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Predictive Maintenance Module for Sistrade ERP

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Dissertação para obtenção do Grau de Mestre em Engenharia Informática, Área de Especialização em Sistemas Computacionais

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Abstract

In recent years, manufacturing industries have faced a major change in manufacturing processes, especially in the pursuit of highly customized products, the shorter product life cycle, as opposed to traditional mass production of standard products.

As a result of this change, organizations, as well as all sectors of manufacturing activity, face the need for adaptation. Maintenance is a major manufacturing process as it affects performance and production quality, having a direct impact on customer satisfaction and product cost.

These days, corrective and planned maintenance strategies are widely implemented. However, manufacturing companies that can update and embrace the new reality by implementing new, innovative, and intelligent maintenance systems that can predict potential failures. Predictive maintenance tools and systems have been developed and continue to be studied and improved. However, industries have little confidence in these systems to implement in their facilities.

Keywords: Maintenance; Smart Maintenance; Internet of Things; Industry 4.0.

Resumo

Nos últimos anos, as indústrias de manufatura têm enfrentado uma grande mudança nos processos de fabrico, especialmente na procura por produtos altamente personalizados, causando um ciclo de vida menor ao produto mais curto, opondo-se à tradicional produção em massa de produtos normalizados.

Como efeito desta mudança, as organizações, bem como todos os setores de atividade de manufatura, enfrentam a necessidade de se adaptar. A manutenção é um dos principais processos de fabrico, visto que influência a produtividade e a qualidade da produção, tendo um impacto direto na satisfação do cliente e no custo do produto.

Nos dias de hoje as estratégias de manutenção corretiva e planeada são amplamente implementadas. Todavia, as empresas de manufatura necessitam de se atualizar e adotar a nova realidade, implementando novos sistemas de manutenção, inovadores e inteligentes, que tenham a capacidade de prever possíveis falhas. As ferramentas e os sistemas de manutenção preditiva têm sido desenvolvidos e continuam a ser estudados e melhorados. Porém a indústria tem uma confiança escassa nestes sistemas para os implementar nas suas instalações.

Palavras-chave: Manutenção; Manutenção inteligente, Internet das Coisas; Indústria 4.0.

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Acronyms and Symbols

CBM	Condition-Based Maintenance
CSV	Comma-Separated Values
ERP	Enterprise Resource Planning
IoT	Internet of Things
I-IoT	Industrial Internet of Things
MES	Manufacturing Execution System
OEE	Overall Equipment Effectiveness
OPC-UA	OPC Unified Architecture
OSA-CBM	Open System Architecture for Condition-Based Maintenance
PdM	Predictive maintenance
RCM	Reliability-Centered Maintenance
RUL	Remaining Useful Lifetime

1 Introduction

1.1 Context

Throughout the years, with the constant evolution of society and the intensification of product demands, competitiveness has increased, leading the companies on a way to try to find solutions to improve their business. In the latest years, companies need to be more competitive and this brought extreme pressure on the industrial sector, forcing companies to reduce the costs and increase the values of their assets and the quality of the final products [1]. This pressure felt by the companies led the sectors related to manufacturing to improve themselves and to decentralize their functionalities.

One of the main concerns in the industrial world is associated with the preservation of physical assets, given the fact that all equipment, or asset, is unreliable since it suffers degradation with age and usage and the failure can occur more quickly and frequently [2]. As such, one of the most commons topics highly discussed is the maintenance and all the functions inherent to this activity.

The concepts, strategies and techniques that exist nowadays are applied in different areas and sectors. However, the maintenance of the manufacturing sector is probably the most difficult type of maintenance, when compared to others, such as construction, transportation, airline industry and power [1]. Due to the number of variables related to the production processes and the volatility to the industrial sector adding the impact that the manufacturing sector has on the economy, business, and society the maintenance in this sector is the most developed and mature compared with other sectors.

In the past, maintenance was a necessary evil, meaning that maintenance operations were executed only if strictly needed. The primary objective of maintenance was to minimize the cost of the life cycle of a physical asset, and these only suffered maintenance when a failure was detected, leading to sudden stops in the production. These stops resulted in a loss of profit and a higher cost of repairing the physical assets [1].

Over the years, the concepts, strategies, and techniques of maintenance evolved according to the needs, the manufacturing sector realized that maintenance plays a major role in increasing the competitiveness of an organization in a competitive worldwide market, this situation led to big changes in the maintenance concept [2]. The process of maintenance goes from the necessary evil to strategic factor and a profit contributor to ensuring productivity in industrial systems [3][4].

Industrial environments are often characterized as dynamic, chaotic, and for being stochastic, so maintenance is essential to ensure the stability and efficiency of production [1]. When maintenance is performed correctly, is a great contributor to safety in the manufacturing environment as well as in the global industrial environment [1]. The process of maintenance becoming a focal point when it comes to asset acquisition, product design, customer satisfaction, and manufacturing sustainability [1].

Through the years of industrial history, several maintenance techniques were developed. Some of the examples of that are schedule maintenance, condition-based maintenance and reliability-based maintenance [1]. In the beginning, maintenance was a production task, and the prevalent technique was corrective maintenance. With the mechanization of processes and the increasing customer demands, organizations could not wait until the machines failed and a maintenance process takes place, these times were necessary to produce. At this point, failure prevention was an issue, that empowered the creation and implementation of scheduled maintenance which is based on the failure history of the assets and is implemented by the scheduling of maintenance interventions. These days, due to automation maintenance techniques as Condition-Based Maintenance (CBM) and Reliability-Centered Maintenance (RCM), are being developed, matured and implemented in the companies [2][5]. In the meantime, organizations are seeking to take advantage of the most recent and intuitive technologies, such as the Internet of Things (IoT), advanced data analysis, real-time monitoring, in order to facilitate their performance and gain safer, smarter and more sustainable environment [6]. The maintenance techniques mentioned previously have revealed themselves very effective, excepted the corrective maintenance, eliminating unexpected failures and unplanned unavailability's [1].

The emergent interest in improving and developing maintenance concepts techniques combined with the advance of Information and Communication Technology (ICT), has generated an eruption of research that has contributed to the development of new, innovative, and intelligent approaches [1].

1.2 Problem

Today's organizations must pay special attention to asset management, as investments in them are sometimes significant and their inoperability can result in critical monetary losses. As mentioned previously maintenance can be a contributor to profit so many organizations choose to have software capable of managing assets and having greater management and control over these.

Digital transformation has recently become a major trend in commerce and industry. It is also an indispensable part of industry 4.0 and IoT. The latest industrial revolution, called industry 4.0, uses artificial intelligence, thus changing the way machines collect and interpret data [7].

Today, industry 4.0 together with I-IoT (Industrial Internet of Things) offers organizations the ability to collect, analyze and act on data. Increased connectivity and the ability to collect and analyze data have led to a shift in the information-based economy. These changes that organizations face continue to shape competitive scenarios, particularly concerning policies maintenance. These days, maintenance is increasingly seen as a strategic business function, where organizations aim to reduce both maintenance costs and downtime and increase equipment lifecycles. Thanks to emerging technologies and industry 4.0, it is now possible to develop intelligent methods and algorithms that avoid costly reactive maintenance strategies such as "*run till you go*" or ineffective preventive maintenance approaches "*fix no matter the consequences*" [7].

By analysing use case studies in the manufacturing industry, it is known that unexpected machine downtime can be mitigated if there is efficient and effective maintenance, at the right time. This intervention sometimes reduces maintenance costs. As such, it is noticeable that traditional maintenance strategies, such as reactive and preventive maintenance, reveal limitations of efficiency, effectiveness, and cost for industrial organizations. To meet the needs imposed by the industry is needed to develop a predictive maintenance system that uses the data available from machine sensors.

1.3 Objective

The main objective of this project is the study and development of a machine failure prediction system that helps companies to maintain their equipment more efficiently, effectively, and profitably. Failure prediction should consider the analysis of data made available by MES/ERP, such as production data, maintenance plans, maintenance orders and machine failures and data from machine sensors. These data must be pre-processed and processed, to guarantee their robustness and suitability for the use of intelligent data analysis techniques, such as forecasting and clustering techniques.

The following are the specific objectives for implementing the project:

- State of the Art Survey:
    - Identification of the most relevant and appropriate approaches to the problem.
    - Identification of existing techniques for solving the problem.
    - Identification and analysis of the most relevant algorithms of the forecast.

- Design and conception of the system architecture to be developed, considering:
    - The different data analysis techniques were identified.
    - The criteria that condition the system's output.
- Construction and development of a failure prediction system.
- Design and experimentation of real scenarios for system testing and validation.

1.4 Hypotheses

This project has as hypotheses to verify if it is possible to implement predictive maintenance recurring to the sensor and MES/ERP data, and this process by intelligent methods and algorithms that generate recommendations.

1.5 Document Structure

The present document is organized in the following chapters:

1. Introduction
2. Context
3. State of the Art
4. Value Analysis
5. Solution Requirements
6. Demonstration and Results
7. Experimentation and Evaluation

In the Introduction chapter, is made a brief presentation of the context and problem associated with the proposed work is made, followed by the objectives to be achieved, the hypotheses to demonstrate and the respective expected results.

In the Context chapter, is made the presentation of Sistrade and Maintenance in the manufacturing world.

In the State-of-the-Art chapter, several maintenance process techniques and intelligent algorithms present in the literature and the market are explored.

In the Value Analysis chapter, the value of the business associated with the proposed work is studied, including the presentation of the value proposal, analysis of the innovation process and presentation of the business model.

The Solution Requirements presents the documentation related to the design of the proposed system, using the analysis of functional and non-functional requirements.

The Demonstration and Results chapter describes the development process that used for the final evaluation.

The Experimentation and Evaluation chapter describes the process that will be used for the final evaluation.

2 Context

The work present in this thesis is part of the R&D project named Pianism - Predictive and Prescriptive Automation Smart Manufacturing, which the main goal is to develop an intelligent approach for industrial maintenance, aligned with Industry 4.0 principles. This approach should consider an advanced analysis of the data collected from the shop floor to monitor and detect earlier the occurrence of disturbances and consequently the need to implement maintenance interventions.

2.1 Sistrade – Software Consulting

Sistrade - Software Consulting, S.A. is a Portuguese organization specializing in software development and providing consultancy services for different sectors of activity, namely for industry and services.

Sistrade mission is "To establish partnerships with our customers to obtain concrete results, innovate and add value through joint decisions in an increasingly competitive electronic market. Emphasize the growth of services / businesses, the use of innovative technologies, the total satisfaction of customers and the realization and enhancement of our company's staff. These aspects will translate into added value for our customers, our human resources and our shareholders.".

2.1.1 Maintenance Software

Currently, Sistrade has in its software an equipment maintenance module that allows the management of assets on a platform, based on the Web and integrated with complementary modules, Stocks and Purchases, Planning, Quality Control. It is a multi-company, multi-location, multi-language and multi-currency system. In this maintenance module, we have the equipment tree, preventive maintenance, corrective maintenance, the record of incidences, maintenance orders, the records of interventions, the management of stocks and spares, integration with planning and subcontracting.

2.1.2 Record of Incidents

The maintenance module allows the recording of incidents, malfunctions, and the request for maintenance orders in a simple way, through interfaces adapted to any device.

2.1.3 Maintenance orders

Preventive maintenance plans, as well as requests for corrective maintenance, when processed and validated, give rise to a Maintenance Order. In the elaboration of a maintenance order in the Sistrade system, information associated with the accomplishment of the same can be defined. In this information, we can find data of the equipment, material needed in the intervention, description of the occurrence, documentation about the maintenance to be carried out and employees involved.

2.1.4 Registration of Interventions

The Sistrade system permanently monitors maintenance, for which the employee, when initiating the resolution of a maintenance order, aggregates the information through a device. In the same way, the spent materials inherent to maintenance can be accounted for.

2.1.5 Integration with Planning

The Sistrade ERP/MES software provides a GANTT diagram to facilitate the planning of all tasks involved in maintenance. This diagram can be crossed with the production planning diagram, thus allowing the analysis of data between production and maintenance.

2.1.6 Subcontracting

Sistrade ERP / MES allows the control of subcontracted processes and activities. Organizations sometimes subcontract other organizations to perform maintenance on their resources.

2.2 Maintenance in Manufacturing

Since the industrial revolution, the maintenance of physical assets has been a challenge. Has been made impressive progress in maintaining physical assets work properly way, but the maintenance is still a challenge nowadays due to some factors like size, cost, complexity, and competition [8].

Maintenance is defined according to the European standard (EN 13306: 2001) as "*the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in or restore it to a state in which it can perform the required function*".

3 State of the Art

3.1 Maintenance

The definitions for this activity depend on the authors that study this subject. However, most of them can agree that maintenance can be defined as a "*set of activities required to keep physical assets in the desired operating condition or restore them to this condition*" [2]. In other terms, the main purpose of industrial maintenance has a focus on the availability and reliability of a manufacturing physical asset [1]. This was the primitive's definition for this activity considering that maintenance aims to restore an asset to its operational state after a stop occurred. Currently, the main objective of the maintenance program is to find the balance between the capability of the system and the costs [7]. The definition of maintenance has grown with the evolution of manufacturing industries and has passed different stages represented in Figure 1. In the beginning, maintenance was nothing more than an inevitable part of the production, it was simply a necessary evil. Repairs and replacements were carried out when necessary and no optimization issues were raised. Later, maintenance was thought to be a technical issue. This not only included the optimization of technical maintenance solutions but also involved the organization's attention in the maintenance work. Later, maintenance became a developed function, rather than a production subfunction. Maintenance management has now become a complex function, encompassing technical and management skills, but it still requires flexibility to handle the dynamic business environment. Senior management recognizes that having a well-thought-out maintenance strategy coupled with careful implementation of that strategy can have a significant financial impact. Nowadays, this has led to treating maintenance as a mature partner in the development of business strategy and, possibly, at the same level of production. In turn, these strategies formally consider establishing external partnerships and outsourcing the maintenance function [2].

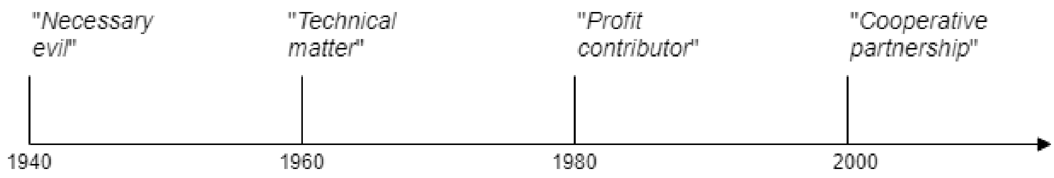

Figure 1 : Maintenance stages in a timeline (adapted from [2])

In Figure 2 an evolution of the manufacturing industries is illustrated, where it is possible to realize the maintenance stages over the years, its objectives and the correspondent enabling factors. The enabling factors for the evolution of the manufacturing system are Interchangeable parts, operations management, computers, Scientific Knowledge and more recently the Analytics. These are the keys factors of change in the manufacturing system, and they have a correspondent objective. The Interchangeable parts resulted in the reduction of costs, the operations management have brought some quality to the companies, the computers have allowed the variety. Scientific Knowledge, resulted in responsiveness and analytics has resulted in transparency, this transparency is becoming more important, because it allows quantifying real manufacturing capabilities and readiness, minimizing the role of uncertain decisions made in production [9].

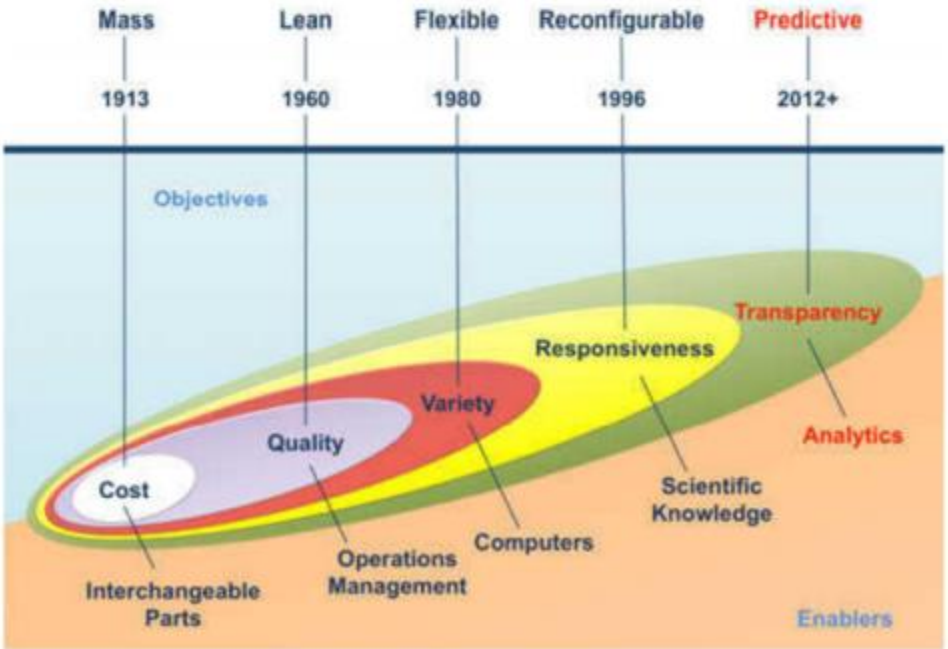

Figure 2 : Manufacturing Systems Evolution [10]

To achieve transparency the companies, must change their paradigm, to a predictive manufacturing paradigm. These transformations can be made by taking advantage of the high volume of data produced on the shop floor and the use of predictive analytics and that data generated can be processed and translate into valuable information. This information can be used to make informed decisions [10].

This paradigm extends to the physical assets, in this way maintenance became a strategic point and its main goal is to contribute to the organization's profit [4]. Thus, as defined in [1] maintenance can be considered as a "*set of activities, technical, administrative, and managerial, performed during the life cycle of an item, workplace or work equipment to preserve the value of an asset*".

Effective maintenance is a system composed of plans and operations, that needs to guarantee material, spares, tools, human and financial resources availability [1]. This proves that industrial maintenance is a multidisciplinary system that requires to be linked with several departments or services to operate properly.

3.2 Maintenance Strategies and Techniques

The occurrence of unexpected machine failures in production leads to the loss of productivity which can have as result in losing business opportunities. The implementation of maintenance strategies and techniques in the production environment can reduce these machines' downtimes and the companies can increase competitiveness.

The maintenance strategies can be divided into four groups, Reactive Maintenance, Preventive Maintenance and Proactive Maintenance.

These strategies and techniques are detailed in the following sub-sections.

3.2.1 Types of Failure

The strategies and techniques exist because the physical assets are composed of multiple pieces, and these have failures or breakdowns. So, maintenance exists because failures and breakdowns happen. A failure of equipment is an event in which the equipment cannot accomplish its purpose. Figure 3 shown the two types of failure, potential failure, and functional failure.

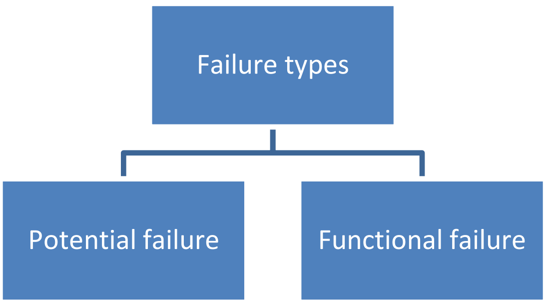

Figure 3: Failure types

The potential failure occurs in an early stage, which indicates that something is wrong, but the physical asset still performing its function. That is if it is not treated it will lead the equipment to functional failure [11][12].

Functional failure is when the physical asset is no longer able to perform its function. So, corrective maintenance will always be linked to potential failure or functional failure [11].

3.2.2 Reactive Maintenance Strategy

Reactive Maintenance Strategy also knowns as Corrective Maintenance can be defined as an unscheduled maintenance intervention performed to restore an asset to its operating state [1]. The interventions only are triggered after a breakdown or a loss of function, are normally known as "fix, only when it breaks!" [2][13].

