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An architecture to predict anomalies in industrial processes

Filipe Miguel Machado Dias

Dissertation presented as partial requirement for obtaining the master's degree Program in Data Science and Advanced Analytics

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AN ARCHITECTURE TO PREDICT ANOMALIES IN INDUSTRIAL PROCESSES

by

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Dissertation presented as partial requirement for obtaining the master's degree in Advanced Analytics, with a Specialization in Data Science.

Supervisor: Vitor Duarte dos Santos

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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Abstract

The Internet of Things (IoT) and machine learning algorithms (ML) are enabling a revolutionary change in digitization in numerous areas, benefiting Industry 4.0 in particular. Predictive maintenance using machine learning models is being used to protect assets in industry. In this paper, an architecture for predicting anomalies in industrial processes was proposed in which SMEs can be guided in implementing an IIoT architecture for predictive maintenance (PdM).

This research was conducted to understand what machine learning architectures and models are generally used by industry for PdM. An overview of the concepts of the Industrial Internet of Things (IIoT), machine learning (ML), and predictive maintenance (PdM) was provided, and through a systematic literature review, it was possible to understand their applications and which technologies enable their use. The survey revealed that PdM applications are increasingly common and that there are many studies on the development of new ML techniques.

The survey conducted confirmed the usefulness of the artifact and showed the need for an architecture to guide the implementation of PdM. This research can be a contribution for SMEs, allowing them to become more efficient and reduce both production and maintenance costs in order to keep up with multinational companies.

Keywords: Predictive Maintenance; Machine Learning; Industrial Internet of Things; Remaining Useful Life

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Acronyms and Abbreviations

AI – Artificial Intelligence

ANN – Artificial Neural Networks

AR – Augmented Reality

CPS – Cyber-physical systems

DSR – Design Science Research

ICT - Information and Communication Technology

IIOT - Industrial Internet of Things

IOT - Internet of Things

IS – Information Systems

ML – Machine Learning

PdM – Predictive Maintenance

SME - Small and medium-sized enterprises

1 – Introduction

1.1 Context

Digital transformation is a defining feature of modern society and a major trend in this century. It is not only the integration of digital technologies into all areas of business, but also a cultural shift that requires companies to constantly rethink the status quo.

At the heart of the digital transformation revolution is the Internet of Things (IoT), which has seen steady growth in recent years. It's about extending the power of the internet to a whole host of other things, processes, and environments. The industry 4.0 revolution that is currently taking place is one of the focus areas of IoT, where innovation for those who want to modernize their business processes is at its core. The convergence of sensor technology with affordable pricing and the increased capacity of information systems to store and analyze vast amounts of data are key components of Industry 4.0, also the ability to easily access data and infer trends and behaviors is transforming the way decisions are made and creating new business models and services. The IoT is ubiquitous, with approximately 35 billion IoT devices installed by 2021 and an estimated 46 billion devices will be connected by the end of 2021(Juniper, 2020) . By the end of 2020, the amount of data generated is estimated to be 44 zettabytes, and by 2025, the amount of data generated daily is expected to reach 463 exabytes (Bulao, 2022; Vuleta, 2021). The fact that all this data is available enables the discovery of disruptive market strategies, the discovery of trends that were previously hidden, the application of machine learning algorithms, the automation of processes and the identification and prediction of anomalies.

Factors driven by the Internet of Things include demand for customization, higher customer expectations, the complexity of a global supply chain, and manufacturing efficiency. To meet these demands, the manufacturing industry must find new and innovative ways to compete. To increase productivity and improve manufacturing and supply chain operations, manufacturers are embracing digital transformation and finding new ways to improve their business (Shiklo, 2021).

The concept of Industrial Internet of Things (IIoT) includes wireless, smart sensors, Big Data, and artificial intelligence (AI). Smart sensors enable the collection of large amounts of data in real time, followed by its processing and storage. Prior analysis enables the discovery of new trends or behaviors, including the identification and prediction of anomalies.

In this era of digital transformation, one of the most challenging concepts is that of predictive maintenance. Recently, the algorithms of ML have seen a great development in terms of their performance and application in industry, especially in maintenance. Their application enables predictive maintenance (PdM), which offers great efficiency gains.

1.2 Motivation

SMEs face several challenges in adopting IIoT: Large investments are required without ensuring ROI (return on investment); data security, 58% of IIoT users believe there is increased risk associated with it; integration of new technology with legacy systems; lack of skilled employees, Inmarsat states that 72% of companies have a shortage of employees with experience in IoT, 80% of employees do not have the skills to use IoT technology. There are also specific skills that are lacking such as analytics with expertise in Big Data, embedded software development, embedded electronics, IT security and artificial intelligence (Shiklo, 2021).

Industrial IoT technology enables SMEs to remain competitive by digitally transforming their industrial operations. However, the adoption of IIoT remains complex and costly for SMEs, and security concerns also remain a barrier (Dhaher, 2021). As the IIoT and predictive market grows and is led by large enterprises, small and medium enterprises need to keep up.

Anticipating outcomes and predicting risks is one of the great benefits of AI. For small and medium sized growing businesses, this can mean business survival and new doors opened. These are at a severe disadvantage compared to competing companies in Asia and the United States, which tend to be one step ahead because they are already successfully using AI. Small and medium-sized enterprises need to do something, but they do not know what and how.

Many SMEs know that artificial intelligence and Big Data are essential for the industrial sector, but they do not know how to process, analyze, and extract value from industrial data or how to use algorithms and tools to implement a solution that works for them.

The existence of an already researched and extensively studied architecture for the different industries, which can be easily adapted by small and medium enterprises, is a great competitive advantage. Even if it does not serve them completely, it is always an indication of the steps to be taken towards the use of AI in the industrial sector.

1.3 Objectives

The research goal is to develop an architecture for predicting anomalies in industrial processes that can assist SMEs in a future IIoT implementation.

It is assumed that Artificial Intelligence techniques, together with cloud computing and open-source software can perform a very important role in this architecture and allow the digital transformation in the field of AI possible for SMEs.

Thus, more than developing a general architecture for predicting anomalies in industrial processes, the aim of this work is to propose a solution that can be easily used/adapted by any industrial SME.

To achieve this goal, the following intermediate objectives have been defined:

- Make a comprehensive study of already implemented IoT architectures.
- Make a comprehensive study of different industries and their associated sensors.
- Make comprehensive study of data science techniques and processes for anomaly detection.
- Create the architecture.
- Test and validate.

1.4 Study Relevance and Importance

SMEs are the engine of the European economy, creating jobs and economic growth. In 2021, around 22.6 million SMEs supported 84 million jobs and they contribute an average value of 56% to the EU economy. Given their importance to the European economy, they receive a lot of attention. The European Commission promotes entrepreneurship and improves the industrial environment for SMEs.

Predictive maintenance (PdM) is an advanced form of maintenance based on the concept of IIoT that offers more benefits than current maintenance methods. For a long time, manufacturers took a time-based approach to maintaining their equipment, where the age of the machine was the most important factor in scheduled maintenance. The group ARC notes that only 18% of equipment fails due to age, while the remaining 82% are random failures (Grizhnevich, 2021). This shows that traditional time-based maintenance is not cost effective as a device can be maintained without needing it.

To avoid this, manufacturers can leverage the IIoT and Data Science by reducing both traditional maintenance and downtime (Vishwa, 2021). Companies are taking advantage of AI and ML technologies to achieve greater precision, accuracy, and speed in analyzing IoT data than with traditional business intelligence tools. Predictive maintenance enables businesses to make predictions 20 times faster and with tremendous accuracy than normal monitoring systems. AI-based IoT applications enable businesses to predict failure in advance. As the industrial sector becomes more aware of maintenance costs and downtime caused by unexpected failures, PdM is becoming increasingly popular in this sector.

According to a study by CGI, 62% of companies surveyed are already implementing digital transformation programs, Bsquare states that 86% of manufacturers have already implemented IoT solutions and 84% of them consider IoT to be very effective, and McKinsey also predicts that manufacturing applications will generate $1.2 to $3.7 trillion annually by 2025 (Shiklo, 2021). According to Gartner, 61% of companies have a high IoT maturity level and 63% of them expect a return on investment for their IoT projects in 3 years (Gartner, n.d.). The PdM market is forecast to grow from $4.0 billion in 2020 to approximately $13.9 billion in 2026, at a Compound Annual Growth Rate of 25% during the forecast period (ReportLinker, 2021). PdM helps to eliminate 30% of time-based maintenance and reduces downtime by 50% (Grizhnevich, 2021).

By predicting anomalies in an industrial process, the company can: reduce costs, increase productivity, improve product quality, optimize the use of maintenance resources, improve asset condition and performance, and increase customer satisfaction. The key drivers for industrial IoT/AI solutions are:

Reduced maintenance cost, machine downtime, machine labor cost, product’s quality Non-conformance; *Increased* machine reliability and availability.

Cost reduction: optimized asset and inventory management, reduced machine downtime, more flexible operations, efficient energy consumption - all leading to lower operating costs. Unplanned downtime due to machine breakdowns can severely impact vertical industries such as offshore oil and gas.

Shorter product cycles: faster and more efficient manufacturing means shorter product cycles. Harley-Davidson reconfigured its plant in York, Pa, reducing production time for a motorcycle from 21 days to 6 hours.

Safety: The IoT is helping to make the workplace safer. Worker health can be monitored with wearable devices, and it also alerts workers to potentially hazardous environments (Shiklo, 2021).

This research in IS will enable knowledge to be gained that will enable architecture development and implementation, improvement or problem solving. Organizations usually have goals such as cost reduction or profit maximization, which they achieve by designing effective business processes. IS plays an important role in enabling the effective execution of such processes.

2- Methodology

The output of design science research in information systems is by definition an "IT artifact" created for the purpose of innovating or improving an organizational problem. Design science research must produce a viable artifact in the form of a construct, model, method, or instantiation (A. R. Hevner et al., 2004). The instantiation of an artifact demonstrates the viability of the design process and the designed product.

Design science research at IT usually solves problems related to the design of an information system so that the generated instantiations are in the form of intellectual tools or software to improve the information system development process.

The architecture to be studied in this paper is an instantiation, therefore Design Science Research is the appropriate methodology.

2.1. Design Science Research

The idea of "design science" was developed almost half a century ago, where the differences between natural and design science were pointed out (Simon, 1996). The obvious purpose of design science is design itself, to produce something that does not exist, or to innovate existing solutions to achieve better results (Lacerda et al., 2013).

The paradigm of design science research (DSR) is problem solving. It aims to improve technology and scientific knowledge by creating artefacts that innovate, solve problems, and thus improve the environment in which they are used. Research in design science has its roots in engineering and the science of the artificial (Simon 1996). The goal of DS research is to push the boundaries of humans and the capacities of organizations by designing new and innovative artefacts represented by constructs, models, methods, and instances (Gregor & Hevner, 2013; A. R. Hevner et al., 2004).

DSR aims to generate knowledge about how things should be constructed and organized, usually by a human actor and to achieve a set of goals. The discipline of information systems (IS) encompasses knowledge about how to make efficient decisions based on data analysis, how to structure and build a database, how to align information systems with organizational strategy, how to model business processes (Becker et al., 2010), and is also aware of how to use information to support sustainable practices (Brocke et al., 2012). DSR is also used as a research paradigm in other disciplines such as engineering, architecture, business, and economics.

The performance of DSR projects can be measured in various ways, e.g., Hevner or Kuchler & Vaishnavi (A. Hevner, 2014; Kuechler et al., 2008). However, the most common model specifically for IS is that of (Peffers et al., 2006). The design science research methodology model (DSRM) is shown in Figure 1.

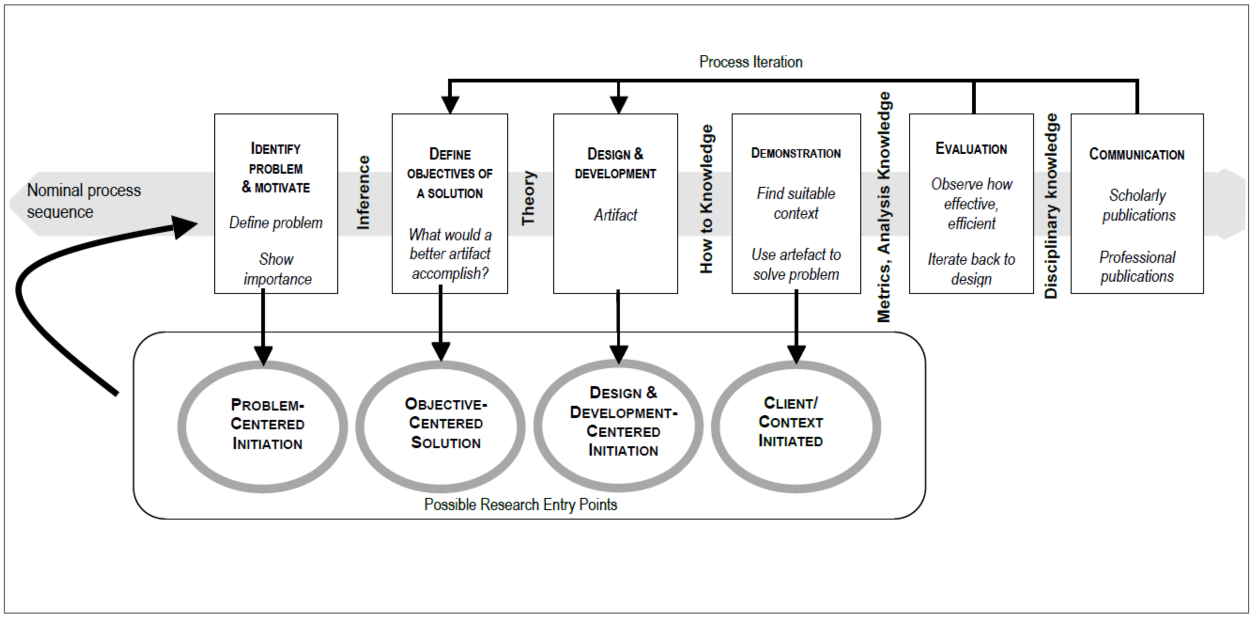

Figure 1 - Design science research methodology model (Peffers et al., 2006).

This methodology includes six steps and four possible entry points. A description of each step of the activity follows:

1st step - Problem identification and motivation. This activity defines the research problem and justifies the value of the solution. Justifying the value of the solution motivates the researcher and the reader to find a solution and shows the reader that the researcher has understood the problem. Since the problem in question serves to develop an artifact that can eventually lead to a solution, it is important to atomize the problem so that the solution can capture its complexity. This activity requires knowledge of the state of the problem and the importance of its solution (Peffers et al., 2006).

2nd step - Define the objectives for a solution. The goals of the solution must be derived from the definition of the problem as well as from what is possible and feasible. The goals can be quantitative, i.e., whether the solution is better or worse than the current one, or qualitative, i.e., how will the new artifact support solutions that were not previously supported. Knowledge of the state of the problems and their solutions and their effectiveness is required.

3rd step – Design and development. In this phase, the artifact is created. Artifacts can be constructs, models, methods, or instantiations (A. R. Hevner et al., 2004). An DSR artifact can be any object that has been designed and has an investigation built into it. This activity also includes determining the functionality and architecture of the artifact. It is necessary to move from goals to design and development. This requires theoretical knowledge that can be used for a solution.

4th step – Demonstration. This activity involves a demonstration of the artifact in solving one or more problems. This demonstration can be experimental, in a case study, or in a simulation. The demonstration assumes that you know how to use the artifact to solve the problem.

5th step – Evaluation. This step measures the effectiveness of the artifact in solving the problem. In this activity, the solution goals are compared to the results of using the artifact to solve a problem. At the end of this activity, if the results are not satisfactory, the researchers may decide to return to step 3 to improve the artifact or they may proceed to the next step, communication.

6th step – Communication. This phase involves communicating the problem and its importance, as well as the artifact, its utility, its novelty, and its effectiveness to researchers and interested parties. Communication requires knowledge of disciplinary culture.

2.2. Research Strategy

1. Step - Problem identification and motivation.

The problem has been identified as an existing need in the market where SMEs are at a distinct disadvantage compared to large enterprises. The motivation is that SMEs need a document to rely on when installing an IoT architecture for anomaly detection.

2. Step - Define the goals for a solution

The objectives defined to achieve a solution is the study of the architectures currently installed and their adaptation to the different types of industries. Investigation of the techniques that have been used depending on the problem. Creation of an architecture based on the previous studies that will allow SMEs to apply an anomaly detection architecture. In this way, the SMEs will have a document that will guide them and show them what is required to implement an anomaly detection architecture.

3. Step - Design and Development.

A global study of predictive maintenance concepts was conducted to understand the scope of the study and the tools required to develop an architecture. A survey of the most commonly used techniques and the technologies that enable predictive maintenance was conducted. An overview of the techniques used in predictive maintenance and the steps required to implement them was created. After this research, it was possible to create a systematic literature review and thus gather the necessary knowledge to propose an architecture.

4. Step - Demonstration.

The artifact is applied in a case where it is supposed to predict the lifetime of a battery. The data used to predict the lifetime comes from the public dataset provided by NASA.

5. Step - Evaluation.

The artifact is evaluated by interviewing the CEO of an SME. This person may not be knowledgeable in technical aspects, so advice on non-technical aspects is expected.

6. Step - Communication.

Scientific communication of this potential item is a possible way to communicate this artifact so that the details of its development are shared and others can make suggestions.

3 -Literature Review

3.1 Industry

It is necessary to have a global theoretical vision in order to perceive the topic addressed in this study. Therefore, some important concepts related to PdM are presented. The following sections provide an overview of the evolution of the industry, which industries use it, and which technologies are used.

3.1.1. Overview

Go back in time to the 1800's when the **first industrial** revolution took place and the first steam engines appeared. Production increased and with-it small businesses that became large organizations. Maddie Walker of Accenture (U.K.) says, "Industrial revolutions are more than a sequence of events, ranging from machines to production." The impact of the first revolution is hard to measure. Agriculture was replaced by the production of essential materials, steam power became the country's main economic source, leading to a population boom and economic growth. It was a great advance for human productivity and production, especially in textiles, where what was once made by hand was now made by machines and with much greater ease. The **second industrial** revolution was triggered at the end of the 19th century using electricity. It was more efficient than steam engines and was therefore used by Henry Ford in mass production on the assembly line in the automobile sector. At the end of the 19th and beginning of the 20th century, new sources of energy appeared, such as gas, oil and electricity, whose presence allowed factories to evolve and improve our processes on the assembly line. In the 1970s, the **third industrial** revolution began with the partial use of computers and programmable controllers. This same revolution introduced computer technology, allowing automated production through electronics and information technology. Semiconductors were invented, giving rise to personal computers, cell phones, and eventually the Internet. **Industry 4.0** - It was in 2011 at the Hannover Messe when the term "Industry 4.0" was first introduced by a group of scientists from Acatech (German Academy of Science and Engineering), symbolizing the beginning of the fourth industrial revolution. Information and communication tools in production. This concept overlaps with other concepts in other European countries, concepts like: IIoT, smart factories, smart industry, advanced manufacturing. The fourth industrial revolution goes one step further: people, machines and products are all connected to each other and to the environment around them. Figure 2 illustrates the 4 industrial revolutions and their influence on manufacturing processes (Acatech, 2013; Wilson, 2021).

