked a more than sufficient value (≥6/10) to the question related to the knowledge of the Industrial IoT are enough aware of the phenomenon and have enough knowledge to consider an investment.

A World Economic Forum paper from a conference held in 2015 divided the future of the Industrial IoT world into two macro periods: near- and long-term. They also stated that near-term transformations would likely accelerate over the following two years, while 79% of the respondents believe that the long-term ones would occur within five years. Today, five years after the publication of that paper, we have the opportunity to look back in time to evaluate what has been achieved and what is still to be done.

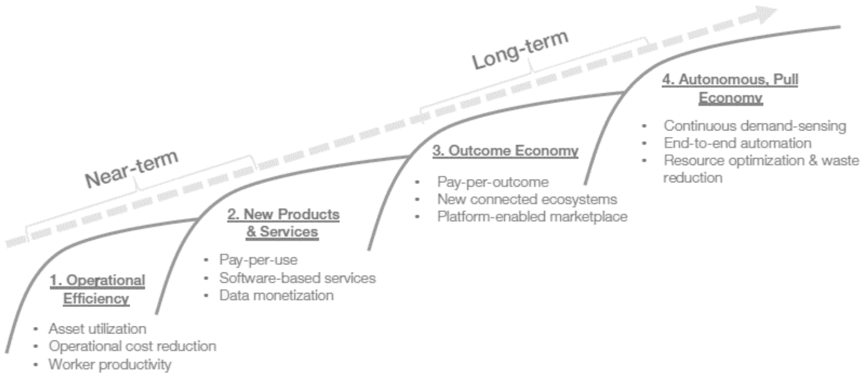

Figure 2.1: The adoption and impact path of the Industrial Internet

Near-term

Near-term opportunities refer to gain in efficiency aimed at increasing revenues and reduce costs. In a 2014 survey by the World Economic Forum, respondents indicate that companies are adopting IoT solution in the near-term either to drive down operational costs, 81% indicate that it is a "very to extremely important" driver for adoption, or to optimise asset utilisation, 7 (World Economic Forum, 2015) application of Industrial IoT in the survey is predictive maintenance and remote management of resources, which can reduce equipment failure or unexpected downtime by analysing operational data now available (World Economic Forum, 2015). According to our global sample, Jeep, TetraPak, Caterpillar, Rio Tinto and ABB are between the early adopters of the Industrial IoT technologies. In particular, Rio Tinto, the world's second-largest metals and mining corporations, implemented sensors, analytics and real-time data to help identify existing maintenance issues before an actual malfunction or accident happens. Collecting data from the company's fleet continuously, they can save $2 million a day each time a breakdown is avoided (McGagh, 2014). Efficiency is not only cost saving, but it also is waste reduction. Sustainability continues to play a central role for companies; 67 % of participants to the survey mentioned above consider the improvement in sustainability as an important driver of adoption of IoT solutions. Companies have been investing in IoT in all these years, and today we can affirm that knowledge of technology and on its potential in terms of increasing efficiency has reached a good diffusion. In light of this awareness, companies are continuing their digitalisation process.

Long-term

In the long-term, the World Economic Forum paper predicted that the Industrial IoT would generate structural changes, creating the opportunity for new business models based on services to disrupt industries. Indeed, the wave of change is so powerful that new digital entrants will increasingly subvert incumbents by bringing the power of software, the speed and scale of the Internet and nimble business models. Few companies, even the world's largest ones, have the necessary instruments to manage this wave. The only way to compete effectively for established companies is to start cooperating in an unprecedented way and start thinking in terms of ecosystems (ICT4Executive, 2014). In this joined scenario, any company must find his position in the value chain, but it is also important to consider that platform providers are those who capture the biggest pie and therefore are the best positioned to lead the formation of the partnership (Agrawal, 2016)

Traditionally, the reputation of product companies has been built around a solid pillar: providing high-quality products at competitive prices. The companies tried to meet customers' needs most efficiently and effectively possible by creating: aircraft with higher capacity but burn less fuel; tractors that plant faster; and light bulbs that last longer but consume less energy. In recent years, thanks to IoT systems, producers have the opportunity to satisfy their customers by providing them only what they need to achieve specific results: the optimisation of the transport of people over long distances, the increase in crop yield and the lighting only when necessary. This attention to the resolution of the *why behind the buy* is a key factor in the ongoing evolution from products to services. The increasing availability of smart products will accelerate this process. In the World Economic Forum paper, this new solution is called "outcome economy", and it is defined as the economy "where businesses compete on their ability to deliver quantifiable results that matter to their customers in a specific place and time." (World Economic Forum, 2015). The two main insurmountable obstacles toward achieving the outcome economy are the deep understanding of customer needs and the context in which products and services will be used, and the possibility of quantifying the results in real-time (World Economic Forum, 2015). The IoT solutions applied to the industrial world have solved both of these problems. Smart objects generate a continuous stream of a tremendous amount of real-time data that can be analysed to get unprecedented insights into the use that consumers make of it.

The World Economic Forum survey also underlines that 74% of the respondent indicated that the possibility to create new revenue streams through new products and services is significant in driving the adoption of Industrial IoT solutions. Indeed, as anticipated in the paper, companies have started to move toward this new service economy. According to our global sample, 55% of the companies have understood the potential of services related to IoT solutions and have introduced them in their offer. For example, Rolls Royce's TotalCare option removes the burden of engine maintenance from the customer and transfers the management of associated risks to the company itself. They provide a suite of predictive maintenance and repair services for their jet engines, including status monitoring and direct maintenance to increase reliability and durability. They completely aligned their business model to the one of the customers, making the uptime the common good (Rolls Royce).

Another example is Taleris America LLC, an American based company resulting from the partnership between Accenture and GE Aviation System. While Rolls Royce is an excellent example of the incumbent that evolve its business model, Taleris is a perfect example of a business outcome of the new service-based economy. Unlike Rolls Royce's TotalCare service, which focuses on jet engine uptime, Taleris addresses the broader issue of airline delays and cancellations caused by equipment failure focusing on the optimization of the airline's entire fleet. In this way, Taleris has control over general maintenance programs. This systemic approach leads to several benefits such as fewer disruptions, lower costs, better spare parts inventory management and more satisfied travellers (World Economic Forum, 2015).

A second long-term goal is to move towards an integrated digital and human workforce. Much has changed since the Industrial Revolution period where employers exploited their workers up to their limit. Nowadays, the workforce became a core resource for the company, their safety and expertise a valuable asset. The Industrial IoT will lead the world towards a mixed workforce, where humans with machines will work together to deliver outcomes that neither could produce alone (Brynjolfsson & McAfee, 2014). According to the World Economic Forum survey, 94% of respondents believe that the Industrial IoT will fundamentally transform what skills and jobs are required in the future. If we design and apply technology to empower rather than replace people, this "human-centred automation" or "augmentation" can redefine existing jobs and create new ones.

An example of this is Amazon with its recent acquisition of Kiva Systems. An AGV system receives the input of where to pick the required shelf, and it brings it to the human just in time to have a reasonable queue in front of the operator (AmazonRobotics). This system of humans and robots work side-by-side allows fulfilling orders 70% faster than a non-automated warehouse (World Economic Forum, 2015). Today, workers must be physically on the shop floor to operate on a machine. Thanks to the Industrial IoT, a manufacturing engineering can potentially receive notifications on his tablet or smartwatch when a machine is malfunctioning. An example of this application is present in our global database. Alfa Romeo, an Italian car manufacturer part of the FCA group, has collaborated with Samsung to create a digital system to visualize, plan and manage the production process. They placed tablets in strategic factory locations and equipped each operator with a smartwatch. In the event of anomalous situations, alerts are displayed directly on the operator's smartwatch that guides him step by step in the operations to follow. After sending the repair confirmation with the smartwatch, the activity is recorded as completed, and the production line can continue to work (Digital4, 2017).

2.2.4 Sizing the Industrial Benefits

It is not easy to define univocally the scale of the opportunity of the Industrial IoT. As we stated at the beginning of this chapter, there is much confusion around the terminology and the boundaries of the term Industrial IoT. There are journalists, firms, international experts and academics that consider the Industry 4.0 to be synonymous with the Industrial IoT. Others to whom Industry 4.0 describe the Fourth Industrial Revolution and the Industrial IoT a technology enclosed in it and some others to whom the Industry 4.0 is only the erroneous translation into English of the German government plan "Industrie 4.0". At the same time, the correct English equivalent is Industrial Internet. Accordingly, there are some to whom the Industrial IoT embed only what is related to the production plant and others that make a clear distinction in the IoT world considering Industrial IoT everything that does not concern the consumers' world. As we have presented in our introduction, in this chapter, we adopted the latter full acceptation that helps us in understand better the potential benefits of this digital revolution. However, it is essential to specify that the focus of this paper will be on the manufacturing production plant, and we will shrink the perimeter only to this later on.

In the attempt to create the clearest picture possible of the opportunities of the IoT, it is useful to understand first the size of the system in which it is integrated. However, there is no single simple measure. Therefore, according to the GE Industrial Internet paper, we suggest three different perspectives: economic share, energy requirements, and physical assets. Although not exhaustive, taking the three measures together gives a useful perspective on the vast potential scale and scope of the industrial IoT.

Economic Perspective

In traditional economic definitions, the industry includes manufacturing, natural resources extraction, construction, and utilities sectors (United Nations, 2008). The global industry, based on these categories, represents in 2018 about 25% of the global GDP, around $22 trillion of the $86 trillion dollars of the world economy. The manufacturing represents the vast majority of the industrial part, 16% of the world GDP, while the other industries together account for 10%. These numbers hide some differences at the regional level that depend on the composition of the economy. In developed countries, the industry counts 23% of the total GDP while in developing one-third of the overall economy (The World Bank, 2018)[11].

Even though 25% of the global economy is an immense value, it does not capture the full extent of the Industrial IoT potential. The Industrial IoT promises to enhance and disrupt a much broader array of sectors: transportation, health-care and agriculture will take part in this tremendous revolution. In recent years, this digital technology created disruptions also in the services sector. Dozens of start-ups providing platform-based solutions to industrial manufacturers receive millionaire funding each year (Columbus, 2019).

Energy Consumption Perspective

[11] Industry corresponds to ISIC divisions 10-45 and includes manufacturing (ISIC divisions 15-37). It includes the value added in mining, manufacturing, construction, electricity, water, and gas sectors. The value-added is the net output of a sector after adding all the outputs and subtracting the intermediate inputs. It is calculated without deductions for the depreciation of manufactured goods or the depletion and degradation of natural resources. The International Standard Industrial Classification (ISIC), revision 3 or 4, determines the origin of the value-added.

As we have seen before, the adoption of IoT technologies to create energy-saving efficiencies and cost reduction is one of the main reasons that has driven investments in this area. Furthermore, the Industrial IoT can even be seen as a solution to the problems related to the scarcity of resources and environmental sustainability that are creating increasing pressures on the energy system. Therefore, the energy footprint associated with the global industrial system represents another interesting perspective to analyse in order to understand the potential of Industrial IoT. The industrial sector uses enormous quantities of energy. If we add energy production and conversion to it, the scale of the benefits of the industrial IoT includes more than half of the world's energy consumption (Evans & Annunziata, 2012).

In the industrial sector, the steel and metal industries and the petrochemical one are the main energy consumers representing around 50% of the energy consumed. Some studies have shown that if the best technological practices were implemented, heavy industry energy consumption could be reduced by 15 to 20% (IEA, 2009). Transport is another sector that consumes a great deal of energy. This sector occupies 27% of global demand (mainly oil), of which approximately 50% is used in the industrial sector for road transport, air and ship connections. Assuming that most large and part of light vehicle fleets can benefit from the use of information technology and networked devices and systems, around 14% of the global demand for transportation fuel can be affected by Industrial IoT technologies. (Evans & Annunziata, 2012).

Physical Asset Perspective

A third perspective that helps us understand the potential of industrial IoT is that of the physical resources involved in various parts of the industrial system. The industrial system includes millions of machines worldwide, ranging from simple electric motors to highly advanced computerized cosmography used in healthcare delivery. All these devices generate a huge amount of information (temperature, pressure, vibrations and other key indicators). They are useful for understanding the performance of the unit itself and concerning to other machines and systems. The

Industrial IoT allows to improve or create systems to monitor, modelled, and manipulate all these crucial metrics remotely, to provide safety, enhance productivity, and operational savings (Evans & Annunziata, 2012).

Until now, we have seen the areas where the Industrial IoT can have an impact, and now we will examine what it can offer to the industrial world. The industrial IoT opens the door to several benefits that are the cause and the consequence of the other. On the one hand, the new sensor technologies allow detecting an increasing number of data more precisely; on the other hand, the increasing computational power allows analysing these data more quickly and more in detail. Together, these two technologies create a combination that transforms machines from automatic to autonomous. Besides, this intelligent instrumentation significantly improves the machine's performance, increases its efficiency by reducing costs and increases reliability. An intelligent machine is a machine connected to a system of machines that allows a previously impracticable level of integration and collaboration. By collecting and analysing data from all these machines, it is possible to obtain valuable insight into the business's operations. With this information, it is possible to optimize the decision-making process that further increases the productivity of the machines and maximize enterprise's performances (Industrial Internet Consortium, 2019). Furthermore, continuous learning allows the better design of new products and services, leading to a virtuous cycle of increasingly better products and services resulting in greater efficiency and lower costs (Evans & Annunziata, 2012).

An interesting point regarding the industrial Internet is what is called the power of 1%. What it relates to is how small improvements, even a small 1%, can produce substantial system-wide savings if scaled up across the sector. For example, in the aviation sector, fuel savings of 1% per year equate to savings of $ 30 billion considering the whole sector. Likewise, the 1% fuel savings for gas-powered generators in a power plant enable operational savings of $ 66 billion. Finally, in the oil and gas industry, a 1% reduction per year in capital expenditure on equipment would generate savings of approximately $ 90 billion. The same goes for the agricultural, transportation and healthcare industries. Therefore, this broad view shows us that in most sectors, if the industrial IoT allows making only a modest 1% improvement, there would still be a huge saving and a return on the investment (Evans & Annunziata, 2012).

2.3 Catalysts, Precursors and Risks of the Industrial IoT

We thought it necessary to end this first chapter by making a brief excursus on the aspects that had and are making possible the digital transition in the industrial world. Today, the Industrial IoT development process has made strides and is emerging as a revolutionary technology globally. However, its success is not yet a foregone conclusion. To achieve its goal of combining the physical world of machines with the digital world of data and analysis to reach its full potential, both continuous progress in software and hardware and continuous government incentives to encourage its adoption and dissemination are essential. In this paragraph, we will first scrutinize the technical enablers of the Industrial IoT. Then, we will take a look at the economic and social dimension, concluding with the main challenges and risks.

2.3.1 Technical Dimension

The technical state of the art is of fundamental importance when we want to investigate the causes that have favoured the development and affirmation of new technologies. The Industrial IoT is the result of innovations already underway, which include technological innovations, innovations of systems, networks and processes, which together represent a set of catalysts and vital activators.

Listed below are some categories of high-level technologies that have been instrumental in the development of industrial IoT[12]:

Sensors

Sensors play the role of "translators" of real quantities into virtual information. The continuous evolution of the sensors with the progressive miniaturization of the devices, the reduction of costs and energy consumption, is one of the fundamental aspects that has stimulated the rapid diffusion of these devices, making smart an increasing number of devices. Furthermore, technological innovation in this field has allowed a significant increase in data quality. By comparing data from the dozens of heterogeneous sensors installed on the machines, it is possible to have very high reliability of the data (Capone, Pitic, Tumino, & Salvadori, 2018).

Networks

Industrial networking is very different from consumer networking. The requirements from applications on the supporting networks are very different, as well as the technical requirements and the application scenarios, the physical conditions encountered in mining extraction, for example, differ significantly from those of agriculture. The industrial network infrastructures and the technologies that support them are constantly evolving. The introduction of new technologies increases the possibilities of the networks (increasing reliability and coverage, reducing the latency and energy needed to operate). It allows an increasing number of industrial resources to connect (Höller, 2018).

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[12] The list complies with that reported in the slides of Giovanni Miragliotta professor of Supply Chain Management at the Politecnico di Milano (Miragliotta G.).

Advanced Analytics

The continuous miniaturization of the processors has led to a continuous increase in computing power, a reduction in the cost and the energy required. This trend led to the creation of increasingly powerful calculators and made the advent of advanced analytics possible. Thanks to advanced analytics, it is possible to examine a large amount of data or content autonomously or semi-autonomously using sophisticated techniques and tools (Gartner). In this way, the Industrial IoT acquires its own brain and is able to discover insights, make predictions or generate recommendations.

Platforms

In order to get value from the Internet of Things, it helps to have a platform on which to create and manage applications, to run analytics, and to store and secure sensible data (Lamarre & May, 2017). The transition from specialized platforms, with the consequent manage of data in a silos way, to general platforms, embedding the entire features from device management to security, represented a fundamental step. Moreover, the addition of an ecosystem of APIs that allows data moving smoothly between platforms and the rise of modular services, together with the possibility of providing these services directly in the cloud and the presence of virtualized interchangeable hardware, has made the development of these solutions cheaper and faster (Miragliotta G.). The world of the IoT platforms is booming, we went from 260 of 2015 up to 620 in 2019, and dozens of platform-based start-ups arise every year (Lueth, 2019).

2.3.2 Economic and Social Dimension

Technical innovations are not the only dimensions that drive the Industrial IoT adoption, and a technical assessment of the reediness level of the technology is not enough for it and the ICT technologies in general. The European Connect Advisory Forum is considering new alternatives to substitute the Technology Readiness Levels

(TRLs) developed in the 1980s by NASA and particularly suited to that context. Indeed, they believe that ICT applications require a development that takes into account adequate business models, user involvement and social aspects and, therefore, they require new models as guidelines. One of the proposed models is the "Market Adoption Readiness Level" (MARL) which, in addition to the technology readiness parameter, requires the evaluation of three values: users, data, and the level of risk (Connect Advisory Forum, European Commission, 2014). We will not go into detail with the parameters of this model that are too general; instead, we will examine some economic and social aspects that we believe fundamental drivers of the Industrial IoT.

Government Programs

According to a World Bank report of 2017, the government have a central role in catalysing the space and contributing as partners/leaders in the long term (The World Bank, 2017). Since the first time Germany activated the 'Industrie 4.0' plan in 2011, several other countries understood the potential of the IoT technology and the key role that the government played as a facilitator and initialised their own. Thus, in the following years, the 'Advanced Manufacturing Partnership' plan was born in the United States in 2012, the 'Made in China 2025' plan raised in 2015 in China and the 'Piano Nazionale Industria 4.0' in Italy in 2016[13]. Only by creating the right infrastructures and implementing the right practices to encourage investments, companies will have the chance to seize the immense opportunity that is the Industrial IoT.

Knowledge and Awareness of the Potential

It is impossible even to imagine investing in IoT unless having a thorough knowledge of the subject. As we have seen before in this chapter, the Industrial IoT is a very confusing and complex issue. Although knowledge at the corporate level has

[13] A detailed analysis of these industrial plans will be conduct later in Chapter 2.

increased significantly in recent years, it is still relatively scarce. It is for this reason that universities with their observatory, researchers, and international consortia, play a fundamental role in the dissemination of knowledge and best practices on the topic. Furthermore, this technology will subvert the current job market, increasingly requiring a skilled workforce. Companies and workers must update if they want to fully understand the potential of industrial IoT in their business and make the correct and necessary investments to keep up with the times.

Commitment to Innovation

A company that adopts Industrial IoT must commit to innovation, as well as adopt a long-term perspective for the return on the investment of the project. Funds will be needed for sensors, to update machines and systems. Investment and patience will be required as the data acquisition process, the configuration of the analysis parameters and algorithms may not give immediate results; success and returns may take some time but the investment will be more than pay off.

2.3.3 Major Challenges and Risks

Despite the great promise and new opportunities of the Industrial IoT, many factors could hinder future growth. As shown by the previously cited survey done by the World Economic Forum, almost two-thirds of respondents agree with the widespread opinion that security and interoperability are the two biggest obstacles. Other significant barriers mentioned include the lack of a clearly defined return on investment (ROI) (53%), legacy equipment (38%) and technological immaturity (24%) (World Economic Forum, 2015).

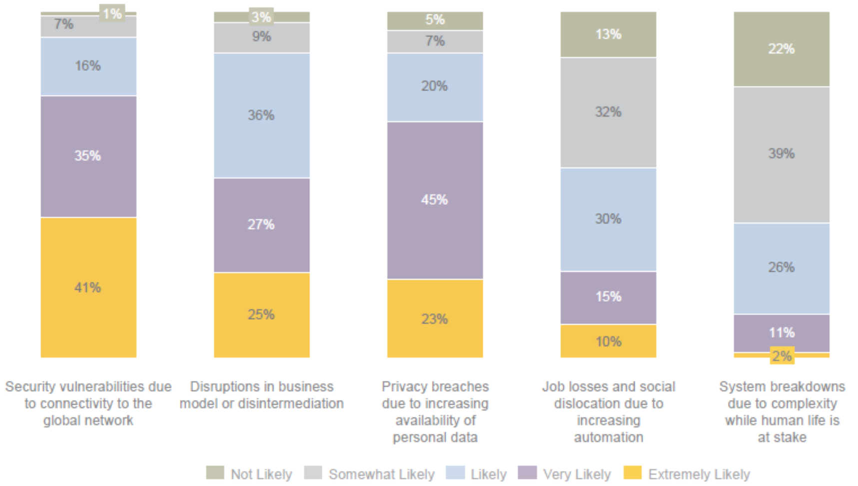
Regarding risks, 76% of the respondents identify cyber-attack vulnerabilities as their most important concern. A related but slightly different risk is the violation of the privacy of personal data, which is also classified at the top (68%). Both are justified when considering the impact that a hacker attack could have on a connected plant, which, for instance, could block the entire production of a manufacturing company or deny the flow of energy from a power plant to an entire city (World Economic Forum, 2015). A World Economic Forum report by 2019 underlines that no industry is untouched by cybercrime. They estimated that from 2019 to 2023, approximately $5.2 trillion in global value would be at risk (Ghosh, 2019)[14]. Investments in countermeasures are increasing as a result.

Since the industrial IoT has the potential to introduce countless innovations in existing business models and disrupt industries, for a large majority of the incumbent surveyed (88%), this represents another significant risk. As this technology reduces the internal barriers to each industry, it opens the doors to new players, even purely digital ones such as platform providers. Companies will have to adapt to this new competitive environment and take advantage of the flexibility offered by this technology by collaborating with many organizations across the ecosystem. Indeed, this collaboration will be essential if companies want to meet the growing expectations of their customers, i.e., it is difficult to see how a company can master the entire digital value chain (World Economic Forum, 2015).

Finally, the last risk that has been most highlighted by respondents is the potential shift of jobs that will occur in some industries due to increased automation. The technological evolution over the years had already shown something similar, such as what happened in the communications sector when technological solutions replaced the switchboard jobs. As smart machines and IoT technology become more and more widespread, more and more jobs will be affected, even those considered purely human. For example, a McKinsey analysis shows that, with the current rate of technology improvement, half of today's work activities could be automated by 2055 (Manyika, et al., 2017). However, it should be noted that, just as previous technologies that have eliminated certain types of jobs have created others, so Industrial IoT will do, creating new jobs that require unique human attributes, such as creativity, critical thinking and collaboration. Industry leaders and governments must note that

[14] For further information regarding the value of the cybersecurity issue see (Desjardins, 2017).

technology is constantly increasing the bar for low-skilled jobs and requires continuous updating of skills. This consideration, again, highlights what has been said previously regarding universities. Together with all kind of educational centre, they will play a primary role in this game. Actions are urgently needed to refocus attention on education, adapting current educational systems and approaches to better prepare the new generations for the upcoming digital work environment (World Economic Forum, 2015).



(World Economic Forum Industrial Internet Survey, 2014)

Figure 2.2: How likely are the following risks or negative consequences associated with the Industrial Internet?

Chapter 3

Industrial IoT Research

Two surveys investigating the theme of Industrial IoT will be presented, and their results discussed. They regard both the Italian manufacturing sector, one looking to the Small-Medium Enterprises (SMEs) and the other to Large Enterprises (LEs). Then, the case of Fabio Perini S.p.A. is reported as an example of a company dealing successfully with the business changes brought by the Industrial IoT, offering services from predictive maintenance to "productivity" consultancy. At the end of this chapter, the predictive maintenance is highlighted as the most interesting Industrial IoT application, considered as the starting point for the literature review.

3.1 Survey Analysis

The Industrial IoT will experiment a great period of diffusion, faster in some areas than others, but with the potentialities to impact the majority of manufacturing companies. For more details on its diffusion and possible applications, we presented two surveys regarding the Industrial IoT with the focus on Italy. They were conducted inside the 'Osservatorio Internet of Things' of the Politecnico di Milano[15]. A survey is related to Large Enterprises (LEs)[16], the other regards Small and Medium Enterprises (SMEs)[17]. Furthermore, about ten direct interviews from the sample of LEs were scheduled and conducted to deepen some of the more interesting survey answers. The

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[15] The 'Osservatorio Internet of Things' is part of the Digital Innovation Observatories of the School of Management of the Politecnico di Milano, that represent the reference point in Italy on digital innovation. The research activities are carried out by a team of almost 100 Professors, Researchers and Analysts working on 40 different Observatories that address the key issues of Digital Innovation in Business (including SMEs) and Public Administration, divided into three areas:

- Digital Transformation, which includes Observatories that analyse in a transversal way the digital innovation processes that are deeply transforming our country;
- Digital Solutions, which brings together the Observatories that study in depth specific application and infrastructure areas related to new digital technologies;
- Verticals, which includes the Observatories that analyse digital innovation in specific sectors or processes (Osservatori Digital Innovation della School of Management del Politecnico di Milano).

[16] In October 2019, 714 questionnaires were sent to companies operating in the Italian industrial context to understand their point of view on the Industrial IoT theme. The research was carried out using the CAWI methodology (Computer Assisted Web Interview). All the details regarding the analysis in Appendix B.

[17] In December 2019, a sample of 525 small and medium enterprises, representative of the Italian scenario by sector, geographical area, number of employees and turnover, was carried out. The research was conducted using the CATI methodology (Computer Assisted Telephone Interview). All the details regarding the analysis in Appendix B.

aim of both the researches was to collect data about: (1) level of knowledge regarding IoT field; (2) the area of completed/underway projects, and related services added; (3) objectives, benefits, and use of data; (4) barriers and how to manage them; (5) economic dimension of the investments done in Industrial IoT, and the area of interest in future projects. The sub-chapters will follow the structure of the survey to deepen the application of Industrial IoT in manufacturing.

3.1.1 Knowledge

The Industrial IoT is bringing opportunities to accelerate productivity and reduce inefficiency in LEs as in SMEs. How aware are these companies? In a first instance, a huge disparity is witnessed between the two groups: only 39% of SMEs respondents respect to 97% of the LE ones indicate to have at least heard about Industrial IoT (see *Figure 3.1*). Furthermore, inside the percentages, it was detailed the level of knowledge with answers between 1 to 10. The medium result between 6 and 6,5 was observed for both the two samples. These results show the need for a significantly increased in awareness (especially for SMEs), necessary to fully understand the potentials and make the correct and necessary investments. As reported previously and now underscored by the surveys, the Industrial IoT is still at an early stage; in this phase, the dissemination of knowledge represents a critical aspect, and universities are called upon to play a key role in overcoming these first steps.

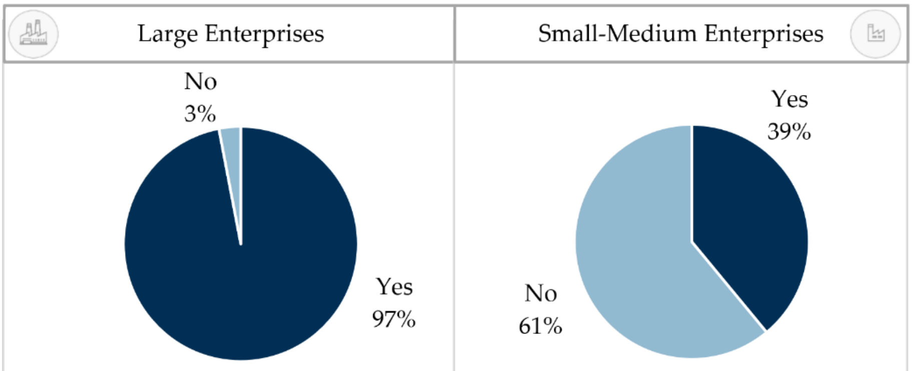

Figure 3.1: Results of Q1.1 - Sample size LEs, 100. Sample size LEs, 525 - Have you ever heard of the Internet of Things (IoT) solutions for Industry 4.0?

3.1.2 Completed/Underway Projects

The majority of LEs, 66%, has in their actual present/past an Industrial IoT project, respect to 13% of SMEs. The observatories of the Politecnico di Milano proposed a categorisation of the Industrial IoT application in three main fields: Smart Factory, Smart Supply Chain and Smart Lifecycle. For each category other sub-classes were individuated. In the Smart Factory, the maintenance (considering preventive and predictive grouped) represents the class with most of the applications (39% in LEs and 24% in SMEs), ensuring equipment's functionalities and status monitoring. The supervision of the equipment is completed with application in energy management, a relevant 18% of the applications reported in the SMEs survey. Production optimisation ensures that existing resources are optimally exploited, taking into account their limitations and constraints. Material handling and quality control are further classes of investment that contribute to maximize the level of service to customers in terms of speed, flexibility and compliance with delivery dates. Digital Twin and Work safety complete the panel of applications in the factory boarders. In a broader perspective, improvement in Smart Supply Chain are achieved including asset tracking and parameter monitoring, logistics asset management, warehouse asset tracking and fleet management. To conclude, in the Smart Lifecycle, the following areas were identified: optimization of the new product development process, end-of-life management and supplier management in the lifecycle management process. In *Figure 3.2*, we showed the results of the LEs' survey broken down for in the difference sub-classes of the Smart Factory field.