The unexpected failures of an asset are difficult to predict but when they happened they cause shutdowns, delays in production and with them, unexpected and unplanned repairs are coming, and these last ones are the most expensive type of maintenance activity [14]. This type of maintenance should be applied only in situations when the failure doesn't need the stop of the machine to be resolved because normally these maintenance actions don't have high capital costs, the consequences of failures are slight, no safety risks are immediate, and the identification and the repair are possible [15].

3.2.3 Preventive Maintenance Strategy

This type is more complex than the previous one because it tries to diminish the failure probability of an asset anticipate and avoid if possible [2].

They are some techniques that applied this type of strategy, that have scored great results in eliminating unexpected and unplanned failures [1]. Examples of these techniques are Predetermined Maintenance and Condition-Based Monitor.

The Preventive Maintenance Strategies can be divided into two largest groups: The Schedule or Predetermined Maintenance and Predictive Maintenance as represented in Figure 4.

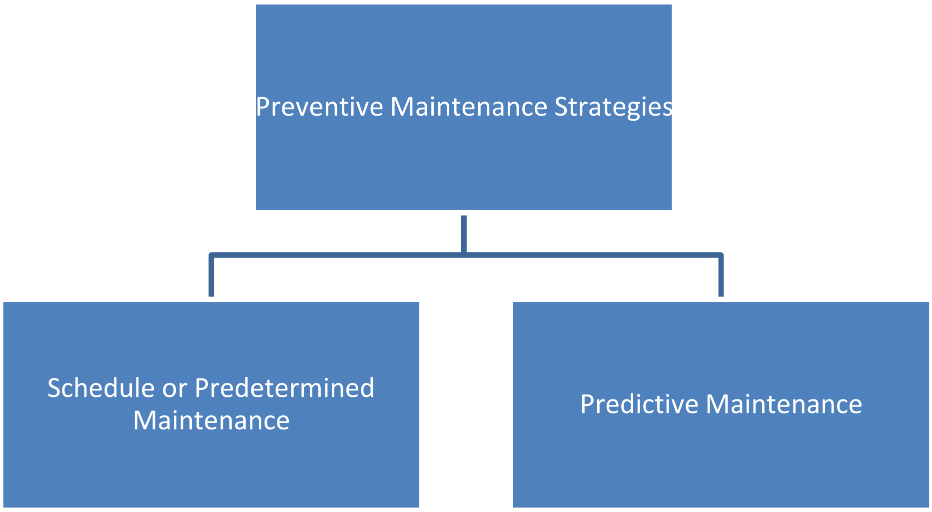

Figure 4 : Preventive Maintenance Strategies

3.2.3.1 Schedule or Predetermined Maintenance

The main objective of this strategy is to diminish the failure probability of the physical assets, which can lead to the extent of the lifetime [1] [2]. This strategy aims to schedule dates for the maintenance interventions of the asset, the time between the scheduled dates is determined by the machine manufacturer, age and condition of the asset. The manufacturer for the calculation of the interval between schedules needs to know some reliability indexes, more commonly are used the Mean Time Between Failure (MTBF) and the Mean Time To Repair (MTTR). The referred indexes can provide an approximate estimation of the time between two nears breakdowns and the meantime needed to restore the system when such breakdowns happen [2].

3.2.3.2 Predictive Maintenance

The principal objective of predictive maintenance is trying to predict when a piece of equipment might fail, and a breakdown occurs. These techniques involve all techniques that aim to early detect failure occurrence and for this, the data generated on the shop floor is very important [16]. This data needs to be processed effectively, providing context and meaning that can be understood and used, otherwise, the data is not useful [16]. There are several techniques to developed, or in development, capable to implement predictive maintenance in a manufacturing system, such as Condition-based Maintenance (CBM), Reliability-Centered Maintenance (RCM) and Prognosis and Health Management (PHM).

PHM uses algorithms to detect anomalies, diagnose faults and predict the Remaining Useful Lifetime (RUL) of the asset. PHM evaluates the reliability of a system in its actual condition, intending to determine the advent of the failure and mitigate the risks [17]. This concept is normally used with other approaches like CBM [18].

The main goal of CBM is to avoid unnecessary maintenance interventions by performing maintenance actions only when the physical asset shows abnormal behaviours [19]. This technique uses data generated on the shop floor to monitor the physical assets [2].

The interest is rising in a predictive manufacturing world, a prognosis layer was added by Open System Architecture for Condition-Based Maintenance (OSA-CBM) [20], and this transforms the CBM into an important tool.

The architecture has suffered changes and nowadays the OSA-CBM is represented by six functional blocks, these blocks are Data Acquisition, Data Manipulation, State Detection, Health Assessment, Prognostics Assessment and Advisory Generation like Figure 5 represents [20].

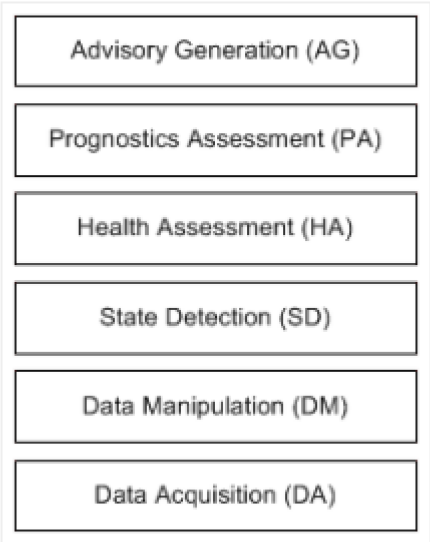

Figure 5: OSA-CBM Functional Blocks

The function blocks of the architecture are defined as following [20]:

1. Data Acquisition: Provide access to the sensor data or transducer data and record this data.
2. Data Manipulation: Perform signal transformations and can apply feature extraction algorithms.
3. State Detection: Performs condition monitoring by comparing features against expected values or operational limits and returning conditions indicators.
4. Health Assessment: Determine if the system's health has degraded by considering trends.
5. Prognostics Assessment: Do a projection of the current health state of the asset into the future by considering an estimation of future usage profiles.

6. Advisory Generation: Provide recommendations related to maintenance actions, modifications of the asset.

For the OSA-CBM architecture, the data follows between adjacent layers, but if it is needed each layer may be able to request data from non-adjacent functional layers [21]. This technique is very helpful to predict breakdowns but has a point against it, that point is the high cost of installation, especially if the physical asset is already installed and is necessary to add further instrumentation [13].

RCM is a multi-maintenance method, that allows the comparison of different maintenance methods, and chooses the most cost-effective without compromising reliability [22].In IEC 60300-3-11 standard RCM is defined as a "*systematic approach for identifying effective and efficient preventive maintenance tasks for items in accordance with a specific set of procedures and for establishing intervals between maintenance tasks*". This technique has a big advantage and there are a structured analysis process and traceable approach to determinate the optimal type of preventive maintenance [23].

Ideally, predictive maintenance allows the maintenance frequency to be as low as possible to avoid unplanned reactive maintenance, without incurring costs associated with performing a lot of preventive maintenance.

All the techniques previously explored need to be implemented used software. There are some guide phases for software development.

3.2.4 Data Sources for Predictive maintenance

As previously mentioned, predictive maintenance needs to use sensor data or machine parameters data, and one of the first steps to accomplish is the selection of the operation and condition parameters to be measures and the way they will be measured. For the determination of these parameters or sensor data is essential to discuss with the involved stakeholders the topics described in Table 1.

Table 1: Determination of parameters

Question	What to Determine	Stakeholders Involved
What?	Parameters (ex: vibration, temperature, etc..)	Equipment Operator Maintenance Staff Management Equipment Manufacturer Technical Partner
How?	Sampling Frequency Sampling Accuracy Sensors Needed	Equipment Operator Maintenance Staff Management Equipment Manufacturer Technical Partner Sensor Provider

For the success of the implementation of a predictive maintenance system, the data need to be processed effectively, providing context and meaning that can be understood, otherwise, the data is irrelevant [16].

Analysis of data is critical to the knowledge of the maintenance team to attribute meaning to the data collected. For predictive maintenance, techniques are five important analyses to be made and there are:

- Data Comparison
- Limit or range tests
- Pattern Recognition
- Correlation analysis
- Statistical process analysis

In the Data Comparison is made the recognition of changes, compared to previous data or baseline data on similar equipment, in the limit or range tests is made specific testing to discover operating parameters that do not follow continuous trends or repeatable patterns. Pattern recognition is the identification of deviations from established patterns. The correlation analysis is the comparison of multiple sources, related technologies, or different analysts. Finally, statistical process analysis is used of statistical techniques to identify deviations from the nom [24].

As mentioned previously in the present document predictive maintenance needs sensor data represented by the Data acquisition layer in the architecture OSA-CBM to get the performance of the physical asset in real-time, so relies on condition-monitoring sensors, the internet of things, or predictive formulas [25].

Condition-monitoring sensors send data of performance and machine in real-time. IoT technology enables the communication between physical assets, software solutions, and cloud technology. Predictive Formulas is the point where predictive maintenance goes beyond condition-based maintenance because the data collected previously is analyzed by machine learning algorithms that can identify trends to detect when a physical asset will need maintenance actions [25].

3.2.4.1 Predictive Maintenance Techniques

Predictive maintenance techniques are an emerging technology that can be employed to detect potential failures recurring to artificial intelligence algorithms that may not be evident through preventive maintenance [26]. If the characteristics of the failures are known predictive maintenance techniques can be applied and detect the failure in advance and measures can be taken to avoid the occurrence of the failure [26]. In this subsection, six techniques will be introduced below [24].

These techniques are alignment, oil analysis, wear particle analysis, infrared thermography, vibration monitoring, and motor analysis, they gone be detailed below.

Alignment

Misalignment of parts of physical assets will cause malfunctions or breakdowns and the parts of the physical assets needs to be checked sometimes, these activities used to be very slow and with the advent of laser alignment systems as reducing the time of this action more than half and increased accuracy [24].

Oil analysis

Oil analysis's full benefit can be accomplished by taking frequent samples and register the analysis by each machine in some software, the length of the sampling intervals varies with the different types of physical assets and operating conditions. Based on the results of the analyses lubricants can be changed or upgraded [26].

Oil analysis typically include eleven tests, and there are [24]:

- Viscosity
- Fuel dilution
- Solids content
- Fuel soot
- Oxidation
- Nitration
- Total acid number
- Total based number
- Particle count

- Spectrographic analysis

Wear particle analysis

The previously described provide information about the lubricant, wear particle analysis provides information about wearing conditions inside of the physical asset. This information is derived from the study of particle shapes, composition, sizes, and quantities [24].

This technique is organized in two stages, the first involves monitoring collected particles to determine normal conditions and trends. The second is the diagnosis of abnormal conditions as indicated by changes in the particle types, sizes, and quantities [24].

Infrared thermography

Infrared thermography analyses the heat energy radiate in proportion to their temperature and emissivity. This type of inspection can be qualitative or quantitative. Qualitative inspection concerns relative differences, hot and cold spots, and deviations from normal or expected temperatures. Quantitative inspection concerns the accurate measurement of the temperature of the target [24].

Vibration monitoring

Vibration monitoring was one of the first techniques used in predictive maintenance. Monitoring the vibration from plant machinery can provide a direct correlation between the mechanical condition and recorded vibration data of each machine in the plant. Used properly, it can identify specific degrading machine components or the failure mode of plant machinery before serious damage occurs [26].

Motor analysis

Until now, predictive maintenance technologies for motors have been limited to vibration tests, high voltage surge tests for winding failures, meg-Ohm and high potential tests for ground insulation resistance, and voltage and current tests to test phase equilibrium. Many of these tests still have their place in the maintenance of the plant, but several of them are impractical, dangerous, or harmful when the tests are carried out with the engines installed [24].

Predictive Maintenance Algorithms

Nowadays exists multiple modelling strategies for predictive maintenance, but there are four that are more commonly used, and they are [27]:

- Regression models to predict remaining useful lifetime (RUL).
- Classification models to predict failure within a given time window.
- Flagging anomalous behaviours.
- Survival models for predicting failures over time.

To use any of the predictive algorithms previously presented, are data characteristics and basic assumptions and requirements to consider, these gone be described below.

Regression models to predict remaining useful lifetime (RUL)

To use this type of algorithm the data available need to be static and historical and need to be labelled. This data also needs to be taken at different moments during the physical asset lifetime assuming that the degradation process is smooth. This algorithm only allows one type of failure by model, so if exists many types of failure the algorithm preceding each one of them differently [27].

Classification models to predict failure within a given time window

Often the maintenance team only needs to know if the machine will fail "soon", and this algorithm has that with the main objective. This algorithm requires static and historical data, and this needs to be labelled. The classification models are very similar to the regression models, but they have little differences like they can deal with multiple types of failures if they are framed as a multi-class problem and the labelled need to be "enough" for each type of failure [27].

Flagging anomalous behaviours

The previous two algorithms required a lot of normal behaviour and failures, but sometimes it does not possibly take the necessary data and this algorithm exists to answer those situations. To apply this type of algorithm the data need to be static and historical, and label data of failure are few or unknown or there are too many types of failure. In this case, needs to be possible to define what is normal and abnormal behaviour and the difference between these. The model of this algorithm should be able to flag every type of failure, despite not having any previous knowledge about them. Anomalous behaviour, however, does not necessarily lead to failure. And if it does, the model does not give information about the period it should occur. The evaluation of an anomaly detection model is also challenging due to the lack of labelled data [27].

Survival models for the prediction of failure probability over time

The previous approaches focus on prediction, giving you enough information to apply maintenance before failure. This algorithm focuses on the degradation process and the resulting failure probability. Static data available, information on the reported failure time of each machine or recorded date of when a given machine became unobservable for failure. The survival model estimates the probability of failure for a given type of machine, given static features, and is also useful for analysing the impact of certain features on lifetime. It provides, therefore, estimates for a group of machines of similar characteristics. Therefore, for a specific machine under investigation, it does not take its specific current status into account [27].

3.2.4.2 Proactive maintenance

Proactive is any type of maintenance performed before any breakdown or failure occurs. It is the opposite of reactive maintenance because the focus is to anticipate and managing machine failures before they take place. To achieve this, this type of strategy requires identifying the root cause of a failure, determining potential failure locations, and avoid breakdowns caused by the malfunction or deteriorating equipment conditions. In short, proactive maintenance aims to correct the root source of the error, rather than the error itself, as shown inFigure 6.

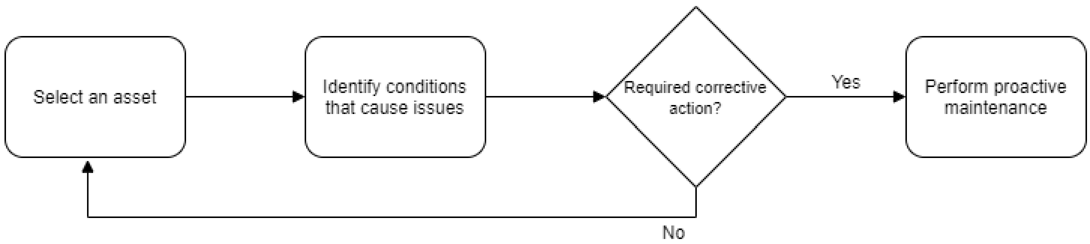

Figure 6: Proactive maintenance

Established reactive maintenance focuses on repairing equipment only after its failure, and planned maintenance on replacing equipment parts at regular intervals. Proactive maintenance aims to identify potential problems that would eventually lead to equipment failure. These potential problems can be improper lubrication of the machinery, contamination, misalignments, or environmental conditions [28].

3.3 A balance between Maintenance Strategies

The emergence of new maintenance approaches has been to find an optimum balance between cost and the ability to maintain the reliability of an asset [22].

When predictive maintenance is performed is achieved the optimum between cost and number of failures like shown in Figure 7.

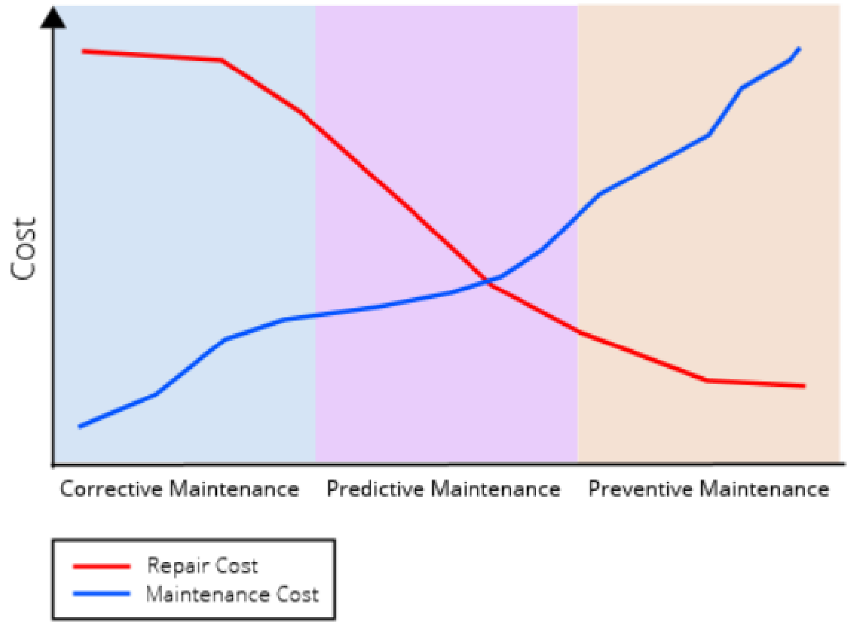

Figure 7: Maintenance costs vs Number of failures [29]

The implementation of Predictive Maintenance presents itself with high costs in the front, due to the additional hardware for example sensors for the physical assets and physical assets parameters, and software investment, cost of manning, tooling, and formation necessary to implement the system. However, it provides the organization with failure diagnostics and maintenance interventions and can supply equipment reliability and enough information to improve scheduling [2]. Preventive maintenance has the lowest repair cost, but the high maintenance costs offset the benefits.

Figure 8 shows the four categories, each with its series and challenges and benefits. Each category defined the Overall Equipment Effectiveness (OEE).

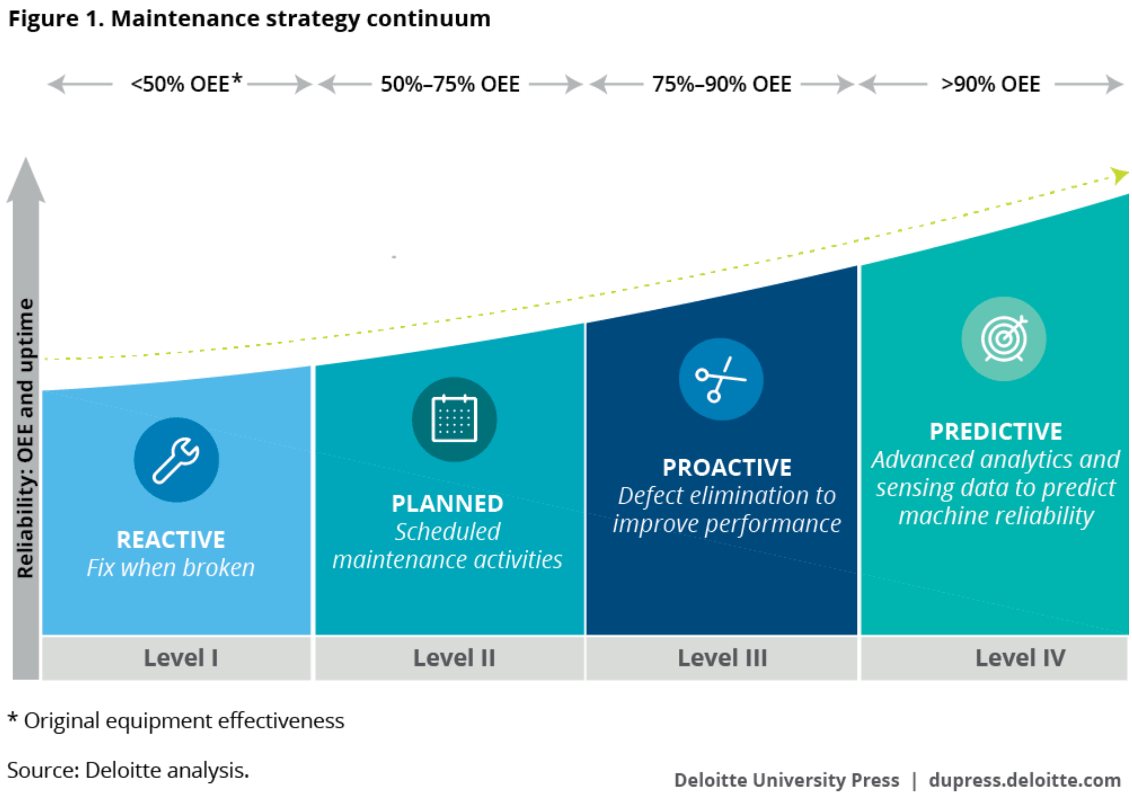

Figure 8: Maintenance Strategy continuum [30]

A brief description of the different types of maintenance is presented in Table 2. However, accurate and reliable predictive techniques, such as CBM, RCM and others, may be that the physics of the failure is not yet fully understood and Unpredictable failures continue to occur. Therefore, predictive maintenance should not be a substitute for more traditional maintenance management methods but as an addition and complementarity value for a maintenance program [31].

