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To my wonderful family

ABSTRACT

Facility management is a developing discipline that has received attention from both professionals and researchers in recent years. In industry, this is mainly due to the importance of efficiency in the production process and to its economic relevance.

Modern facility management considers various interests related to material resources, and among others, social and environmental interests. An important opportunity for the improvement of this discipline derives from the introduction of industry 4.0 technologies for the management of material resources.

The goal of this research is to develop a general approach for maintenance management of industrial facilities based on Industry 4.0 technologies, to support decision-making in maintenance schedules and contribute to the continuous improvement of maintenance activities, from which also derives the improvement of the production process performance.

Starting from a facility management model for the maintenance of industrial assets, we develop a general approach to maintenance based on the Internet of Things and Cyber-Physical Systems, which allows us to reason about the implementation of an effective Organisational Facility Management Unit. Then, leveraging on the Internet of Things, Big Data and Machine Learning technologies for acquiring, analyzing, and processing industrial data, we contribute to the improvement of industrial facilities management by delivering a new methodology that has allowed the design and implementation of new tools to support the management of industrial facilities.

In particular, we will focus in this work on the problem of machine tool maintenance and propose two new software tools that take advantage of Industry 4.0 technologies to improve the traditional approaches proposed in the Total Productive Maintenance area.

The first tool is a software application developed to support the processes of planning and execution of maintenance operations, maximizing the effectiveness of the maintenance management strategies Time-Based Maintenance and Breakdown Maintenance. The second tool is a Predictive Maintenance application developed to support decision-making processes in maintenance schedules, using the Gaussian mixtures technique. The predictive model has been applied to real data from the Italian automotive manufacturing industry.

This study proposes a methodology that can be used as a guideline for the implementation of a facility maintenance office that pursues continuous improvement in the management of industrial assets within the scenario of Industry 4.0.

ACKNOWLEDGMENTS

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1. INTRODUCTION

Effective management of non-essential business activities is necessary for an organization to function more efficiently. Facility management (FM) is a form of business management that aims to provide relevant, cost-effective services to support the core business activities and allows to optimize them [1].

With the aim of continuous improvement of the FM, also pursuing the improvement of core activities, this document proposes a model and a top-down methodology that can be used to implement the coordinated management of industrial assets.

The effort for coordinated management of company support services as a corporate practice has not always been understood in this way, as it is often closely associated with the building management, construction, and real estate disciplines. According to Potkany et al.[2], FM should not only be understood as general building management connected with everyday building operation, but it should also include long-term planning and focus on its users. In the same way, Atkin [3] argues that the significance of facility management is nowadays far more recognized embracing a wide range of interests.

As presented by Hodge et al.[4], those single-source outsourcing services, which started out as soft FM services (cleaning, catering, etc. [5]), saw a change in the late 1980s to hard FM services (mechanical, electrical, etc.). In the 1990s, there was a move toward service integration, supported by FM automation through Computer-Aided Facility Management [4] and Computer-Aided Maintenance Management [6].

In the early 2000s, the concept evolved to Total FM by including waste management, human resources, finance, and other internal or outsourcing services[4]. Throughout the 2000s and 2010s, sustainability management, with concepts as value-driven design, customer performance, and regional and global contracts started to become more common [7]. Finally, workplace management, sustainable workspace, environmental performance, intelligent building management [8], [9], risk mitigation, among other strategic initiatives [10], as a way to increase the business value using new technologies and tools to enhance services delivered and client's satisfaction [11], are part of FM discipline in the 2020s.

Nowadays, facilities management can cover a wide range of services [3], [12]. However, the literature does not provide sufficient coverage of facility management in the industrial scenario, an application domain that requires specialized methods and techniques for the management of industrial assets.

1.1. Industrial Facility Management

Several definitions of Facility Management have been proposed in the literature, each one trying to put into evidence one or more characteristics of this discipline [13], [14]. One that is suitable for the FM in an Industrial context is [15]:

‘*Facility Management is an integrated approach to operating, maintaining, improving and adapting the buildings and infrastructure of an organisation in order to create an environment that strongly supports the primary objectives of that organisation*’.

In the scenario of Industry 4.0, FM is evolving as a consequence of the introduction of new technologies that can enhance the capabilities of roles devoted to the management of structures. The technologies of Digital Twin (DT), Internet of Things (IoT), Cyber-Physical Systems (CPS) and their respective specialization to industry, Industrial Internet of Things (IIoT) and Cyber-Physical Production System (CPPS), are considered in this project to increase the effectiveness of FM.

Facilities maintenance (Fm) is a vital function for effective FM programs, since facility maintenance strategies do have an impact on higher-level organizational objectives, thereby highlighting the importance to consider maintenance performance during strategic decision making [16].

Fm is defined by the British Standard (BS 8210:2012) as the “*work needed to maintain the performance of the building structure, fabric and components, and engineering installations*” [17]. So facility maintenance decisions include those that are required to keep the facility fit for the intended use. As a result, different maintenance strategies would have different impacts on a facility’s supportiveness to the processes conducted within it [16]. In this sense, the overall maintenance goal is to provide economical maintenance and housekeeping services to allow the facility to be used for its intended purpose [18].

As mentioned before, FM has been being successfully applied to maintaining and operating diverse types of industrial facilities, including those for logistics and warehousing. In this context, maintenance plays a significant role. In fact, it assures the full service of the warehousing system, which includes both, building, utilities, and material handling equipment as mentioned by Mangano et al. [19].

In general, maintenance is defined as all the technical and managerial actions taken during the period of use to maintain or restore the required functionality of a product or resource [20]. According to different authors [21]–[23], Maintenance is defined as “*a set of activities or activities used to restore an element to a state in which its designated functions can be performed*”.

For the manufacturing industry, in particular, maintenance consists in carrying out all the necessary actions to restore the durable equipment or keep it in specific operating conditions. The very word "durable" means that the equipment is intended to last a long time and must therefore be maintained [24]. In this sense, the purpose of industrial maintenance is to maximize the effectiveness of the machines, production lines and industrial assets.

In this research, we first adopt a systemic investigation of the asset's maintenance in Industry 4.0. We propose a meta-model that considers the general patterns of planning, monitoring, and control for the maintenance of industrial assets. Since a production system is a complex system made of several parts and relationships, the meta-model needs to be instantiated according to the properties of the goods to be maintained. For example, the maintenance of machine tools, material handling equipment, and industrial plants can be addressed by referring to the model discussed in detail in section 3.1.1.

On the other hand, in the case of building maintenance, even if the pattern "planning/monitoring/control" can be reused, it is necessary to adopt intervention methods and technical procedures appropriate for the object under maintenance. This document shows how views at different levels can increase the understanding of how hardware/software systems must be integrated to provide support to facility managers during operations. We proposed a methodology that can be used as a guideline for the implementation of a facility maintenance office that pursues continuous improvement in the management processes of industrial assets.

Our proposal takes as a starting point the studies on the *Total Productive Maintenance* (TPM) philosophy and its associated tools and techniques, but it refers to a field of applicability, the set of industrial facilities subject to maintenance. TPM is the term used today to refer to activities that constitute a systemic approach to eliminate device failures and increase the efficiency of production lines [25]. The objective of this coordinated group of activities, according to Groover [26], is to minimize production losses due to equipment failures, malfunctions, and low utilization through the participation of workers at all levels of the organization.

The main idea of the TPM approach adopted in this research is the implementation of different strategies, techniques, tools and modern solutions in equipment maintenance operations to improve equipment uptime and reliability [27], through eliminating equipment breakdowns and related defects.

The assumptions of TPM are implemented in a number of topic areas among the pillars of *World Class Manufacturing (WCM)* idea, which is based on the implementation and use of the best working practices available in the field of administration and the organization of work to achieve the best operational efficiency of the company [28], [29].

The pillar under interest in this research is entitled *Professional Maintenance (PM),* a technical methodology closely aligned with TPM strategies, which states all the actions of the specialised services of maintenance which deal with structural approach to eliminate the break-downs of devices [25]. Those activities aimed at building a maintenance system capable of reducing machine and plant failures and micro-stops to zero and obtaining savings, extending the life cycle of machines through the use of maintenance practices based on the ability to extend the life of the components (preventive and corrective maintenance) [30].

As PM is related to the continuous improvement of downtime and breakdowns, it establish the following objectives:

- Maximize the reliability and availability of the machines (at economic costs).
- Eliminate the activities of extraordinary maintenance.
- Reach the zero failure of the plants (failures, micro-leaks, defects etc.) with the collaboration of the production staff.

The application of PM principles has the purpose of increasing the efficiency of the machines by using fault analysis techniques and facilitating the cooperation between the operators (equipment specialists) and the maintenance workers (maintainers) to achieve zero failures [28].

With the introduction of Industry 4.0 technologies as the Internet of Things (IoT) [8], Big Data and Machine learning (ML) [10], and Cyber-Physical Systems (CPS) [11], new maintenance opportunities arise in networked factories with the availability of massive data from processes, machines, and systems. This permits operators, or even intelligent scheduling systems, to monitor the machinery conditions instead of their faults, hence anticipating possible failures, and optimizing the assets utilization [12]. One of these opportunities is the *Predictive maintenance (PdM)* approach, which can be considered as an evolution of preventive maintenance by enabling just-in-time work strategies.

PdM has acquired great relevance for industrial scenarios as a maintenance strategy for diagnosing and prognosing a machine based on its condition. Compared with other maintenance strategies, the predictive maintenance strategy has the advantage of lowering maintenance costs and time [35].

As this research also proposes a predictive maintenance approach using the unsupervised learning model Gaussian mixtures to support decision-making in maintenance schedules as an application of Big Data Analysis in the industry 4.0 context, a brief description of the PdM approach and the Unsupervised ML method is presented below.

1.2. Predictive maintenance and Unsupervised Machine learning

PdM concerns the detection of hidden and potential faults and the prediction of future equipment conditions [36]. To do this, predictive maintenance programs are established, which require the periodic determination of variables to verify the condition of the critical industrial machinery, the diagnosis of defects, and the evaluation of the Remaining Useful Life (RUL) of the machine [37].

As argued by Busse [38], to use PdM, a condition monitoring system must be in place that provides information on the current machine condition (Diagnosis) and, depending on the system's maturity, predicts the future condition (Prognosis).

ML as extension of Artificial Intelligence is one of the trend methods used to make prediction and estimation by using real world datasets [39]. According to Zong et al. [40], unsupervised anomaly detection is a fundamental problem in ML, with critical applications in many areas [24], [41], [42].

The problem of discovering the incoming faults (prognosing) can be seen as a special case of outlier detection, since an outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism [43]. In this field supervised, semi-supervised and unsupervised methods are employed [44].

While Supervised learning provides a clean approach to building ML models, in practice, labeled data in manufacturing is not easily accessible or abundantly available. Unsupervised learning aims to build the representation of a given dataset without any label-based feedback mechanism [45].

In this research, we focused on an Unsupervised ML methodology to support maintenance operations in situations where there is unlabeled data, as a tool to support decision makers for predicting and planning maintenance, thanks to the indication of anomalous behaviours of industrial machines in a job shop manufacturing context.

We propose an abstract framework for PdM and unsupervised learning to support maintenance teams to make informed decisions, propose better maintenance scheduling, and establish effective maintenance policies based on the condition of factory equipment. The approach was implemented through a predictive maintenance system using the Gaussian Mixture model for the diagnosis and prognosis of machinery failures.

1.3. Research aim and objectives

The research aim is to develop a general approach for maintenance management of industrial facilities based on Industry 4.0 technologies, to support decision-making in maintenance schedules. This will contribute to the continuous improvement of maintenance activities, from which also derives the improvement of the production process performance. For what concerns the application domain, the research takes as a starting point the study of a small Italian mechanical enterprise, STAMEC s.r.l., that operates in the automotive sector and is representative of the companies that build molds for the automotive industry. The general objective, a methodology for managing industrial structures/plants, is pursued by achieving the following sub-objectives:

1. Achieve a Manufacturing Enterprise Architecture model capable of representing Industrial Facilities and that allows the reasoning about the management of these facilities in Industry 4.0 scope.
2. Deliver a methodology for maintenance management of industrial facilities in a manufacturing scenario as a solution strategy to the problem of maintenance management.
3. Define a CPPS model from which a real system can be implemented to support the maintenance management processes in manufacturing industry scenarios.
4. Establish a Big Data Analysis solution for the predictive maintenance of industrial machinery under unsupervised conditions.

1.4. Project methodology

As it is a research, innovation and development project, the proposed methodology for its development was divided into the following five phases:

Phase 1 is related to the understanding of the manufacturing industry, specially the Manufacturing Enterprise Architecture of the company in which the research project is executed. To do this, different views of the architectural structure of the company are modeled.

Similarly, Phase 2 consists of modelling the Industrial facilities maintenance management processes to propose new management strategies based on the different maintenance approaches in the literature. The methodology for maintenance management of industrial facilities is obtained in this stage.

Phase 3 studies several CPS reference models to propose a new CPPS model for Industry 4.0, thus contributing to the improvement of maintenance activities of industrial machinery. Based on this model, two software applications were developed. The first tool supports the processes of planning and execution of maintenance operations as described in chapter 3.

An abstract framework, centered around Big data and IoT technologies has been developed during phase 4. A significant part of this framework is the second developed software tool based on an unsupervised ML algorithm to support decision-making processes in maintenance schedules.

Finally, in Phase 5 a real-world application of the proposed approach was pursued through a case study in an italian automotive manufacturing industry located in the south of Italy. The results of the previous phases were applied using the enabling technologies of industry 4.0 for the continuous improvement of maintenance operations.

Figure 1 shows a graphic description of the mentioned phases of the proposed methodology, from which some of the main artifacts obtained are derived.

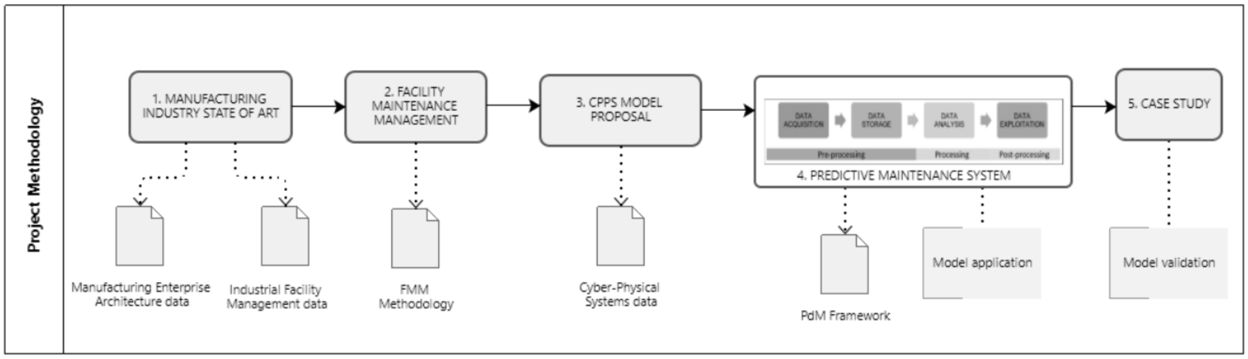


Figure 1. Project methodological scheme.

1.5. Document organization

This document is structured as follows. In chapter 2 the organizational structure of the company STAMEC s.r.l. and its main processes and services are diagrammed through the Archimate language notation, as part of the manufacturing enterprise architecture. Next, in chapter 3, a top-level model that comprises several views for Facility Maintenance Management (FMM) and a classification of several maintenance approaches for machine tools are introduced. The steps of the proposed methodology for FMM are also discussed in this chapter.

As part of chapter 4, in which CPS reference models are studied, a CPPS for the management of production assets discussed has been pursued. In chapter 5 the Big Data Analysis concepts and characteristics are studied. Based on it, an industrial Big Data and IoT architecture is designed to meet the needs of a data-driven analytics system, focused on predictive machinery maintenance in the Industry 4.0 scenario. An unsupervised approach for predictive maintenance using the Gaussian mixtures unsupervised ML algorithm is also discussed.

Finally, a real-world application of the proposed models was pursued through a case study in STAMEC s.r.l. as discussed in chapter 6; the case study allowed us to collect experimental evidence on the model's effectiveness and validate this research. The conclusions summarize the research results discussing benefits, limitations, and future developments.

2. MANUFACTURING ENTERPRISE ARCHITECTURE

The notion of architecture is used in a wide range of domains, from town planning to building and construction, and from computer hardware to information systems, each being characterized by the types of ‘structures’ or ‘systems’ being designed. However, we can recognize some common concerns in all these approaches [46].

Architecture is concerned with understanding and defining the relationship between the users of the system and the system being designed itself, defining its structure, behavior, and other properties based on a thorough understanding of this relationship.

This representation of the system’s architecture forms the basis for analysis, optimization, and validation and is the starting point for the further design, implementation, and construction of that system.

The architecture is also concerned with the relationship between an enterprise and its IT support, which is why the architecture should express the structure, behavior, and coherence of both the business processes and the IT support [46]. In this way, a deep understanding of the enterprise can be reached through its architecture, aiming at the introduction of improvements, according to specific business goals.

2.1. Enterprise Architecture

The Enterprise Architecture aims to provide a clear overall view of the organization, its components, and interrelationships [47], facilitating to meet desired organizational objectives. In this sense, understanding business and technological aspects of the enterprise architecture contribute to its organizational goals, to improve decision-making processes, to innovate and to coevolve with its environment.

To achieve this, it is important to first provide a definition of *Architecture*, as indicated by ISO/IEC/IEEE 42010: 2011 [48] that describes the architecture of a system as:

"*The architecture of a system is its fundamental organization, contained in its components, in the relationships they have with each other and with the surrounding context and in the principles that guide its design and evolution*".

The definition therefore shows that each system can be represented by an architecture if it is possible to describe:

1) The structure (the components and relationships)
2) How it behaves (interactions, that is the relationships activations [49], [50])

3) How it evolves (the principles)

The previous one is a general definition that applies in different scenarios such as, for example, the architecture of an industrial plant or a software architecture. As we are interested in the concept of business architecture, it is better, first of all, to refer to a definition of enterprise and then specialize the definition of architecture to that of business architecture.

"Enterprise is one or more organizations sharing a definite mission, goals, and objective to offer an output such as a product or a service" [51].

From this definition, it is possible to understand that a company is a complex organization of different domains, relationships, and dependencies within it and with the environment. To manage this complexity in any organization is a challenging task, and often a common way to describe the construction and operation of business processes, organizational structures, information flow, IT systems, and technical infrastructures is required.

In the same way, to have a clear understanding of the enterprise structure, processes, products or services, operations, technology, and relations that allow achieving the organizational goals an important instrument is the architecture.

Therefore, linking both Enterprise and Architecture concepts, it is possible to define *Enterprise architecture (EA)* as "*a coherent whole of principles, methods, and models that are used in the design and realization of an enterprise's organizational structure, business processes, information systems, and infrastructure*" [48].

An Enterprise Architecture provides a holistic view of a company that considers both business and technological aspects [52] acting as a means of coordination between:

- Corporate planning aspects, such as objectives, vision, strategies and governance principles;
- Operational aspects related to the business, such as organizational structure, processes and data;
- Automation aspects, such as information systems and databases;
- Technological support infrastructures such as computers, operating systems and networks.

This approach looks at business processes, the structure of the organization and the type of technology used to guide the processes" [53], [54].

From this perspective, Strategic business and Information Technology (IT) alignment (henceforth referred to as strategic alignment) takes on special relevance to clarify the scope and importance of Enterprise Architecture and its different aspects.

In the literature, it is possible to identify many definitions of strategic alignment [55]. Tallon and Kraemer [56] define strategic alignment as the extent to which the IS strategy supports and is supported by the business strategy, while Reich and Benbazat [57] define strategic alignment as the degree to which the IT mission, objective and plans support and are supported by the business mission, objectives and plans. For his part, Silvius [58] defines strategic alignment as the degree to which the IT applications, infrastructure and organization, the business strategy and processes enable and shape, as well as the process to realize this.

However, the Strategic Alignment Model (SAM) proposed by Henderson and Venkatraman (see Figure 2) is one of the most cited strategic alignment models [59].

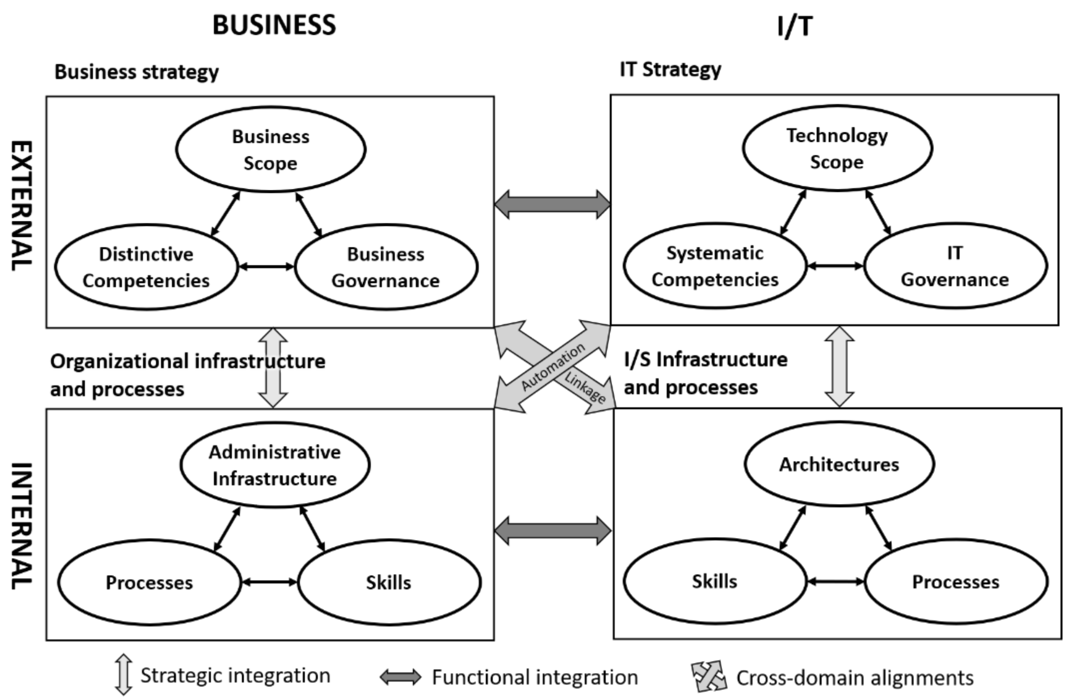


Figure 2. Strategic Alignment Model. (adapted from [60])

The conceptual model in the figure above is defined in terms of four domains of strategic choice: business strategy, IT strategy, organization infrastructure and processes, and IT infrastructure and processes. Each has its constituent components: scope, competencies, and governance at the external level; and infrastructure, skills, and process at the internal level.

The model is conceptualized in terms of two fundamental characteristics of strategic management: strategic fit (the interrelationships between external and internal domains) and functional integration (integration between business and technology domains) [61].

The linkage between strategy and infrastructure and processes is examined in terms of process, structure and people, rather than at an abstract level of attempting to relate internal architectures to strategic goals [61].

As exposed in the model, people play an important role in the strategic alignment of the four components, as well as in the definition of enterprise architectures. During this definition process, it is important to communicate with all stakeholders of the system, ranging from clients and users to those who build and maintain the resulting system, in order to balance all their needs, requirements and constraints, in such a way that the resulting artefacts, be they buildings or information systems, meet those criteria.

According to [46], these can only be met if the architects have an appropriate way of specifying architectures and a set of design and structuring techniques at their disposal, supported by the right tools.