Indicate, for each IoT project for Industry 4.0 launched by your company, the state of progress (pilot project and executive project). Sample size LEs, 90 (a total of 212 application).

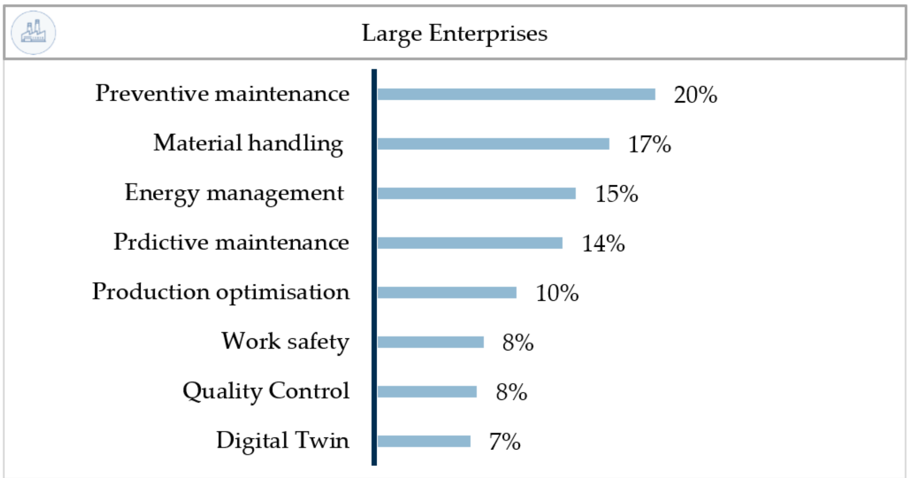

Figure 3.2: Results of Q2.2 related to Smart Factory - Sample size LEs, 90. Sample SMEs, 31 – Indicate the category (and sub-classes) for each IoT project for Industry 4.0 launched by your company (pilot project and executive project). The graph indicates how the applications inside the Smart Factory category are distributed between the sub-classes.

In the IoT application presented above, additional service could be embedded, varying from information services, based on sending real-time notifications in case of predefined events, to pay-per-use logics, services that require payment for related items (i.e. machinery, logistics assets) based on actual use and not at the time of purchase. Energy management services have a large presence as well, and they include the receipt of reports/alerts with the analysis of energy consumption trends and personalized advice on how to save money. A service related to preventive or predictive maintenance was indicated by one in two respondents, representing with information services the category more reported. At the opposite, insight the LEs sample, no demand has been found regarding insurance coverage based on actual use of related objects.

3.1.3 Objectives

Both the two surveys testify efficiency as the key driver that motivate the adoption of Industrial IoT solutions. This result is in line with the near-term macro period illustrated in chapter 1, in which efficiency has a leading role. Effectiveness is the next most indicated driver for LEs, while the results of SMEs show the company image improvement, nominated 40% of the times by the respondents. Other relevant drivers, with a percentage higher than 15% present in one of the two surveys, are (a) the willingness to experiment with new solutions, (b) the adaptation to legal or regulatory obligations, and (c) the creation of a database rich with data made available by the connected objects (*Figure 3.3*). Regarding benefits, they are rarely evaluated in SMEs (in 86% of the companies); this percentage grows to 95% adding who evaluated benefits only qualitative. In the LEs survey, results are more desirable, but, as a counterpart, the several following calls testified the missing of a comprehensive analysis of return on investment also in this group. A comparison of expected costs and benefits is confirmed to be a challenging task.

Furthermore, it was asked to indicate the use of the data collected. The answers vary from a profitable use (the data collected, both raw and reprocessed, have been used profitably by the company) to a data collection ending (data are collected without extracting real value, the company has not used them). The analysis of the results inside LEs, shows that 45% of the companies have not used /little used the data collected. The definition of appropriate strategies to enhance the value of collected data is a significant issue for companies. Regarding this point, five data valorisation schemes could be formalised (Osservatorio IoT - Politecnico di Milano, 2017): (1) process optimisation, (2) new generation of product/service, (3) Product/service customization, (4) direct data monetization and (5) Advertising & Commerce.[18] Aptiv,

[18] The five data valorisation schemes are reported in more detail:

1. Process optimization: the data collected are used to improve the internal processes of the companies themselves, with positive effects in terms of increasing efficiency (reducing time and costs) and / or effectiveness (customer service);

a multinational company in the automotive sector for highly technological solutions with a manufacturing plant in Italy, belong to the first group. It controls the consumption of all the machines in the plant, obtaining the visibility to tackle waste. In their agenda, a predictive maintenance application to reduce the time to repair and the downtime is marked for the next years.

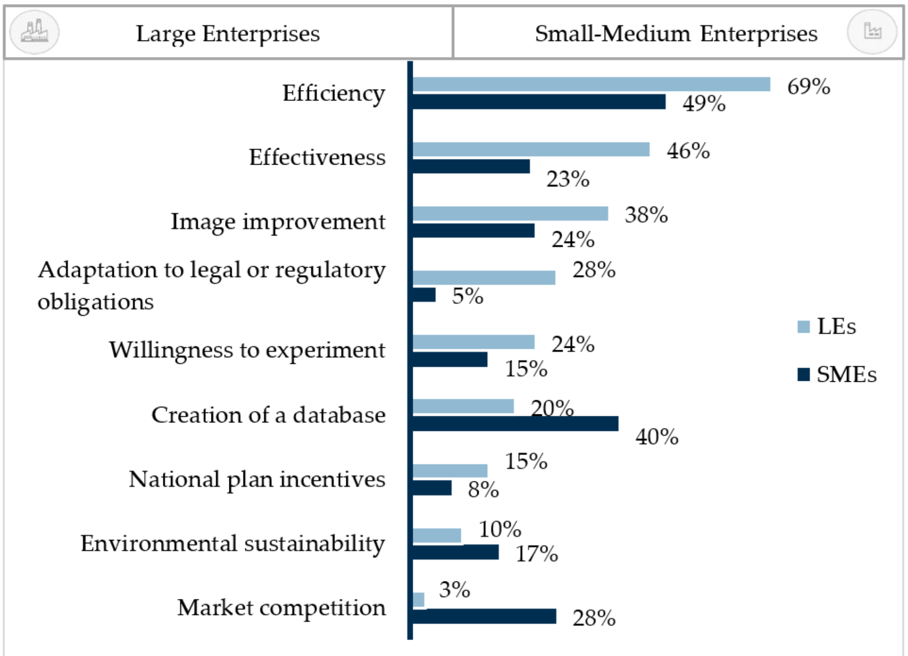

Figure 3.3: Results of Q3.1 - Sample size LEs, 61. Sample SMEs, 47- What were the main objectives that led the company to launch IoT projects for Industry 4.0? Up to three options can be entered.

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2. New generation of product / service: data on the use of connected objects by customers can be exploited in the process of developing improved versions, to reduce the most common defects and improve usability;
3. Product / service customization: a company can decide to customize its offer based on the data collected, in order to be able to better meet the specific needs of customers;
4. Direct data monetization: a company can decide to sell the collected data to interested third parties, thus generating a new source of revenues;
5. Advertising & Commerce: the possibility of proposing targeted advertising is extended to the world of connected objects, in which therefore the source of information is the habits that occur in the real world.

3.1.4 Barriers

Lack of knowledge of the Industrial IoT application/ lack of internal skills is the major recognized barriers both in the SMEs that LEs survey, indicated by more than half of respondents. Concerning to this barrier, it was asked what companies have done to cope with the gap in knowledge: more than half of the respondents have not taken any specific action to try to reduce it (even though the lack was recognized). Who is tackling this issue proceeds to train internal staff, acquire new dedicated professional skills, and work with external consultants with specific expertise. At the same time, hardly anyone experienced the miss of new professionals on the market or external consultants. Besides, survey respondents cite several other potential challenges and concern:

- Lack of understanding of the value of solutions;
- Difficulties in integrating new and old hardware and software;
- Poor availability of economic resources;
- Internal resistances;
- Lack of suitable products/ IoT technologies not yet mature;
- Cybersecurity issues;
- Privacy issues;
- Difficulty in accessing government incentives;
- Lack of suppliers.

In *Figure 3.4*, the results of the surveys regarding this topic are represented.

In line with the barriers cited 'Technoform Bautec Italia' (an Italian medium company, specialist for standard and tailored plastic solution) reports the difficulty of collecting data, managing them in real-time and evaluating a return of the investment.

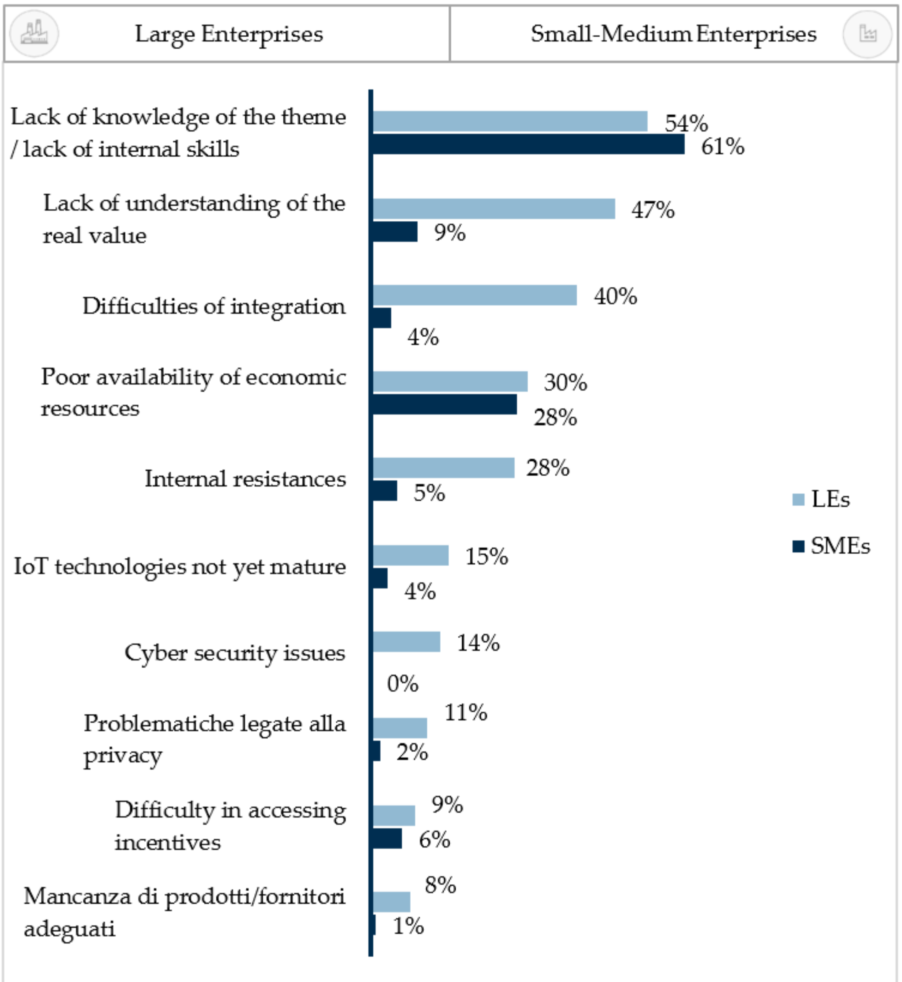

Figure 3.4: Results of Q4.1 - Sample size LEs, 88. Sample SMEs, 525 - What are the barriers (internal and external) that in your opinion, can slow down or prevent the start of IoT projects for Industry 4.0? Up to three options can be entered.

3.1.5 Investment Dimension and Future Orientation

How much are companies investing in Industrial IoT solutions? Among those who activated a project, one in four allocates less than 5% of the company's turnover. Subsequently, an optional question asked more specific details of the economic dimension: results report that investments included in a range from 20k€ to 2mln€. In this scenario, the ability to exploit the government incentives needs to be understood. In the narrow circle of the SMEs that develop at least one application, the importance of exploiting the incentives can be considered underestimated: only 24% of the respondents declare that being able to access incentives is a substantial driver. To conclude the as-is situation, the most used government instruments highlighted by the survey are the increased value (+ 250%) of the depreciation for the assets and the tax credit for incremental R&D expenses.

The attention for Industrial IoT application will increase in future. As shown by the surveys, approximately 70% of the companies will confirm investments related to the specific field where they already developed a project. The total number of applications will increase due to new adopters. An even more significant growth will arise from the adoption of services related and reported in *Figure 3.5* applications and services about preventive and predictive maintenance.

Regarding the maintenance services, a significant boost of the predictive part can be observed. The question 5.1(*Figure 3.5*) investigated the service activated in the past project and the one willing to be used. The answers are scaled for the number of respondents to the one regarding the future. Sample base regarding the past project is 59 companies. The sample base regarding future project is 83. This trend of shift towards services was analysed with a case study, Fabio Perini S.p.A., a company present in the LEs survey and then interviewed (Antonio Mosca – Head of Digital). In the survey, this company reports a level of knowledge of 10 over 10, active Industrial IoT application (internal processes efficiency) and a profitable use of data. The prominent relevance of this company was not considering it as part of the Demand as solution adopter but of the Supply, as a successful example of service delivery for external clients.

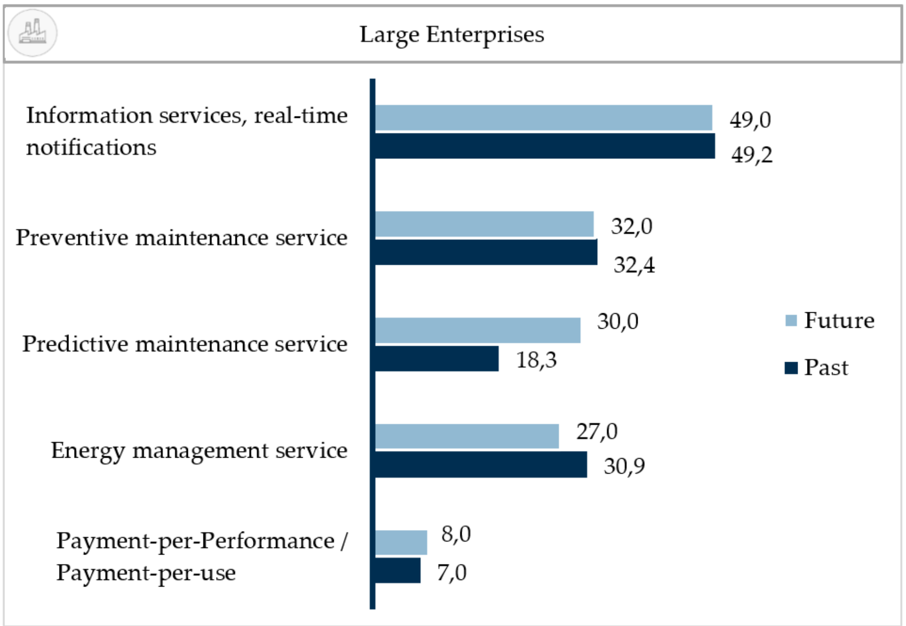

Figure 3.5: Results of Q 5.1 Sample base regarding past project, 59. Sample base regarding future project, 83 - (the answers are scaled for the answers received regarding the future) – (future) What additional services enabled by the Internet of Things technologies is the company interested in activating inside the factory? (present) Up to three options can be entered. (Have the IoT applications for Industry 4.0 that you have launched included additional services?).

3.2 Case study – Fabio Perini S.p.A. (Körber Tissue)

Established in Italy, in 1966 by the inventor/entrepreneur Fabio Perini, Fabio Perini S.p.A. is a mechanical engineering company. The company is specialized in the manufacturing and design of industrial machinery for the papermaking industry and the tissue converting industry. The company has eleven overseas divisions located in three continents (Europe, America and Asia). Thanks to many original design patents, in 20 years the company Fabio Perini transformed itself from a one-man business to a multinational enterprise, covering up the 75% of the worldwide market of the tissue converting machinery. Since 1994 Fabio Perini S.p.A. is part of the German technology group Körber and belongs to the division Körber Process Solutions. The company employs 616 workers and has a turnover of 163.5mln€ (AIDA, 2019).

Fabio Perini S.p.A. was the first mover in its specific sector. Its primary service solution consists in to optimise the OEE of the client's whole plant. This result is obtained by managing data in the cloud and elaborating them in its internal performance centre, associated machine experts within advanced technology (data collection, measuring, analyse, reporting, machine learning). At first, Fabio Perini promoted this service with SMEs, promising insights and pillars for OEE improvement, and in a year since October 2018, it has been possible to connect a thousand machines around the globe. This outcome was achievable by having investments already in place: a relevant part of the sensors (measuring vibration, temperature, etc.) and a useful front-end monitor, previously inserted as after-sale service and then proved to be very useful for Industrial IoT application. With SMEs, no barriers were reported, and in case the client is worried about the cloud solution, it is possible to switch on the premise. In a second phase, also LEs, initially reluctant already having their internal team at their disposal, begin to buy Fabio Perini's services to leverage on its Tissue Performance Centre.

The company is proceeding in its digital transformation, aiming to become the leading provider of complete solutions for the tissue ecosystem, to optimize the Overall Equipment Effectiveness of the entire lines. A set of smart software are proposed, such as a digital solution for predictive maintenance, to identify deviation in process functionality and plan maintenance operations, or virtual production supervisors, to measure and keep under control, in real-time, the most critical properties of tissue and finished product. Technology devices are proposed as well: wearable glasses provide technicians with augmented reality that allows for remote, interconnected sharing and viewing to rapid troubleshoot problems, therefore the possibility to resolved issue remotely with no need to send a technician on site.

The last significant point to talk concerns servitization, a new business model for this specific industry by which customers are guaranteed help from Fabio Perini in raising their efficiencies and expanding their production capacity without adding capital expenditures. Pay-per-Performance and Pay-per-User are the new payment methods that Fabio Perini is experimenting (Körber Tissue, 2019) with related characteristics. The former lets the client pay by sharing the economic value, agreeing with Fabio Perini to raise and maintain the operational efficiency to a pre-defined level. The latter let to pay for what they use with related benefits from no upfront capital cost, flexibility in payments and viable long-term business opportunity in place.

3.3 Remarks and Checkpoint

Recalling the definition proposed in the second chapter, the Industrial IoT "[…] enables real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information in the industrial environment to optimise overall production value" (Boyes, Hallaq, Cunningham, & Watson, 2018). The answer to the question 'Why now?' was given by Porter & Heppelman (2014): "An array of innovations across technology landscape have converged to make smart, connected products technically and economically feasible". As we have seen in the surveys, much has already been achieved. Looking to the next years, the field of maintenance results to be highly attractive, as highlighted by the number of direct applications and by the relevant part of services. Maintenance that in its noblest form is expressed in predictive maintenance acquires more exquisitely the features of the Industrial IoT when the vendors manage the maintenance process in a centralized way, making predictions much more accurate. Every client will manage this information to gain benefits also from the coordination and optimisation of production and logistics. Predictive maintenance has always existed "from the moment a man puts his ear to the machine, and he foresees that it will soon break down", and now it can be entrusted entirely to the vendor of the machine. Vendor has the structural knowledge base, and with Industrial IoT, he can exploit the data arriving in real-time from the various interconnected machines of the clients. Outsourcing of maintenance can be assessed. The sharing of operating data externally to the company could represent a barrier, and a change in mentality may be necessary, improving the existing supplier relationship. For the demand side, the benefits lie in optimising production with cost savings and increased productivity. On the supply side, a competitive advantage can be unlocked considering the scalability potential of predictive maintenance, as well as being able to trigger mechanisms for improving the machines by knowing the problems in their actual usage (in the field of smart lifecycle application). The investment in IoT has to be seen from the perspective of a path that will lead from time to time in adding solutions to obtain ever-greater overall advantages.

Chapter 4

Literature Review

The literature review is a crucial point for any academic project. In this chapter, a literature review to understand the benefits of predictive maintenance is performed to deepen the theme and discover possible gaps on which perform further analysis. First, the chapter presents the steps and the analysis conducted to obtain the final sample of papers. Then it shows a descriptive analysis to provide the reader with essential information about it. Categories have been selected based on documents content and our goal to get insight from the papers. A specific analysis is conducted on them to describe the information included. Finally, gaps are presented and discussed.

4.1 Introduction to Literature Review

The first essential step to carry out any academic project on a particular topic is to understand the level of knowledge achieved in that area completely. Therefore, the literature review assumes a crucial role in this context (Webster & Watson, 2002). Indeed, it aims to identify what has been written on a topic, reveals any interpretable trends or patterns, identifies issues or questions that require further investigation to generate new frameworks and theories where there are gaps in the literature (Paré & Kitsiou, 2017).

In this chapter, we analyse the current literature in the area of predictive maintenance that represents the focal point in the Industrial IoT era (Kaur, Selway *et al.*, 2018). For our analysis, we decided to adopt the content analysis approach as proposed by Seuring & Gold (2012). We chose this approach because the content analysis allows exploring the manifest content of texts and documents and, at the same time, makes it possible to excavate the latent one underlying the meaning of terms and arguments. "It is a specific strength of content analysis that this method can combine qualitative approaches retaining rich meaning with powerful quantitative analyses, where it seems meaningful for the analyst" (Seuring & Gold, 2012).

The chapter is organized as follows. The first section presents the methodology for the research and the selection of the papers. The second presents the descriptive analysis (i.e. the year of publication and research methods), the third exhibit the selection of categories for the analysis of the theme deriving from the review and the following description of these categories. In the final section, we report the conclusions and highlight the potential directions for future research in this field.

4.2 Material Collection and Selection

The first step of the literature review analysis is the collection and selection of the material (Seuring & Gold, 2012). Here we will present the identification process and the subsequent steps that led us to a delimitated papers selection, as well as the formalized approach that we applied to validate the sample we obtained to eliminate possible subjective bias and enhance reliability.

4.2.1 Articles Collection

According to Seuring & Gold (2012), the first step is to define the unit of analysis. We decided to include in our literature sample English-speaking peer-reviewed paper and conference paper on Industrial IoT in manufacturing. Given the novelty of the topic, we decided not to limit the years of publication; rather it was considered an important issue to understand the dawn of the literature and the beginning of the ferment. For compiling the paper sample, we fulfilled a literature search in three of the primary source of online literature databases: Scopus, ISI Web of Science and Google Scholar. It is important to underline that, to have good coverage of the research field, many other references have been investigated with the same keywords as well. The search was applied to the title of the articles, the abstracts and the keywords in order to conduct the most comprehensive research possible without including papers not centred on the topic.

The search was carried out based on different keywords, such as Industrial IoT or Industrial Internet. However, the sample size obtained with these keywords and the extent of the topic is so wide that a more narrow analysis was required (more than six thousand paper has been found only on Scopus). Moreover, because of the lack of clarity of the terms as we have identified in the previous chapters, we have also included the word Industry 4.0. In order to refine the search of the published papers, we decided to delimit the topic to the maintenance of manufacturing assets. Therefore, we combined the words Industrial IoT, Industrial Internet and Industry 4.0, with manufacturing, maintenance, predictive, and benefits also complementing the sample by cross-referencing them (Seuring & Gold, 2012).

4.2.2 Article Selection

From the database investigation, 655 results have been found, downloaded and organized in excel (Polanin, Pigott, Espelage, & Grotpeter, 2019). The second step was to eliminate all the duplicated papers. Since the research words are a bit redundant (for example, the word Industrial IoT appears in all the searches), the number of duplicates was around 20%, and only 508 papers were kept. Then, in step three, authors screened the title of all these papers deciding whether to include or exclude them from the selection. Both the reviewer conducted the screening independently in order to foster objectivity (Paré & Kitsiou, 2017). For this step, we established some exclusion criteria: (E1) studies not explicitly focused on IoT; (E2) studies that do not address the manufacturing domain; (E3) studies that have not been published in books and book chapters or well-known international conferences. After this screen, 155 papers remained.

For the last step of the screening phase, we decided to read the abstracts and give a quick look at the text of these studies in order to see if the focus of the selected papers was in line with ours. According to Polanin *et al.* (2019), we conducted this screening separately using an abstract screening tool with questions. Given the advanced state of the procedure, we preferred to limit our assessment (yes/no/unsure) to two questions: "Is the focus of the paper on predictive maintenance?" and "Is the focus of the paper not on a specific analytic aspect of predictive maintenance?". At the end of this process, the disagreement was around 20%, and a reconciliation occurred (Polanin, Pigott, Espelage, & Grotpeter, 2019).

According to the screening criteria mentioned, from the initial sample of 508 articles, 57 studies remained, ready for an in-depth review. The final number of articles has not been established a priori, but is the result of a careful process of combined research and screening. Eventually, the material was categorized following two steps in accordance with Seuring & Gold (2012). A descriptive analysis was conducted first (i.e., distribution over the time, nationality) and then categories based on the content following an iterative process that will be explained later in the chapter.

4.3 Descriptive Analysis

The reviewed articles are categorised according to the research methods used by the authors following the typologies used by Meixell and Norbis (2008) and Perego, Perotti, and Mangiaracina (2011). A quick overview of the definition of the different methods follow:

- *Literature Review*: the paper collects and analyses studies and papers previously published on a given topic, presenting them in the most objective way possible.
- *Conceptual Framework*: it models a phenomenon through the use of causal maps, matrices, diagrams;
- *Analytical Method*: a scientific analysis methodology that allows to solve a problem through a well-defined mathematical calculation procedure;
- *Simulation*: a model of reality that allows to evaluate and predict the dynamic unfolding of events or processes following the constraints imposed by the analyst or user;
- *Case study*: empirical analysis that investigates a contemporary phenomenon in its real context. It is often aimed at verifying a theoretical model and illustrating its applications;
- *Survey*: a statistical survey aimed at a predetermined sample of people and at collecting a set of opinions, preferences and behaviours in relation to the purposes it is conducted. It can be structured, semi-structured and

unstructured, depending on the margin of discretion granted to the interviewee;

- *Action research*: it is essentially a research through action. It requires the direct involvement of the researcher in the action process. The purpose is to analyse a field-related practice, to solve a particular problem and to introduce guidelines for best practice.

Overall, about half of the works are a conceptual framework, whereas the others are based on empirical research (e.g. case studies, surveys). Only a few of them (7 out of 57) are analytical or simulation models. The distribution of the analysed papers shown in *Table 4.1*. It is important to mention that some works present more than one research method. For example is the case of Farooq, Bao *et al.* (2020), they present a predictive maintenance model to improve the reliability of the system and then demonstrate the feasibility of the proposed model in a case study.

Conceptual frameworks account for 49% of the total papers (or 28 out of 57) (Terrissa, Meraghni *et al.*, 2016; Sahal, Breslin *et al.*, 2020; Garcia, Costa *et al.*, 2020; Bengtsson & Lundström, 2018). For example, Chehri & Jeon (2016) propose an efficient framework for the Industrial IoT, providing a state-of-the-art approach for industrial applications. Another example is given by Kaur, Selway *et al.* (2018), who present a framework to extend previous open standards to achieve predictive maintenance. The article first presents international standards for condition-based maintenance, then presents an industrial interoperability ecosystem (OIIE) that allows devices and

Research method	**%**
Action Research (2)	3.5%
Analytical Method (6)	10.5%
Case study (11)	19.3%
Conceptual Framework (28)	49.1%
Literature review (6)	10.5%
Simulation (1)	1.8%
Survey (3)	5.3%
Total (57)	**100%**

Table 4.1: Research method summary

systems to communicate effectively in both inter and intra-enterprise contexts using a variety of standards, models of data and exchange protocols, thus improving predictive maintenance.

Empirical studies are based on case studies, surveys and action research and represent 19%, 5% and 4% respectively). While the surveys mainly aim to understand the level of knowledge of the Industrial IoT technology in predictive maintenance, trying to understand the opinions regarding the possible future implications, the case studies are mostly empirical demonstrations to validate different types of models for predictive maintenance. Roda, Macchi & Fumagalli (2018) are representative of the first type. They interviewed nine Italian companies to investigate the vision of the future of maintenance in the Industrial IoT era and "to show empirical evidence on how manufacturing companies are approaching the digital transformation process of maintenance.by interviewing." For the case studies, it is pertinent the paper of Ruiz-Sarmiento, Monroy *et al.* (2020), "which describes a predictive model based on a Bayesian filter […] to estimate and predict the gradual degradation" of the machineries involved in the production of steel sheets and allow operators to make informed decisions regarding maintenance operations.

Quantitative model (analytical model or simulation count 11% and 2% respectively) are relatively limited, although progressively increasing, and are generally associated with economic evaluations of the potential benefits that would be obtained from the application of the Industrial IoT to predictive maintenance. For example, He, Han *et al.* (2018) propose a cost-benefit analysis model based on the state of reliability of the machine concerning the task for which it is assigned. More recently, Huang, Chen *et al.* (2020) published a study on a revenue-sharing model to demonstrate the convenience of purchasing the maintenance service directly from the vendor, service that requires the Industrial IoT for data transmission.

Finally, literature reviews represent 11% of the overall sample and have no specific relation one to the other. For example, Del Ser, Galar & Sierra (2019) provide a comprehensive review in the field of data fusion and machine learning for industrial prognosis. While Bousdekis, Lepenioti *et al.* (2019) made a review of the literature on the field of decision making in predictive maintenance in the context of intelligent manufacturing.

Regarding the year of publication, we decided not to limit the period of the research, knowing about the novelty of the theme, to figure out when scholars started to work on it. We did not find any significant studies related to our research topic prior to 2015. The distribution of the reviewed papers, which were published between 2015 and 2020, is shown in *Figure 4.1*. The number of papers published remained stable for in the biennium 2015 – 2016. From 2017 an incredible growth path started, publications doubled each year, reaching their peak in 2019, revealing the greater attention that to the theme. The majority of the papers concentrate in the two years 2018, 2019: 35 papers out of 57. A final consideration worth to be done in this concern. Since this review was performed in early 2020, the publication number for this year is lower. However, considering that we are only in the first quarter of the year, we expect the previous growth rate to be confirmed again for this year[19].

