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Virtual Architecture of the Automation Pyramid based on the Digital Twin

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Dedication

This work is dedicated to all those people who have supported me with their love and patience, with their knowledge and enthusiasm.

Also, I dedicate this work to those who during this process offered me a hand and gave me a word of encouragement.

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Virtual Architecture of the Automation Pyramid based on the Digital Twin

by

Edwin Mauricio Martínez Galicia

Abstract

Industry 4.0 has been empowered by new emerging technologies to improve the competitiveness in companies. One of these technologies is the digital twin (DT) which is an advanced virtual model that enables to predict, detect and classify normal and abnormal operating conditions in a factory or a particular production process to improve the features of a physical system.

On the other hand, the manufacturing processes generally follow standards to segment and distribute their processes, information, and implementation areas. Among the most widely recognized standards in the manufacturing industry is the ISA-95 standard that incorporates the business functions and control systems performed in a company with the objective to enhance the implementation of interfaces between business and control systems.

Some architectures, as the Automation Pyramid (AP), hierarchically place the elements that take part in a manufacturing process, from the basic elements such as sensors and actuators, to the decision-making systems, whose functions and shared information are defined in the ISA-95 standard.

In industry, one of the main functions of decision-making systems, such as the Manufacturing Execution System (MES), is to provide critical data in real-time at the operational level to increase productivity and process capability of the manufacturing process. However, these systems usually do not have capabilities to offer a prompt/autonomous/learning-based response to face unpredicted changes in the course of operating resources. Therefore, when a fault condition occurs, not only quick responses are required but also predictive information to prevent future failure scenarios.

Thus, this work proposes to provide responsiveness to decision-making levels in the face of unforeseen scenarios, through the incorporation of intelligent algorithms. The main objectives of this thesis are presented below:

- To propose a complete Virtual Architecture of the Automation Pyramid based on the Digital Twin: This enables the simulation of scenarios with elements from the shopfloor to the management levels, considering the advantages that the DT provides.

- To align the proposal with international standards: The model is driven by the ISA-95 standard incorporating the functions and information flow defined in it for decision-making levels.

- To provide learning capabilities to the decision-making systems through artificial neural networks, incorporated in a model based on the DT concept: Since neural networks are

able to learn and generalize knowledge, they can learn specific conditions for helping the decision-making process.

- Evaluate a manufacturing system for educational purposes through the proposed model: The parts of the virtual model of the AP will be identified in a manufacturing cell system used for education at Tec de Monterrey. Its components will be evaluated within the framework of the proposed architecture and the elements to complete the virtual model of the AP will be identified.

As a result, this work proposes the complete virtual model of the Automation Pyramid based on the concept of the Digital Twin, where it is proposed to add autonomy capabilities to the decision-making levels through neural networks. The proposed model is aligned with the international standard ISA-95 as an alternative to be applied directly to a process or factory that can be based on the standard.

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Article

Automation Pyramid as Constructor for a Complete Digital Twin, Case Study: A Didactic Manufacturing System

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Abstract: Nowadays, the concept of Industry 4.0 aims to improve factories' competitiveness. Usually, manufacturing production is guided by standards to segment and distribute its processes and implementations. However, industry 4.0 requires innovative proposals for disruptive technologies that engage the entire production process in factories, not just a partial improvement. One of these disruptive technologies is the Digital Twin (DT). This advanced virtual model runs in real-time and can predict, detect, and classify normal and abnormal operating conditions in factory processes. The Automation Pyramid (AP) is a conceptual element that enables the efficient distribution and connection of different actuators in enterprises, from the shop floor to the decision-making levels. When a DT is deployed into a manufacturing system, generally, the DT focuses on the low-level that is named field level, which includes the physical devices such as controllers, sensors, and so on. Thus, the partial automation based on the DT is accomplished, and the information between all manufacturing stages could be decremented. Hence, to achieve a complete improvement of the manufacturing system, all the automation pyramid levels must be included in the DT concept. An artificial intelligent management system could create an interconnection between them that can manage the information. As a result, this paper proposed a complete DT structure covering all automation pyramid stages using Artificial Intelligence (AI) to model each stage of the AP based on the Digital Twin concept. This work proposes a virtual model for each level of the traditional AP and the interactions among them to flow and control information efficiently. Therefore, the proposed model is a valuable tool in improving all levels of an industrial process. In addition, It is presented a case study where the DT concept for modular workstations underpins the development of technologies within the framework of the Automation Pyramid model is implemented into a didactic manufacturing system.