In general, the notations used to define EA refer to frameworks for the description of EA. This is useful to dominate the complexity of formalization by subdividing the whole system into domains (or levels) of representation. This aspect is further explored in the following paragraph.

2.2. Archimate

ArchiMate is an open and independent business architecture modeling language developed by Open Group consortium and supported by various consulting firms and software tool retailers that provides the tools to support business architects in describing, analyzing and putting into it relates the different domains of architecture in a non-univocal way, similar to that used in civil engineering that uses internationally accepted standards to describe the projects. The TOGAF (The Open Group Architecture Framework) standard is one of them.

TOGAF is a framework used to develop an Enterprise Architecture and improve business efficiency [62]. ArchiMate can be perfectly integrated with TOGAF in the various phases of the cycle by providing a visual representation of the various components of the business architecture.

ArchiMate presents a clear set of internal concepts and relationships between architectural domains and offers a simple and uniform structure to describe the contents of these domains; it is a real language to describe the construction and operations on:

- Business process
- Organizational structures
- Information flows
- IT systems
- Technological infrastructure

All this helps stakeholders to plan, estimate and communicate the consequences of changes and decisions within and between business domains.

Archimate uses a tiered, service-oriented view of architectural models. The three main levels of the Archimate Core Framework are:

1. The **Business Layer** offers products and services to external customers that are created by business processes performed by corporate actors.

2. The **Application Layer** supports the business layer with application services that are created by software applications.

3. The **Technology Layer** offers infrastructure services (for example processing, data storage and communication services) necessary to run applications created by the computer, the communication hardware and the software system.

The following levels and extensions have also been added in the most recent versions:

4. The **Strategy Layer** includes the elements (capability), resources and line of conduct that have been added to support the modeling strategy and represent how the use of resources and abilities allows to reach some strategic objectives.

5. The **Physical Layer** contains additional elements with respect to the Technology Layer useful for modeling physical structures and equipment, distribution networks and materials.

6. The **Implementation and Migration** extension adds concepts for modeling a transition state or supporting the last stages of business architecture modeling related to the implementation and migration of architectures, such as work packages, deliverables, gaps, etc.

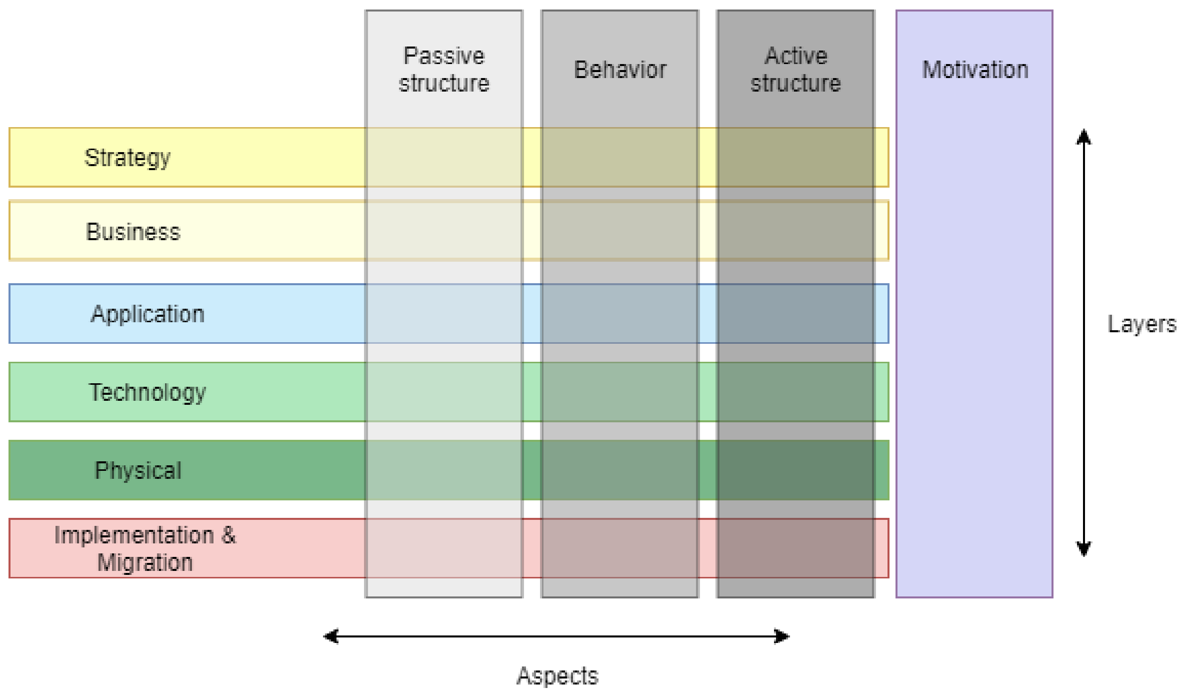


Figure 3. *The Archimate full framework [63]*

The core of the language is made up of three main types of elements:

- **Active structural elements:** defined as an entity capable of performing a behavior (actor, component, device, etc.). They represent the "subjects" of the activities.

- **Behavioral elements:** defined as units of activity performed by one or more active structural elements. Active structural elements are assigned to behavioral elements to show who or what performs the behavior.

- **Passive structural elements (objects):** they represent the objects on which the behaviors are performed (for example, digital data or paper documents).

These modeling elements were inspired by natural language where a sentence has:

- a subject (active structure)
- a verb (behavior)
- an object complement (passive structure)

Figure 3 shows the elements made available by Archimate divided by level. As can be seen from the figure, in Archimate it is the use of color is very important to distinguish between the different levels; in fact, focusing on the three main levels, the following models are used:

- **Yellow** for the elements of the Business Layer
- **Blue** for those of the Application Layer e
- **Green** for the Technology Layer

2.3. Manufacturing system organization

In Groover [26] it is possible to find a series of fundamental definitions and explanatory graphic models of both automated production systems and Computer-Integrated Manufacturing techniques (CIM). CIM systems are the starting point for the study of CPS in which IoT and Big Data Analytics (BDA) will have to combine with traditional approaches to industrial automation, in order to obtain a CPS with an Industry 4.0 perspective.

The main definitions that highlight the decomposition of a production system into subsystems are reported below.

> ***Manufacturing*****:** can be defined as the application of physical and/or chemical processes to alter the geometry, properties, and/or appearance of a given starting material to make parts or products. Manufacturing also includes the joining of multiple parts to make assembled products.
>
> ***Manufacturing systems:*** the logical groupings of equipment and workers that accomplish the processing and assembly operations on parts and products made by the factory. Manufacturing systems can be individual work cells consisting of a single production machine and a worker assigned to that machine.
>
> ***Manufacturing support systems:*** people and procedures by which an industry manages its production operations. These are the procedures used by the company to manage production and to solve the technical and logistics problems encountered in ordering materials, moving the work through the factory, and ensuring that products meet quality standards. Product design and certain business functions are included in the manufacturing support systems.

Manufacturing systems are components of the wider production system:

> ***Production system:*** a collection of people, equipment, and procedures organized to perform the manufacturing operations of a company.

Manufacturing activities can be considered as being composed of multiple levels, from the level of the individual devices where unit processes take place, through to that of the enterprise, incorporating all the activities in the manufacturing system, including supply chain externalities [64]. From this perspective, Duflou et al. [65] structure the organization of the manufacturing system in five levels, similar to those mentioned in Groover's model:

1. ***Device/unit process:*** Individual device or machine tool in the manufacturing system, which is performing a unit process. Support equipment of the unit process is included here [66].

2. ***Line/cell/multi-machine system:*** It is a grouping of machines organized in a line layout (multiple workstations arranged in sequence, and the parts or assemblies are physically

moved through the sequence to complete the product) or cellular layout (consisting of several workstations or machines designed to produce a limited variety of part configurations, specializes in the production of a given set of similar parts or products) [26].

3. ***Facility:*** This refers to the relative location of equipment and/or work centers on the factory floor [67].

4. ***Multi-factory system:*** Different facilities whose proximity to one another allows them to make use of possible synergies in terms of reuse of waste and lost energy streams [65].

5. ***Enterprise/global supply chain:*** This includes the flow and transformation of goods (as well as the flow of the associated information) from the raw materials stage to the end user, including the supplier's supplier and the customer's customer. This flow of goods and information may encompass several different facilities (plants, warehouses, sales, and distribution centers) belonging to several different business entities located in various parts of the globe [67].

Similarly, the ISA 95 model, also known as the *IEC/ISO 62264-1 standard* [68] is a well-consolidated model suitable for representing the manufacturing system organization. In its 2018 version it received the name of "*Enterprise-Control System Integration*", which suggests that the study of corporate systems must be integrated with that of control and manufacturing systems. ISA 95 deals with all aspects related to automation, providing an overall overview of the most important automation concepts and processes.

Focusing on the structure of the ISA 95 company organization, it proposes two models:

1. A hierarchical model for the representation of the physical elements that make up a production system.

2. A logical model which represents the hardware/software elements that participate in the information exchange that affects the 5 levels of the ISA 95 architecture, named as *the automation pyramid of the ISA 95 model.* The model description can be found in [69].

In manufacturing, coordination and control activities include both the regulation of processing and assembly operations, and the management of activities at the factory level. In this project, although the sensors are provided at the machine level, it will operate at the factory/facility level as the planning and control activities will be implemented for the preventive maintenance of machinery malfunctions. For this reason, the Industrial Facility Management and related concepts are further explored in section 3, while the case study of this research is formalized in the next section using the Archimate language notation.

2.4. The Case Study: Molds Production Mechanical Company

This research work was developed during the realization of the three-year "SMART INDUSTRY 4.0" project[1] at STAMEC S.R.L, a small and medium-sized company in southern Italy. The context within which the SMART INDUSTRY project took place was formalized using the Archimate language, identifying the problems to be solved and the research approach aimed at creating a new management system for industrial structures and the production process.

Since 1969 STAMEC is a company specialized in production of:

- Moulds for pressure die-casting for Alluminium, Zinc, Magnesium
- Injection moulds for plastic
- Permanent moulds for gravity and low-pressure castings, Core-boxes, tools and high precision machining, precision mechanical working.

The products realized by moulds, for automotive, electro sanitary or household appliance, are tested in order to obtain a first sampling from whom extract a detailed dimensional report of the tool. In addition, check-points are made by STAMEC before the delivery to the customer, in order to grant an efficient product. The company tools allow it to do careful checks on the materials and on the production process, ensuring a product accordant to the highest quality standards [70].

The organizational structure of the company, as well as the main processes managed for the production of molds are presented below.

2.4.1. Organizational Structure

Essentially the company structure is divided into functions (see Figure 4):

- The administrative, accounting and financial area are staffed by the Company Management and;
- The production area is divided into two strategic business areas, mainly the production of molds and mechanical equipment and the pre-series production of cold-pressed sheet metal products. The company also has two production plants: one located in the main office, which deals with the production of small and medium-sized mechanical molds and for pre-series production, and the other, decentralized, where it is production of large molds.

[1] MISE project "SMART INDUSTRY 4.0" n. F/050493/01-02/X32, decreto MISE n.5195 del 19/12/2017.

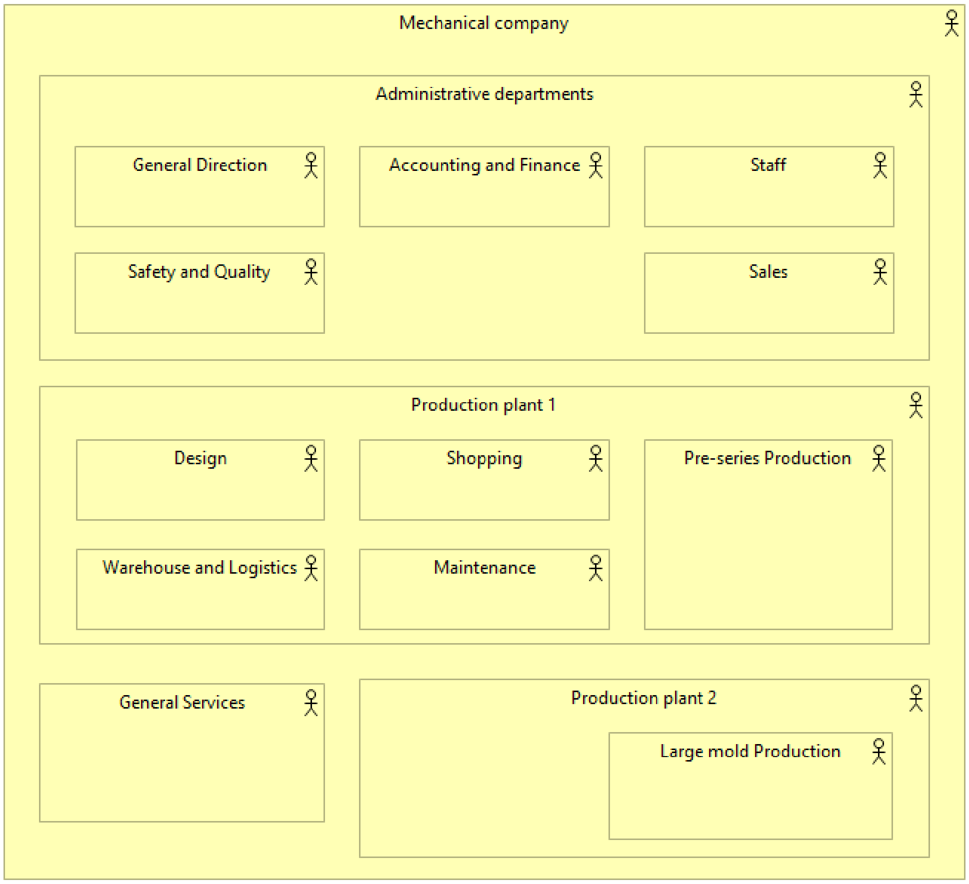


Figure 4. *The organizational structure of STAMEC.*

2.4.2. Primary and support processes

STAMEC is an enterprise that works under the Engineering-to-Order (ETO) modality, an approach proposed since 1983 by Wortmann [71] in which engineering activities need to be added to product lead time. In this sense, upon receipt of a customer order, the order engineering requirements and specifications are not known in detail, and therefore, there is a substantial amount of design and engineering analysis required.

This is a process that requires high collaboration with the customer and a much closer relationship with clients, which is why it is important that the fundamental processes managed by the industry are supported by technological services that facilitate communication and management.

Therefore, based on the analysis of the fundamental processes managed by STAMEC, the vision derived from the implementation of the project is established, discussed through the use of Archimate diagrams in Figure 5. The color of the objects in the diagram shows that the diagram is structured in levels: the yellow part refers to the actual business processes managed by the company, while the blue part refers to the applications that must be developed to support the business processes.

At the business level, starting from the different processes managed by the industry such as production, purchasing, warehousing and maintenance, a series of business services are provided to the supply chain, supported by business applications and a corporate cloud.

The main services provided to stakeholders for the control and monitoring of production-related activities are also shown in the figure. In the specific case, the term actors or stakeholders of the supply chain means not only customers and suppliers, but also logistics and transport companies assigned to deliveries and those that deal with specialized maintenance of machinery.

Customers are obviously interested in following the status of the order, while suppliers must be given the opportunity to view the status of payments or if the sent delivery has been received. Likewise, companies involved in logistics must be able to check whether a delivery has arrived (unloading of goods) or if there are new requests for delivery to customers (loading).

In the case of a Maintenance company partner, the possibility of having a Maintenance status visualization service related to the Machinery maintenance management process would be helpful.

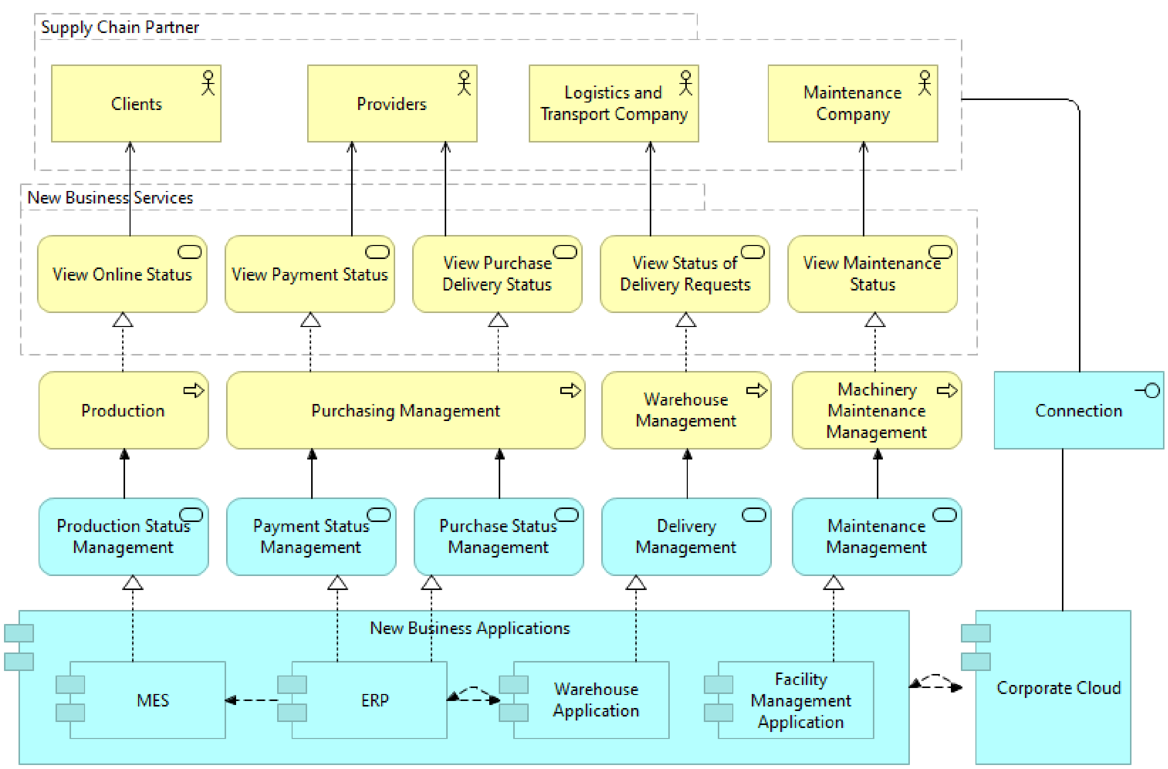


Figure 5. *The main processes and services managed by STAMEC.*

As regards management processes, at the beginning of the SMART Industry 4.0 project, STAMEC had practically no computerization for management processes. Figure 5 therefore shows the vision of the project under construction as regards the use of new software applications in the context of the primary process (the production of molds) and some support processes.

Thus, the project contemplates equipping the company with vertical software applications for both accounting management (ERP) and production management (MES). Furthermore, following the new guidelines on Industry 4.0, the trend is to adopt sensor systems applied to machinery for automatic production control and for preventive and predictive maintenance, which are covered by the Facility Management Application.

All partners will also be able to make general use of the corporate cloud, linked to new business applications. The access to this system will be guaranteed through the connection interface since each actor will have access in protected mode exclusively to the data and functions of the system within its strict competence.

In this research, the topic of Machine maintenance will be studied in depth, as a particular case of the Facility management system, which is presented in greater detail in the next section.

3. INDUSTRIAL FACILITY MANAGEMENT

Facility management is a term which is closely associated with building management. More broadly, facility management should not only be understood as general building management connected with everyday building operation, but it should also include long term planning and focus on its users [72].

According to Vetráková et al. [73], Facility management is an effective form of outreach business management which aims to provide relevant, cost-effective services to support the main business activities (core business) and allow them to optimize.

To explain better the scope of facility management we can use the definition of IFMA (International Facility Management Association), which has defined Facility Management as "*a method whose task in organisations is to mutually harmonize employees, work activities and the work environment that includes principles of business administration, architecture and humanities and technical sciences*" [74].

In more recent years, the definition has included aspects such as processes and technology: "*Facility management is a profession that encompasses multiple disciplines to ensure functionality of the built environment by integrating people, place, process and technology*" [75], and also maintenance and effectiveness as proposed by Atkin et al. [17] when defines FM as "*the integration of processes within the organization to maintain and develop the agreed services that support and improve the effectiveness of its primary activities*".

FM has been gaining increasing credit for the crucial role it can play to generate efficiency and cost savings in business operations [19], and the most common forms of application of facility management in the enterprise is a partial or complete outsourcing [72].

In recent years there is a renewed interest in FM because the advent of Industry 4.0, and in particular of IoT and CPS, constitute an important opportunity to improve facility management processes.

31. Facility Management in the industry 4.0 scenario

With the introduction of the Industry 4.0 in recent years a new scenario for Facility Management is derived. The fourth industrial revolution 4.0 has introduced digital technologies, sensor systems, intelligent machines, and smart materials to the industry [76], encompassing the widespread integration of information and communication technologies that converge the physical and digital many areas of industry.

Successful enterprises are using a full stack of technologies to achieve the goals of Industry 4.0: efficiency, speed, agility, and customer-centricity [77]. One of these technologies is the *Digital Twin (DT)*, recognized as a key part of the Industry 4.0 roadmap.

DT is the exact representation of, for example, a building as digital data [77], and is a technology that is rapidly being adopted by the industrial enterprise, in which there are multiple use cases across: engineering, manufacturing and operations, and maintenance and service.

Digital twins are made possible (and improved) by a multitude of Industry 4.0 technologies -IoT, Augmented Reality (AR), Computer-Aided Design (CAD), Product Lifecycle Management (PLM), Artificial intelligence (AI), Edge Computing, to name a few– to create a powerful tool that is driving business value [78].

A DT or digital replica of a physical entity can target industry in several sub-areas [79], as Facility management, Product Lifecycle Management, Smart Buildings, Smart energy, Optimization, Analyze complex structures, Structural Health Monitoring, Increase human safety, Reduce maintenance costs, Materials testing, Smart Cities, any kind of other IoT solution [80].

The application of the mentioned technologies to the facility management processes represents a breakthrough for the development and integration of new processes that support the development, maintenance, and functionality of the facilities, and brings new development opportunities in this field. Maintenance of industrial machinery, as a particular case of Facility Management from an Industry 4.0 perspective is one of them, and is presented below.

3.1.1. Facility Maintenance Management

As mentioned before, FM has been being successfully applied to maintaining and operating diverse types of industrial facilities, including those for logistics and warehousing. In this context, maintenance plays a significant role. In fact, it assures the full service of the warehousing system, which includes both, building, utilities, and material handling equipment as mentioned by Mangano et al. [19].

Despite increasing recognized importance of FM as an integrated component of business operations, most companies still complain about the rising cost of maintenance of industrial and logistic facilities. Managers often seek to cut FM spending by reducing repair interventions to a minimum and by delaying preventive maintenance actions, leading to a cascade of extra costs in the medium and long term [81].

The proposed model here, drawn in ArchiMate notation, takes into consideration a systemic approach to the maintenance of industrial facilities. Assuming that the generic industry has an Organizational Unit (OU) that deals with FM, we introduce the top-level model of Figure 6. It represents the Facility Management OU and several offices hierarchically organized (Building Maintenance, Machinery Maintenance, etc.). The model takes into consideration the general aspects concerning both the decision-making process and the approaches to maintenance.

For what concerns the decisional process, the role of "Executive Director" acts with the collaboration of technical support roles in order to make informed decisions. The involved decisional processes has the duty to establish: a) the FM program to implement in a given time period; b) which maintenance services must be implemented internally and which must be requested from service providers (make or buy choice); c) identify the technology that must support the maintenance activities (that may depend on the asset under maintenance); d) allocate the resources for the maintenance operations.