Focusing on the country of origin of the published papers, the most significant contribution is given by Italy and China, which together represent 22% of the sample. In it also interesting to notice that European countries together provide the large majority of the papers, which provide together more than 68% of the papers.

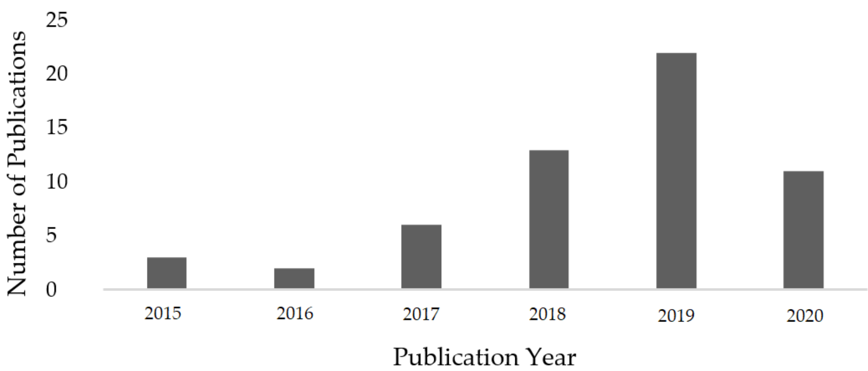

Figure 4.1: Paper distribution per year

[19] There is also to consider that publications in 2020 may have been slowed down by the recent problems caused by the sanitary emergency.

4.4 Category Selection

In their guidelines on how to conduct a rigorous content analysis, Seuring & Gold (2012) particularly highlight the central role of defining categories to classify the reviewed material. Following their suggestion, we decided to use a two-step-process (deductive and inductive). From the first screen of the selected literature, we deductively defined some categories based on some authors' classification to refine and introduce new ones in a subsequent inductive approach. However, the novelty of the themes covered required much effort to adapt and create ad-hoc categories, since the existing ones were too general or too specific in a given area.

In our analysis, we were interested in understanding the role of Industrial IoT in predictive maintenance, the improvements and transformations it can produce from an economic and productivity perspective, and the problems that hinder its adoption. Therefore, we grouped the analysis around four key themes (see *Table 4.2*):

1. <u>The approach with which authors deal with the theme of industrial IoT</u> (*Authors' approach*): It is important to know on which aspect of the Industrial IoT in predictive maintenance the authors focus on, what the purpose of the article is, in what terms the topic is analysed. Is the author focusing on future trends of predictive maintenance, on presenting a structure of the Industrial IoT framework, or on business organisational change taking care of the economic aspects?
2. <u>Benefits achieved after adoption</u> (*Benefits*): This variable measure how much each paper consider the benefits that predictive maintenance can generate on production with the implementation of Industrial IoT solutions;
3. <u>Criticalities, barriers to adoption and risks</u> (*Barriers & Risks*): Even with the support of Industrial IoT, predictive maintenance still presents barriers and risks that limit its adoption and diffusion. This variable aims to assess how much each paper deals with this problem and whether the criticalities come from a technical or a more business perspective;
4. <u>Business model transformations</u> (*Servitization*): The Industrial IoT in the field of predictive maintenance also presents great opportunities to shift towards

new business models based on services. This variable aims to assess how much and in which terms the literature considers this topic.

Categories	Definition
1. Authors' approach	It state whether the focus is on *Industrial IoT-framework, Business decision* or *Factory field*
2. Benefits	Degree to which papers address the role of benefits: *Core/Ancillary/Absent*
2.1 Type of benefit	Whether the benefits are related to *Oprational efficiency or Cost reduction*
3. Barriers & Risks	Degree to which papers address the adoption barriers and risks: *Core/Ancillary/Absent*
3.1 Barrier's category	Whether the barriers and risk are *Socio-Economic* or *Technical*
4. Servitization	Degree to which papers address new services: *Core/Ancillary/Absent*

Table 4.2: Analytical categories and their definitions

4.5 Evaluation and Discussion of the Review

The sample of literature review papers on the adoption of industrial IoT in the context of predictive maintenance was analysed based on the categories presented in the previous chapter. The results are presented and discussed to understand where the literature is focused on with an objective perspective. Gaps are eventually presented.

Before going into detail and explore all the variables carefully, it is necessary to generally analyse how the literature refers to the theme of predictive maintenance. Looking on the web libraries for the key words previously mentioned (Industrial IoT, Predictive maintenance, Industry 4.0…), thousands of results are generated, and all of them were subsequently refined using the screening process previously described.

However, it is interesting to notice that some papers that still satisfy all the screening criteria and have their focus on predictive maintenance, present the Industrial IoT in manufacturing with a much more general focus. These papers represent only 21% of the sample. For instance, Khan, Ateeq *et al.* (2017) provide a holistic view of the different stages of IoT projects to see how it generates business value for an organization focusing then on predictive maintenance as a use case. Similarly, Kans & Ingwald (2016) trace the evolutionary path of services up to Service Management 4.0 whose purpose is to create value for the customer. In this context, predictive maintenance is reported as one of the main services that create this value.

4.5.1 Authors' Approach

The first proposed categorization divided the literature according to the different themes. It was decided a strict division that identifies the paper according to its main characteristic, bearing in mind possible interdependencies. *Industrial IoT framework* represents the most tackled argument, 27 papers over the 57 selected (47%) reporting the architecture and guideline details for the Industrial IoT application enabling predictive maintenance. The variable *Business decisions* is represented by 18 papers (32%) that point out the focus on the economic aspects and organizational impacts beyond the Predictive Maintenance technical application. Finally, in the variable *Factory field* 12 papers (21%) have been categorized, gathering all those papers brings survey, perspective and trends of the maintenance sector. The main topics covered in these three classes will be detailed below.

Industrial IoT Framework

Different architecture models are presented[20], a multilayer structure characterizes each model, and despite the different name of the individual level of technical design, the described architecture is similar. As reported in Strauß, Schmitz *et al.* (2019) at the lowest level, measured variables and the sensors suitable for monitoring must first be determined. The selection of the interfaces for connecting the sensors is addressed in the gateway or communication level, necessary in order to reduce the data volume, to pass only the selected and extracted characteristics and not all measured data to a central cloud. Concepts of using edge computing reduce data volume, save computing power in the cloud and allow real-time data analysis (De Leon, Alcazar *et al.*, 2017). In the central cloud, data from various sources is stored, aggregated and abstracted to enable data analysis. Finally, the top layers of the reference architectures describe an integration into the business processes, i.e., the integration of machine learning models within the process organization of the maintenance division (Strauß, Schmitz *et al.*, 2019). Due to the absence of largely adopted open standards, the Industrial IoT architecture must be an interoperability solution that enables devices and systems to communicate effectively in both inter- and intra- enterprise contexts using a variety of standards, data models, and exchange protocols (Kaur, Selway *et al.*, 2018). The set of features necessarily moves from Real-time capability to Modularity and Security (Wan, Tang *et al.*, 2017). In a broader perspective, Industrial Iot-based manufacturing aspires to be an ecosystem able to manage the 5Vs of big data (volume, velocity, variety, value, and veracity) concerning data ingestion, management, analytic, and visualization layers (Yu, Dillon *et al.*, 2020). Lastly, papers focusing more on application case regarding Predictive maintenance are classified in this variable, i.e., proof of concept, case study and simulation (Bergonzi, Colombo *et al.*, 2017; O'Donovan, Leahy *et al.*, 2015; Ayad, Terrissa *et al.*, 2017; Chacada, Barbosa *et al.*, 2019).

[20] In the first chapter, we discussed the several reference frameworks and among those presenting we adopted the widely accepted three-level model which includes the edge, the platform and the enterprise levels.

Business Decision

A possible evaluation of the cost of maintenance is approached (Osako, Matsubayashi *et al.*, 2019; Drewniak & Gabriś *et al.*, 2019; Tsao, Lee *et al.*, 2019) and different case studies with benefit considerations are reported. Since failure of critical assets has been rated as the most significant risk to operational performance, manufacturers increasingly see maintenance no more as a necessary evil but as a strategic business function. The majority of manufacturing companies lack in reliability engineers, and even more in data scientists. Investment in data analytics roles or the introduction of new roles that bring complementary skills to those inherent to maintenance processes is essential. The success depends on skills and knowledge, and the promotion of cross-functional teams is suggested (Bousdekis, Apostolou *et al.*, 2020). From a broader perspective, the diffusion of a culture of continuous improvement inside the organization needs to be considered: the digital transformation is seen as a journey towards Industry 4.0 and not as a one-shot investment. Change management and a corporate governance strategy would be highly relevant. In this journey, the maintenance function is transforming its role in order to better support value creation (Jasiulewicz-Kaczmarek & Gola, 2020). The industrial-scale deployment of Predictive Maintenance involves many other aspects and impacts various sectors of the workplace, like logistics, occupational health, safety & environment, design and top management. Above all, the objective of supporting decision making to act on the physical systems optimally is pursed (Compare, Baraldi *et al.*, 2019). Strictly related to this variable, two different categorizations will be treated subsequently: Benefits and Servitization.

Factory Field

New trends and techniques in the field of predictive maintenance arose, representing alternatives to traditional management policies relying on visual inspection and early identification of signs of abnormalities during operation. Predictive Maintenance, frequently linked in papers to PHM (Prognostic & Health Management) (Baur, Albertelli *et al.*, 2020), is the core of this new change and it heavily relies on sensor technologies[21]. Nowadays, based on Predictive Maintenance, the cognitive maintenance is getting more and more attention: a concept of maintenance completely integrated in industrial plant management that will gradually force an interaction between maintenance and management of production processes solutions (Drewniak & Gabryś, 2019). The adjective cognitive stays for advanced technology at the intersection of big data, machine learning, and artificial intelligence analytics. Strictly related to Predictive Maintenance, it is reported e-Maintanance, a management concept whereby assets are monitored and managed over the Internet. Similar field to Remote Maintenance and Management Systems (RMMS), which makes possible to execute Predictive Maintenance works especially in isolated or hazardous locations. Data visualization, digital twins, and augmented reality are further new technologies and concepts that provide companies with highly advanced efficient systems in maintenance (Noureddine, Solvang *et al.*, 2020), new capabilities for remote and ubiquitous maintenance. Bokrantz J., Skoogh *et al.* (2017) enclosed these concepts inside the definition of Smart Maintenance:

"An organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies […] a multidimensional concept constituting of the four dimensions of data-driven decision-making, human capital resource, internal integration, and external integration. [...] it aims to achieve effective and efficient decision-making and responsiveness to internal and external components."

Lastly, Bengtsson & Lundström (2018) highlighted the risk in the future of leaving basic maintenance concepts and management underdeveloped or even

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[21] Sensor devices constitute a fundamental layer, directly interact with the environment by measuring variables of interest and by processing acquired data to perform onboard analysis tasks. Sensor techniques can be broadly categorized into (a) process parameter measurements, (b) vibration analysis, (c) oil analysis, (d) thermographic analysis, (e) acoustic analysis and (f) other Predictive Maintenance techniques (Sule, 2015). Sensor technologies have evolved concurrently to sensor fusion techniques (Turner, Emmanouilidis *et al.*, 2019).

unimplemented, putting too much trust in technological advancement. In order to achieve a "total maintenance effectiveness", the combination of the "new" with the "old" is requested.

4.5.2 Benefits

The papers addressing the benefit topic, reporting discussion and in-depth analysis, count for 26% of the considered literature (15 of 57). Overall, the literature focus has been mainly on the technical deployment of Predictive Maintenance, and further contributions to define economic benefits and IoT investment justification are still missing (Drewniak & Gabryś, 2019). Regarding the benefits analysed, two main classes have been highlighted: operational efficiency and cost reduction. Other aspects (i.e. safety) will be discussed after the focus on these first two main perspectives.

Operational Efficiency

The possibility to rely on Residual Useful Life computation (predicting failure of the equipment inferred by degradation pattern) maximizes the equipment availability and reliability (Sezer, Romero *et al.*, 2018). A better scheduling of maintenance could be pursed, achieving an improvement in key sector indicators, i.e. Mean Time Between Failure (MTBF) and Mean Time To Repair (MTBR). The historical trade-off regarding Preventive Maintenance (PvM) of trying to maximize the useful life (lifetime extensions) of the production equipment while avoiding unplanned downtime and minimizing planned downtime, is overcome with Predictive Maintenance (Poosapati, Katnevi *et al.*, 2019). Furthermore, a significant part of the value of Predictive Maintenance would come from improvements in production quality and a better orchestration of maintenance-related processes, i.e. a better coordination in the logistics for maintenance operations.

Cost Reduction

In the optic of just-in-time maintenance equipment, unnecessary work orders are eliminated with a gain in time efficiency and a reduction of costs per parts and labour. The warehouse management could reduce the stored spares setting a just-in-time logistics. As often quoted phrase is the following: "The right part in the right place, at the right time".

Other reported benefits regard the safety of people, which could represent a key point for specific equipment and manufacturing workspace; few papers explicit the environmental benefits that could be ensued. Poosapati, Katnevi *et al.* (2019) distinguished different factors: prevention of environmental damage, emissions reduction and land conservation, energy consumption reduction and energy savings or efficiency.

Percentages of improvement after adopting predictive maintenance could be considered as a useful benchmark (Poosapati, Katnevi *et al.*, 2019; Sahal, Breslin & Ali, 2020; Bokrantz, Skoogh *et al.*, 2020):

- Savings in maintenance costs up to 30%;
- Up to 75% less failures/breakdowns;
- Decrease of the total machine downtime from 30% to 50%;
- Extension of the operation life from 20% to 40%.

These percentages testify the possible benefits of the development of IoT-enabled Predictive Maintenance for Industry 4.0, but they did not mention the as-is situation or other possible maintenance strategies. Even if CM and PvM presented structural limits (i.e. PvM could not manage hysteresis of the processes), a comparison with these most-used maintenance strategies needs to be performed. Maintenance cost models must be developed to evaluate the economic benefits of predictive maintenance; an example of this attempt is the dynamic cost-oriented predictive model (Tobias & Yanpei, 2019). As reported in Drewniak & Gabryś (2019), the identification of the components that could be eligible for Predictive Maintenance is the first step to be taken to address the issue of selecting the best maintenance strategy in a system.

4.5.3 Barriers and Risks

The literature reports several papers that address the adoption issues (O'Donovan, Leahy, & Bruton, 2015; Yu, Dillon *et al.*, 2020; Müller & Däschle, 2018; Compare, Baraldi, & Zio, 2019; Nikolic, Ignjatic *et al.*, 2017). Overall, the behaviour of the companies seems to be influenced by both the characteristics of the company itself and by the reliability of the technology. On the one hand, some main *socio-economic barriers* have been identified, such as the ability to demonstrate to the customer the greater value and the ability to it consequently (Müller & Däschle, 2018). On the other hand, some *technical barriers*, which discourage many players from adopting such solutions are reported. We focus on this distinction to examine more in depth the main obstacles that prevent companies from adopting Industrial IoT solutions for predictive maintenance.

Socio-Economic Barriers

According to the examined literature, the most recurrent economic barrier to predictive maintenance adoption with an Industrial IoT architecture is the cost of the investment. Adu-Amankwa, Attia *et al.* pointed out that the initial investment into the technological infrastructure can be significant when retrofitting to the factory's original design and Strauß, Schmitz *et al.* (2018) reported that "75% of the industrial companies would not be willing to invest more than 500 EUR to digitize their machine". Companies are so reluctant to make such investments because of the intrinsic difficulty in establishing the payback in the digital transformation of maintenance (Roda, Macchi & Fumagalli, 2018; Compare, Baraldi & Zio, 2019).

Other authors address the same monetary issue from another point of view. They set their perspective in the supply of industrial machines and figured out that suppliers may face some challenges as well in integrating digital solutions for predictive maintenance in their offer. This aspect is caused by the difficulty of the customer to recognize its value and the subsequent impossibility of the vendor to capture it with the traditional business models (Müller & Däschle, 2018; Omar, Minoufekr & Plapper, 2019).

Other socio-economic barriers that authors reports are the lack of organization culture (Omar, Minoufekr & Plapper, 2019; Roda, Macchi & Fumagalli, 2018) and lack of skilled workforce with the subsequent cost of training the personnel to interpret data to schedule maintenance accordingly (Adu-Amankwa, Attia & Janardhanan, 2019; Baur, Albertelli & Monno, 2020; Roda, Macchi & Fumagalli, 2018).

Technical Barriers

Technical barriers deal with the reliability and security of the technology. The Industrial IoT "enabled factories to rapidly scan many millions of unstructured data items in different formats from a multitude of diverse sources" (Yu, Dillon *et al.*, 2020). This capability creates the opportunity to reduce uncertainty in the prediction and allow a better schedule on the one hand (Diez-Olivan, Del Ser *et al.*, 2019), but a greater vulnerability to cyberattacks. Roda, Macchi, & Fumagalli (2018), figured out in their survey that one of the barriers perceived as critical is the potential lack of guarantees from current Cyber Security technologies on the complete effectiveness in data protection. Adu-Amankwa, Attia *et al.* (2019) identify maintenance and security data infrastructure as a key challenge of adoption.

Finally, it is relevant to notice that even if several papers deal with the data collection and management, only one mentions the lack of a widespread standard solution for new technology as a barrier perceived by companies (Roda, Macchi, & Fumagalli, 2018).

4.5.4 Servitization

The industrial IoT not only promises to transform the factories' plant, but it also has the capability to transform the intrinsic way of doing business (Noureddine, Solvang *et al.*, 2020). Bokrantz, Skoogh *et al.* (2020) in their survey, demonstrate that companies recognize the importance of transmitting data and are ready to share relevant information with suppliers and partners. The Industrial IoT technology links all these players together, paving the way for new practices and techniques to be used in maintenance operations (Noureddine, Solvang *et al.*, 2020). On the one hand, the supplier has access to valuable information to improve product development and develop services based on extended knowledge bases. On the other hand, the customer receives back this value in the form of more relevant knowledge, more reliable products and better services (Bokrantz, Skoogh *et al.*, 2020). While some authors only recognized the potential of the data streaming as a possibility for new revenue streams (Noureddine, Solvang *et al.*, 2020), others propose a variety of possible business model features that can be offered to the customer (Müller & Däschle, 2018). The Industrial IoT is driving the "transition of traditional pure products business models to Product/Service-Systems (PSS)" enabling "the creation of value through services in different parts of the network." (Osako, Matsubayashi, Takey *et al.*, 2019). On the same line are Kans & Ingwald (2016) that present a four-level framework representing the logical development of the service business model from a narrow technical perspective to a holistic product-service perspective. Huang *et al.* goes a step further modelling the value generate both for the supplier and the customer in the Product/Service-Systems. They theoretically and practically demonstrated that a PSS reduces the downtime of the equipment and brings many other monetary benefits to customers, manufacturers and local repair companies included in the transaction as third parties.

4.6 Results and Future Direction from the Literature Review

Since the first appearance of the IoT theme in the industrial field, academic papers have had an exponential growth. Industrial IoT is revolutionizing all sectors and the traditional way of doing business. Among the others, the theme of the Industrial IoT in predictive maintenance is about the major focus point of this transformation (Kaur, Selway *et al.*, 2018).

We directed a literature review most systematically and transparently possible, following the guideline of Seuring & Gold (2012). We examined 57 research contributions to the application of the Industrial IoT technology to improve predictive maintenance in manufacturing. The period of publication of the paper cover six years, from 2015 to 2020. Furthermore, the vast majority of them, is concentrated between 2019 and 2020 (33 out of 57), highlighting the novelty of the theme and the growing interest that researchers have in this topic. As for the methodology, our review revealed that many of the articles examined are conceptual articles. A fair number of empirical studies (i.e. mainly based on surveys, or case studies or interviews) were also analysed. We found very few contributions based on simulation and mathematical modelling.

We developed this structured review that provides a guide to previous research in predictive maintenance in the 4.0 era. In general, we have found several interesting topics in the literature. Firstly, we have analysed on which aspects of the Industrial IoT in the field of predictive maintenance the authors focus the most: *Industrial IoT framework*, *Business decisions*, and *Factory field*. Secondly, we have examined the improvements and transformations it can produce from an economic and productivity point of view: benefits and servitization. Finally, we have observed the problems that hinder its adoption.

Although the novelty of the theme, the potential of the Industrial IoT in the various areas of manufacturing, and in particular in predictive maintenance, has aroused great interest from scholars all over the world. However, some themes are still underrepresented or missing, as emerged from the revised literature. In order to provide some insights that lead to further research, we list the main shortcomings.

1. The benefits of adopting predictive maintenance with the aid of the Industrial IoT technology are little investigated

   Costs – benefits analysis to the adoption of the Industrial IoT technology for predictive maintenance are rare, even if the importance of their role in the adoption process is acknowledged by various authors (Roda, Macchi, & Fumagalli, 2018; Compare, Baraldi, & Zio, 2019). Furthermore, it would be interesting to understand the level of knowledge of these technologies among companies to figure out how deeply companies perceive the benefits. For example, Strauß, Schmitz *et al.* (2018) report that companies are reluctant to invest too much in improving their machines to the smart level, a signal of a poor understanding of the potential reachable benefits and, therefore, the return on investment.
2. There is no unanimous sharing of the direction of predictive maintenance using Industrial IoT solutions

   Even if authors recognize the potential that Industrial IoT has to evolve maintenance, there is no such unanimity in which direction this evolution will be. The vast majority of them believe that IoT technology has the potential to improve the accuracy of predictive maintenance and focus their studies mainly in this direction. Others believe that this technology takes maintenance to the next level and consider predictive maintenance as a key but not a unique element. The problem that derives from this is a continuous proliferation of names (e.g., Smart Maintenance, e-Maintenance, Maintenance 4.0), which can be traced back to a single universal matrix: the Industrial IoT technology. In this regard, a holistic view of the different nomenclatures is rare in literature and would be necessary to enhance clarity and direct efforts in a common direction.
3. Studies on the evolution of traditional business models to adapt to the future of the maintenance are rare

> If on the one hand the transition toward the digital world is deeply analysed by all the authors, on the other, only a few of them investigate the possibilities for the companies to transform the business model with the use of the Industrial IoT and the subsequent disruption that can cause to the industries. The magnitude of the change requires much more effort and attention in the attempt to smooth the transition toward the servitization of the world and the maintenance in particular.

To conclude, it is necessary to highlight that this study has a significant limitation that must be considered. Despite the efforts to include all relevant papers in the research, some articles may have been inadvertently omitted. However, we believe that the sample accurately represents the literature on the implementation of the IoT strategy to predictive maintenance and therefore, we believe that confidence may be placed on the resulting assessment.

No.	Authors (year)	Country	Title	Research method	Authors approach	Addressed themes: Benefits	Addressed themes: Barriers & Risks	Addressed themes: Servitization
1	O'Donovan, Leahy *et al.* (2015)	Ireland	A data pipeline for PHM data-driven analytics in large-scale smart manufacturing facilities	Case study	IoT-framework	Absent	Core	Absent
2	Gregor, Haluška *et al.* (2015)	Slovak Rep.	Model of intelligent maintenance systems	Conceptual framework	Business decision	Core	Absent	Absent
3	Selcuk (2015)	Bosnia	Predictive maintenance, its implementation and latest trends	Literature review	Factory field	Core	Absent	Absent
4	Terrissa, Meraghni, *et al.* (2016)	Algery	A new approach of PHM as a service in cloud computing	Conceptual framework	IoT-framework	Ancillary	Core	Ancillary
5	Kans & Ingwald (2016)	Sweden	Business Model Development Towards Service Management 4.0	Conceptual framework	Business decision	Ancillary	Absent	Core
6	Khan, Pohl *et al.* (2017)	Germany	A holistic view of the IoT process from sensors to the business value	Conceptual framework	Business decision	Ancillary	Core	Ancillary
7	Wan, Tang, *et al.* (2017)	China	A Manufacturing Big Data Solution for Active Preventive Maintenance	Analytical method	IoT-framework	Absent	Absent	Absent
8	Bergonzi, Colombo *et al.* (2017)	Italy	Data and knowledge in IIoT-based maintenance application	Simulation	IoT-framework	Ancillary	Absent	Ancillary
9	Chiu, Cheng *et al.* (2017)	China	Developing a factory-wide intelligent predictive maintenance system based on Industry 4.0	Conceptual framework	IoT-framework	Absent	Absent	Absent
10	Civerchia, Bocchino *et al.* (2017)	Italy	Industrial Internet of Things monitoring solution for advanced predictive maintenance applications	Action research	IoT-framework	Ancillary	Absent	Absent
11	Nikolic, Ignjatic *et al.* (2017)	Austria	Predictive manufacturing systems in industry 4.0: Trends, benefits and challenges	Literature review	Business decision	Core	Core	Absent
12	Sezer, Romero, *et al.* (2018)	Mexico	An Industry 4.0-Enabled Low Cost Predictive Maintenance Approach for SMEs	Action research	IoT-framework	Absent	Absent	Absent
13	Ayad, Terrissa, *et al.* (2018)	France	An IoT approach for a smart maintenance	Conceptual framework	IoT-framework	Absent	Ancillary	Absent
14	Katona & Panfilov (2018)	Austria	Building predictive maintenance framework for smart environment application systems	Conceptual framework	IoT-framework	Absent	Absent	Absent

No.	Authors (year)	Country	Title	Research method	Authors approach	Addressed themes: Benefits	Barriers & Risks	Servitization
15	Müller & Däschle (2018)	Austria	Business model innovation of industry 4.0 solution providers towards customer process innovation	Conceptual framework	Business decision	Core	Core	Core
16	He, Han *et al.* (2018)	China	Cost-oriented predictive maintenance based on mission reliability state for cyber manufacturing systems	Analytical method	Business decision	Core	Absent	Absent
17	Vafeiadis, Nizamis *et al.* (2018)	Greece	Data analytics and data modeling for predictive maintenance and automated waste management: An integrated (IoT-Industry 4.0) sensor-based solution to improve factory procedures	Case study	IoT-framework	Absent	Absent	Absent
18	Bousdekis *et al.* (2018)	Greece	Enabling condition-based maintenance decisions with proactive event-driven computing	Case study	Business decision	Ancillary	Ancillary	Absent
19	Truong (2018)	Austria	Integrated Analytics for IIoT Predictive Maintenance Using IoT Big Data Cloud Systems	Conceptual framework	IoT-framework	Absent	Absent	Absent
20	Kosicka, Kozłowski *et al.* (2018)	Poland	Intelligent systems of forecasting the failure of machinery park and supporting fulfilment of orders of spare parts	Conceptual framework	Factory field	Absent	Absent	Absent
21	Cachada, Barbosa *et al.* (2018)	Portugal	Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture	Conceptual framework	IoT-framework	Absent	Absent	Absent
22	Bengtsson & Lundström (2018)	Sweden	On the importance of combining "the new" with "the old" - One important prerequisite for maintenance in Industry 4.0	Conceptual framework	Factory field	Absent	Absent	Absent
23	Roda, Macchi *et al.* (2018)	Italy	The future of maintenance within industry 4.0: An empirical research in manufacturing	Survey	Factory field	Core	Core	Absent
24	Kaur, Selway *et al.* (2018)	Australia	Towards an open-standards based framework for achieving condition-based predictive maintenance	Conceptual framework	IoT-framework	Ancillary	Ancillary	Absent
25	Adu-Amankwa, Attia, *et al.* (2019)	UK	A predictive maintenance cost model for CNC SMEs in the era of industry 4.0	Survey	Business decision	Core	Ancillary	Ancillary
26	Omar, Minoufekr, *et al.* (2019)	Luxembourg	Business analytics in manufacturing: Current trends, challenges and pathway to market leadership	Conceptual framework	Business decision	Ancillary	Core	Ancillary

No.	Authors (year)	Country	Title	Research method	Authors approach	Addressed themes: Benefits	Barriers & Risks	Servitization
27	Compare, Baraldi, *et al.* (2019)	Italy	Challenges to IoT-enabled Predictive Maintenance for Industry 4.0	Conceptual framework	Business decision	Core	Core	Core
28	Drewniak & Gabryś (2019)	Poland	Cognitive Maintenance and Polymorphic Production as the Leading Industry 4.0 Paradigms	Conceptual framework	Business decision	Core	Absent	Absent
29	Osako, Matsubayashi *et al.* (2019)	Brazil	Cost evaluation challenges for Internet of Things (IoT) based Product/Service-Systems (PSS)	Analytical method	Business decision	Ancillary	Absent	Core
30	Rousopoulou, Nizamis *et al.* (2019)	Ireland	Data Analytics Towards Predictive Maintenance for Industrial Ovens A Case Study Based on Data Analysis of Various Sensors Data	Case study	IoT-framework	Ancillary	Absent	Absent
31	Diez-Olivan, Del Ser *et al.* (2019)	Spain	Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0	Literature review	Factory field	Ancillary	Ancillary	Ancillary
32	Bousdekis, Lepenioti *et al.* (2019)	Greece	Decision making in predictive maintenance: Literature review and research agenda for industry 4.0	Literature review	Factory field	Absent	Absent	Absent
33	Yang & Lin (2019)	Thaiwan	Development of a predictive maintenance platform for cyber-physical systems	Case study	IoT-framework	Absent	Absent	Absent
34	Poosapati, Katneni *et al.* (2019)	India	Enabling cognitive predictive maintenance using machine learning: Approaches and design methodologies	Conceptual framework	IoT-framework	Absent	Absent	Absent
35	Strauß, Schmitz *et al.* (2019)	Germany	Enabling of Predictive Maintenance in the Brownfield through Low-Cost Sensors, an IIoT-Architecture and Machine Learning	Conceptual framework	IoT-framework	Absent	Ancillary	Absent
36	Prajapati, Arno *et al.* (2019)	Canada	Enhancing reliability of power systems through IIoT - Survey and proposal	Case study	Business decision	Ancillary	Absent	Core
37	Nardelli, Papadias *et al.* (2019)	Finland	Framework for the identification of rare events via machine learning and IoT networks	Case study	IoT-framework	Absent	Absent	Absent
38	Tsao, Lee *et al* . (2019)	China	Imperfect economic production quantity models under predictive maintenance and reworking	Analytical method	Business decision	Core	Absent	Absent

No.	Authors (year)	Country	Title	Research method	Authors approach	Addressed themes: Benefits	Barriers & Risks	Servitization
39	Turner, Emmanouilidis *et al.* (2019)	UK	Intelligent decision support for maintenance: an overview and future trends	Literature review	Factory field	Ancillary	Ancillary	Absent
40	Him, Pohy *et al.* (2019)	Malasya	IoT-based predictive maintenance for smart manufacturing systems	Case study	IoT-framework	Absent	Absent	Absent
41	Apiletti, Barberis et al. (2019)	Italy	ISTEP, an integrated self-tuning engine for predictive maintenance in industry 4.0	Case study	IoT-framework	Ancillary	Absent	Absent
42	Jasiulewicz-Kaczmarek & Gola (2019)	Poland	Maintenance 4.0 Technologies for Sustainable Manufacturing - An Overview	Conceptual framework	Business decision	Core	Absent	Ancillary
43	Pauli & Lin (2019)	Germany	The Generativity of Industrial IoT Platforms: Beyond Predictive Maintenance?	Case study	Factory field	Ancillary	Absent	Absent
44	Chehri & Jeon (2019)	Singapore	The Industrial Internet of Things: Examining How the IIoT Will Improve the Predictive Maintenance	Conceptual framework	IoT-framework	Absent	Absent	Ancillary
45	De Leon, Alcazar *et al.* (2019)	Columbia	Use of Edge Computing for Predictive Maintenance of Industrial Electric Motors	Conceptual framework	IoT-framework	Absent	Ancillary	Absent
46	Cachada, Barbosa *et al.* (2019)	Portugal	Using internet of things technologies for an efficient data collection in maintenance 4.0	Conceptual framework	IoT-framework	Absent	Absent	Ancillary
47	Farooq, Bao *et al.* (2020)	China	A Data-Driven Predictive Maintenance Approach for Spinning Cyber-Physical Production System	Conceptual framework	IoT-framework	Absent	Absent	Absent
48	Yu, Dillon *et al.* (2020)	Australia	A global manufacturing big data ecosystem for fault detection in predictive maintenance	Conceptual framework	IoT-framework	Ancillary	Core	Absent
49	Ruiz-Sarmiento, Monroy et al. (2020)	Spain	A predictive model for the maintenance of industrial machinery in the context of industry 4.0	Case study	IoT-framework	Absent	Ancillary	Absent
50	Baur, Albertelli, *et al.* (2020)	Italy	A review of prognostics and health management of machine tools	Literature review	Factory field	Absent	Ancillary	Absent
51	Sahal, Breslin *et al.* (2020)	Ireland	Big data and stream processing platforms for Industry 4.0 requirements mapping for a predictive maintenance use case	Conceptual framework	IoT-framework	Absent	Absent	Absent

No.	Authors (year)	Country	Title	Research method	Authors approach	Addressed themes: Benefits	Barriers & Risks	Servitization
52	Bousdekis, Apostolou *et al.* (2020)	Singapore	Predictive Maintenance in the 4th Industrial Revolution: Benefits, Business Opportunities, and Managerial Implications	Conceptual framework	Business decision	Core	Core	Absent
53	Noureddine, Solvang *et al.* (2020)	Norway	Proactive Learning for Intelligent Maintenance in Industry 4.0	Conceptual framework	Factory field	Core	Absent	Core
54	Garcia, Costa *et al.* (2020)	Spain	Requirements for an intelligent maintenance system for industry 4.0	Conceptual framework	Factory field	Absent	Ancillary	Absent
55	Bokrantz, Skoogh *et al.* (2020)	Sweden	Smart Maintenance: an empirically grounded conceptualization	survey	Factory field	Ancillary	Absent	Core
56	Pedersen & Schjølberg (2020)	Norway	The Economic Dimension of Implementing Industry 4.0 in Maintenance and Asset Management	Analytical method	Business decision	Core	Absent	Ancillary
57	Huang, Chen *et al.* (2020)	China	Value-based contract for smart operation and maintenance service based on equitable entropy	Analytical method	Business decision	Core	Absent	Core

Chapter 5

Methodology

The chapter presents all the path that has been followed to define the research questions and the way to answer them. Moreover, it presents and explains all the approaches used to obtain information.