Keywords: digital twin; automation pyramid; industry 4.0; innovative products; manufacturing model; educational innovation; higher education

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1. Introduction

New smart-connected devices facilitate information flow to different levels of decision-makers. Consequently, the traditional factories are migrating their manufacturing processes to more innovative, optimized enterprises. Thus, the smart factory concept emerges as dramatically intensified manufacturing intelligence applications throughout the manufacturing and supply chain enterprise [1]. Smart factories are called to transform into companies with more dynamic economic and supply chain services determined by business and market demand. Some experts addressing the manufacturing changes attend to customer demands, the nature of products, the production economics, and the value chain economics [2].

Within the smart factory are emerging systems that can supplant or complement the automated processes currently found in most industries worldwide; these are the cyber-physical systems (CPS). These new elements are the fundamental part of recent smart

Chapter 1

Introduction

In the last decade, with the incorporation of new technologies in industrial processes, a transformation in the production and management systems has been observed. With this, new schemes, models and methodologies emerge to deploy traditional production processes on environments with an increased number of intelligent elements and more connectivity.

One of this emerging trends is the Intelligent Manufacturing (IM). This term refers to the effort to design, deploy and manage business manufacturing operations and systems that activate the proactive management of the manufacturing company through informed executions in time [1]. To aspire to the development of IM systems, the understanding, planning and administering real-time management of all aspects of the business and operational manufacturing process is required and facilitated by the widespread use of sensor-based data analysis, modeling and simulation, etc. [2].

The environment where the elements belonging to the IM systems make synergy is called Industry 4.0 (I4.0). According to Federal Ministry of Education and Research of Germany , the I4.0 refers to the intelligent networking of machines and processes for industry with the help of information and communication technology [3]. Over the years, the I4.0 and its fundamentals have evolved with greater clarity and objectivity for its rise and credibility in the academic and industrial areas. With this evolution, some elements comprised in I4.0 become more relevant in the deployment of IM systems. One of the fastest growing technological elements in I4.0 is the Digital Twin (DT). This concept was born from the availability of new elements such as smarter sensors, flexible programming platforms, and advanced artificial intelligence algorithms which enable the generation of virtual models that represent the characteristics of a physical asset with high fidelity and whose interaction enables the improvement of the physical counterpart.

Under the same tendency, methodologies, architectures and even standards are evolving to adapt their contents to the incorporation of technologies with more connectivity and intelligence capabilities, facilitating the factories to evolve into smart manufacturing companies. Despite the manufacturing environment continues to transform, the current standards still continue as a reference to develop a manufacturing structure with order and efficiency. One of the worldwide reference standards is the ANSI/ISA-95.00.01-2000, in this work referred to as ISA-95 standard for practicality.

The ISA-95 is an international standard for the integration of enterprise and control systems, developed by the International Society of Automation (ISA) [4]. Currently, the ISA-95 standard is composed by 7 parts which defines the activities and information that will be exchanged between business and control systems in order to reduce the risk, cost, and errors associated with implementing these interfaces [5].

Part 1 of this standard presents a hierarchical model associated with manufacturing control and business management systems. Based on this hierarchical model, some conceptual representations such as the Automation Pyramid (AP) provide an overview of what should be accomplished by process automation. By following the hierarchy set in the ISA-95, the AP concept has been used as reference to represent the functional levels and locates the elements belonging to each automation processes, from the level 0, where the physical processes takes place, to the 3 and 4 levels where the operational and business management systems are identified.

The functions accomplished by the decision-making levels are driven by IT-based systems such as the Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems. The ERP systems manages those activities related to sales, accounting, purchases, human resources, etc. While MES is focused on providing information in real-time about the activities deployed on the shop-floor and it serves as a bridge between the ERP systems and the manufacturing control (usually carried out by a SCADA system). Hence, the integration of smarter devices within the shop-floor has obliged ERP and MES to evolve into systems with more connectivity and advanced self-driven capabilities to take advantage of the large amount of data now available.

Despite having a common goal, academic research has enabled the development of intelligent decision-making systems in different ways, under different points of view. Some authors propose composite intelligent systems where a digital-networked manufacturing paradigm is suggested as the future of production processes [6]. These systems are defined by human, cyber and physical activities interacting to develop production with specific manufacturing goals considering the optimization as critical point. The sensing, decision making and analysis activities migrates from a human stage to the cyber-physical stage, taking the human knowledge management as a base to enhance the production efficiency [7].

In addition to Cyber Physical System (CPS) approaches, mobile technologies, cloud manufacturing systems, big data analytics, robotics, 3D printings, Industrial Internet of things (IIoT), Augmented and Virtual Reality (AR and VR), and Digital Twins (DTs) are distinguished by authors such as [8–10], as enablers of smart factories, particularly to their application and practical implementation at decision-making levels (MES, ERP).