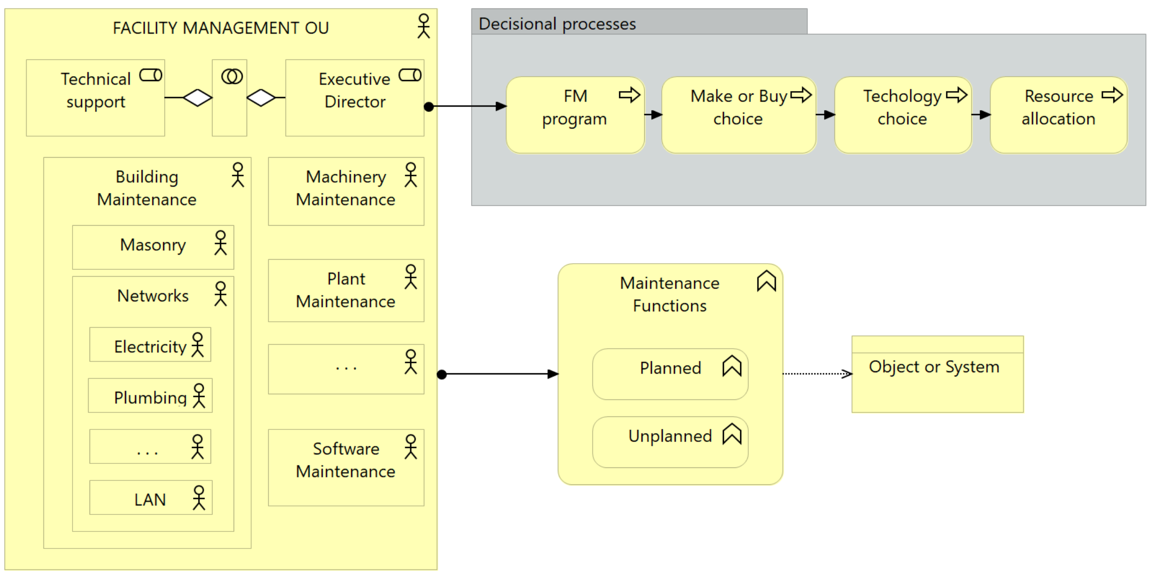


Figure 6. *Facility Maintenance Management top-level model.*

The second aspect concerns the maintenance functions. The model states that there are two valid general approaches: planned maintenance and unplanned maintenance. According to the good characteristics, one or both can be considered as appropriate. For example, planned and unplanned maintenance are normally required for complex machinery, while for the power grid, the unplanned approach usually works well in order to save on maintenance costs. The bottom parts of the model states that the Facility Management OU is assigned to the Maintenance functions which have access to an object or a system to perform a behavior.

In order to provide better clarity on the application of the proposed model for the management of facilities and its usefulness for the industry, a specialization in the machinery maintenance functions is presented in the view shown in Figure 7. It is important to indicate that in the particular case of machinery maintenance, the two general functions, Planned and Unplanned maintenance reported in the top-level model must be detailed (see Figure 8) to assure adequate equipment operating conditions.

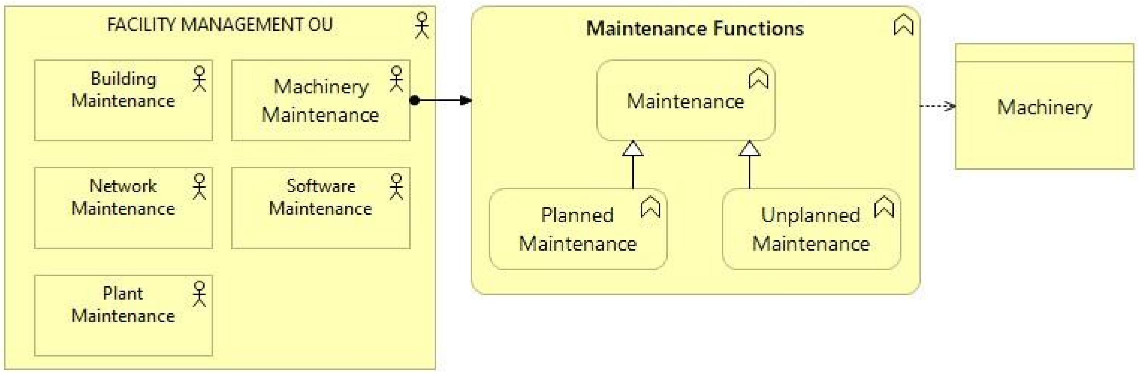


Figure 7. *Machinery maintenance as part of Facility management*

Maintenance is an integral part of facility management and requires clear definition of arrangements to prevent and deal with failure or breakdown of parts, components, systems and other elements [12]. Consequently, some fundamental concepts related to maintenance approaches in an industrial context are presented below, starting from Total Productive Maintenance as part of World Class Manufacturing (WCM), to some maintenance strategies.

3.2. Maintenance of industrial machinery

In general, maintenance is defined as all the technical and managerial actions taken during the period of use to maintain or restore the required functionality of a product or resource [20]. According to different authors [21]–[23], Maintenance is defined as "*a set of activities or activities used to restore an element to a state in which its designated functions can be performed*".

For the manufacturing industry, in particular, maintenance consists in carrying out all the necessary actions to restore the durable equipment or keep it in specific operating conditions. The very word "durable" means that the equipment is intended to last a long time and must therefore be maintained [24]. In this sense, the purpose of maintenance is to maximize the effectiveness of the machines and production lines.

Considering that there are different approaches to maintenance, some general definitions and considerations are presented below, starting from the first postulates made in the literature and reviewing the positions that new authors have today in this regard.

3.2.1. Total Productive Maintenance

Total Productive Maintenance (TPM) is the term used today to refer to activities that constitute a systemic approach to eliminate device failures and increase the efficiency of production lines [25]. The objective of this coordinated group of activities according to Groover [26] is to minimize production losses due to equipment failures, malfunctions, and low utilization through the participation of workers at all levels of the organization.

The assumptions of TPM are implemented in a number of topic areas among the pillars of *World Class Manufacturing (WCM)* idea, used initially by Hayes & Wheelwright and more developed as a model in the 80s by Richard J. Schonberger, which is based on the implementation and use of the best working practices available in the field of administration and the organization of work to achieve the best operational efficiency of the company [28], [29], topic also addressed in more recent studies such as those of Poor [82] and Szczepaniak [83].

According to Fiat Group Automobiles [30], WCM is: "*a structured and integrated production system that includes all plant processes, the safety environment, from maintenance to logistics and quality"*. The goal is to continuously improve production performance, seeking a progressive elimination of waste, in order to guarantee product quality and maximum flexibility in responding to customer requests, through the involvement and motivation of the people who work in the plant.

The benefits of WCM integration include increased competitiveness, the development of new and improved technologies and innovations, greater flexibility, greater communication between management and production employees and an increase in job quality and strengthening of the workforce.

The WCM model is implemented through two lines of action known as pillars: 10 technical pillars and 10 managerial pillars. The pillar structure represents the "Temple of the WCM" and underlines that, in order to reach the standard of excellence, a parallel development of all the pillars is necessary. Each pillar focuses on a specific area of the production system using appropriate tools to achieve global excellence.

For the specific case of this project, we will focus on the principles established for the pillar called *Professional Maintenance (PM)*, which is related to the continuous improvement of downtime and breakdowns and has the following objectives:

- Maximize the reliability and availability of the machines (at economic costs).
- Eliminate the activities of extraordinary maintenance.

- Reach the zero failure of the plants (failures, micro-leaks, defects etc.) with the collaboration of the production staff.

The application of these principles has the purpose of increasing the efficiency of the machines by using fault analysis techniques and facilitating the cooperation between the conductors (equipment specialists) and the maintenance workers (maintenance workers) to achieve zero failures [28].

According to [30], the *Professional Maintenance* technical pillar includes the activities aimed at building a maintenance system capable of reducing machine and plant failures and micro-stops to zero and obtaining savings, extending the life cycle of machines through the use of maintenance practices based on the ability to extend the life of the components (preventive and corrective maintenance).

To better understand the purpose and methods of maintenance activities, it is advisable to know the different approaches to maintenance from which different types of maintenance derive.

3.2.2. Maintenance Approaches

There are various types of maintenance that can be performed based on certain conditions or characteristics, but they are mainly classified into two general functions based on the repair timing: *planned* (before a detected fault) and *unplanned* (after a detected fault), as presented in Figure 8. Both maintenance operations must be performed to assure adequate equipment operating conditions.

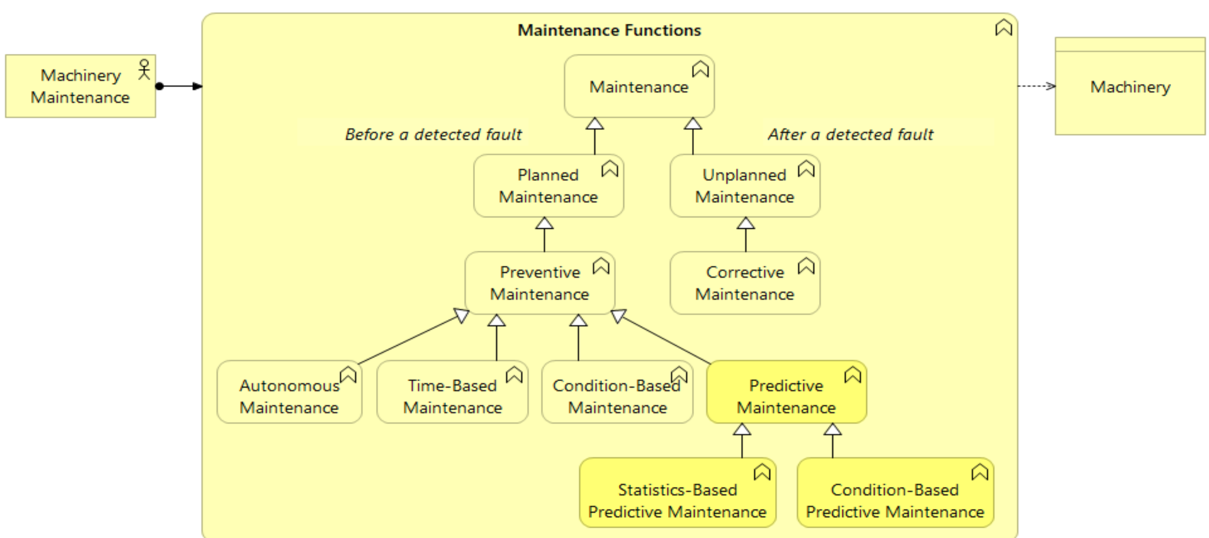


Figure 8. *The Machinery Maintenance Management view, as part of Facility management.*

Corrective maintenance (CM) refers to "*maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function*" [84]. This strategy is often applied to low-cost or non-critical equipment for production.

In contrast, Preventive maintenance (PM) strategies [85] involve carrying out maintenance activities before equipment failure, contributing to minimizing the costs of breakdown and downtime (loss of production) [86] and the increase in product quality [87]. This type of maintenance strategy in turn includes:

- *Autonomous Maintenance (AM):* it deals with increasing the efficiency of the production line through the actions of the device operators [25], which aims to take care of small anomalies/problems (small faults, abnormal operation of the device, minor errors related to the work of machines and devices) before they cause equipment failures.

- *Time-Based Maintenance (TBM):* maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation [84].

- *Condition-Based Maintenance (CBM):* it consists of diagnosing the state of resources based on a combination of condition monitoring and/or inspection and/or testing [84], and performs appropriate maintenance actions, usually based on real-time equipment condition evaluation, such as repair and replacement before serious problems occur [20].

- *Predictive Maintenance (PdM):* also known as "*prescriptive maintenance*", concerns the detection of hidden and potential faults and the prediction of future equipment conditions [36]. To do this, predictive maintenance programs are established, which require the periodic determination of variables to verify the condition of the critical industrial machinery, the diagnosis of defects, and the evaluation of the RUL of the machine [37]. PdM can be dissociated into two specific subcategories [88]:

  a) Predictive maintenance based on statistics: involves the meticulous recording of all interruptions of articles and plant components [89]. The generated information facilitates the development of statistical models for predicting bankruptcy and therefore allows preventive measures to be taken through a scheduled maintenance policy [90].

  b) Condition-based Predictive Maintenance (CbPM): it is based on the principle that wear or degradation is responsible for a large number of mechanical failures and even where not directly responsible, some elements of the phenomenon are usually present [91]. As mentioned before, degradation is a gradual process that affects industrial machines and components over time. The wear process will not cause a sudden mechanical failure but is preceded by changes in the sensitive behavior of the machine [92]. Condition-based monitoring revolves around examining these wear processes in mechanical components, in order to predict their future behavior and tendency to fail.

Predictive maintenance exhibits several inherent benefits, namely by Lee et al. [93]: optimized parts usage, reduced costs, increased machinery lifetime, plant safety, product quality (near zero failure manufacturing), reduced number of accidents, or effortless integration with company scheduling, among others. However, to enable the implementation of PdM strategies in an industry 4.0 scenario, it is necessary to have a technological architecture that adequately supports the deployment of the developed systems.

The Big data and IoT architectural model designed for the proposed predictive maintenance system is presented in section 5.

3.2.3. Maintenance strategy

To know all the approaches to maintenance and the different types of maintenance is important to develop a strategy that defines the best mix of approaches and types, in relation to the characteristics of the organizational context.

A maintenance strategy involves identifying, finding and performing many repairs, replacing and inspecting decisions [94]. It deals with the formulation of the best life plan for each unit of the plant and the formulation of the optimal maintenance program for the plant, in coordination with the production and other interested functions [95].

A maintenance strategy describes which events (e.g. Fault, elapsed time, condition) determine which type of maintenance intervention (inspection, repair or replacement). A maintenance strategy consists of a mix of policies and/or techniques, which vary from structure to structure [96], [97]. This depends on several factors such as the maintenance objectives, the nature of the structure or the equipment to be maintained, the workflow models (process focus, product focus) and the work environment [98], [99].

The Figure 9 presented below shows the organization of the various types of maintenance according to the needs of the organization and the priority level of their plants in the production process.

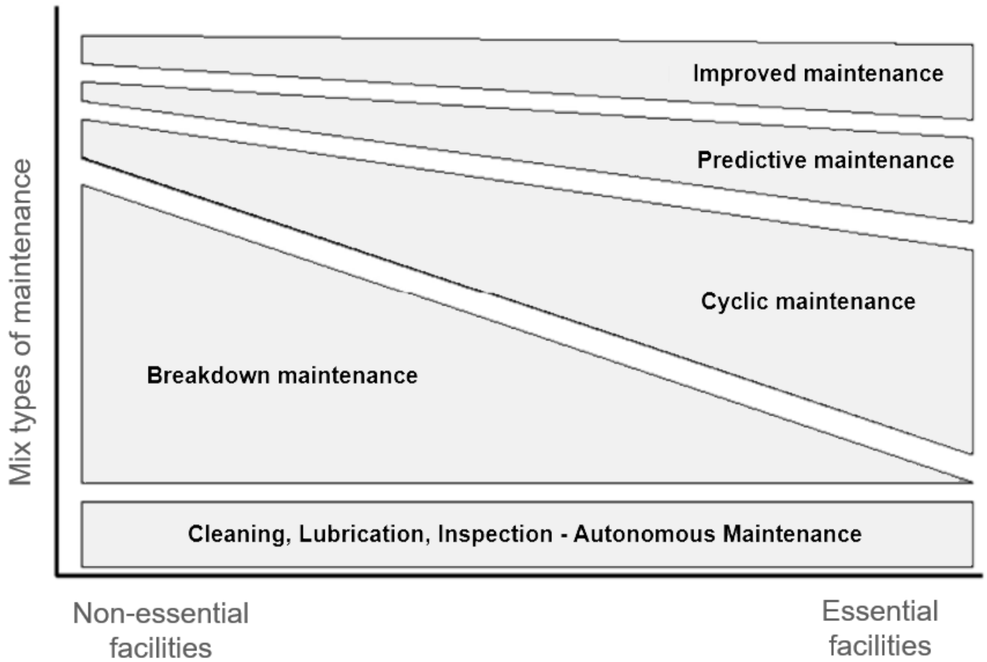


Figure 9. *Maintenance strategy.* (adapted from [100])

According to the above, for a type of organization where systems are not essential and instead there is a strong presence of work, as in an assembly operating unit, the best combination is that which provides basic autonomous maintenance, cleaning, lubrication, inspection, fault maintenance and less periodic, preventive and corrective maintenance.

On the other hand, for a type of organization in which systems are essential, such as an operating unit for panels or painting, the best combination is an autonomous basic maintenance, without failed maintenance, periodic, predictive and corrective maintenance [95].

It should be noted that in practice more than one approach could be used at the same time. Therefore, it is very important to know which maintenance approach, from the various applicable maintenance approaches, is the most convenient and fits the technical system in its operational context.

According to a report by WCM Development Center [100], if the maintenance strategy involves only reactive failures, the maintenance costs are relatively low, but the losses could be high. If preventive maintenance is introduced, maintenance costs increase: for example, some activities must be carried out using overtime, detectors for predictive maintenance are introduced, time is devoted to training activities to increase the skills of operators and maintainers.

As a result, maintenance costs increase. However, transformation costs are reduced because losses due to faults and micro-stops are reduced. The balance between transformation costs and maintenance costs is the one in which the choice of maintenance strategy, i.e. the mix of types of maintenance adopted, is the best. The move towards a more sophisticated strategy produces a further increase in maintenance costs, which is no longer balanced by a decrease in transformation costs.

The planning and execution of these strategies, however, require well-defined guidelines according to the characteristics of the facilities to be maintained and the FM OU structure. For this reason, we propose below a methodology designed to support the FMM programs.

3.3. A methodology for Facility Maintenance Management

Figure 6 shows how a top-level model for FMM while the top-down decomposition method allows us to dominate the problematic complexity inherent to the management of industrial assets.

Although the decisional process outlined in Figure 4 provides a guideline on how to set up an FM program, more detailed information is necessary to indicate the essential actions to perform for effective facility maintenance. For this reason, we propose a step-by-step methodology for FMM based on two main phases: planning time, and operation time.

- *Planning time*
  a) Focus on the area of intervention and identify the roles to be allocated
  b) Select the management methods for the area of intervention
  c) Acquire detailed knowledge about the appropriate technology for the object/system to be maintained
  d) Plan the management activities for the object/system

- *Operation time*
  e) Implement management support hardware/software systems and big data technologies/techniques
  f) Measure, monitor, and control the object/system
  g) Execute the maintenance activities
  h) Feedback the process

As the models discussed in section 3.1.1 and the methodology follow a top-down approach to FM, in the next section we define two business processes, planning and execution, that show how the points d) and g) can be developed. An example of how the step c), e) and f) can be used in an Industry 4.0 scenario is presented in the case study of section 6. Points a) and b) have been briefly considered by the models of figure 5 and figure 6 and will be further elaborated in the case study. Point h) comes from the feedback management approach [101], and enables a systematic integration [102] between planning and operation processes for better maintenance decision-making processes.

3.3.1. Machine maintenance planning flow

During the development of this research, we observed the planning and execution processes for machine maintenance managed by several factories. The model in figure 10 describes the planning processes that the observed factories usually adopt to cope with the problem of machine tool maintenance using the planned and unplanned approaches. It is representative of many manufacturing scenarios where machine tools and equipment of various kinds must be maintained in good health condition to reduce the amount of time in which the manufacturing system does not produce.

As the model shows, preventive and corrective maintenance activities are planned on a biannual and weekly basis; unplanned activities, as well as those related to Emergency Work Orders (EWO) that correspond to failures or anomalies, are performed during daily operation. In the three processes below, the involved roles "Equipment responsible", "Workforce manager" and "Maintainer responsible", are particular cases of a more generic planner role.

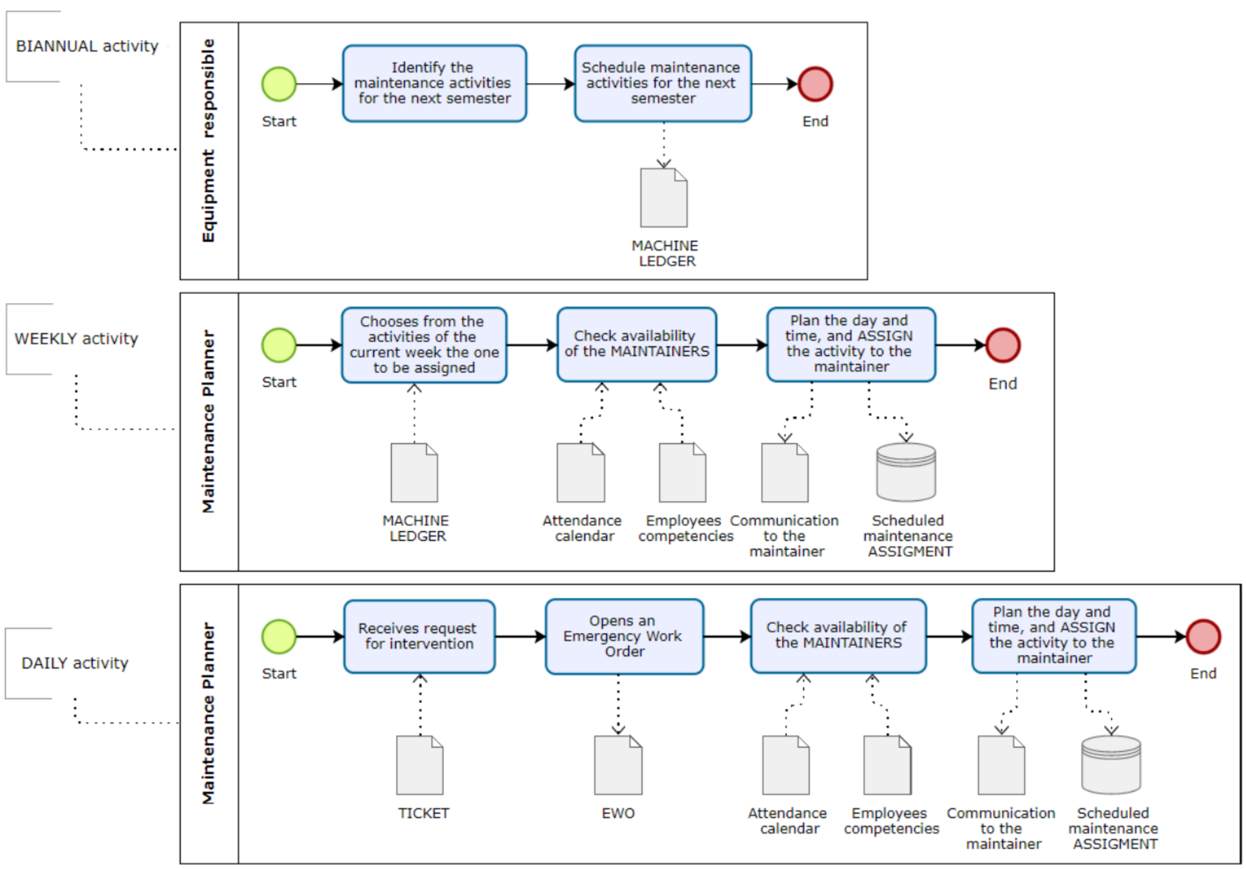


Figure 10. The machinery maintenance management flow for planning [103].

The tasks related to the biannual planning process, carried out by the *Equipment responsible*, consist of defining the maintenance activities that must be performed each semester and planning the execution of the activities on a weekly basis. This planning is stored in a *Machine Ledger*, a graphical visualization tool that allows maintenance teams to better understand maintenance/breakdown trends and patterns at the machines, assemblies, and components levels, so they can more effectively predict failures and plan preventive actions.