5.1 Research Questions and Methodology

As we have seen in previous chapters, the manufacturing sector represents a pillar for the economy of most countries in the world. In recent years, developed and developing countries are relying more and more on the growth of this sector for the expansion of the whole economy, and digital transformation is playing a fundamental role. Among the most relevant technologies of the digital transformation, the Internet of Things has the most significant potential. According to a McKinsey paper, the Industrial Internet of Things, Industrial IoT, can generate an economic impact of $1.2 trillion to $3.7 trillion per year. This considerable value "would arise chiefly from productivity improvements, including 10 to 20 per cent energy savings and a 10 to 25 per cent potential improvement in labour efficiency. Improvements in equipment maintenance, inventory optimization, and worker health and safety are also sources of value in factories." (McKinsey&Company, 2015). However, even if several countries put in place much economic measure to help companies in the digital transition, the Industrial IoT technology is still spreading slowly.

Given these premises, we first set out to analyse this technology in the manufacturing sector to understand its potential and investigate its benefits. We realized that the potential of this technology is innumerable and there are several areas in which is possible to start a project that requires specific investments (predictive maintenance, material handling, rather than monitoring parameters along the cold chain). Given the size of the field, we decided to focus on the application that seems to benefit the most and have the most significant impact: predictive maintenance.

Subsequently, we analysed the literature to investigate first how the IoT improves this technology and creates value for the different players in the value chain. Secondly, we have deepened the theme to fully understand its characteristics, the IoT structure necessary to set up, the technical and economic benefits, the barriers and any new business models that may derive from it. From this analysis, we found out that among the major barriers to adoption, there is a poor understanding of the benefits and the consequent economic return of the investment. The papers on the subject report the benefits only of a qualitative nature and without providing a deep analysis. They are generally used as evidence to substantiate their thesis. On the other side, those who venture into the creation of a model limit themselves to roughly estimate the costs rather than giving an estimate of the benefits obtainable. For this reason, our thesis work tries to fill this gap, to create a tool to quantify these benefits and able to calculate the return on investment.

Besides, we believe IoT technology gives many vendors the ability to incorporate new services into their business model that result from greater remote asset control. In an attempt to create a model that looks to the future, we decided to incorporate the predictive maintenance service, the amount of which is calculated based on the hours of actual machine activity. The vendor is able, thanks to the sensors installed on the machine, to have all the data regarding its use. Thus he can align its business model with that of its customer without risking moral hazard or opportunistic behaviour by the manufacturer. Given the potential benefits that predictive maintenance can generate for the customer, it seemed appropriate that these be shared in part with the vendor. It is in this light that we thought that our model could have a dual-use. If on the one hand, it allows the user of the machine to understand what the return on his investment will be, on the other hand, he allows the person who sells the machine to understand the benefits of which his customer benefits and consequently to define his margin.

To summarize, we can say that we first asked ourselves to understand what the benefits of IoT were in the manufacturing sector. After identifying predictive maintenance as one of the main ones, we questioned ourselves why it was so important, and we sought an answer in the literature on this by tightening the focus and creating a tailor-made research question. From this arose our research question:

Q1: Does an investment in Industrial IoT for predictive maintenance generate value for the company?

As stated earlier, the literature makes very few contributions to this topic. To try to answer as precise as possible, we decided to create an analytical tool that allows the user to evaluate the value of the investment following the insertion of variables. In this way, not only we can answer our research question but also we can adapt our model to different situations.

Primarily we asked ourselves what the tool that an entrepreneur or manager of a company uses to evaluate whether or not to invest was. In this way, we aligned as much as possible the output of our model with what is required in the strategic decision-making sphere. We have identified two main tools useful for our decision: the NPV and the ROI index. To decide between the two tools, we asked ourselves about the pros and cons, comparing them with the goal we had in mind. By needing a tool capable of evaluating the return on investment in an absolute manner, also considering the time value of money, we agreed that the VAN tool was the most appropriate for our purpose. Once we defined that the model output would be a cost-benefit analysis using the traditional NPV approach, we started looking for literature papers to follow a systematic approach. Although applied to a different area, we decided to follow the guidelines by Hanley and Spash (1993). They defined seven main steps to conduct the cost-benefit analysis (CBA):

1. According to Hanley and Spash (1993), the first step corresponds with the definition of the project and the identification of the resources to be used. In this first step, we also gather as many models as possible we found in the literature in order to have a framework to base on. Unfortunately, as stated before the topic is not much addressed; only a few contributions were found. One, in particular, was very useful for laying the foundations of our model. The paper in question dates back to 2006, when the IoT still had not made its appearance in an industrial way, and predictive maintenance was still based on rudimentary methods of data collection. However, the paper presents a simple but effective model for estimating the benefits based on the average repair time in the case of scheduled and unscheduled operations. This value multiplied by the hourly cost of the work allows us to calculate the benefit that is obtained by scheduling the interventions each an intervention is

necessary. This value then multiplied by the number of times that the predictive maintenance is successful, allows to obtain the total benefit (Hecht, 2006). However, this model has numerous limitations such as the fact that it exclusively considers a repair time differential as a benefit, does not consider the value of money over time and considers a rough estimate of the efficiency of the prediction that does not allow it to compare with any other type of maintenance if not corrective.

2. The second step corresponds to the identification of all possible impacts of the project (i.e. benefits and disadvantages). To gather as many ideas as possible and to make sure that we take into consideration all the aspects influenced by investment in predictive maintenance, we used different sources. We have collected all the benefits listed in the previously analysed literature and used the citations to investigate thoroughly. We carried out interviews in the industrial field, to have practical feedback on the main problems that emerge during a break. Finally, we used secondary sources to have the widest possible spectrum.
3. In the third step, all the possible impacts previously identified are examined, and their relevance in economic terms is assessed. In this step, many of the benefits and all the disadvantages that we previously identified were eliminated because they were considered irrelevant in economic terms and would have only added uncertainty to the model.
4. The Hanley and Spash model (1993), is structured to provide the guidelines for an application of a CBA analysis, considers in the fourth phase, the physical quantification of the economically relevant impacts. In our case, this step translates into the development of physical variables that will be quantified in economic terms in the next step.
5. The fifth step involves the transformation of the previously identified variables into monetary variables.
6. The sixth phase of the analysis applies the net present value test (NPV), which assesses whether the sum of discounted benefits exceeds the sum of discounted costs. While the model part stops at the previous step, these sixth and seventh steps are presented in the model application phase.

7. The seventh and final step of the CBA analysis is the sensitivity analysis to evaluate which variable has the most significant effect on the NPV. A scenario will be presented precisely for this purpose.

This approach presented will not be structurally present in the subsequent chapters where, for reasons of clarity, we preferred to follow a different logical course. However, it is essential to underline that these steps have been carefully followed during the model definition phase. It should also be noted that during all these steps we have tried to keep the model as generic as possible while making some assumptions and imposing some limitations that will be presented at the beginning of the next chapter. However, the idea was to create a tool as faithful as possible to reality, for this reason, the interviews carried out were useful for understanding the most used maintenance strategies (e.g. preventive and corrective maintenance).

Finally, in order to ensure that IoT technology spreads rapidly and widely also in the industrial sector, all the players involved must make a profit from investments in digital technology. What could be the incentive of a vendor to invest in making his machinery intelligent, if all the resulting benefit is captured by his manufacturer? The price surplus and the competitive advantage are certainly two aspects that should not be underestimated, but the new business models to which the IoT allows access is the real treasure. In an attempt to include this aspect in the search, we have created a research sub-question:

Sub. Q1: How can the vendor benefit from the value generated to the manufacturer?

We decided to include this aspect in the model in the form of a predictive maintenance service offered to the manufacturer to replace previous subscriptions. To bring this into the Net Present Value formula, we interpreted all the costs of the interventions previously carried out as benefits and the cost of the new subscription as a cost and therefore subtracted from the total value.

To sum up, we can affirm that the methodology we used comprehends different approaches. In particular, we have used:

- *Literature:* It represents the first step we have taken to deepen the theme of Industrial IoT, to fully understand the context and define the boundaries of this work. The analysis of the literature was fundamental to understand all the introductory notions that we then needed for our thesis work. Furthermore, once the primary thesis topic was defined, the literature was extensively revised (57 papers were analysed) to go deeper into the specific context and find the existing gaps and where to concentrate the work.
- *Interview:* To validate and find confirmation of the notions collected with secondary sources and to collect data regarding real situations, we carried out some interviews. In particular, they were essential to recover the data that allowed us to test the model, both to give a real dimension in the two imaginary scenarios, and to create the presented case study. The total interviews with industrialists are three.
- *Secondary sources:* Secondary sources were also used as a first step together with the literature to deepen the theme of Industrial IoT. In the same way, they were used at a later stage to fill in some deficiencies in the literature, as well as a secondary verification of the benefits, and therefore of the variables to be taken into consideration in the model. (papers from companies or major consultancy companies). Among others, the main sources used were the articles found on the websites of major companies, large consultancies, white papers and databases recognized as valid globally.
- *Analytical model:* To answer the research question concretely, an analytical model has been formalized, which allows evaluating the economic feasibility of investment in Industrial IoT for predictive maintenance.

Chapter 6

Model Design

This model is a new approach to the analysis of the benefits achievable from an implementation of a predictive maintenance service, introducing the vendor actor offering this service in a pay-per-performance agreement. The financial tool is the NPV. After some initial hypotheses, the formulas are described, explained the variables contained and presented its functioning. The manufacturing field appears complex, and it would be an ambitious claim stating to be able to manage it completely; therefore, we need to present a flexible structure that remains valid beyond the various estimates that will be presented, and that allows to insert new/other cost items if necessary

6.1 Model Introduction

Many variables in a production plant affect the total cost of the maintenance activity, from the downtime to the cost of the replaced spare parts. According to Komonen 2002, the percentage of maintenance costs compared to the total capitalized assets varies between 1% and 25% (Komonen, 2002). Such an incidence rate shows how fundamental it is to design the maintenance strategy better, choosing the right balance between the various maintenance policies, which maximizes both efficiency and effectiveness. The choice of maintenance policies must follow precise logics, deriving from in-depth knowledge of the plants, from failure analysis, from economic evaluations on the cost of the life cycle of company assets. The model we developed presents a detailed way of analysis of ongoing maintenance costs and helps to make informed decisions on the implementation of a new predictive strategy.

More in detail, based on input variables that characterize the state of the initial system taken into consideration, the model provides an estimation of the benefits that can be obtained by transforming the traditional maintenance paradigm into an intelligent one that implements predictive maintenance. In addition to this benefits deriving from purely technical variables, the model also takes into consideration the transformation of the business model allowed by the IoT system. The quantity and quality of data that the sensors can collect, together with the technology of transmitting information at very high speed, permit the vendors to have the opportunity to complete their business model by offering the manufactures (i.e. the companies that uses the machine) services more aligned to their needs. The model gives the possibility to consider the benefits deriving from abandoning the traditional logic of a fixed annual subscription or payments per service call (generally in urgency and at very high costs) to switch to a payment-per-performance logic. The total benefit obtained from the sum of these two is then used as a differential cash flow within a classic NPV formula for cost-benefit analysis, which allows understanding the feasibility and the goodness of the investment.

This model to estimate the economic value creation has been implemented in Excel and tested in different scenarios. Thanks to a division into two parts between costs deriving from technical variables and those deriving from the implementation of the new subscription, the model can evaluate the benefits deriving from the two and suggests whether to invest in Industrial IoT for a predictive maintenance solution or just a new type of subscription.

This structure of the model allows the results to be interpreted from two points of view: the manufacturer and the vendor himself. The manufacturer can objectively evaluate the convenience of an investment in Industrial IoT solutions for predictive maintenance on each of his machines; the vendor, on the other hand, can take advantage of the model to understand the benefit generated for the user of his machinery, leveraging on this value as a competitive advantage over competitors.

In the next sections, we will go in deep with the functioning of the model. We will first set the hypotheses necessary to let the model works, and we will explore the formulas that compose the model to have an entire overview. Once the general and secondly go in deep in understanding the functioning step-by-step.

6.2 Hypotheses

The model is a simplification of reality intended to promote understanding and comprehension. Hypotheses are essential to achieve these objectives, and to arrive at their definitions, the base terminology of the different maintenance approaches is initially presented.

6.2.1 The As-Is and To-Be Overview

According to Zio & Compare (2012), there are two macro areas of possible approaches in maintenance: corrective and preventive. In the first group, the components are managed until failure, and then repairs or renovations are conducted[22]. Preventive maintenance, on the other hand, includes all the actions performed in the attempt to keep an item in specified conditions, providing systematic inspection, detection and prevention of incipient failures. Accordingly, preventive approaches can be further divided into three subgroups: scheduled maintenance, if the actions are performed based on a predetermined condition[23]; condition-based maintenance, which uses monitoring to identify problems at an early stage and performs actions when the level of degradation reaches a threshold; and predictive maintenance, the degradation of component is predicted in the future, and its Remaining Useful Life (RUL) is estimated. Even if different approaches of the same macro area, the last two can be considered as one the evolution of the other. Indeed, the predictive maintenance approach takes its roots in the condition-based type and evolves it. Starting from this macro classification, the proposed model considered two possible as-is situations: the corrective maintenance and the scheduled maintenance (specifically the time-based one, based on a calendar schedule). In this way, we can have a more realistic starting point of the model since several companies adopt both these strategies and a more representative value of the return on the investment. It would be an error considering predictive maintenance as only a substitute for the corrective one (Compare, Baraldi, & Zio, 2019). Based on this consideration, we could set a hypothesis zero to highlight the starting point of the model:

H0: As-is is represented by corrective and time-based maintenance.

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[22] The corrective maintenance is the oldest approach and is nowadays still adopted, especially for equipment which is not crucial for the production performance of the plant or considers safety-critical, and whose spare parts are easily available and not expensive (Zio & Compare, 2012).

[23] The key issue in the Preventive Maintenance is to determine the optimal intervention intervals (i.e., the time spans between two successive maintenance actions), which balance the costs of actions with the production and safety benefits obtained from repairing/substituting a component before it experiences a failure.

Some considerations regarding the solution proposed are also necessary. The Predictive Maintenance is based on different procedures/methods: knowledge-based, analytical and data-driven (Alzghoul, 2014). The experience needed to perform the first method and the difficulty in modelling the machine/system failure with the second (van Rijn, 2007), leave space for growth to the third option, empowered by data accessibility enabled by Industrial IoT. Literature concentrates much effort into explaining the framework to implement data-driven predictive maintenance, from data collection and preparation to algorithm evaluation (examples, supervised or unsupervised). The architecture to be adopted is widely present as well, evaluating from edge to fog and cloud solutions, structure capable of managing real-time and big data. In the model, this part is assumed to be already performed by the vendor of the machinery/system, which provides the manufacturer with a complete solution for monitoring and predictive analysis. The to-be considered is represented by a predictive maintenance service bought from the manufacturer, furthermore, in a pay-per-performance agreement (a virtuous example of this offer is Fabio Perini spa, the case study presented in the section 3.2). It is supposed that different failures can be monitored using the same architecture, enhancing the multi-use and interoperability characteristics of an Industrial IoT solution, no more closed in a silos perspective. The model is designed for a cost-benefit analysis of a single machinery at a time. Application does not exclude old machinery (where no data acquisition and connectivity are available in the as-is, the so-called brownfield problem[24]), as long as a retrofitting with sensors allows the creation of the cyber-physical system for predictive maintenance.

H1a: For a specific machinery, the manufacturer buys a predictive maintenance service offered by the vendor in a Pay-per-Performance agreement.

[24] The so-called brownfield problem is the challenge of embedding predictive maintenance solutions into existing framework conditions (Strauß, Schmitz, Wöstmann, & Deuse, 2018).

H1b: The initial investment includes the "acquisition" of the Industrial IoT architecture, enabling a complete monitoring and predictive analysis.

6.2.2 Type of Intervention and its Characteristics

A further hypothesis regards the cost per intervention. Following the definition given on the type of maintenance (with a first division between corrective and preventive), the maintenance interventions could be generally divided into two groups as well, depending on whether they are performed before (and so we assumed a scheduled intervention) or after the component failure (unscheduled intervention) (Zio & Compare, 2012). Intervention costs could be expanded, including all the effects of the stop on the overall system (for example, penalties). Unscheduled intervention cost can be supposed more volatile than scheduled one, due to the uncertainty of the timing of the breakdown event. The time when a component fails is crucial on the general performance (Hecht, 2006), influenced even just from different availability of maintenance capability. In the model, an estimate of the necessary variables will be formalized, giving them an average annual value.

H2: The formalization of costs per intervention lies in the division into two types, unscheduled and scheduled intervention cost, estimated on an annual basis.

The next argument regards the types of failure that could affect the system/machinery. The non-accidental failures are characterized by an unavoidable natural phenomenon: the degradation (Baur, Albertelli, & Monno, 2020). Traditional analysis tools are adopted to investigate the causes and effects of failure (for example, root cause analysis, fault tree analysis, and Failure Mode and Effect Analysis). In a conceptual phase, the asset behaviour/conditions depending on time can be represented by a health time curve. What is usually reported is the P-F curve, that generally it represents the same concept but specifically highlighting two essential ideas of predictive maintenance: the potential fail (detectable state) and the functional fail (failed state). The interval between the two represents the time windows in which predictive maintenance should be executed to limit the consequences. Only components emitting signals of deterioration can be successfully managed with predictive maintenance. In the model, we assumed that once the intervention is performed, the initial conditions are restored. The system is supposed to run until its design life, regardless of the maintenance approach used. With this assumption, the potential benefits from moving from a corrective to predictive maintenance could be underestimated, considering preventive interventions being able to extend the useful life of the machinery (McKinsey&Company, 2015).

H3: The intervention will restore the initial condition of the machinery, letting the system runs until the design life.

In this section, we discussed the starting point and the hypothesis of the model, from maintenance approach definitions to the key concepts that will be relevant in the next chapters. Other smaller assumptions will be taken during the model’s explanation, coherent with the objective of this thesis to represents the possible benefits and costs of an Industrial IoT application from the manufacturer’s but also from the vendor’s point of view.

6.3 Model Principles

The final output of the model is represented by the Net Present Value of an Industrial IoT solution enabling a predictive maintenance service in a pay-per-performance agreement with the vendor. The NPV allows keeping different cash flows per year. The cash flows are represented by the two major themes of the model: the savings deriving from the transition from as-is maintenance to predictive maintenance, and the cost difference between the dynamic subscription Pay-per-Performance, and previous maintenance cost.

The investment in sensors can be declined in various applications, allowing a predictive analysis as well as a more diffuse check of the operating status of the machinery. This aspect will be taken into consideration in order to evaluate a transition to a pay-per-performance payment agreement even if the predictive maintenance shift results disadvantageous on some failure type clusters. The NPV structure taken as a reference is the following.

$$NPV = -Inv_0 + \sum_{i=1}^{n} \frac{Sav_{PdM,i} - DiffMSC_i}{(1 + WACC)^i} \tag{1}$$

- NPV [€] *(Net Present Value)*: It represents the final object of this model, taking into account the different value of the cash flow over the useful life of the asset;
- $Sav_{PdM,i}$ [€] *(Savings Predictive Maintenance per year)*: The global Saving that derives from the shifts to a Predictive Maintenance approach;
- $DiffMSC_i$ [€] *(Difference in Maintenance Service Cost)*: The differential between the cost of the Pay-per-Performance subscription and the previous maintenance cost;
- Inv_0 [€] *(Initial Investment)*: The investment is presented as the undividable cost to digitalize the machinery (Hypothesis *H1a*);

- $WACC$ [%] *(Weighted Average Cost of Capital)*: This variable represents the Weighted Average Cost of Capital of the firm. It is supposed to be fixed over the year during the lifetime of the machinery;
- n [$year$] *(Useful Life)*: Year of useful life (i is the variable used to move from year 1 to n).

In the next two sub-chapters the Sav_{PdM} and $DiffMSC$ variables are described more in detail.

6.3.1 Maintenance Strategy Comparison

To perform the correct assessment of the investment and to consider the different types of failure of the single machinery, it is necessary to identify different clusters that can be formed according to the following variables:

- The maintenance strategy adopted;
- The economic impact of the intervention;
- The performance of the forecasting algorithm for the specific failure type;
- Other failure characteristics;

The change from as-is to predictive maintenance needs to be analysed cluster by cluster, and this is required to take into account the wide diversity of machine failures that leads to different saving evaluation. Predictive maintenance can be disadvantageous in some circumstances, and in those cases, the algorithm will suggest maintaining the as-is maintenance strategy. Only the positive savings of the specific clusters will be taken into account for the calculation of the Sav_{PdM} to be included in the NPV formula.

$$Sav_{PdM} = \sum_{j=1}^{k} Sav_{PdM,\mathrm{j}} \quad with \ Sav_{PdM,\mathrm{j}} > 0 \tag{2}$$

- Sav_{Pdm} $[€/y]$ *(Savings Predictive Maintenance)*: Annual savings achievable overall considering the ones of clusters that predictive maintenance change results to be positive. This calculation is repeated year by year;
- $Sav_{Pdm,j}$ $[€/y]$ *(Savings Predictive Maintenance per Cluster)*: Annual savings per cluster, which has its specific form in case the as-is situation is corrective (3) or preventive maintenance (4);
- k $[\#cl]$ *(Cluster Number)*: The number of clusters taken into account per machinery (j is the variable used to move from cluster 1 to k).

As anticipated, the structure of the savings for each cluster is a function of the maintenance strategy. The resulting formula for corrective maintenance is:

$$Sav_{PdM-CrM} = IC_{un} \cdot TP - IC_{sc} \cdot (FP + TP) + EXC_{CrM} \tag{3}$$

In case of preventive maintenance, the formulation changes in:

$$Sav_{PdM-PvM} = IC_{un} \cdot (B - FN) + IC_{sc} \cdot (S - FP - TP) + EXC_{PvM} \tag{4}$$

In both cases, the structure results to be similar, presenting the estimate of the number of times an unscheduled or scheduled intervention is necessary during the year, multiplied by the cost per intervention of that type, plus costs directly attributable to that maintenance approach. The shared variables are related to the intervention cost and the predictive algorithm performance.

- IC_{un} $[€/_{int}]$ and IC_{sc} $[€/_{int}]$ *(Cost per intervention)*: they represent the cost per unscheduled and scheduled intervention respectively;
- TP $[^{int}/_{y}]$: True Positive;
- FP $[^{int}/_{y}]$: False Positive;
- FN $[^{int}/_{y}]$: False Negative.

True positive, false positive and false negative are variables indicating the ability of the predictive maintenance algorithm to provide the right forecast of the failure. They will be declined in the concept of Precision and Recall (section 6.9). For the comparison with corrective and preventive maintenance, other variables were declared.

In case of corrective maintenance, the specific variable is:

- EXC_{CrM} $[{}^{€}/_{int}]$ *(Exclusive Cost related to corrective maintenance)*: It takes into account the cost of service intervention (internal or external) and an explicit warehouse cost.

In the preventive maintenance approach, the specific variables are:

- EXC_{PvM} $[{}^{€}/_{int}]$ *(Exclusive Cost related to preventive maintenance)*: In this case, it considers the service cost as fix subscription or a portion of the internal maintenance department cost;
- S $[{}^{int}/_{y}]$: Number of service intervention per year;
- B $[{}^{int}/_{y}]$: Estimate of the number of corrective interventions still required in case of preventive maintenance.

It is essential to understand how the cost per intervention IC is calculated. In the model, it has a structure shared either the intervention is unscheduled or scheduled. The specific cost variables are mutual between the types of intervention. When the model is applied, those same variables acquire a different value. We could identify three large cost groups:

$$IC = DTC + SpC + Pnlt \tag{5}$$

- DTC $[{}^{€}/_{int}]$ *(Downtime Cost)*: The downtime-related cost considering the impact of a stop of the considered machinery;
- SpC $[{}^{€}/_{int}]$ *(Spare part Cost)*: The cost to replace or repair the component/system;

- $Pnlt\ [^{€}/_{int}]$ *(Penalties)*: The penalty cost in case of miss client agreement.

These variables will be further explored in the following chapters. Ultimately, a more general consideration wants to widen the scope of this formulation, which leaves, if necessary, the possibility to insert additional costs to fit the specific case of application. This flexible structure can be considered a salient point of the goodness of the model.