Regarding the Internet of Things (IoT), a tech combination with MES is addressed in [11]. Here, the authors aim to incorporate the IoT technology into a MES in a motor assembly plant analyzing the real-time monitoring capabilities throughout the manufacturing process that the IoT contributes to. Also, the IoT technology supposes to provides access to a broad range of sensor data.

With a different technology, the work presented in [12], provides intelligent features throughout radiofrequency identification-based MES (RFID-MES). Based on the mass-customization company scenario, the authors identified inefficient scheduling due to the manual handling of information. The work presents an RFID-enabled real-time MES for managing the data collection, real-time scheduling as well as real-time work-in progress tracing and tracking. RFID devices were deployed into the production environment converting typical manufacturing resources into smart objects enabling their real-time tracing and tracking. The RT-MES utilized the real-time information to support the planning, scheduling, execution and control functions. The authors conclude that real-time data collection and scheduling help the visibility and traceability of materials and the work-in-progress inventory control.

In proposals such as the presented in [13], the authors make use of cloud-based MES systems to enable on-demand configuration of distributed applications and integration of distributed systems, with the help of business approaches such as Service-oriented Architecture(SOA) which builds IT systems allowing business to leverage and create new assets and enables the changes required to support the business [14]. Also, the cited authors use Web-Service technologies for presenting Web-based MES for data integration among heterogeneous systems.

In recent years, agent-based modeling has had considerable development in the real-world business area. Therefore, several approaches have been proposed to use agent-based systems for modelling decision-making systems taking advantage of its benefits: to capture emergent phenomena, to provide a natural description of a system, and to be flexible [15]. Precisely, in [16] the authors presented an agent-based architecture of a MES, considering the functional models conferred in the ISA-95 standard. They applied CPS (holons) to collect the information from the shop-floor to later be sent to the agents which processed using internet services. With this, a local optimisation focused on individual orders provided by order agents replaces globally optimisation from MES.

Following the agent-based approaches, the work presented in [17] employed knowledge-driven decision support with learning agents which are able to predict future disruptions and react automatically through the adaptive decision-making in distributed execution control and emergent scheduling. The learning capabilities were added to a previous automatic decision-making system by adding a Q-learning agent. The results shows noticeable improvement on learning capabilities with the addition of the agent-based feature.

Although there are different proposals on improving the autonomy and intelligence of decision-making systems, the literature still indicates the lack of response to unforeseen scenarios. In [18], after conducting one of the most complete reviews of MES, the authors point out that in the implementation of decision-making systems, the shop-floor needs more than data analysis. These systems require tools to dynamically respond to unexpected changes as well as to provide them with learning capabilities which enables more defined autonomy. For example, through the MES the enterprises may access to critical data in real time and propagate the decision made based on it. To do the above, the decision-making systems solutions need to combine different solving tools with multiple data sources to elaborate solutions in reasonable time compatible with the planning.

In [19], it is identified two main categories of technologies employed to provide quickness to the manufacturing systems. These technologies are addressed as basic and emerging technologies. The authors designated the simulation, the autonomous robots, the additive manufacturing, etc. as examples of basic technologies. On the other hand, they labeled as emerging term those technologies such as the Industrial Internet of Things (IIoT), the CPS, the Augmented Reality/Virtual Reality (AR/VR), the Big Data Analitycs, the Cloud/Cloud Computing, Ciber-security, Artificial Intelligence (AI), etc. The quick response, adaptation, and organization of tasks are addressed by the authors as major challenges in order to face the dynamic change of demand. Despite an exhaustive revision, they state the lack of autonomous evolution mechanisms and autonomous schemes of intelligent manufacturing systems to solve different defiance.

With regards the emerging terms mentioned above, one of the elements that best represent a CPS is the Digital Twin (DT). Initially, the DT was defined as a nonphysical element described by digital models to represent physical elements' behaviours in real-world environments [20, 21]. Over years, some authors have worked with DT adding characteristics to the original concept. According to [22], a DT is comprised of five main elements: the physical object/process, its virtual counterpart, a connection between these two elements, the data and finally, a service element. The real-world device is the base for building the virtual element, the virtual one allows running ”n” quantity of simulations to enable decision-making and control of the physical asset.

Through innovative and effective tools such as DTs, it is conceivable to develop new manufacturing elements that collaborate to incorporate the new emerging CPS into the companies in their current state. These tools can adapt these emerging smarter systems to processes or methodologies that already have some automation feature built-in.