Table 2: Maintenance strategies (adapted [13])

Category	Maintenance approaches			
Subcategory	Corrective Run-to-fail	Preventive		
		Predetermined	Predictive	
	Fix when fail	Planned maintenance	Based on maintenance condition	Based on the condition of predictions
When to schedule?	Unscheduled maintenance	Maintenance based on a fixed schedule to inspect, repair and overhaul	Maintenance based on the current condition	Maintenance based on the forecast of the remaining life of the equipment
Schedule why?	N/A	Intolerable failure effect and Possibility to prevent the failure effect	Maintenance planning based on evidence of a need	Maintenance is projected as likely within the mission time
When to schedule?	N/A	Based on component life predicted during design and updated through experience	Continuous collection of condition monitoring data	Forecast of remaining equipment life based on current usage
Forecast type	None	None	Online and offline, almost in real-time, trend analysis	Online and offline, almost in real-time, trend analysis

3.4 Data Processing

This subsection, are presented the different steps for intelligent data, the techniques to perform data pre-processing and attribute selection. Analytical models will be presented that can be used to extract knowledge and make predictions from the data.

3.4.1 Data pre-processing

One of the most important steps in data processing is pre-processing data, which involves transforming raw data into an understandable format. The data obtained is disorganized and "dirty", which implies that it is necessary to transform it before being used for analysis [32].

The real world provides normally incomplete data, with missing values or aggregated data. These are also subject to noise and may contain errors and/or outliers, and inconsistencies [32].

The phases with the most work involved, in the data pre-processing, are [32] :

- Data cleaning
- Data integration
- Data transformation
- Data reduction

In the data cleaning phase, it consists of filling in missing values, this value can be filled in several ways, highlighting the use of the average value of the respective attribute, using a learning algorithm to predict this value, or else it is possible to ignore the record associated with the value however, this last option will result in a loss of information. In this phase, the identification of outliers is made, which can be done using clustering techniques. To clean the inconsistencies, it is necessary to know the domain [32].

In the data integration phase, conflicts between values are removed and duplicate data is removed.

The data transformation phase includes some standardization tasks, of which I highlight the transformation of values, aggregation of data and construction of attributes [32].

The data reduction phase, as well as the transformation phase, are related to the engineering of attributes that will be described in the following subsection.

3.4.2 Attribute Engineering

Attribute Engineering represents the step between data preparation and data modelling, with the process of transforming raw data into attributes that represent the underlying problem, resulting in better model accuracy when applied to new data. This process is crucial, as having the right attributes helps with data modelling and, therefore, the entire machine learning process has a better chance of achieving success [33].

3.4.3 Attribute Selection

The selection of attributes can be advantageous as it improves the predictive performance of the attributes, facilitates the visualization and exploration of data, facilitates the understanding of the problem underlying the data creation process [34].

For the selection of attributes, an algorithm is used that starts with the use of a research technique to choose a subset of attributes, followed by a metric to evaluate it and assign a score. The simplest technique is to search and evaluate all available subsets, choosing the one with the best score in the evaluation. However, this technique is computationally demanding, as it requires an exhaustive search, which becomes unenforceable [34].

The methods of selecting attributes are determined by choosing the evaluation metric, these methods can be filtering methods, wrapper methods, embedded methods, attribute extraction.

3.4.4 Analytical Models

Analytical models are static algorithms that discover connections and patterns in the data and reveal them in the form of mathematical equations. These models include a variety of machine learning and data mining techniques that, using current and historical data, discover and interpret relevant patterns to make predictions about future events.

The machine learning and data mining subjects are similar, the difference lies in the objective of each one. Machine learning aims to forecast based on known properties of training data, while data mining aims to find unknown properties of the data. Machine learning uses data mining methods in the data pre-processing phase [8].

Machine learning is mainly divided into three categories, these are represented in Figure 9.

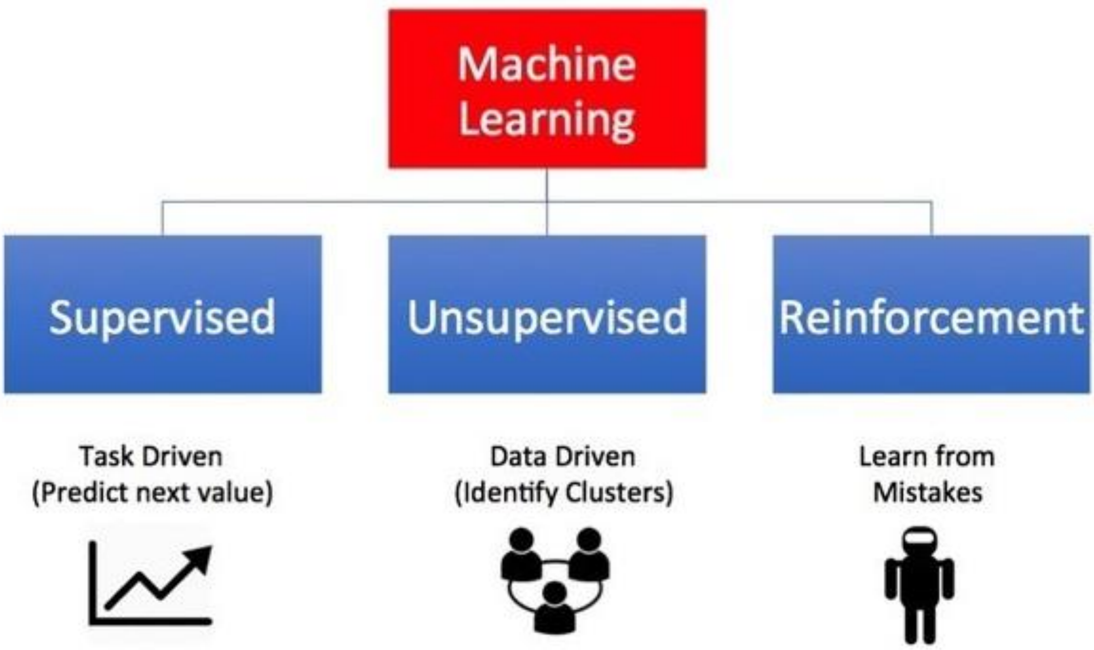

Figure 9: Machine Learning Types [35]

3.4.4.1 Supervised Learning

In supervised learning, algorithms are trained using marked data, where input and output are known. The data are entered into the learning algorithm as a set of resources, indicated by X, together with the corresponding outputs, indicated by Y, and the algorithm thus learns by comparing its actual production with the correct outputs, thus finding errors [8].

The raw data is divided into two parts, the first part is to train the algorithm and the second part is used to test the trained algorithm as shown in Figure 10.

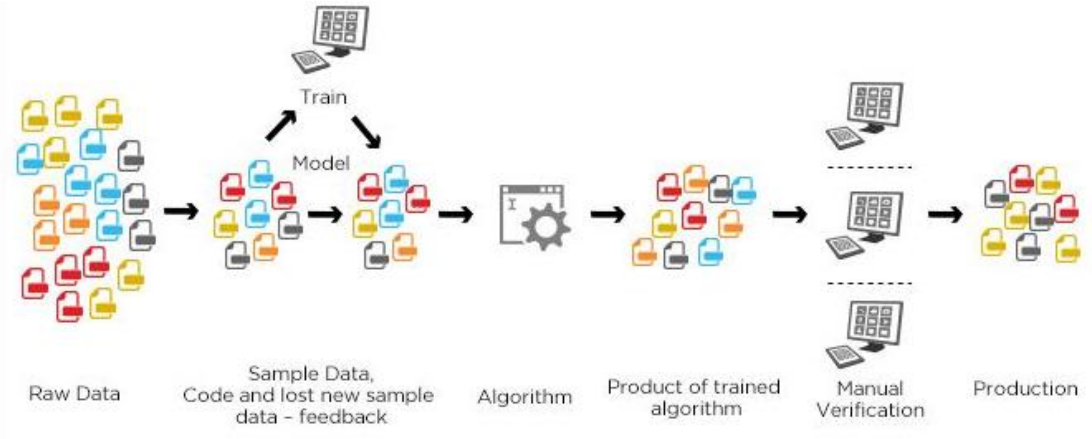

Figure 10: Supervised Learning [35]

3.4.4.2 Unsupervised Learning

Unsupervised learning is the second type of machine learning, in which the unlabelled data is used to train the algorithm, which means that it is used against data that does not have historical labels. The goal is to explore the data and find a structure. In this technique, data cannot be divided into training data and test data, as in supervised learning. The algorithm discovers the data, and according to these, it creates clusters of data with new labels [8]. Figure 11 is a representation of how the algorithm works.

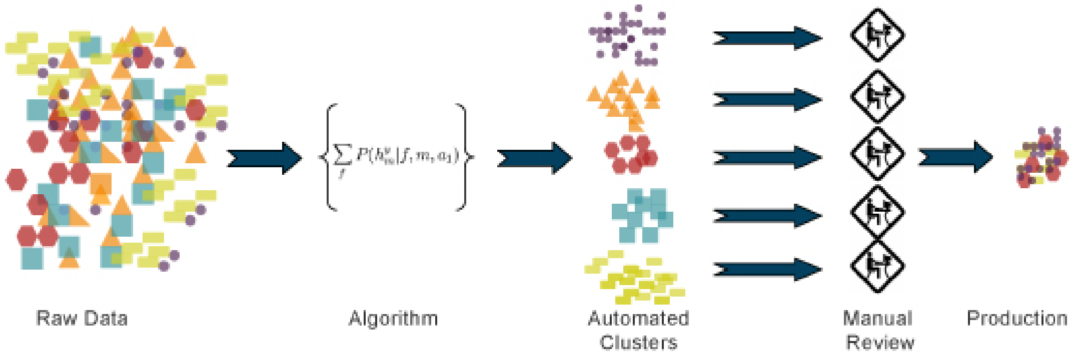

Figure 11: Unsupervised Learning [35]

3.4.4.3 Reinforcement Learning

Reinforcement learning is the third type of learning in which there is no raw data to provide as input. This algorithm needs to discover autonomously what behaviour it must adopt to fulfil the objective. With reinforcement learning, the algorithm discovers by trial and error which actions produce the most significant rewards. This type of training has three main components: the agent, who is the one who makes the decision, the environment that describes everything the agent interacts with, and the actions that represent what the agent can do [8], in Figure 12 we have the representation of these components.

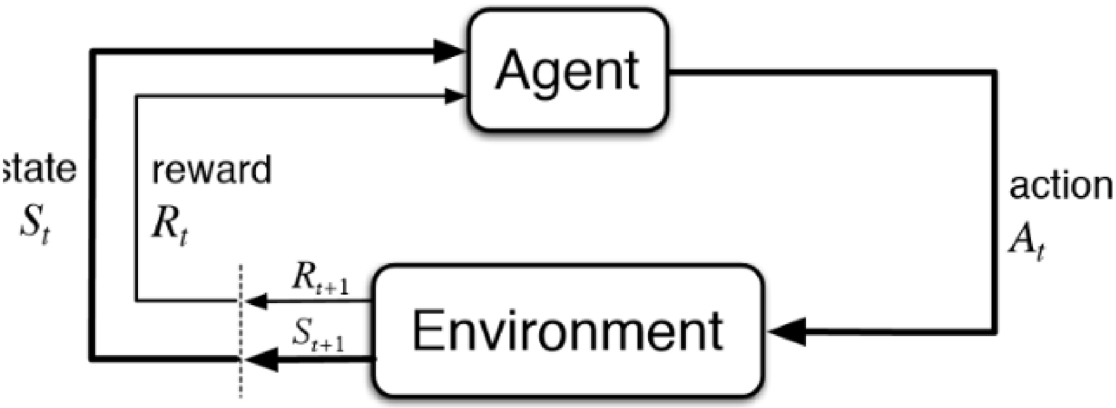

Figure 12: Reinforcement Learning [35]

4 Value Analysis

In this chapter, the value of the proposed system is studied, followed by the presentation of the value proposition, innovation process analysis and the business model.

4.1 Definition of Value

Value is defined through concepts like a necessity, interest, desire, and preferences, and its creation is fundamental to any organization [36].

The value for the client is an important concept because the principal focus is on product creation, this concept has been defined by Woodall as a "*personal perception of the advantage of its association with the organization's offer*" [37]. Distinct costumers gone have different points of view, of the value proposition, because each one of them has their needs and individual preferences.

The customer point of the view has resulted from combinations between benefits and costs of the offer presented to the customer, in other words for the customer the benefits are more important than the costs proposal. This offer has a positive value for the customer. Otherwise, this offer has a negative value to the customer.

To estimate the value to the customer, Table 3 was elaborated. This table shows the benefits and costs associated with the proposed project.

Table 3: Benefits and cost to the customer

Benefits		Costs
Attributes	**Results**	
System Portability	Adequate monitoring of equipment	Sensing of machines and their manufacturing space
Alerts of possible failures	Increased time for action in the event of possible breakdown	Adaptation to the System
Increased machine production time		
Reduction of Maintenance Costs		
Monitoring of equipment maintenance		

Table 3 presents to the customer the benefits and the costs. The benefits are divided between attributes and results, indicating a time factor between product purchase and use. It introduced by Woodall the longitudinal perspective of customer value, illustrated in Figure 13 [37].

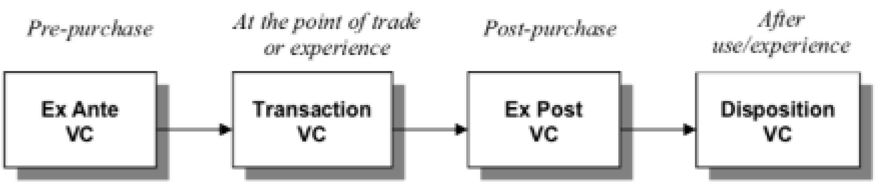

Figure 13: Longitudinal perspective of customer value [37]

The value for the customer is separated by Woodall in four states, namely Pre-Purchase, Purchase, Post-Purchase, Post utilization. For each one of these stages, their associated benefits and sacrifices are identified and evaluated.

In the Pre-Purchase stage, customers tend to look for an affordable and efficient product for maintenance processes. The sacrifice for the customer during this period will be the time spent during the analysis of the product.

In the Purchase stage, the focus will be the cost of the system, a sacrifice for the customer, with the benefits of flexibility in monitoring equipment maintenance and the accuracy of the data obtained during it.

In a Post-Purchase stage, the customer will have the benefits of reducing costs with equipment maintenance. At this stage, the phase of adaptation to the system is identified as a sacrifice.

After the use of the product, the increase in the production time of the machines and the reduction in costs in the maintenance of the equipment will be verified, resulting in satisfaction with the product.

Table 4 presents the benefits and costs of each stage in a longitudinal perspective applied to the scope of the proposed work.

Table 4: Benefits and costs of each stage in a longitudinal perspective

	Benefits	**Cost**
Pre-purchase	System Portability Increased time for action in the event of possible breakdown	Time spent analyzing the product
Purchase	Monitoring of equipment maintenance Accuracy of the data obtained	Product cost
Post-purchase	Reduction of Maintenance Costs	Adaptation to the System
After use	Increased machine production time	

4.2 Value Proposition

The purpose of this chapter is to briefly present the solution's value proposition. The value proposition is defined as the "general presentation of the organization's products and services that represent value for customers" [38].

The value proposal is intended to describe the product and its value to the end customer, and the reason why customers should choose it [39].

This solution has as main objective to allow customers a significant improvement in the maintenance of production assets, to be able to fulfil the objectives proposed by them.

4.3 Innovation Process

The evolution of information technologies translates into a greater number of new products on the market, as well as a greater demand for quality from customers. The speed associated with the growth of new products on the market can sometimes compromise the quality of the products, as organizations want to be competitive and keep up with market trends.

Koen defined a model that explains the various phases of the innovation process, to guarantee the development of a product with quality and value for customers. This model is divided into three phases: Fuzzy Front End, New Product Development and Commercialization.

The initial phase of the innovation process is the Fuzzy Front End (FEE), which aims to explore new opportunities that will impact the rest of the process [40].

Figure 14 has the New Concept Development (NCD) model that allows us to define the initial phase of the business and innovation process.

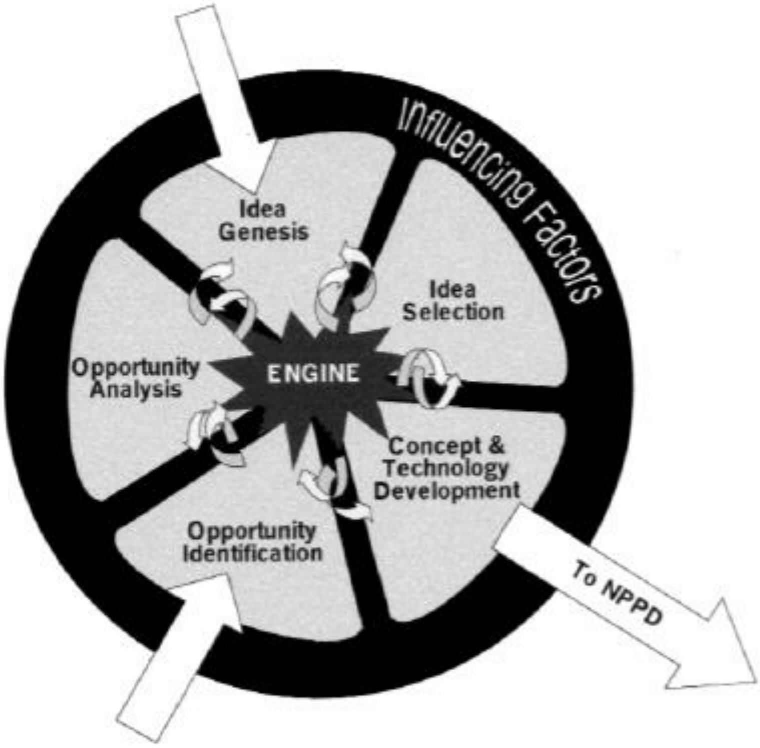

Figure 14: New Concept Development Model[40]

The NCD Model consists of three major components:

- Influencing factors: the various characterizing factors that characterize an organization, focusing on its organizational capabilities, its business strategy, and abroad, where we have distribution channels, customers, and competitors. The innovation process is directly affected by these processes [40].
- Key Elements: the five key elements are, identification of the opportunity, analysis of the opportunity, generation of enrichment of Ideas, selection of Ideas and definition of the concept.
- Engine: is responsible for putting into execution/movement the five key elements, under the organization's leadership and culture [40].

4.3.1 Opportunity analysis and identification

In this phase of the NCD, the opportunity to be followed for the creation of new ideas in the organization is identified.

Techniques for maintaining an industry's assets are a common problem in manufacturing industries that directly affect an organization's productivity and competitiveness.