Based on the previous planning, the *Workforce responsible* verifies the availability of the technician through an attendance calendar as well as the fulfillment of the employee's competencies to perform the required activity and assigns the weekly maintenance activities (second phase, once a week) on a specific date and time, also indicating the estimated time for the intervention. This assignment is stored in a database and communicated to the corresponding maintainer.

On the other hand, the management of unplanned activities (third phase, one or more times a day) is carried out by the *Maintainer responsible*, who is in charge of receiving the intervention requests that may be submitted during the day (ticket) and opening an EWO. To carry out their assignment, the availability of the maintainers is verified as well as the fulfillment of the competencies required to effect the maintenance activity and the assignment is done. As soon as the activity is assigned, the maintainer is notified.

Both the machine maintenance management flow described above and the availability of machine data are essential for planning. In this sense, as will be seen in section 6.1.2.1, the application of technology plays a fundamental role.

Once the planning phase is complete, the proposed activities are executed in the Operation time phase, as presented below.

3.3.2. Execution of maintenance operations

As related in the previous section, planner roles are responsible for the maintenance planning and assignment of biannual and weekly maintenance activities to maintainer roles. From these processes, several planned maintenance orders are sent to each maintainer during the day. A second assignment modality is executed when emergencies arise during the working day that must be attended, which are handled as unplanned activities for which the corresponding EWO is generated and assigned.

Once the maintenance activity has been assigned to a particular Maintainer, he receives a notification of the corresponding assigned maintenance order. Before starting with the execution of the activity, all the information related to the intervention (area of intervention, typology, estimated intervention time, required materials, procedure description, among others) must be verified by the maintenance technician. This allows the intervention to be carried out efficiently and avoiding delays due to ignorance of the procedure or lack of supplies.

The lower part of Figure 11 shows a brief representation of the process executed by a Maintainer to perform the assigned maintenance activities.

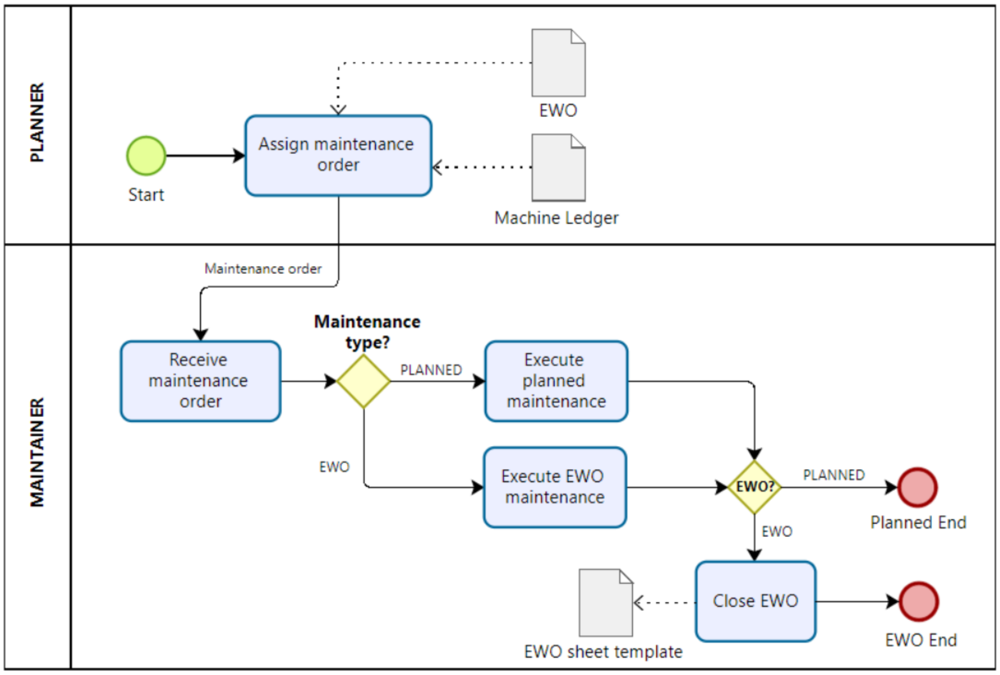


Figure 11. Maintenance activities execution process.

For each assigned planned activity, an activity sheet must be opened in which the Maintainer, once positioned in the workstation (machine), can start the maintenance activity and report information as the description of the performed activity, start date/time and stop date/time.

Similarly, when an unplanned maintenance activity is completed and the first part processed after maintenance (Job1) is verified, the Maintainer must indicate the completion of the activity and register it in an EWO sheet, to be subsequently closed.

A second type of unplanned maintenance activity refers to Extra activities that must be carried out but are not necessarily related to damage or failure, such as changing the oil or fuel. They are generally related to AM actions performed by machine operators to preserve normal machine operating conditions. In this case, the EWO sheet is not required.

To support both planning and operation processes, a software application based on Figure 7 was developed for the management of maintenance activities, which, together with the application of the methodology presented in section 3.3, is introduced in the case study in section 6.1.2.1 Planning and executing maintenance operations.

4. CYBER-PHYSICAL SYSTEMS

In recent years, we are witnessing a new industrial revolution called Industry 4.0. The fourth industrial revolution aims to introduce changes to improve the efficiency of production processes, to reduce costs, to increase services to customers and their quality [104]. Apart from improving industrial value chain processes, the introduction of Industry 4.0 technologies constitutes also an important opportunity for the improvement of the industrial facility management.

In this sense, technologies such as DT, IoT, CPS and their respective specialization to industry, IIoT and CPPS, are considered in this document to increase the effectiveness of FM.

The view introduced in this section describes some technologies of Industry 4.0 necessary for the creation of an integrated system consisting of CPPS, IIoT, DT, and Production Planning and Control (PPC) software, aiming to make the management of maintenance activities more effective. In this sense, the next section considers the definitions and main characteristics of those concepts, seeking to better understand the contribution they make to the integrated system model proposed in section 4.4, in which these technologies are implemented.

4.1. Cyber-Physical Systems definition

The term CPS has been defined as the systems in which natural and human-made systems (physical space) are tightly integrated with computation, communication and control systems (cyber space) [65].

The disruptive technologies emerging from combining the cyber and physical worlds could provide an innovation engine for a broad range of industries: manufacturing, transportation, infrastructure, health care, emergency response, defense; as indicated in [105].

According to Herrmman and Thiede [106], CPS can be used to address these issues in today's industry by bringing autonomous control, self-awareness, and self-management capabilities to industrial machines.

Similarly, CPS can be understood as smart systems that encompass computational (i.e., hardware and software) and physical components, seamlessly integrated and closely interacting to sense the changing state of the real world. These systems involve a high degree of complexity at numerous spatial and temporal scales and highly networked communications integrating computational and physical components [107].

CPS are capable of increasing productivity, fostering growth, modifying the workforce performance, and producing higher-quality goods with lower costs via the collection and analysis of malicious data [105]. Ivanov et al. [108] argue that dynamic models are needed in CPS to coordinate activities in manufacturing procedures and to achieve an optimization of production.

In the Industry 4.0 scenario, a CPS for Facility management consists of microcontrollers that interact with sensors and actuators that exchange data and information through a communication network to facility management systems.

This "cyber-physical ecosystem" as called by Ivanov et al. [108], should be developed to achieve real-time monitoring and optimization of maintenance activities. In this way, maintenance planning strategies, with implications for decision-making processes, cost management, and energy consumption of the manufacturing system can be improved through the facility management system.

A specialization of CPS related to the Industry 4.0 scenario and some technologies necessary for a better industry performance are the CPPS, whose definition is presented in [104]:

> "*Cyber-Physical Production Systems comprise smart machines, warehousing systems, and production facilities that have been developed digitally and feature end-to-end ICT-based integration, from inbound logistics to production, marketing, outbound logistics, and service*".

4.2. Internet of Things

The IoT is a novel paradigm that is rapidly gaining ground in the scenario of modern wireless telecommunications [109]. Recent developments in facility management methods are based on the use of these new technologies (IoT and CPS), with their corresponding specialization into IIoT and CPPS to the industrial context.

For what concerns the building facilities, one study by Weiwei Chen has proposed models that show the use of IoT for automatic scheduling of maintenance work orders and predictive maintenance strategy for building facilities [110]. Cheng et al. [111] discuss how Building Information Modeling and IoT have the potential to improve the efficiency of FMM.

The basic idea of the IoT concept is the pervasive presence around us of a variety of things or objects such as Radio-Frequency IDentification (RFID) tags, sensors, actuators, mobile phones, etc. which, through unique addressing schemes, are able to interact with each other and cooperate with their neighbors to reach common goals [109].

A simple IoT definition given in [112], describes a system where objects in the physical world, and sensors within or attached to these items, are connected to the Internet via wireless and wired network connections.

It is important to distinguish between IoT and IIoT. Even if they are closely related concepts, they cannot be used interchangeably [113]. As seen in the previous definitions, the frequently adopted definitions of IoT [114] state a network of physical objects –vehicles, machines, home appliances, and more– that use sensors and APIs to connect and exchange data over the Internet. These definitions are suitable for the building facilities and many other application fields. However, a more specialized definition is necessary to reason about its application in the manufacturing field.

Essentially, IIoT can be seen as a specialization of IoT to manufacturing; indeed, the *Industrial Internet of Things* is about connecting all the industrial assets, including machines and control systems, with the information systems and business processes [113].

Concretely, the IIoT refers to "the use of certain IoT technologies – certain kinds of smart objects within cyber-physical systems – in an industrial setting, for the promotion of goals distinctive to industry" [115]. Some short definitions found in the literature review present the concept of IIoT as "*the use of Internet of Things (IoT) technologies in manufacturing*" [116], or "*a short-hand for the industrial applications of IoT"* [117].

In the manufacturing industry, IIoT is relying on wireless devices such as RFID and wireless sensor networks [118] to gather real-time data from the shop floor, such as a machine status, inventory levels, shipment progress, and energy consumption data [119].

4.3. Digital Twin

In the Industry 4.0 scenario, FM is evolving as a consequence of the introduction of new technologies that can enhance the capabilities of roles devoted to the management of structures. The Digital Twin (DT) is one of these disruptive technologies.

A simple definition of DT is "*Digital representation of a real-world object with focus on the object itself*" [120]. This is a general definition that outlines the essential characteristics of this concept. Many definitions highlight the purpose of DT. For example, Bolton et al. [121] define a DT as: "*a dynamic virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning and reasoning*". A comprehensive review of the concept of DT can be found in the work of Negri et al. [122].

DT has been used in manufacturing industries focusing the attention either on the object to produce [123], [124] or on the manufacturing systems [125], [126]. For what concerns the application of DT for facility management in the industrial context, the literature does not offer sufficient references. This point will be addressed by the model proposed in the next section discussing the management of a variety of industrial assets.

The CPPS, IIoT and DT definitions are used in the model presented in the next section, which proposes a high-level model that can be considered for the creation of an integrated system consisting of CPS, DT and Professional maintenance (PM) software, as part of a Facility management system.

4.4. Cyber Physical Production System

In order to make the management of maintenance activities more effective, the view introduced in this section describes some technologies of Industry 4.0 necessary for the creation of an integrated system consisting of CPPS, IIoT, DT, and PPC software.

A simplified version of the view of Figure 12 has first been introduced in [127] for the problem of real-time Production Planning and Control (PPC); the variant illustrated here appears instead in [128] that proposes a contribution to the topic of energy saving during the execution of batch processes[129].

We further contribute to the semantics of the CPPS model by considering an extension of DT that comprises non only the digital representation of structures but also technical parameters necessary for the maintenance. On the other side, the PPC, originally designed to drive the production process, is enriched with functionalities described in the model of Figure 6 and Figure 8 for both the decision process and the maintenance functions.

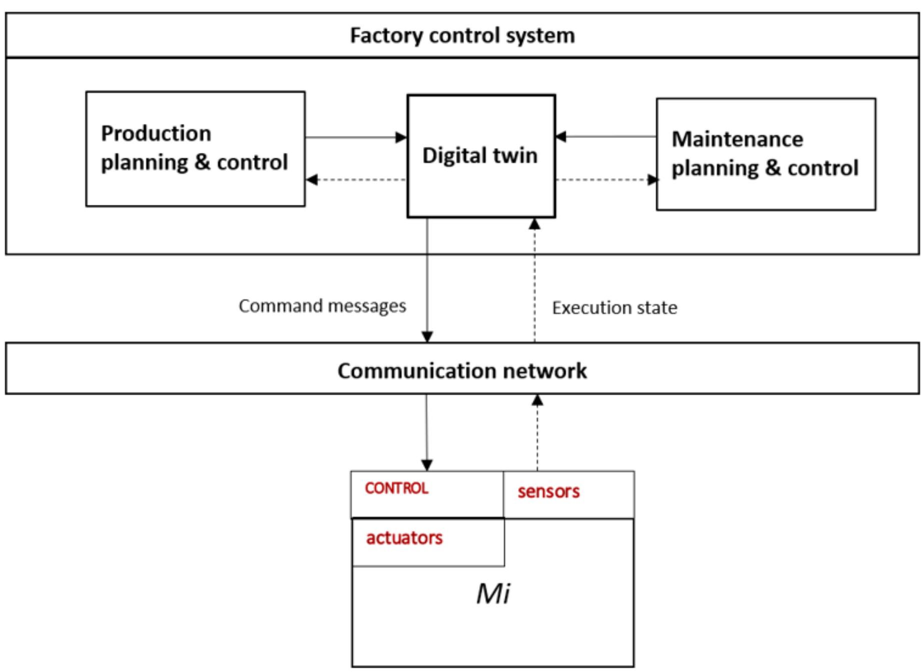


Figure 12. *A schema for the design and implementation of a Cyber-physical production system [128].*

In the presented CPPS, the IoT devices such as smart (embedded) sensors and actuators installed in the machines and connected to the communication network provide important information for the planning of *Condition based maintenance (CBM)* strategies, and to support *Breakdown maintenance (BdM)* activities since they send data on anomalous behaviors in the production process through the DT. This permits operators, through intelligent scheduling systems such as the PPC software, to monitor the machinery conditions instead of their faults and generate early alerts or stop production in case of breakdown, hence anticipating possible failures by self-adjusting their operations at different levels and optimizing the assets utilization.

Similarly, the Maintenance Planning & Control (MPC) module uses the data to define the techniques and methods that can be employed for maintenance in the area of intervention, as well as to manage their execution.

In this way, the CPPS in conjunction with the MPC software contribute to improving the resilience [130] and performance of the maintenance support system and factory control system. Furthermore, the software modules DT, PPC, and MPC, enriched with the functionality of facility management discussed so far, provide support to the application of the methodology described in section 6.1.2.1.

The following section focuses on the study of CPS reference models for manufacturing scenarios, which form the basis of a new complex system metamodel proposed in section 4.6, considering the new technologies available in today's industry context.

4.5. CPS Reference Models

In this section, the 5C and 8C models are briefly resumed. The interaction type metamodel proposed by Nota et at. [131] on which a new proposal of CPPS is based is also described.

In literature, one of the most cited models for the representation of CPS systems is that of Lee et al. [132], which presents the 5C architecture.

5C model: the essential elements of the 5C architecture for each level of Lee's model are:

I. **Smart Connection Level:** it is the architectural level in which all those devices of the IoT are identified, represented and put in communication to enable forms of integration and interoperability between different, distributed and heterogeneous data sources.

II. **Data-to-Information Conversion Level:** at this level, the data is converted into information. It is the level in which the ability to process (pre-process, analyze, interpret, merge, etc.) the data that comes from a machine is implemented. Specific algorithms can be used with predictive purpose to evaluate parameters on the "health status" or on the "prognostic" of the machine (examples: a) RUL or, b) a data or a correlation between data in which an impending breakdown). At this level, the machine acquires self-awareness.

III. **Cyber Level:** it is the central level where the other levels of architecture are intertwined. It identifies all the factory resources that can be managed and participate in the production processes. Each identified resource is then given a virtual representation in order to first represent it and then manage it through specific software subsystems, each characterized by functions that depend on the type of resource managed. From analytical algorithms that use large amounts of data it is possible to obtain additional information.

IV. **Cognition Level:** it is to define what is the useful knowledge to provide and what are the right ways of displaying information with respect to the job of the specific user (e.g., the cognitive load per worker, production manager, manager, etc.). The adequate presentation of the knowledge acquired allows expert users to make appropriate decisions. For example, the priority on what to service can be easily determined based on the individual state of the machines and comparative information. Augmented reality technologies may also be involved at this level.

V. **Configuration Level:** The configuration level constitutes feedback from the context of the digital representation (cyber space) to the context of the physical system (physical space) and acts as supervision and control to make the machines self-configuring and self-adaptive. This level acts as RCS (Resilience Control System) to apply the preventive and corrective decisions, taken at the cognition level, to be applied to the monitored system.

The 5C architecture for the implementation of a CPS proposed in Lee's work differs from those previously described in that it emphasizes the role of factory 4.0. The architecture highlights how, starting from the data collected by machines and sensors, it is possible to obtain large quantities of data (Big Data) from which intelligent applications allow:

a) the improvement of the performance of the industrial process,
b) the resilience and self-adaptability of the machines.

The architecture focus is more on vertical integration and less on horizontal integration, since vertical flow refers to company activities development and execution, including basic elements such as: the organizational structure, human factor, departments relationships, technological and management level; while the horizontal flow includes external relations, establishes supplier and customer networks integration, information and management systems and others [133]. This weakness is also found in ISA 95 and Groover architectures, mentioned in section 2.3 (manufacturing system organization).

A variant of the 5C architecture is the one called 8C, proposed by Jiang [134] for the modeling and implementation of CPS that take horizontal and vertical integration into consideration. The 8C architecture adds three aspects to the 5C called:

- *Coalition:* for the integration of the production system in the supply chain.
- *Customer:* to highlight the role that the customer plays during the design process, production and after-sales interaction.
- *Content:* focuses on extraction, storage, and querying of records for product traceability.

In the next section, a new solution to the formal modeling needs of the CPS that will be used for the development of the project is proposed, since there is still the problem of defining a metamodel that is more than the reference frameworks that have appeared in the literature, and can formally define the components and relationships of a CPS.

4.6. The proposed complex system metamodel

To describe the proposal for a new system metamodel able to represent complex systems as CPS, we first discuss the *interaction type metamodel* proposed by Nota et al. [131], first from a *structural* and then from a *behavioral* point of view. Subsequently, the generalized version of the composite pattern will be integrated into the metamodel to obtain a new CPS metamodel suitable for the digital representation of the factory with an Industry 4.0 perspective.

4.6.1. The Interaction type metamodel

The purpose of the interaction type metamodel is to provide a formalization that includes both the concept of *active entity* and those of *relationship*, *interaction,* and *interaction type,* capable of describing the static and dynamic aspects of a system. First, consider the following definitions:

- *Active entity:* It is an organization, an individual or an automated component capable of performing behavior while interacting with other active entities.

- *Relationship:* Represents a logical or physical connection between the components of a structure. Through relationships, communication becomes possible at the basis of the interaction between active entities.

- *Interaction:* An interaction is a concrete action between two active entities in order to achieve a goal.

- *Interaction type:* It is the structural element that shapes a kind of interaction. This form qualifies one or more interactions in the sense that it provides a description or configuration external to interactions of that type. The structure of an interaction type can be suitably represented considering the structure of messages between active entities.

A set of interaction types concerning active entities delimits the type of actions admissible between them or allows us to limit our attention to the interaction types we are interested in. As for our model, we focus on exchanging messages; this will allow us to represent the exchanges (interactions) between active entities.

An interaction type that participates in the structuring of a relationship can be simple or aggregate. The formalization of an interaction type is as follows:

sitName = {activeEntity1, activeEntity2, goal, messageStructure, constraints}

aitName = {activeEntity1, activeEntity2, goal, setOfInteractionTypes, constraints}

where a *simple interaction type*, called by the *sitName*, represents the structure of an atomic interaction between two active entities in terms of messages exchanged; *goal* is something you want to achieve, and *constraints* act as a guard for activating the interaction type.

An *aggregate interaction type* is a set of two or more interaction types called by its *aitName*; goal expresses the purpose of the entire set of interactions and constraints can be applied to the elements of *setOfInteractionTypes*.

We consider two different times when we refer to a relationship: *construction time* and *activation time*. At the time of construction, the structure of the relationship is defined as a set of interaction types. At the time of activation, systemic behavior emerges in terms of interactions between active entities. These interactions are mediated by the interaction type in the sense that the communication that takes place between active entities becomes possible when the structure of the messages exchanged is compatible with that of the interaction types.

Approaching the diagram in Figure 13 on the side of the relationship, we can say that there is a relationship between two active entities when there is at least one interaction type that connects them. When the structure is created, the interaction can occur (systemic behavior).

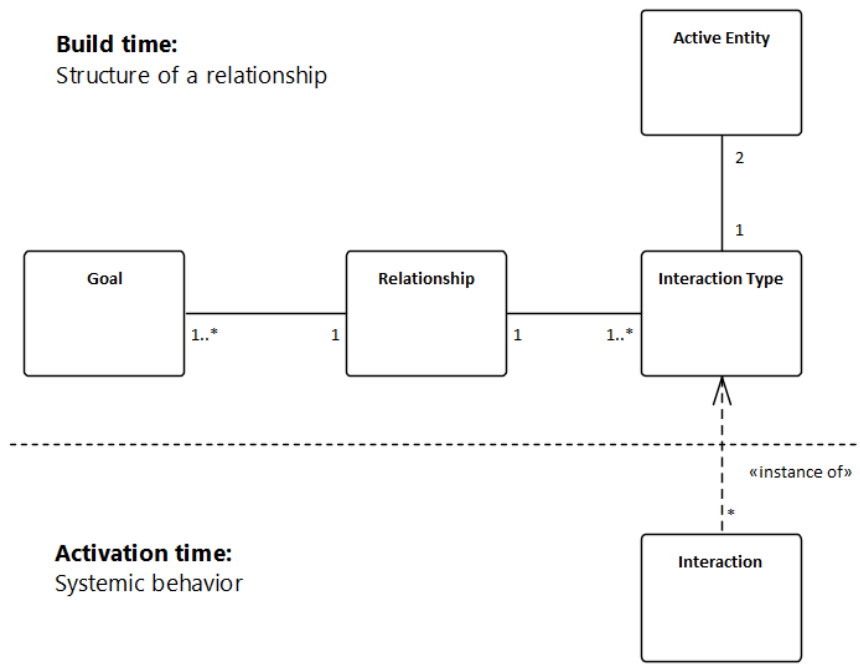


Figure 13. *Description of the interaction type metamodel [131].*

This basic metamodel is general enough to be applied to each of the models presented in the previous paragraphs. In particular, the proposal of this research is to apply it as regards the description of the relationships and interactions between:

a) entities present in the same level, for example level L;
b) entities present between adjacent levels, for example between L and L+1, or between L and L-1;
c) entities present between non-adjacent levels, for example between L and L+2 or between L and L-2.

It should be noted that the formalization of the reports relating to point a) will allow for horizontal integration. Similarly, the identified relationships concerning points b) and c) will allow the vertical integration of factory and/or supply chain components and systems.

The approach adopted in the determination of the new metamodel proposed in this paragraph considers the strengths of the models described so far. It was agreed to start from the Groover model which well represents a production system and control systems that operate at various levels. The Groover model and the ISA 95 model are quite similar, which is why it is natural to combine them in a single model that highlights the strengths of each of them.