Taking the concept of the automation pyramid as a reference, some authors have focused on working on it and have proposed updating the AP through the DT concept. In [23], a shop floor virtualization case was proposed. This work explored the digitalization of the four main shop-floor components: physical, virtual, service, and data shop-floor systems. Some authors have proposed innovations in the AP decision levels. For instance, in [24], the paper focused on the practical implementation of a DT concept in a MES. The proposed DT was built to monitor energy consumption inside a laboratory dedicated to Industry 4.0. Also, some authors have proposed modifying the architecture of MES from a static state to a flexible, dynamic information model. In [25], the proposal focused on the case-based approach to information modeling to generate new manufacturing systems that can integrate new flexible materials models. In this work, a link between classical MES and Enterprise Resource Management (ERM) is shown. The modeling was designed using the Reference Architecture Models applied to Industry 4.0 (RAMI4.0) [26].

With the transformation of the current automation systems towards systems with greater connectivity and intelligence, several authors point out a need to transform the current schemes, such as the AP, towards models that adapt or incorporate elements that provide greater connectivity, intelligence and prediction capacity applicable to decision making. In [27], the authors point out that the traditional pyramid does not cover current application needs, since intelligent automation requires the real-time exchange of information through all the layers of the pyramid, simultaneously. Thus, this work proposes a framework based on a middleware that provides interoperability between the layers of the pyramid with cloud functionalities and big data warehousing. The framework is based on features such as interoperability, virtualization, decentralization, real-time, traceability, modularity, etc. through all the layers of the traditional pyramid. This proposal addresses the need to strengthen the pyramid model by adding dynamics and flexibility through the middleware that covers the lack of information exchange in real time through all the layers of the AP.

Until now, few works consider a complete virtualization of the pyramid. The main reason is because the MES and ERP systems, in charge of managing management and decision-making tasks, are themselves virtual systems. Although in recent years, these business and operational management platforms have increased their capabilities to be at the level of the new industry 4.0, there are still some areas of opportunity to detonate their capabilities towards more intelligent systems. ERP systems have incorporated their platforms to cloud services, while MES have developed better ERP integration functionalities, planning and executing production orders from the ERP, and have managed to improve the collection and delivery of data for decision-making, adapting to the inclusion of devices such as sensors, controllers, machinery, etc. that now have more connectivity and intelligence.

In the state of the art, digital twins are the most used tool for digitizing the pyramid. Before having a complete DT model, there are proposals that start from the Digital Shadow model (DS), the predecessor of the DT. In [28], together with a MES, the integration of a DS is proposed to add decision-making capabilities to the MES. According to the authors, the DS becomes a DT due to the presence of an intelligent integration layer to the MES that hosts the rules and knowledge to choose between alternatives. The model is applied to two different frameworks, the first to manage error states and the second to improve the process of an assembly line. Starting from models such as the DS, Digital Master (DM) and the relationships between variables from the workshop to the decision-making levels (System Dynamics) in [29], the DT is adopted for teaching automation concepts to students and an approach to a full virtualization of the AP is presented. The dynamics of the system is based on the simulation of some of the functions defined for the higher levels of the AP within a digital platform. The simulation of this dynamic and the rest of the elements of the lower levels of the pyramid offers an advantage in the connection between all the elements. In this way a complete digital pyramid is achieved.It is an interesting proposal, since it dispenses with the use of ERP and MES systems following the AP model and is applied to an educational model, however, the dynamics of the system still lacks prediction functions and intelligent decision making, fundamental characteristics in the DT. Through the different proposals presented in this state of the art, an attempt has been made to show the trend of the manufacturing industry towards the incorporation of more sophisticated and intelligent elements. Today, industry 4.0 begins to permeate manufacturing, driving it to have processes with better connectivity, communication, and intelligence. which opens the possibility of having more efficient and cutting-edge decision-making platforms.

Thus, the current manufacturing models must evolve towards new proposals that incorporate technological elements that provide decision makers with a more precise vision that helps them trace the route of a product in each stage of production more efficiently. Recent work shows a growing need to transform manufacturing through the virtualization of the components of its processes on the path of integration towards a new reality called industry 4.0.

Even with the transformation of current manufacturing and automation systems, the AP is still valid and is point of reference for many research works. The main reason is the support provided by the internationally accepted standard ISA-95. Although the figure of the AP is still latent, there is a tendency to change its original model. Most of the proposals consider the virtualization of some of its levels. However, the common denominator of this partial digitization is the problem of interaction with the rest of the levels, rarely addressed and sometimes omitted. In an industrial environment with a greater volume of data, in the transition towards a more intelligent manufacturing, the flexible and agile flow of information between the levels of the AP is crucial for an efficient coexistence of the model, for which the virtualization of a single stage seems to be insufficient from the perspective of this work.