6.3.2 Dynamic Payment Method

Pay-per-performance agreement is an ever-existing payment method, and in this last period, it is experiencing a new popularity in the BtB sector. The re-discovery of the term can be related to the digital innovation that, through the Industrial IoT, provides increasingly advanced data collection and analytical methods, making possible more immediate and easy-to-build analyses, from establishing system performance onwards. The transition to a dynamic payment agreement will be taken into consideration even if not all the clusters of the machinery move from the as-is to the predictive maintenance type. This assumption relies on hypothesis *H1a* in which the Industrial IoT investment on the machine is unique and leads to a complete acquisition of the operating data. The different declination of the investment (not only for a predictive maintenance application) wants to enhance the multi-use characteristics of Industrial IoT solutions. Below the cost of the Pay-per-Performance subscription is presented.

$$DiffMSC = PpPSub - MSC_x \tag{6}$$

$$PpPSub = Fee \cdot (Wh - DownTime) \tag{7}$$

- $DiffMSC\ [^{€}/_{year}]$ *(Difference in Maintenance Service Cost)*: The difference between the cost of the Pay-per-Performance subscription and the previous fixed annual one (not already accounted in the savings from the shift from as-is to predictive maintenance);

- $PpPSub\ [^{€}/_{year}]$ *(Pay-per-Performance Subscription)*: It represents the cost of the Pay-per-Performance subscription. A possible formulation of this cost is represented by the cost per ensured hours established from the vendor (Fee $[^{€}/_{hour}]$) multiplied by the possible UpTime of machinery operation, represented by the difference between agreed working hours and the machinery downtime ($Wh - DownTime\ [^{hour}/_{y}]$);
- $MSC_x\ [^{€}/_{y}]$ *(Previous Maintenance Service Cost)*: it represents the previous fixed annual subscription or service intervention cost not already accounted in the savings (2), which means when the cluster of failure is not taken into account for the shift to predictive maintenance approach. It could be formulated as follows:

$$MSC_x = \sum_{j=1}^{k} EXC_j \quad with\ Sav_{PdM,\mathrm{j}} < 0 \tag{8}$$

The shift to a Pay-per-Performance agreement will create a closer relationship between the company owning the machinery and the vendor, giving to the maintenance the typical flexibility of a service. To conclude the chapter model principles, the formula of the DownTime (the dynamic part of the subscription cost) is presented:

$$DownTime = \sum_{j=1}^{k} (MTTR_{un,j} \cdot I_{un,j} + MTTR_{sc,j} \cdot I_{sc,j}) \tag{9}$$

- $DownTime\ [^{hour}/_{y}]$ *(Downtime)*: The downtime represents one of the key variables in the maintenance sector, with the Mean Time To Repair declined in $MTTR_{un,j}$ and $MTTR_{sc,j}$, in case we considered an unscheduled or scheduled intervention respectively (j is used to indicate which cluster has been referred to, moving from 1 to k)

- $I_{un,j}$ $[int]$ and $I_{sc,j}$ $[int]$: These variables refer respectively to the estimated number of corrective and preventive interventions of the specific cluster with the type of maintenance chosen after the evaluation performed in formula (2).

6.4 Flowchart of Model Functioning

In the previous paragraph, we provided an overview of the model and the more general formulas has been presented. In this part, we will analyse step by step the model in order to provide a more detailed guide and enhance comprehension. The diagram in *Figure 6.1* shows the macro areas that characterise the model and define its functioning. First, it is necessary to understand the production plant and machine characteristics on which the model is to be applied. Depending on these characteristics, the initial costs change and consequently, the convenience to activate a predictive maintenance solution with the use of Industrial IoT. Among these variables, a separate discussion is dedicated to those relating to the failure rate and the failure distribution. Subsequently, in section 6.8, the possible IoT systems that can make the failure prediction system smart are presented. Finally, in section 6.9, any benefits deriving from the predictive maintenance solution are assessed. After the definition of some variables by the user, the NPV of the solution is calculated. In the following sections, we will deepen all of these parts to explain in detail the formulas and the variables that must be considered.

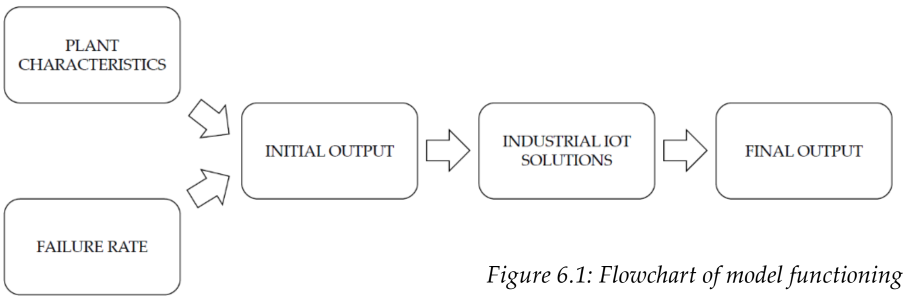


Figure 6.1: Flowchart of model functioning

6.5 Plant Characteristics

The first step in making the model work is the definition of the general initial conditions, the as-is situation. The first values to insert in the model are the number of clusters and the correspondent maintenance policies according to the variables expressed in section Maintenance Strategy Comparison. Many variables contribute to the definition of the total maintenance cost: the costs deriving from downtime, those deriving from the personnel assigned to the interventions and the necessary spare parts represent only a part of the total which according to Bevilacqua & Braglia (2000) represents between 15 and 70% of total production cost (Bevilacqua & Braglia, 2000). An estimate that has a vast range but that makes the idea of the value at stake. In this section, the first variables to be taken into consideration and inserted in the model are explained.

To calculate in detail the total cost of maintenance, it is, therefore, necessary to first define the total cost of maintenance intervention. In this regard, we start from the general formula 10, which will then be declined, in the different types of maintenance in question.

The cost formula is:

$$IC = DTC + SpC + Pnlt \tag{10}$$

Where IC is the cost activated every time there is a maintenance intervention (i.e. Intervention Cost). It is composed by a variable part that depends on the time the machine is not working because of the intervention (i.e. downtime cost - DTC) and a fixed part: the cost of spare parts the technician has to replace (SpC) and the penalties that must be paid in case of delay (SpC).

As stated previously in the hypothesis, the model base is functioning on the application of this formula for the computation of the cost per unscheduled and scheduled intervention. Apart from the corrective maintenance, which considers only the cost of the unscheduled intervention, both the preventive and the predictive are a composition of the two. Therefore, whatever type of maintenance the company is implementing, it is fundamental to underline that both, the unscheduled and the scheduled cost must be completed to let the tool work.

Several other costs contribute to the overall cost of the intervention. However, some of them will be considered later since they do not vary according to the number of interventions. Some other costs are intentionally left aside because we believe that their calculation is of marginal importance. For instance, the cost of non-compliant pieces produced after a breakdown occurs, that can be considered the sum of the cost of the pieces worked while the machine is working in bad condition. The cost of re-working these pieces is minimal respect to the overall amount of pieces that cannot be produced while the machine is not working. Moreover, this value strongly depends on the situation and can have huge differences from time to time, making his estimate highly inaccurate and therefore adding uncertainty to the system.

6.5.1 Downtime Costs

Downtime is the time when the machine is not working, which means that no value is being produced for the company. Process managers struggle to try to make their impact as lower as possible. However, even if companies are aware of the effect of the downtime, 80% of the companies are unable to calculate their exact downtime costs correctly (Immerman, 2018). A distinction between planned and unplanned downtime must be made because the greatest expenses come from the unplanned one (for example, excessive tool changeover, excessive job changeover, lack of operator, and unplanned machine maintenance). Besides, it is important to specify that unscheduled interventions are entirely unplanned, while scheduled one is planned intervention even if they can generate unplanned downtime if not carried out correctly. Since the focus of our model is on maintenance, we will only consider the downtimes linked with these type of interventions and therefore, their costs.

Since a downtime generate not only the stoppage of the faulty machine but also it produces efficiency losses in the production lines or the machines nearby, the formula sum both of them as follow:

$$DTC = DTC_{machine} + DTC_{plant} \tag{11}$$

The downtime cost of the machine is:

$$DTC_{machine} = MTTR \cdot \sum_{h=1}^{m} (RPR_h \cdot BK_{\%,h} \cdot GP_{u,h}) \tag{12}$$

Where:

- $MTTR\ [^{h}/_{int}]$ *(Mean Time To Repair)*[25]: It corresponds to a metric used by the maintenance departments to measure the average time needed to determine the cause and repair the failed equipment. Il includes:
    - Notification to maintenance technicians and, since case the intervention is made in outsource, the time to intervene on the spot;
    - Diagnosis of the problem;
    - Solve the problem;
    - Reassembly, alignment and validation of equipment;
    - Restore, test and start the equipment or system for production.

  In addition to these standard values, in the corrective case for our model, it is important to also include any other time that the machine stops due to the fault (e.g. lead time spare parts). Furthermore, it is important to specify that even if in theory the value is used exclusively to respond and

[25] In this paper, *Mean Time To Repair* and *Mean Time To Recovery* are assumed as synonymous.

repair unplanned failures, in this model the MTTR is also used for planned maintenance interventions with the necessary arrangements.

In particular, to have a rough estimation of the MTTR in case of scheduled intervention, it is possible to consider only the time needed to solve the problem and restart the machine. All the other time can be considered wasted and therefore eliminated in a scheduled maintenance activity. In case it is not possible to have an estimation with this level of detail, the Mean Time To Repair in scheduled and unscheduled situations can be obtained from the historical series applying the following formula:

$$MTTR = \frac{Total\ maintennce\ time}{Number\ of\ repairs}$$

In case the scheduled time wants to be obtained, the ratio has to be done between the total maintenance time of the scheduled intervention and the total number of scheduled repairs; for the unscheduled MTTR, it has to be calculated as the ratio of the unscheduled time and the following repairs.

In case the company only performs unscheduled maintenance and does not have any data about scheduled interventions, or vice versa, a good approximation can be obtained using a percentage reduction (or increase) of the unscheduled MTTR. According to the Federal Energy Management Program publication, this value is around 35-45% less than the corrective one (U.S Department of Energy, 2010), while a McKinsey analysis of 2015 estimate that the gain can be up to 50%.

- RPR_h [$^{pc}/_{h}$] (*Real Production Rate)*: The real production rate refers to the number of goods that can be produced in an hour considering the mix, the availability of the machine and all the other aspects that can reduce the overall output. The subscript h indicate the products (from 1 to m) that are worked on the faulty machine. For example, supposing that machine 1 produces products A, B and C with a production rate (that already considers all the operative downtime of the machine) of 100 pc/h, 50 pc/h and 200 pc/h respectively. The machine works 2 hours a day on product A, 3 hours a day on product B and 3 hours a day on product C.

To calculate the hourly mix of three it must be multiplicate the number of hours the machine works each piece by its production rate, and the result divided by 8, the total number of hours a machine work a day. This value is an estimation of the hourly mix produced by machines since it can vary from year to year or even every day. These values should be well known to the COO of the companies or even to the owner itself.

- $BK_{\%,h}$ [%] (*Percentage of slowdown due to the Breakdown)*: This value is used to adjust the effect of a breakdown. It is a measure of how much a breakdown slow down the production of the product h produced by the faulty machine. This percentage can vary according to different characteristics of the plant. For example, assuming to be in a job shop layout, where piece A, B, C, D and E are worked on machine 1 in a given mix. Supposing no other machine in the plant can process products A, B and C and no other time windows where recover the loss production, the breakdown of machine 1 stop their production by 100%. Therefore, the $BK_{\%,A}$, $BK_{\%,B}$and $BK_{\%,C}$ is equal to 100%. Slightly different is the case of D and E. These two products can also be processed by machine 2. Machine 2 processes product F, G and H, and it is fully saturated with their production. In this case, if the company want to continue to produce product D and E has to decrease the quantity of the products already processed on the machine[26]. Therefore, the slowdown due to the break of machine 1 on product D and E is not total and their $BK_{\%,h}$ is to be considered lower than 100%.

When the value is different than 100%, it is difficult to provide a precise and general formula to evaluate it because it depends on too many variables. Therefore, the value to be entered is left to the interpretation of the user machinery based on his experience.

[26] The algorithm does not provide a logic to follow to redirect the flow.

- $GP_{u,h}$ [$^{€}/_{pc}$] *(Unitary Gross Profit)*: It represents the unitary gross profit of the good h processes by the faulty machine. It is the difference between the price and the production cost of the good.

The formula of the downtime cost for the plan has the same appearance as the one of the machine:

$$DTC_{plant} = MTTR \cdot \sum_{h=1}^{m} (RPRO_h \cdot OE_{\%,h} \cdot GPO_{u,h}) \qquad (13)$$

Where:

- $MTTR$ [$^{h}/_{int}$] *(Mean Time To Repair)*: It corresponds exactly to the same amount considered in the formula (12).
- $RPRO_h$ [$^{pc}/_{h}$] *(Real Production Rate of the plant)*: As the previous production rate, this value corresponds to the real number of goods that can be produced in an hour considering the mix, the availability of the machine and all the other aspects that can reduce the overall output. However, contrary to the other, it is not focused on a single machine, but it considers all the other machines that are affected by the faulty machine.
- $OE_{\%,h}$ [%] *(Percentage of slowdown due to the breakdown in other machines)*: This variable corresponds to the percentage of slowdowns of all the other products that are produced on machines that are influenced by the breakdown. $OE_{\%}$ varies according to the same characteristics as the $BK_{\%}$, and it is difficult to provide a single formula to calculate it. Taking the previous example, if the production manager decides that product D and E cannot stop, they must divert them on machine 2. However, machine 2 is already fully saturated by product F, G and H and therefore to move the production on machine 2 their amount must be reduced. This second part of the formula for the downtime cost take into account this aspect, all the products that are not produced on the faulty machine but are still affected are considered, and $OE_{\%}$ is used as the percentage reduction.

Even if the value could be considered in the machine downtime cost and only one formula can be computed, we separated them for two reasons. First, it is clearer what the contribution of each part is; secondly because this formula can be used to take into account eventual loss in productivity of other machines due to other indirect costs that are linked with the lower production rate due to the breakdown. From the example, it is evident that provide a formula for the calculation of $OE_{\%}$ has the same obstacles of the formula of $BK_{\%}$ because it is not easy to calculate mathematically how the breakdown of one machine can influence the others. Therefore, since too many variables influence this value, it is left to be estimated by the end-user of the model based on his experience.

- $GPO_{u,h}$ $[{}^{€}/_{pc}]$ *(Average Unitary Gross Profit)*: This value corresponds to the average gross profit of the entire products whose production is slow down by the breakdown. It is calculated with the same logic of the previous.

6.5.2 Spare Parts

A spare part is an interchangeable part that is stored in a warehouse and used for the repair or replacement of failed units. Under this denomination, many costs could be considered. However, for the calculation of the intervention cost, only the variable part (i.e. the pieces that are replaced in the intervention) are considered. Other costs as the rent of the space, the salaries of the warehouse staff, all the handling costs and other "out-of-pocket" expenses are not considered in this calculation. While in the next sections we will deepen the opportunity cost of the invested capital in the spare parts warehouse, we did not include in the model the other costs related to the warehouse storage previously mentioned due to their high uncertainty in the allocation and the low incidence at a single piece level.

The formula of the spare part is:

$$SpC = DSpC + ASpC \tag{14}$$

Where:

- $DSpC$ $[^{€}/_{int}]$ *(Direct Spare part Cost)*: This variable represents the cost of the spare part that technicians have to change after the breakdown occurs (or when they perform preventive interventions) to fix the machine. To calculate it, the total number of spare parts replaced in one year must be divided by the overall amount of the interventions conducted.
- $ASpC$ $[^{€}/_{int}]$ *(Additional Spare part Cost)*: When no preventive action is taken to avoid fault, the breakdown that occurs, if not detected promptly, can cause the breakdown of other pieces. This variable takes into account this aspect, and therefore, it is different to zero only in case of unscheduled interventions. The value is calculated as the previous one.

6.5.3 Penalties

The agreement between a supplier and a buyer for the delivery of goods generally provides for an attractive delivery date for the seller. Since a failure to deliver the goods within the established times could cause a loss for the customer, to encourage the supplier to meet the deadline and divide the risk, it is possible to specify in the contract the application of penalties for delayed delivery. This variable is included to consider this aspect in the model. Indeed, a failure in the machine, if not fixed in time can generate delay in the delivery. While the impact of this variable is extremely high in the case of an unscheduled intervention, in case of scheduled we assume it equal to zero, since there is the possibility indeed to schedule the intervention in the best moment possible. It is difficult to provide a univocal way to calculate the formula since it varies enormously from case to case; different subjective aspects could be taken into account. In the GDO industry, for example, a delay in the delivery of the products can cost the company to be substitute with another who sells the same products or in the machine production industry can be a penalty caused by the fact that the client cannot produce and sell a specific good. Therefore, because of these conditions, this variable is left to be estimated to the end-user of the model, according to the contract they have.

6.5.4 Additional Costs

Although at a glance, it may seem that the downtime costs are exclusively costs related to the repair of the machine, we have seen in the previous paragraphs that several others must be considered. When a machine stops working due to a breakdown, the costs of spare parts must be considered as the cost of non-production, (the cost of loss of efficiency of the workers) and the cost of possible breaches of the contract with the customer (for example, delayed delivery).

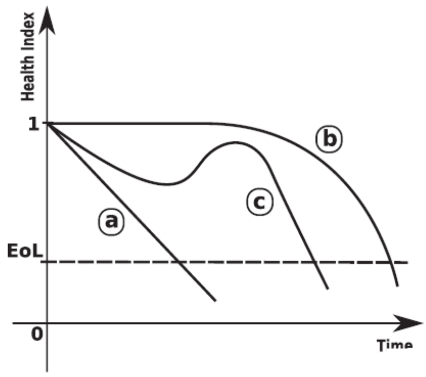
Other costs can be taken into account when calculating the total cost of downtime. There may be recovery costs, such as the cost of employees working overtime and the costs of data recovery, or there may be the costs of reworking some pieces that have gone wrong and the costs of the pieces to be discarded. However, as mentioned above, these costs are not taken into account in the model because they have a reduced impact compared to those considered.

Besides these, there are other more difficult costs to determine (i.e. intangible costs), such as any damage to reputation or brand, stress. Intangible costs may be difficult to predict, but having a thorough understanding of the potential long-term impact on future sales and customer retention can help entrepreneurs and managers to have a clear view of the real cost of downtime and take countermeasures to stem it. Our model does not provide a specific cost item for each of these, because as we have seen, they can have a huge impact in certain industries and be completely irrelevant in others. However, if one or more of these intangible costs that have a notable impact on the overall cost and they are known or can be estimated, these can be simply considered in the intervention costs summing them in the penalties variable ($Pnlt$).

6.6 Failure Rate

The failure of the machine could be caused by several reasons, from wear and corrosion to fatigue, fracture and instability. Failures can be divided into complete and partial, both of which are classified into sudden and gradual (Nakagawa, 2006). The progress of the unavoidable natural phenomena listed before, can be represented by a health index function of time. Different patterns can be identified depending on the degradation mechanism involved:

a) A single-stage degradation pattern, associated with a monotonic and continuous degradation process until machine failure or stop; the curve profile is usually represented by linear or exponential function (*Figure 6.2*);
b) A two-stage degradation pattern, characterized by an initial healthy stage with no evidence of fault and a second stage leading back to the described pattern 1 (*Figure 6.2*);
c) A three-stage degradation pattern, happening when, next to a worsening of the health index, it can be observed a decrease of the defects in happening, after which an increase in size will manifest again (an example, the rolling bearings inner surface fault: initially characterized by many vibrations due to the bumps of the rolling elements on the surface; then the defects is smoothed by the continuous impacts before starting to increase again) (*Figure 6.2*);
d) A multi-stage degradation pattern, it is often the case of a complex system by multiple, interactive and concurrent faults (Baur, Albertelli, & Monno, 2019).



(Baur, Albertelli, & Monno, 2020)

Figure 6.2: Examples of health index time profiles.

The health (or degradation) curve can also be used to define the right time of intervention in case of condition-based or predictive maintenance. The object is to minimize the risks associated with the failure (Basson, 2017). In this case, the curve changes its name in the P-F curve. As for the health curve, asset performance or condition declines over time, leading to the loss of function for which it was intended. The transition from a healthy to an unhealthy stage, could vary from being instant to a long degradation process (Bousdekis, Apostolou, & Mentzas, 2020). The time windows between the potential failure P (representing in the P-F curve the time when it is possible to detect that the equipment is in the process of failing), and the functional failure F (the time where satisfactory performance standard are no longer met) will be key in understanding the ability of predictive maintenance to arrange on time an intervention. An example that results challenging to predict is often consider the electronic component faults with degradations not progressive and observable (Baur, Albertelli, & Monno, 2019).

In this scenario, the definitions of the primary variables are required. How long can a unit/system operate without failure? Reliability is the answer to this question defined as "the probability that the system/unit will perform a required function under stated conditions for a stated period"[27]. Failure is usually represented by mechanical breakdown, deterioration beyond a threshold or, looking to system performance, appearance of certain defects or decrease beyond a critical level; the failure rate is the most important quantity in maintenance theory, used as a measure for the aging phenomenon (how a unit/system deteriorates with its age) (Nakagawa, 2006). The Weibull statistical distribution (with parameter η and β) is the used function to represent the behaviour of reliability through the life of the asset (Durán, Afonso, & Durán, 2019). With the Weibull parameters, it is possible to estimate the failure rate λ for a given component in time:

$$\lambda(t) = \frac{\beta}{\eta} \cdot \left(\frac{t}{\eta}\right)^{\beta-1}$$

Setting different specific values of β[28], the profile obtained will result to be the bathtub curve (in

Figure 6.3, it is represented by the SP_3 pattern), which is used to describe the behaviour of failure rate over time. Three phases can be described: (1) the infant mortality, where the failure rate λ decreases over time, (2) the useful life where λ remains constant and (3) the wear-out phase, λ increases until the equipment will be discarded (Durán, Afonso, & Durán, 2019).

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[27] The reliability presents a mathematical formulation passing through the integral of the *failure density function* from t to infinity. For the rigorous structure of the formula we referred to Nakagawa (2006).

[28] β is called the shape parameter due to their effect on the λ profile. The other parameter η is representative of the scale and of the characteristic life of the equipment; its value corresponds to the time in which 63,2% of the failures are expected to occur.

(Durán, Afonso, & Durán, 2019)

Figure 6.3: Examples of three-failure rate pattern

Different sub-optimal environment conditions (e.g., reactive agents, temperature, vibration) will affect the parameters of the equation, moving them dynamically. The proposed model needs as input a single value per year that could be represented by the sum of the failure rate of the specific cluster. A fixed/constant failure rate assumption could be considered a good approximation of reality, when different distribution functions for a variety of components are combined (Geitner & Heinz, 2006).

Failure rates are usually expressed in events per million hours. Machinery component failures will lie mostly between 1 and 100 failures per million hours (Geitner & Heinz, 2006). A failure rate of $\lambda = 123 \times 10^{-6}hr$ corresponding to almost one failure yearly (over 8000 hours per year). The estimate of the failure rate could be calculated at the component level until considering the entire machinery. The complexity of a multi-component system in a changing environment represents a crucial aspect if it also considered the correlation between different failure mechanisms. The information about the failure rate is expected to be retrieved directly from the vendor, who can leverage the design engineer capabilities. The effect of the environment could be considered evaluating the best and worst scenario. If the manufacturer has operating experience to rely on, he can estimate the failure rates starting from field statistics. An example taken from Geitner & Heinz (2006) is reported below in the table: from a recorded percentage of failure regarding an element, the failure rate can be found as the multiplication of the percentage by the equivalent failure rate of two incidents yearly on the machinery.

Elements	Failures (%)	Rate per 1×10^6 hr
Valves	43.0	98.4
Pistons and cylinders	19.0	43.0
Lube systems	18.0	41.0
Piston rods	10.0	22.8
Packings	10.0	22.8
Total	100.0	228.0[a]

[a] Equivalent to two incidents per year.

(Geitner & Heinz, 2006)

Table 6.1: Example of how failure rate data for machinery components can be obtained from field statistics starting by the total number of the registered failure

From a broader perspective, the model will consider describable by a failure rate every condition that will be subject to maintenance intervention, from example, the machinery level of oil, the corrosion of some components exposed to adverse environmental condition or the crack of the mechanical component.

6.7 Initial Output

At this point, we could calculate an initial cost value of the situation as-is for each cluster. This step allows to highlight how the costs of the intervention explained in chapter 6.5 are weighed and to present the other cost variables not yet covered (specific to the maintenance considered). As anticipated in the hypotheses, the as-is is represented by two starting scenarios, corrective and preventive maintenance, which therefore need to be treated in separate locations. Regardless, the structure in the two assessments presents some common points that could be noted. The modelling field (i.e., the manufacturing field) appears complex, and it would be an ambitious claim stating to be able to manage it completely. Therefore, we need to present a flexible structure that remains valid beyond the various estimates that will be presented, and that allows us to insert new/other cost items if necessary. As anticipated, the calculations of maintenance costs are performed for each cluster for which it was decided to examine the machinery.

6.7.1 Corrective Maintenance Charge

Corrective maintenance is an approach undertaken when an obvious fault has been located. This approach is still a common practice[29], especially for equipment, neither crucial nor safety-critical (Zio & Compare, 2012). However, the high percentage of corrective activities can be considered an indicator of possible improvements. In the model, the failure rate is assumed as an estimate of the expected number of interventions, modifying its dimensions from failure per million of hours to failure per year.

The formula of the cost of corrective maintenance is:

$$Charge_{CrM} = IC_{un} \cdot \lambda + EXC_{CrM} \tag{15}$$

The cost of unscheduled intervention is multiplied by the failure rate λ, and the exclusive cost related to could be formulated as follow:

$$EXC_{CrM} = ECSI \cdot \lambda + WC \tag{16}$$

Where:

- $ECSI$ $[{}^{€}/_{int}]$ *(Extra Cost for Service Intervention)*: It has the dimension of cost per intervention (it is necessary to multiply it by λ $[{}^{fail}/_{y}]$ *(Failure rate)*. This

[29] More than 55% of maintenance activities of an average facility are still corrective/reactive (U.S Department of Energy, 2010). This value was confirmed also by a survey conducted in Sweden during a condition-based maintenance seminar, showing a 56% of a mean value of the utilization grade of corrective maintenance (Bengtsson, 2004).

value wants to take into account the cost of the service. For an evaluation, a distinction between internal or external intervention has been considered:

- Internally: In case of internal intervention, the formula for $ECSI$ is the multiplication of the number of people, on average, who must be involved for the intervention by their hourly cost and the hours of intervention needed (Mean Time To Repair of the corrective intervention);
- Externally: If the maintenance intervention is managed externally, an estimation of the cost of the urgent call starting from descriptive variables of the failure could be misaligned, and what can be recommended is to take the invoices made by the maintenance provider to understand the cost per year.

- WC [$€/y$] *(Warehouse Cost)*: The cost of maintaining stock, taken into account as a cost of capital. An estimate of the spare parts kept in stock is required, multiplied by the unit cost and the weighted average cost of capital.

6.7.2 Preventive Maintenance Charge

Preventive scheduled maintenance is set as a fixed time, meter interval, or a combination of the two (the intervention will be performed at the first expired term). As previously specified, the former has been considered for the comparison. The predictable and frequent failure modes are usually tackled with a preventive maintenance approach. The problem highlighted regarding preventive maintenance is the high number of interventions carried out, which could be executed without a real need. In the model, the number of preventive interventions is enclosed in the variable S, determined from the vendor's guidance mostly or experience. By carrying out regular preventive maintenance, the intent is to try to intervene before the breakdown occurs; however, not all the scheduled interventions are carried out at the most appropriate time, and unscheduled interventions could still happen. The variable B is formalized to keep into account this phenomenon.

$$B = \begin{cases} \lambda - (1 - R_b) \cdot S, & \lambda > (1 - R_b) \cdot S \\ 0, & else \end{cases} \tag{17}$$

An example of the function with $\lambda = 4$ $[{}^{\#fail}/_{y}]$ and $R_b = 33\%$ is reported in *Figure 6.4*, in which, also from a graphical interpretation, it can be deduced the need to carry out six preventive fixed time intervention not to have unscheduled intervention. R_b can be valued from considerations about the variability of the occurrence of the failure, or more roughly taking as reference that generally 30% of preventive fixed time interventions are performed unnecessary (IBM, 2016), assuming the difficulty to evaluate the right timing to intervene. The proposed scenario, evaluated in the model functioning chapter, will adopt this second method.

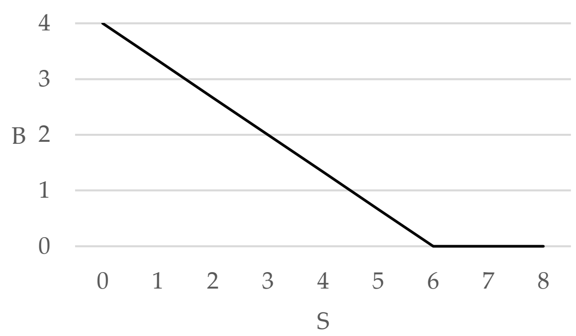

Figure 6.4: Plot of the function combining variable S to B.

After this introduction, the formula for the calculation of the cost of preventive maintenance is presented:

$$Charge_{PvM} = IC_{un} \cdot B + IC_{sc} \cdot S + EXC_{PvM} \tag{18}$$

The costs of unscheduled and scheduled actions are multiplied by the two variables previously presented. The exclusive cost is represented as:

$$EXC_{PvM} = SubP_u + MDC_u \tag{19}$$

Where:

- $SubP_u$ [$€/y$] *(Preventive Subscription Cost per cluster)*: The subscription on that particular cluster is taken into account. The subscript u denotes the division of this cost per cluster. As for the evaluation of the external cost per corrective maintenance, what can be recommended is to take the invoices made by the maintenance provider to estimate the general cost per year of the machinery. A division for the number of preventive maintenance clusters brings to the specific cost to allocate.
- MDC_u [$€/y$] *(Maintenance Department Cost)*: In case there are linked internal maintenance costs, a possible hypothesis to take them into account is to divide the costs of the maintenance department by the number of machines present in the plant. Providing an average estimate might be considered too naive, but it could result appropriate in case of similar machines. Ultimately, as before, a division for the number of preventive maintenance clusters brings to specific cost to allocate.

We wanted to present a modelling of the possible more relevant factors, bearing in mind, as already mentioned, the possibility to insert additional costs to fit the specific case of application if necessary. In the next chapter, the introduction of the Industrial IoT solution is discussed.

6.8 Industrial IoT Solutions

This part represents the turning point of the model. After calculating the initial output (section 6.7), the traditional approaches are abandoned, and the whole system is moved toward the computation of the differential advantage of the predictive maintenance solution. However, the aim of this paragraph is not to present the formulas to calculate these benefits, instead expose the Industrial IoT solutions to achieve better results in this type of maintenance, from the sensor to the analytics.