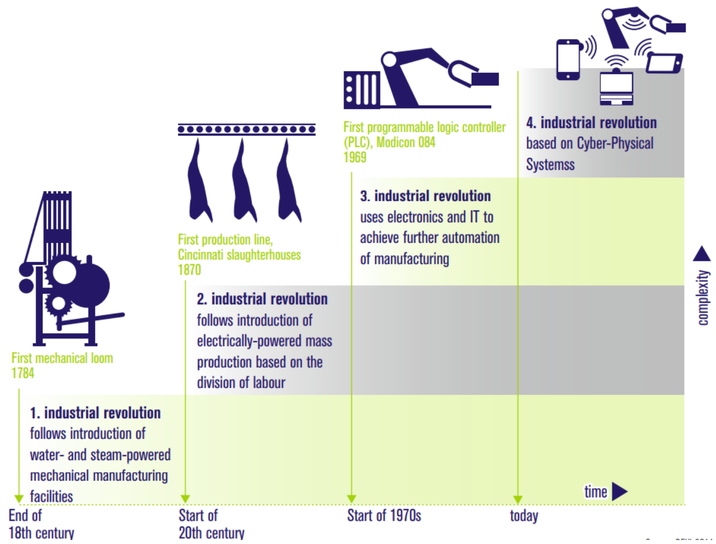

Figure 2 - The four stages of industrial revolution (Acatech, 2013).

The goal is to include the individualization of customer needs, the flexibility and adaptation of the production and logistics system and thus better decision-making, the integration of cyber-physical systems of ICT and CPS, the introduction of advanced production technologies, intelligent automation systems, adapted business models and concepts for sustainable production and logistics (Spath et al., 2013).

Smart factories:

A smart factory represents the transition from traditional automation to a networked system that uses data (Sage, 2019). The concept of smart factory is broad, a smart factory is a digital and networked factory. The entire process is based on optimized and self-organizing processes. This includes processes such as logistics, production planning and product development. In a smart factory there is very little human interaction, the processes are controlled by artificial intelligence, Big Data and IoT (LeanIX, n.d.-b). Manufacturing is about rapid decision making, constant change, and big data. This new approach to manufacturing, where industrial assets are connected to communicate their condition and health, is having a major impact on the way factories operate. By analyzing large amounts of data, it is possible to create knowledge and information upon which decisions can be made in a safe manner. A smart factory has several benefits: Cost savings, less wasted materials, fewer workers, and lower operating costs. It is also more agile as it can quickly change the way a product is made depending on customer needs without sacrificing quality (Sage, 2019). James Woodall, CTO of Infoware said, “Moving towards the smart factory doesn’t mean a complete overhaul with huge upfront investment”. It means a factory can start small, for example, by retrofitting the sensors on existing machines by finding a vendor that offers an IoT retrofit solution (Sage, 2019).

SMEs:

A small or medium-sized SME is a company whose profits, assets and number of employees are below a certain level. The definition of SME is not uniform around the world, each country has its own definition criteria which may also vary from industry to industry. An example of this is the difference in the definition of SME between the United States and Europe. In Europe, a company with less than 250 employees is considered an SME, while in the United States this number can be as high as 1200 (Ward, 2020). In the European Union, an SME is defined by either the number of employees, annual turnover, or annual balance sheet total. The number of employees is a mandatory criterion; for the other two criteria, companies can choose any one and exceed one of them. The following table shows the values of the above criteria (European Commission, 2020).

Enterprise category	Headcount: annual work unit (AWU)	Annual turnover	or	Annual balance sheet total
Medium-sized	< 250	≤ EUR 50 million	or	≤ EUR 43 million
Small	< 50	≤ EUR 10 million	or	≤ EUR 10 million
Micro	< 10	≤ EUR 2 million	or	≤ EUR 2 million

Figure 3 - SME Thresholds (European Commission, 2020)

Maintenance strategies:

Industrial maintenance programs are the foundation of a productive and reliable business. The best way to keep maintenance costs down is to implement maintenance strategies. The maintenance of equipment, machinery, systems, and plants is becoming increasingly sophisticated and requires continuous improvement of the maintenance process. Maintenance includes several activities: Monitoring, routine maintenance, condition analysis, overhaul, repair or rebuild. According to the European standard 13306:2017, maintenance is defined by a combination of technical, administrative and management activities during the life cycle of a plant (European Committee for Standardization, 2017).

Maintenance strategies can be divided in four big groups:

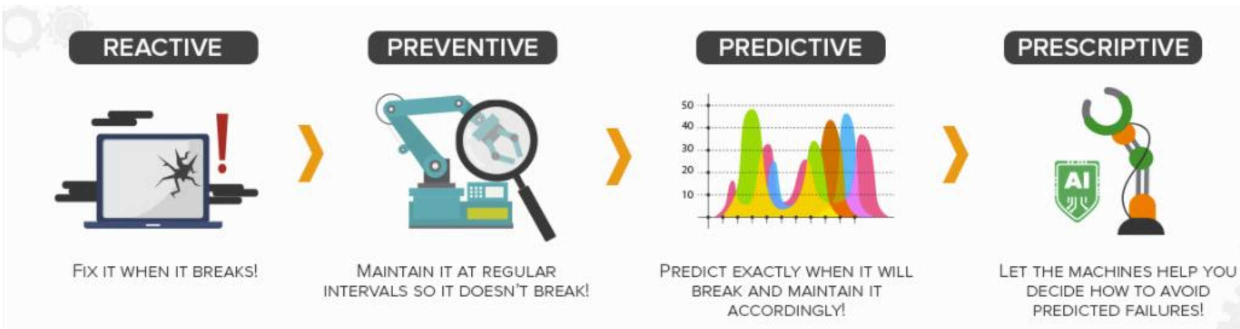

Figure 4 - Maintenance Strategies (Heavy.AI, n.d.).

Reactive Maintenance, also known as corrective maintenance. This type of maintenance is based on the principle of repair when equipment deteriorates or fails. There is no planning for the repairs. This method is applicable to equipment that is not essential to the operation. It is not usually used as a strategy because it can lead to unplanned downtime and usually results in longer downtime and high maintenance costs (Valuekeep, 2021).

Preventive Maintenance (schedule maintenance), Is the most common strategy. It is performed according to predefined maintenance schedules; it relies on visual inspection and other routine health checks like adjustments, cleaning, lubrication, repairs and parts replacement (MRI, 2021). Most of the companies rely on this type of maintenance to prevent having to recur to reactive maintenance (Valuekeep, 2021).

Predictive Maintenance (PdM), Its goal is to predict when equipment malfunction will occur. When undesirable conditions are detected, repairs are scheduled before the equipment fails, reducing repair costs compared to reactive maintenance. This type of maintenance uses machine sensor data and ML techniques to alert you to the risk of failure. Using Computerized Maintenance Management System (CMMS) software is one of the easiest ways to apply this type of strategy (Valuekeep, 2021).

Using control graphs like the one in Figure 5, you can see if the device is operating correctly between the upper and lower limits, defined by the green area. If the values are outside the upper or lower limits, the process is statistically out of control.

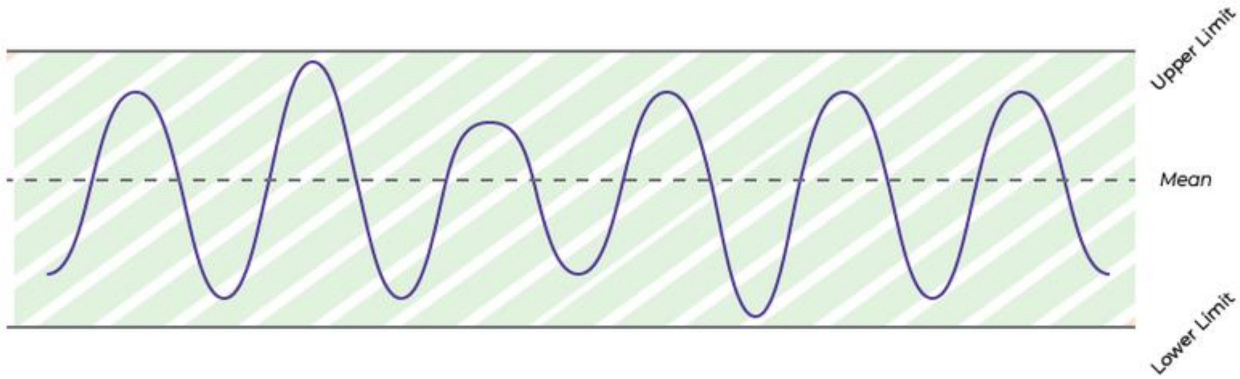

Figure 5 - Illustration of a control chart for condition-based maintenance (Jensen, 2019).

Predictive maintenance is based on advanced statistical methods, such as machine learning, that dynamically determine when a machine needs maintenance. This type of model attempts to find a pattern among all the sensors involved in the process, resulting in a multivariate predictive model. The amount of data is crucial, the more data, the better the model's predictions and the better it can predict future failures. This type of model can find complex patterns that would be impossible for a human to detect. On a temporal level, the model's predictions can range from minutes to hours. This depends on the quality of the data and the frequency with which it is available (Jensen, 2019).

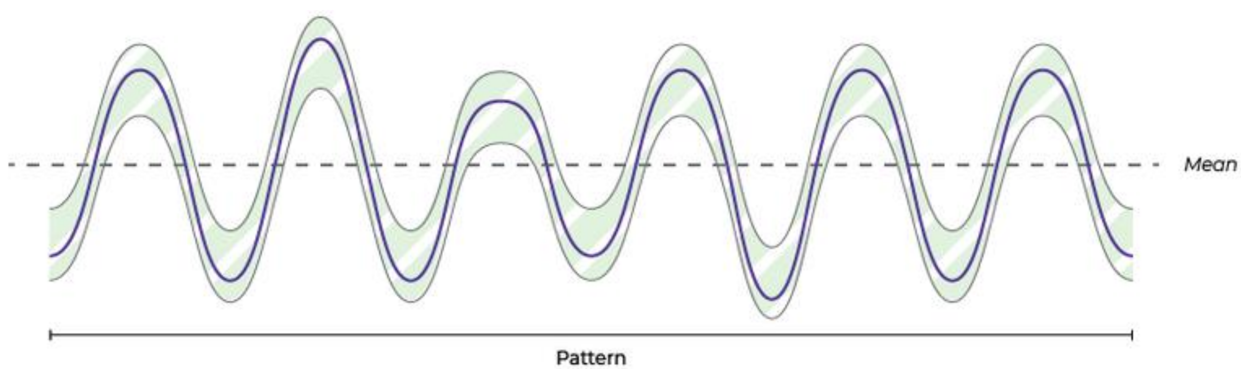

Figure 6 - Illustration of a simplified predictive maintenance model (Jensen, 2019).

In Figure 6, it is possible to detect small variations in behaviour. Again, the entire green range is considered normal, any value outside this range is considered an anomaly. In table 1 there's a summary of differences between condition-based maintenance and PdM.

Condition-based maintenance	Predictive Maintenance
Some types rely on data	Relies on data
Human defines decision-rule	Data defines decision-rule
Static decision rule	Dynamic decision rule
Tells if something is wrong here and now	Predicts failures in the future
Can lead to excessive maintenance	Can be used for just-in-time maintenance
Sensitive to noise	Less sensitive to noise

Table 1 - Summary of similarities and differences of condition-based maintenance and predictive maintenance (Jensen, 2019).

Prescriptive Maintenance, this type of maintenance deals with the analysis of all possible failures in each device and automatically creates a maintenance plan that corresponds to the situation of each device (Valuekeep, 2021). By combining the above maintenance strategies, prescriptive maintenance determines the best maintenance strategy depending on the current context of the operation (MRI, 2021). This strategy ensures that maintenance is performed efficiently, cost effectively, reliably, and safely. This maintenance can be preventive, predictive or inspection. Prescriptive maintenance was originally used in the aerospace industry but has been adopted by many other industries. Of all the strategies, this is the most complex. It requires a maintenance team that is proficient in prevention, predictive maintenance, inspections, and has access to reliable data (Valuekeep, 2021).

3.1.2 Industries

There are a variety of industries using IIoT for predictive maintenance: Gas and Oil, Manufacturing, Energy and Utilities, Transportation and Logistics, Healthcare, Agriculture, and others. In this work we are going to focus on the 5 industries that take the most out of predictive maintenance.

Oil and Gas Industry: One of the pioneering industries for this type of maintenance was the oil and gas industry. The need was based on a desire to reduce maintenance costs while reducing the risk of environmental disasters. The fact that these companies have such a predictive maintenance system in place means that there is no need for constant secondment of workers to carry out technical checks on equipment (Christiansen, 2019; Lee, 2019).

Manufacturing Industry: In this industry, failures, or downtime cost so much that large manufacturers can lose thousands of dollars per minute. Any type of reactive maintenance is extremely expensive, and sometimes it is impossible to predict how long production will be down and how much it will cost the company. However, with enough data and research, downtime can be significantly reduced. Using PdM can extend the useful life of equipment by 3 to 5%. Another plus is that there are sensors that support predictive maintenance, as well as predictive analytics that also improve product quality and equipment efficiency. With PdM it is possible to monitor and test various indicators like, vibration, infrared and sonic acoustical (Christiansen, 2019).

IT Industry: As in other industries, computers show signs of fatigue and future failure. Since any signal coming from one of these machines is much more difficult to identify than in other industries, extremely sensitive sensors are used to detect the anomalies. Anomaly detection is important in various fields as it avoids the disruption of essential services in our society, such as government, hospitals, data centers, navigation controls, and telecommunications. For example, a telecommunications server failure can affect millions of people (Christiansen, 2019; Industry Perspectives, 2016).

Energy Industry: Power plants must provide a continuous and reliable supply of energy. Predictive maintenance is able to ensure an uninterrupted supply by detecting faults in the various components that make up the different energy sources. In the case of wind energy, for example, the equipment that needs to be monitored are pumps, fans, gearboxes, and generators. There are companies in this field that present interesting data: 90% of faults can be detected 5 months in advance, greater efficiency in maintenance and longer uptime lead to an annual return on investment of 175%, energy consumption is reduced through access to efficient metrics and emergency maintenance trips are reduced by 50% (Christiansen, 2019; Samotics, n.d.).

Railways: Companies that manage railroads take advantage of predictive maintenance to ensure that the rails and rolling stock are in good condition. A variety of sensors can be installed, from infrared to audible signals, which can be used to detect malfunctions in wheelsets, bearings, brakes, rail curves, or even immediate damage. This solution improves the speed of rolling stock, reduces delays due to breakdowns and increases safety (Grizhnevich, 2021).

3.1.3 Technologies

Industry 4.0

Industry 4.0 is the information-based transformation of manufacturing in a connected environment of Big Data, people, processes, services, systems and IIoT assets that generate data and information that can be used to create smart industries and ecosystems for industrial innovation and collaboration (I-Scoop, 2022). We are in a transitional phase in the way things are produced, and that is closely linked to the IoT. Advances in networks, machine learning, data analytics, robotics, 3D printing, and other technologies are improving industrial processes and reducing reliance on human labor and decision making (Buchberger, 2021). There are clearly defined frameworks and architectures for Industry 4.0, characterized primarily by the connection of physical assets with digital technologies through cyber-physical systems (I-Scoop, 2022). The Internet of Things (IoT) plays a big role in Industry 4.0, from multi-level layers to IoT platforms to industrial gateways. There are other technologies that are part of this revolution: Cloud computing, Big Data (which implies advanced analytics, data lakes, edge intelligence and enables the application of artificial intelligence), data analytics, storage and edge computing, data communication over mobile networks, changes in systems such as HMI and SCADA, manufacturing execution systems (MES), enterprise resource planning, programmable logic controllers (PLCs), sensors and actuators. The combination of these technologies with AI is coming to fruition in various business areas, such as information management and business process management (I-Scoop, 2022). There are four design principles for the industry 4.0, Interconnection, information transparency, technical assistance, decentralized decisions (Buchberger, 2021).

According to the definition of the European Commission (Davies, 2015), Industry 4.0 consists of the following technologies:

- **ICT** - The application of **information and communication systems** to digitize information and thus integrate all systems at every stage of product creation and use, including logistics and delivery, both inside and outside companies.
- **CPS - Cyber-physical systems** use ICT to monitor and control physical systems and processes.
- **Network communications -** Communication and technology networks that enable machines, products, systems, and people to be connected, both inside the factory and outside with suppliers and distributors.

- **Simulation** through virtualization and modeling in product design and manufacturing process implementation.
- **Data** - Storage of large amounts of data for analysis and exploration that can be processed in the factory or via cloud computing.
- **Intelligent tools** – Digital assistance systems for workers through ICT, including robots, augmented reality, artificial intelligence.

Big data Analytics.

Big Data is the field that deals with processing and analyzing data to obtain information when the data set is too large to analyze using conventional systems. It is usually defined by five V's: Volume, Velocity, Variety, Veracity and Value. The interest in IIoT and predictive maintenance gives meaning to Big Data in the industrial sector. Data is collected from various sources, through common systems, sensors and electronics, the amount of data stored is huge. The industry is working on developing methods to interpret and analyze this data for use in production. It is expected that most devices will change in terms of incorporating sensors, making it possible to generate knowledge in real time. This technology combined with cloud computing will enable manufacturers to better understand their business, which is essential for decision making (Boggess, 2022; Saratchandran, 2021; Twi-Global, n.d.).

Cloud Computing.

This technology has the ability to connect all parts of a company, from manufacturing to logistics to factories within the same company. This technology is already being used on a large scale. This technology is one of the most important factors in a manufacturing revolution. Massive computing power offered as a service is changing manufacturing in many ways. Be it how companies operate, how their products are designed and manufactured and how they are used by customers. It is enabling manufacturers to deploy new manufacturing systems such as 3D printing, high-performance computing (HPC), robotics, IIoT and subsequently predictive maintenance. In this way, access to these technologies becomes more democratic and enables SMEs to use them (Ezell & Swanson, 2017; Laura, n.d.; Saratchandran, 2021).

Automation.

Automation is the use of equipment to automate production systems or processes. The overall automation process aims to increase efficiency, increase production capacity, or decrease costs, usually both. Automation is usually associated with the use of machines to reduce the amount of work done by humans. It is associated with electromechanical processes that are programmed to perform a variety of work, an example of which is robotics. With technological advances in robotics, there is a tendency for robots to become cheaper, smarter, and more efficient, they are used in numerous areas of a manufacturing process (Saratchandran, 2021). It is hard to imagine the manufacturing industry without robotics. It is an area where there have been great technological advancements and it is having a huge impact on manufacturing. Robots replace human labor in repetitive tasks without tiring, with high accuracy, high efficiency, and a very low error rate, allowing workers to focus on more productive tasks (Acieta, n.d.). Automated manufacturing processes are key to an operation that seeks maximum efficiency, competitive advantage, and safety. In the world of manufacturing, there is a shift in jobs. Instead of seeking workers for production and the manufacturing process, companies are seeking skilled workers for robotics (Twi-Global, n.d.).