The metamodel of the interaction types of Figure 13 will therefore be used to formalize the structural relationships that exist between active entities of the same level and between different levels. The strength of the interaction type metamodel is goal orientation. When two entities act, each goal is identified and represented. In general, the goal of a relationship can be further broken down into lower level goals. Reaching the most basic set of goals allows you to reach a goal at a higher level.

The fundamental requirement of the proposed metamodel is the ability to express, define and represent each entity involved in the architectures described above and, in particular, consider the relevant aspects from an Industry 4.0 perspective.

The metamodel is also capable of representing and classifying all the relationships, types of interaction and interactions that exist between the present entities.

Figure 14 shows the proposed complex system metamodel. Although this complex system scheme can be used to represent a CPS, it is presented in a general form that allows it to be used, after being contextualized in the application domain of interest, in all those situations potentially represented by the metamodel (systems: corporate, physical cyber, corporate information, supply chain information, etc.). It should be noted that for the purposes of contextualization to the application domain, the set of properties associated with *Entity Type*, *Entity Class* and *Interaction Type* are relevant.

A system can be studied in its structural and dynamic perspectives. In this sense, the metamodel of Figure 14 reflects this apparent dichotomy. The upper part of the figure is richer and represents the structural view of a system. The structural view is divided, in turn, into two levels:

1. The metamodel, in light blue color, in which those consolidated concepts of systems theory and, in particular, of the Viable System Approach (VSA) [50], [135] are made explicit. At this level, the exposed concepts are recognizable, belong to every observable system and are therefore expressible at the meta level. For brevity, the suffix "*type*" has been omitted; e.g. "Entity" must be understood as "Entity type" and "Interaction" as "Interaction type".

2. The model, in light yellow color, in which objects, relationships and properties of a system are made explicit in a context (e.g., production planning subsystem rather than equipment maintenance subsystem).

The lower part of the diagram explains the dynamics of the model. Active entities (e.g. a machine tool or a worker) are represented here and interact with each other through an information, energy, or other exchange (Interaction). The interactions are represented in the model so that the implementation of the same can consider the registration of exchanges between active entities, deemed relevant to maintain the state of the system and reconstruct its evolutionary history.

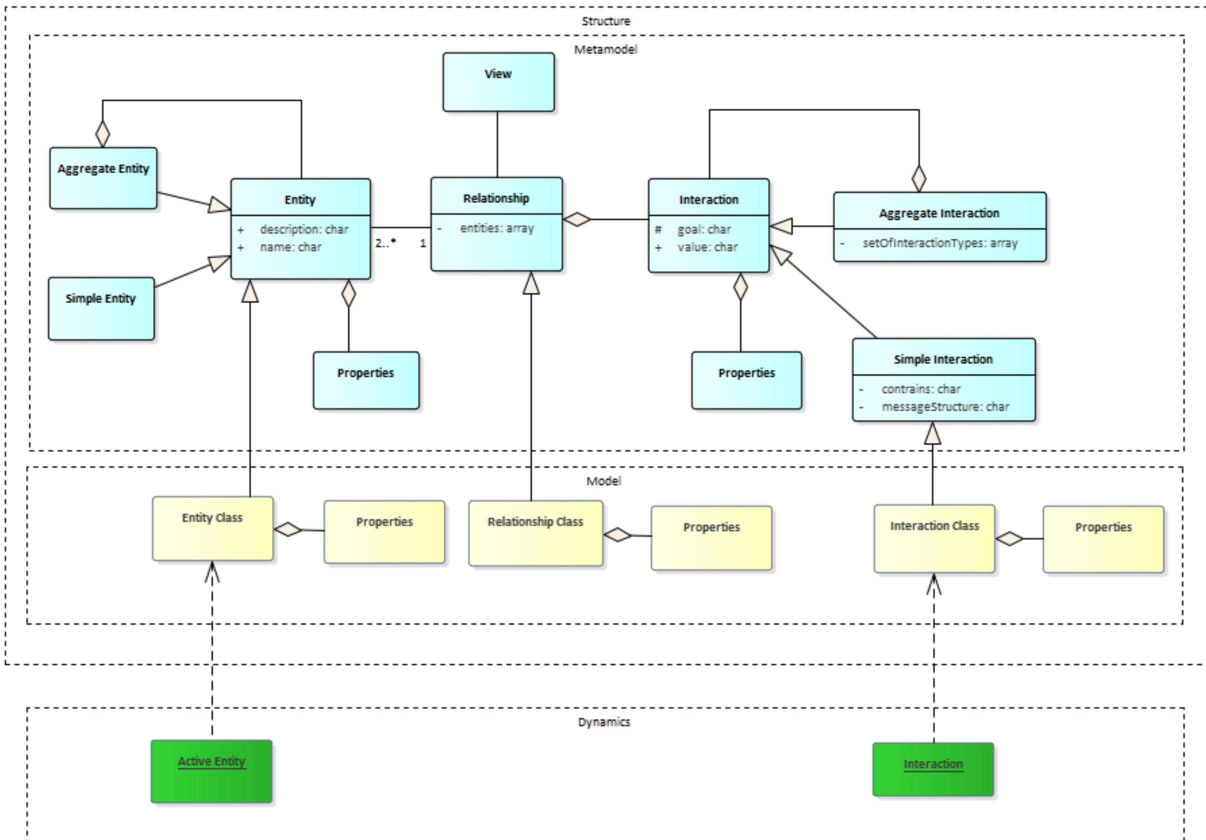


Figure 14. *Structure and dynamic behavior of a complex system: UML class diagram.*

4.6.2. CPS metamodel applications to Smart industry 4.0

According to the nature of the real scenario to be represented and once contextualized in a domain of specific interest, the metamodel (blue in the graph) allows to represent in general the structural and dynamic perspectives of each physical or abstract object of the real world (Entity) together with its properties. This characteristic can be used to explain, for example, the organizational structure of a company, a complex system, a machine or a physical object with all its components, a supply chain or the hierarchical structure of a company's business processes together with their respective control systems, as expressed in the ISA 95 Model.

In different words, the metamodel is able to represent both physical and abstract entities from different points of view (expressed by the metamodel through the *View* element), allowing a better understanding of its shape and behavior in a given situation.

To obtain the above and implement it using a cybernetic system, this structural representation of the system at the meta level must be referred to a real-world context and specified by means of a data model (light yellow) which allows to represent the characteristics of the particular system of interest. In this regard, the Entity class characterizes, in the application context, the set of entities described above (a machine, a company, etc.) considering certain properties or attributes (*Properties*), as mentioned in the previous section.

From the point of view of system dynamics, this model allows us to represent all the interactions existing between entities in the cybernetic system. Interactions must conform to specific predefined types (interaction type) in order for communications and exchanges between active entities to take place.

Dynamic behavior is represented by the interactions that the Active entity elements entertain with other active entities, in an attempt to pursue common purposes. Through the qualification of relationships, types of interaction (structure of the relationship) and interactions (dynamics of the exchange between active entities) it is possible to rigorously specify the control logics of the cybernetic system.

With the above in mind, four application examples of the metamodel are presented below, showing its capabilities to represent both static and dynamic views.

Example 1: Structural representation of the factory (Static View: ISA 95 model)

As already mentioned, through the metamodel it is possible to express conceptual elements, such as those present in the 5 levels mentioned by the ISA 95 model to represent the hierarchical structure of the company, based on roles (Company, Site, Area, Work centers, Work units). The example presented below shows how the metamodel developed can be used to represent the division of the factory into areas and work centers through these abstract entities.

Let us assume that the "Smart Industry 4.0" company exists, made up of different departments, areas, and organizational units. The following branches are managed by the General Management of the company: Site1, Site2 and Site3 with headquarters in different locations. Each Site is made up of various Organizational Units or Areas, such as Production, Logistics, Commercial, Purchasing, IT, Maintenance, among others. The organizational unit can be divided into Work Centers based on the corresponding activity, for example, Production line, Storage, Process cell, etc. Finally, each Work center can contain one or more Work units such as Milling, Cutting, Pressing, Molding, etc.

As can be seen in Figure 15, the structure of the Smart Industry 4.0 company corresponds to a hierarchical organizational model in which the headquarters is Smart Industry 4.0, and the sites, the organizational units, the work centers and the work units are dependent one from the other in the order listed from left to right.

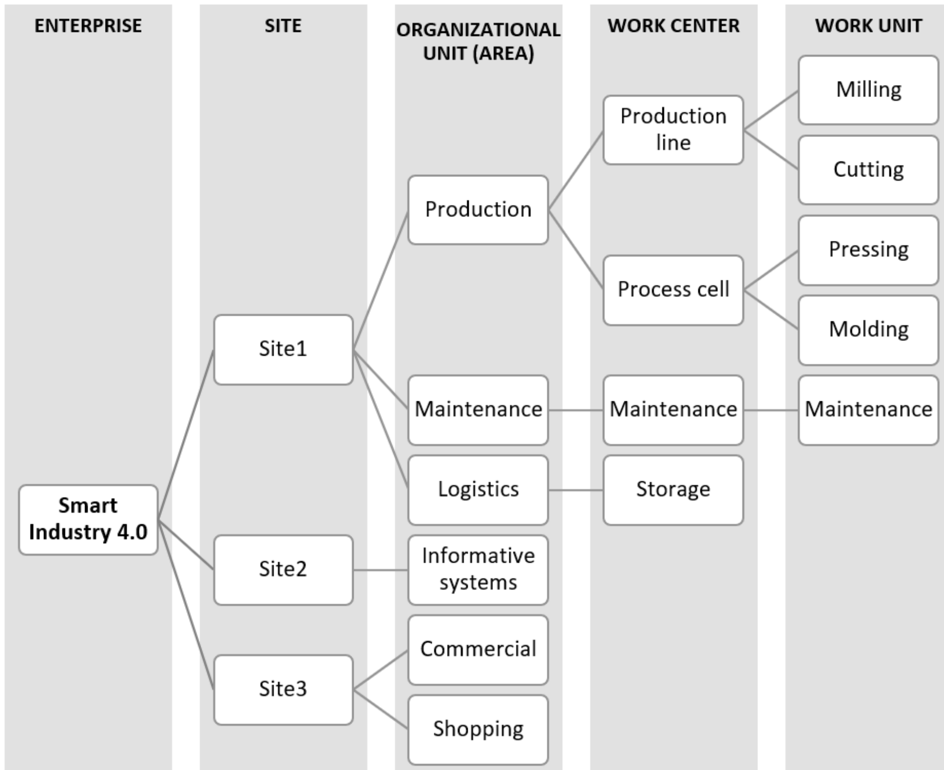


Figure 15. *Hierarchical structure of the Smart Industry 4.0 company.*

Figure 16 below is a diagram showing this hierarchical division for Smart Industry 4.0 companies, through the Entity class and the *Entity class Properties* elements indicated by the metamodel.

Entity Class Properties

Entity class

Entity

Active entity

ENTERPRISE	SITE	ORGANIZATIONAL UNIT	WORK CENTER	WORK UNIT
Smart Industry 4.0	Site1	Production	Production line	Stamping
				Cutting
			Process cell	Pressing
				Molding
		Maintenance	Maintenance	Maintenance
		Logistics	Storage	Storage
	Site2	Informative systems	-	-
	Site3	Commercial	-	-
		Shopping	-	-

Figure 16. *Example of representation of the organic structure of the Smart Industry 4.0 company through Entity class and Properties.*

Example 2: Structural representation of the machine (Static View: Groover model)

The following lines show how the meta-model can represent the structure of the factory and, as a particular case, the census of the machines and their composition. To do this, Table 1 summarizes the information of some of the machines present in the factory, as well as the main properties associated with each of them. For example, multiple values such as Milling, Drilling, Tapping and Boring are possible for the "Machining name" property.

Table 1. *Example of inventory of STAMEC machines.*

Machine	Internal ID	IP Address	Manufacturer	Model	Year	CN brand	CN model	Version	Machining name
Milling Machine	ME1	192.168.49.155	Mecof	CS88	-	Selca	S4045P	1.12.8	Milling Drilling Tapping Boring mill
	ME2	192.168.49.117	Mecof	CS500	-	Selca	S4045P	1.7.2	Milling Drilling Tapping Boring mill
	TE1	192.168.49.55	Tecmu	-	-	Selca	3045	45030131.ITA-F	Milling Drilling Tapping Boring mill
	KI1	192.168.49.103	Kitamura	Mytrunnion 5	2015	Fanuc	300i-B PMC NX00-0F	3-E96807	Boring mill Drilling Tapping Boring mill
	JO1	192.168.49.151	Jobs	Linx	2003	Fidia	C20	V3R1.18	Milling
	MK1	192.168.49.99	Gfac	Mikron HSM 600 U	2008	Heidenhain	iTCN530	340490 04 SP6	Milling Drilling Tapping Boring mill
Presse	MO1	-	Mossini	630Ton	-	Siemens	S7-300; CPU 315	-	Molding
Laser cutting	TR1	-	Trumpf	TrueLaserCell 7040	-	Trumpf	Trumpf Op.Sys- 840D	05.20.00	Cutting

The Machine column (vertical view), is represented in the metamodel by the Entity type element and can represent various types of machines, equipment or devices that have a set of characteristics that differentiate it from the others; for this case, these attributes called by the model as Properties, are the titles of each of the columns that are located to the right of the Machine column (horizontal view): *Internal ID, IP Address, Manufacturer, Model, Year, CN Brand, CN Model, Version, Machining Name*. The latter is a multivalued property because it can change according to the different processes for which the machine has been prepared.

In this way, the titles of each column of the table (metadata) form the structure of the physical cyber system to be represented, using only the Entity type and Entity class Properties elements, which finally, when developing an information system, will be the fields required by its interface. These elements are shown in Figure 17.

Entity type

Properties

Machine	Internal ID	IP Address	Manufacturer	Model	Year	CN brand	CN model	Version	Machining name

Figure 17. *Structural representation of metadata.*

Once the static structure of the system has been formed and the table populated with the information corresponding to each of the machines, the metamodel interprets them as an Entity class element, which allows it to host various types of machines with their respective attributes (data representative of each Properties or tuple).

Therefore, for an instance of the Milling type Entity class as a single Active entity, to take only one case (row highlighted in blue, Figure 18), the following values can be identified for each of the Properties of the machine: Internal ID {*ME1*}, IP address {*192.168.49.155*}, Manufacturer {*Mecof*}, Model {*CS88*}, Year {*2015*}, CN Brand {*Selca*}, CN Model {*S4045P*}, Version {*1.12.8*}, Machining Name {*Milling*}. More examples are presented below in Figure 18.

Entity class Properties

Entity type

Entity class

Active entity

Machine	Internal ID	IP Address	Manufacturer	Model	Year	CN Brand	CN Model	Version	Machining Name
Milling Machine	ME1	192.168.49.155	Mecof	CS88	-	Selca	S4045P	1.12.8	Milling Drilling Tapping Boring mill
	ME2	192.168.49.117	Mecof	CS500	-	Selca	S4045P	1.7.2	Milling Drilling Tapping Boring mill
	TE1	192.168.49.55	Tecmu	-	-	Selca	3045	45030131. ITA-F	Milling Drilling Tapping Boring mill
	KI1	192.168.49.103	Kitamura	Mytrunnion 5	2015	Fanuc	300i-B PMC NX00-0F	3-E96807	Boring mill Drilling Tapping Boring mill
	JO1	192.168.49.151	Jobs	Linx	2003	Fidia	C20	V3R1.18	Milling
	MK1	192.168.49.99	Gfac	Mikron HSM 600 U	2008	Heidenhain	iTCN530	340490 04 SP6	Milling Drilling Tapping Boring mill
									Molding
Press	MO1		Mossini	630Ton		Siemens	S7-300; CPU 315		Cutting
Laser cutting	TR1		Trumpf	TrueLaserCell 7040		Trumpf	Trumpf Op.Sys- 840D	05.20.00	Milling

Figure 18. *Example of structural representation of the factory: census of machine tools using the Entity class and Properties.*

Example 3: Dynamic representation of the maintenance process (Dynamic View: Interaction Type Metamodel)

From a dynamic point of view, the metamodel also has the ability to represent the relationships and interactions that exist between the entities that make up the cybernetic system. This dynamic behavior allows to represent activities and processes of high value for the company, such as those related to the maintenance of the machines mentioned in (Table 1).

To do this, the model uses the Relationship and Interaction type elements to represent the existing relationships between entities and their structure; and the Interaction element, which is the dynamic correspondent of the type of interaction.

From what has been mentioned in section 4.6, it is important to underline that each interaction has a well-defined Goal and that these interactions can be simple or aggregate, allowing to represent through it a set of interactions (setOfInteractionTypes). Similarly, the metamodel states that each interaction can identify a set of properties or attributes, expressed through the *Interaction Properties* element.

On the basis of the above, the example below shows the applicability of the model presented in Figure 14 to represent the problem of Preventive maintenance of the machines. This problem is representative of a larger class of scheduled maintenance types (see section 3.2.2) that can be performed based on various considerations and needs.

Supposing to take as reference the Milling machine *ME1* of Table 1 as Active entity, and *Operator1* as actor responsible for its operation. There is a relationship between Operator1 and ME1 whose purpose is the management of the machine by the operator, through a maintenance activity. The maintenance to be performed is of the *Autonomous maintenance (AM)* type, which can be understood as the set of first level activities performed by the operator before, during and after use of the machine, such as changing the oil or cleaning it.

Table 2. *Example of representation of the Interaction types for the problem of machine maintenance.*

No.	Entity 1	Entity 2	Relationship	Interaction type
1	Operator1	ME1	Maintenance	Autonomous maintenance
2	Operator2	JO1	Maintenance	Autonomous maintenance
3	Internal Maintainer 1	ME1	Maintenance	Time-based maintenance
4	External team of maintainers 1	MK1	Maintenance	Condition based maintenance
5	Manufacturer 1	TR1	Maintenance	Corrective maintenance
6	Operator 3	Robot 1	Maintenance	Autonomous maintenance
7	Operator 3	Robot 1	Maintenance	Time-based maintenance
8	Internal Maintainer 2	Conveyor belt	Maintenance	Time-based maintenance
9	External team of maintainers 2	Press 1	Maintenance	Condition based maintenance
10	Manufacturer 2	Robot 3	Maintenance	Corrective maintenance

In the same way, Table 2 expressed other types of maintenance that require specialized personnel belonging to another organizational unit of the company (*local-first maintenance strategy*), such as *Time-based maintenance (TBM)*, which consists in running the scheduled programs in the specified time interval, for example, every month or every week; or a subcontracted external institution (*second-level maintenance strategy*) as happens in some cases with *Condition based maintenance (CBM),* or when it is necessary to perform *Corrective maintenance (CM)* due to an emergency or a failure that cannot be corrected by internal factory personnel or subcontracted company, and requires the intervention of the original machine manufacturer (*third-party maintenance strategy*).

According to the metamodel, the relationships presented in the Relationship column form an array with the different entities involved in the relationship, in this way it is possible to know the different levels of interaction in which one or more entities participate. In other words, the relationship is formed by the aggregation of interactions between entities that have a specific goal, in this case, to perform the different types of maintenance on the machine.

So, for example, in a level 0 of interaction, the ME1 machine of our previous example is an entity that has a relationship with the Operator1 which has autonomous maintenance as Goal, but in level 1 it can also have a relationship with the *Internal Maintainer 1*, whose Goal is to perform a TBM, which in turn has been programmed by a *Planner* in a level 2, as shown in Figure 19.

In the same way, it can happen with CBM or with CM, activities that can be programmed by a Planner actor and performed by other entities such as the *External team of maintainers 1* or the *Manufacturer 2*, based on certain conditions or needs, as already explained over it.

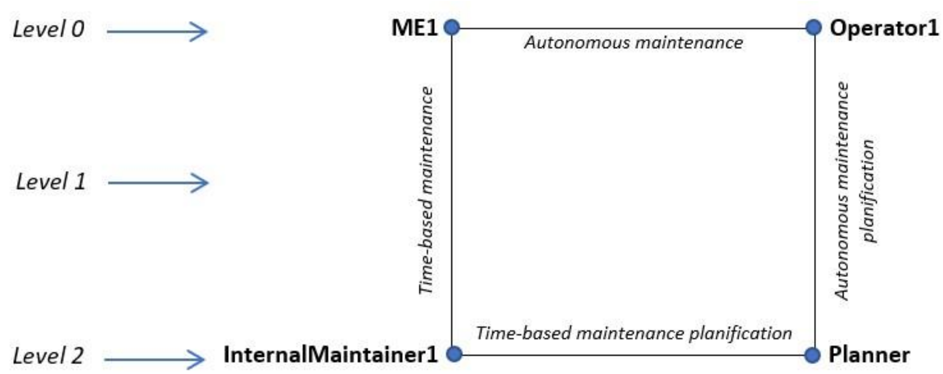


Figure 19. *Representation of the Interaction types between factory entities.*

Once the relationships linking the four active entities and the types of interaction associated with each relationship have been identified, we can say that, in general terms, the maintenance activities of the machines present in the STAMEC plant can be expressed as a set of types of interaction that are connected through a corresponding relationship, which is activated by the exchange of messages at various levels of interaction, as presented in the following reports:

Level 0 (operator1, ME1, atonomousMaintenance)
Level 1 (internalMaintainer1, ME1, time-BasedMaintenance)
Level 1 (planner, operator1, autonomousMaintenancePlanification)
Level 2 (planner, externalTeamOfMaintainers1, time-BasedMaintenancePlanification)

To emphasize the interaction, the metamodel proposes the use of the *Interaction type* element, which, according to Nota et al. [131], it is a Simple interaction type or Aggregate interaction type, in which:

- Simple interaction type, represents the structure of an atomic interaction between two active entities in terms of messages exchanged:

  simpleInteractionTypeName = {activeEntity1, activeEntity2, goal, messageStructure, constraints}

where goal is something you are trying to do or achieve, and the constraints act as a guard for activating such an interaction;

- Aggregate interaction type, is a set of two or more types of interaction:

  aggregateInteractionTypeName = {activeEntity1, activeEntity2, goal, setOfInteractionTypes, constraints}

Therefore, we could say that in our example, the exchange of messages between Active entities, which facilitates an interaction between them to perform a certain goal, can be expressed, in the case of a Simple interaction type, as follows:

timeBasedMaintenanceInstance1 =
{internalMaintainer1, ME1, "Perform Time-based maintenance", <list of maintenance operations>,
start at "2020-07-14-8:00"

in which, the variables present in the structure of the simple interaction type are enhanced in the interaction instance, identified by *timeBasedMaintenanceInstance1*, as follows:

- *activeEntity1 = internalMaintainer1;*
- *activeEntity2 = ME1;*
- *goal = Perform Time-based maintenance;*
- *messageStructure = list of maintenance operations;*
- *constraints= start at "2020-07-14-8:00.*

The Maintainer who must take care of the periodic maintenance (*activeEntity1*) of the ME1 machine (*activeEntity2*) operates through a list of maintenance operations (represented here as messages that flow from the operator to the machine). The constraint that appears in the application establishes that the maintenance operation must be started on July 14, 2020 at 8:00 am. The latter is a constraint that may have been established by the manager of the maintenance department (Planner in Figure 19) during a previous interaction between Planner and Maintainer.

Now, since this project delves not only into the application of CPS and IoT in the development of applications in an industrial-type domain but also in the application of Big Data Analysis techniques, a further explanation of the BDA approach is presented in the next section, with special emphasis on industrial applications.