A predictive maintenance programme consists of three main steps: data acquisition, data processing and maintenance decision-making (Jardine, Lin, & Banjevic, 2006). From its definition onward, better ways of collecting, transmitting and processing data have been sought. Today, Industrial IoT provides a very high amount of data collected by low-cost sensors, transmitted, analysed and made available to all users in real-time. Therefore, we can assess that Industrial IoT is the disruptive technology that shifts the S-curve of predictive maintenance upwards, promising improvements and increasingly widespread applicability in the near future, making it more efficient and more effective.

6.8.1 The Initial Investment

Up to now, we spoke about Industrial IoT, predictive maintenance and the benefits that follow. However, an important and often painful aspect to talk about is the cost of the investment necessary to make the system functioning. Traditional solutions such as SCADA, MES or CMMS systems have always allowed the collection and analysis of data for maintenance purposes. Therefore, it seems logical to ask why an Industrial IoT system should be implemented.

As previously mentioned, Industrial IoT is the technology that makes predictive maintenance efficient, making prediction more reliable and precise. To improve reliability, large quantities of data must be collected, transmitted and processed by sophisticated algorithms that cannot be implemented on traditional systems. For a robust IoT-based predictive maintenance solution, an architecture designed specifically for the production plant and specific machinery is necessary. Consequently, the necessary investments for the sensors, the infrastructure and software may differ from case to case. For the estimation of this variable, it is important to underline that it must be considered both in the case of new machinery to be purchased and in the case of machinery already in use in the plant. The estimation of the two is slightly different. In one case, there is an overall value to improve the production plant and make it smart, while in the case of purchasing of new machinery must be considered the difference between how much the machine costs and how much it would have cost without an IoT instrumentation.

6.8.2 Remote Monitoring

Another fundamental aspect of Industrial IoT and a key element of our model is remote monitoring. The Industrial IoT allows the collection and transmission of data anywhere. In this way, the vendor, or more generally OEM of a specific machine, can offer new services and thus open new avenues for the business that they had never had before. Specifically for our model, a remote monitoring system allows OEMs to collect data from anywhere and provide predictive maintenance service to their customers. In this way, the OEM can exploit scale economies gathering data from all its machinery to train its algorithms and therefore make them more effective. Moreover, thanks to the data collected, if an unexpected error occurs, the OEM can determine what was happening before the problem occur and where the problem is, speeding up recovery operations[30].

[30] In the model, the speeding up of the recovery operations is considered only in the case the predictive maintenance solution is implemented. Therefore, the benefits of remote monitoring can be slightly underestimated.

This new way of performing predictive maintenance should not only be seen as a new source of revenue stream for OEMs. A Bain survey of 2019 underlines that barriers to adoptions to predictive maintenance has declined its attractivity to the customers. Therefore, vendors that want to boost adoption needs to focus on helping customers implement this practice, and remote monitoring is the solution. Moreover, the United States Department of Energy, assessed that the equipment needed to perform predictive maintenance “should not be purchased for in-house use if there is not a serious commitment to proper implementation, operator training, and equipment monitoring and repair.” Consequently, it specifies, “if such a commitment cannot be made, a site is well advised to seek other methods of program implementation—a preferable option may be to contract for these services with an outside vendor and rely on their equipment and expertise.” (U.S Department of Energy, 2010). Back in 2010, when the paper was written, the term Industrial IoT was not dubbed yet, and the technology had almost no application in the business sector. However, the manual implicitly underlines the need for this communication system that the Industrial IoT allows and highlights the need for the adoption of this service for all those companies that do not want or cannot support a huge investment in the matter.

In the next section, the concept of remote monitoring will be presented in the form of a pay-per-performance subscription that the manufacturer agrees with the vendor. Given the high level of monitoring that the technology allows, the vendor can align his business model with the manufacturer and share with him the risk of machine downtime, agreeing to pay only for the uptime. In this way, the vendor not only demonstrates his confidence in the reliability of the system convincing more easily manufacturers to shift to the pay-per-performance solution, but he also improves the customer satisfaction and, therefore, his relation. Thanks to the Industrial IoT, the OEM can transform a costly activity, usually seen from the manufacturer as a waste of money, to a source of competitive advantage.

6.9 Final output

In this last section, the conclusion of the cost and benefit evaluation process of an Industrial IoT application is presented, thus arriving to estimate all the latter necessary terms for the NPV formula.

The computation of the differential advantage of the predictive maintenance solution is performed for each cluster for which it was decided to model the machinery (the variables will be populated k-times). Here below, the formulation in case of the comparison of predictive maintenance respect to corrective and preventive approach:

$$Sav_{PdM-CrM} = IC_{un} \cdot TP - IC_{sc} \cdot (FP + TP) + EXC_{CrM} \tag{3}$$

$$Sav_{PdM-PvM} = IC_{un} \cdot (B - FN) + IC_{sc} \cdot [S - FP - TP] + EXC_{PvM} \tag{4}$$

Regarding these formulations, the majority of the variables have been already presented in the previous subchapters. What represents novelty is the insertion of the variables TP (True Positive), FP (False Positive) and FN (False Negative). They refer to the confusion matrix (*Figure 6.5*), a method for summarizing the performance of a classification algorithm. What it is necessary to define is the ability of the algorithm to forecast a failure in time to be able to schedule the intervention. This result assumes the form of a binary outcome, positive if it is possible to schedule, and negative, the opposite[31]. With this method, instead of providing the life time remains, it will be predicted whether a machine will fail within the next time T.

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[31] The other predictive maintenance method is focused on the regression algorithm, predicting how much time is left before the next failure.

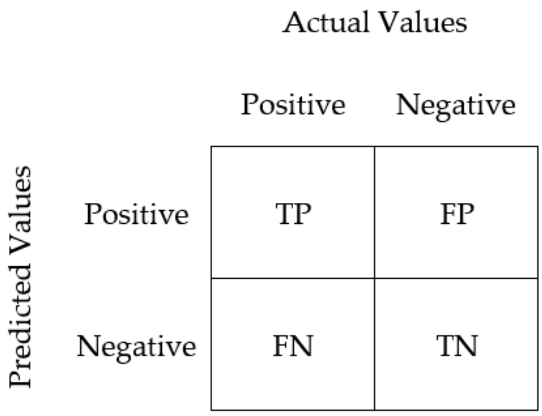


Figure 6.5: Confusion Matrix

The valorisation of these variables could represent the grey field of the model, where a tiny difference in time will result in a possible big difference in the cost per intervention. If, as reported, 99% of machine failures are preceded by some indicators (Bloch & Geitner, 2012), accurate estimates are not present on how much time before the algorithm can give warnings of the failure. The aim is not only to predict the failure event but also the time interval of its occurrence. This capability is also a function of what kind of analysis is used; for example, there are cases in which vibration analysis can spot failure months earlier (Selcuk, 2015). The P-F curve, already presented in chapter 6.6, represents this concept in the time interval width between potential and functional failure. In general, to have an evaluation of the algorithm, two relevant variables can be introduced, the precision and the recall, defined as follow:

$$P = \frac{TP}{TP + FP}$$

- *P (Precision)*: it represents how many right suggested interventions are accurate respect the actual one.

$$R = \frac{TP}{TP + FN}$$

- *R (Recall)*: it is a metric of the proportion of the failure that is going to happen without being intercepted. In general speaking, what has been predicted against what it should be.

In a perfect algorithm, precision and recall will assume values close to one. In reality, these two entities are in balance between them, as it will be reflected in the model.

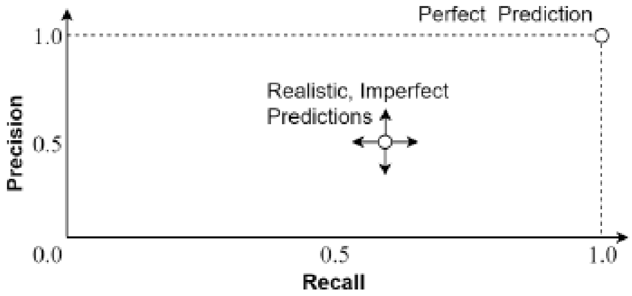


Figure 6.6: Perfect versus realistic prediction

From the system formed by the formulas of R and P plus the interpretation of the failure rate as $\lambda = TP + FN$, it is possible to calculate the missing variables of the model:

$$FN = (1 - R) \cdot \lambda \tag{20}$$

$$FP + TP = {}^{R}/_{P} \cdot \lambda \tag{21}$$

$$TP = \lambda - FN \tag{22}$$

The criticality of the evaluation is closed in the variables R and S; however, considering the amount of data available by the vendor offering the predictive maintenance service, it can be assumed that this information could be provided from him. For a first estimation (as taken into account also in the chapter of model findings), it could be considered the precision and recall of the algorithm present in the literature referring to the pattern classification performance.

After having managed this aspect, the savings respect the as-is maintenance strategy could be calculated. The model is structured considering only the positive ones: not always, a shift to the predictive maintenance is advantageous.

$$Sav_{PdM} = \sum_{j=1}^{k} Sav_{PdM,\mathrm{j}} \;\; with \;\, Sav_{PdM,\mathrm{j}} > 0 \qquad (2)$$

The second term to be analysed is the cost of the new subscription.

$$DiffMSC = PpPSub - MSC_x \qquad (6)$$

MSC_x variable needs some further explanation It takes into account the exclusive cost not considered in savings. In fact, for the cluster where savings are negative, the exclusive cost (which can be seen as the cost of the maintenance service) will be summed in this term. A change of subscription to pay-per-performance will be evaluated on the whole machine. For this reason, the exclusive costs (that correspond to the cost of maintenance that will be substituted by the new subscription) need to be included.

$$MSC_x = \sum_{j=1}^{k} EXC_j \quad with\, Sav_{PdM,k} < 0 \qquad (8)$$

For the calculation of the cost of the new payment agreement, the formula is defined as follows.

$$PpPSub = Fee \cdot (Wh - DownTime) \qquad (7)$$

Where:

- Fee [$^{€}/_{y}$] *(Fee)*: The fee is entrusted by the vendor, and, as a starting point, it may be calculated from the previous cost with the downtime related. A shift to the predictive maintenance will lead a drop of the downtime; the vendor (or the OEM providing the maintenance service) will obtain a gain for the better performance achieved by the manufacturer;

- Wh $[^h/_y]$ *(Working Hours)*: it can be established by the number of shifts multiplied by the working days per year;
- $DownTime$ $[^h/_y]$ *(Downtime)*: The estimate of the downtime can be calculated using the summation below:
-

$$DownTime = \sum_{j=1}^{k} (MTTR_{un,j} \cdot I_{un,j} + MTTR_{sc,j} \cdot I_{sc,j}) \tag{9}$$

Where:

- $I_{un,j}$ $[^{\#int}/_y]$ and $I_{sc,j}$ $[^{\#int}/_y]$ *(number of interventions)*: they represent the estimate of the number of interventions expected divided per each cluster, taking into account if the cluster moved to a predictive maintenance approach;
- $MTTR_{un,j}$ $[^h/_{\#int}]$ and $MTTR_{sc,j}$ $[^h/_{\#int}]$ *(Mean Time To Repair)*: they measure per each cluster the average time needed to determine the cause and repair the failed equipment in case of unscheduled and scheduled intervention, respectively.

Finally, all the data can be inserted in the Net Present Value formulation that will evaluate the investment over n year, the useful life of the machinery.

$$NPV = -Inv_0 + \sum_{i=1}^{n} \frac{Sav_{PdM,i} - DiffMSC_i}{(1 + WACC)^i} \tag{1}$$

Chapter 7

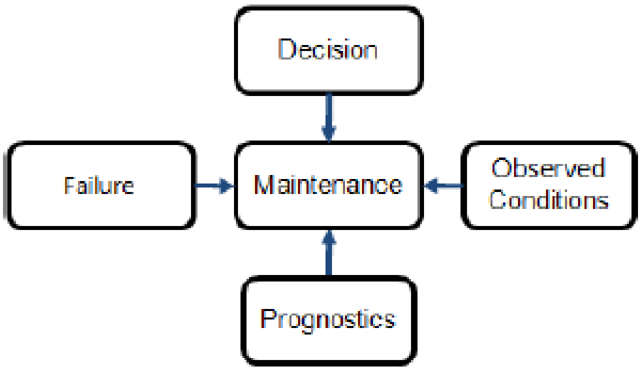
Model Application

The structure of the model is adaptable and gives several possibilities in personalisation. In this perspective, comprehension is vital to be able to tailor the model to a specific case. To give the reader a complete insight of its functioning, this chapter will present first a concept scenario and then an application to a real case. The former is about an invented manufacturing plant, with a specific layout and product flow. The variables Recall and Precision will be subjected to a sensitivity analysis, to see a possible effect of the propagation of the uncertainty to the results. One real case is then presented, fundamental to understand effectively how the model could work inside a real context. Some decisions regarding a simplification of the model have been taken in the first part of this chapter.

7.1 Simplifications Adopted

The model leaves the possibility to enter different values year by year, and obviously, this multiplies the necessary implementation effort. In this section we present some difficulties in proceeding in this direction, arriving at the end to declare some further hypotheses, most of which regard in keeping the variables constant year by year (and so the cash flows). However, as will be pointed out in the conclusions, it remains the possibility (if data are available) to use the model considering different entries year by year. This step is necessary when the data available are limited. In the concept scenario, the same decisions were taken to present clear results and to let understand better the functioning of the model.

A general scheme describing the maintenance approach is presented (*Figure 7.1*) to give a point of view regarding the difficulties in estimate the variables necessary for the model.



(Zio & Compare, 2012)

Figure 7.1: Maintenance explanation schema

Corrective maintenance can be described taking into consideration the boxes Failure and Maintenance. Preventive approach will add the Decision part, focus on balance the costs of maintenance actions with the safety and production benefits obtained from substituting/repairing a component before experience a failure. In case of predictive the other two quadrants are added: a monitoring part (Observed

Conditions) where the real-time data are a necessary condition, and a Prognostics module where the actual state of the equipment is projected in the future to predict the Remain Useful Life (RUL). The Failure rate, as presented in section (6.6), has a complex behaviour and its complexity (in the estimation of the parameters) enlarged in case of multi-component or multi-degradation system, assessing not only the parameter of each single degradation path but also the correlation between the different mechanism taking into account synergies and dependencies effects. In these cases, physical and stochastic methods leave space for the experience-based ones to try to describe the failure behaviour.

Another relevant point to be considered is the uncertainty derives from factors like the maintenance action and the human reliability regarding its effectiveness; model the effect of a maintenance policy is a critical point. Is it a minimal repair (As Bad As Old, ABAO) or a perfect repair (As Good As New, AGAN)? Reality is reasonably between these two extremes. As said before, with the preventive maintenance, the Decision box (referring to *Figure 7.1*) is introduced. In literature, the right optimisation in setting the variable S (Number of service intervention per year) is widely discussed. In the model, we did a step towards preventive maintenance formalisation introducing the variable R_b to take into account maintenance action reliability/effectiveness. The variable S, in these applications, will be estimated considering the number of actions performed in the last years. This number is generally considered higher than the necessary. Observed conditions (or monitoring) encloses some difficult in modelling too, considering that in some cases further investigation of the warning could take place without stopping the equipment (improving the performance of a preventive maintenance). The assumption here it will be the ability to provide an overall estimate to consider the correct cost. At the end, prognostic remains a challenging task, requiring the prediction of the evolution of the failure behaviour. The performance of the model is expected to improve along the years, considering either the use of traditional statistical approach or artificial intelligence. Every algorithm has different performance that vary along time, and what has been considered in the application was a value of 80% both for Recall and Precision, the performance algorithm indicator adopted. The reference derives from Zhang, Liu, Su, Han, & Li (2018) that obtain positive results in classifying highdimensional data in a power plant, with precision and recall vary from 80% to 95%. After this starting point, a sensitivity analysis varying these variables from 50% to 100% has been conducted to have a better evaluation of the benefits related. What is interesting also to consider is an update/fix of the equipment by design for frequent predicted failure, exploiting the possibilities of smart life cycle concept.

In addition to this part, the complexity in understanding how the flows of the products are subjected to a stop due to a failure is hidden inside the variable $BK_{\%,}$. Simplifications could result in not considering possible buffer to absorb the stop of the production. An analysis of a bottleneck machinery simplifies the considerations of $BK_{\%,}$. To conclude, we assume all the variable introduced constant along the lifetime of the machine, and this will bring constant cash flow.

7.2 Concept Scenario

A fictional manufacturing plant is presented, useful for better comprehension. The company is in the mechanical engineering sector, hot forging of non-ferrous materials (e.g. aluminium, copper, etc.); a turnover of 20 million per year, characterised by orders of various sizes, generally small lots. In the case of some customers from the automotive sector, large lots are present as well. In the next subchapters, the layout and the division into clusters of the chosen machine will be defined. The calculation of the various variables follow. The presentation of the benefits is associated with the sensitivity analysis of variables P and R.

7.2.1 Layout

The layout presents a division into four areas, a logical sequence followed by the flow of products: the cutting department (3 machines used to cut extruded bar at the desired length), the hot forging area (10 screw presses with different operating power and possibility to use specific moulds), the heat treatment zone (for solubilisation, quenching and age of aluminium products) and the trimming department (where the flash generating by the forging process is removed) (*Figure 7.2*). For the cost and benefit analysis, a screw press that processes two product codes per month is taken into consideration; the product codes are: P1, a component of the car shock absorber, and P2, the motorcycle brake lever. An assessment of the criticality of the machine is not explicitly presented: the starting situation is simply represented by the machine vendor who is proposing a predictive maintenance service in pay-per-performance agreement. An assessment of this proposal is conducted.

The company works on a single shift, 20 days a month for 12 months, resulting in 1,920 hours per year. The production of P1 and P2 is divided into 15 and 5 days per month, respectively. The effective production rate for P1 is 160 pieces per hour; 180 pieces per hour for P2. Given this data, it can be estimated that 120 pieces of P1 and 45 pieces of P2 representing in a sample hour. The sample hour is a significant concept in the model, and not knowing the time of the failure leads to the need to summarise the production mix (of the year) in a single hour. Other considerations regarding the product flow concern P2, which can only be processed on that specific press (press A), the production cannot be rescheduled; P1 does not have these limitations, and it could be worked on the nearby press (press B), where a generic product, P3, is worked as well. During a stop due to a machine failure, this flexibility will be used to give continuity to the production.

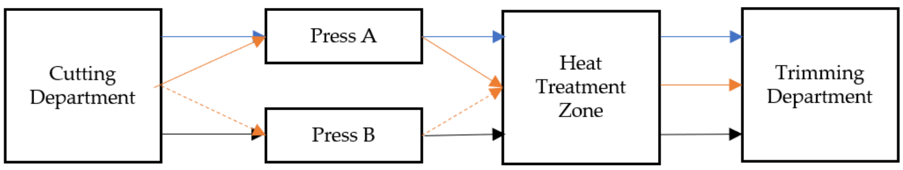


Figure 7.2: Production cycle in the concept scenario

7.2.2 Definition of the Maintenance Strategy

After an analysis most convenient of the machine failures, for this conceptual model, we divided them into two primary clusters: the failures addressed through a corrective approach (cluster 1) and those with a preventive approach (cluster 2). As reported in the model design chapter, the creation of clusters can also be performed looking to the economic evaluation of the failure impact, to the performances of the predictive algorithm, or other characteristics of the failure. Here following the analysis of the necessary variables computed for the two identified cluster.

Cluster 1

Different parts compose the structure of the cost per intervention. Starting from the analysis of the downtime cost, and specifically the downtime of the machine, we can estimate the following variables[32]:

Type of intervention	$MTTR_1$ $[h]$	$RPR_{P1,1}$ $[{}^{pz}/_{h}]$	$BK_{\%,P1,1}$ [%]	$GP_{u,P1}$ $[{}^{€}/_{pz}]$	$RPR_{P2,1}$ $[{}^{pz}/_{h}]$	$BK_{\%,P2,1}$ [%]	$GP_{u,P2}$ $[{}^{€}/_{pz}]$
intervention	40	120	50%	10	45	100%	6
Scheduled	20	120	0%	10	45	100%	6

Table 7.1: Variables of the downtime cost – Cluster 1

The value of Mean Time To Repair in case of unscheduled is retrieved by averaging the historical series. For the scheduled $MTTR$ a 50% reduction is considered in line to what reported in McKinsey's report (McKinsey&Company, 2015). For the percentage of $BK_{\%}$, as anticipated in 7.1, various assumptions can be made to simplify

[32] All the variables related specifically to the cluster 1 will present the subscript 1.

its calculation. The fact that there is no idle production time is one of them. Several considerations follow: P1 can be processed on another machine that at that time of failure shows production capacity availability. This operation requires planning, that means time, and in the case of an unscheduled production a quick turnaround. This aspect is reported in the $BK_{\%}$ difference between scheduled and unscheduled. The other product code P2 can not be worked on another machine, and therefore a failure leads to a complete production stop. As already mentioned, we have decided to keep the gross profit as the economic multiplier. In this way, the production costs are assumed recoverable. By giving an example, the workforce in the case of a failure can be immediately shifted to another occupation. If this does not happen, this term can be used to add any production costs that have been removed. The downtime cost of the machine can be calculated.

$$DTC_{machine} = MTTR \cdot \sum_{h=1}^{m} \left(RPR_h \cdot BK_{\%,h} \cdot GP_{u,h}\right)$$

$$DTC_{machine,un,1} = 34{,}800 \text{ €}/int$$

$$DTC_{machine,sc,1} = 5{,}400 \text{ €}/int$$

The passage of P1 to the second machine can lead to a slowdown of the other production. This consideration is taken into account in the general downtime of the plant. The formulas for the calculation have the same structure of the downtime cost of the machine. In this case, only P3 is impacted.

$$DTC_{plant,un,1} = MTTR_{un} \cdot RPRO_{P3} \cdot OE_{\%,un,\mathrm{P3}} \cdot GPO_{u,\mathrm{P3}} = 40 \cdot 300 \cdot 10\% \cdot 5 = 6{,}000 \text{ €}/int$$

$$DTC_{plant,sc,1} = MTTR_{sc} \cdot RPRO_{P3} \cdot OE_{\%,sc,\mathrm{P3}} \cdot GPO_{u,\mathrm{P3}} = 20 \cdot 300 \cdot 15\% \cdot 5 = 4{,}500 \text{ €}/int$$

In these first variables lies the ability to react quickly to the failure, whether it has been scheduled or not. Summed together, it turns out:

$$DTC_{un,1} = DTC_{machine,un,1} + DTC_{plant,un,1} = 34{,}800 + 6{,}000 = 40{,}800\ €/int$$

$$DTC_{sc,1} = DTC_{machine,sc,1} + DTC_{plant,sc,1} = 5{,}400 + 4{,}500 = 9{,}900\ €/int$$

As regards the other two costs linked to the interventions, they are represented by the cost of the spare parts and the cost of penalties for late delivery/non-production. The former is considered an average of the annual historical cost divided by the number of interventions executed (which amounted to 5,000 €/int). An extra cost of 3,500 €/int has been added in the case of unscheduled intervention; indeed, a delayed failure detection can lead to the replacements of several other parts. There is a cost linked to the penalty for non-delivery within the time agreed with the customer (a practice present in the automotive sector). This cost was estimated to be 10,000 €, only considering in case of unscheduled intervention. The total cost per intervention can be calculated:

$$IC_{un,1} = DTC_{un,1} + SpC_{un,1} + Pnlt_{un,1} = 40{,}800 + 3{,}500 + 10{,}000 = 59{,}300\ €/\#int$$

$$IC_{sc,1} = DTC_{sc,1} + SpC_{sc,1} + Pnlt_{sc,1} = 9{,}900 + 5{,}000 + 0 = 14{,}900\ €/\#int$$

The unscheduled intervention cost is five times the scheduled one for this cluster. As we have seen, the amount of the downtime cost, composed of the opportunity cost, represents the highest percentage (78.9% in the unscheduled and 95.2% in the scheduled).

The missing variable for the computation of the true positive and false positive, is the failure rate, having already assumed a precision and recall of 80%. If the machine is not represented by an already existing one, an analysis of the faults had in the last years can be conducted (). Besides, there is always the possibility to ask direct information to the vendor. In this application, we assumed an average of 1.2 faults per year (considering a single shift, 20 days a month for 12 months, a year corresponds to 1,920 hours). With these variables, we could move on to calculating the true positive TP and the false positive FP.

$$TP_1 = R_1 \cdot \lambda_1 = 80\% * 1.2 = 0.96\ int/y$$

$$FP_1 + TP_1 = {}^{R_1}/_{P_1} \cdot \lambda_1 = {}^{80\%}/_{80\%} \cdot 1.2 = 1.2\ int/y$$

Service cost of the maintenance in the as-is misses to be calculated (the evaluation of the new expense of the pay-per-performance subscription is considered in the next section). The service cost variables of the corrective are the cost of the urgent intervention and any costs related to the spare parts warehouse. In this application, the maintenance is assumed external. The cost of the service request to the maintenance technician(s) has been entered at the cost of 1,000 €/int (the other possibility is represented by the cost of internal maintenance, calculated as the hourly cost for the downtime). The cost for the service request must be multiplied by the failure rate, to reach the estimated on annual; 1,200 €/y is the result to consider.

Regarding the warehouse, the cost of capital has been calculated: an average stock of about ten spare parts with an average cost equal to the one previously considered (5,000 € per piece). The fact of having ten pieces in stock with only one failure per year should not mislead to think of an overestimation error: the failure rate is representative of the whole cluster covering several failures, therefore the need to have several spare parts. Considering the WACC of 5%, the cost of capital in stock is 2,500 €/y. Below, the formula for the annual cost estimate of the corrective service followed by the sensitivity analysis letting the variable recall and precision vary from 50% to 100%.

$$\begin{aligned} Sav_{PdM-CrM} &= IC_{un,1} \cdot TP_1 - IC_{sc,1} \cdot (FP_1 + TP_1) + EXC_{CrM,1} \\ &= 59{,}300 \cdot 0.96 - 14{,}900 \cdot 1{,}2 + 1{,}200 + 2{,}500 = 42{,}748\ €/y \end{aligned}$$

Precision \ Recall	50%	55%	60%	65%	70%	75%	80%	85%	90%	95%	100%
50%	(12.203) €	(11.400) €	(10.598) €	(9.795) €	(8.993) €	(8.191) €	(7.388) €	(6.586) €	(5.783) €	(4.981) €	(4.179) €
55%	(10.855) €	(9.918) €	(8.981) €	(8.044) €	(7.106) €	(6.169) €	(5.232) €	(4.295) €	(3.358) €	(2.421) €	(1.483) €
60%	(9.732) €	(8.683) €	(7.633) €	(6.584) €	(5.534) €	(4.485) €	(3.435) €	(2.386) €	(1.336) €	(287) €	763 €
65%	(8.782) €	(7.637) €	(6.493) €	(5.348) €	(4.204) €	(3.059) €	(1.915) €	(770) €	374 €	1.519 €	2.663 €
70%	(7.967) €	(6.741) €	(5.515) €	(4.289) €	(3.063) €	(1.838) €	(612) €	614 €	1.840 €	3.066 €	4.292 €
75%	(7.261) €	(5.965) €	(4.668) €	(3.372) €	(2.075) €	(779) €	518 €	1.814 €	3.111 €	4.407 €	5.704 €
80%	(6.644) €	(5.285) €	(3.927) €	(2.569) €	(1.210) €	148 €	1.506 €	2.864 €	4.223 €	5.581 €	6.939 €
85%	(6.099) €	(4.686) €	(3.273) €	(1.860) €	(447) €	965 €	2.378 €	3.791 €	5.204 €	6.617 €	8.029 €
90%	(5.614) €	(4.153) €	(2.692) €	(1.230) €	231 €	1.692 €	3.153 €	4.614 €	6.076 €	7.537 €	8.998 €
95%	(5.181) €	(3.676) €	(2.172) €	(667) €	838 €	2.342 €	3.847 €	5.351 €	6.856 €	8.361 €	9.865 €
100%	(4.791) €	(3.247) €	(1.703) €	(160) €	1.384 €	2.927 €	4.471 €	6.015 €	7.558 €	9.102 €	10.645 €

As we might have expected, the result is strongly influenced by Recall R and Precision P. A variation of the recall has a greater effect on the final output than the precision. This is due to the fact that the cost of unscheduled intervention has a more significant impact. In this cluster it results to be about four times greater than the scheduled one. Assuming 80% for both Recall R and Precision P, the savings obtained compared with the as-is costs (74,860 €, referring to the initial output formula) highlights an improvement rate of 57,1%.

Cluster 2

The second cluster groups all the failure addressed by preventive maintenance. For the calculation of the costs of the intervention, the steps seen above are replicated. We reported the summary table of the variables for the downtime cost estimation.