Based on the problem defined in section 1.2, organizations are constantly looking to reduce or eliminate these consequences. In this context, equipment maintenance software appears. This software is capable of planning and recording maintenance, helping organizations to achieve greater productivity and greater competitiveness.

With this, the idea of creating an asset maintenance technique that is more effective and innovative, thus providing organizations with several gains, came up. It is intended that this module can respond to the various problems of maintaining production assets.

4.3.2 Idea creation

This phase is related to the definition of the idea to be developed. The idea can be analyzed in several iterations [41], changing until the ideal definition is reached.

The process of creating the idea within the scope of the present work consists mainly of analyzing the problem in question, presented in section 1.2. From the analysis of the exposed problem, several questions are formulated, which are listed below:

- How to reduce maintenance costs?
- How to increase production times?
- How to monitor the machines?

The brainstorming process was used to answer these questions, several solutions to the problem are identified, which resulted in several ideas.

4.3.3 Idea selection

After the process of creating and discussing ideas, it is necessary to select the idea that will be developed, this is one of the critical phases of the process, given that the organization's success depends on the selection of the best idea.

Within the scope of this work, this phase consists of selecting the idea that answers all the questions presented in the previous section. For each of the questions, the corresponding answer was presented below:

How to reduce maintenance costs? Use of a system that allows predicting failures in production assets, using the presentation of notifications that the organization's maintenance team must adopt.

How to increase production times? Use of a system that allows predicting failures in production assets, using the presentation of notifications that the organization's maintenance team must adopt.

How to monitor the machines? Use of a system that records data on the status of production assets.

4.3.4 Concept development

The final phase of this process consists of the development of a business case based on the market potential, needs and the risk of the project in general [40].

The idea to be followed, in the scope of the proposed work, to provide value to the customer will be the development of a system, which will have as main functionalities:

- Registration and analysis of the status of production assets.
- Remote monitoring of asset maintenance.
- Presentation of recommendations regarding maintenance behaviours that the maintenance team must adopt.

4.4 Business Model

The business model can be represented using the Canvas model [42], which aims to make your perception easier and more intuitive. This model has nine different topics that allow the strategic planning of a business. Each of these topics is presented in Figure 15.

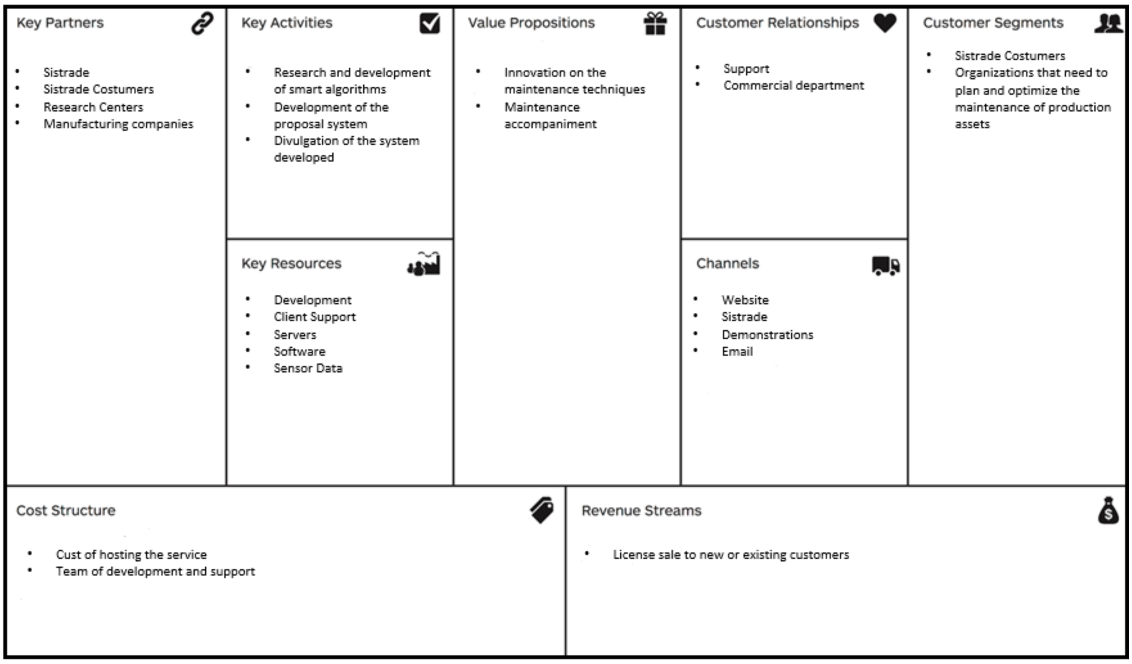

Figure 15: Business Model

5 Solution Requirements

5.1 Requirement’s analysis

In this section, the main actors of the solution are identified, and the functional and non-functional requirements are specified.

5.1.1 Main Actors

The following actors were identified:

- Maintenance manager - entity responsible for managing the maintenance process.
- Production Technician - entity responsible for managing the production process.
- Administration - gaining greater competitiveness for the organization and reducing maintenance costs.
- System - in charge of processing knowledge and sending recommendations.
- Software consultant – entity responsible for helping with predictive maintenance technique implementation.

5.1.2 Functional Requirements

From the problem, the following functional requirements were defined:

1. Processing of sensor data.
2. Sistrade ERP data processing.
3. Correlate sensor and Sistrade ERP data.
4. Sending recommendations.
5. Save Recommendation
6. Receive recommendation feedback.

7. Create, edit and delete user accounts
8. Create, edit and delete machines
9. Create, edit and delete machine components
10. Create, edit and delete sensors
11. Create, edit and delete sensors rules
12. Record maintenances
13. View Sensor alerts
14. Receive e-mail of sensor alerts

Figure 16 shows the use-case diagram, drawn from the defined functional requirements.

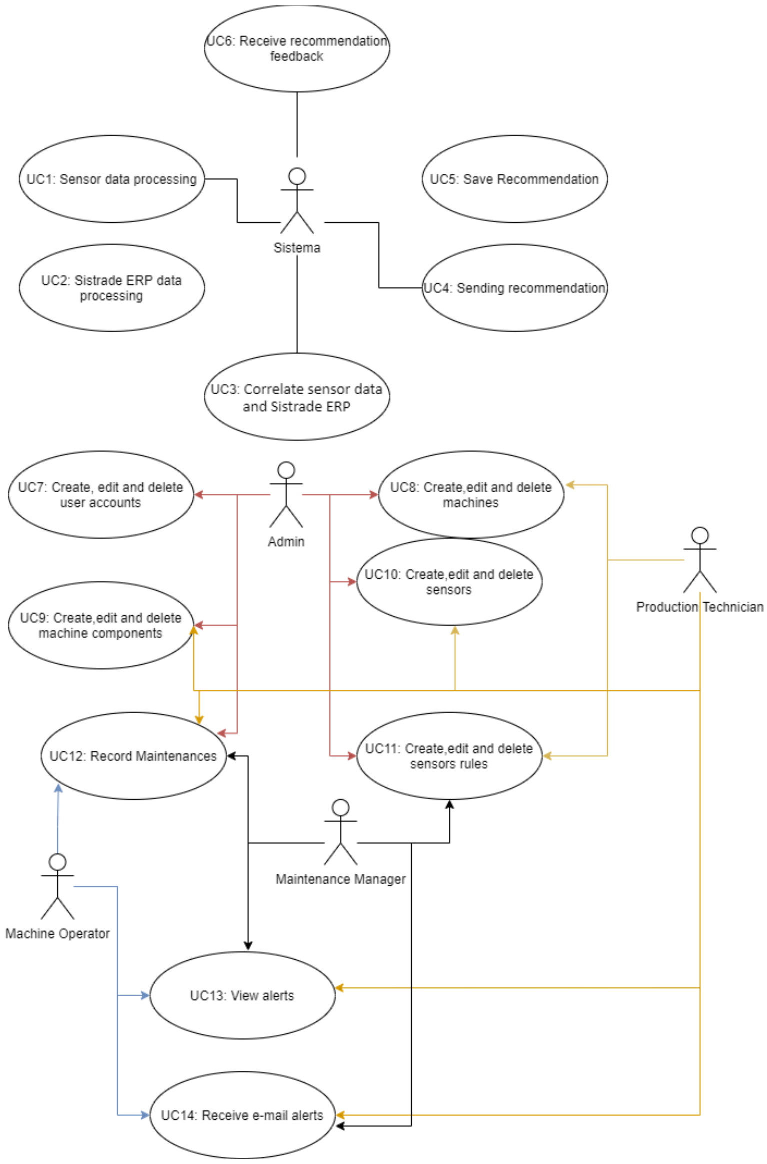

Figure 16: Use case Diagram

Table 5 describe the use case by the actor involved in each one.

Table 5: Use Case by Actor

	System	Admin	Production Technician	Maintenance Manager	Machine Operator
UC1	✓	-	-	-	-
UC2	✓	-	-	-	-
UC3	✓	-	-	-	-
UC4	✓	-	-	-	-
UC5	✓	-	-	-	-
UC6	✓	-	-	-	-
UC7	-	✓	-	-	-
UC8	-	✓	✓	-	-
UC9	-	✓	✓	-	-
UC10	-	✓	✓	-	-
UC11	-	✓	✓	✓	
UC12	-	✓	✓	✓	✓
UC13	-	✓	✓	✓	✓
UC14	-	✓	✓	✓	✓

A more detailed description of the use cases identified in Figure 16 is provided in the next sections of this thesis.

5.1.2.1 UC1: Sensor data processing

Use case 1 consists of processing information from sensor data. This information is obtained by receiving information from the sensor data, coming from the machine.

Pre-conditions

The machine needs to be equipped with sensors on the critical parts, where the failure can occur. And needs to exist enough historical data to understand the behaviour of the machine

Post-conditions

Have a pipeline consuming the processed sensor data or a database where to store this data.

The main success scenario is as follows:

- The system starts processing the information. The system obtains relevant information from the database. The system processes the information, generating the respective recommendations.

Alternative flows

- The production technician and the maintenance manager define a maximum and a minimum value and the sensor data needs to be inside the defined interval, otherwise, a recommendation is generated.

5.1.2.2 UC2: Sistrade ERP data processing

Use case 2 consists of processing information from the data collected through Sistrade ERP. This information is obtained by receiving the information inserted in the software by the technician in the manufacturing process, and by the maintenance manager.

Pre-conditions

The company where the predictive maintenance technique goes to be installed is using the maintenance module provided by Sistrade ERP.

Post-conditions

Have a pipeline consuming the processed data or a database where to store this data.

The main success scenario is as follows:

- The system starts processing the information. The system obtains relevant information from the database. The system processes the information compared to the recommendations generated in the previous use case and generates the respective recommendations.

Alternative flows

- The company can share data about maintenance techniques of another software or by CSV. This data will be stored in a database. The system obtains relevant information from the database. The system processes the information compared to the recommendations generated in the previous use case and generates the respective recommendations.

5.1.2.3 UC3: Correlate sensor data and Sistrade ERP

The present use case consists of the correlation between the data of the sensors with the data of the Sistrade ERP. The system must label the sensor data with the status of the machine, if a breakdown happened in the machine the sensor data needed to be labelled with a failure tag.

Pre-conditions

Exist sensor and Sistrade ERP data.

Post-conditions

Have a pipeline consuming the correlated data or a database where to store this data.

The main success scenario is:

- The system after processing the data of the sensors and the Sistrade ERP labels the sensor data with the status of the machine.

Alternative flows

- The correlation between the data of the sensors and the Sistrade will be done manually by the software consultant.

5.1.2.4 UC4: Sending recommendation

Use case 4 starts after the previous use case, related to information processing, is performed, and aims to send the generated recommendations. The recommendations generated are sent to the integrated system, which will then forward the recommendations to the actors.

Pre-conditions

The previous use case is realized successfully.

Post-conditions

Existence of an interface where the recommendations can be showed.

The main success scenario is:

- The system starts the recommendation submission process. The system obtains the desired recommendation from the database. The system sends the recommendation to the integrated system.

Alternative flows

- The production technician or the maintenance manager seeing the values of the sensors do a recommendation submission process. The system sends the recommendation to the integrated system.

5.1.2.5 UC5: Save recommendation

Use case 5 starts after the previous use case, relative to the sending of recommendations, is made and aims to save the recommendations made in the database.

Pre-conditions

The previous use case is realized successfully.

Post-conditions

Show historical notifications to the user.

The main success scenario for this use case is as follows:

- The system generates recommendations, saving this information in the database.

Alternative flows

- The production technician or maintenance manager see the recommendation and does an insertion on Sistrade software.

5.1.2.6 UC6: Receive recommendation feedback.

The present use case consists of receiving feedback regarding the recommendation. This feedback (for example: if you found the appropriate recommendation) is provided by the stakeholders, which is subsequently sent by the maintenance support module from the integrated system.

Pre-conditions

Generates the recommendation and the user do the feedback of the failure.

Post-conditions

-

The main success scenario for this use case is as follows:

- The system receives feedback. The system records the feedback in its database.

Alternative flows

- The user makes a list of the feedbacks, and this feedback is introduced manually.

5.1.2.7 UC7: Create, edit and delete user accounts

Use case 7 is the first step in the parameterization of the predictive maintenance platform. The admin needs to manage the user accounts and their roles for the end-users of the platform.

Pre-conditions

-

Post-conditions

-

The main success scenario for this use case is as follows:

- The admin can do the management of the user accounts needed.

Alternative flows

- The Software consultant do management of users accounts through the backend API.

5.1.2.8 UC8: Create, edit and delete machines

Use case 8 is the second step of the parameterization of the predictive maintenance platform. This use case is where the users can do the management of the machines.

Pre-conditions

The previous use case is realized successfully.

Post-conditions

-

The main success scenario for this use case is as follows:

- The user can do the management of machines.

Alternative flows

- The Software consultant does the management of machines through the backend API.

5.1.2.9 UC9: Create, edit and delete machine components

Use case 9 is the following step of the previous use case. In this use case, the users can do the management of machine components and the is established the relation between machines and machine components.

Pre-conditions

Exist machines on the platform.

Post-conditions

-

The main success scenario for this use case is as follows:

- The user can do the management of the machine components

Alternative flows

- The Software consultant does the management of machines components through the backend API.

5.1.2.10 UC10: Create, edit and delete Sensors

Use case 10 is where the relationship between machine components and sensors is made.

Pre-conditions

Exist machine components in the platform

Post-conditions

-

The main success scenario for this use case is as follows:

- The user can do the management of sensors.

Alternative flows

- The Software consultant does the management of sensors through the backend API.

5.1.2.11 UC11: Create, edit and delete sensor rules

In this use case, the user does the management of sensor rules to be used in the Rule-Based Model component.

Pre-conditions

Exist sensor in the platform.

Post-conditions

-

The main success scenario for this use case is as follows:

- The user can do the management of sensor rules.

Alternative flows

- The Software consultant does the management of sensor rules through the backend API.

5.1.2.12 UC12: Record Maintenance

In use case 5 the user can record maintenances on the machine.

Pre-conditions

The machine stops, existing machines and machines components created in the system.

Post-conditions

-

The main success scenario for this use case is as follows:

- The user can record maintenances in the platform.

Alternative flows

- The Software consultant does record maintenance regists through the backend API.

5.1.2.13 UC13: View Alerts

The present use case consists of sending alerts regarding the sensor rules. This alert is provided by the prediction application, which is subsequently saved in the database.

Pre-conditions

Exist sensor rules in the platform.

Post-conditions

The user take an action to resolve the problem.

The main success scenario for this use case is as follows:

- The prediction application generates an alert and sends it to the application.

Alternative flows

-

5.1.2.14 UC14: Receive e-mail alerts

The present use case consists of sending alerts by e-mail regarding the sensor rules. This alert is provided by the prediction application, which is subsequently saved in the database.

Pre-conditions

Exist sensor rules in the platform.

Post-conditions

The user take an action to resolve the problem.

The main success scenario for this use case is as follows:

- The prediction application generates an alert and sends it by e-mail to the user.

Alternative flows

- The user sees the alert on the platform.

5.1.3 Non-functional Requirements

Non-functional requirements are an indispensable part of this project, as they ensure that the software produced respects the restrictions and defined quality attributes. Based on the FURPS + model [43], we have the following quality attributes:

- Functionality – Capability, Reusability, Safety
  - Simple and efficient graphical interface, in the visual;
  - Smooth feature transitions;
  - It should be simple and intuitive to use the features;
- Usability – Responsiveness
  - The size of the look must be adjustable in the web application;
  - The application must be available on any device.
- Reliability – Availability, Predictability
  - After a failure, the server-side must be able to remain available and functional;
- Performance - Speed, Efficiency
  - The look should be fast regardless of the size of the database.
- Supportability
  - The system must support different platforms (mobile and web);
  - The platform must operate on different servers with different operating systems;

In module security, requirements are identified as the need for user authentication and user permissions, to have access only to data and permitted features, which will also contribute to the integrity of the module.

The user's easy use of the module fits into usability.

In the scope of the module's reliability, the need for interoperability was identified as a requirement, which allows communication with the other modules.

Regarding performance, it must be said that it must be fast during information processing.

The module will support HTTP / REST requests, identified in the interface requirements.

5.2 System Architecture

The system is composed of three main components and two optional components. The three main components are Database, Application Server and Web Browser. With these three components is possible for the organization to implement reactive and planned maintenance techniques. With the two optional components, the organization can implement predictive maintenance techniques. The other two components are IoT Application and the Prediction Application.

The system architecture is based on five components as shown in Figure 17.

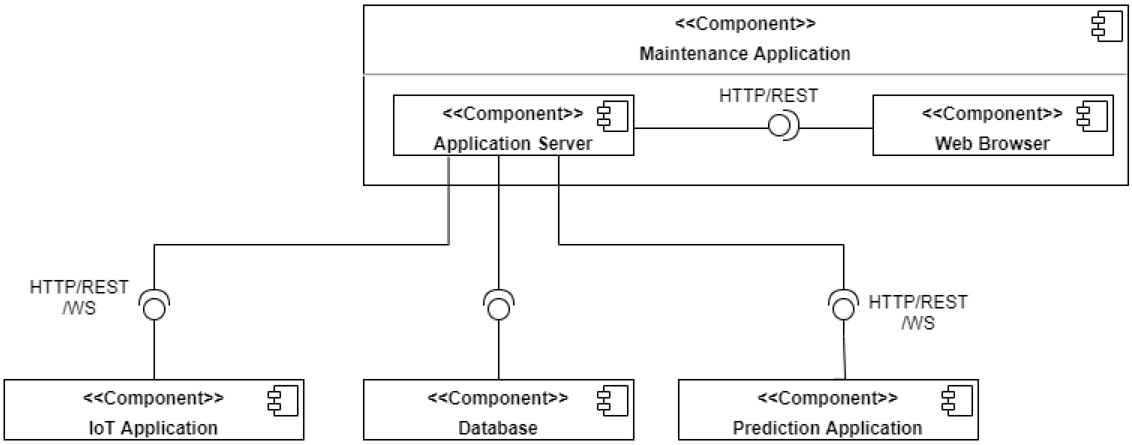

Figure 17: Component Diagram

As mentioned previously the system architecture is shown in Figure 17, the architecture of this module follows the pattern 3-Tier. The component Database represents the database, responsible for the persistence of the maintenance application information.

The Maintenance Application Frontend is responsible for the interaction with the user, this component is dependent on the Maintenance Application Backend component.

The Maintenance Application Backend component is responsible to interact with the Prediction application component, with IoT Application and with the database. This component is also responsible for the application logic.

The IoT Application component is responsible to do the data acquisition of the sensor data making available an interface to interact with the main system.

The Prediction Application component is responsible for the generation of recommendations and has an interface to interact with the main system.

5.2.1 IoT Application

In the IoT Application is made the data acquisition for the system. The system provides the following three types of data acquisition:

- CSV
- SQL Server
- OPC-UA

These three were chosen because it is what was experienced in the machines provided by the use case partner, but new ways of data acquisition can be implemented and added to this application. These three types have pros and cons that can influence the maintenance platform.