Cyber-physical systems.

Fundamental enabler of industry 4.0, are systems that integrate computers, networks, and physical processes and monitor and control processes in real time. The merging of cyber and physical processes is critical to manufacturing technology. Cyber systems monitor processes, identify where changes need to be made, and control physical systems accordingly. This technology is one of the great advances of Industry 4.0, which has transformed many aspects of our lives and made concepts such as autonomous cars, robots in surgery, smart buildings, smart grids, and smart manufacturing a reality (Twi-Global, n.d.).

Cybersecurity.

Manufacturing processes contain confidential information and data from many areas of the enterprise, from IT to operating systems. Companies are often hesitant to adopt these cybersecurity technologies for fear that it will compromise a process, slowing it down or resulting in lost revenue (Ava Reveal, 2021). They can no longer be satisfied with the "normal" levels of security that are in place in their factories. Many of these companies thought they were safe, but the connectivity of Industry 4.0 has changed that. Cybercrime increased in 2017 and 2018 and did peak in 2020 as companies rely on remote work due to pandemic-related restrictions. Manufacturing rose from eighth in 2019 to second in 2020 in the ranking of industries most affected by cyberattacks. According to the Global Threat Intelligence Report (GTIR) 2021 report, these numbers represent a 300% increase in attacks per year. Cybersecurity and IoT certification regulations were published in 2020. Implementing a cybersecurity strategy must be a priority in a factory that takes advantage of today's digital processes (LeanIX, n.d.-b; Miller, 2021).

Digital Twin.

A digital twin is a virtual representation of a device or object such as machines, tools, products, robots, or even a factory in general. They allow the analysis of data and the simulation of scenarios. Through this technology, it is possible to make predictions and perform tests without affecting real production, protecting the process from possible errors, and saving time. It is also an essential tool for predictive maintenance (LeanIX, n.d.-b).

Artificial Intelligence and Machine Learning.

AI is being used extensively and is making significant progress in the manufacturing sector. Machine learning techniques are becoming more advanced, advances in sensors and computing power have helped to create a new generation of automation. AI allows machines to collect data, recognize patterns, learn, and adapt to new things. This technology facilitates automation processes, enables prediction of design flaws, ensures the quality of manufactured products, enables predictive maintenance, efficiently forecasts product demand and price, manages inventory, and more (Allinson, 2021; Columbus, 2020; Yap, n.d.).

Augmented reality.

Is the combination of real and virtual world created by a computer. An image is captured via video and then enhanced with digital information. Not to be confused with virtual reality, where there is a separation from the real world. AR has the ability to show digital content in the real world, which allows visualization of data, finished products, machine components that exist only in design, and identification of unsafe working conditions (Koelsch, 2021). It allows a worker to be trained without endangering them or the equipment and informs them that a part is hot without having to touch it. It gives the worker a sense of what's going on around them, which machines are nearby, which ones are out of order, where they are, where co-workers are, and even prohibited zones in the factory. With remote assistance, it's easy for a technician to troubleshoot the problem (Saratchandran, 2021). This technology is new and evolving quickly. Implementing augmented reality is difficult, more difficult than implementing VR. AR systems need a mechanism by which you can locate things (Koelsch, 2021).

5G.

The 5G network has accelerated the fourth industrial revolution that is already underway, enabling faster development of the factory of the future (Galea-Pace, 2020). This network allows for low latency and high fidelity, enabling the switch from fixed to wireless connections. This switch will speed up the manufacturing process and provide more flexibility, lower costs and shorter times for reconfiguring manufacturing processes and changes in production (Ericsson, n.d.). Compared to 4G, this technology is twenty-five times faster and has very low latency, approaching virtually zero. It will allow factories to use many more sensors to monitor the various processes so that virtually everything can be connected (Galea-Pace, 2020).

Additive Manufacturing.

Also called 3D printing has come a long way in the last decade, allowing the production of virtually any component from a variety of materials such as metals, plastics, and others (NI Business Info, n.d.). It is mainly used to produce spare parts and prototypes faster and cheaper (I-Scoop, 2022; Stefanini Group, 2020).

IoT & IIoT:

The difference between Industrial Internet of Things and Internet of Things:

IoT, it is about connecting devices with a unique identity that are connected to the Internet and have software, electronics, and sensors that enable the collection and transmission of data over the Internet without human interaction. The goal of IoT is to transform "dumb" devices into smart devices capable of exchanging data in real time. It is possible to connect everyday objects such as thermostats, home appliances and televisions to the internet. For example, it is possible to raise or lower the blinds through an application on a smartphone (Geeksforgeeks, 2020).

IIoT, uses smart sensors and actuators to improve manufacturing processes. Harness the power of smart machines and analyze in real time using data generated by machines over the years (Trend Micro, n.d.). The term IIoT was coined by General Electrics in late 2012. The Industrial Internet of Things brings together critical assets, predictive and prescriptive analytics, and a well-trained workforce (Parris, n.d.). Both IoT and IIoT concepts share the same characteristic: they are available, intelligent, and connected. While the term IoT is mostly used for the consumer market, IIoT is used for industrial purposes. It is a network of industrial devices that are connected through communication processes, resulting in systems that can monitor, control, share, analyze, and deliver valuable knowledge. The philosophy behind IIoT is that machines are more efficient than humans at capturing and analyzing data in real time and communicating critical information for informed business decisions (Trend Micro, n.d.). These networks are used in manufacturing, logistics monitoring, and management systems (Gunawan, 2017). The application of an IIoT network is more sophisticated and rigorous when it comes to the devices used to monitor industrial systems. They provide a broader and more detailed view and enable automated controls and advanced analytics. As the IIoT is used to manage critical systems, more sensitive and accurate sensors are used, also the security of the network is more demanding (Gunawan, 2017).

IIoT reference architectures.

There are several reference architectures related to the IIoT that are being collaborated on to achieve standardization. There are three reference architectures, each related to a continent: Reference Architecture Model for Industry 4.0 (RAMI 4.0), which was introduced in Germany as a European solution; Intelligent Manufacturing System Framework (IMSA), which was introduced in China; Industrial Internet Reference Architecture (IIRA), which was introduced by the Industry IoT Consortium (IIC) in the United States (Heidel et al., n.d.). These model architectures present unified concepts and methodologies with the goal of stakeholders managing complexity and speaking the same language. In this way, a basic structure for a concrete description and specification of architectures is created. There is international collaboration between the three architectures to standardize the IIoT internationally (Heidel et al., n.d.). The Reference Architecture Model for Industry 4.0 (RAMI 4.0) is an architecture that focuses on IoT and cyber-physical systems in the field of industrial manufacturing, taking into account fundamental aspects such as assets. Comparing RAMI 4.0 with IIRA, the latter has a broader focus, it tries to push all industrial applications (The Open Group, n.d.), while RAMI 4.0 is presented as a reference model for Industry 4.0 (Schweichhart, 2016). Figure x provides an overview of the different focuses of IIRA and RAMI 4.0.

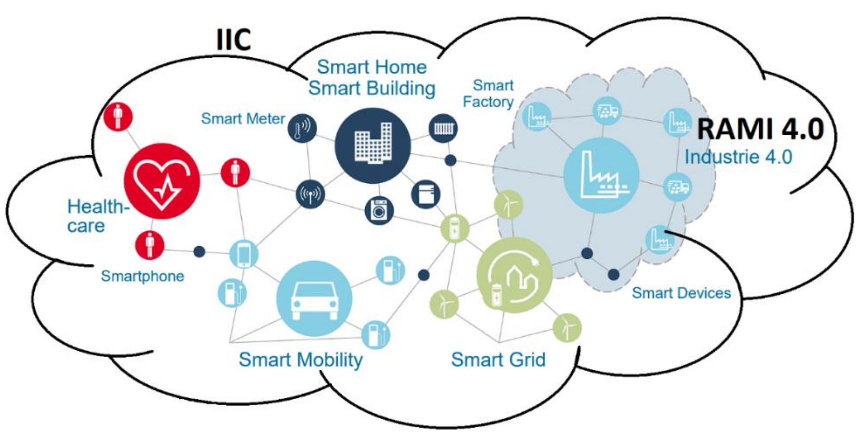

Figure 7 - The Internet of Things and Services, Bosch Rexroth AG

RAMI 4.0, Reference Architecture Model Industry 4.0 was developed and presented by the German company ZVEI with the aim of supporting initiatives in Industry 4.0. This architecture intends to define communication structures and develop a common language. It is represented by a three-dimensional map on which one can find an indication of how to approach each issue in a structured way. This will ensure that all stakeholders can discuss in a common language, ensuring interdisciplinary standardization of technologies that apply to different fields such as mechanical, electronic, electrical, communication and information technology (Lydon, 2022; Schweichhart, 2016). The main focus in the development of RAMI 4.0 has been on industrial production. Concepts are applied to processes to achieve holistic integration of automation, information, and manufacturing execution to improve all aspects of production and commerce. There are adjacent projects that help to consolidate the RAMI 4.0 application, projects such as: "Process Sensor 4.0 Roadmap" which aims to create building blocks to further develop system architectures for process automation, initiated by NAMUR and VDI/VDE in collaboration with market leaders such as ABB, BASF, Bayer, Bilfinger, Siemens, Fraunhofer, etc.; the creation of an independent protocol by the OPC Foundation and FieldComm Group for an information model for automation devices (PA-DIM) based on the industrial interoperability standard OPC UA. It aims to reduce implementation times for advanced analytics, Big Data projects, and cloud solutions (Lydon, 2022). The RAMI 4.0 architecture and Industry 4.0 components enable companies to create a framework for developing products and business models. RAMI 4.0 is a three-dimensional map that shows how to approach the application of Industry 4.0 in a structured way. The architecture has been standardized as DIN SPEC 91345 (Lydon, 2022) and internationally as IEC PAS 63088 (Heidel et al., n.d.).

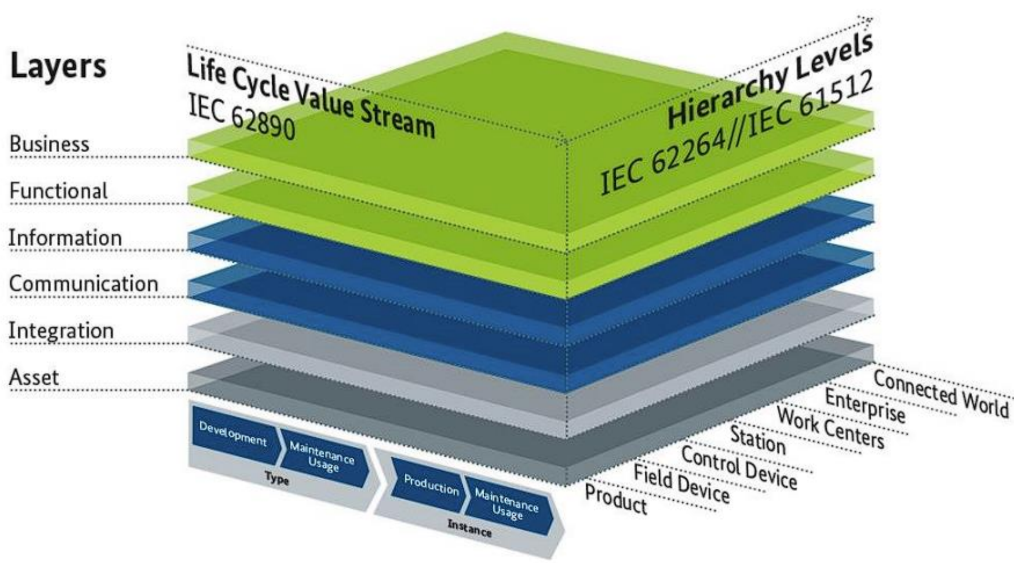

Figure 8 - RAMI 4.0 (Schweichhart, 2016)

RAMI 4.0 consists of three axes: "hierarchy levels", "life cycle value steam" and "layers".

"Hierarchy levels" axis: this axis represents the different standardized levels for IT companies and control systems, they are based on IEC 62264. these levels represent the different functionalities within the factory floor (Heidel et al., n.d.; Lydon, 2022). They include the workpieces labeled "Product" and the services and IoT connections labeled "Connected World" (Lydon, 2022).

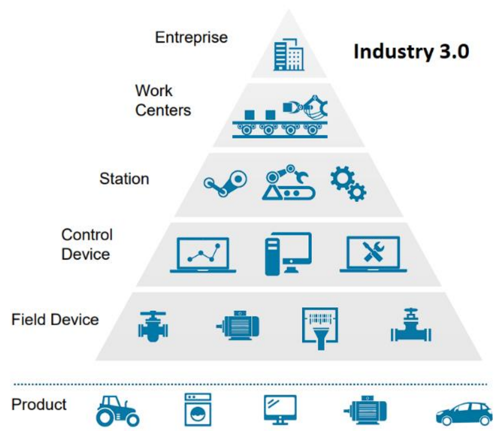

Figure 9 - Factory world with Industry 3.0 (Schweichhart, 2016).

In the "old world" represented in figure 9 we have following characteristics: a hardware-based structure; the functions are bound to hardware; hierarchy-based communication; isolated product (Lydon, 2022; Schweichhart, 2016).

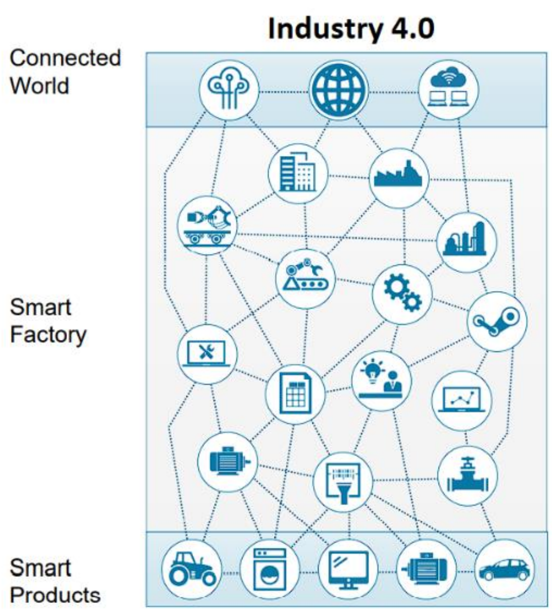

Figure 10 - Factory world with Industry 4.0 (Schweichhart, 2016).

In “new world”, represented at figure 10, we have the following characteristics: flexible systems and machines; functions are distributed throughout the network; participants interact across hierarchy levels; communication among all participants; the product is part of the network; RAMI 4.0 structure (Lydon, 2022; Schweichhart, 2016).

"**Life cycle value stream**": this axis represents the lifetime of products and equipment, it is based on the IEC 62890 standard, Life cycle management for systems and products. This standard is used for measurement, control, and automation of industrial processes. In this axis, a distinction is made between "type" and "instance". The "type" becomes an "instance" only when the product is real, i.e., when its development, production and manufacture are completed. All elements and components of IT are also summarized in the layer and life cycle model (Lydon, 2022; Schweichhart, 2016)**.**

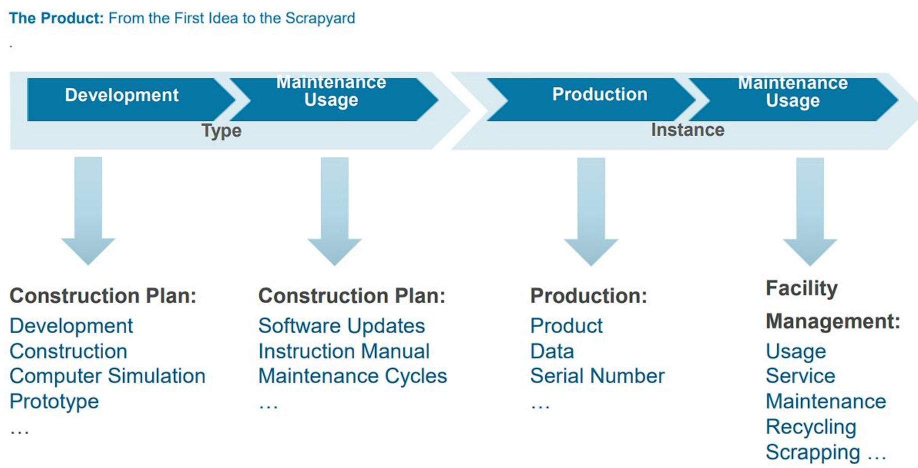

Figure 11 - Product Life Cycle (Schweichhart, 2016).

"Layers/Architecture”: The six vertical planes represent a layered representation of the machine that acts like a virtual map of the machine. The representations shown are from information, communication, and technology systems whose properties are divided into layers (Lydon, 2022; Schweichhart, 2016).

Figure 12 - Product Life Cycle (Schweichhart, 2016).

With the definition of these three axes, the most important aspects of Industry 4.0 have been established. In this way, the concepts of Industry 4.0 can be described and implemented through RAMI 4.0. This enables a gradual transition from the current state to Industry 4.0 (Lydon, 2022; Schweichhart, 2016). The digitization of the real physical object takes place via a management shell. This can be defined as: the interface that connects the physical object to I4.0; where data and information about the object is stored; serves as an interface to the standardized communication network. The object is connected to Industry 4.0 and the management shell forms the digital part (Schweichhart, 2016).

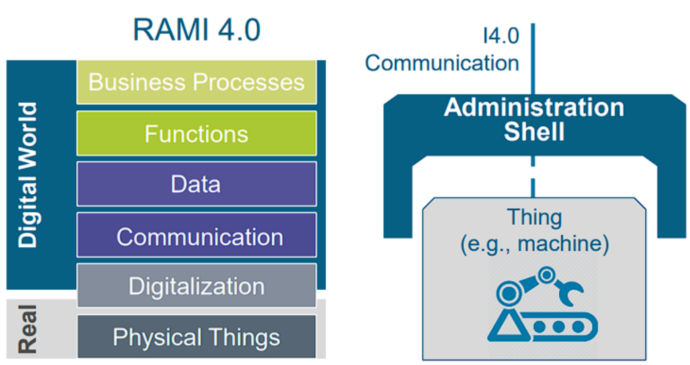

Figure 13 - Administration Shell that allows integration of the object into Industry 4.0 (Schweichhart, 2016).

Each physical object must have its own management shell, and it is possible to have a common management shell for several physical objects.

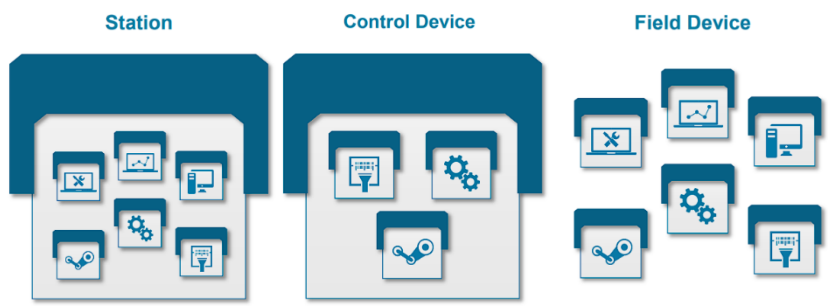

Figure 14 - Administration Shell for thematic units (Schweichhart, 2016).