Type of intervention	$MTTR_2$ $[h]$	RPR_{P1} $[{}^{pz}/_{h}]$	$BK_{\%,2,P1}$ [%]	$GP_{u,P1}$ $[{}^{€}/_{pz}]$	RPR_{P2} $[{}^{pz}/_{h}]$	$BK_{\%,2,P2}$ [%]	$GP_{u,P2}$ $[{}^{€}/_{pz}]$
Unscheduled	6	120	50%	10	45	100%	6
Scheduled	4	120	0%	10	45	100%	6

Table 7.2: Variables of the downtime cost– Cluster 2

The previous reasoning about estimating the variables $BK_{\%,}$ remain valid. The RPR and GP_u variables are independent of the cluster considered, and therefore these remain the same. What is varied in this case is the Mean Time To Repair $MTTR$. Whether the intervention is planned or unplanned the repair times was chosen much shorter than those of cluster 1. Looking to the internal differences, the scheduled interventions was thought smaller for the ability to arrive on the machine and already know what to fix; apart of this, a detection delay does not lead to a significant worsening of the situation and the $MTTR$ remains at low value even for the unplanned intervention. For $MTTR$ estimation, we can assume the possibility to retrieve it from historical data.

$$DTC_{machine,un,2} = 5{,}220\ €/\#int$$

$$DTC_{machine,sc,2} = 1{,}080\ €/\#int$$

$$DTC_{plant,un,2} = 900\ €/\#int$$

$$DTC_{plant,sc,2} = 900\ €/\#int$$

For the costs related to spare parts, 200€ have been added for each intervention and 400€ additional in case of unscheduled ones. There are no penalty costs. The intervention cost can be calculated:

$$IC_{un,2} = DTC_{un,2} + SpC_{un,2} = 6{,}120 + 600 = 6{,}720\ €/\#int$$

$$IC_{sc,2} = DTC_{sc,2} + SpC_{sc,2} = 1{,}980 + 200 = 2{,}180\ €/\#int$$

The failure rate has been set at 6.4 and the number of annual interventions by operators S at 10.2 (in line with the simplification decisions taken in the first part of this chapter).

$$FN_2 = (1 - R_2) \cdot \lambda_2 = (1 - 80\%) \cdot 6.8 = 1.36\ int/y$$

$$FP_2 + TP_2 = {}^{R_2}/_{P_2} \cdot \lambda_2 = {}^{80\%}/_{80\%} \cdot 6.8 = 6.8\ int/y$$

The cost of preventive maintenance service is the cost of the internal maintenance department divided by the number of machines monitored. Assuming an initial cost of 48,500 €/y and 15 machines involved, the cost allocated per machine is 3,233 €/y. The final savings for the cluster 2 can be calculated:

$$\begin{aligned} Sav_{PdM-PvM} &= IC_{un} \cdot (B - FN) + IC_{sc} \cdot [S - FP - TP] + EXC_{PvM} \\ &= 6{,}720 \cdot (0 - 1.36) + 2{,}180 \cdot (10.2 - 6.8) + 3{,}233 = 1{,}506\ €/y \end{aligned}$$

Precision \ Recall	50%	55%	60%	65%	70%	75%	80%	85%	90%	95%	100%
50%	(12.203) €	(11.400) €	(10.598) €	(9.795) €	(8.993) €	(8.191) €	(7.388) €	(6.586) €	(5.783) €	(4.981) €	(4.179) €
55%	(10.855) €	(9.918) €	(8.981) €	(8.044) €	(7.106) €	(6.169) €	(5.232) €	(4.295) €	(3.358) €	(2.421) €	(1.483) €
60%	(9.732) €	(8.683) €	(7.633) €	(6.584) €	(5.534) €	(4.485) €	(3.435) €	(2.386) €	(1.336) €	(287) €	763 €
65%	(8.782) €	(7.637) €	(6.493) €	(5.348) €	(4.204) €	(3.059) €	(1.915) €	(770) €	374 €	1.519 €	2.663 €
70%	(7.967) €	(6.741) €	(5.515) €	(4.289) €	(3.063) €	(1.838) €	(612) €	614 €	1.840 €	3.066 €	4.292 €
75%	(7.261) €	(5.965) €	(4.668) €	(3.372) €	(2.075) €	(779) €	518 €	1.814 €	3.111 €	4.407 €	5.704 €
80%	(6.644) €	(5.285) €	(3.927) €	(2.569) €	(1.210) €	148 €	1.506 €	2.864 €	4.223 €	5.581 €	6.939 €
85%	(6.099) €	(4.686) €	(3.273) €	(1.860) €	(447) €	965 €	2.378 €	3.791 €	5.204 €	6.617 €	8.029 €
90%	(5.614) €	(4.153) €	(2.692) €	(1.230) €	231 €	1.692 €	3.153 €	4.614 €	6.076 €	7.537 €	8.998 €
95%	(5.181) €	(3.676) €	(2.172) €	(667) €	838 €	2.342 €	3.847 €	5.351 €	6.856 €	8.361 €	9.865 €
100%	(4.791) €	(3.247) €	(1.703) €	(160) €	1.384 €	2.927 €	4.471 €	6.015 €	7.558 €	9.102 €	10.645 €

A sensitivity analysis regarding the annual savings achievable has been realised in this second cluster (characterised by a preventive maintenance approach described previously). A switch to the predictive maintenance is not always advantageous, considering also having to add the cost of the new subscription in a second step. For many combinations of precision and recall, the resulting savings are negative. This depends from case to case, regarding the cost variables considered. The potentiality to bring advantages is anyway always present, and it need to be discussed. Assuming 80% for both Recall R and Precision P, the comparison between savings obtained and as-is maintenance costs (25,469 €/y, referring to the initial output formula) brings to a percentage of improvement of 5,9%. In this concept scenario the unscheduled intervention cost results three times greater than the scheduled one

7.2.3 Benefits Evaluation

The first formula presented summed the savings of the cluster that result to be positive:

$$Sav_{PdM} = \sum_{j=1}^{k} Sav_{PdM,j} \;\; with \;\; Sav_{PdM,j} > 0 = \; 38{,}698 + 2{,}915 = 41{,}623 \text{ €}/y$$

If there are negative clusters (therefore a switch to predictive maintenance is assessed as economically disadvantageous), the as-is approach is maintained. The switch to a pay-per-performance service is however evaluated, considering the related propose on the whole machine[33]. For this reason, as it is correct to choose the more

[33] In the model, to otherwise obtain an evaluation of the shift to only a predictive maintenance approach without the pay-per-performance agreement, the cost of the new subscription can be set to zero. Consider evaluating zero also the variables relative to as-is service costs, to not overestimate the benefits obtained.

convenient maintenance approach, it is necessary to recover all those service costs that will be replaced by the new subscription. In case of a cluster switching to a predictive maintenance approach, those costs will be already considered in the savings. Otherwise, those costs, represented by the exclusive maintenance cost term introduced previously, will be considered in the MSC_x. In our application (recall and precision set both to 80%), we obtained a positive savings for both the cluster, so the MSC_x variable results to be zero.

$$MSC_x = \sum_{j=1}^{k} EXC_j \quad with\, Sav_{PdM,j} < 0 = 0\ €/y$$

The cost of the pay-per-performance subscription is based on the uptime of the machine, and therefore, it reflects the downtime assessment. In the annual downtime estimate, the repair time established for each cluster is taken into account multiplied it by the number of interventions expected in the year. The formula is here presented:

$$DownTime = \sum_{j=1}^{k} \left(MTTR_{un,j} \cdot I_{un,j} + MTTR_{sc,j} \cdot I_{sc,j}\right) = (40 \cdot 0.24 + 20 \cdot 1.2) + (6 \cdot 1.36 + 4 \cdot 6.8) = 69\ h/y$$

The more the vendor will reduce this downtime, the higher his profit will be. Obviously, a central aspect for the vendor is fixing the value of the fee. An initial estimate can be obtained from the previous total service cost divided by the established number of working hours (one shift and 240 working days per year bring to 1960 hours per year). An initial value of the fee results to be 3,61 €/h. Then, it is legitimate to request some extra payments by evaluating the benefits that the manufacturer could obtain. What has been considered is a fee represented by the initial estimate increased by 20%, arriving at 4,33 €/h. The resulting subscription cost is:

$$PpPSub = Fee \cdot (Wh - DownTime) = 4{,}33 \cdot (1920 - 69) = 8{,}015\ €/y$$

Remember that the vendor's benefits may not only be economical, but he may be more interested in the possibility of introducing smart life cycle logics that can be obtained from the analysis of the acquired data. Considerations on lowering the cost of the fee to make the investment more attractive for the manufacturer can be evaluated. Another case, in which to lower the fee, is represented by the period of the first evaluations of the predictive maintenance service, which can be done in collaboration with specific manufacturers sharing the maintenance service costs.

Below, it is reported a formality step regarding where to take into account the term MSC_x (presented before), for then be ready to evaluate the overall Net Present Value.

$$DiffMSC = PpPSub - MSC_x = 8{,}015 - 0 = 8{,}015\ €/y$$

For the calculation of the Net Present Value, a remaining useful life for the machinery of 20 years was considered, and as the weighted average cost of capital a value of 5%. The initial investment has been valued at 50,000 € (U.S Department of Energy, 2010).

$$NPV = -Inv_0 + \sum_{i=1}^{n} \frac{Sav_{PdM,i} - DiffMSC_i}{(1 + WACC)^i} = 401{,}620€$$

Payback time is less than two years considering an algorithm with 80% precision and recall. By entering the extreme situations of 50% and 100% for both variables, we obtained an NPV of 158,172 € and 691,918 € respectively. We would like to remind that these results are achievable by respecting the various starting hypotheses. If the application of the Industrial IoT predictive maintenance solution was implemented independently from the manufacturer, the costs he may incur will be different. For example, it would require the training of internal staff on the new technology and a continuous investment along the years. The other major hypothesis made is not to considerate any buffer between the machines: a lack of production leads to a loss of sales (unless flexibility given by other production lines, managed with the term $BK_{\%}$ and $OE_{\%}$). This consideration is part of the downtime cost, represented then by an opportunity cost and by the Mean Time To Repair, which are obviously central variables in the estimates. On the costs of the intervention considered in this concept scenario, the downtime cost has a weight from 65 to 90%.

The variability given by the difficulty in defining the Precision and Recall was studied in a sensitivity analysis. Generally, we can expect that the algorithms will become more and more accurate as the quantity and quality of the available data increases.

In this concept scenario, a transition to predictive maintenance from a corrective as-is is certainly to be taken into account. On the other hand, when as-is is preventive, various evaluations will have to be examined as the economic benefits do not allow any margin of error.

The validation of these results comes both from the literature and from the meeting with managers. In the former, although analytical models are almost absent, some estimates are present: savings provided by the shift from corrective and preventive to predictive (40%-50%, 8-12% respectively), return on investment (10 times) and downtime reduction (up to 35%) (U.S Department of Energy, 2010). These values are comparable to those obtained in the two applications conducted. As far as managers are concerned, a positive opinion was received regarding the evaluation of the cost structure and the final NPV obtainable.

7.3 Real Cases Application: ConBio

In this section, the model is tested in a real situation. We conducted several interviews with a manager from ConBio srl. to obtain all the data we needed to implement the cases that reproduce reality as accurately as possible.

7.3.1 About the Company

Recently merged into the Granarolo S.p.A group, ConBio was born as a pioneering activity in the production of biological and vegan ready meals in 1998 thanks to the intuition of its founders who advocate and encourage what is today a thriving and booming market. ConBio products respond to the need for human well-being and environmental sustainability: the company uses only 100% organic and vegetable ingredients, preferably of Italian origin. All products are produced internally, directly following all the steps from the raw material to the packaged product, establishing deep and lasting relationships with all the players in the supply chain, in particular for basic raw materials such as soy and flours. The company distributes its products under three brands and manufactures private label productions for some of the main players in the large-scale retail trade (GDO).

7.3.2 Layout

ConBio has its headquarter situated in Rimini. They produce many different products in small batches to satisfy a very fragmented market demand among the different actors. Therefore, the production layout must adapt to this high degree of flexibility imposed by the market, react quickly to any changes in the quantities requested and in the mix and be able to support the production of new products provided by the R&D department. This flexibility is guaranteed by a job shop layout.

After a careful analysis of the layout of the company, we identified which machines we believe would be appropriate to implement predictive maintenance to avoid excessive downtime due to breakages that could cause delays for many products. Our analysis underlined that the production of many products depends on some critical machines. This is the case of the decanter, a machine once used typically in the field of oil production for the separation of oil from water. Today no longer in use in this sector, it is employed by ConBio to process soybeans to make tofu (a vegetable protein) which is then reused in many products, as well as being sold in bulk.

7.3.3 The Flow on the Machine

The production process for the preparation of tofu in ConBio starts from the soybean. It is left to soak for a long time in containers in a special area (A) to soften and rehydrate the dried bean. Once ready, an operator picks the beans up and takes them to the work area B where they are loaded into a cutter, which chops the bean and begins to heat it (machine 29). Once sufficiently crushed, they are taken and loaded into a heat exchanger, which brings the liquid pulp obtained to 103/104 degrees (machine 26). Once heated, the product is placed in the decanter (machine 38 and 39) which separates the filtrate, then curdled to obtain the tofu, from the pulp that is

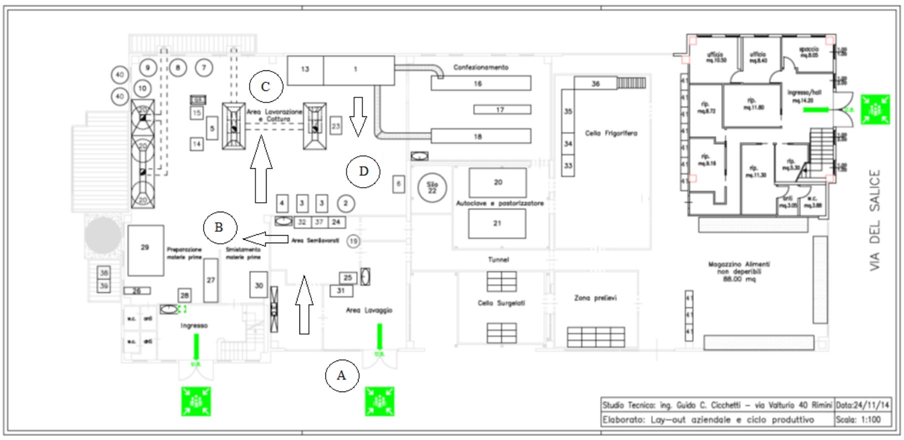


Figure 7.3: Layout of ConBio

reused in the production of some dishes. The curd filtrate that comes out of the machine goes back into the production process with a tube and is transported on a press (machine 27) to make the shapes. Once the shape has been obtained, the tofu is brought to department C, where it is placed in a blast-chilling cell. Once the tofu path has cooled down it is divided into two: on one side the tofu, which is sold without further processing, is brought to department C, where it is cut by a portioning machine (machine 6) and proceeds towards packaging, on the other, the tofu shape enters other production cycles for the preparation of other products. The tofu line works 220 days a year on three shifts of 6 hours each.

7.3.4 Maintenance Strategy – As-Is Situation

Among all the machines used in the tofu production cycle, we chose the decanter as it was considered one of the most critical machines in terms of breakage. Two are the most common types of breakage:

a. Shaft breakage: The machinery shaft break about once every two years. No preventive intervention is implemented to avoid the breakdown to occur therefore it perfectly fit the case of corrective maintenance;
b. Breakage of bearings and seals: this breakdown occurs much more frequently but has much less impact in terms of downtime. Also in this case, even if the

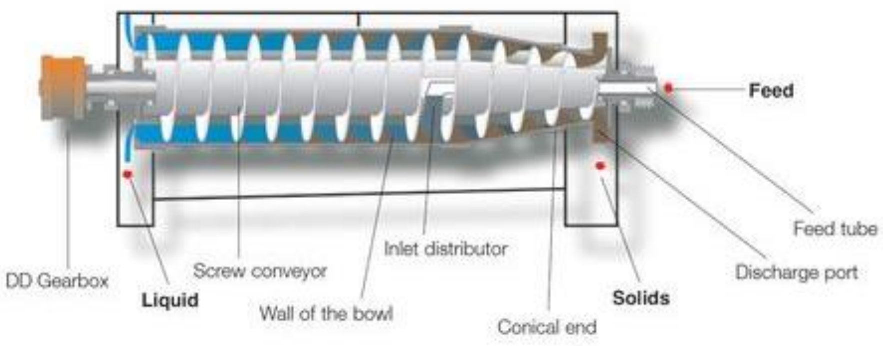


Figure 7.4: Decanter

seals is occasionally oiled, there is not a real maintenance schedule and therefore this second cluster is considered a case of corrective maintenance.

As the entire tofu line, this machine works three shifts of 6 hours each. However, setups and other inefficiencies reduce its operation to 16 hours.

Cluster 1 – Shaft

The breakdown of the shaft is the most serious break that can happen to the machinery and stop the production for about seven working days. This long stop is due to the fact that the process for restoring the machinery is very long and complex and involves more people during its course. Let's see it in detail. When the piece breaks an external, non-specialized technician with whom the company has to deal with various maintenance interventions is called to intervene urgently. The technician, assisted by an internal staff member, disassembled the machinery and tried to understand if the fault could be adjusted on-site or by the company of which the maintenance technician is part. If the repair could be carried out directly by them, generally, the repair lasted a day, otherwise, it is necessary to call the Italian distributor of the vendor, situated in Bologna, which sent a technician, if available, the following day. The specialized technician finishes to dismantling the machine and make his diagnosis. He disassembles the piece completely, takes it to Bologna[34]and contacts the

[34] The manager we spoke with stated that the technician is used to take the piece to the distributor in Bologna to try to fix it, but even if they managed to repair or they require a new product the time is always the same and the price is similar. Therefore, we assume that the piece is ordered every time.

manufacturer in Germany to have a new piece sent. After the piece arrives, the technician returns to the ConBio factory and assembles the new part. Since most of the time the repair required the entire cycle described above, we put ourselves in the worst-case and assume the maximum time of seven days. completely different is the case of a scheduled intervention that would only take one day to restore the machinery.

The produced tofu is used for various products including natural tofu (bulk), tofu cutlet, grilled tofu and soy burgers[35]. Other products use this raw material but have not been considered in the calculation because they generally employ tofu in such a low quantity that production, in case of decanter breakdown, is not stopped because stocks are used.

		Unschedule Int. Cost	Schedule Int. Cost	
Cluster 1		**IC_un**	**IC-sc**	UdM
		71,905.21€	12,843.60€	€/int
Mean-Time-to-Repair	MTTR	112	16	h/int
Downtime cost	DTC	302.73 €	302.73 €	€/h
Fine if the order is in late	Pen	30,000.00 €	0.00€	€/int
Average cost spare part	CSPavg	8,000.00 €	8,000.00€	€/int
Average cost per additional spare part to change after breackdown	CASPavg	0.00€	0.00€	€/int

Figure 7.5: An example of the data insert in the model from Cluster 1

Cluster 2 – Bearings and Seals

The second cluster that we have formed belongs to the machine's bearings and seals, which break twice a year. We put these two elements together because the costs of breakdown linked to them are very similar. This time a possible unscheduled breakage of one of these two pieces stops the machine for only about six hours. Particularly critical is the case of bearings in which the bearing balls spread throughout the machine and, if not stopped in time, can cause breakage of other pieces including the shaft. After stopping the machine to avoid further damage, the aforementioned external not specialized maintenance company is called, who repairs the machinery.

[35] The unitary gross profit values are not shown for privacy reasons.

Gross profit follows the same logic previously described and therefore the overall value is the same.

7.3.5 Benefits Evaluation

By evaluating the transition from corrective to predictive maintenance applying our model, it appears that predictive maintenance has a significant economic advantage, expressed in annual savings, compared to a corrective.

	Cluster 1	Cluster 2
Initial Output Corrective	37,853 €	*13,280 €*
Savings Predictive vs Corrective	18,655 €	*7,477 €*

Table 7.3: Cost of the initial solution and savings passing to a predictive maintenance solution.

The percentages of improvement for the cluster 1 and 2 are respectively of 49,3% and 56,3%. Assuming to activate a subscription with the OEM based in Bologna with a value of 50 cents per hour of machine uptime, the total annual benefit is € 24,388.93. It was assessed together with the company manager that the investment necessary to install the sensors and the IoT system for remote monitoring should be around € 5,000. Assuming a useful life of the machinery of 30 years (the machinery has never been changed in 20 years of production and has an almost infinite useful life) and the company's WACC to date of 4.75%, the corresponding NPV is € 380,843 € and the investment would payback from the first year.

FINAL OUTPUT	
NPV	380,843.13€
Cluster 1:	You should implement a predictive solution.
Cluster 2:	You should implement a predictive solution.
Subscription:	It is convenient to adopt a Pay-per-Performance solution at a cost of 1743.4 € per year. The total benefit is calculated taking into

Table 7.4: The final output of the model for the ConBio example

Chapter 8

Conclusions and Discussions

A cost-benefit analysis of an Industrial IoT application that enables the predictive maintenance service in a pay-per-performance contract was discussed in this dissertation. The main variables of the model were reported, underlining the topic of collaboration between the manufacturer and vendor, and reporting possible final outputs.

Interests in the topic of predictive have grown exponentially in recent years, intertwined with the availability of data now made accessible by Industrial IoT. The literature has grown from about 200 to almost 700 published paper per year in the last five years. The literature is still highly focused on technical aspects (hardware or software development), and the benefits are discussed qualitatively; when they are considered quantitatively, only little depth analyses are conducted. There is a need for a cost sounding model that starts to bring clarity on overall benefits. The survey on small and medium enterprises highlighted a need for understanding the Industrial IoT theme at all levels. The other survey on large enterprises brings positive results in some respects, showing several active projects in the predictive field. Nevertheless, at the moment of a direct interview, the prevalence of predictive application is re-evaluated: predictive maintenance is still minimal, in some circumstances not well understood. Excellent cases are however present, among which we have reported Fabio Perini's case study. After an initial period of offering services related to the monitoring of machinery in pay-per-performance formulas, the company is beginning to offer a predictive maintenance service. The interest in the subject is relevant from both the scientific and the practitioner side. Significant changes are imminent for maintenance, which is not bound only to the cost of the maintainer but keeps in mind the ability to reorganise with production and warehouse processes. Integrating maintenance is key to achieving high levels of efficiency and productivity.

Our attempt is aimed at bridging the gap in the literature regarding benefit evaluation by proposing an analytical model with a flexible structure. One hypothesis of the model is that the predictive maintenance analysis, which is in many ways complex, is carried out by the vendor who can potentially have access to all the different machines being sold (once the manufacturers have granted authorisation for data processing). We wanted to link the maintenance service to a pay-per-performance agreement to highlight where the vendor can have its economic return, as well as having obtained a competitive advantage over those who do not offer this service. The theme of a closer relationship is becoming more and more present. The use of the model is therefore addressed both to the manufacturer (to estimate the investment) and to the vendor (to adapt its offer better).

The tool used to conduct the analysis is the NPV. To calculate the cash flows, a differential between the costs of the previous maintenance and those of the predictive was considered. These costs have a simple structure: a mutual part between all types of maintenance and another part specific. In the first one, the cost per intervention is modelled, where the cost variables of downtime, materials used and lack of customer service are present. A focus on the cost of downtime is appropriate; it is a function of the Mean Time To Repair (a key concept in maintenance), the gross profit of the machined products, and the percentage of slow down/stop of the production flow due to breakdown (the presence of buffers and alternative work cycles can significantly limit this effects). The cost of the intervention will be calculated in two cases: unscheduled and scheduled. The unscheduled one is by its nature more expensive. However, the ability to react quickly leads to a decrease in the distance between the two costs. This concept has to be combined with the number of interventions made for each maintenance (*Figure 8.1*)

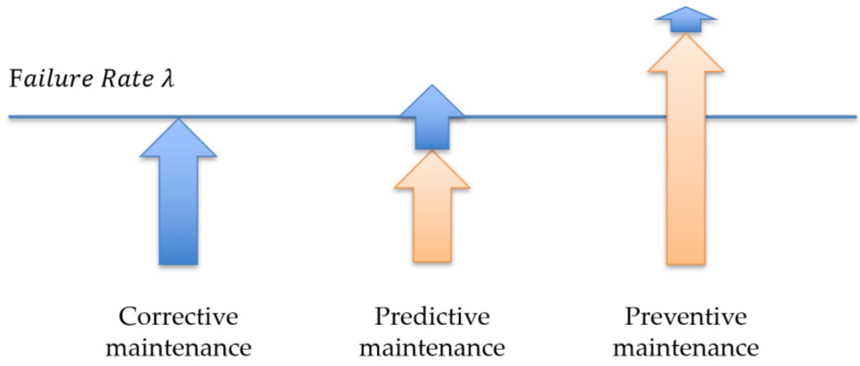


Figure 8.1: The number of interventions is shown on the y-axis. The colours blue and orange represent when the intervention is unscheduled or scheduled respectively.

The number of annual interventions undertaken in corrective maintenance corresponds to the number of faults per year (represented by the failure rate), which is the minimum number of interventions to be carried out. The preventive time based, to deal with the same number of faults expected, implements several interventions at fixed intervals; nevertheless, a separate quota of unscheduled interventions can be considered to take into account the result of an optimisation method or the possible inaccuracy of a fix intervention. The predictive maintenance is in the middle, trying to anticipate faults exactly. Fundamental to describe this capability are the variables Precision and Recall. For the proposed model, it is necessary to have an estimation of these variables, which is based on the number of failures predicted with a time interval T in advance, large enough to be able to organise a scheduled intervention. The difficulties in the evaluation of the algorithm performance can be severe, and they could not always be overcome. These considerations lead to the need to analyse different scenarios for the different values of Precision and Recall, performed in the form of sensitivity analysis. Ultimately, in the specific part for the type of maintenance approach, the cost of labour/maintenance service and the cost of the warehouse have been considered.

The topic of predictive maintenance is vast, and some aspects have not been considered in the model. The increase in the useful life of the equipment is an example, which in some cases, could represent an important factor in the implementation of a predictive service. Other evaluations not considered, concern redundant parts/machines: an improvement in availability resulting from a predictive maintenance approach can change the choice of whether or not to include redundancy in the system, thus bringing as savings the cost delta between the two situations. Lastly, it may be useful to address a possible risk (and opportunity) assessment, such as the financial risk assessment caused by the breakdown. These further considerations could represent some interesting follow-up to be explored.

In the model, what could constitute the main future development is an extended calculation to include all maintenance strategies. Next, other types of intervention cost could be added, in addition to scheduled and unscheduled types, as can be represented by a quick intervention; it could be arranged to be more precise in the evaluation of the benefits of the predictive (or possible condition-based) approach that quickly notice out-of-normal parameters to have to be corrected immediately. The goal is to create a general model that evaluates the optimal maintenance solution. In this dissertation, we have chosen to evaluate a to-be represented only by predictive maintenance. This choice was taken to remain focused on the object of the thesis, an Industrial IoT application that enables the predictive maintenance service.

The model's hypothesis of assuming predictive maintenance as a service reduces its usability so far considering this offer still little present. A maturity of this offer may still require a certain amount of time. However, it should be pointed out that many resistances of data sharing by the manufacturer are disappearing (reported in the case of Fabio Perini). This aspect represents the correct starting point for the development of the predictive maintenance service.

In addition to the analysis that guided the structure of the model, a conceptual scenario and a real case (represented by the company ConBio, a vegan ready meal producer part of the Granarolo Spa group) have been considered. We are now ready to answer the research questions.

Q1: Does an investment in Industrial IoT for predictive maintenance generate value for the company?

Each case must be evaluated; the benefits will be calculated thanks to the presented model, flexible enough to be adapted to different situations. From the tests conducted, a shift from a corrective to a predictive approach leads to a positive NPV, considering even deficient prediction performance. A payback time in the short term (less than two years) is obtained. Regarding a shift from preventive maintenance, a positive result is not sure, and further assessments of benefits are to be taken into account.

The validation of these results comes from both the literature and the meeting with managers. In the former, although analytical models are almost absent, some estimates are present: savings provided by the shift from corrective and preventive to predictive (40%-50%, 8-12% respectively), return on investment (10 times) and downtime reduction (up to 35%) (U.S Department of Energy, 2010). These values are comparable to those obtained in the two applications conducted. As far as managers are concerned, a positive opinion was received regarding the evaluation of the cost structure and the final NPV obtainable. This investment can be considered part of the path of digitalisation of the company, and it can be envisioned as part of that overall project.

Sub. Q1: How can the vendor benefit from the value generated to the manufacturer?

The vendor, which takes on a primary role, has as a direct return the pay-per-performance subscription. Secondly, being on the market with such an offer can lead to considerable competitive advantages; he has the potentiality to scale the solution to all his clients. In a final perspective, the large amount of data collected, in addition to being used for maintenance service purposes, can have applications in the context of smart lifecycle.

Significant changes are imminent for maintenance sector, where over the total maintenance resource and activities of an average facility, the percentage regarding the predictive is expected to grow from 12% to 45%/55% (U.S Department of Energy, 2010). These changes will impact the industrial sector in the following years, and, in this dissertation, we aimed to be promoters of knowledge related the future developments allowed by the Industrial IoT, and more specifically, to foster the interest in understanding and considering the development of a predictive maintenance solution.

Appendix A

An Introduction to the Internet of Things

The appendix examines the new technological paradigm of IoT, a paradigm with the potential to radically change the way we live. The main characteristics of the interconnected intelligent objects and the IT architecture necessary for their correct operation are therefore explained. In the end, the main applications areas of the Internet of Things are summarized.

Brief introduction to the new paradigm

An increasing number of devices will be able to access the Internet and actively interact with the web. The new reference scenario, which is revolutionizing the consumer and business world, has been called the Internet of Things (IoT). The potential benefits of the new paradigm are undoubtedly extraordinary, and its applications are radically changing work and private life habits, saving time and resources, and opening new opportunities for growth, innovation and knowledge development.

As an essential tool to reach and connect millions of objects and acting as a generic enabler of a new hyper-connected society, the IoT has all the potential to help the Western society that grows older, to improve the energy efficiency of cities and to optimize mobility and transport. The complementarity with "cyber-Physical Systems", cloud technologies, Big Data and new network technologies like 5G, is then evident.

IoT definition

To provide an adequate definition of the IoT paradigm, three specific and different IoT definitions of three of the most accredited expert bodies on the subject in the Italian, European and international fields were taken into consideration. The ‘Osservatorio Internet of Things’ of the Politecnico di Milano: "The expression “Internet of Things” indicates a path in technological development based on which, through the internet, potentially every object of our daily experience acquires its own identity in the digital world. It is a structured route, characterized by countless fields of application and from different - for variety and dynamism - enabling technologies." (Osservatorio IoT - Politecnico di Milano, 2015).