The CSV data acquisition type normally register data from certain components of the machine and save it into a CSV and at the end of the day, this file is deleted to not take up space in machine memory, but this file can be stored in a server in the same network of the machine. So CSV most of the time can not provide real-time data to the system, and in this way, the rule-based model will be put aside because the definition of sensor rules do not make sense in historical data.

The SQL Server type works most likely the CSV type, but instead of storing the data into a CSV file store the data in a SQL Server Database and at the end of the day the data is deleted from the tables. But at the same time is an improvement to the previous type because allows real-time, but does not have a historical record. This is a non-problem because exist ways to save this data using SQL events such as triggers. The data can be saved into other SQL databases in the same network.

The OPC-UA is a protocol that aims to "create data transfer standards multi-vendor, multi-platform, secure and reliable interoperability in industrial automation" [44]. This type is like SQL because we have the same pros and cons. What is different between the two is the way to do the historical data. The OPC-UA can provide historical data by itself if the OPC-UA Server is developed in that way [44]. In this case, it is necessary to develop an OPC-UA client and store the data in a database. The OPC-UA is organized into three nodes, which node has a different ID. Since are the developer doing this OPC-UA client the data can be stored in any type of database, and the data acquisition to historic can be made in a time interval on when the value change or when a new published are made to a node.

Table 6 details the pros and cons of the three protocols.

Table 6: Pros and cons of data acquisition

	CSV	**SQL Server**	**OPC-UA**
Real-time	-	✓	✓
Historical Data	✓	Needs development	Needs development
Rule-Based Model	-	✓	✓
Machine Learning Model	✓	✓	✓

This application was developed with NodeJs.

5.2.2 Database

This section will be described the databases used in the IoT Application and the Maintenance Application.

5.2.2.1 IoT Application Database

The database used on the IoT Application only stores sensor data has a common structure whether it's SQL or Non-SQL. The structure is one table per Sensor with the concerning data. The database used was SQL Server.

5.2.2.2 Maintenance Application

This database store data of the Prediction Application and from Maintenance Application and have the structure represented in Figure 18.

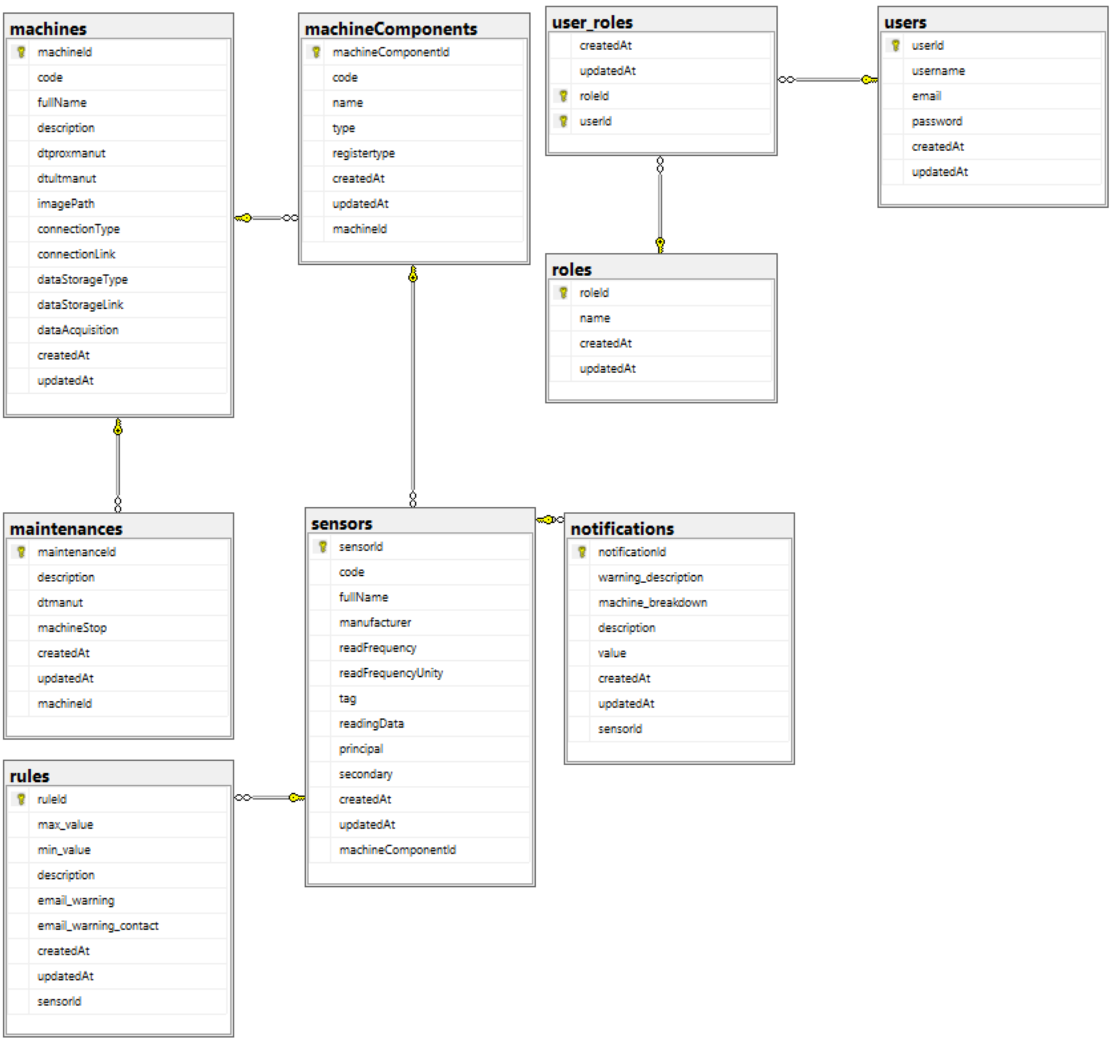

Figure 18: Database diagram

The database diagram is composed of eight tables, which will be detailed below:

- User – store all the users on the platform
- Roles – store the permissions of the users.
- Machines – Store the information of machines
- Machine Components – Store the components of a machine and established the relation between the machine and the sensor.
- Sensor – Store the information of sensors.
- Notifications – Store the alerts from the Rule-Based Model and recommendations from the Machine Learning Model.
- Rules – Store the information of sensor rules.

The database chosen to support the information was SQL-Server.

5.2.3 Prediction Application

As presented previously the Prediction Application is a subsystem, this system is dependent on data from the IoT Application and the Maintenance Application Backend because needs data to work. From the IoT Application, this system gets the data from the sensors presented in the assets, and from the Maintenance Application Backend, the system gets the from failures as represented in Figure 19.

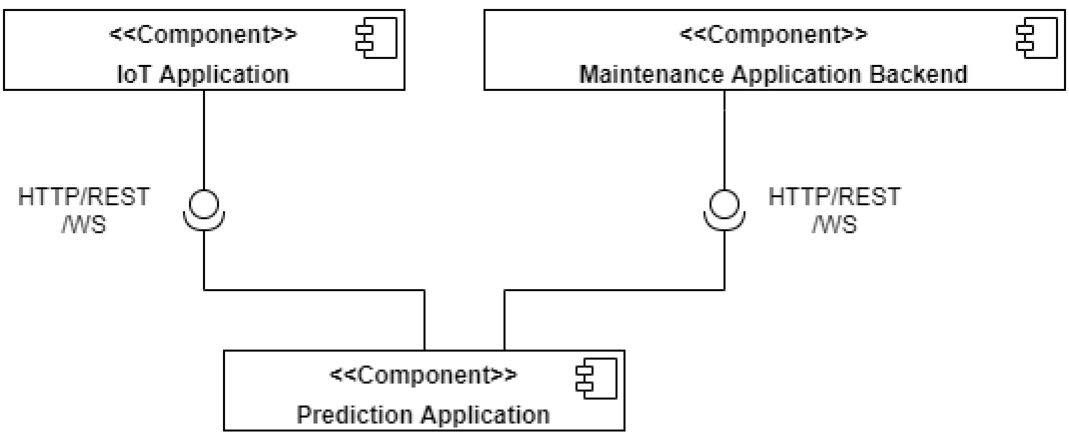

Figure 19: Diagram Component of Prediction Application

The Prediction Application is made of two components the Rule-Based Model and the Machine Learning Model like Figure 20 shows.

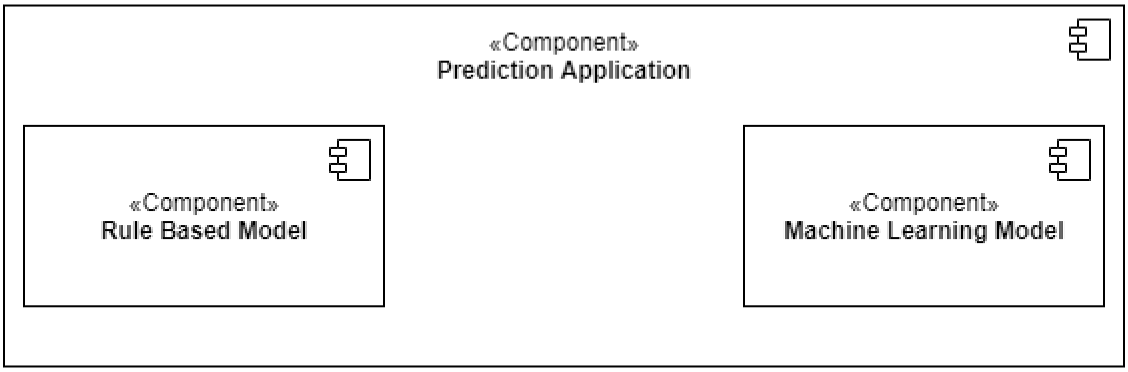

Figure 20: Maintenance Application Component

These two components gone be detailed in the following sub-points.

5.2.3.1 Rule-Based Model

The Rule-Based Model Component is responsible for Rule-Based Predictive Maintenance, these models are very much dependent on the knowledge of the domain and from the knowledge given by the maintenance team and machine operators. This knowledge can provide insights on what causes a machine failure or which specific parts are likely to break down. The rule "IF-THEN" model is implemented on the practical experience of the team [45].

These rules are established using threshold, if the value register by the sensor goes down or above a notification are triggered.

To Rule-Based Model have the logic represented in Figure 21.

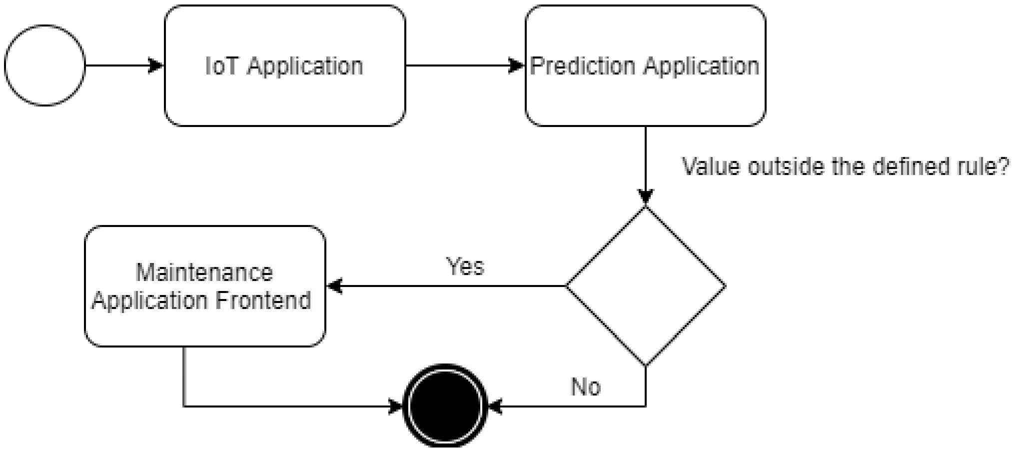

Figure 21: Logic of Rule-Based Model

This logic starts on the IoT Application where the data acquisition is made. After the data has been acquired with success the IoT Application sends the sensor value through Rabbit MQ to the Maintenance Application Backend, the Maintenance Application verify if the sensor has any rule associate if the sensor has a rule associated, the rule identifier and the sensor value are sent by Rabbit MQ to the Prediction Application, if not the process stops here. In the Prediction Application the sensor value is compared with the sensor rule, if the value goes out of the threshold defined notifications are triggered to the Maintenance Application Frontend and by e-mail defined in the rule, if not the process stops here. The rules are defined by the actors in the system that has domain knowledge.

The rules have the following attributes:

- ruleId
- Max_value
- Min_value
- Email_warning
- Email_warning_contact
- Creation Date (createdAt)
- Update Date(updatedAt)
- SensorId

The Rule-Based Model Component is responsible to verify the rule and the send notifications if needed. The notification is showed to the user in the frontend and sent by email if the user wants it. The notifications generated by this component can be the following:

- Upper limit exceeded
- In the upper limit
- Lower limit exceeded
- In the lower limit

This notification is shown in the Web Browser in real-time for that WebSockets were used.

5.2.3.2 Machine Learning Model

The Machine Learning Model component is responsible for predicting the failures using techniques of machine learning, the domain knowledge of the maintenance team and the machine operator, especially in the feature engineering process.

To fit the machine learning models is required input and output. The input is called the independent variable, the dependent variable are very often alarm, warning or failures. The output is the desired results in Figure 22 is represented the machine learning pipeline used on this project.

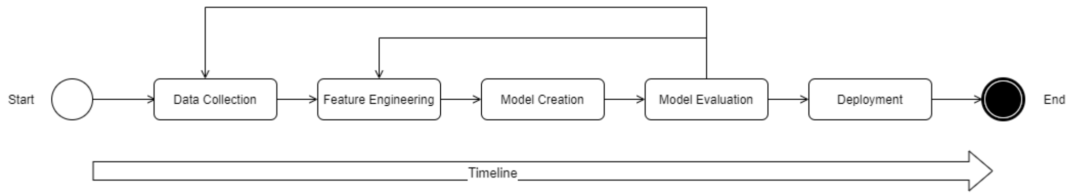

Figure 22: Machine learning pipeline

5.2.4 Maintenance Application Backend

The Maintenance Application Backend is responsible for all the logic and the management of the platform, is a Restful API that accepts HTTP(S) requests to perform the tasks perform by the user. The MVC Controller Pattern us used to design this API. The API connects to the database using the Sequilize ORM.

The API was developed with Nodejs.

5.2.5 Maintenance Application Frontend

The Maintenance Application Frontend is the interface with the end-user, this application was developed with React with a resource of Bootstrap and Material UI to use some components.

6 Demonstration and Results

This chapter appears intending to demonstrate the work done. The platform is composed of a set of features, referenced in the chapter previous. Thus, this chapter was divided into subchapters, each corresponding to different functionalities or modules.

In section 6.1 is demonstrated the data acquisition process for the IoT Application component. Section 6.2 is demonstrated of the Prediction Application. Section 6.3 is demonstrated the components Maintenance Application Backend and Maintenance Application Frontend.

6.1 IoT Application

The IoT Application is responsible to do the data acquisition and the data monitoring, this component offers an interface, this interface is an API restful with routes for historical data and real-time data of the sensor chosen.

For CSV and SQL a little development is need when is necessary to apply the data acquisition from sensors, when is OPC-UA the IoT Application have a broker for that protocol, this broker is triggered by the user on the machine creation or the sensor creation. Figure 23 represents the broker do the data acquisition of some data.

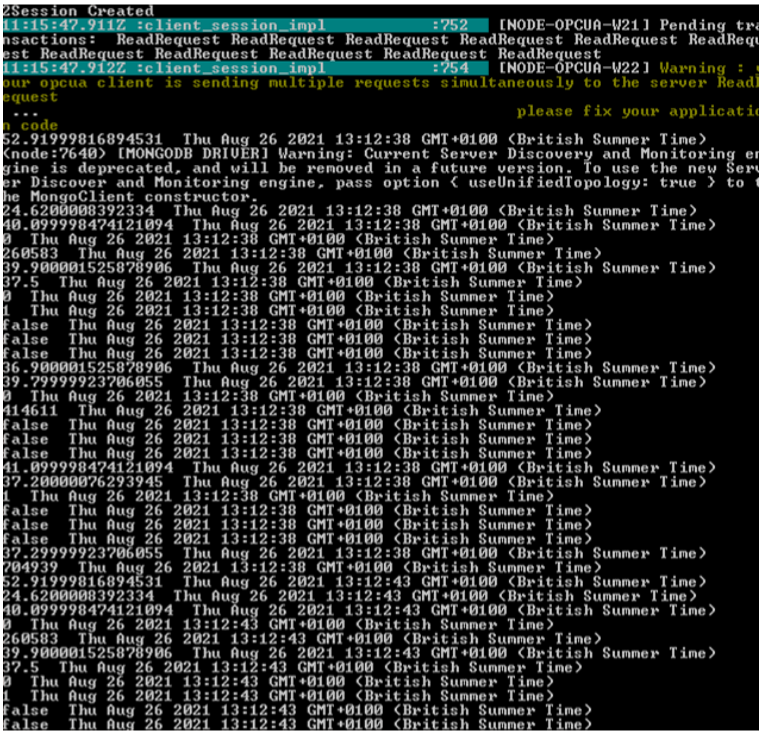

Figure 23: OPC-UA broker

To run the OPC-UA broker this terminal application does not need to be running in the server because this has a feature that turns it on service in the host operating system.

6.2 Prediction Application

Prediction application is responsible for the machine learning pipeline of the entire application. This application also makes the communication between the IoT Application presented in the previous chapter and the frontend application which will be presented later in the document.

6.2.1 Rule-Based Model

Rule-based Model like previously mentioned it is dependent on the knowledge of the user that operates the machine. This user can give the feedback and pass the knowledge to the production technician and the maintenance manager and these can define the rules presented forward in the present document.

The Rule-Based Model was developed in NodeJS, Figure 24 show the code used for the send of notification when the sensor is in the upper limit for the other limits the base code is the same, the difference is in the message send in the Rabbit MQ and the saved into the database.

```
amqp.connect('amqp://rabbitmq', function (error0, connection) {
    if (error0) {
        throw error0;
    }
    connection.createChannel(function (error1, channel) {
        var exchange = 'logs';
        channel.assertExchange(exchange, 'fanout', {
            durable: false
        });
        channel.publish(exchange, '', Buffer.from("In the upper limit"));
    });
});

Notification.create({
    warning_description: 'In the Upper limit',
    machine_breakdown: '',
    description: 'The value is in the upper limit ',
    sensorId: id,
    value: sensorValue
}).then(notification => {
    res.send({ message: notification });
}).catch(err => {
    res.status(500).send({ message: err.message });
})
```

Figure 24: Trigger event when the value is in the upper limit

The first block of code is the connection to the Rabbit MQ and is made the publishing of the message into the rabbit MQ buffer. The buffer type used on Rabbit MQ was the exchange, for the possibility to send the message to various clients.

The second block of code is where the notification is saved into the database.

6.2.2 Machine Learning Model

6.2.2.1 Data Collection

As mentioned previously to implement a maintenance predictive maintenance strategy is need data from assets sensors. The data provided by these can be very different depending on the equipment to be monitored, the essential thing is that they have data from the critical parts of the machine. The critical parts of the machine are the parts that usually have the most failures or that are too expensive to repair. Figure 25 shows how the Prediction Application gets information from the sensors present in the IoT Application and data relative to machine failures from the Maintenance Application Backend and relates the data. The application of this use case has used labelled data from the Kaggle website since the use case provider doesn't have enough data from the machines. The dataset used will be detailed then.