RAMI 4.0 integrates different perspectives and presents a common path for implementing Industrie 4.0 technologies. In this way, it can be taken up by industry associations and standardization bodies. In this way, an understanding of patterns and use cases is provided to all who use this architecture (Lydon, 2022). RAMI 4.0 can be used as a map for Industry 4.0 solutions that are deployed nationally and internationally. There is international interest in collaboration so that the different reference architectures are identical (Heidel et al., n.d.; Lydon, 2022).

IoT Architectures

An IoT is an architecture that consists of smart devices that are interconnected to form systems that enable the monitoring, collection, and analysis of data in real time (Avsystem, 2019).

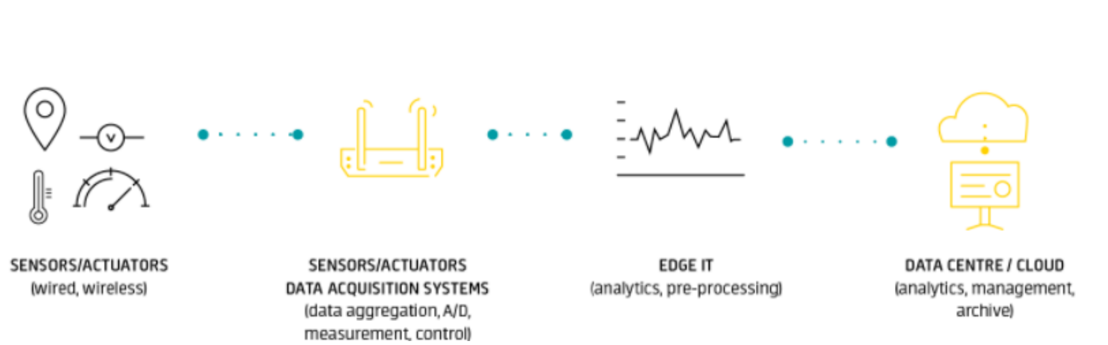

Figure 15 – The four Layers of IoT architecture, (Avsystem, 2019)

Although every IIoT solution is different, the 4 layers listed below are essential to building an architecture that ensures availability, maintenance, and cost effectiveness (Avsystem, 2019).

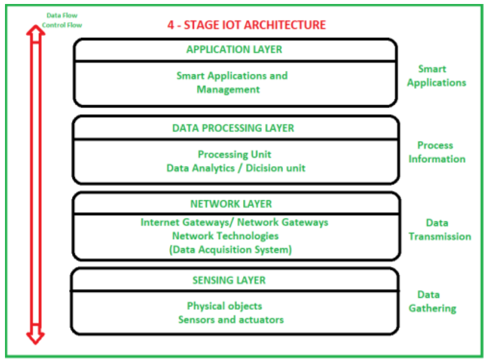

Figure 16 - Four Stage IoT Architecture (Geekforgeeks, 2022).

- **Perception or sensing layer:** this consists of things, like, sensors, actuators, and devices, collectively called edge nodes (IIRA). It is responsible for converting analog signals into digital data and vice versa (Altexsoft, 2020; Record Evolution, 2020). These devices, connected at farthest edge of the IoT network, form the bridge between the digital and real worlds and provide the essence of the IIoT, data (Altexsoft, 2020; Avsystem, 2019).
    - Sensors: They collect data about the state of a process, environment, or device. They can capture information such as temperature, humidity, chemical composition, vibration, fluid levels, or even the speed of a manufacturing process. They can be integrated into the device or stand-alone (Altexsoft, 2020; Avsystem, 2019; Jahnke, 2020).

    - Actuators: They work in the opposite direction of sensors, they receive information from the network to act in a physical way, they are used in motors, lasers, robots, etc (Altexsoft, 2020; Avsystem, 2019). When a sensor detects an anomaly, the actuator can act in real time to fix it (Jahnke, 2020).

    - Devices: These may have the sensors or actuators as an integral part or be connected to them (Altexsoft, 2020). It is important that the connected devices not only be able to communicate in both directions, but also have the ability to communicate with each other to add value to the IIoT network (Avsystem, 2019).

- **Network Layer:** This layer operates in close proximity to sensors and actuators and is essential for processing the collected data, filtering and compressing it for later transmission to an edge infrastructure or cloud platform. This second layer is the bridge for communication between all devices, networks and cloud or edge services that are part of the IIoT network (Altexsoft, 2020). This network consists of internet/network gateways, data acquisition systems (DAS) (Avsystem, 2019; Geekforgeeks, 2022; Jahnke, 2020). DAS is responsible for capturing and converting analog data into digital data, aggregating, and formatting it before sending it through an internet gateway to the next stage of processing. In this layer, the volume of data is enormous, so it is necessary to

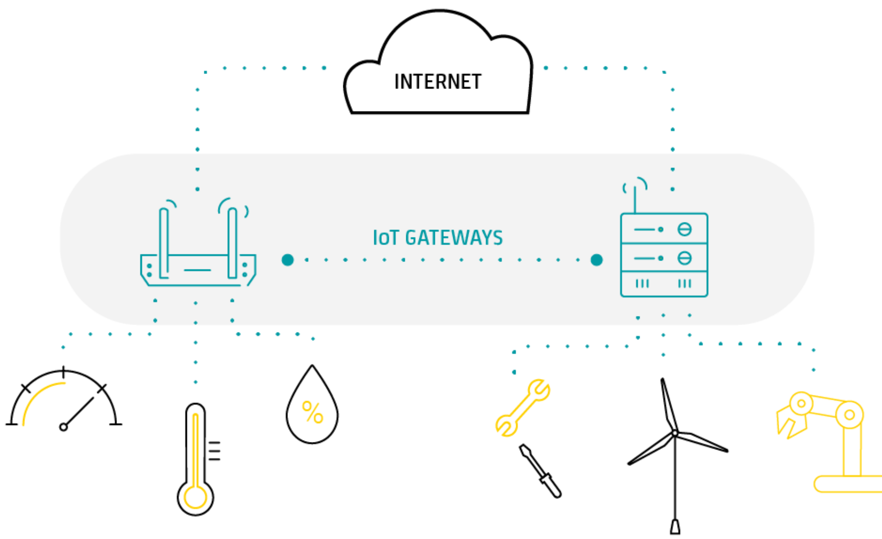

Figure 17 – Gateways and Data Acquisition, (System, 2020).

ensure that the data is compressed and filtered so that it can be sent optimally (Jahnke, 2020). The connection between the physical layer and the cloud can be done in two ways: directly via TCP or UDP/IP or via gateways, which are hardware or software modules that encrypt or decrypt data (Altexsoft, 2020). Communication between the cloud and the gateways takes place via various network technologies.

Once you have an IoT solution, you need to determine the protocols for messaging between devices and between devices and the cloud. See the table below for the most used protocols.

Ecosystem	Description
DDS (Data Distribution Service)	Directly connects IoT devices to each other and to applications addressing the requirements of real-time systems.
AMQP (Advanced Message Queuing Protocol)	Peer-to-peer data exchange between servers.
CoAP (Constrained Application Protocol)	A protocol designed for constrained devices – end nodes limited in power and memory. Wireless sensors are a good example.
MQTT (Message Queue Telemetry Transport)	A light protocol built on top of TCP/IP for centralized data collection from low-powered devices.

Table 2 - Communication protocols, (Altexsoft, 2020).

- **Data Processing Layer:**

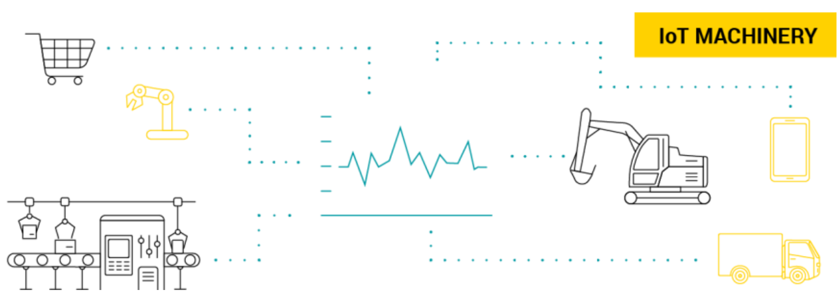

Figure 18 – Edge Analytics (Avsystem, 2019).

Here, the data digitized by the previous layers is processed by devices close to the data source, called edge devices. This reduces latency and volume before transmission to the cloud, also, it enables initial analysis and preprocessing (Avsystem, 2019; Jahnke, 2020). As a result, they enable faster responses and flexibility in processing and analyzing data, essential factors for certain industries where making fast and correct decisions is crucial (Avsystem, 2019). Machine learning plays an important role in this phase and enables consistent feedback from the system (Jahnke, 2020). This layer is essential for IoT systems that want to meet the requirements of 5G mobile network such as speed, security, and scalability (Altexsoft, 2020). Related to this level is the concept of Fog or Edge Computing, which is based on the idea of processing and storing data as fast as possible and as close to the source as possible.

- **Edge Analytics and computing:** Occurs on gateways, local servers, or edge nodes across the network (Altexsoft, 2020). It relies on an IT infrastructure that performs data processing close to the source, usually from sensors. In this way it is possible to define workloads for the different machines without relying on a single computer to process a large number of devices. Only the results that can be processed are transmitted to the servers or the cloud. This results in better bandwidth, less delay compared to systems with central servers and less data storage in the cloud. This infrastructure has the advantages of better performance, shorter response times, real-time information, and unlimited scalability (Altexsoft, 2020). In this layer, the data is: evaluated to determine if it will be processed at the next levels, formatted so that it can be processed further, decrypted, filtered, and forwarded to another destination if necessary (Altexsoft, 2020).
- **Fog computing:** It's another way of processing data close to the source, it takes place in the local network, between edge devices and servers. A bridge is built between the edge and the cloud or datacenters. In this layer, data processing is done by gateways. Although this layer has more processing power than the Edge, there are still many systems without this layer, because Edge computing does not rely on Fog computing, but the opposite is not true (Altexsoft, 2020).

- **Application Layer / Cloud platform:** Unlike edge solutions, this layer is designed to store, process, and analyze large amounts of data in depth, which enables machine learning in a way that is not possible in an edge system (Avsystem, 2019). At this stage, the information is stored in the cloud or in data centers. Here it is possible to combine data from all devices and locations from which knowledge is gained and which provide an overview of the company (Jahnke, 2020). In recent years, this technology has become more and more prevalent. Cloud computing paves the way for higher production, less unplanned downtime, and lower energy consumption. When deployed properly, the appropriate solutions enable not only the provision of information about the business, but also human interaction with the system, control, and monitoring to make informed decisions through reports, dashboards and data displayed in real time (Avsystem, 2019).

Sensors

Sensors are used to monitor the entire factory, from finished products, their quality, machinery, and other equipment, all in real time. This allows for monitoring that would otherwise not be possible. Different industries use multiple sensors depending on their needs and processes. These are essential for early detection of anomalies. The best strategy for detecting anomalies in an industrial process is to use multiple types of sensors associated with different anomaly detection techniques. The following is a table of the most used sensors for anomaly detection in industrial processes.

Measurement	Sensor	Key Information	Target Faults
Vibration	Piezo accelerometer	Low noise, frequencies up to 30 kHz, well established in CbM applications	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Vibration	MEMS accelerometer	Low cost/power/size, frequencies up to 20 kHz+	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Sound pressure	Microphone	Low cost/power/size, frequencies up to 20 kHz	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Sound pressure	Ultrasonic microphone	Low cost/power/size, frequencies up to 100 kHz	Pressure leaks, bearing condition, gear meshing, pump cavitation, misalignment, imbalance

Motor current	Shunt, current transformer	Low cost, noninvasive, usually measured at motor supply	Eccentric rotors, winding issues, rotor bar issues, supply imbalance, bearing issues
Magnetic field	Hall, magnetometer, search coil	Low cost/size, frequencies up to 250 Hz, stable over temperature	Rotor bar, end ring issues
Temperature	Infrared thermography	Expensive, accurate, multiple assets/sources of heat at one time	Heat source location due to friction, load changes, excessive start/stop, insufficient power supply
Temperature	RTD, thermocouple, digital	Low cost, size, accurate	Change in temperature due to friction, load changes, excessive start/stop, insufficient power supply
Oil quality	Particle monitor	Viscosity, particles, and contamination	Detect debris from wear

Table 3 - most used sensors for predictive maintenance (Murphy, n.d.).

3.1.4 Challenges and Opportunities

Challenges:

Companies are increasingly embracing the technologies that define them as part of the industry 4.0 revolution. Virtually every day we hear about the terms Industry 4.0 or digital transformation. The adoption of 4.0 technologies presents companies with challenges they have never seen before. There are opportunities and challenges to be overcome for a successful digital transformation (Stefanini Group, 2021). Businesses are made up of people, interaction between people, and are run by people. Therefore, before all the technical difficulties in implementing the technologies that enable successful digital transformation, it is important to understand the difficulties that normally arise in a company. First and foremost, it is necessary to define a strategy for Industry 4.0 that includes rethinking and implementing new business models, understanding the business case, understanding the company for the necessary changes, pilot testing, a good connection between departments, developing and recruiting new talent, and finally changing leaders (i-SCOOP, 2022; Rudinschi, 2017). The latter is often overlooked. Lack of alignment and preparation between managers, where different business units disagree on how to proceed, leads to delays.(Ellingrud et al., 2021; Infopulse, 2019).

Technical challenges:

The gap in technical skills: Technological progress means that humans are no longer the main labor force in production, machines replace humans in many tasks. Automation will have a significant impact on employability in the coming years and will greatly change jobs, leaving most workers unable to develop their skills (Ellingrud et al., 2021). Difficulties in the use of advanced knowledge, information management and artificial intelligence (Khan et al., 2017). There is a need for an evolved workforce as some workers often lack the ability to keep up. New hires need to have digital skills and understand the process globally, how manufacturing processes work, and the digital tools that support those processes. Only with the right workforce is it possible to implement certain business models, introduce new technologies, and maintain operations (Stefanini Group, 2021).

Data: Technology has advanced and so has the concern for data. Companies try to keep their data private, which means there is no sharing of data between companies. If that were the case, it would be much easier to train artificial intelligence algorithms (Stefanini Group, 2021). If you look at the internal system of the companies themselves, there is often no interdepartmental sharing, data is stored and often lost because no one or I am a department uses it. To get business intelligence, data and information needs to be shared across all departments (Sykes, 2019). In the case of manufacturing companies, one of the biggest challenges is knowing how to get value from the data. Data can come from a variety of sources, data from machine control systems, product or process quality, manual records, anomaly monitoring systems, logistics and customer information. Some of this data is structured, others are semi-structured or completely unstructured, in any case, this data is often not used (Schuldenfrei, 2019).

Interoperability: A key factor that often prevents a company from innovating in Industry 4.0 is the lack of interoperability (Schuldenfrei, 2019). Technologies, systems, data types, protocols, components, and products are not aligned. It is not easy to swap parts from one vendor for another, limiting opportunities for upgrades(Schuldenfrei, 2019; Stefanini Group, 2021). There is no doubt that Industry 4.0 is moving very fast and greatly improving the productivity of companies in various industries, but right now we have old systems connected to new systems that do not always work well together

(Sykes, 2019). Data can be collected by aftermarket sensors or by sensors already installed in the machines. It must be ensured that all these sensors are able to communicate with each other and with the central system, usually a CMMS (Computerised Maintenance Management System). This communication must be as fast and efficient as possible. In the case of implementing predictive maintenance, this is a crucial step because all devices must function correctly as a set (ATS, 2021).

Security: Because of their connectivity, the threats associated with Industry 4.0 are high. Although rare, a cyberattack on a company can expose it in a variety of ways, exposing or damaging data, stealing intellectual property, and thus threatening its competitive advantage (Sundblad, 2019). These attacks can be done through ransomware or even a targeted attack on the company in question (E. Anderson, 2020). The digital and physical systems that form the backbone of Industry 4.0 are a great asset to a company, but they also increase the attack surface. The fact that multiple machines are connected to one or more networks makes them vulnerable to attack (Stefanini Group, 2021). Manufacturers need to make sure that their company is secure. IT departments need to be supported financially and culturally to ensure network security (Sundblad, 2019).

Data Growth:

With the increasing use of AI in businesses, companies will get more data faster and from different sources (Schuldenfrei, 2019; Stefanini Group, 2021). It is difficult for traditional IT systems to store and process a volume of data of this magnitude. Therefore, enterprises need a solid, state-of-the-art platform to take advantage of manufacturing with ML, AI, and predictive analytics (Stefanini Group, 2021).

Initial investment:

One of the factors holding manufacturers back from implementing Industry 4.0 is the fact that ROI is low (N. Anderson et al., n.d.). There is no doubt that implementing all the sensors, devices, software, and the cost of skilled personnel in this field will cost (ATS, 2021). However, the current prices are much more attractive and make the investment possible (N. Anderson et al., n.d.).

Opportunities:

The benefits are numerous: optimization and automation lead to higher efficiency and productivity, real-time data monitoring of supply networks to improve supply and demand, intelligent monitoring and maintenance to reduce maintenance downtime and costs, real-time monitoring of robots through the IIoT leads to better quality products, better sustainability and better working conditions, sales increases, energy efficiency and gaining customer trust through personalization capabilities(Infopulse, 2019; LeanIX, n.d.-a; Stefanini Group, 2021). The application of ML and data analysis of industrial systems makes it possible to find information to make strategic decisions. This information can provide benefits in reducing maintenance costs, schedule control, significant reduction in unplanned downtime, reducing repair times, reducing spare parts inventory, extending the life of spare parts, increasing production, improved equipment safety, increasing operator safety (ATS, 2021; Khan et al., 2017).

3.2 Anomaly detection

3.2.1. Overview

Data science techniques

The field of data science consists of several components: Mathematics and statistics that extract valuable information from data, techniques and algorithms that make it easier to work with large datasets through advanced methods and tools that help put the data into the desired format (Schmelzer, 2020). Some of these techniques have been around for many years, others are new and come from recent research in ML (Schmelzer, 2020).ML is an essential part of AI that manages to use data in new ways by suggesting articles, as is the case with Facebook, or by letting computers learn and improve through the experience they have with programs that can automatically access data and perform tasks such as prediction or recognition (Priyadharshini, 2022). ML is based on algorithms that can learn without requiring code rules. It became a scientific discipline in the late 1990s due to major advances in digitization and cheaper computing power. Instead of data scientists creating ready-made models, they started training computers to do so (Pyle & José, 2019).

Overall, there are 3 types of ML techniques, supervised learning, unsupervised learning, and reinforcement learning:

Supervised learning: in this type of learning, the process ML begins with inputting data into a particular algorithm with the goal of developing a final model. To find out if the algorithm works, it is tested by inputting new data and then comparing the prediction with the actual results. If the result is not good, the algorithm is trained until the desired result is achieved (Priyadharshini, 2022).

Supervised learning can be divided into two types of problems: Classification and Regression.