5. BIG DATA ANALYTICS

The term Big Data Analytics refers to applications of AI, ML techniques, data mining techniques, and time-series forecasting methods, into the way a massive volume of data is acquired, processed, analyzed to extract insight from available data. Hence, the volume, velocity, value, and variety are regarded as four primary attributes of big data [136]. For its part, Analytics denotes the systematic computational analysis of data or statistics, and is defined as a set of technologies, processes and tools that use data to predict likely behaviour by individuals, machinery or other entities [137].

In fact, BDA is set to transform virtually every business activity, bringing opportunities for enhanced customer service, optimized production levels, superior capacity planning, reduced repair and maintenance costs and improved working capital utilization, as argued by Bughin [138].

For these purposes, the most popular categories of analytics according to Davenport and Dyche [139] are *descriptive*, *predictive* and *prescriptive*, as shown in Figure 20. These categories build on each other and enable enterprises to make faster and smarter decisions [140].

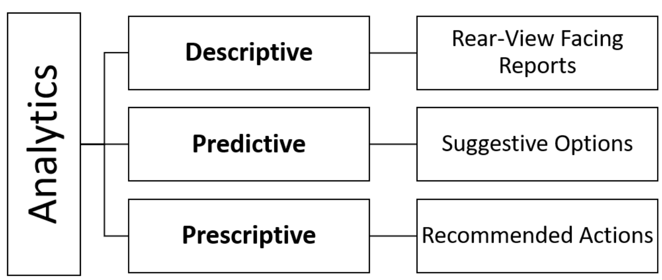


Figure 20. *Key categories of Analytics. Based on [140].*

Descriptive analytics is a process of answering what happened in the past by analyzing historical data through the summarization and description of knowledge patterns using simple statistical methods [141] and summarizing them in charts [142].

The descriptive tasks of BDA identify the common characteristics of data with the purpose of deriving patterns and relationships that exist in the data. According to [143], the descriptive functions of big data mining include classification analysis, clustering analysis, association analysis, and logistic regression.

- **Classification Analysis:** Classification is a typical learning model used in BDA, which aims to build a model for making predictions on data features from the predefined set of classes according to certain criteria. A rulebase classification is used to extract IF-THEN rules to classify as different categories. The examples include neural networks, decision trees and support vector machines.

- **Clustering Analysis:** Clustering analysis is defined as the process of grouping data into separate clusters of similar objects, which helps to segment and acquire the data features. Data can be divided into different subgroups according to the characteristics. The practitioners may formulate appropriate strategies for different clusters. The common examples of clustering techniques are K-means algorithm, self-organizing map, hill climbing algorithm and density-based spatial clustering.

- **Association analysis:** Association model helps the practitioners to recognize groups of items that occur synchronously. Association algorithm is developed for searching frequent sets of items with minimum specified confidence level. The criteria support and confidence level helps to identify the most important relationships among the related items.

- **Regression Analysis:** Regression represents the logical relationship of the historical data. The focus in regression analysis is to measure the dependent variable given one or several independent variables, which support the conditional estimation of expected outcome using the regression function. Linear regression, non-linear regression and exponential regression are the common statistical methods to measure the best fit for a set of data.

The collection and comprehensive evaluation of data from many different sources production equipment and systems as well as enterprise and customer-management systems will become standard to support real-time decision making [144].

The data analysis of previously recorded data is used to find out the threats occurring in different production processes earlier in the industry and also forecast the new issues occurring as well as the various solutions to stop that from occurring again and again in industry [145]. In these purposes, BDA plays a fundamental role in industry production performance, as presented in the following section.

Predictive analytics, is an extension to descriptive analytics where historical data is analyzed to predict the future outcomes. In particular, predictive analytics for prediction combines numerous advanced analytics tools: ad-hoc statistical analysis, predictive modeling, data mining, text analytics, optimization, real-time scoring and ML [146]; become tools that help companies to accurately predict different future events.

In maintenance, it is used to predict type of failure and time to complete failure [142]. The data analysis of previously recorded data is used to find out the threats occurred in different production processes earlier in the industry and also forecast the new issues occurring as well as the various solutions to stop that from occurring again [145]. In this research, clustering analysis was implemented to predict machine failures through the Gaussian Mixtures algorithm, which will be described in section 5.4.1.

Prescriptive analytics is a process of optimization to identify the best alternatives to minimize or maximize the objective, generally, by determining the cause-effect relationship among analytic results and business process optimization policies [141], based on the feedback provided by predictive analytic models [147]. In maintenance, according to Amruthnath and Gupta [142], this can be used to optimize the maintenance schedules to minimize the cost of maintenance.

As shown in this section, intelligent predictive and preventive maintenance are key requirements of large-scale IIoT systems [148]. In this sense, Industrial BDA (IBDA) acquires great importance in the context of IIoT systems, since it allows the application of various methods based on computational intelligence to optimize and improve production systems [149], since its main goal is to maximize production according to customer needs, as mentioned by Saldivar et al. [150].

The IBDA process can help in off-line forecasting (for example, forecasting based on historical data) and online maintenance (e.g., maintaining machines without shutting down production units). This concept is further explained in the next section.

5.1. Industrial Big Data Analytics

BDA is now a vital foundation for forecasting manufacturing and proactive maintenance [151]. Compared to big data in general, industrial big data has the potential to create value in different sections of the manufacturing business chain [152].

As mentioned by Courtney [153], the Industrial Big Data Analytics (IBDA) will focus on high-performance operational data management systems, cloud-based data storage, and hybrid service platforms. The complexity [154] and the concepts of the six V's are also adopted in industrial big data characteristics, which include volume, velocity, variety, variability, veracity, and value. With this adoption, the current data analytics requires new techniques in handling enormous data. As a result, the analytic process becomes complex with massive data from several sources, but helps in the creation of an impactful analytic process and facilitates the decision-making process with easy analysis and accurate prediction results [155].

Technologies such as Hadoop, Spark, MapReduce, SAS, and Rapid Miner offer flexibility, scalability, and good performance to improve the industrial analytic process [156], [157]. As mentioned by Amalina et al. [158], these advanced tools co-exist with programming languages, such as Python, Scala, R and SQL. This coexistence boosts the potential of BDA in transforming unstructured to structured data in many domains. In this research, the Python programming language was used for the implementation of the ML algorithms, in which unlabeled data was used to predict machine data anomalous behavior.

In addition, to carry out data analytics processes in any of its categories (descriptive, predictive or prescriptive), and enable early fault detection, fault identification, health assessment of the machine and predict the future state of the machine in an industrial scenario, it is essential to analyze machine data with statistical and AI techniques. ML approach as one of these techniques is presented in section 5.4.

As this project deals with unlabeled data coming from industrial machines, the main focus has been on the use of unsupervised learning as the foundation of an unsupervised predictive maintenance approach. In this sense, some considerations for PdM in an unsupervised context are presented below.

5.2. PdM in an unsupervised context

The analysis of the literature made in the previous sections frames the problem of maintenance in its various facets. In this section and the following of the work, we will focus on the PdM in an unsupervised context.

The problem of discovering the incoming faults (prognosing) can be seen as a special case of outlier detection, since an outlier is an observation which deviates from the other observations to arouse suspicions that it was generated by a different mechanism [43]. In this field supervised, semi-supervised and unsupervised methods are employed [44].

While Supervised learning provides a clean approach to build ML models, in practice, labeled data in manufacturing is not easily accessible or abundantly available. Unsupervised learning aims to build the representation of a given dataset without any label-based feedback mechanism [45].

In literature, several studies oriented to predictive maintenance using the unsupervised learning approach can be found. Amruthnath and Gupta [142] suggested a methodology using unsupervised learning for rapid implementation of predictive maintenance activity, which includes fault prediction and fault class detection using density estimation via Gaussian Mixture Model Clustering and K-means algorithm [159]. They have also conducted a research study on unsupervised ML algorithms for early fault detection in PdM, using simple vibration data collected from an exhaust fan to fit different unsupervised learning algorithms to test its accuracy, performance, and robustness.

Similarly, Patra et al. [160] considered data collected from the bearing and fit different unsupervised learning algorithms such as the Gaussian mixture model and clustering technique, to check its performance, accuracy, and sturdiness. In conclusion, they proposed a methodology to benchmark different algorithm techniques and select the best one.

For his part, Bao et al. [161] developed an unsupervised learning system of aero-engine predictive maintenance based on Cluster Analysis, aiming to perform predictive maintenance on aero-engines under unsupervised conditions and reduce the cost of traditional periodic maintenance.

In Farbiz et al. [162], a framework based on the concept of cognitive analytics with unsupervised learning for machine health monitoring, anomaly detection, and predictive maintenance is described. The experimental results on an industrial robot demonstrate the effectiveness of the framework in the identified use case.

Kim et al. [163] stated a predictive maintenance framework based on unsupervised learning which can be applied directly in the industrial field regardless of run-to-failure data. The proposed framework consists of data acquisition, preprocessing data, constructing a Health Index, and predicting the remaining useful life. The usefulness and applicability of the proposal were conducted through two different real-life cases: monitor the condition of a pump in a manufacturing plant and, a robotic arm in a production line of automobiles.

However, despite the existence of studies like these conducted in the industrial field, few of them have focused on the manufacturing industry, for which some limitations and challenges had been identified in the literature. The acquisition of relevant manufacturing data is a very common limitation for ML application, as the availability, quality, and composition of the manufacturing data at hand have a strong influence on the performance of ML algorithms [164].

Pre-processing of data also has a critical impact on the accuracy of the results, and a lot of time is spent on preparing the data and extracting information, the reason for which performance problems (low speed, low accuracy, high memory complexity [165]) may occur.

A major challenge of increasing importance is the question of what ML algorithm to choose, a task related not only to the efficiency of the algorithm but also to the cost (to choose buy or develop). The same happens with the interpretation of the results. According to Wuest [164], in some cases, there might be no expert feedback available about the results, which makes it difficult to interpret them.

In this study, our approach focuses on unsupervised context. The goal is to contribute to filling some gaps described in the literature related to the acquisition and analysis of manufacturing machine data through a Big Data and IoT architecture. In particular, we propose an abstract framework for the implementation of PdM in unsupervised learning contexts, which is formed of several steps that are independent of the algorithms used and therefore, provides an abstract structure for testing different unsupervised learning solutions.

However, to enable the implementation of PdM strategies in an industry 4.0 scenario, it is also necessary to have a technological architecture, based on Big Data and IoT technologies that adequately supports the deployment of the developed systems.

5.3. A Big Data and IoT architecture

In this research, Industry 4.0 principles have been adopted for the predictive maintenance of assets, as a critical aspect of companies' efficiency and product quality. Figure 21 presents a generic PdM system architecture designed for the implementation of the project, which is based on the CPS, IoT, and Big Data Analysis (BDA) technologies. This set of technologies is completed with the Internet of Services (IoS) one, which takes the processed information from Big Data tools and deploys it at the right place and in the right form [109]. A real-world application of this architecture was pursued through a case study in an Italian automotive manufacturing industry, which was fundamental for the deployment of a predictive maintenance system.

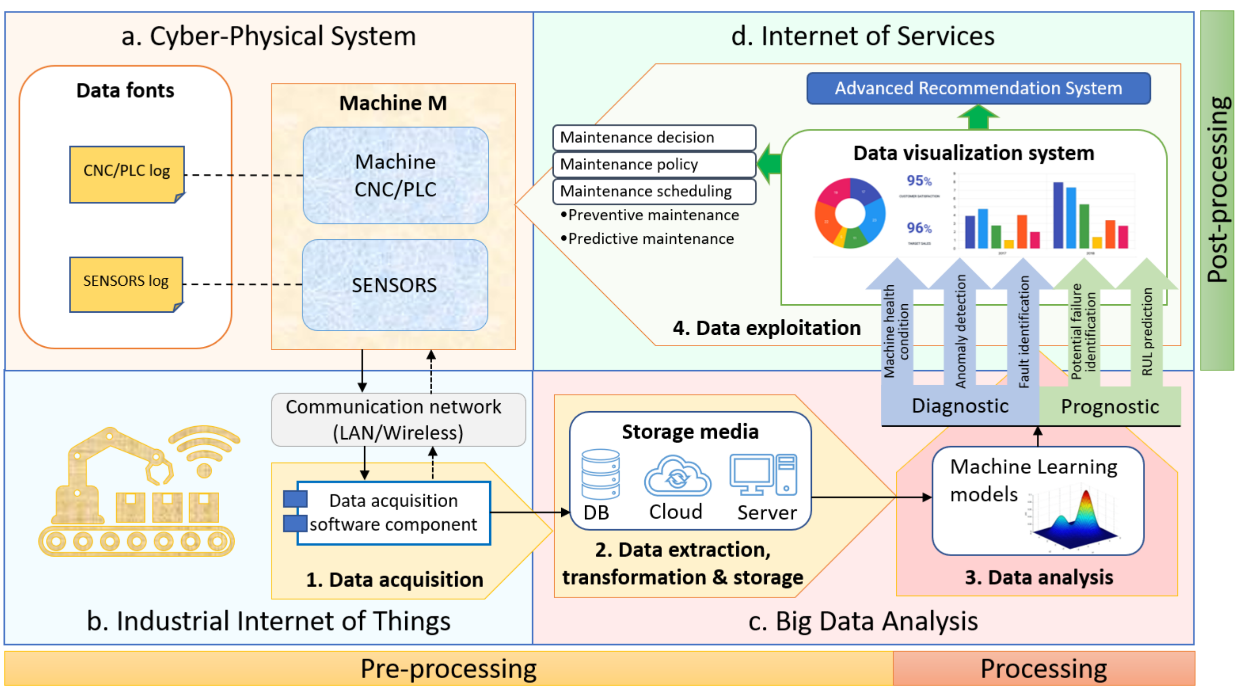


Figure 21. *A generic predictive maintenance system architecture, based on the integration of the CPS, IoT, BDA and IoS concepts mentioned in [34].*

Generally, in the life cycle of Big Data in a data processing environment, it is always necessary to acquire data, store data temporarily or permanently, analyze data and produce outputs/results [166]. Therefore, the methodology for the extraction and analysis of large amounts of data, and the development of an analytical model of industrial big data that can be used for preventive and predictive maintenance, is typically carried out in three major stages: *pre-processing (I),* *processing (II), and post-processing (III).* Inside these stages, the four phases of the Big Data life cycle are contained: *(1) data acquisition, (2) data storage, (3) data analysis, and (4) data exploitation*.

I. **Pre-processing:** this stage is related to the acquisition and storage of data from various sources of information. It involved the implementation of the following phases:

   a. Data Acquisition: in this phase, the data is collected from several sources such as machines CNC (computerized numerical control)/PLC (programmable logic controller), and sensors connected to the machines (energy and vibration sensors). After this, filtering and cleaning data processes are performed before storage.

   b. Storage: once content from mentioned data sources is retrieved, it is stored in a centralized server through a software component developed as an automatic storage mechanism, which allows managing the large-scale datasets with reliability and availability. The stored data is subsequently processed, reorganized, and finally analyzed using big data analysis algorithms, as presented below.

II. **Processing (data analysis):** this stage is mainly related to the preparation of the data obtained in the previous phases for its subsequent analysis and, based on this, to develop the analytical model of Big Data for the preventive and predictive maintenance of the machine. Hence, this stage involves the implementation of the ML model and the algorithm used to process and analyze the collected data for the PdM system. The phases performed to achieve it are the following:

   a. Understanding of data: this activity focused on the analysis of Big data obtained from the log files of machinery and sensors, structured in a single information repository that can later facilitate its analysis. This task requires separating, grouping, and filtering the data into a subset of variables in which the analysis is to be performed.

   b. Cleaning and pre-processing of data: before the analysis, duplicated data, errors, and states where the machine does not work are removed, since this data does not provide useful information and can be considered as noise. In the same way, data showing the same semantic information can be merged, so that the analysis can be performed more effectively.

   c. Modeling and algorithms: it consists, in this architecture, in the development of an ML analytical model for preventive and predictive maintenance. Details of the analytical model of big industrial data implemented will be presented in the section describing Gaussian Mixtures (GM) as an indication of machine anomalous behavior.

III. **Post-processing (data exploitation):** this stage concerned the exploitation of the results of the performed analysis employing the following phases:

a) Data interpretation: it includes the interpretation of the discovered patterns, as well as the visualization of the extracted patterns.

b) Data communication/visualization: the knowledge acquired is organized and presented so that the client can use it. To achieve this, thresholds are created and used in the visualization tool with the aim of instant communication with all the involved stakeholders, and thus help them to identify patterns, trends, and correlations.

c) Evaluate the results: the results are evaluated to verify the effectiveness of the approach and to find improvement opportunities, allowing new and better functionalities to be subsequently integrated from feedback mechanisms.

As presented in Figure 21, the execution of the life cycle of Big data analysis within the technological architecture established through CPS, IoT, and IoS devices and applications occurs as follows: the integration of systems of sensors and actuators with the machine turns the machine into a CPS (quadrant *a*, upper left) capable of obtaining production data through its management systems, which corresponds to phase 1 of the Big data analytics process: *data acquisition*. Through a communications network, IoT technologies and, a developed data acquisition software component (quadrant *b*, lower left), this information is received and sent to a central server, database, cloud system, data warehouse, or any other storage solution, as part of phase 2: *data extraction, transformation, and storage.* These first two processes constitute *stage I* of the life cycle of Big Data: *pre-processing*.

Once the data has been stored, Big data analysis (quadrant *c*, lower right) processes through ML algorithms can be performed to diagnose machine health conditions, anomaly detection, or fault identification; as well as to prognosing potential failure identification or RUL prediction. This corresponds to phase 3: *data analysis*, which is performed in *stage II*: *processing*.

Finally, in the IoS (quadrant *d*, upper right), data visualization, as part of phase 3: *data exploitation*, enables maintenance responsible to make informed maintenance decisions, establish maintenance policies, and plans preventive maintenance activities. In this way, *stage III*: *post-processing* is carried out with the help of specialized data visualization tools.

5.4. Machine Learning for predictive analysis

ML refers to the process of teaching a computer system by exploring patterns and discovering inferences among data without the use of explicitly programmed instructions [136], that is, an algorithm that is capable of learning with minimum or no additional support. In maintenance, ML can be used to predict potential faults and future equipment conditions (prognostics).

ML algorithms are commonly divided into supervised and unsupervised models [136]. The supervised models predict the future events from learning models that are trained using labeled data points [167], while unsupervised models are trained on all data points and are mainly used for data clustering. In this research, given unlabeled data coming from industrial machines, the main focus has been on the use of unsupervised learning as the foundation of an unsupervised predictive maintenance approach.

In this sense, the problem of PdM using unsupervised learning was approached with the definition of a framework with several abstract steps, which aims to provide an abstract structure for testing different unsupervised learning solutions. In Figure 22 it is shown the definition of the proposed approach at an abstract level; the abstract steps are independent of the decision of the algorithm and evaluation metrics to be used, and therefore different techniques could be used and tested in different contexts.

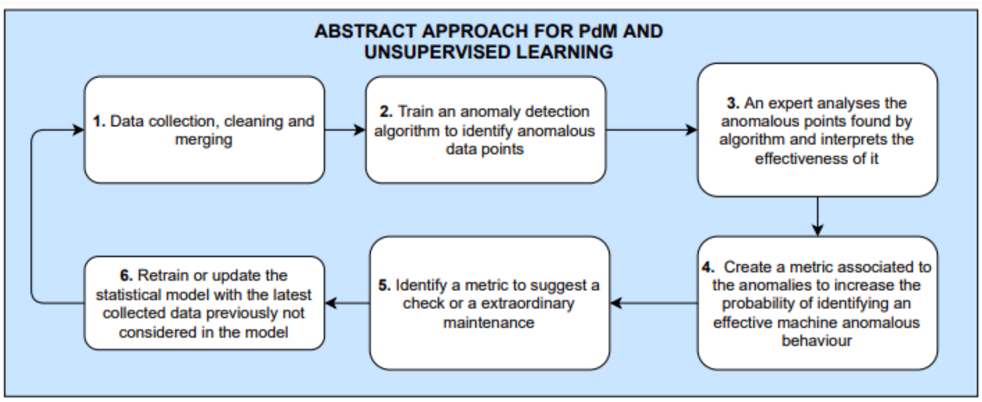


Figure 22. *The framework for PdM in an unsupervised context.*

Based on the framework and according to the characteristics and behavior of the variables used in this research which correspond to energy and vibration data, we have used clustering to group points based on a defined algorithmic criterion. In particular, we have chosen the Gaussian Mixtures model and trained it for detecting anomalous data points, as mentioned in the next section. The unsupervised model for anomaly detection represented a crucial step in our approach used to support predictive maintenance capabilities.

5.4.1. Gaussian Mixtures as an indication of machine anomalous behavior

The GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in several systems [168]. GMM is one of the most popular data clustering methods where each cluster obeys Gaussian distribution and the task of clustering is to group observations into different components through estimating each cluster's own parameters [169].

GMM parameters are estimated from training data using the iterative *Expectation-Maximization (EM)* algorithm [168], a general method of finding the *Maximum Likelihood Estimation (MLE)* [170], which is used to estimate the parameters of an assumed probability distribution, given some observed data.

GMM can be used as an anomaly detection algorithm. In particular, an anomaly is a point in space that does not belong to any cluster. The anomalous points can be further processed to obtain a metric for an effective and probable anomalous behavior of the machine.

The discussion of how the GMM is used in a particular industrial application is further explained in the case study of the next section.

6. CASE STUDY

The case study was conducted in a mechanical company in the manufacturing industry to validate the effectiveness of the developed approach on preventive and predictive maintenance, which attempts to improve the facility maintenance management activities through the implementation of Industry 4.0 technologies.

First, the application of the FMM and the proposed methodology is illustrated in this section, which attempts to improve the facility management activities through the implementation of CPPS and IIoT technologies.

Then, unsupervised ML techniques are applied with the goal of fitting a ML model able to support the prediction of machinery degradation. In this sense, we developed a software system oriented to CbPM of machinery with the adoption of sensor systems as part of a CPS that comprises two milling machines.

6.1. Facility Maintenance Management

The application of the FMM and the proposed methodology to a mechanical company in the manufacturing industry is illustrated in this section, which attempts to improve the facility management activities through the implementation of CPPS and IIoT technologies. The AS-IS scenario is shown first, followed by the TO-BE scenario where the implementation of the CPPS and the application of the methodology steps are described.

6.1.1. The AS-IS scenario

As shown in Figure 4 of section 2.4.1, the organizational structure of the STAMEC production company, which produces moulds for automotive, electro-sanitary, and household appliances, is divided into administrative and production functions.

Accounting and financial, staff, sales, safety and quality areas are staffed by the Company Management and are structured into administrative organizational units. Design, manufacturing, warehouse and maintenance are managed by the Production department. The company has two production plants: one located in the main office, which deals with the production of small and medium-sized mechanical molds and the other, decentralized, dedicated to the production of large molds.

The analysis of the AS-IS scenario highlighted that the company had very simple maintenance procedures, such as autonomous and breakdown maintenance directly managed by the production department, together with a low level of computerization. A more detailed representation of this structure through the CPS metamodel proposed in section 4.6 is presented below.

6.1.1.1. Structural representation of the STAMEC factory (Static View: CPS Metamodel)

The flexibility of the metamodel allows us to represent the structure of the STAMEC company, which is made up of a different organizational model from the ones presented in section 4.6.2.

Figure 23 below shows the two large Organizational Units of the company: *Administrative and General Direction*, and *Production Direction*. These, in turn, group various *Support Units*: Accounting and Finance, Staff, Shopping, Safety and Quality, Sales, R&S, and General secretary as part of the first Organizational unit. General services, Maintenance and Warehousing, as part of the second Organizational unit.