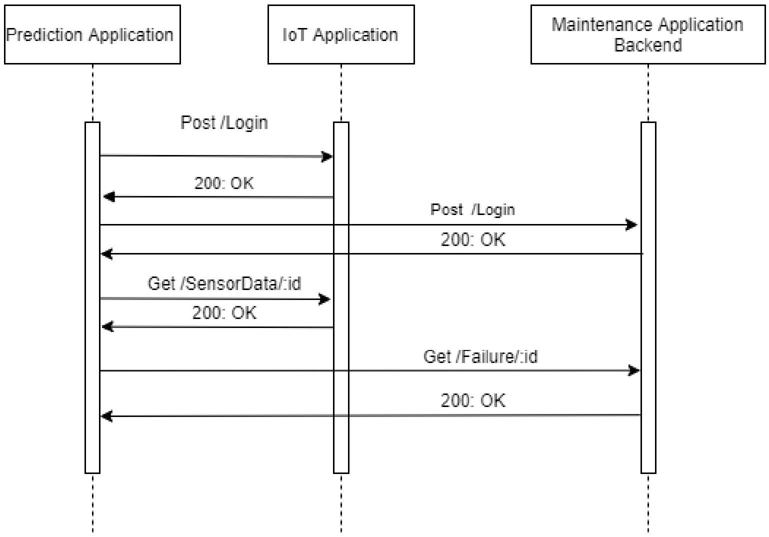

Figure 25: Get data Sequence Diagram

Figure 25 shows how the Prediction Application communicates with the other components, before any data request the system need to do authenticate, that measure as done to increase security. After the authenticate process the system can request sensor data represented by “Get /SensorData/:id”, where “:id” represents the machine ID. The request of machine failures follows the same logic. The field “date” return on each request is the junction point between the data of the request. This represents Use Case 3.

The data needs to be analysed and understand so that the best model can be created to predict the failures, the dataset used to have three hundred seven thousand seven hundred fifty-one (307751) rows and have data from four hundred twenty-one machines. The dataset does not contain any duplicate values, otherwise, the duplicates values need to be removed from the dataset as null or zero values.

The dataset is composed of 16 variables:

- ID – Unique representation of a specific machine
- DATE – Date of the register
- REGION_CLUSTER – Section of the machine
- MAINTENANCE_VENDOR – Maintenance Team
- MANUFACTURER – Manufactured of the machine
- WELL_GROUP – Type of machine
- S15 – Sensor Value
- S17 – Sensor Value
- S13 – Sensor Value
- S5 – Sensor Value
- S16 – Sensor Value
- S18 – Sensor Value

- EQUIPMENT_FAILURE – Failure indicator
- S8 – Sensor Value
- AGE_OF_EQUIPMENT – Age of the machine in days.

After identifying the variables present in the dataset, and some data we examine the dependent variables in more detail. Figure 26 shows the failures present in the dataset for a machine.

EQUIPMENT_FAILURE	ID
0	307330
1	421

Figure 26: Number of failures per machine

The dataset only has 421 failures in 307751 rows, this corresponds to a failure rate of about 14%, which means the data presented in the dataset is very unbalanced because for 1 failure have over 700 non-failures.

6.2.2.2 Feature Engineering

The dataset contains some columns that do not matter for the process of machine because they do not have useful information, these columns are REGION_CLUSTER, MAINTENANCE_VENDOR, MANUFACTURER and WELL_GROUP. By the analysis of the data previously made the feature windows will be of 90 days. One way to increase the number of failures is to expand the failure window. That is, make the dependent variable, not just the day the equipment failed, but the number of days leading up to the failure.

6.2.2.3 Model Creation and Model Evaluation

For the following process that is model creation and model evaluation, the data has been divided into three groups, the Testing, Training and Validation, because the type of data is cross-sectional time-series. To not aggregate all the records of one machine in a group the decision was doing a random selection of ID's and place all the records for each machine in a group. Figure 27 shows the number of rows present in each group.

MODELING_GROUP	
TESTING	108919
TRAINING	106726
VALIDATION	92106

Figure 27: Rows per group

Figure 28 shows the number of failures of each group.

```
MODELING_GROUP
TESTING       4151
TRAINING      4071
VALIDATION    3518
```

Figure 28: Failures per group

Like both figures show the distribution of data by the groups was done well because we have approximately the same number of rows and failures on each group.

Before the creation of the model is define true positives, true negatives, false positives, and false negatives. In this case, a true positive occurs if the machine fails and there was a signal within a forecast window. A false negative occurs if and only if the machine fails and it is not a true positive. A False Positive occurs if there is a failure signal, and a failure does not occur in the failure time window defined. If an observation is not a False Positive, a False Negative or a True Positive it is a True Negative.

For prediction has been used XGBClassifier from xgboost sklearn [46] with all the features, this was the solution founded because unable to know and understand the domain knowledge in terms of production and the machine work mode. The XGBClassifier also was used because is an ensemble of models and combine different machine learning models into one.

Deployment

This pipeline was developed with python.

6.3 Maintenance Application

The maintenance application is thought to work like a hierarchy wherein the top is the machine, in the middle the machine components and the bottom are the sensor like shown in Figure 29. This means that a machine has components, and the components have sensors. Sometimes the data acquisition is made at the top level other times a work of installing sensors on machine components are necessary to develop.

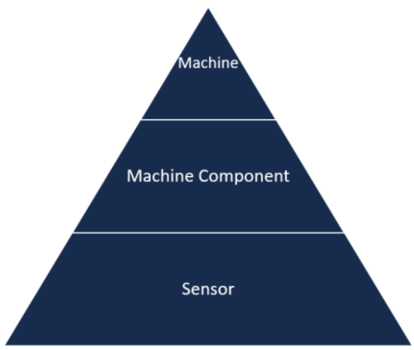

Figure 29: Platform hierarchy

6.3.1 Maintenance Application Backend

The maintenance application backend is responsible for the communication between the database and the frontend. So every persistent data is saved in an SQL Server database through the maintenance application backend. This application is a REST API developed in NodeJS.

This API is supported by documentation made in Swagger as showed in the following subsections, each subsection represents an endpoint.

6.3.1.1 Authentication

For the authentication, the API has two endpoints one for signup and another for sign in like shown in Figure 30.

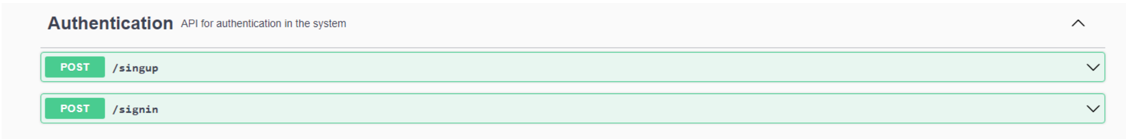

Figure 30: Authentication endpoints

These two endpoints allow user account creation and management access to the platform.

6.3.1.2 Machines

For the endpoint, the machine exists five routes as shown in Figure 31.

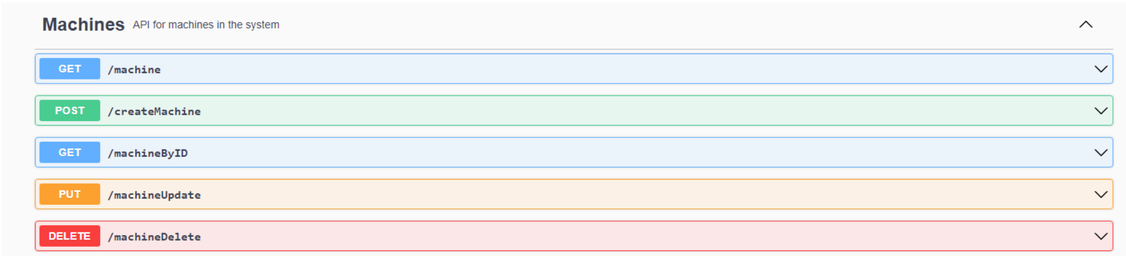

Figure 31: Machine endpoints

These machines endpoints allow the creation of machines, a list of machines, an update for machines, the machines by their id's and the delectation of machines.

6.3.1.3 Machine Components

For the machine components endpoint, exists five routes as shown in Figure 32.

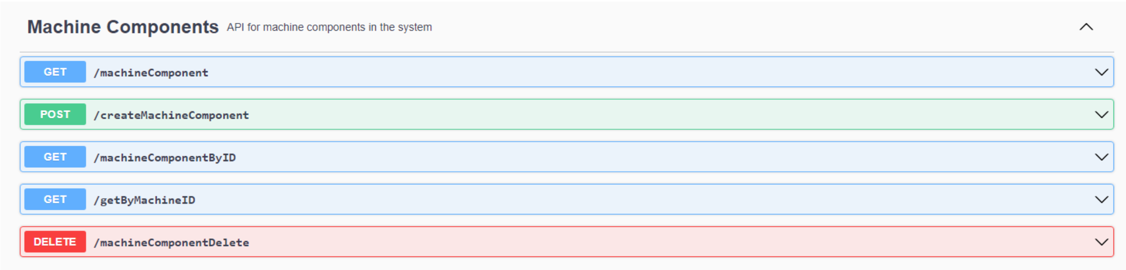

Figure 32: Machine Components endpoints

These machines components endpoints allow the creation of machines components, a list of the machine components, an update for machine components, machine components by their id's and the delectation of machine components.

6.3.1.4 Notifications

For the endpoint notifications, exist three routes as shown in Figure 33.

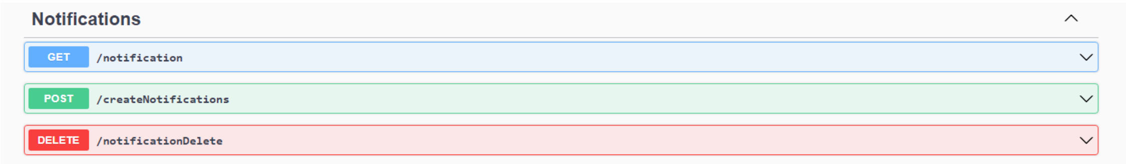

Figure 33: Notification endpoints

These notification endpoints allow the creation of notifications, a list of the notifications and the delectation of notifications.

6.3.1.5 Rules

For the endpoint rules, exists four routes as shown in Figure 34.

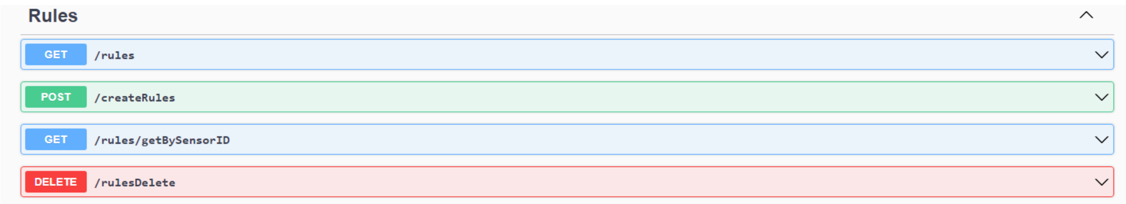

Figure 34: Rules endpoints

These rules endpoints allow the creation of rules, a list of rules, a list of rules by sensor ID and the delectation of rules.

6.3.1.6 Sensor

For the endpoint sensor, exists nine routes as shown in Figure 35.

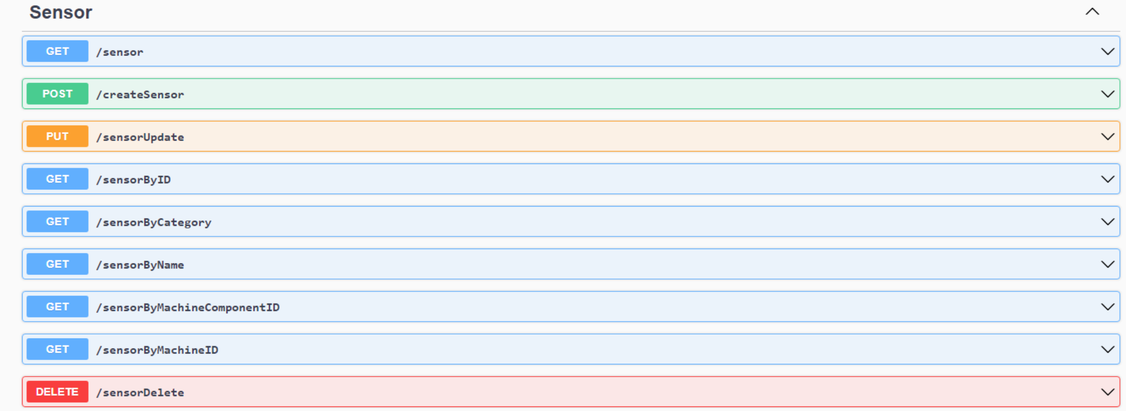

Figure 35: Sensor endpoints

These sensor endpoints allow the creation of sensors, a list of sensors, a list of senor by ID, name, category and by machine component ID and the delectation of rules.

6.3.1.7 Users

For the endpoint users, exists one route as shown in Figure 36.

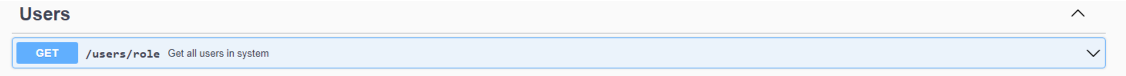

Figure 36: Users endpoints

The endpoint of users only has one endpoint that returns the role of the user.

6.3.2 Maintenance Application Frontend

The maintenance application frontend is the way that user interacts with all the platform, and perform the other components, first, the user needs to make the authentication process, for that the user is presented to the Login page shown in Figure 37.

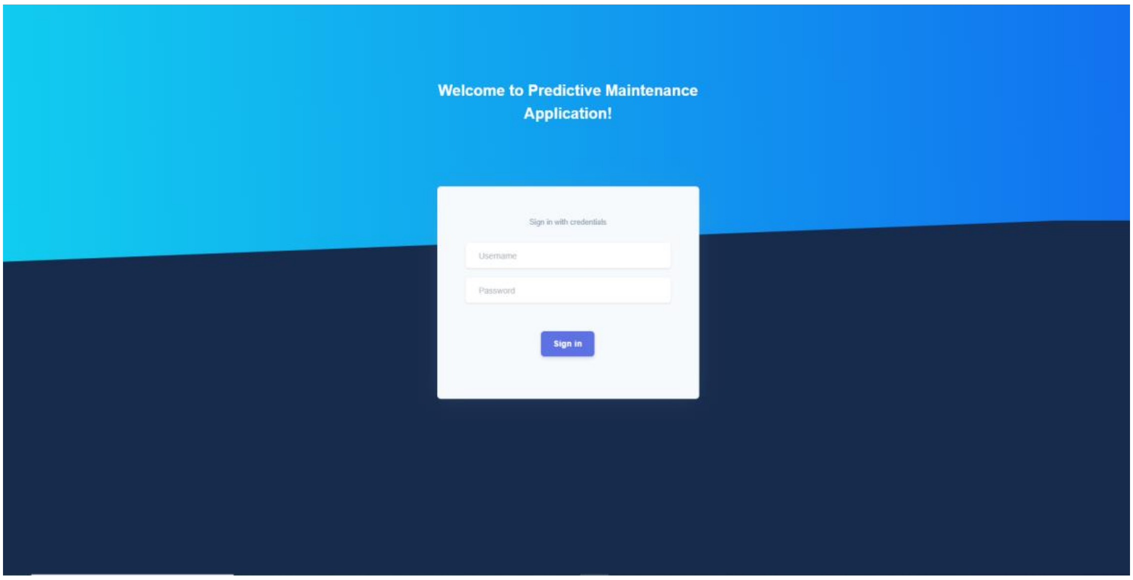

Figure 37: Login page

After the login, the user is presented to their dashboard dependent on the role they play in the company. The roles can be administrator, production technician, maintenance manager or machine operator. The dashboard for the administrator is shown in Figure 38. This role can perform the use cases UC7, UC8, UC9, UC10, UC11, UC12, UC13 and UC14.

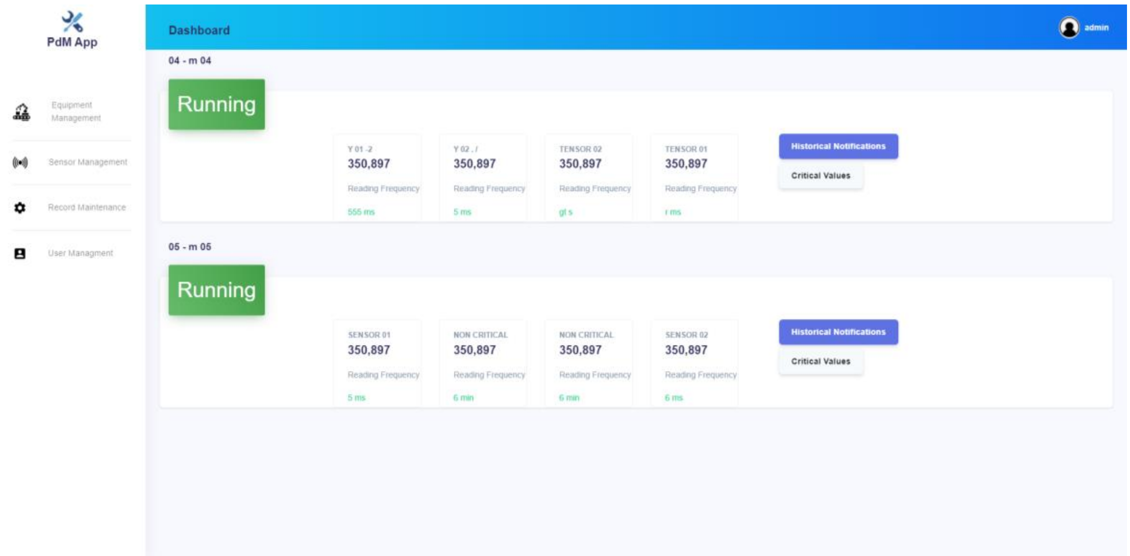

Figure 38: Admin dashboard

The dashboard for the production technician and maintenance manager are presented because they have the same role and can perform the following use cases UC8, UC9, UC10, UC11, UC12, UC13 and UC14.

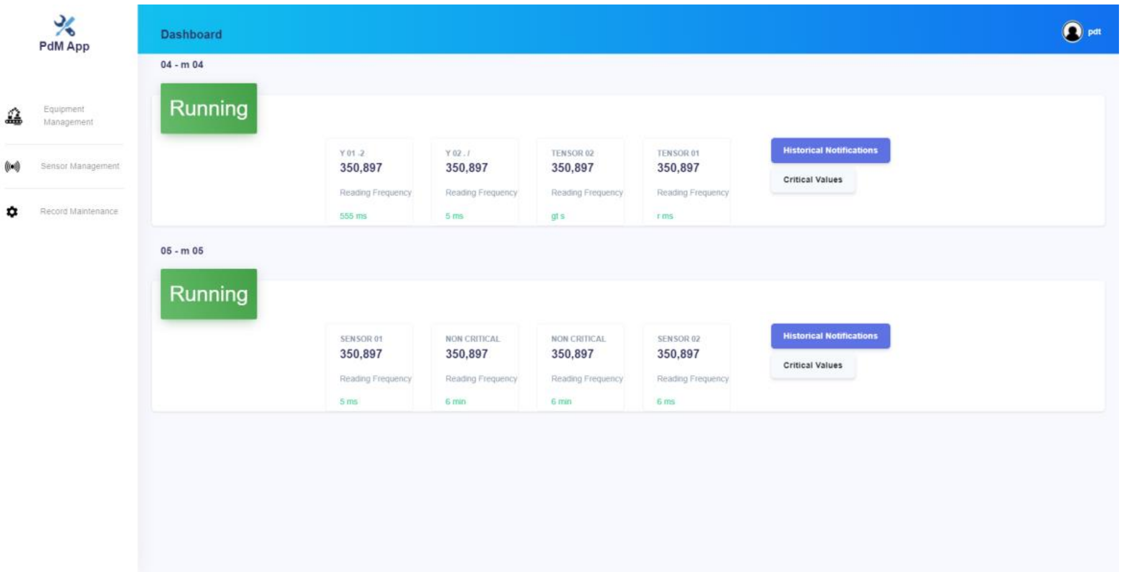

Figure 39: Production technician and maintenance manager

The machine operator is the role with lower permissions, the dashboard is presented in Figure 40. This user only can perform the UC12, UC13 and UC14.