Classification is about predicting a class. The algorithm needs to accurately assign data to a specific category, for example, sorting spam emails so that they are directed to a different folder. Common algorithms for classification are: Linear classifier, SVM (Support Vector Machine), Naïve Bayes classifier, K-nearest neighbor, Logistic regression, Random Forest and decision trees, (Delua, 2021; Priyadharshini, 2022; Schmelzer, 2020).

Regression predicts a numerical value. The algorithm is used to learn the relationship between input or independent variables and the target or dependent variable (Brownlee, 2020a; Delua, 2021). Regression models are used to predict values such as sales profit. Common algorithms for regression are: Linear regression, lasso regression, multivariate regression, and polynomial regression (Delua, 2021; Priyadharshini, 2022; Schmelzer, 2020).

Unsupervised learning: in this type of learning, algorithms analyze and cluster unlabeled data to extract patterns (Brownlee, 2020a; IBM, 2022). In contrast to supervised learning, only the input variables are used here, without a target variable (Brownlee, 2020a).The fact that the data is unknown means that there is no way to assign it to a particular algorithm, hence the term unsupervised. The data is provided to the model and the model tries to find patterns. The algorithm tries to understand the relationships between the data without direct human intervention (Priyadharshini, 2022).

Unsupervised learning can be divided into 3 groups:

Clustering: this is a technique that groups unlabeled data based on their similarities. These algorithms process unclassified data into groups represented by existing structures or patterns in the data. There are different types of clustering algorithms namely exclusive, overlapping, hierarchical, dense, and probabilistic. Exclusive clustering algorithms specify that a point can belong to only one group. They are also called "hard" clustering, an example of which is K-means. In overlapping clusters, a point can belong to more than one cluster, and its membership in one group can be more pronounced than in another. An example of this is fuzzy K-means. Some examples of algorithms for clustering are K-means, K-NN (K-nearest neighbors), Hierarchical Clustering, Gaussian Mixture Models (probabilistic), Mean-Shift Clustering, Fuzzy K-means, DBSCAN (density) (Brownlee, 2020b; IBM, 2022; Schmelzer, 2020).

Association: it is a method for discovering relationships between variables. For example, someone who buys a house usually also buys furniture (guru99, IBM). They are also used to understand the relationships between products bought in the supermarket. They allow the company to identify the relationship between different products (IBM). There are various algorithms used to create association rules such as Apriori, Eclat and FP -Growth. Apriori is the most commonly used (Brownlee, 2019; IBM, 2022).

Dimensionality reduction: Usually more data means better results, but this can also be a problem due to overfitting and difficulty identifying the most important variables (IBM, 2022; Sunil, 2021). Dimensionality reduction is a technique used when the data set has a large number of variables or dimensions. This technique allows you to reduce the number of variables while better preserving data integrity. It is also used in the preprocessing phase of the data (Delua, 2021). Some examples of dimension reduction algorithms: PCA (Principal Component Analysis), SVD (Singular Value Decomposition), Autoencoder (IBM, 2022).

Reinforcement Learning: These algorithms train the machine to make certain decisions (Brownlee, 2019). They work by exposing the machine to an environment where it learns by trial and error from past experiences and tries to find the best way to make good decisions (Sunil, 2021). In this case, there is no data set for the machine to rely on, but a goal, an action to perform, and feedback on its performance (Brownlee, 2019).

In this article, the focus is on anomaly detection algorithms, i.e., techniques that identify rare events, objects, or observations (AVI Networks, n.d.; Johnson, 2020; Valcheva, 2020). The anomaly detection technique is to identify rare events or observations, i.e., something that does not fit the normal behavior of a dataset (Gupta, 2021; Valcheva, 2020). This type of anomaly can have different names, outliers, exceptions, surprises or peculiarities (Valcheva, 2020).

There are different types of anomalies (Cohen, 2022; Gupta, 2021; Valcheva, 2020):

- **Point Anomalies** or point outliers, these points are also called global outliers and are far from the whole dataset.

- **Contextual anomalies** or contextual outliers, they are anomalies that occur in a particular context, a point that is different from all others in a particular context. A point may be an anomaly in the context of one data set and not in another. This anomaly often occurs in time series data. A good example is someone spending money on ice cream in the winter. In summer this is normal, in winter it is strange.

- **Collective anomalies** or collective outlier is a set of points that are different or abnormal compared to other data. An example is the interruption of rhythm in an electrocardiogram.

3.2.2 Techniques for anomaly detection

There are several ML techniques for detecting anomalies, the most common being: K-NN, K-means, LOF (Local Outlier Factor), SVM, NN, Isolation Forest, DBSCAN (Brownlee, 2020b; Garbade, 2018; Valcheva, 2020).

K-nearest neighbor (k-NN): It is one of the simplest techniques in the supervised learning category. It is most commonly used in classification problems (Patwardhan, 2021). As the name suggests, this algorithm considers the k nearest points (data) to predict the class of the new point. The learning of this algorithm is instance-based, there are no weights for learning a prediction, all the points are used to predict the outcome of data which has never been seen. This classification is based on distance similarities like Euclidean distance or hamming distance. This algorithm is lazy to learn, as nothing is learned from the existing data until new data comes up, only then are predictions made. This algorithm is also non-parametric, there is no function you need to predefine (Patwardhan, 2021; Valcheva, 2020).

Local Outlier Factor (LOF): LOF is an important anomaly detection algorithm. It is based on the concept of local density and uses the distance between nearest neighbors to estimate this density. It compares the density of an element with the density of its neighbors and is thus able to detect differences in density, considering members with lower density as outliers (Valcheva, 2020). Each element is assigned a score indicating how isolated it is, or how likely it is to be an outlier, based on the size of its neighborhood (Brownlee, 2020b).

K-means: This algorithm is widely used in data mining. It partitions groups based on similarities between data points. It is a very easy algorithm to implement (Thelin, 2021; Valcheva, 2020). There are some things to consider with this algorithm. It requires a predefinition of the number of clusters and works only with numeric data (Valcheva, 2020).The process starts by randomly assigning k centroids to be used as starting points for each cluster, and then performs several iterations to compute the optimal position of the centroid. The algorithm for optimization when the centroids are stable, that is, when the value of the centroids does not change or when the number of iterations is reached (Garbade, 2018). This algorithm is able to detect anomalies by pointing out the points that do not match the rest of the clusters (Thelin, 2021).

Support Vector Machine (SVM): This algorithm is one of the most efficient in detecting anomalies, especially in its one-class SVM strand. It is a technique used in regression and classification problems, but mainly in classification problems (Thelin, 2021; Valcheva, 2020; Verma, 2021). The SVM algorithm is based on the idea of finding a hyperplane that divides the data into two classes as best as possible (Bambrick, 2016).

The support vectors are closest points to the hyperplane. These points are critical data elements whose removal would cause a change in the position of the hyperplane. The hyperplane can be thought of as a line that linearly separates a set of data. When you test new data, it is sorted by which side of the hyperplane it lies (Bambrick, 2016).

For anomaly or outlier detection, the one-class SVM is best. It is so called because it aims to classify the anomalies into a different category. There are two ways to apply the algorithm. In the first method, anomalies are separated from the feature space and the distance between the hyperplane and the feature space is maximized. This technique results in a feature that focuses on the density of the space, where observations that lie in the region with more density are assigned +1 and observations that lie in the region with less density are assigned -1. The second technique uses a spherical boundary instead of planes, resulting in a hypersphere with a center and a radius. The dense space is defined by the distance between the center of the hypersphere and the points that are less than or equal to the radius. The remaining points that lie outside the radius are considered anomalies (Verma, 2021).

Artificial Neural Networks (ANN) – When we talk about modern anomaly detection algorithms, we should mention neural networks (Valcheva, 2020).Artificial neural networks are inspired by the human brain and try to mimic the way it works, so computers are able to recognize patterns and solve problems (IBM, 2021).NNs consist of several layers with nodes, an input layer, one or more hidden layers and an output layer. They are connected by nodes with an associated weight and threshold (IBM, 2021).They can be trained for classification, regression, and prediction problems.

Decision Trees: It is a popular algorithm for sorting and predicting. They work like a flowchart where the structure is based on a tree. Each node is a test on an attribute, each branch is the result of the test, and each leaf node or terminal node contains information about the class (GeeksforGeeks, 2021). Decision trees are used for anomaly detection because they are easy to interpret and because they are less prone to the curse of dimensionality (Reif et al., 2008). Anomalies are not as common as the rest of the values, so they are much closer to the root of the tree and with fewer separations (Garbade, 2018).

Random Forest: It is an ensemble technique capable of solving regression and classification problems with multiple decision trees. This technique is called bagging (Dutta, 2022). A decision tree has a large variance, but when we combine them in parallel, the variance is smaller because each tree is trained in different parts of the dataset, so the output does not depend on a single tree, but on several. The final decision is based on the output of this group of trees and is made by majority vote. The process of assigning random parts of the dataset to each tree is called bootstrapping (Casas et al., 2016; Dutta, 2022).

Isolation Forest: They consist of decision trees such as the Random Forest. They were constructed based on the fact that anomalies are data points that are different and in small numbers. As with the Random Forest, data is randomly assigned to each tree. Data deeper in the tree is less likely to be anomalies, so it is easier to identify data in the shortest branches that are likely to be anomalies(Analytics Vidhya, 2021; Garbade, 2018).

Extreme Grandient Boosting (XGBoost): It is an ensemble method of decision trees, usually CARTs. It is an improvised version of the gradient boosting algorithm. A key difference with the gradient boosting algorithm is that XGBoost implements parallel processing at the node level, making it better and faster. It manages to reduce overfitting and achieve better performance through regularization techniques as it can be adjusted by hyperparameters (Morde, 2021; Walia, 2021).

Adaptative Boosting (Adaboost): It is a ML technique used as an ensemble. The algorithm most commonly used in Adaboost is single-level decision trees, meaning there is only one subdivision, these trees can also be called decision stumps (Walia, 2021). This works by giving more weight to instances that are harder to sort and less weight to instances that have already been sorted easily (Desarda, 2021).

3.3 Systematic literature review

3.3.1 Methods

The systematic review of the literature allows an evaluation of the contributions of the scientific community on the subject of anomaly detection in industrial processes. The method used is based on the PRISMA approach (Moher et al., 2009). The phases of the PRISMA method are as follows: 1- Identification of relevant manuscripts to the field of interest; 2- Screening of titles, abstracts, articles without experiments and opinion articles; 3 - Eligibility; 4- Full screening of texts; 5- Articles analyzed in detail.

According to the proposed method, this section is organized as follows: Research questions; article search strategy; bibliometric map followed by exclusion and inclusion criteria; selected articles; Literature.

Literature Research Questions

The purpose of this study is to provide an overview of studies that have been conducted in the area of predictive maintenance. In particular, it aims to investigate which methods are used in the field of predictive maintenance in different industries. In this way, the following research questions will be answered:

Literature Review Question 1:

What techniques are used to detect or predict anomalies in an industrial context?

Literature Review Question 2:

What performance metrics are used to measure the success of each technique?

Search Strategy

To answer the above questions, the most relevant studies need to be selected. It is recommended to search different sources such as journals or conference proceedings to determine which studies are relevant. Two databases were used, Scopus and IEEE Xplore, the former being a more general database and the latter a more specific database. The search was performed using a Boolean query and, in order to include the most recent studies, was limited to papers published in the last 5 years. The search string was as follows**:**

("anomaly detection" or "predictive maintenance") AND ("Industry 4.0" or "smart factories") AND ("IIoT" or "sensor")

All articles that were not in English or were not academic were not included.

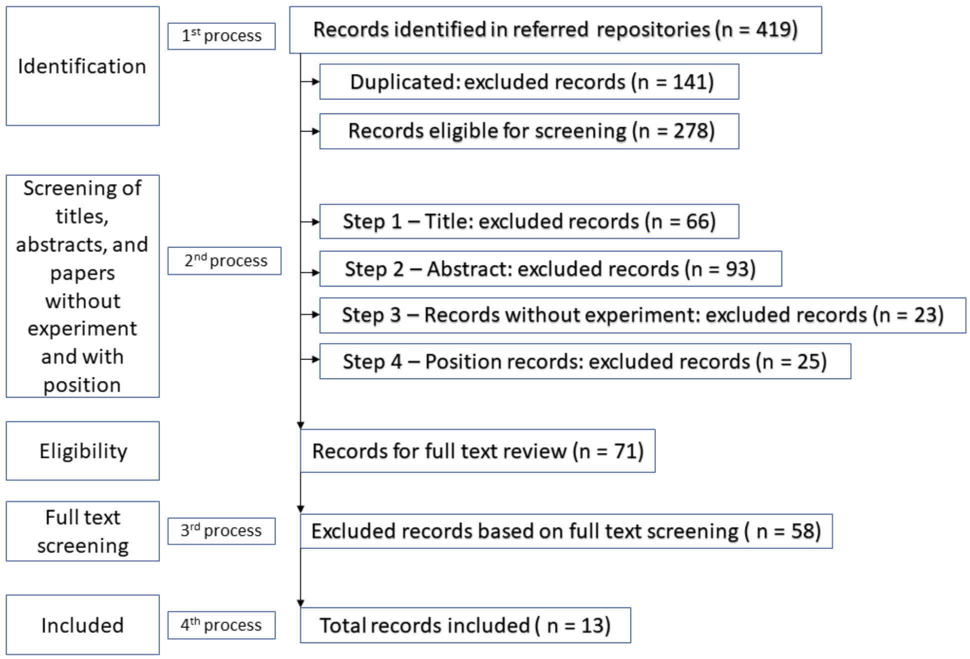

Figure 19 - PRISMA flow chart.

The result was a total of 419 articles searched in online repositories on the proposed string between 2016 and 2022.

1st process: All duplicates 141 duplicated records were eliminated. Leaving a total of 278 records. **2nd process:** Consists of several steps. In the first step, records are deleted based on their title, removing the articles that do not belong in the scope, leaving a total of 212 records. In the second step, 93 records were removed based on abstract analysis, leaving a total of 119 records. In the third step, the records without experience were excluded, leaving a total of 96 records. Finally, in the fourth and last step of this process, opinion articles were removed, leaving a total of 71 records for a complete review of the entire text.

4th process: in this step, the records were fully read, resulting in the deletion of 58 records. Therefore, the result of the search is a list of 13 articles to be analyzed in detail.

In the following table presents an overview of the analyzed items: the methods that were used and for what purpose, in what industry it was applied and what performance metrics were used to measure success. As for the objectives, three types are defined: Remaining Useful Life (RUL), Detecting Anomalies (AD), and Predicting Anomalies (AP).

ID	Reference	ML Techniques	Industry	Method Objective	Performance Metrics
1	(Ferraro et al., 2020)	Gramian Angular Field and deep learning CNN	IT Infrastructures HDD	RUL	Accuracy, Precision and Recall
2	(Kaleli et al., 2021)	Deep Learning - GRU	Nasa Turbofan Engine Degradation Simulation Data Set	RUL & AP	Regression (MAE, R2), Classification (Accuracy, precision, Recall, F1, AUC)
3	(Dhibi et al., 2021)	Kernel PCA + Ensemble Learning (Bagging, Boosting, Random Subspace) with SVM + KNN + DT	Photovoltaic Systems	AD	Accuracy, Precision, Recall and F1
4	(Canizo et al., 2019)	Deep Learning Multi-head CNN-RNN	Service Elevator	AD	G-mean
5	(Iftikhar et al., 2020)	Ensemble Learning & clustering algorithms	Industry sensors in general	AD	Silhouette Coefficient/Calinski-Harabasz Index/Davies-Bouldin Index
6	(Castellani et al., 2021)	Weakly Supervised Learning & Siamese auto encoders based on Neural Networks	Electrical System - Combined heat and power (CHP) module	AD	AUC, Average Precision (AP)
7	(Hsieh et al., 2019)	Deep Learning LSTM with Auto Encoders	Factory Production Line	AD	Precision, Recall, F1-Score
8	(Hatanaka & Nishi, 2021)	Deep learning - Generative Adversarial Network (GAN)	Refrigeration Units	AD	F1-Score

9	(Rousopoulou et al., 2019)	Deep Learning & Clustering Techniques	Industrial Ovens	AP	Accuracy, Precision, Recall, F1-Score
10	(Karagiorgou et al., 2019)	Deep Learning LSTM Regression	Manufacturing Production Line	AP	MAE, RMSE
11	(de Vita et al., 2021)	Semi-Supervised Bayesian	IIoT systems	AP	Accuracy, Precision, Recall and F1
12	(Langone et al., 2020)	Logistic Regression	Chemical Plant - Plunger Pump	AP	Kappa scores, F1, AUC, PRAUC
13	(Pezze et al., 2022)	Deep Learning + Transformers + NLP	Manufacturing - Dairy product packaging	AP	Macro F1, Macro Precision, Macro Recall

Table 4 -Techniques used by industry.

3.3.2 Discussion

This section provides for a detailed analysis of the articles found, in order to find scientific gaps and thus allow the creation of a new model that overcomes the difficulties pointed out. The research helped to understand the gap in the literature. The discussion is divided into the three main techniques used in PdM. The main techniques are anomaly detection, anomaly prediction, and remaining useful life estimation. A summary is given of the ML techniques used in each article and what metrics were used to measure their effectiveness.

1- **RUL - Remaining useful life approaches:**

Articles **A1** and **A2** are about predicting the lifetime of devices. Both use models based on neural networks. Article **A1** presents a novel approach that aims to extend Remaining Useful Life (RUL) by predicting the state of hard disk drives (HDD), it predicts 4 classes, *Good, Very Fair, Warning* and *Alert*. It is based on Convolutional Neural Networks where the input are images generated by Gramian Angular Fields (GAF). It highlights that HDDs are the most important type of storage in IT infrastructures, which are highly prone to failure and are the main cause of data center downtime. The results show that it was possible to predict failures 45 days in advance with a precision, accuracy, and recall of 85.22%, 74.6%, and 85.1%, respectively. The values are the average of the values for the four classes. In **A2**, a solution for simultaneously predicting the useful life of a machine and possible anomalies in a turbo fan motor using the dataset NASA is presented. The proposed architecture is based on a combination of two GRU networks, one predicting RUL and the other predicting possible anomalies, in order to reduce computation time. In this section we will present the results of both approaches. For the RUL results, MAE and R2 are 11.29 and 0.86, respectively. For anomaly prediction, the Accuracy, Precision, Recall, and F1 metrics yielded the following results: 0.99, 0.97, and 0.98, respectively.