The European Research Cluster on the Internet of Things (IERC), supported by the Commission European which facilitates the sharing of knowledge on the IoT and supports and supports best practices and new business models in this regard: "A dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual ’things’ have identities, physical attributes and virtual personalities, and are seamlessly integrated into the information network." (IERC, 2014)

The Internet Engineering Task Force (IETF), an international organization founded in 1986 and composed of an open community of network designers, operators, vendors and interested researchers to the technical and technological evolution of the Internet. "[...] IoT will connect objects around us (electronic, electrical, non-electrical) to provide seamless communication and contextual services provided by them." (IETF, 2010)

The motivations that led to the pervasiveness of the IoT paradigm

The convergence in recent years of a series of innovations within the broad technological scenario has pushed the diffusion of the IoT, not leaving it confined within market niches. Among these innovations must certainly be mentioned: major improvements in performance, miniaturization and energy efficiency of sensors and batteries; the new systems for processing and storing extraordinarily compact data economically accessible, allowing to turn individual objects into small computers; antennas and low-cost wireless ubiquitous connectivity; the tools that enable rapid and "agile" prototyping of the software; the so-called Big Data analytics; the new IPv6 Internet registration system that allows activating, in addition to those already existing, 340 trillion addresses that can be associated with a single device; the new protocols designed to guarantee greater security of information, which make easier to pass a device between different networks and allow servers to automatically delegate and address without the need for IT support.

All these factors have made connected smart objects cheaper (technically and economically) for both enterprises and final consumers (Porter & Heppelmann, 2014).

A brief historical background

To realize a synthetic framework of the Internet of Things, it is necessary to start from RFID (Radio Frequency Identification) technology, the basis of the subsequent development of the IoT paradigm. RFID, the simplest technology with which an object can enter the IoT, is based on the ability of small tags (or transponders), constituted of a chip and an antenna, to store transmitted information from the outside that can then be read by other objects, called readers, able to read them at a distance using radio waves. In the ’50s and ’60s, several studies were carried out on the remote identification of objects through radiofrequency energy. Between the 60s and 70s of the last century, the cold war and the nuclear race between the United States and the

Soviet Union have pushed the development of RFID technology even further and laid the foundations for the birth of the internet. Another important period for the development of this technology was the early ‘90s when the World Wide Web was born thanks to the publication of the first site by Tim Berners-Lee. The IBM engineers developed for the first time a UHF (ultra-high frequency) RFID system with one better reading skills and faster data transfer. The development of UHF-type RFIDs dated back to 1999, when the Uniform Code Council, the European Article Number (EAN), Procter & Gamble and Gillette have decided to finance and establish the Auto-ID Center in Massachusetts Institute of Technology (MIT) to study how to exploit low-cost RFID tags to track any produced throughout the Supply Chain. It was Kevin Ashton (director for many years of that research centre) to indicate himself as the one who had coined the "Internet of Things" neologism in 1997 within a publication of the International Telecommunication Union (ITU).

Intelligent interconnected objects and their characteristics

Devices that are part of an interconnected network are called “smart objects” or “smart things” because, in addition to being constituted by traditional physical components, that materially constitute the object, they also present "intelligent" components and connectivity components. The connectivity amplifies the potential of intelligent components, thus creating a virtuous circle of incremental generation of the value of the object.

Intelligent components and enabled properties

Intelligent components are all sensors, actuators, microprocessors, control systems data storage, software and controls for the user interface on the device. These "smart" components enable three particular properties of the product (Osservatorio IoT - Politecnico di Milano, 2015), not necessarily co-present:

1. "Self-awareness". This characteristic can be summarized in the ability of the object of being able to be uniquely identified (the digital code of a product must be unique) and universally in the digital domain (understanding of the ID worldwide), in the ability of being able to be located in real-time (for example through GPS technology) and the possibility to check the operating status (with detail levels of the internal systems more or less accentuated).
2. The smart objects have three different capabilities in relation to the type of information received: metering capability, that is the automatic measurement and recording of a flow of information on a particular physical quantity such as cubic meters of water or gas used, kilowatts hour of energy consumed, miles travelled for example; capability of sensing or receipting certain information from outside that are not a continuous flow over time (for example the perception of movement, fumes in the environment, brightness); ability to implement or perform a specific action that changes the status of an element (for example, switch off the light, close the shutters, activate the alarm).
3. The third is instead the possibility to process information obtained from the outside through predetermined algorithms, implementable at a time after the acquisition. Data, for example, can be aggregated, filtered, crossed, correlated etc. to improve and increase knowledge of the surrounding environment by the device (and therefore of all those who can access it such information).

Connectivity components

For connectivity components, reference is made instead to the antennas, to the doors and to the protocols that make the connection with the device possible. Communication may occur individually or simultaneously and generally takes three different forms (Porter & Heppelmann, 2014):

- "One-to-one": a single object connects with another single entity (the user, the manufacturer or another object).
- "One-to-many": according to a central-star configuration, a central access point communicates at the same time with two or more devices in continuous or intermittently.
- "Many-to-many": more products are connected both to each other and possibly also to sources external data. Connectivity, in its three different forms, must be implemented together to reach highs product functionality levels. Firstly, it allows the exchange of data and information between the reference object and the external environment (such as users, producer, other intelligent products, operating systems). Secondly, it makes possible the existence of some features external to the product in the so-called "Product Cloud" (definition provided by Michael Porter), that is software that runs remotely, on the company's server or an external partner.

The four main capabilities of intelligent objects

The components of smartness and connectivity have enabled a completely new range of functionality and capabilities of the products. It is possible to classify them into four main groups (Porter & Heppelmann, 2014):

1. Monitoring: connected intelligent objects can be remotely monitored in a complete and historicized way. Final users or companies are able in this way to know their working criteria, operations, as well as the conditions of the external environment. Furthermore, the product can send reports or warnings in case of particular changes in the parameters sensed.
2. Control: remote commands or software integrated into the product or in the cloud, can remotely control the various functions of the smart objects. Thanks to the embedded algorithms, the object (and its actuators) react in case of specific changes. This feature enables personalization of the performance, in ways that in the past were not economically viable or possible.

3. Optimization: the previous two capabilities allow the creation of algorithms that optimize the operation and use of the object. In this way, it is possible to improve the performance of the product itself and to programme in advance maintenance services, assistance and timely repairs (through software).
4. Autonomy: monitoring, control and optimization, if combined, can allow interconnected intelligent objects to reach levels of autonomy that in the past were hardly achievable except through unsustainable economic efforts. Through sensors and embedded software, the product can "become aware" of the external environment in which it is located and make decisions without human intervention. This refined feature allows the smart devices also to detect problems and to adapt, thanks to the understanding of the data and information received, to the needs of the client. Each capacity integrates and enriches the one that precedes it. Theoretically, an intelligent, interconnected object could have all four.

A difficult convergence on the standards

Even today, the world of the Internet of Things is very fragmented and not standardized in terms of:

- Hardware (Mica, Motes, Sunspot, Jennic, etc.);
- Software (Tiny OS, SOS, Mantis, Contiki, FreeRTOS, etc.);
- Middleware (Tiny DB, GNS, DNS, SWORD, etc.); Communication under the point of view of the nature of technology (radio, wired, mobile phone) and of protocols (eg ZigBee, Bluetooth LE, Wi-Fi, etc.). (Osservatorio IoT - Politecnico di Milano, 2015)). Often, due to the variety characterizing the Internet of Things ecosystem, the development for the generation of IoT solutions followed mainly a "vertical" approach: starting from one specific application problem, an ad hoc design of hardware, operating system, application software, middleware, and communication standards for the first two levels of network architecture, is conduced. The aim is substantially to optimize the specific application (for example in terms of performance or

energy savings) instead of abstracting the design from the single problem, allowing the implementation and use of a wider range of applications. The IoT architecture of the near future makes of the interoperability at single product level its foundation. In this way, the access and exchange of information between devices becomes free and direct switching to application level, without the presence of a hub control centre is therefore possible. By exploiting this logic, each application can communicate and command the objects, consequently abstracting from the specific application problem.

IoT Application Fields

The various fields of application of the Internet of Things, defined within the research carried out in (Osservatorio IoT - Politecnico di Milano, 2015), are the following:

- Smart City & Smart Environment: with the aim of improving liveability, sustainability and competitiveness of a city, IoT enables the monitoring and management of the elements such as vehicles for public transport, public lighting, parking lots, and the surrounding environment (for example rivers, woods, mountains).
- Smart Metering & Smart Grid: the so-called smart meters for measuring consumption (electricity, gas, water, heat) exploit the IoT paradigm in order to improve billing and remote management; "Intelligent" electricity grid (Smart Grid) is instead an interesting field in order to optimize distribution and to manage distributed production and electric mobility.
- Smart Home & Building: for energy saving, comfort, safety purposes, IoT objects give the users the possibility to automatically manage systems and building equipment (for example those for lighting, air conditioning and appliances).
- eHealth: thanks to real-time of remote monitoring of vital parameters, it is possible to reduce the recourse to hospitalization, diagnosis and care.

- Smart Car: by connecting vehicles (among them or to the surrounding infrastructure), it is possible to detect and prevent accidents and also to open new opportunities for innovative insurance model and for georeferenced information on the road traffic.
- Smart Logistics: IoT has an interesting potential in improving supply chain traceability, brand protection, cold chain monitoring and security in complex logistics poles.
- Smart Asset Management: IoT enables the remote control to manage breakdowns, tampering, localization, traceability and inventory remote management of valuable assets.
- Smart Factory: new production management, supply chain planning logic and product life cycle management are some of the industrial application fields to which IoT (through Cyber-Physical Systems, connection of machinery, operators and products) gave the birth.
- Smart Agriculture: lastly, IoT can also support agriculture. By monitoring the micro-climatic parameters, it is possible to improve the quality of products, to reduce both the resources used and the environmental impact.

Appendix B

Survey Analysis

The results of the two surveys conducted inside the 'Osservatorio Internet of Things' of the Politecnico di Milano and presented in the thesis are grouped. They both concern the Italian manufacturing sector, one looking to Large Enterprises (LEs) and the other to Small-Medium Enterprises (SMEs).

Regarding the LEs survey, in October 2019, 714 questionnaires were sent to companies operating in the Italian industrial context to understand their point of view on the Industrial IoT theme. The research was carried out using the CAWI methodology (Computer Assisted Web Interview).

Regarding the SMEs survey, in December 2019, a sample of 525 small and medium enterprises, representative of the Italian scenario by sector, geographical area, number of employees and turnover, was carried out. The research was conducted using the CATI methodology (Computer Assisted Telephone Interview).

The aim of both the researches was to collect data about

1. Level of knowledge regarding IoT field;
2. The area of completed/underway projects, and related services added;
3. Objectives, benefits, and use of data;
4. Barriers and how to manage them;
5. Economic dimension of the investments done in Industrial IoT, and the area of interest in future projects.

The results have been compared between the two. In caption, the reference sample.

Q 1.1: Have you ever heard of Internet of Things (IoT) solutions for Industry 4.0?

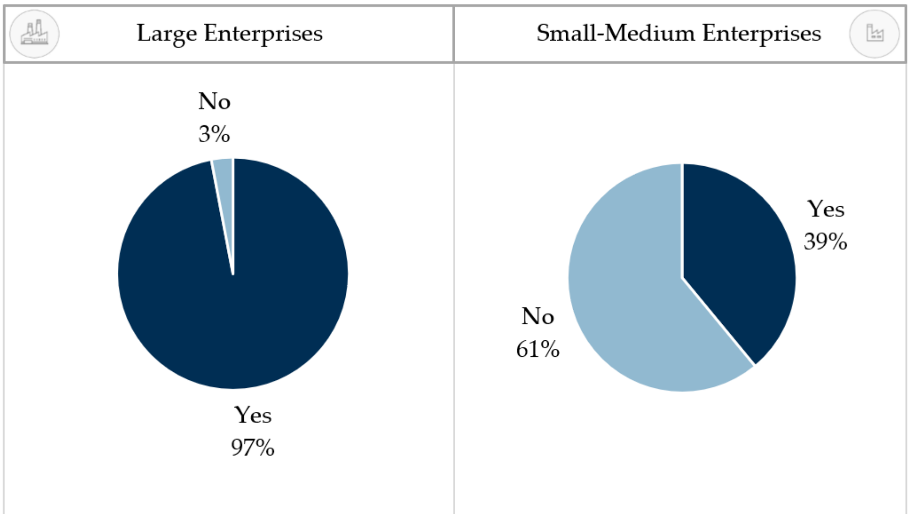


Figure A.1: Results of Q1.1 - Sample size LEs, 100. Sample size LEs, 525.

Q 1.2: What is your level of knowledge of IoT solutions for Industry 4.0?

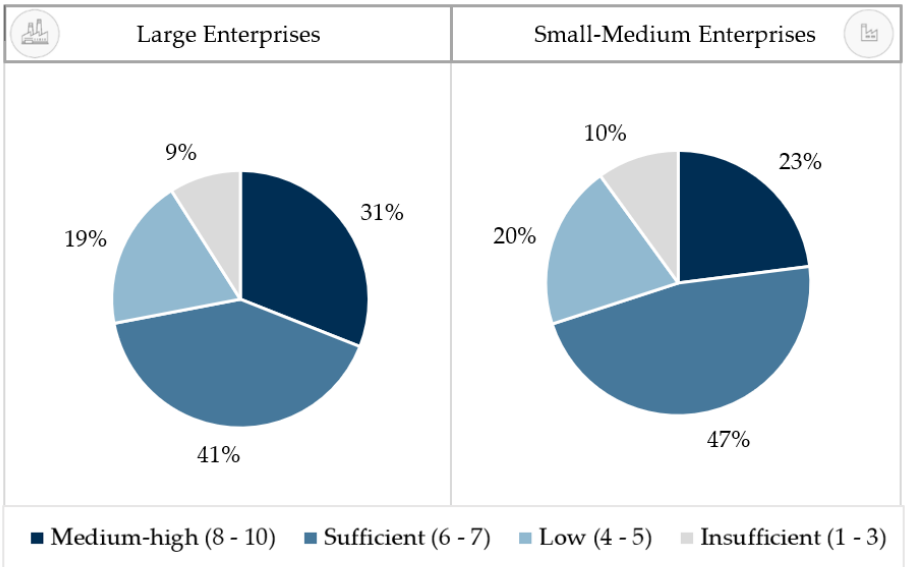


Figure A.2: Results of Q1.2. - Sample size LEs, 97. Sample size LEs, 218. The mean in the survey LEs and SMEs corresponds to 6.4 and 6.2.

Q 2.1: Has your company initiated IoT projects for Industry 4.0 in the past?

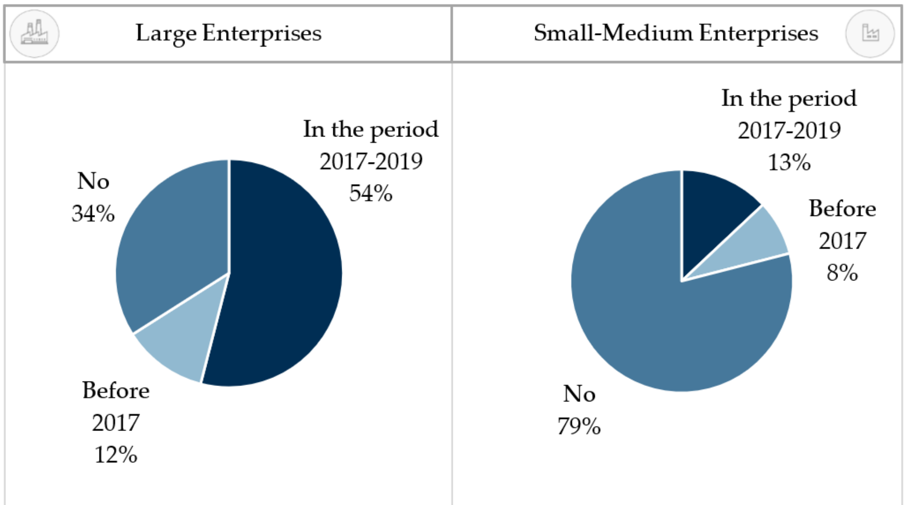


Figure A.3: Results of Q2.1. - Sample size LEs, 97. Sample size LEs, 218.

Q 2.2: Indicate, for each IoT project for Industry 4.0 launched by your company, the state of progress (proof of concept, pilot project, executive project).

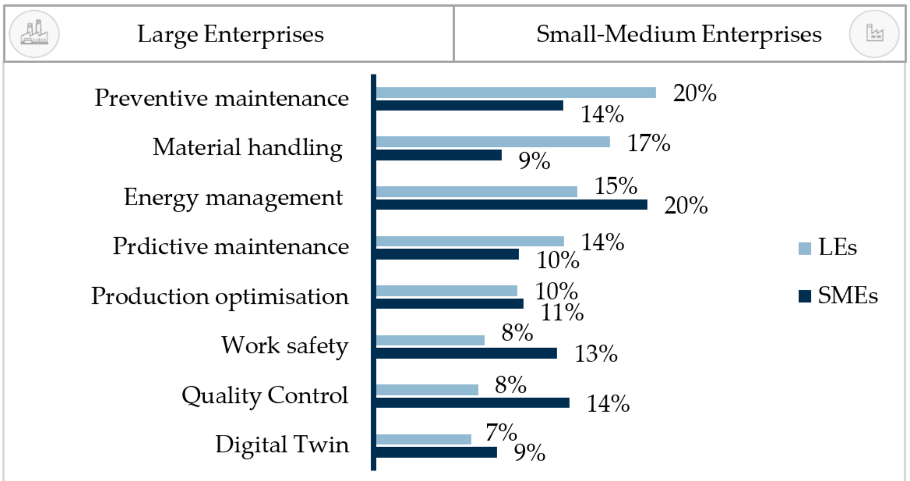


Figure A.4: Results of Q2.2 related to Smart Factory - Sample size LEs, 90. Sample SMEs, 31 – Indicate the category (and sub-classes) for each IoT project for Industry 4.0 launched by your company (pilot project and executive project). The graph indicates how the applications inside the Smart Factory category are distributed between the sub-classes.

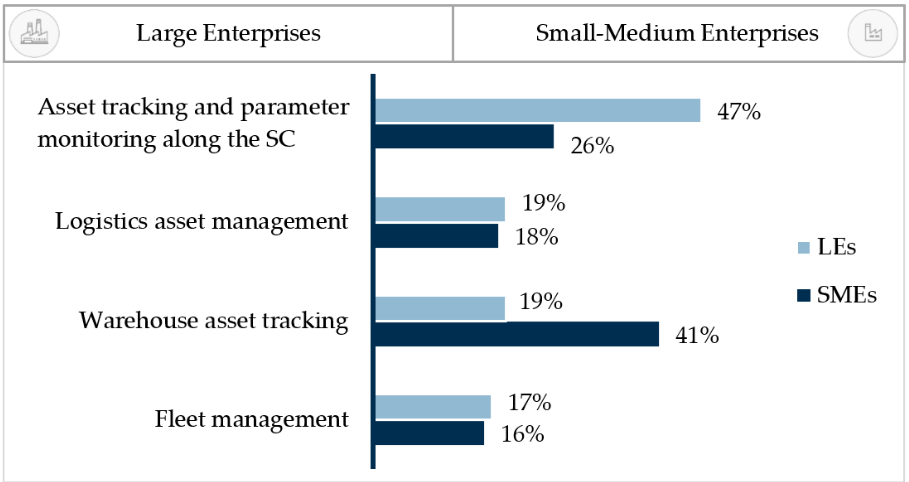


Figure A.5: Results of Q2.2 related to Smart Supply Chain - Sample size LEs, 41. Sample SMEs, 23. - Indicate the category (and sub-classes) for each IoT project for Industry 4.0 launched by your company (pilot project and executive project). The graph indicates how the applications inside the Smart Supply Chain category are distributed between the sub-classes.

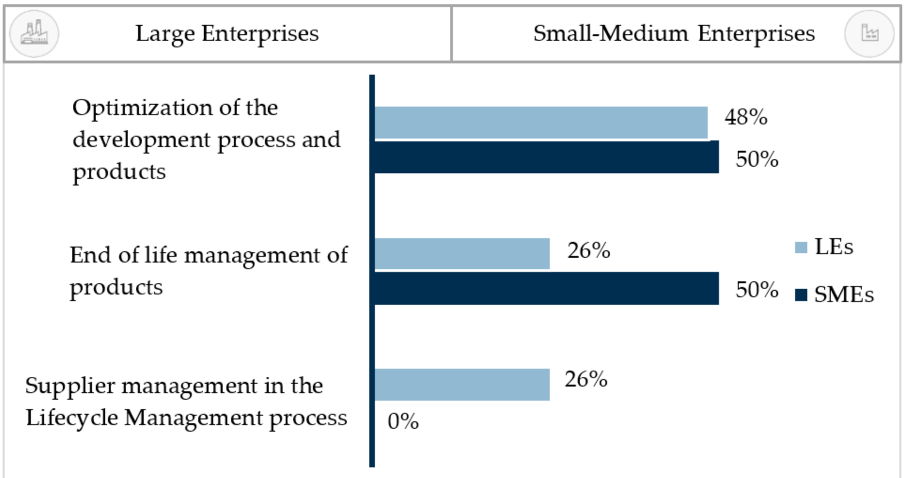


Figure A.6: Results of Q2.2 related to Smart Lifecycle - Sample size LEs, 24. Sample SMEs, 15 - Indicate the category (and sub-classes) for each IoT project for Industry 4.0 launched by your company (pilot project and executive project). The graph indicates how the applications inside the Smart Lifecycle category are distributed between the sub-classes.

Q 3.1: What were the main objectives that led the company to launch IoT projects for Industry 4.0? Up to three options can be entered.

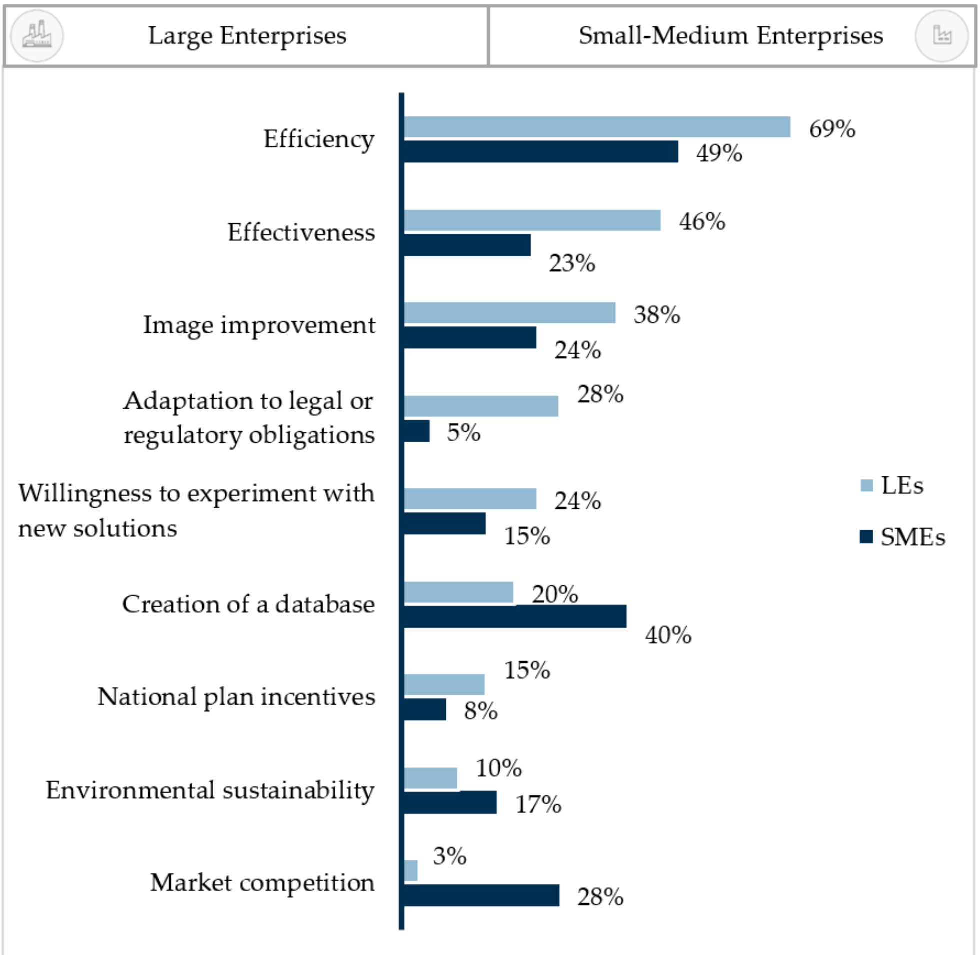


Figure A.7: Results of Q3.1 - Sample size LEs, 61. Sample SMEs, 47.

Q 4.1: What are the barriers (internal and external) that in your opinion can slow down or prevent the start of IoT projects for Industry 4.0? Up to three options can be entered.

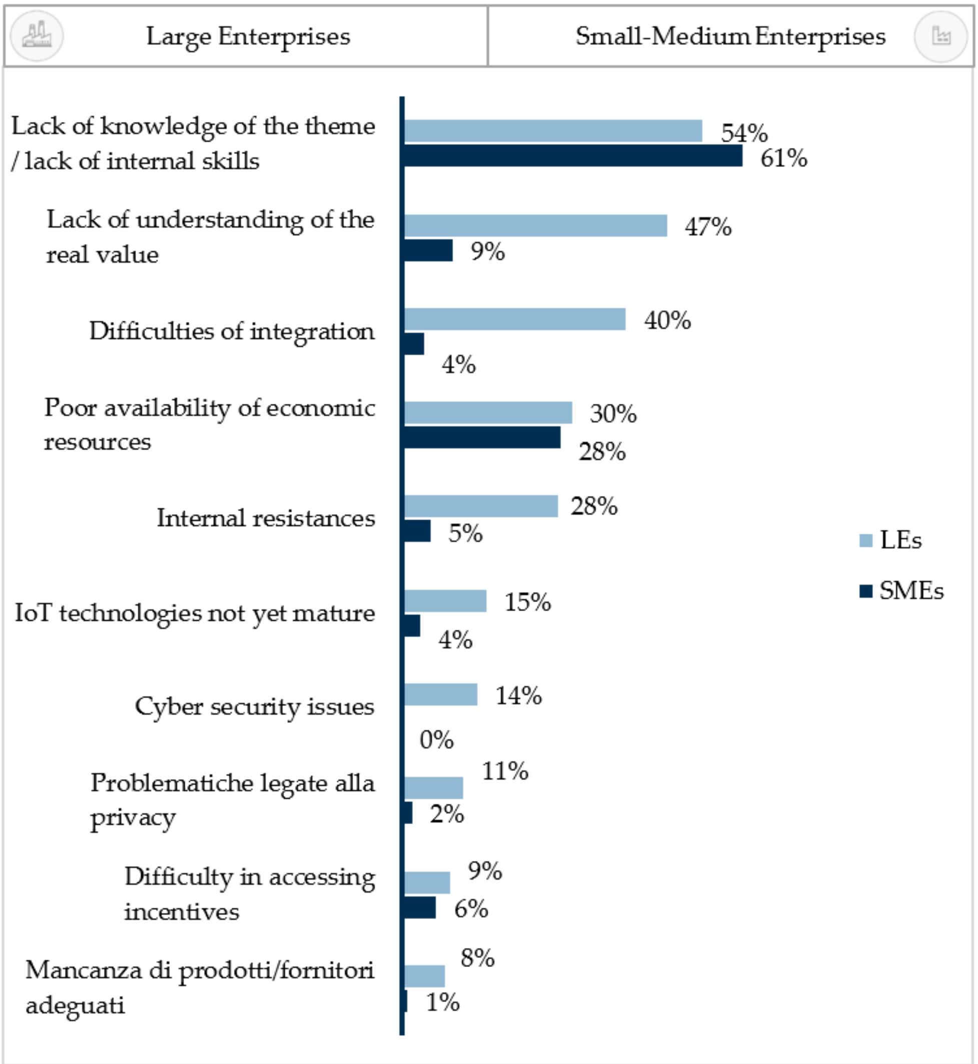


Figure A.8: Results of Q4.1 - Sample size LEs, 88. Sample size SMEs, 525.

Q 5.1: What additional services enabled by the Internet of Things technologies is the company you are part of interested in activating inside the factory? Up to three options can be entered. (Have the IoT applications for Industry 4.0 that you have launched included additional services?).

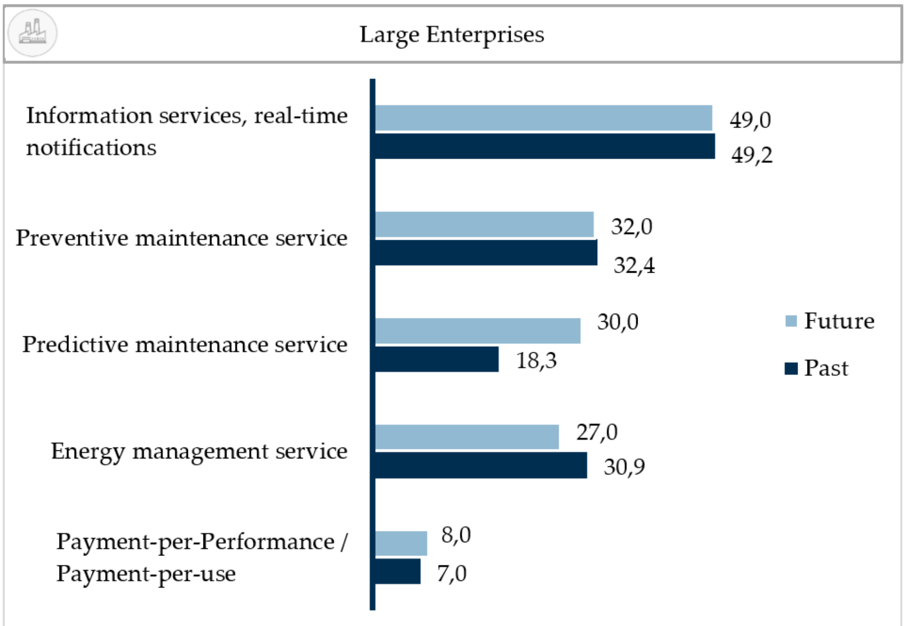


Figure A.9: Results of Q 5.1 - Sample base regarding past project, 59. Sample base regarding future project, 83 - The answers are scaled for the answers received regarding the future.

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