The Production Direction Organizational unit is subdivided into *Organizational Unit of Line*, which includes: Technical office, between 0 and 85% mold production line, prototypes, pre-series and series production; and 85-100% mold production line, assistance and series production. Finally, the Organizational Unit of Line group supports units such as: CAM, Machine tools, The realignment, MAP, Metrology and Mass production.

Entity class properties

Entity type

Entity class

Active entity

ENTERPRISE	ORGANIZATIONAL UNIT	SUPPORT UNIT	ORGANIZATIONAL UNIT OF LINE	SUPPORT UNIT
STAMEC	ADMINISTRATIVE AND GENERAL DIRECTION	Accounting and Finance	-	-
		Staff	-	-
		Shopping	-	-
		Safety and Quality	-	-
		Sales	-	-
		R&S	-	-
		General secretary	-	-
	PRODUCTION DIRECTION	General Services	-	-
		Maintenance	-	-
				-
				-
		Warehouse	-	-
				-
				-
		-	Technical office	-
		-	0-85% mold product line, prototypes, pre-series and spare parts	CAM
				Machine tools
				The realignment
		-	85-100% mold product line, assistance and series production	MAP
				Metrology
				Mass production

Figure 23. *Organizational structure representation of the STAMEC company through the CPS metamodel.*

In the same way, the metamodel contemplates the existence of single entities such as a sensor, a component or a part of a machine and uses the Simple entity element to indicate them as an Entity type. The use of the Aggregate entity symbolizes those entities that can be composed of different components, for example a machine consisting of the union of several parts or a production line, consisting of a certain number of machines, robots, control devices and communications, among other elements that are part of the line.

It is important to note that each element of the structure contains a well-defined set of attributes, represented by the metamodel with the Properties element. This individualization of the components together with their properties or attributes is fundamental for the problem of preventive and predictive maintenance, since having the data of each device in real time will allow to know the health status of the machines at all times, to carry out the maintenance activities in a timely and manage these company assets more efficiently.

In this sense, the use of sensors is relevant for the automation of the process as it will allow us to continuously and uninterruptedly collect the information of each device, which will be available for later use, ideally, by a software that allows the management of the machine register, which is called *Machine Ledger*.

6.1.2. TO BE scenario

During the implementation of the SMART Industry 4.0 project, STAMEC decided to change the organizational structure, inserting a new Facility Management OU in the administrative department compliant with the one shown in Figure 6.

At the same time, a CPS was implemented for the improvement of production performance. This provided the opportunity to use the technological substrate to implement ad hoc software for the preventive maintenance of two pilot machines.

6.1.2.1. Planning and executing maintenance operations

The step-by-step methodology for FMM presented in section 3.3 was implemented based on two main phases: planning time, and operation time. The development of the methodological steps required the creation of a specific software application described below ("make or buy" choice of the model in Figure 6). The main activities carried out in each of the points of the methodology are summarized below.

- Planning time
  a) Focus on the area of intervention and identify the roles to be allocated: the application developed for the management of maintenance activities emphasizes the area of intervention (organizational unit, work center, work unit) and the type of intervention (electrical, electronic, hydraulic, mechanical) according to the type of machine or asset to maintain. Likewise, the access levels to activities are determined according to specific planning (Planner) or execution (Maintainer) roles. As well, for the execution of maintenance activities, specific skills are required according to the type of intervention, which is why the application is capable of selecting only maintainers who have the appropriate skills to perform it, as shown in Figure 24. When these skills are not available, or they are highly specialized activities that are not typical of the organization's internal maintenance team, outsourcing should be done.

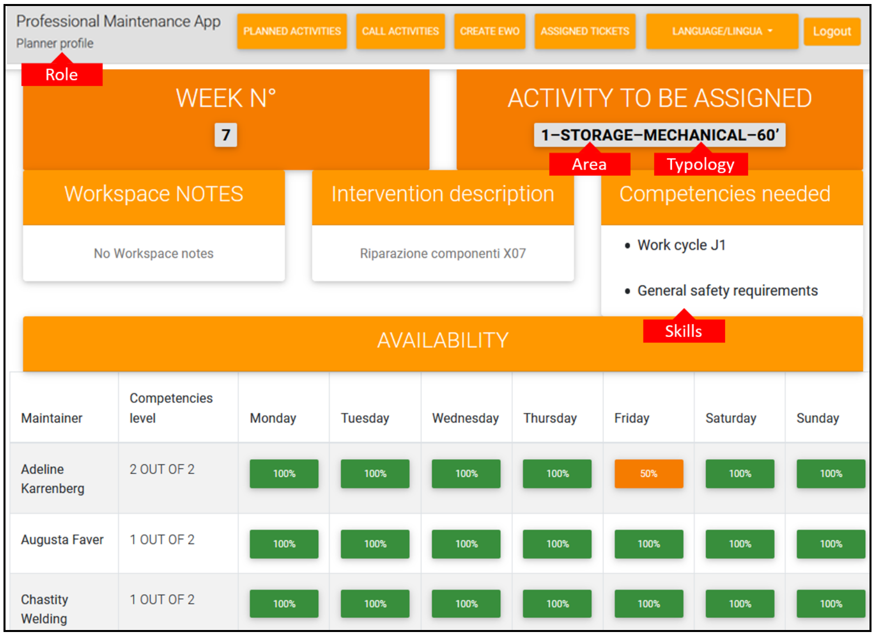


Figure 24. *Software application example to support the weekly maintenance planning processes.*

b) Select the management methods for the area of intervention: the machine considered in this case study was maintained periodically, and, therefore, was following a time-based maintenance approach, however, the necessity of preventing production stops when the machine presented considerable problems required the management to shift to a preventive maintenance method.

c) Acquire detailed knowledge about the appropriate technology for the object/system to be maintained: on the machine, two sensors measuring the temperature and the vibrations have been installed. The data has been used by an anomaly detection algorithm that identified anomalous temperatures and vibration rates, allowing to know the state of health of the machine.

d) Plan the management activities for the object/system: planning preventive maintenance activities based on the results of the aforementioned algorithm is performed at this point. The information obtained facilitates decision-making processes aimed at avoiding future problems, such as the possibility of carrying out pre- or post-production maintenance to reduce the need to stop production for longer due to faults that could be avoided. In this way, CBM strategies were planned based on the condition of the machines, and PdM strategies could be implemented in the future.

- Operation time

e) Implement management support hardware/software systems and big data technologies/techniques: a software application as presented in Figures 25 and 26 was developed that supports the management, planning, and recording of the execution of preventive and corrective maintenance activities of the machines, considering aspects *a)* and *b)* related in the planning time phase. An example of the time recording of a performed maintenance activity is shown in Figure 25, while Figure 26 is related to the selection of one of the following root causes for closing EWO when a BdM strategy is applied: RC1: External factors, RC2: Human error, RC3: Design defect, RC4: Insufficient maintenance, RC5: Wrong operating conditions, RC6: Lack of basic conditions. Both examples are performed by a user with the Maintainer role.

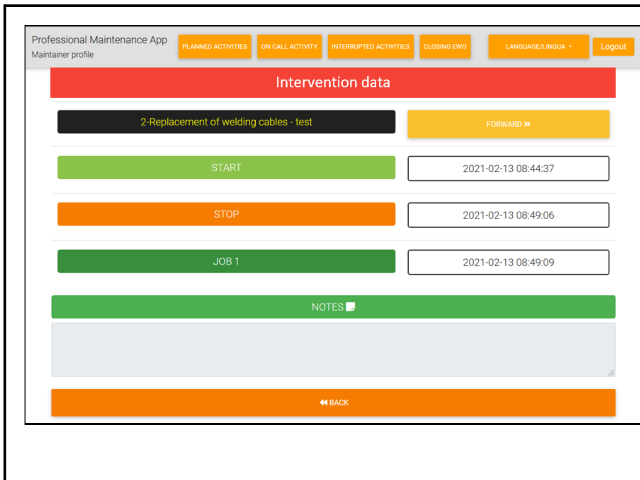


Figure 25. *Maintenance activity time register.*

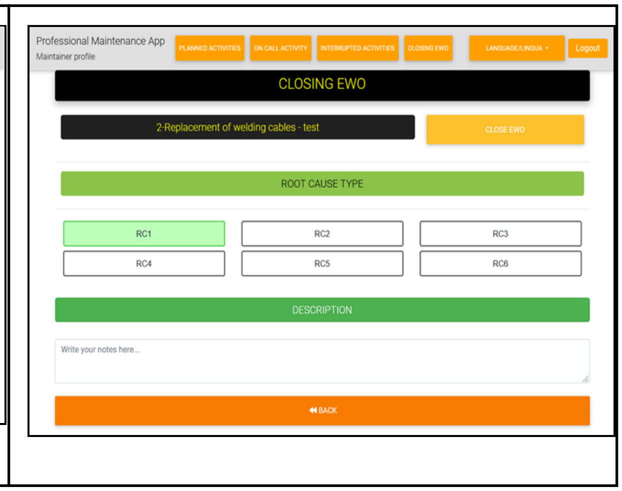


Figure 26. *Root cause selection for closing EWO.*

Similarly, based on the CPPS proposed in Figure 12, sensors were installed in the machines to capture and analyze in real-time the information related to the machine health condition and plan the corresponding preventive maintenance strategies, as mentioned in points *c)* and *d)* of the methodology.

f) Measure, monitor, and control the object/system: the integration of hardware and software systems for monitoring the health conditions of the machine, through IoT devices as smart sensors, as well as the control of the data obtained, allow the generation of early emergency alerts in the event of data indicating a problem, for example, spindle temperature too high, machine downtime detected by a sensor while the machine was running, or even the deterioration of the performance of the machine detected by an accelerometer and an energy sensor. This facilitates the early detection of anomalies and the prevention of failures through the execution of preventive maintenance activities, as CBM.

g) Execute the maintenance activities & h) Feedback the process: once the maintenance activity is performed, the Maintainer must carry out a feedback process that allows continuous improvement of the maintenance planning and operation processes, which directly reaches the Planner role.

It is worthwhile to observe that thanks to the CPPS, the information related for example to machine stops due to failure or deterioration of the functioning of the machine, reaches the planner directly coming from the sensors. This signal immediately activates the process of assigning the EWO to the maintenance technician through the maintenance management software developed, significantly reducing the time of assigning the maintenance order for the machine out of production. On his part, the technician receives the information detected by the sensors together with the maintenance order on his tablet/mobile device, also making it possible to decrease the attention time by intervening more quickly. In this way, it is possible to improve productivity by reducing the time and costs associated with repairs.

Similarly, in the case of degradation or deterioration of the machine's operation, the most appropriate preventive maintenance times can be planned to extend the life cycle of the machines. An example of this is the so-called "opportunistic strategies", where on a line that stops, simple preventive maintenance operations are carried out even on machines other than the one that caused stopped and have shown a degradation through the sensors.

In this sense, the next section presents the PdM system model designed for the implementation of our approach on a milling machine. In the following, the discussion is focused on a single milling machine. The method, models, and used technology can be applied to other milling or lathes machines as well with little or no variation.

6.2. Machinery Maintenance

The first step of the analysis was to structure the problem by mapping the Archimate views with the classification proposed by Groover for the automation and control of manufacturing industries.

According to Groover, the automated systems and the corresponding control systems can be applied at different levels of factory operation, as presented in section 2.4; therefore the proposed model is structured in five levels numbered from 1, the device level in which sensors, actuators and other hardware elements are located, up to 5 which is the level of the information system of the industry.

As for the Archimate model of the proposed maintenance system (Figure 27):

- The enterprise level (5) corresponds to the set of *Business* and *Application* views. As far as the objectives are concerned, the company's Management wants to reduce machine downtimes and as drivers and capabilities we can identify those for improving FM and, in particular, maintenance of machinery. The main intervention is then carried out on the Preventive maintenance and Predictive maintenance processes.

- On the application side, we will work by modifying the pre-existing software applications for preventive maintenance and introducing software for the preventive analysis of malfunctions.

- The entire production plant is considered as a *Factory level*.

- *System level* is considered to be anything related to the implementation of the new company Maintenance system, in particular, the set of industrial machines concerned, and the sensor systems applied to them, plus the control software.

- The *Machine level* focuses on the individual industrial Machine and the control systems connected to it.

- Finally, the *Device level* focuses on the system of sensors installed on the single machine.

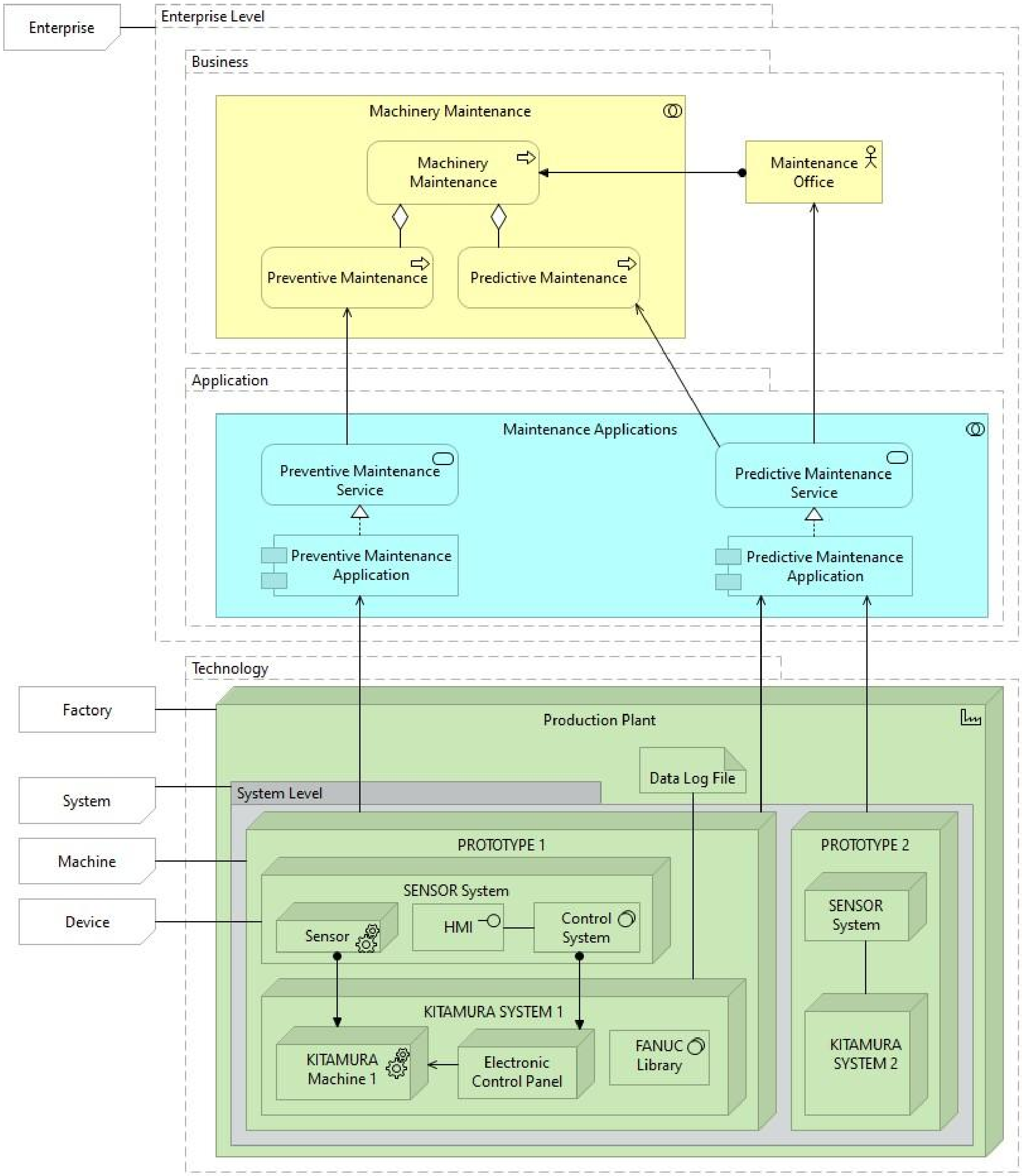


Figure 27. *Mapping of the Maintenance system according to the Groover classification.*

6.2.1. A predictive maintenance system model

In this section, we present the PdM system model designed for the implementation of our approach on a milling machine. A milling machine is used to remove metals from the workpiece with the help of a revolving cutter called a milling cutter.

Due to the operating characteristics of the machines, we decided to analyze the energy, acceleration, and velocity variables, since they are associated with some of the main reasons for failure in this type of machine. The developed software stores and analyzes the data collected from machines and visualizes potential energy and vibration anomalies, the latter as a possible consequence of alterations of acceleration or velocity.

As shown in Figure 28, the prototype created as a PdM system is based on KITAMURA milling machines with CNC. Energy and vibration sensors have been applied to these machines for energy and vibration monitoring and analysis, since these sensors take care of measuring parameters that change according to modifications and disturbances in the mill process.

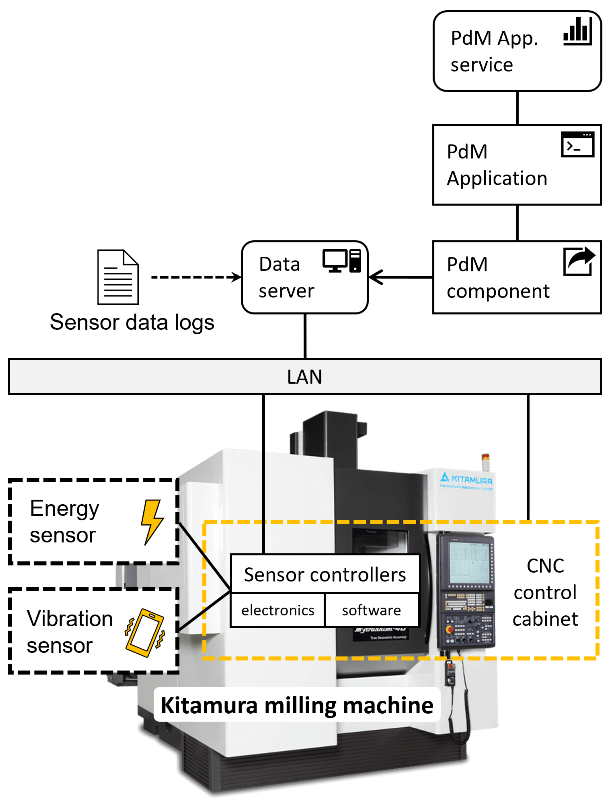


Figure 28. *The predictive maintenance system model for the case study.*

The sensors were connected directly to the machine, while the sensor control devices, divided into physical devices (the Electronics) and the control software, were inserted in the machine control cabinet, which also houses the numerical control system. These sensors are connected to a local network, which becomes part of a CPS as shown in quadrant a of the architecture presented in Figure 21. In turn, IoT techniques are used to retrieve the information collected from the sensors and send it securely to a centralized server.

The preventive maintenance application is served by a software component that directly accesses the data server. In this way, the data produced by the sensors (Sensor data logs) are first read and then processed to analyze the machine's performance. The Big Data Node-Red framework has been used to manage this networked data in daily and sensor-wise synchronized CSV files (see quadrant b of the architecture).

Once the massive data produced in the factory is rendered into a more concise and informative form, it is used to train and fit an anomaly detection algorithm, which identifies anomalies in the data. For the specific case of this study, the GMM was implemented according to the abstract steps of the framework for PdM in unsupervised learning. The data processing phase, presented in the next section as part of quadrant c of the architecture, describes a particular instance of the abstract framework focused on the data analysis process.

Finally, through a developed IoS utility represented in Figure 28 by the PdM application service (data exploitation as part of quadrant d of the architecture), the anomalies extrapolated from the data are represented temporally as the sum of the anomalies in a defined time interval, and graphically shown to the maintenance responsible to carry out informed maintenance scheduling activities. In case of excessive acceleration, velocity, or energetical alterations during machine operation, the application triggers the appropriate alerts as necessary, which can be related to preventive checks or extraordinary maintenance. In this sense, the CbPM approach is being implemented. The next section further describes the application of the abstract framework focused on the data analysis process, as part of the generic PdM system architecture presented in section 5.

6.2.2. PdM approach implementation

This section presents details of the practical application of the theoretical concepts introduced before, following the execution of the activities corresponding to the three major stages indicated in the Big data and IoT architecture of Figure 21: pre-processing (I), processing (II), and post-processing (III). This includes the implementation of the abstract framework which supports the data analysis process as part of stage II, where the GMM was used as the anomaly detection algorithm.

I. Data collection and pre-processing

As part of the Data collection phase, industrial machine data in this research was collected from the machines CNC using energy sensors and vibrational sensors. Among the numerous variables returned by the energy and vibration sensors, for the purposes of this work we have selected those described in Figure 29. The energy sensors collected the tension (Volts), current (Amperes), and power (Watts) data every 200 milliseconds; while the vibration sensor collected acceleration, velocity, and displacement data every 100 milliseconds.

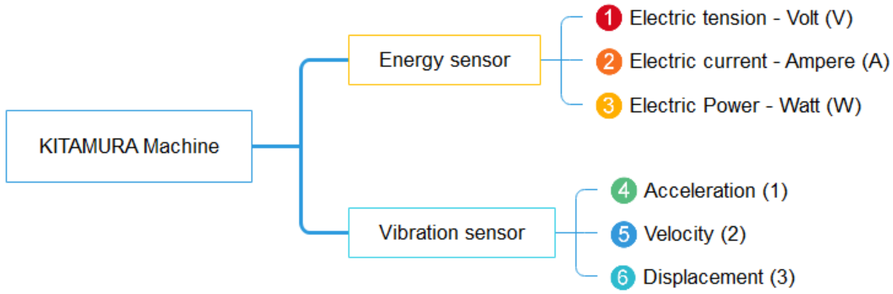


Figure 29. *The collected industrial machine data.*

Voltage and current values correspond to data of a three-phase power installation. We also have the value of average voltage, average current, and total power respectively (Vsis, Asis, and PAtsis), as well as the timestamp. Figure 30 shows an extract of the energy data log.

KI2-SENTOT-2021-04-08.txt

variable_type	phase	value	time
Volt;	V1N;	109.41230010986328;	1617860515395
Volt;	V2N;	109.64459991455078;	1617860515395
Volt;	V3N;	109.59760284423828;	1617860515395
Volt;	V12;	189.4940948486328;	1617860515395
Volt;	V23;	189.93141174316406;	1617860515395
Volt;	V31;	189.8134002685547;	1617860515395
Volt;	Vsis;	189.74876403808594;	1617860515395
Current;	A1;	16.780000686645508;	1617860515395
Current;	A2;	18.440000534057617;	1617860515395
Current;	A3;	16.200000762939453;	1617860515395
Current;	AN;	0;	1617860515395
Current;	Asis;	17.139999389648438;	1617860515395
Power;	PAt1;	1511.81005859375;	1617860515395
Power;	PAt2;	1546.239990234375;	1617860515395
Power;	PAt3;	1306.18994140625;	1617860515395
Power;	PAtsis;	4364.240234375;	1617860515395

Figure 30. *Energy data log.*

On the other hand, Figure 31 shows the data contained inside the acceleration, velocity, and displacement data log, where the machine state indicates whether the machine is running (1) or is stopped or turned off (0). As an example of the cleaning process, the data that do not offer a significant contribution to the analysis are removed or not taken into account, such as those corresponding to machine state 0, since they do not generate any variation in the machine acceleration and velocity measurement.

log-110-2021-04-08.txt

machine_state	time	variable_type	max_value	min_value	max_value_media	min_value_media
0;	1617857920;	1;	0,00;	0,00;	0,00;	0,00
1;	1617857954;	3;	2,00;	0,00;	2,00;	0,00
0;	1617857954;	0;	0,00;	0,00;	0,00;	0,00
1;	1617857964;	2;	4,00;	0,00;	4,00;	0,00
1;	1617857964;	3;	6,00;	0,00;	6,00;	0,00
0;	1617857964;	0;	1,00;	0,00;	1,00;	0,00
1;	1617857967;	3;	2,00;	0,00;	2,00;	0,00
0;	1617857967;	0;	1,00;	0,00;	1,00;	0,00
1;	1617857981;	3;	2,00;	0,00;	2,00;	0,00
0;	1617857981;	0;	1,00;	0,00;	1,00;	0,00
1;	1617857981;	2;	2,00;	0,00;	2,00;	0,00

Figure 31. *Acceleration, velocity, and displacement data log.*

For each of the vibration sensor variables (variable type: acceleration-1, velocity-2, and displacement-3), the data has been obtained as a summary of the original signal. The original signal was divided into intervals and each interval was summarised with the following values: maximum value, average of highest values, minimum value, average of lower values, and timestamp.