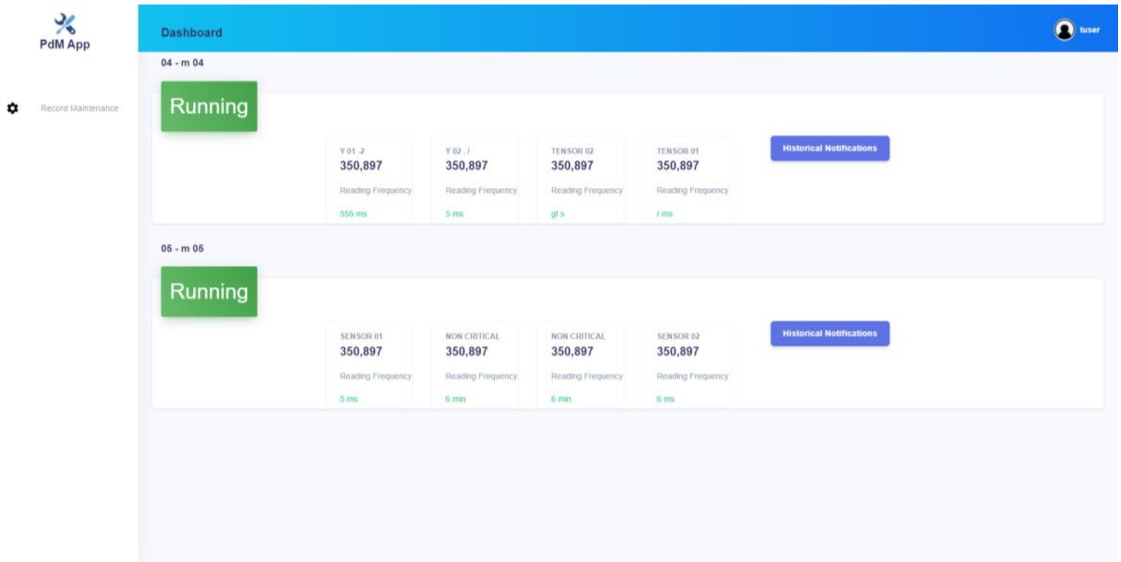

Figure 40: Machine operator dashboard

6.3.2.1 UC7 - Create, edit, and delete user accounts

This use case only can be performed by the user with the role of administrator. Figure 41 represents the list of the users present in the platform.

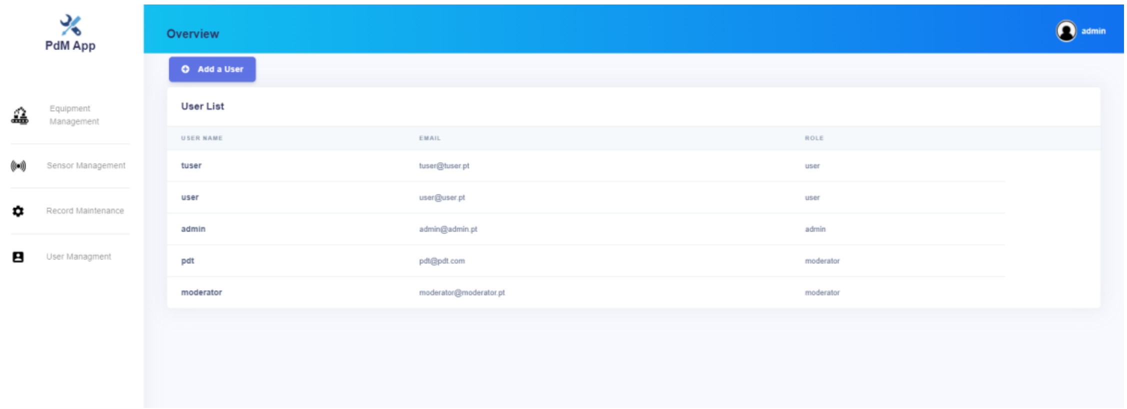

Figure 41: User list

To add a new user to the platform the administrator needs to click on the button "Add a User" and the form showed in Figure 42 is presented. The fields are all required.

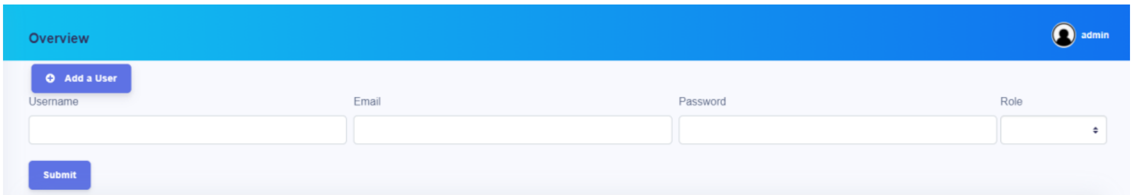

Figure 42: Add a user form

6.3.2.2 UC8 - Create, edit, and delete machines

To perform this use case the user is presented to the page with the list of all machines, a creation of a machine can be performed by clicking on the button "Add a Machine" present in Figure 43.

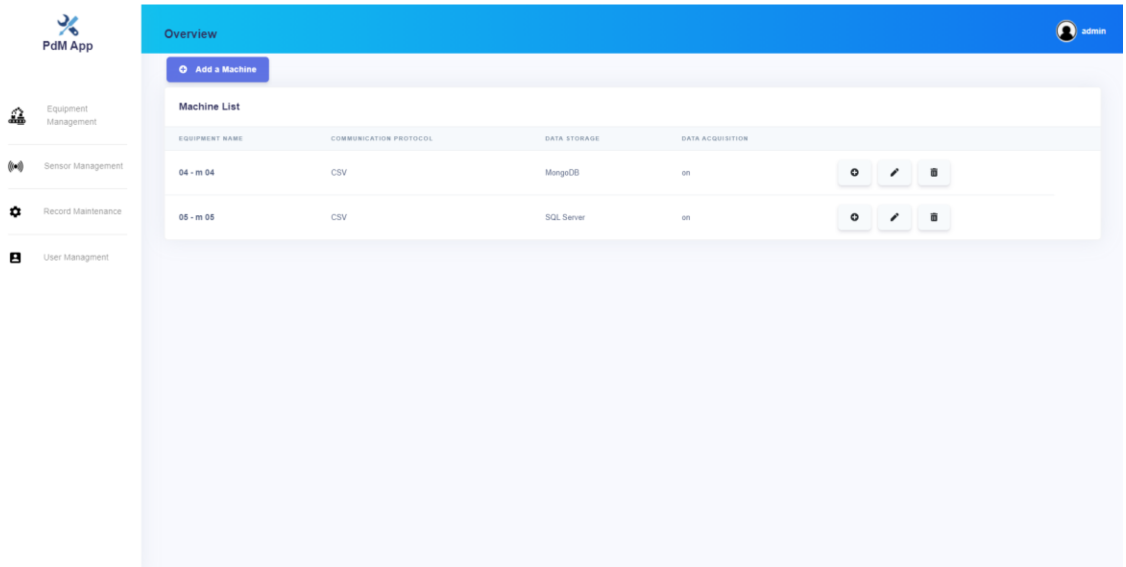

Figure 43: Machine List

For the creation of a machine the user needs to fulfil the following fields:

- Code – Represent a machine in the platform (abbreviation);
- Full Name – Original name of a machine;
- Description – Type of machine, or some description of a machine;
- Connection Type – Type of connection offered by the machine;
- Connection Link – Link for the connection offered by the machine;
- Storage Type – Type of storage offered by the machine;
- Storage Link – Link for the storage offered by the machine;
- Data Acquisition – Represent if the machine can collect data.

The fields Code, Full Name are required, the fields Description, Connection Type, Connection Link, Storage Type, Storage Link and Data Acquisition are optional. The form with these fields showed in Figure 44.

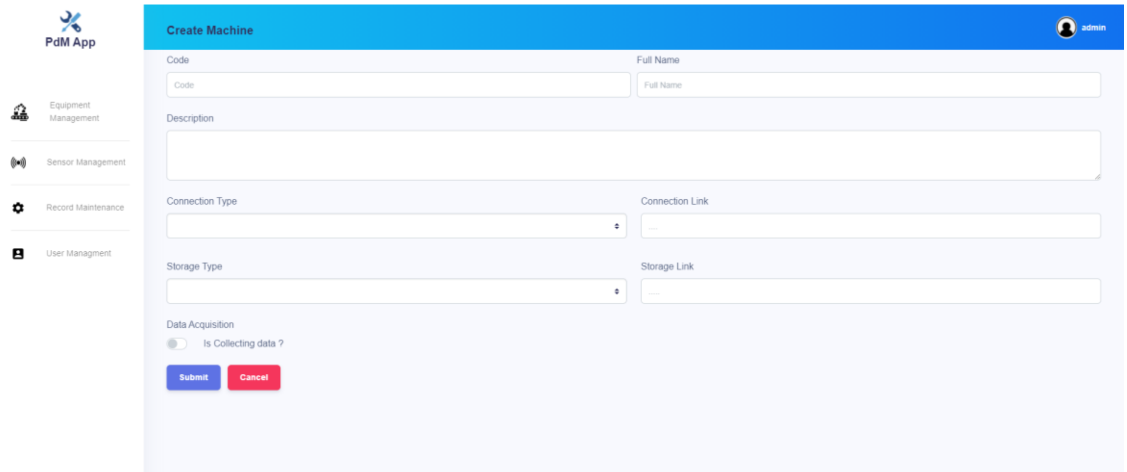

Figure 44: Create Machine Form

Like mentioned previously sometimes the data acquisition is made at the top level and in these cases and if the connection type of the machine is OPC-UA and if the user selects the option of data acquisition the application sends this information to the IoT Application, and this reads the OPC-UA tree and saves the node tags in the table of sensors. In this case, the step of the creation of the machine component is jumped but the user later can create the respective machine components of the machine and do the mapping with the collected sensors.

For each Machine, the user can perform three tasks detailed below and represented in Figure 45.

- Go to the creation of new machine components– using the button plus icon ( ) ;
- Edit a machine – using the button with the pencil icon ( );
- Delete machine – using the button with the trash icon ( );

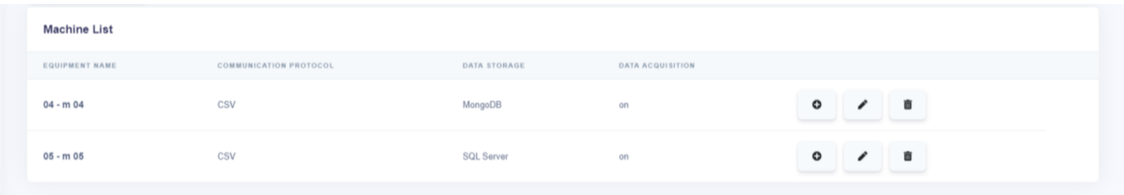

Figure 45: Tasks per machine

Figure 46 show the form presented to the user where he can edit the machine values.

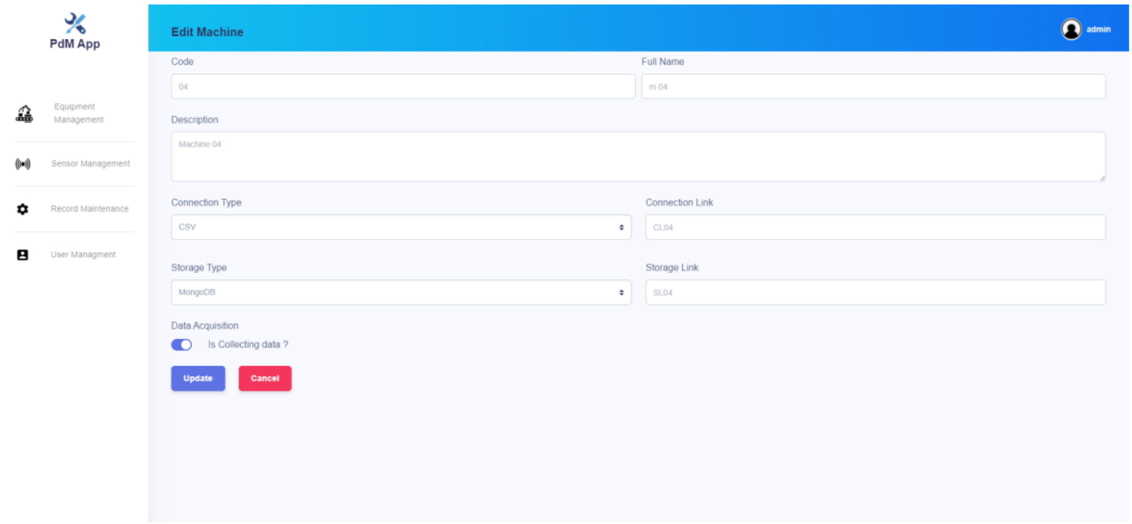

Figure 46: Edit Machine Form

If the user wants to delete the machine on click on the button mentioned above and the machine will be deleted from the platform

6.3.2.3 UC9: Create, edit and delete machine components

To add a new machine component the user must click on the button like shown in Figure 45, after this click the application shows to the user a list of machine components of the machine row represented in the table like shown in Figure 47.

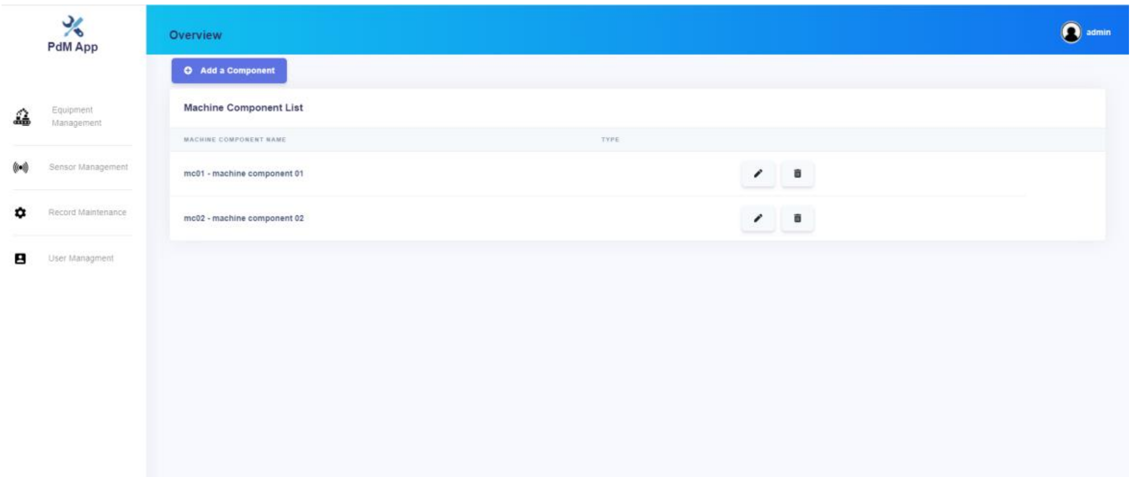

Figure 47: Machine Component List

To create a new machine component the user must click on the button "Add a Component" and a modal showed in Figure 48 is presented to the user.

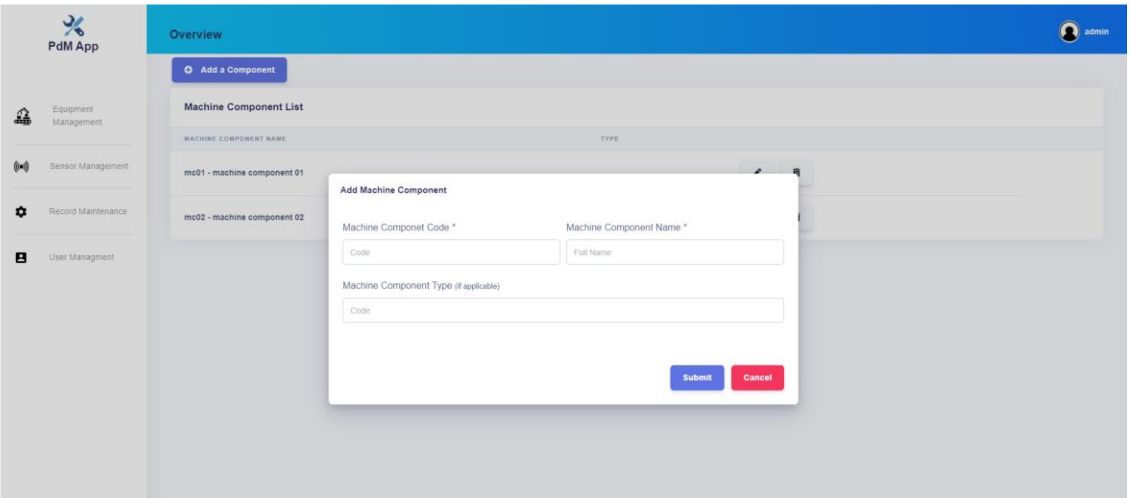

Figure 48: Create Machine Component Form

The fields required to create a new machine component are:

- Machine component code - Represent a machine component in the platform (abbreviation);
- Machine component name - Original name of machine component;

The field Machine Component Type is optional. In this field, the user can specify the type of machine component for example if it is an external motor.

6.3.2.4 UC10: Create, edit and delete sensors

To create a new sensor in the platform the user must click on the button “Add a Sensor” as shown in Figure 49. This page also contains a list of all the sensors presents in the platform.

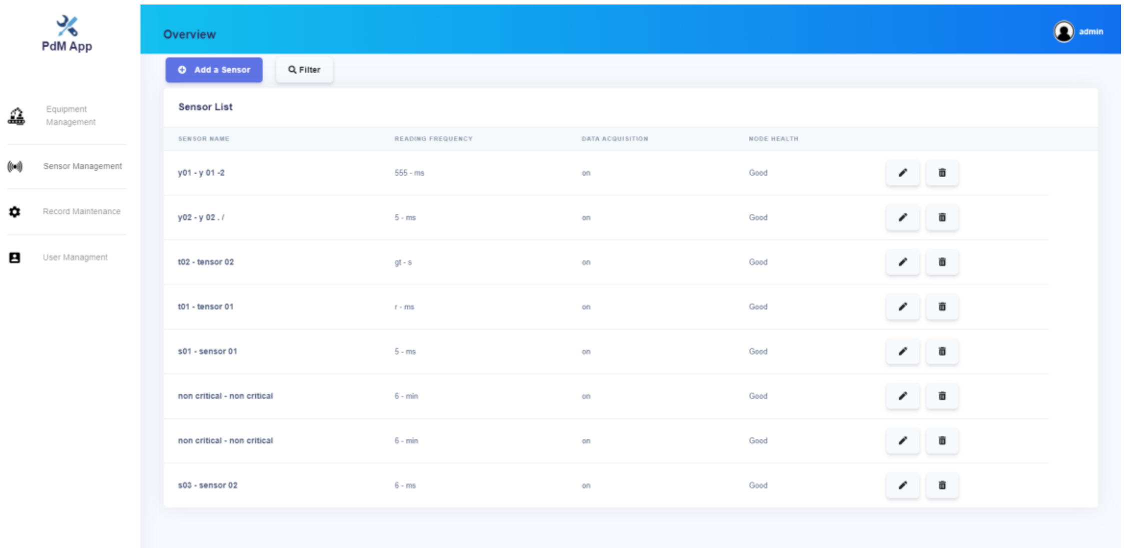

Figure 49: Sensor List

After the click the modal of Figure 50 is presented to the user, the required fields:

- Sensor Code – Represent a sensor in the platform
- Sensor Name – Original name of the sensor
- Machine Component - where the sensor belongs the
- Sensor Category – If the sensor is Critical (important to monitor), Non-Critical (not important to monitor)
- Sensor Manufacturer – brand of the sensor
- Read Frequency – Reading frequency of the sensor
- Time Unit – of the reading frequency
- Sensor Tag – OPC-UA tag (only for OPC-UA)
- Reading Data – select the data acquisition of this sensor

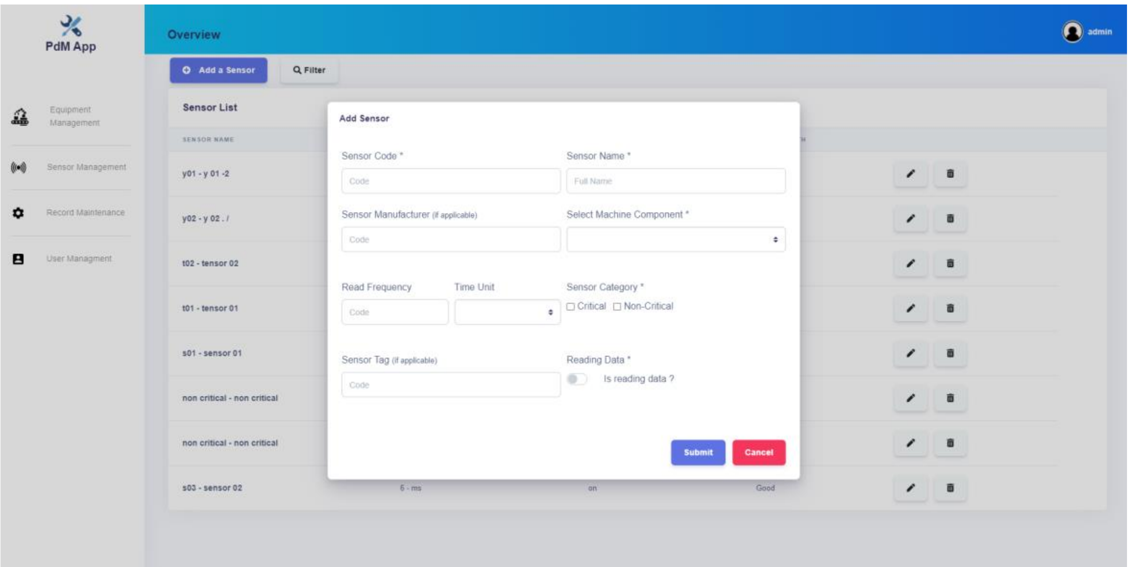

Figure 50: Create Sensor Form

As mentioned in UC8: Create, edit and delete machines if the sensors are acquired by that way after the user has created the machine component it is here where we can do the mapping between machine component and sensor Figure 51 shows the edit form of a sensor.