2- Anomaly detection approaches:

The articles from **A3** to **A8** aim to identify anomalies in a wide range of industries. Methods based on neural networks, ensemble learning, and clustering are used. In **A3** the authors propose an extended ensemble learning method (EL) for anomaly detection in grid-connected photovoltaic (PV) systems. Faults in PV systems are due to harsh environmental conditions or internal malfunctions, which can range from short circuits to efficiency problems. The proposed method combines EL techniques and a data-driven approach with data set reduction. The EL technique consists of 3 algorithms, Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Decision Tress (DT). Since these classical machine learning algorithms ignore the temporal dependencies of the data, a novel technique was developed. The EL method is fused with multivariate statistical analysis Kernel PCA (KPCA), which allows sensitive and significant features from the data to be transferred to the EL algorithms. KPCA is used for feature selection and extraction. The result was an accuracy of 100% with a computation time of 110.36 seconds. In **A4,** a supervised Deep Learning architecture for multi-time series using Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) is presented. The model is applied to data related to a service elevator. Unlike other solutions that access all sensors at once, the authors of this method use multiple convolutional heads (multi-head) to access each sensor independently without pre-processing the data. Since the data comes from sensors of different types present in an industrial environment, applying a convolutional head to each sensor allows the model to better fit the type of sensor and extract relatively important features. The results presented have a g-mean of approximately 0.97 for all RNN variants. In **A5**, an ensemble method based on unsupervised machine learning is presented to predict possible outliers in a medium-sized manufacturing company. Clustering techniques are used in a first phase, and classification algorithms are used in a second phase to separate normal from anomalous clusters. The presented clustering technique is a combination of classical clustering techniques such as K-means, Mean-shift, K-modes and DBSCAN with biclustering techniques such as Coclust Mod/Spec Mod, Spectral biclustering/Co-Clustering, Delta biclustering. Classical techniques are used to find patterns globally while biclustering is used to find local patterns. Biclustering techniques help to find abnormal patterns and reduce the dimensionality of the data by selecting small subsets of data based on local patterns. After the clustering techniques are applied the algorithms are trained for one-class classification, using models such as One-Class Support Vector Machines (OC-SVM), Isolation Forest (IForest), Local Outlier Factor (LOF). The model with the best results was the combination of K-modes and SpectalBiclustering with OC-SVM with event accuracy of 85% and 80% for normal and rare events, respectively. In **A6**, new approaches to multivariate time series using weakly supervised learning for anomaly detection are presented. The authors point out that much of the data in the industrial world is unlabeled, highlighting the importance of unsupervised learning algorithms. They also point out several problems that are commonplace in industry: the problem of false positives, where the complexity of machines makes it difficult to define what an anomaly is. Another problem is drift, which is related to the fact that sensors are decalibrated and wear out, so algorithms need to be trained periodically. Two approaches are proposed: cluster centers (CC) as weakly unsupervised classification and Siamese auto-encoders (SAE) as weakly supervised classification. The approach SAE was the one that achieved the best results on the three metrics evaluated by the authors: AP = 0.872, AUC ROC = 0.935, F2 = 0.823. In **A7**, the authors propose a semi-supervised Bayesian anomaly detection algorithm that model's uncertainty because generating false alarms can be expensive in an industrial setting. Bayesian Gaussian Mixtures (BGM) are used to cluster data points while measuring a degree of uncertainty. Compared to traditional clustering algorithms such as K-means, BGM is considered a more general model due to the assumption of ellipsoidal clusters with different sizes and orientations in space. The probabilistic property of BGM allows the algorithm to perform soft clustering instead of hard clustering by calculating the probability of a data point belonging to a particular cluster, thus measuring the degree of confidence in diagnosing the data points. Two approaches are proposed, one supervised and one semi-supervised. To test the presented technique, the authors did not use data from a real industry but created a full-scale replica of an assembly line for transporting car parts, with two motors and six belts to transport the car. The test platform was equipped with 5 sensors: current, vibration, noise, temperature, and distance. An important feature of the test rig is the ability to enter manual mechanical faults. This helps solve a common problem in IIoT, namely the lack of empirical data. For the supervised learning proposal, the results for the following metrics Accuracy, Precision, Recall, and F1 are 0.98, 0.97, 1, and 0.985, respectively. For the semi-supervised proposal, the results for the same metrics are 0.998, 0.997, 1, 0.998.

3- Anomaly prediction approaches:

The articles from **A9** to **A13** aim to identify anomalies in a wide range of industries. Methods based on neural networks, Bayesian techniques, and logistic regression are used. In **A9**, study is conducted on predictive maintenance of industrial furnaces used in Boston Scientific's printed circuit board (PCB) production line. A common problem in these furnaces is the fans inside, which are responsible for maintaining a balanced temperature inside the furnace. These fans deteriorate over time, resulting in suboptimal conditions inside the furnace that later lead to machine deterioration and malfunction. Two proposals are presented for predicting anomalies in the fan/motor set. One is based on deep learning techniques where the model is trained on data from historical logs of existing sensors, focusing mainly on temperature sensors. The other is based on outlier detection techniques such as Mean Absolute Deviation (MAD), Local Outlier Factor (LOF), and Density-Based Spatial Clustering of Applications with Noise (DBSCAN), along with the Support Vector Machine (SVM) classification technique and is trained on data from external acoustic sensors attached to the furnaces. The proposal based on deep learning techniques showed the following results (for a 25-minute prediction) for the metrics Recall, F1, and Matthew's correlation coefficient: 0.79, 0.83, and 0.691, respectively. The proposal based on outlier detection techniques obtained the following results for Accuracy, Precision, Recall, and F1 score: 0.85, 0.76, 1, and 0.86, respectively. In **A10**, a method called Interpretable Anomaly Detection (IAP) is presented, the core of which is based on regularized logistic regression as a predictive model. The goal is to present a method that is explainable and easy to interpret, where explain ability is a direct effect of interpretation. The model is applied to data related to a plunger pump from a chemical plant. The data are represented by a multivariate time series with high class imbalance, about 3 million corresponding to normal operation and only 13 malfunctions. The presented model starts the process by representing the time series in a hump-based plot. It also calculates various statistics such as: Mean, Standard Deviation, Skewness, Kurtosis, Trend, Average Autocorrelation, Burstiness, etc. These allow the model to be more accurate. The authors call it an extended bucket-based representation. Results obtained for AUC, F1, kappa, PRAUC: 0.76, 0.56, 0.55, 0.44, respectively. In **A11**, the authors propose a deep-learning approach to predict rare alarms in dairy packaging equipment to avoid downtime and maintenance costs. The approach is called FORMULA (alarm FORecasting in Multi-Label setting). It uses natural language processing (NLP) and object recognition through a popular neural network architecture called transformers in the NLP field. The goal is to predict which alarms will occur based on knowledge of previous alarms. A list of different possible alarms that may occur in a future time window is much more interesting to the operator. Therefore, a multi-label classification approach is proposed where it is possible to predict whether an alarm will occur based on previous alarms. Three NN-based models were considered: REC: a bidirectional recurrent model based on gated recurrent units; ATT: combines an attention mechanism with recurrent units; TRM: based on a transformer block (FORMULA). When comparing the proposed algorithms trained with different loss functions, the proposed TRM + WFL approach is the one with better results for target alarms (S.T) and rare alarms (S.R), with a macro F1 of 0.546 and 0.367, respectively.

In the solutions presented, there is little mention of the sensors used. There seems to be a general lack of feature engineering, most articles only apply a simple normalization process. Most of the presented models are very specific, i.e. they are only used for data from a specific industry. There is a lack of a global model architecture applicable to more than one industry. There is also a lack of information on connectivity and data management. Few models have been found to predict RUL.

4- Architecture to predict anomalies in industrial processes

4.1 Assumptions

The systematic review of the literature made it possible to identify the companies in which PdM is applied. Table 5 lists the ML techniques used in each industry and their respective objectives.

		Predictive Maintenance Objective		
		Remaining Useful Life	**Anomaly Detection**	**Anomaly Prediction**
Technics	Deep Learning – LSTM		Manufacturing	Manufacturing
	Deep Learning – GRU	Airspace		Airspace
	Deep Learning – CNN	IT	Transport&Logistics	
	Deep Learning – GAN		Transport&Logistics	
	GAF – Gramian Angular Fields	IT		
	Transformers	Manufacturing		
	NLP	Manufacturing		
	Autoencoder		Energy Manufacturing	
	Semi-Supervised Bayesian		Manufacturing	
	Ensemble Learning		Energy; Manufacturing	
	Biclustering algorithms		Manufacturing	
	Kernel PCA		Energy	
	Support Vector Machines		Energy	
	Distance Clustering algorithms		Energy	
	Density Clustering Algorithms			Manufacturing
	Decision Trees		Energy	
	Siamese Autoencoders		Energy	

Neural Networks		Energy	Manufacturing
Logistic Regression			Manufacturing

Table 5 - A resume table of technics and approaches taken per industry.

LRQ1 raises the question of what algorithms are used to detect or predict anomalies in industrial processes. After examining articles 1 to 13., it was found that there are three types of approaches: Detection of anomalies (60%), prediction of anomalies (33.3%), and remaining useful life (13.3%). The articles are analyzed according to the mentioned groups. In general, several methods were found, with neural networks being the most used method with 73.3% of the models found, the rest being ensemble learning, logistic regression, and Bayesian methods. Another conclusion is that predictive maintenance is used in a wide range of industries, such as IT infrastructure, energy sector, production lines in factories or elevators. The most represented industry is the manufacturing sector with a share of 60%.

Regarding **LRQ2**, the metrics that stand out are Accuracy, Precision, Recall and F1 Score due to the fact that most of the models presented in the literature review are classification problems. The table x resumes the results found.

Accuracy	Precision	Recall	F1	AUC	MAE	Others
33,3%	60%	53,3%	60%	20%	13,3%	6,7%

Table 6 - Resume of the sensors and technologies found in the literature.

Artificial intelligence techniques combined with cloud or edge computing and all available open-source software are expected to play an extremely important role in this architecture, facilitating the digital transition for SMEs.

The following table provides an overview of the industries using PdM and the various sensors, technologies, and algorithms.

Industry	Process	Sensors	Support Technologies	Algorithms
Manufacturing	Production Line (4)	Vibration/Acoustic/Temperature/Distance/Current/ Power consumption/movement/velocity	IIoT, Stack4Things (open Stack), Influx DB, Kafka, TensorFlow	LSTM
Manufacturing	Chemical Plant	Pressure/ voltage/current/rotational speed/temperature/ flow	IIoT	Logistic Regression with elastic Net Regularization
Manufacturing	Industrial Ovens (PCBs)	Temperature, Power consumption, Pressure, acoustic	IIoT	Deep Learning - LSTM
Airspace	Turbofan Engines (NASA)	Turbofan engine sensors	IIoT	Deep Learning - GRU
IT	HDD Health	Data From Smart Attrbutes	HDD Smart Technology	Gramian Angular Field & CNN
Energy Sector	Photovoltaic Systems – Power Module	Emulated with Grid Emulator	Grid Emulator/IIoT	RKPCA-EL
Energy Sector	Electrical Systems	Not Specified.	IIoT	SAE - Siamese Auto Encoders
Transport & Logistics	Refrigeration Units	Directional acoustic sensors.	IIoT, Digital Twins	Efficient GAN
Transport & Logistics	Service Elevator	20 Sensors (not identified).	IIoT	Multi Head CNN

Table 7 - Resume of the sensors and technologies found in the literature.

4.2 Architecture to assist SMEs in implementing PdM.

Before describing each step, it is important to mention that the business part must be considered, even though it is outside the scope of this article. In this phase, a decision must be made as to the direction in which digitization for PdM should go. The feasibility of the project must be assessed, considering the benefits and challenges related to the process. It is also necessary to weigh all the necessary investments, both in terms of human resources and financial resources. In addition to the invested capital, coordination with all departments in this regard should not be ignored. Determine which machines or process will be monitored to decide what type of sensors and what type of network connections are required. At this stage, the goal of the PdM must also be defined, i.e., whether it is to detect anomalies, predict anomalies, or predict RUL. Below is a swot matrix that should be considered when making decisions about project implementation.

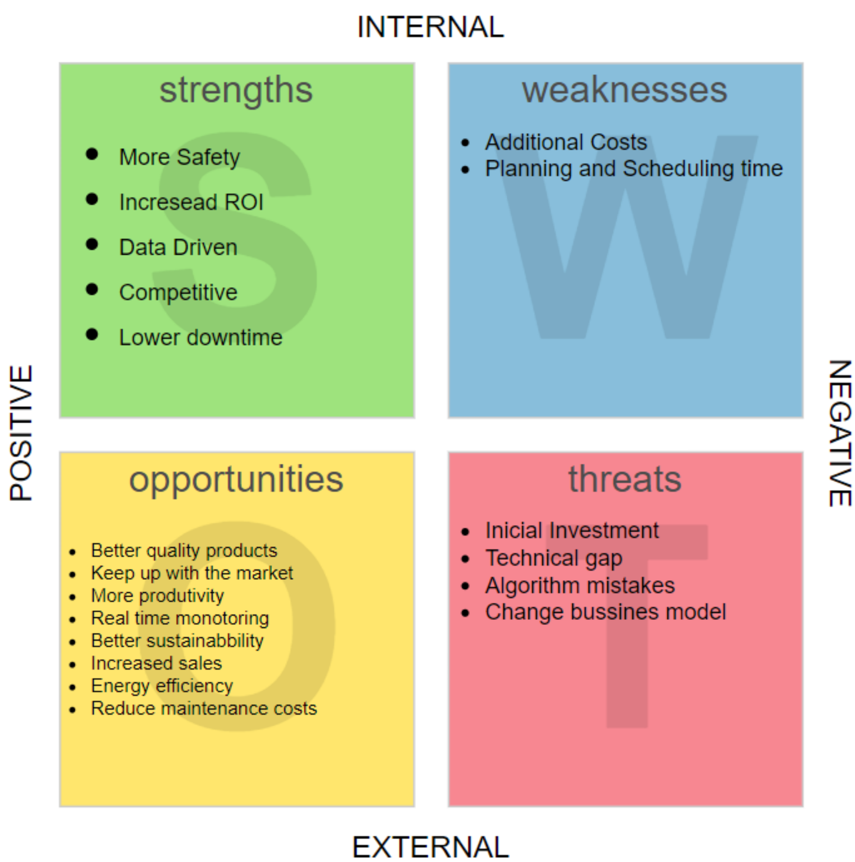

Figure 20 - SWAT Analysis.

The conditions are met to propose an implementation guide for an IIoT architecture to predict anomalies in industrial processes. The following guide shows the steps required to implement a PdM architecture.

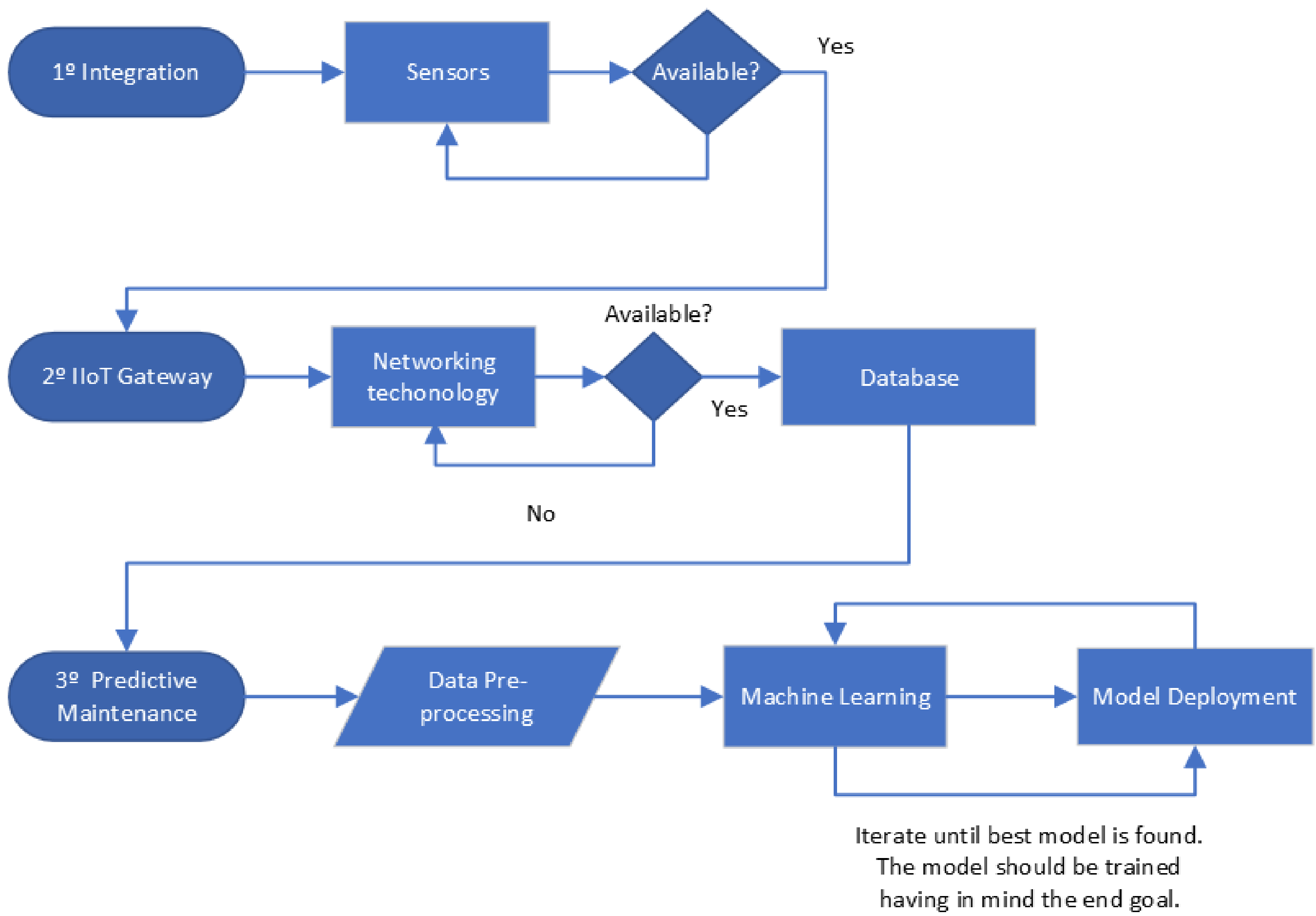

Figure 18 - Architecture Framework.

The RAMI 4.0 - Reference Architecture Model Industry 4.0, is the reference architecture in Europe. The following flowchart correlates the previous flowchart with this architecture. This is important because interoperability is an important aspect of Industry 4.0. The main goal of the architecture is to create a common framework so that all stakeholders in the different industries understand each other.