The data collected by the energy and vibration sensors was sent to the data server on the local network. The data server is responsible for filtering and cleaning out the data incoming from sensors while the machine is not running and organizing the data in CSV files related to a single day. The file format CSV has been chosen for both its flexibility and its low storage requirements.

After collection and cleaning, the data is requested by a centralized server by means of a shared Samba directory on the network (for accessing the energy data) and an HTTP request (for the acceleration, velocity, and displacement data). Several access mechanisms are due to the different knowledge of the developers working on the project. The different collection mechanisms give the possibility to maintain independence among teams working in the data collection and cleaning from different sensors.

II. Data processing

To carry out the *Data analysis* phase established by this stage, we derived from the abstract framework presented in chapter 5 a particular instance using GM and ML as shown in Figure 32.

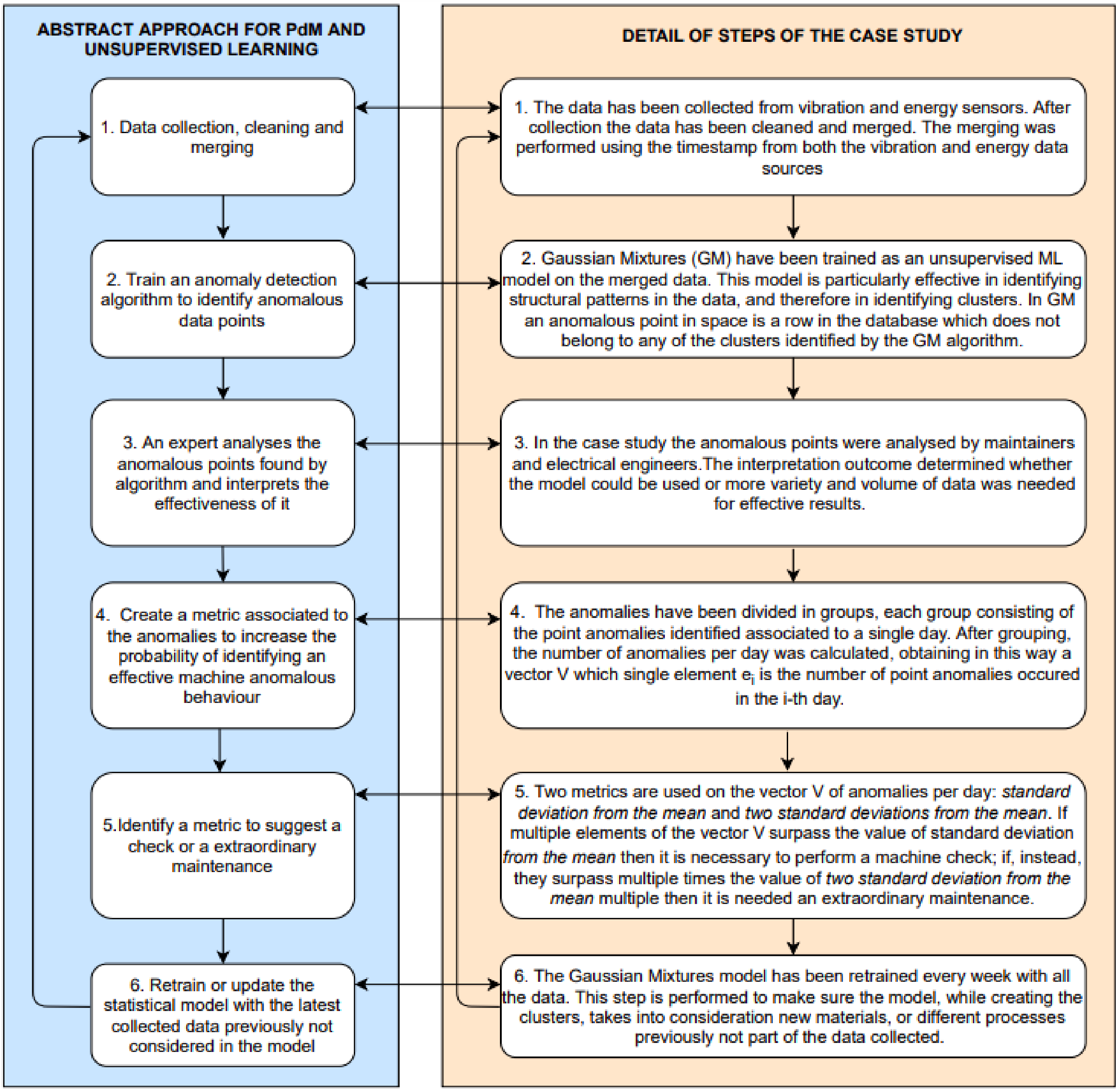


Figure 32. *The abstract framework for PdM and unsupervised learning is on the left, while on the right the details of the implementation of the abstract steps in the case study.*

Once the data was collected from different sources, and stored on a centralized server as part of the Data collection and pre-processing phase, it was organized in five directories on the computer: *Current, Power, Tension, Vibration, ElectricalAndVibrational*. Each directory represents a variable group, while, in the case of the *ElectricalAndVibrational* directory, it contains temporally synchronized data from power, acceleration, and velocity variable groups.

The unlabeled data in the directories have been used to create five different GM models whose goal is to give an indication of an electrical problem (current, voltage, or power anomalies), a mechanical problem (acceleration or velocity anomalies), or a problem related to an anomalous relationship between mechanical and electrical variables.

It is possible to elaborate anomalies starting from the clusters given as output of the GMM. A point is considered anomalous if it does not belong to any cluster. Specifically, a point *P* does not belong to any cluster when the probability of *P* belonging to each cluster is less than a threshold *T*. For example, if the threshold *T* is 40% and there are four clusters, then a point *P* is considered anomalous if, for each cluster, the probability of *P* belonging to it is less than 40%.

In most cases, an anomalous point does not define an anomalous behavior of the machine nor a failure; but it actually only defines an anomalous instantaneous condition of the machine. For this reason, in this paper the proposed approach exploits anomalies for predictive maintenance by using this simple assumption:

"*The greater the number of anomalies of a variable group is present in a specific time interval, the greater the probability of a real failure occurring*".

In other words, the assumption states that: the higher the number of anomalies of a specific variable group over time, the higher the probability of a real anomalous behavior of the machine.

The data processing steps can be summarised as follows:

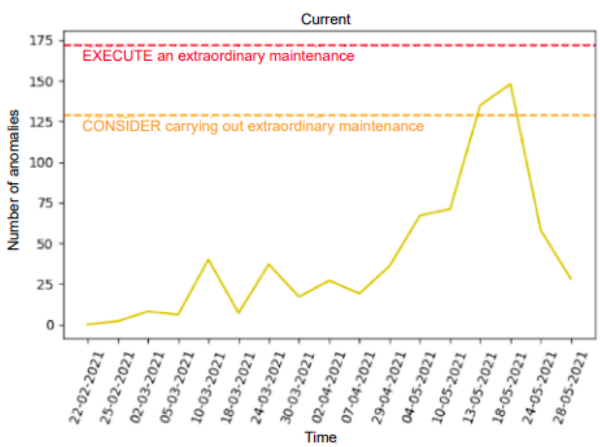
1. Data is stored in CSV format and synchronized temporally.
2. Five GM Models elaborate the clusters over five different variable groups (current, power, tension, acceleration and velocity, and power, acceleration and velocity variable groups).
3. For each GM model, the anomalous points are elaborated with a threshold *T* (in the test case generally close to 40%), with *T* calculated heuristically as the threshold guaranteeing few anomalies in the data, but more than zero per each day.
4. For each GM Model, the anomalies identified are summed over a specific time interval (eg. one day).
5. Every week the models are retrained to ensure more reliable results.

The fourth step is the one representing the assumption and is necessary for creating the appropriate graphical tools needed to support predictive maintenance. These graphical tools have been developed using the software that will be described in the next section.

III. Data exploitation

As part of the PdM system, a software application was developed for data visualization (data visualization/communication phase*)*, providing the maintainer with a graphical tool that allows him/her quick, clear understanding of the information. Thanks to graphic representations, we summarised the multivariate analysis of industrial machines data in an understandable and coherent way, which in turn helps to comprehend the information and establish preventive maintenance decisions, from simple revisions to emergency maintenance activities.

The system is able to show information about anomalous events ordered and summed temporally in different time intervals (1 day, 3 days, 1 week, 2 weeks, and 1 month) and for different variable groups (current; power; tension; acceleration and velocity; and power, acceleration and velocity). As an example, Figure 33a shows potential anomalies in a 1-day interval for the *tension variable group*, Figure 33b shows them for the *acceleration and velocity variable group*, while Figure 33c includes the combination of *power, acceleration, and velocity*; the points of the line drawn by each graph represent the number of anomalous conditions in a specific day. Therefore, the more the trend grows in the graph, the more it is necessary to consider control of the machine and to plan maintenance.



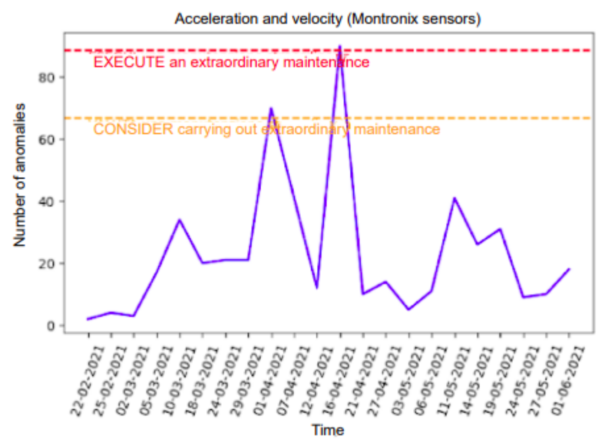


Figure 33a. *Tension variable group resulting chart.* ***Figure 33b.*** *Acceleration and velocity variable group resulting chart.*

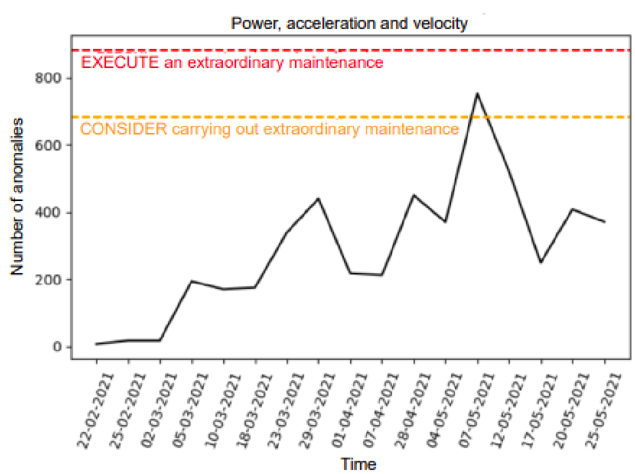


Figure 33c. *Power, acceleration, and velocity combination resulting chart.*

The horizontal yellow line represents the maximum level that the number of anomalies can exceed before requiring a preventive check, while the red line indicates the need for extraordinary maintenance. The position of the yellow line is given by one standard deviation from the mean, while that of the red line is by two standard deviations from the mean.

Standard deviations are a simple anomaly detection tool in single variable distributions, and are used in this case for detecting a higher-than-normal number of anomalies that occurred in a single time interval, (eg. one day) compared to the other time intervals. To summarise, an anomalous number of anomalies in a time interval is a probabilistic indication of an increased failure on the machine. Those patterns have been analyzed by domain experts after a data visualization tool has shown the analysis obtained, based in this case, on GM (data interpretation phase).

These tools have been used to suggest when to do maintenance, depending on which chart shows the yellow or red line surpassed, if the problem is electrical, mechanical, or if it is a problem caused by the interaction of the mechanical and electrical phenomena. However, a long observation period will be needed to fully evaluate the performance of the approach in the diverse environment where it has been deployed (data evaluation phase). At the moment, some promising results in the test case indicate early positive signs of the effectiveness of the approach.

6.3. Preliminary results

From the changes made in the management of maintenance activities and the implemented systems, the following results can be summarized that demonstrate the usefulness of the approach presented in the previous sections.

About the organization of the company, the fact of including the management of the facilities in the administrative division has allowed improving the planning and programming of the maintenance activities, initially of machinery and software applications, thanks to a program of effective preventive maintenance based on the analysis of the data obtained through the technologies implemented starting from the model shown in Figure 10 and the methodology presented in section 3.3.

Related to the two pilot machines object of the experimentation, significant results have been evidenced regarding the efficiency of the production process, as shown in Table 3.

Table 3. Summary of the main results evidenced after the introduction of the new maintenance system, in comparison with the previous year.

	Before the intervention	**After the intervention**	**Percentage of improvement**
Downtime (number)	29	21	27%
Breakdown (hours)	87	48	45%
Production capacity (hours)	1865	1912	2,5%
Production output (n° moulds)	35	39	12%
Maintenance costs (€)	21.750,00 €	17.400,00 €	20%

By comparison with maintenance data taken in the year before the introduction of the new maintenance system, we have observed a reduction in downtime occurrences of 27% and a 45% reduction in breakdown, which has allowed an increase in production capacity of 2.5%, which represents a 12% increase in production output. These improvements have been achieved in the same operating conditions (two 8-hour shifts, 5 days/week, 50 weeks/year and a similar quantity of production orders).

In the same way, the improvement of maintenance planning and the implemented actions from the new model have allowed a reduction in maintenance costs of 20%. These results rely on the early diagnosis of anomalies and failure patterns through the real-time data analysis enabled by CPPS, providing planning and operational teams with effective information on future downtime problems on machines with a higher risk of failure or that may result in more defective products.

About the company's maintenance management activities, the establishment of CbM policies, as part of an effective preventive maintenance program, was performed based on the technological architecture implemented from the model shown in Figure 21, and the PdM system model presented in Figure 28. At the time of writing, the realization concerns the two KITAMURA pilot machines object of the experimentation but, shortly, all the machine tools in the production department will be equipped to be part of the CPS.

Experimental data, for the two pilot machines, have been collected from the start of February to the end of August 2021. Our approach allowed us to study the influence on machine's behaviours of: 1) a single variable; 2) a group of variables of the same type representing a machine behavior (e.g. the three current variables in a three-phase system) and 3) combined variables of different types (such as power and acceleration). This is possible because the ML algorithm can be instructed to learn from a single variable type or a combination of variables. In the case of potential machine anomalies, this feature allows providing selected information to an expert, useful to orient the analysis of potential causes of an imminent fault.

During this period, it has happened four times that the system has shown an increasing trend of data anomalies provided as an output of the methods used on the KITAMURA machines.

Case 1: an anomaly has been signaled because of an anomalous trend of the variables A1, A2, and A3 representative of current data. As shown in step 3 of the proposed framework (Figure 22) the analysis of the expert has shown incorrect electrical wiring that has been fixed with a corrective maintenance operation.

Case 2 and 3: An increasing trend of the number of anomalies detected by the model analyzing power and acceleration variables was observed, indicating a potential failure in the imminent future. In both cases, it was decided to continue the production and to observe the machine's status. In case 2, the machine KITAMURA1 has produced a not negligible number of defective pieces; as a consequence, a mechanical engineer identified the causes in a nearly broken spindle bearing. In case 3, concerning the machine KITAMURA2, the expert has identified in a tool wear-out the cause of the anomalous behaviour.

Case 4: In this case, the anomalous behaviour signaled by the model, has not been associated with any cause.

The results provide a first indication of the effectiveness of the system in detecting preventively anomalous machine behaviours, and effectively transmit this information to maintainers and production managers who can decide, if necessary, to start a maintenance operation based on the system output.

7. CONCLUSIONS

Traditionally FM has been understood as a discipline that tends to preserve value (safety, comfort, etc.) [171]. Its evolution leads us today to see a different aspect of FM as a discipline that creates value. In this sense, the combined approach (model + methodology + technology) presented in this research allows planning and control of industrial resources that can achieve maintenance cost reduction, increased machinery availability by means of predictive maintenance, and better product quality. It is important to emphasize that the contribution of this project to facility management is strongly related to the use of industry 4.0 technologies such as IIoT, CPPS, Digital Twin, Big Data and ML.

In this sense, being maintenance a fundamental aspect in FM, the diagnosis and prognosis concepts were considered in this work since they are two important aspects of preventive maintenance programs. Prognostics is usually applied to achieve zero-downtime performance through prediction, while diagnostics are required when faults occur. Data analysis is used to perform both diagnosis and prognosis, which is why big data analytics in industrial contexts is now a vital foundation for forecasting manufacturing and proactive maintenance.

On this basis, several strategies were presented in this work to support maintenance as part of FM. From the study of the STAMEC s.r.l. manufacturing enterprise architecture as a starting point, a general model that brings together the various assets that need to be supported by the FM organizational unit was initially presented, as well as the main maintenance functions that can be applied to them to guarantee their operating conditions. In particular, the main advantage of the proposed model lies in the unifying approach to the maintenance of the industrial assets present in the organization and this can lead to significant savings. This particularity allows the manager of the FM organizational unit to adopt a management pattern for planning, monitoring, and maintenance control of the industrial resources, customizing the technical methods necessary for each type of resource.

The model is also accompanied by a step-by-step methodology for FMM that guides the planning and operation of an effective facility maintenance program, facilitating the decision-making process through a top-down decomposition method. In particular, the methodology requires detailed knowledge acquisition about the appropriate technology for the object/system to be maintained; this led to choice Industry 4.0 technologies such as IIoT, vertical/horizontal integration, Cloud Computing, CPS, and Big Data in the case study presented in section 6.

A general approach to the maintenance of resources through the implementation of a CPPS was also developed, which makes use of IIoT, Digital Twin, and PPC technologies to maximize the effectiveness of the maintenance management activities, facilitating the planning and execution of preventive maintenance strategies mainly oriented towards CBM and BdM. In this way, the CPPS together with the MPC software developed contribute to improving the performance of the maintenance support system by achieving zero signaling time of machine downtime or degradation in machine operation, allowing timely intervention to return the machine to normal operating conditions and plan preventive maintenance strategies at the most appropriate times, bringing benefits in reducing non-production times and repairment costs.

In addition, a generic PdM system architecture based on the CPS, IoT, BDA, and IoS technologies was presented in this research. An abstract framework for PdM of industrial machines using unsupervised learning was also proposed. The framework supports the identification of machine anomalies through several steps that are independent of the used algorithms, providing a general reference structure for testing different unsupervised learning solutions.

Furthermore, a real-world application of both the framework and the architecture was implemented through a case study in an italian automotive manufacturing industry. The description of the case study demonstrates the practical use of the proposed approach for the maintenance of machine tools, but it is general enough to be applied in other scenarios.

The positive implications of the developed general approach for maintenance management of industrial facilities are the generation of value by means of industrial technologies integration, and facilitating the management of resources and facilities by delivering new strategies that support the decision-making process in maintenance schedules. This contributes to the continuous improvement of maintenance activities, which also derives the improvement of the production process performance.

From the PdM solution, we contribute to enriching an area, the one of frameworks for predictive maintenance based on unsupervised ML, not sufficiently covered in the scientific literature. The data analysis was positively impacted by means of a PdM system developed for data acquisition, analysis, and visualization, which uses unsupervised ML models for early failure diagnosis and prognosis in situations where there is unlabeled data. Thus, the maintenance manager has a graphic tool that helps to better understand the behavior of the machines through the information collected by energy and vibrational sensors, providing support for more effective preventive maintenance decisions.

The abstract representation of our approach gives a general perspective that allows the use of different unsupervised ML for anomaly detection, which means that the framework does not depend on a specific algorithm. Additionally, our model is automatically re-trained to improve the accuracy of the results.

The findings of this research are twofold. First, the decision-making process is modeled and the methodology clearly states the necessary steps for FM; then the continuous improvement takes advantage of the modernization of the processes related to the management of resources and facilities. Our approach to FM promotes the early identification and diagnosis of anomalies in real-time through the implementation of preventive strategies supported by IIoT devices, CPPS and Big data technologies.

This work is not without limitations, particularly for what concerns the maintenance of industrial assets allocated to production processes. In fact, in this scenario, the cost and time of FM programs can be high. However, CPPS are often implemented to improve the production process performance and are already there to be used with little additional cost for maintenance purposes.

Several future developments can be conducted from this work, such as the optimization and automation of maintenance management processes of other assets, resources allocation simulation, and the implementation of the abstract PdM framework based on different ML techniques to analyze unlabeled data from different machine types and operations, enabling potential failure prognosis or RUL prediction. Similarly, other research and development directions could be considered based on the integration of the proposed CPPS and PPC software with different 4.0 technologies, such as virtual reality and various Big data techniques that allow transforming processes in various phases of the supply chain.

In the same way, the integration of the designed IoT and Big data architecture with different ML algorithms, such as those for prescriptive analysis [36], could be used to optimize maintenance programs through the development of advanced recommendation systems, helpful for suggesting the actions to undertake during maintenance.

Finally, studying how human factors affect the FM in a Cyber-physical manufacturing context is another future direction of the work on this subject, as there is growing evidence that human factors play an important role in determining the performance of a manufacturing system [172].

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9. APPENDICES

APPENDIX A - Publications during the Ph.D.

In Appendix A are listed the publications of TORO LAZO Alonso written during the Ph.D. years. Section A.1 presents the list of published papers, while Section A.2 gives the list of submitted or accepted papers (but not yet published). We also include the papers not covered in this thesis.

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A.1 Personal Publications

List of papers published during the Ph.D. studies:

- G. Nota, F. D. Nota, D. Peluso, and A. Toro Lazo, "**Energy Efficiency in Industry 4.0: The Case of Batch Production Processes**," Sustainability, vol. 12, no. 16, Art. no. 16, 2020, doi: 10.3390/su12166631.
- G. Nota, D. Peluso, and A. T. Lazo, "**The contribution of Industry 4.0 technologies to facility management**," Int. J. Eng. Bus. Manag., vol. 13, p. 18479790211024132, Jan. 2021, doi: 10.1177/18479790211024131.

A.2 Submitted or Accepted Papers

List of submitted or accepted papers (but not yet published) during the years of Ph.D., in addition papers to be submitted are also reported.

- **A framework for unsupervised learning and predictive maintenance in the industry 4.0**, (F. D. Nota, A. Toro Lazo, M. Nastasia) - Submitted at International Journal of Distributed Sensor Networks (IJDSN).
- **Environmental maturity model for manufacturing sustainability in the industry 4.0,** (G. Nota, A. Toro Lazo) - To be submitted.