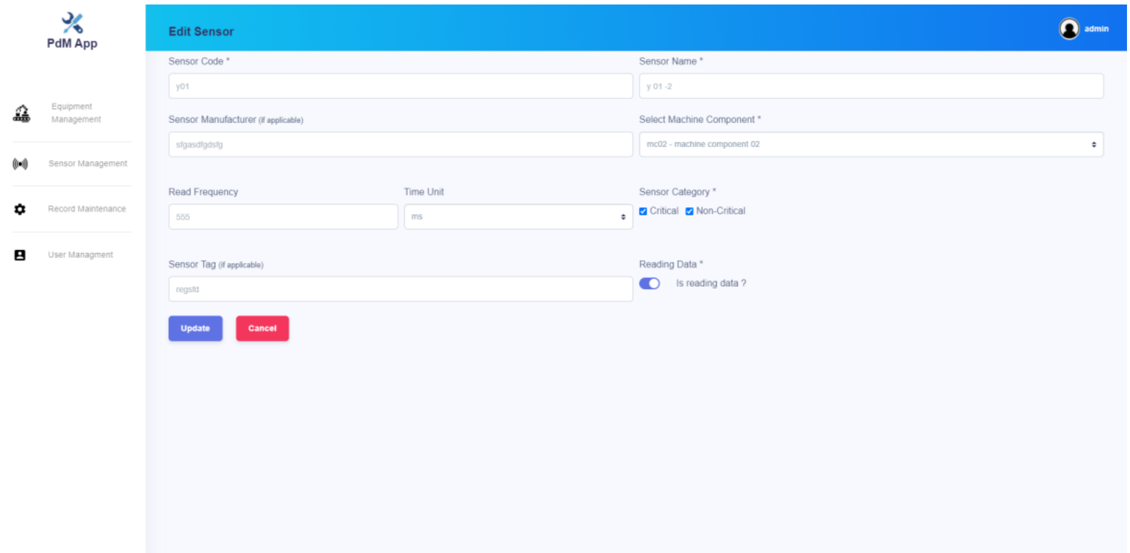

Figure 51: Edit Sensor Form

As mentioned in the introduction of this section the sensors are the most abundant and important thing and in that way was developed a searches method to find more easily the sensors present in the platform.

The first one is to search all the sensors that belong to a machine component as showed in Figure 52.

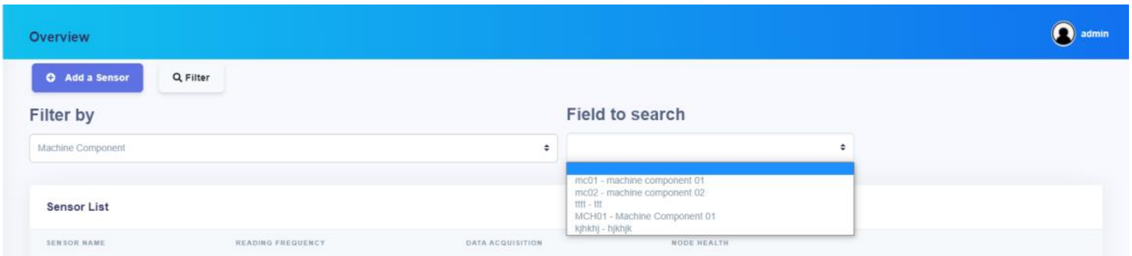

Figure 52: Search Sensor by Machine Component

The second alternative is searching for the sensor by type as shown in Figure 53.

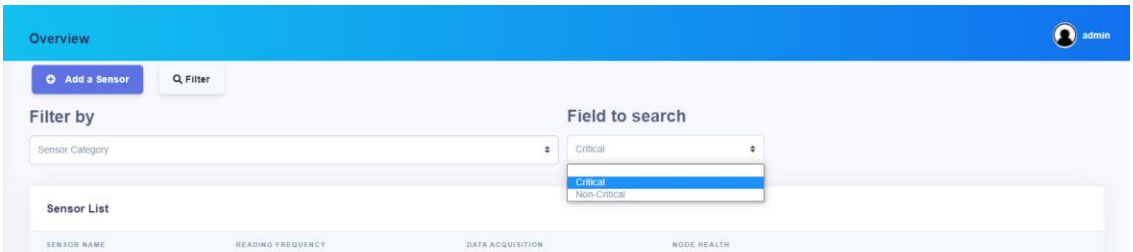

Figure 53: Search Sensor by type

The third option is searching for the sensor by his name as shown in Figure 54.

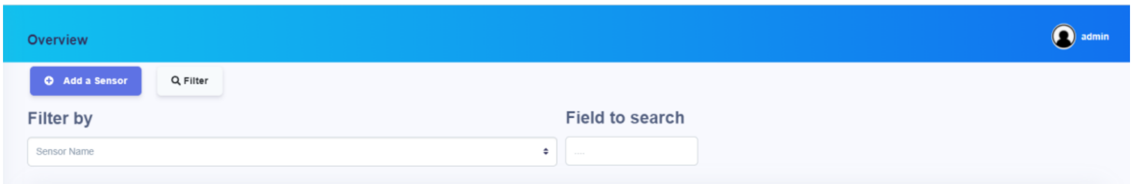

Figure 54: Search Sensor by name

6.3.2.5 UC12: Record Maintenances

To record maintenance in the machine the user must access the page shown in Figure 55, where the user can see all the maintenances recorded in the platform. To record maintenance, the user must click on the button “New Maintenance”.

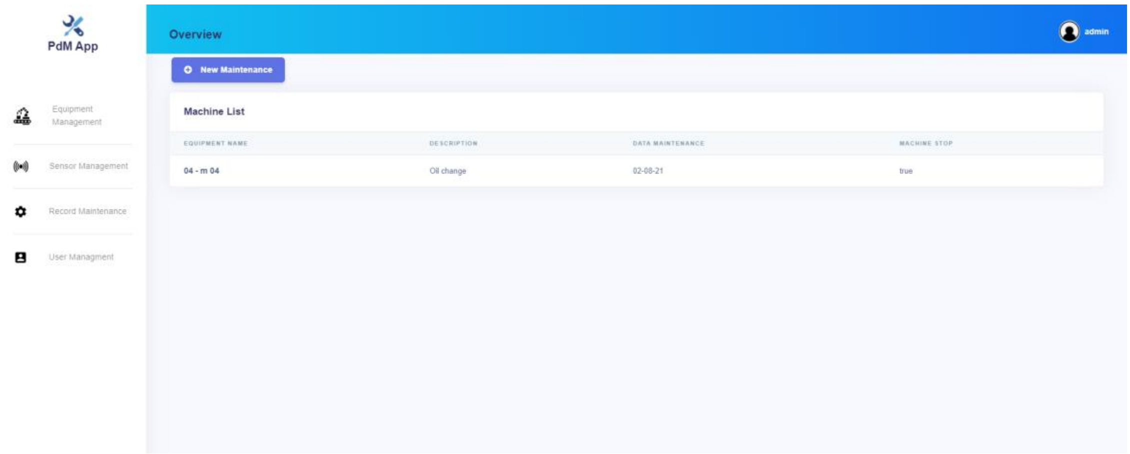

Figure 55: Maintenances List

After the click the fields showed in Figure 56 are presented to the user, the user must fulfil all fields:

- Description – Maintenance description
- Maintenance – Maintenance date of the intervention
- Select Machine – Machine where the maintenance was performed
- Machine Stop – Select if the machine stopped during the maintenance

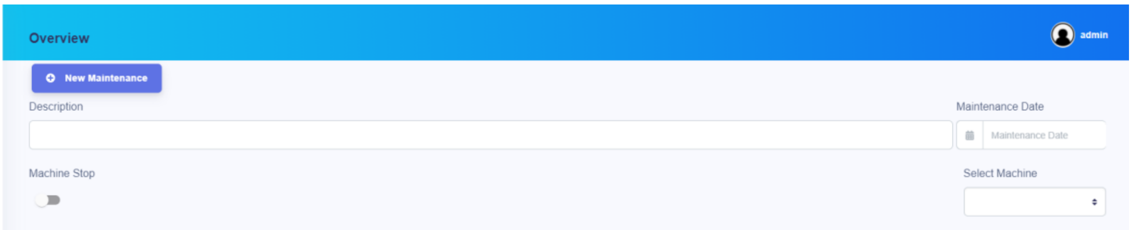

Figure 56: Record Maintenance

6.3.2.6 UC11: Create, edit and delete sensors rules

To create sensor rules the user must click the button “Create Rules” present in the Dashboard, only the users with permission for creating rules are gone seeing the button. After the user must select the machine and the sensor, he must click on the Button “Add a Rule”, shown in Figure 57 if the sensor already has a rule the fields presents in the modal are fulfil otherwise the user needs to fulfil or update the fields:

- Description – Sensor rule description;
- Max. Value – Maximum value for the sensor;
- Min. Value – Minimum value for the sensor;
- Email Warning – Check to receive the alerts by email;

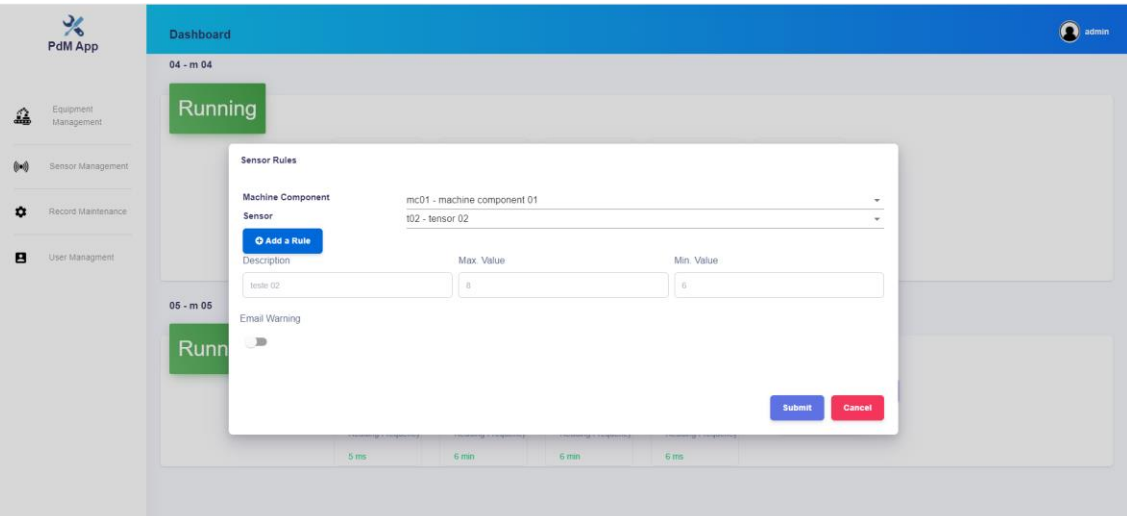

Figure 57: Create Rule Form

6.3.2.7 UC13: View alerts

All the users present in the platform are allowed to consult the historical notifications returned by the rules, to perform this action the user must click on the button “Historical Notifications” presented in the Dashboard, and the modal shown in Figure 58 will be presented to the user.

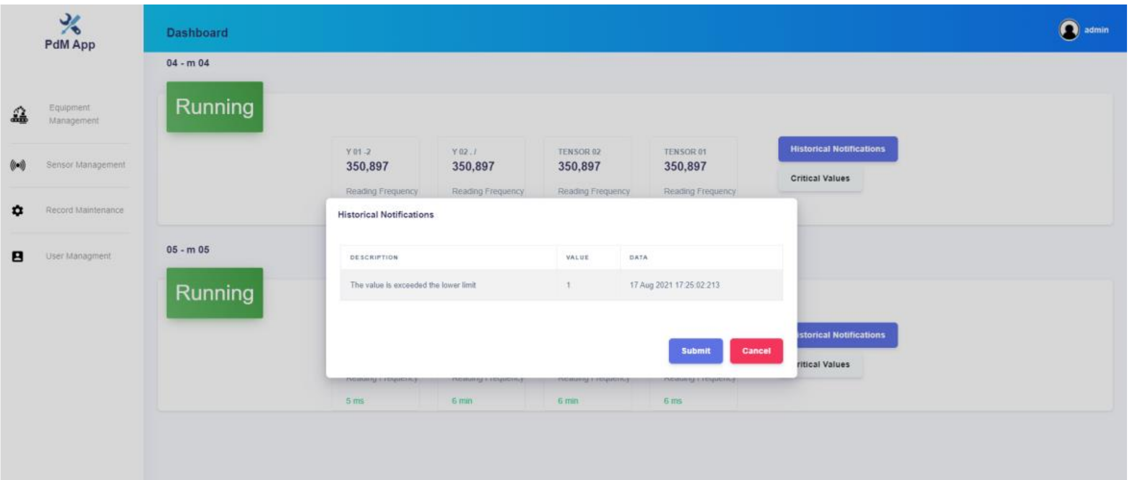

Figure 58: List of Notifications

These warnings are visible on the platform as shown in Figure 59.

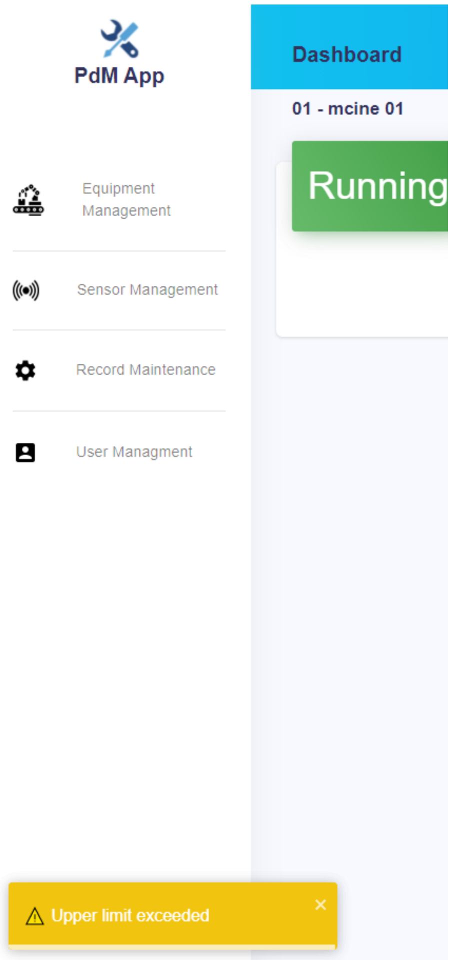

Figure 59: Notification

7 Experimentation and Evaluation

In this chapter the process of experimenting and evaluating the final solution will be described, starting with the hypothesis to be tested, followed by the presentation of the evaluation methodology and a description of how the hypothesis will be validated.

7.1 Hypothesis

To carry out a correct assessment of the final assessment it is necessary to define specifically what will be validated. For that, hypotheses are defined that will be tested during the evaluation process.

With the main objective of providing recommendations, the proposed work needs to assess whether they are correctly generated.

As mentioned earlier, the generation of recommendations will be done using machine learning techniques.

In the present work, the following hypothesis to be validated was defined:

- The use of machine learning algorithms allows the generation of recommendations.

7.2 Evaluation Methodology

After identifying the hypothesis, it is necessary to define how it will be tested. As such, a process was designed to obtain information and how it will be analyzed to assess the hypothesis.

For the validation of the hypothesis defined in section 7.1, several simulations will be carried out on the predictive maintenance module developed. First, historical data will be used with the identified equipment failures, these data will be analysed by the predictive maintenance module, to generate recommendations. After this processing, the resulting recommendations will be collected, checking the number of recommendations generated by just using the rules.

Finally, statistical tests will be applied to the collected values to assess whether the use of the machine learning algorithm has a positive impact on this process, that is, whether the machine learning algorithm allows the generation of recommendations.

7.3 Evaluation Indicators

The evaluation of the developed solution will be based on the results obtained after the processing of the historical data, as mentioned in the previous section, that is, the evaluation will be quantitative, based on the number of recommendations generated.

From the collected numbers, averages will be calculated for both cases, that is, for the use of only the rules and the use of the rules. This will enable a comparison between the two machine failures and the recommendations, and it can be verified whether the machine learning algorithm has a positive impact on the process or not.

7.4 Hypothesis Validation

As mentioned in section 7.2, the validation of the defined hypothesis will be carried out with the aid of statistical tests, but specifically, analysis data.

Hypothesis tests have as focus on the acceptance or rejection of the defined hypothesis, through the analysis of collected data.

To understand better the results of this master thesis need to be presented that the IoT Application and the rule-based model were developed with a resource of an industrial use case provider. The Maintenance Application and the Machine Learning Model were developed without an industrial use case provider.

The data used in this project is from the Kaggle website since the use case partner provided don't has enough data in the time window of the realization of this master thesis project. The data has been provided in CSV files.

The initial dataset as mentioned previously has 421 failures detected the machine learning pipeline cannot come nearly of the value on any phase like is shown in Figure 60 represents the results of the pipeline.

CATEGORY	FALSE_NEGATIVE	FALSE_POSITIVE	TRUE_NEGATIVE	TRUE_POSITIVE
MODELING_GROUP				
TESTING	98	131	108639	51
TRAINING	41	107	106473	105
VALIDATION	79	98	91882	47

Figure 60: Results from pipeline

With the results returned by the pipeline has been concluded that with this machine learning pipeline are presented 47 alerts for appropriate maintenance, but exist 79 failures not detected by the machine learning pipeline and 98 fails detected but no real occurred. So in this way, the machine learning pipeline needs to be more refined to lower the number of false-negative and false positives alerts.

So for a better prediction of failures in the machine components instead of using a generical machine learning model is better to develop one that fits the necessity of the client and reflects the way that is normally used on the factory floor.

For the other components developed in this master thesis project the results were satisfactory, the IoT Application has been running for five months, the data collected from each sensor is in the read frequency-time announced by the machine supplier.

The rule-based model as tested in the same period of the IoT Application only gives a few alerts because the machine is developed to not go above or below the values indicated by the machine component supplier.

The maintenance application has never been used by any use case, but in my vision, I think that can be very helpful in the implementation of strategies for predictive maintenance and IoT data collection.

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