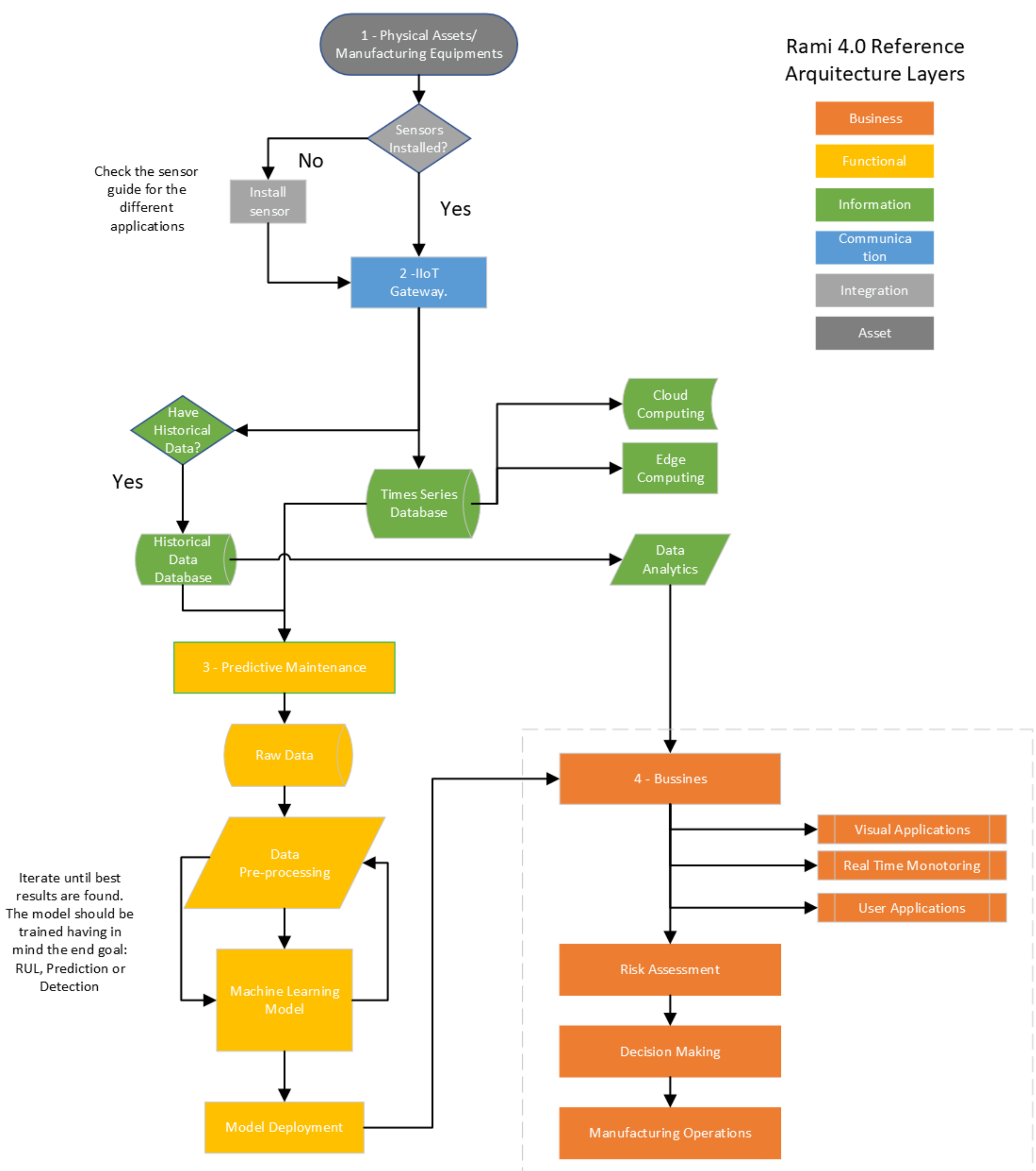

Figure 19 – RAMI 4.0: Reference Architecture Model Industry 4.0

1º – Integration

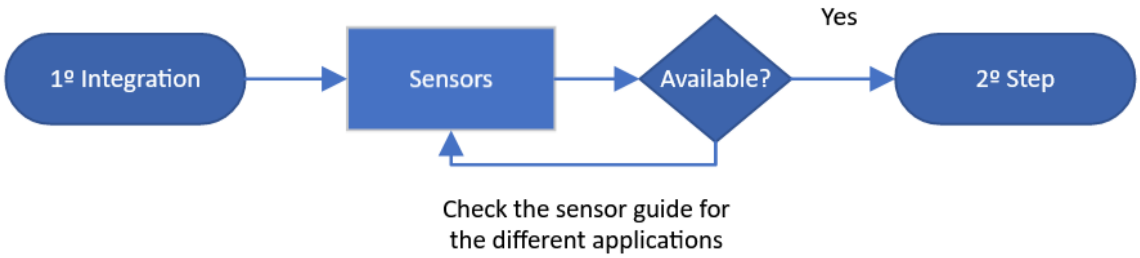

Figure 20 - 1st Step Architecture

This phase consists of a single step, but it is extremely important because without sensors installed, it is not possible to obtain information about the operation of the machines. After determining in which plant or part of the plant the PdM is to be used, an inventory must be made of the plants that already have some type of sensor and whether it can be used. It should be noted that the sensor may be present but may not be able to transmit this information to the network. A table with sensors normally used for PdM with type of sensor, key information and target faults can be found in the annexes.

2º IIoT Infrastructure

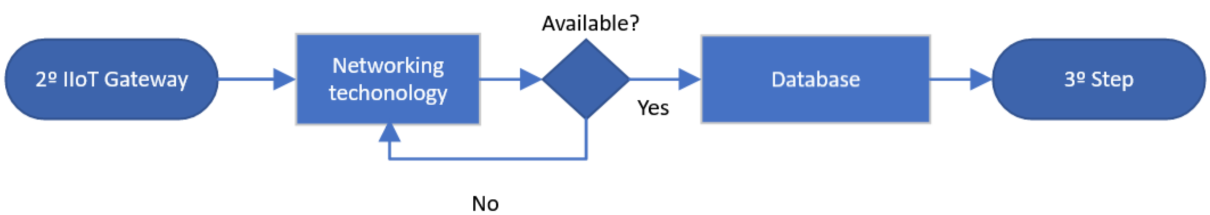

Figure 21 - 2nd step of the IIoT infrastructure.

In this step, the framework for the IIoT must be defined, which serves as a bridge between sensors and data collection systems. The type of connectivity must be chosen based on the location of the devices and the amount of data to be transmitted. The collected data must be stored in a database. If historical data databases do not exist, it is necessary to wait until there is sufficient data to proceed to the fourth step. If historical data exists, it must be migrated to the new database. Due to the technical part of this step, it is advisable to use solutions already on the market, both in terms of hardware and software. It is possible to do this with your own resources, but the cost of errors, security flaws and lost time does not justify it. You should start with a small project, with one or two machines, to ensure the quality and frequency of the data. Once the foundation is established, the project can easily be expanded to include more machines. In the initial phase, preference should be given to a local database, as cloud services are expensive.

Network	Connectivity	Pros & Cons	Use cases
Ethernet	Wired, Short-range	High speed Security Range limited due to wire length Limited mobility Expensive due to cable install.	Simple applications in the industry.
Wi-Fi	Wireless Short-range	High speed Good compability Limited Range (50 m with 5Ghz) Security High power consumption	Small applications
Zigbee	Wireless Short-range	Low power consumption Scalability Limited range Compliance issues	For applications with sensors powerd by battery with low data output.
Bluetooth	Wireless Short-range	High speed Low power consumption limted range (10m) low bandwidth	Lights, chemical monitors, HVAC systems.
Cellular networks – LTE-M & NB-IoT	Wireless Long-range	Good global coverage High speed (250Kbps to 1Mbps) Realibility Design specially for IoT devices. High Cost High power consumption	LTE-M: For applications that require data from very far, like predictive maintenance on a supply chain. NB-IoT: Utility Monotoring
LPWAN	Wireless Long-range	Long range Low power consumption Low bandwidth High Latency Region locked (China)	For connected devices over unlicensed spectrum with small data output over long distances.
5G	Wireless Long-range	Long Range Low Latency High speed Supports 1 million devices (from 1000 from 4G) Limited Global Coverage Decreased Broadcast Distance Cyber Security Upload speeds	Can be used for big projects, like smart grids, smart factories.

Table 8 - Networks and respective characteristics.

In Figure 22, we can see how an IIoT infrastructure is defined.

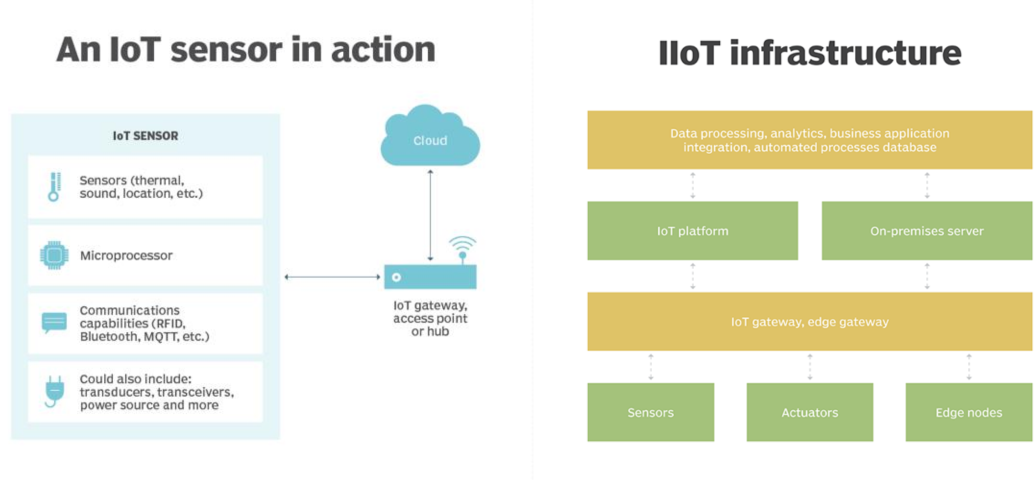

Figure 22 - IoT infrastructures example (TechTarget)

3º - Predictive Maintenance

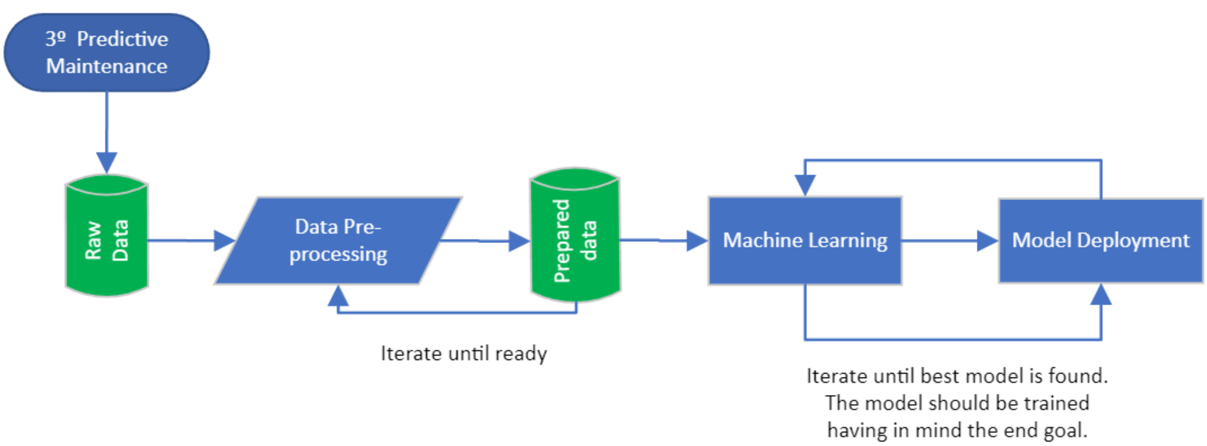

Figure 23 – 3rd step of the IIoT infrastructure.

At this stage, the data for training the algorithm can come from the past or from the collection of an IIoT system. Most of the data for anomaly prediction comes from sensors and is therefore often time series; all the steps and techniques mentioned below are in the spirit of preprocessing time series data. This entire phase is possible when the IIoT framework is installed, when data is collected either in a cloud or in a local database, and when the customer has access to this data. In this phase, tools from the contracted cloud service or free tools available on the market can be used. In the initial phase, it is advisable to use the on-premises service with the support of free tools. The entire cloud service is chargeable, including traffic, data storage and eventual training of the models.

Objective definition	It must be determined which approach to take, i.e., whether we want to detect or predict anomalies or predict RUL. It is important that this step is specified because the overall preprocessing and algorithm will vary depending on the nature of the problem.
Raw data	The data is usually in a raw and unstructured state, i.e., stored without any processing and often in complicated formats, which is a very time-consuming phase.
Pre-Processing	The data of a device are represented by variables related to different indicators such as pressure, temperature or current, depending on the sensors installed. These variables can be manipulated and transformed into features used for predictions with machine learning algorithms. There are several phases that can and should be performed in this phase.
Outlier removal	Outliers should be removed from the data, keeping in mind that there are cases where the outliers are the target, so it makes no sense to eliminate them, i.e. anomaly detection or prediction.
Handling missing data	There are some rules for dealing with missing data that must be followed. If you remove them, you've to make sure that they don't exceed 5% of the total data.
Smoothing	Time series smoothing is usually applied to time series data to facilitate algorithm prediction.
Stationarity	Stationarity is often applied to time series whose statistical properties are not constant over time. When a series is non-stationary, it is more difficult for the model ML to make predictions on that basis. One way to make time series stationary is through mathematical transformations, including first difference. Predictions made on the basis of a stationary time series are also stationary, so it is necessary to reverse the mathematical transformation applied. One should never attempt to extrapolate regression problems based on non-stationary time series.
Scaling	All data must be on the same scale, because if pressure is in the thousands and temperature is in the tens, the algorithm will give more importance to the variable with the largest dimension when passing this information. In this step, it is necessary to take into account that it must be performed only for the training data, i.e., after splitting the data into training, validation and test. The normalization parameters used for normalizing the training data must be the same as those used for normalizing the validation and test data. Any kind of information about the latter must not be accessible during training.
Principal Component Analysis (PCA)	This technique is used for dimension reduction while forming relevant features. The resulting data is a linear combination of the original data, capturing most of the variance in the data. This technique can be used when there is multicollinearity between features, when there are many features, or when noise reduction or data compression is required.
Feature engineering:	Here, raw data can be transformed into new features not present in the original dataset to improve the model. The features can be statistical or topic related.

Categorical Data	Categorical data cannot be fed into the model, it must be converted to numbers, so techniques such as one-hot encoding should be used when possible.
Feature Selection	This is an important preprocessing process to select the most important features. It helps to reduce the number of features to be input into the predictive model and to reduce redundancy. There are several ways to perform this process: by correlation between features, by algorithms specifically designed for this purpose such as RFE (Recursive Features Elimination), or with auto-encoders, the latter being a more sophisticated approach.

Table 9 - Technics used to pre-process data.

Modeling: The goal of this step is to train a model that performs well on new data. Normally, there is no access to new data, so this must be simulated using a procedure called train test split. In this procedure, the data is split into three subsets: Training data, validation data, and test data. The first subset is used to train the model, the second subset is used to fine-tune the model's hyperparameters during training, and the third subset is used as a final test of the model after fine-tuning is complete. The 2nd subset is important because this way we ensure that the model never sees the 3rd subset. If we only had two subsets, training and testing, while fine tuning the model, there would be data loss. If there is no need to tune the model in terms of hyperparameters, then the creation of the 2nd subset can be done. Normally, when using train-test split techniques, the data is split randomly, meaning there is no dependence between data points, which is not the case for time series where data points have dependence. In this case, the data must be split in an orderly manner, i.e., older data should be used for training and newer data should be used for testing. Typically, the split ratio is 80% for training, 10% for validation, and 10% for testing.

4.3 Use case

The company in question is an SME whose business is based on the sale and installation of burglar alarm systems. The company intends to apply PdM to its intrusion detection systems, focusing on the backup batteries built into the control system. Since the battery is an important element in the event of a network power outage, it is responsible for keeping the system operational during this time. The goal is to predict battery life RUL to make maintenance more efficient while ensuring that customers never have a battery in poor condition, meaning that it is unable to power the system during a power outage. If the company can predict when a battery will reach the end of its life, the delivered system also becomes safer, and maintenance becomes more efficient. The company benefits financially by not having to replace batteries unnecessarily, and it also benefits in terms of quality of service by assuring the customer that the batteries have the required capacity in the event of a power outage.

1º Integration:

At this stage, it is necessary to consider what kind of data can be collected through the control system. Often the data is already read but not transmitted. If there is no type of reading, it is necessary to ensure that sensors are installed that can collect data on the battery. The installation of the collection mechanism must be done together with the next step, hiring specialized companies. In the case of batteries, the most important data are voltage, amperage, internal resistance, number of cycles, charges/discharges.

2º IIoT Infrastructure:

At this stage, it is advisable to hire a company specialized in this field. The entire process is extremely technical and requires skilled labor. This company will opt for a framework that includes a cloud service because of the need to monitor the systems installed remotely. The customer also decided that the application of the PdM framework should only be carried out at two customers to test the functioning of the system. Although the data would be uploaded to the cloud, the customer decided that it should also be stored in a local database for testing purposes. This decision was made because in an initial phase, several tests are performed on different models and techniques, all of which are paid for in the cloud service. So, until the best model is decided, if the data is of the quality and frequency required for the best model, all the tests can be done with this database on site, reducing the initial cost.

3º PdM:

To exemplify the prediction of RUL in a battery, the NASA dataset that is available for public use will be used. This is a univariate regression problem, we will only use battery capacity to predict battery life. All tools used to perform this task are open source software. Tools such as VSCode and Jupyter notebook were used. Python was the language used, it is the indicated language due to the large amount of libraries available for data manipulation and modeling. In figure 24 are the libraries used to predict the battery RUL. The random state must be set at the beginning so that all operations are reproducible.

```python
# Utils
import datetime
import numpy as np
import pandas as pd
from scipy.io import loadmat
# Pre-processing packages from sklearn
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
# Visualization packages
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.pyplot as plt
# Statistical packages
from scipy import stats
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
# Scalecast package
from scalecast.Forecaster import Forecaster
from scalecast.SeriesTransformer import SeriesTransformer
from scalecast.Forecaster import _estimators_
# Setting a random seed for reproducibility
seed = 42
np.random.seed(seed)
```

Figure 24 – Imported libraries

The data collected are variables such as: the number of charge and discharge cycles of the battery, the ambient temperature, the remaining data are measured directly on the battery, namely the capacity, voltage, current and temperature of the battery itself. drums. In the figure below, the first step, we see their arrangement after import. It is not possible to determine the time interval between the measured values, because the timestamp in this data set always records the same time.

```python
dataset.head()
```

✓ 0.4s Python

datetime	cycle	ambient_temperature	capacity	voltage_measured	current_measured	temperature_measured	current_load	voltage_load	time
2008-04-02 15:25:41	1	24	1.891052	4.199360	-0.001866	23.937044	-0.0004	0.000	0.000
2008-04-02 15:25:41	1	24	1.891052	4.199497	-0.002139	23.924074	-0.0004	4.215	16.781
2008-04-02 15:25:41	1	24	1.891052	3.985606	-1.988778	24.004257	-2.0000	3.003	35.703
2008-04-02 15:25:41	1	24	1.891052	3.963247	-1.992558	24.162868	-2.0000	2.987	53.781
2008-04-02 15:25:41	1	24	1.891052	3.946647	-1.988491	24.346368	-2.0000	2.972	71.922

Figure 25 – Sample of the dataset variables

In figure 26 there is a summary of the dataset, indicating the number of data points, the times between which they were found, the number of variables, the data type of each variable, and the amount of memory this dataset occupies.

```python
dataset.describe()
```
✓ 0.1s Python

	cycle	ambient_temperature	capacity	voltage_measured	current_measured	temperature_measured	current_load	voltage_load	tim
count	50285.000000	50285.0	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.00000
mean	88.125942	24.0	1.632911	3.516153	-1.910982	32.374078	1.471671	2.499169	1546.20892
std	45.699687	0.0	0.152751	0.268665	0.387120	4.004486	1.294697	0.550780	906.64029
min	1.000000	24.0	1.400455	1.737030	-2.006038	22.969923	-2.000000	0.000000	0.00000
25%	50.000000	24.0	1.497822	3.408859	-1.990432	29.683138	2.000000	2.470000	768.56300
50%	88.000000	24.0	1.605663	3.520359	-1.989406	32.294479	2.000000	2.582000	1537.03100
75%	127.000000	24.0	1.785885	3.681617	-1.988328	35.230784	2.000000	2.743000	2305.98400
max	168.000000	24.0	1.891052	4.233325	0.005072	42.332522	2.000000	4.249000	3690.23400

Figure 26 – Data statistics summary

In figure 27 there is a brief statistical description of the variables included in the dataset

```python
dataset.info()
```
✓ 0.9s Python

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 50285 entries, 2008-04-02 15:25:41 to 2008-05-27 20:45:42
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   cycle                 50285 non-null  int64
 1   ambient_temperature   50285 non-null  int8
 2   capacity              50285 non-null  float64
 3   voltage_measured      50285 non-null  float64
 4   current_measured      50285 non-null  float64
 5   temperature_measured  50285 non-null  float64
 6   current_load          50285 non-null  float64
 7   voltage_load          50285 non-null  float64
 8   time                  50285 non-null  float64
dtypes: float64(7), int64(1), int8(1)
```

Figure 27 - Dataset summary

Figure 28 shows how to check for missing data in any of the data points. All variables turn out false so there are no NaN(Not a number).

```python
#Checking if there's any missing data

dataset.isna().any()
```
✓ 0.7s Python

```
cycle                   False
ambient_temperature     False
datetime                False
capacity                False
voltage_measured        False
current_measured        False
temperature_measured    False
current_load            False
voltage_load            False
time                    False
dtype: bool
```

Figure 28 - Check for NaN

Although this problem is a univariate one, it is important to know that there are tools that are essential for multivariate problems. The correlation between variables is important for feature selection. A correlation table in figure 29 can be used to see which variables are redundant and which variables contribute to the target variable. The value zero stands for uncorrelated, the value 1 for fully correlated and the value -1 for inversely correlated.

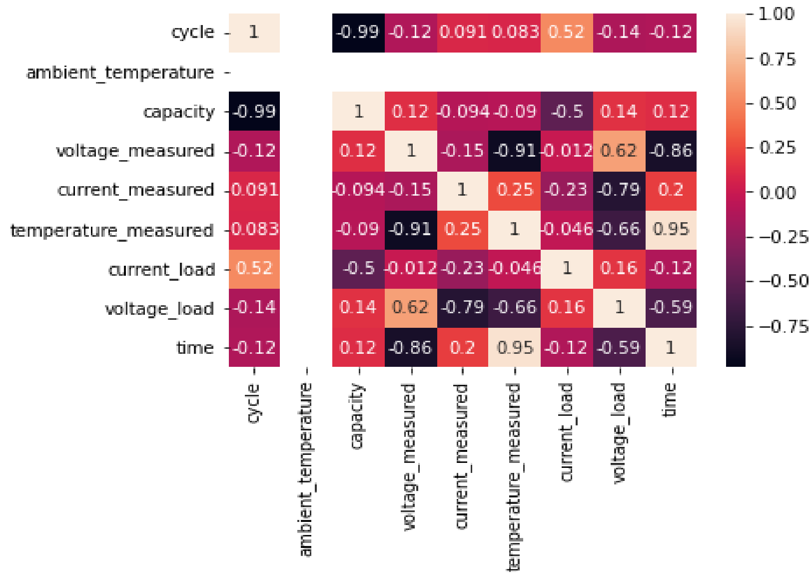

Figure 29 - Correlation table, Pearson method.

In figure 30, descriptive box plot statistics graphical tool was used to check for outliers in the capacity variable.

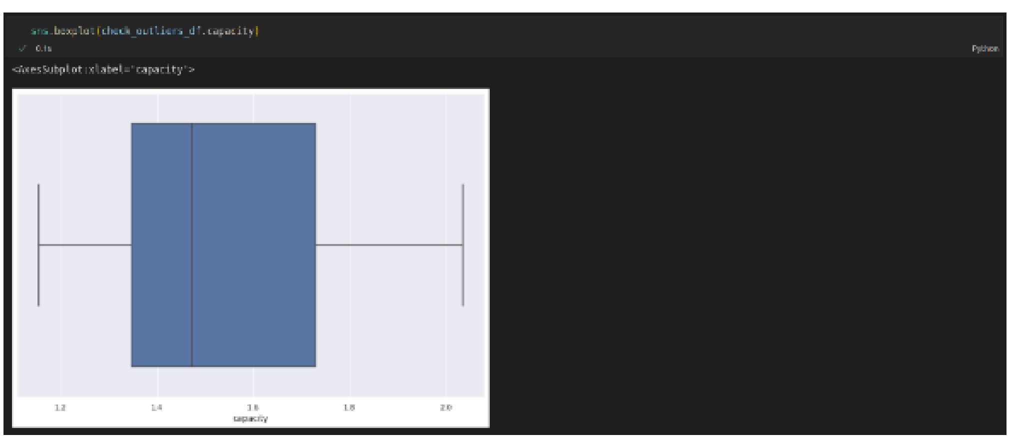

Figure 30 - Capacity Boxplot

Data points were down sampled to daily values by applying the average. In figure 31 we can see that after resample 56 days of data remain, where 14 are NaN due to resampling, normally there's missing timestamps, and that translates to NaN.

```
data_test.info()
✓ 0.4s                                                          Python

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 56 entries, 2008-04-02 to 2008-05-27
Freq: D
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   cycle                 42 non-null     float64
 1   ambient_temperature   42 non-null     float64
 2   capacity              42 non-null     float64
 3   voltage_measured      42 non-null     float64
 4   current_measured      42 non-null     float64
 5   temperature_measured  42 non-null     float64
 6   current_load          42 non-null     float64
 7   voltage_load          42 non-null     float64
 8   time                  42 non-null     float64
dtypes: float64(9)
memory usage: 4.4 KB
```

Figure 31 - Resampled datapoints

We can double check for NaN, there are 14 days for which there is no data. To fill the missing data an interpolation was performed using the spline method, figure 32.

```
#Checking if there's any missing data
data_test.isna().sum()
✓ 0.6s                                                          Python

cycle                   14
ambient_temperature     14
capacity                14
voltage_measured        14
current_measured        14
temperature_measured    14
current_load            14
voltage_load            14
time                    14
dtype: int64
```

Figure 32 - Checking NaN after down sample.

In figure 33 we can analyze time series related to capacity, the degradation of the capacity along time is obvious.

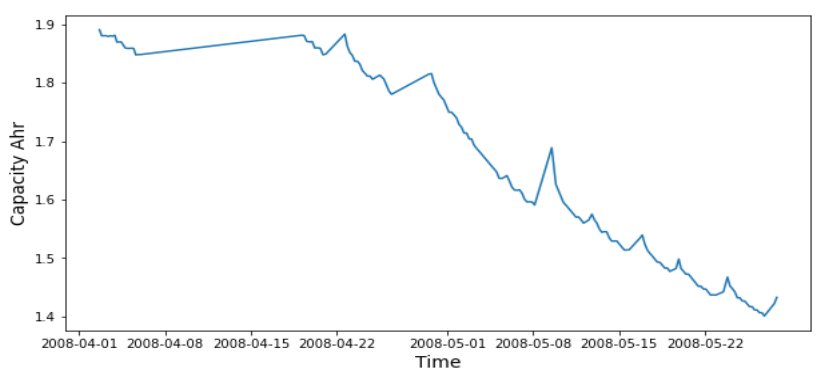

Figure 33 - Capacity Time Series

In figure 34 the time series is decomposed using an additive model. We can see that the time series is not stationary but has a downward trend. It is also possible to check if it is seasonal. Another way to check whether the time series is stationary or not is the Augmented Dickey Fuller Test.

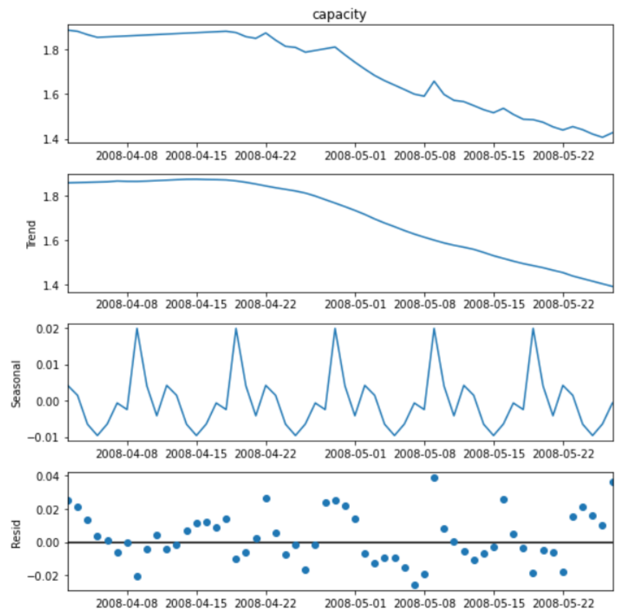

Figure 34 - Time series decomposition.

For RUL prediction of the battery, we use a linear degradation model, where our HI -Health index is the battery capacity. The idea is to predict the battery capacity in 20 days. If it reaches the defined threshold of 1.4 Ahr, the minimum capacity for normal operation, the maintenance team receives a warning that the battery needs to be replaced; if the threshold is not reached, there is no warning. For this task, we used a library called ScaleCast, which is specifically designed to easily work with time series, such as a forecast for 20 days. With this library we can easily decide what percentage of the test data set, how many days we want to forecast, whether we want to differentiate the time series or not, since it is easily reversible, we can add autoregressive terms or even a time trend. Two models are tested, MLR - Multiple Linear Regression and lightGBM. It should be mentioned that there is often a mistake made when predicting time series: The models make predictions in one step, i.e. instead of predicting, say, 20 days, they predict one day at a time, making the results look good even though they are not.

Figure 35 - Twenty-day prediction results for both algorithms, LightGBM and MLR.

In figure 35 we can see the prediction made by both models. In the case of the MLR model, better results were obtained without differentiating the time series, that is, without making it stationary, for LightGBM the results are better making the time series stationary. Both approachs showed a good result regarding RMSE.

Metric	MLR	LightGBM
RMSE	0.016	0.014

4.4 Evaluation & Discussion

In an attempt to verify usefulness and obtain suggestions for improvement, the architecture was evaluated. In accordance with the chosen methodology, an interview was conducted with the head of an SME, not a specialist, to understand the usefulness of the architecture and obtain feedback on possible improvements. The interview was conducted online via a video call and recorded. After a short presentation of the architecture, the participant was asked some questions:

Question 1 - Do you think the proposed framework is useful and why? If not, why do you think it is not useful?

I think the architecture is useful because with a plan that defines the different phases of the process, it is possible to get an overview of the need for human and financial resources. The architecture is informative, it has value for a possible application, the fact that the architecture includes the different steps from the sensors to the application of the model is important for those who will analyze it to understand how it is done. In general, the architecture is good because it has defined an input and an output, meaning you have the situation you are in now and where you will arrive.

Question 2 - Do you have any criticisms of the proposed framework? Please elaborate on them.

I think that in some ways the architecture presented is very general in its application, at an academic level it works, but in a real-world application there would have to be changes that are not accounted for by the proposed architecture.

I think that there should be a procedure as the first step of the architecture that says that a survey of the existing needs and resources should be done, that is, the technology that the company has already installed for other purposes and that serves for this application. The mentioned procedure is important in the sense of reusing equipment that may not be the most advanced, but if it works, we save the company money. It is also important in case we conclude that it is not worth using any of the current technologies and it is better to invest in a new infrastructure.

Question 3 - Do you have any recommendations or suggestions for further improvements to the proposed framework?

I think that in the first step of the architecture, a table of necessary requirements for the implementation of the architecture should be created to validate the existing technology. I also think that a financial approach is needed because the first question a business owner will ask you is, "How much am I going to spend?". What technology are you going to use in terms of data integration? What database are you going to use? I think it added value to the framework to explain what technologies will connect between the IIoT gateway and the database.

5- Conclusions

This chapter is a reflection of the work developed in this dissertation, discussing the main conclusions and limitations, as well as future work. In this way, it is possible to have an overall view of the achievement of the objectives. Considering that the artifact gives an overview of the steps to be considered in an implementation and the positive feedback given in the evaluation process, we can assume that the objectives have been achieved.

5.1 Synthesis of the developed work

During the development of this thesis, several topics related to the IIoT, ML and PdM were addressed. This knowledge enabled the development of an architecture that will serve as a guide for SMEs that want to implement PdM. The architecture was validated by a CEO of a metalworking company that has a strong interest in implementing PdM.

5.2 Limitations

Due to time constraints, only one interview was conducted, although feedback at the business implementation level was good, more interviews should have been conducted with both technical and non-technical audiences. Clearly, in the case of this dissertation, technical revisions were lacking.

In an attempt to simplify the architecture and not make it exhaustive, certain technical aspects were not taken into account, an example being the technologies related to databases and data processing.

The communication step, scheduled in the methodology, remained to be fulfilled. Thus, its usefulness, novelty and efficiency for other researchers and interested parties was compromised.

5.3 Future Work

Regarding the evaluation of architecture, one step for future work is to gather more information from others, both technical and non-technical.

Since this is a field that is constantly evolving, it would be important to keep the architecture up to date with new technologies and devices that appear on the market. In addition, research into each of the steps proposed in the architecture should be deepened to provide more clarity. Another need is to include as many available devices and technologies as possible and analyze them to decide on the best integrations between technologies.

Finally, this dissertation needs to be published to be available to the general public and contribute to other research.

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Annexes

ANNEX 1: Major Networking Technologies used in IoT projects.

Major Networking Technologies used in IoT projects, (Altexsoft, 2020).

NETWORKING TECHNOLOGIES USED in IoT

Network	Connectivity	Pros and Cons	Popular use cases
Ethernet	Wired, short-range	High speed Security Range limited to wire length Limited mobility	Stationary IoT: video cameras, game consoles, fixed equipment
WiFi	Wireless, short-range	High speed Great compatibility Limited range High power consumption	Smart home, devices that can be easily recharged
NFC	Wireless, ultra-short-range	Reliability Low power consumption Limited range Lack of availability	Payment systems, smart home
Bluetooth Low-Energy	Wireless, short-range	High speed Low power consumption Limited range Low bandwidth	Small home devices, wearables, beacons
LPWAN	Wireless, long-range	Long range Low power consumption Low bandwidth High latency	Smart home, smart city, smart agriculture (field monitoring)
ZigBee	Wireless, short-range	Low power consumption Scalability Limited range Compliance issues	Home automation, healthcare and industrial sites
Cellular networks	Wireless, long-range	Nearly global coverage High speed Reliability High cost High power consumption	Drones sending video and images

ANNEX 2: Table with information about sensors and their respective target faults.

Measurement	Sensor	Key Information	Target Faults
Sound	Acoustic sensor	Acoustic sensors measure sound levels and convert this information into digital or analogue data signals.	Bearing/engine condition, detect equipment change.
Vibration	Piezo accelerometer	Low noise, frequencies up to 30 kHz, well established in CbM applications	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Vibration	MEMS accelerometer	Low cost/power/size, frequencies up to 20 kHz+	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Sound pressure	Microphone	Low cost/power/size, frequencies up to 20 kHz	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Sound pressure	Ultrasonic microphone	Low cost/power/size, frequencies up to 100 kHz	Pressure leaks, bearing condition, gear meshing, pump cavitation, misalignment, imbalance
Motor current	Shunt, current transformer	Low cost, noninvasive, usually measured at motor supply	Eccentric rotors, winding issues, rotor bar issues, supply imbalance, bearing issues
Magnetic field	Hall, magnetometer, search coil	Low cost/size, frequencies up to 250 Hz, stable over temperature	Rotor bar, end ring issues
Temperature	Infrared thermography	Expensive, accurate, multiple assets/sources of heat at one time	Heat source location due to friction, load changes, excessive start/stop, insufficient power supply
Temperature	RTD, thermocouple, digital	Low cost, size, accurate	Change in temperature due to friction, load changes, excessive start/stop, insufficient power supply
Oil quality	Particle monitor	Viscosity, particles, and contamination	Detect debris from wear
Distance	Ultrasonic	Low cost, Low range, low read freq, not for complex objects, external conditions sensitive, not 3D image compatible.	Robot applications, distance measurement, production line distances
Distance	Infrared Distance	Low cost, Low range, low read freq, suitable for complex objects, not sensitive to external conditions, not suitable for 3D imaging.	Robot applications, distance measurement, production line distances
Distance	Laser Distance: LIDAR	High cost, High range, high read freq, suitable for complex objects, not sensitive to external conditions, 3D imaging compatible	Robot applications, distance measurement, production line distances
Distance	Time of Flight	Medium cost, High range, high read freq, suitable for complex objects, unsensitive to external conditions, 3D imaging compatible	Robot applications, distance measurement.
Rotation Speed	Rotational Speed	Wide range of frequencies, can be pressure resistance, leak proof, resistent to oil, salt, acid/alkaline solutions, wide range of temperatures.	Hydraulic drives, machine tools, wind power plant, transmissions, eletric drives
Movement detection	Motion/occupancy detection	Wide range of working temperatures, analogue and digital, medium/high cost. The occupancy sensor returns a signal when something is still.	Flow of products in a production line, check if a producti is in fact where it's supposed to be.
Velocity, acceleration	Motion velocity sensors and accelerometers	Motion velocity sensors are linear or angular and indicate how fast an object is moving or rotating along a straight line. Accelerometers measure changes in velocity.	CNC cutting speed, production line movement speed, robots' movements
Chemicals	Chemical sensors	Chemical sensors measure the concentration of chemicals in a system. It is usually trying to identify a specific chemical from a mixture. A CO2 sensor, for example, only detects carbon dioxide.	Fire detection systems. Chemical leak detection.
Pressure	Pressure sensors	Pressure sensors are related to load cells and measure the force exerted by liquids or gases. Pressure is measured in terms of force per unit surface area	Lack or surplus of pressure in gas pipelines.
Liquid Flow	Flow sensors	These sensors record a liquid's flow rate. They measure the volume (mass flow rate) or the quantity (flow rate) of liquid going thought a system.	Detect lack or surplus of flowrate.

Force Applied	Load cells	Force sensors detect whether a physical force is being applied and whether this exceeds a certain threshold.	Bearings load: Stress and strain levels, a gradual or sudden change in weight, a gradual or sudden change of forces.
Humidity	Humidity sensors	Humidity sensors detect the humidity (amount of water vapour) in the air or in a mass. Humidity can be measured in several ways.	Moisture in oil; Humidity in controlled environments.
Position	Position sensor	A position sensor measures the position of an object. This can either be absolute (location) or relative to certain markers (displacement). Position sensors can be linear, angular, or multi-axis.	Gas turbine shell expansion; bearing vibrations;

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