In addition to the above, although ERP and MES systems have evolved to platforms that seek to join industry 4.0 adding technologies such as cloud storage, big data analysis, interaction with smarter devices with through the internet of things (IoT), etc., there are still areas of opportunity to be exploited to have platforms with more intelligence capable of collaborating more efficiently in decision-making through the simulation and prediction of scenarios. In other words, the initiative of this work is to provide management and planning systems with the ability to perceive, understand and act for different scenarios, through artificial intelligence.

In summary, there are two main reasons for having a complete model of the pyramid based on a single intelligent entity. The first of these is the difficulty of integrating with the rest of the levels when a single level is virtualized. This problem means that the now big amount flow of information in processes and systems with greater connectivity is not efficient and does not allow valuable information to be available at the time necessary for decision-making at any level, eliminating the possibility of reacting to unforeseen scenarios or in case of sudden failures, for example. The second is the lack of intelligence in current decision-making systems. Through a DT, a sudden failure prediction and response feature can be added to ERP and MES systems without human presence. In other words, taking advantage of the characteristics of the DT and with the help of artificial intelligence algorithms, in the decision-making levels of the virtual pyramid, provided with the vast amount of data available in the rest of the virtual levels, scenarios can be simulated with how many possibilities are desired for each function executed in the ERP and MES (based on the functions and information flow defined in the ISA-95 standard). The database for these simulations can also be nourished by the communication that the DT has with its ”physical” twin.

Therefore, a complete virtual model of the AP is relevant, since with the incorporation of devices with greater connectivity and sensory capabilities, the volume of data available in a manufacturing process or system has increased considerably. With the latent development of data science techniques, this information becomes valuable, because through it the future behavior of the system is understood and can be known. Currently, the existing proposals only consider the virtualization of some level of the pyramid, and little is discussed about its virtual interaction with the rest of the levels of the pyramid. Thus, in order to manage all the information that is generated and flows at all levels of the pyramid, the complete virtualization of the pyramid from the same model could facilitate communication and the flow of information between the virtual model and its physical counterpart.

”Virtualizing” the pyramid through a DT will allow the availability of information through the entire pyramid, enabling effective communication and facilitating its integration and interaction with its physical counterparts. Addressing the current little-discussed problem of information flow between levels by digitizing only some levels of the pyramid. In addition, the development of the DT on the same entity will enable effective communication and will facilitate its integration and interaction with their physical counterparts. Additionally, the creation of DT through artificial intelligence algorithms provides the ability to predict and respond to unforeseen scenarios at decision-making levels, something that ERP and MES systems currently do not have.

Thus, the contribution of this work is to lay the foundations for the attention of the problems exposed through the proposal of a virtual model of the complete pyramid. This work conceptualizes a new complete AP model based on the DT concept that permits the simulation of scenarios with elements from the shop-floor to the management levels. The full virtualization can facilitate an efficient flow of information under a single platform and streamline decision-making from the lowest level to the highest levels of hierarchy. Particularly, for decision-making levels, it is proposed to include neural networks' algorithm to provide learning capabilities at these levels and provide autonomy and responsiveness to unforeseen scenarios at different levels of the production process.

To evaluate the model, this work shows a case study of a DT applied to an educational environment. The characteristics of the proposed model are identified in a manufacturing cell system approached in the manufacturing laboratory of Tec de Monterrey CCM. In this system, augmented reality (AR) and virtual reality (VR) are included as part of the development of DT as emerging technologies. The model proposed in this work is used for the evaluation of the educational system, identifying the elements still lacking to complete a complete model of DT based on the AP.

Chapter 2

Theoretical Background

2.1 The ISA-95 Standard and the Automation Pyramid (AP) Concept

The goal of the ISA-95 standard is to provide consistent terminology that is a basis for manufacturer communications that provide consistent information and operating models. In addition, the ISA-95 standard allows selecting the information to be exchanged between sales, finance, logistics and production, maintenance and quality systems [30]. Besides, the ISA-95 standard can be used as a guide for the definition of user requirements, for the selection of manufacturing execution systems (MES) suppliers, or as a basis for the development of MES and databases [31]. When well structured communication is required to integrate enterprise control systems, the ISA-95 standard could be implemented allowing the selection of information transmitted and received between systems.

The model depicted in Fig. 2.1 shows the most accepted format of the Automation Pyramid (AP). This conceptualization is based on the hierarchical model shown in the first part of the ISA-95 standard, where the enterprise manufacturing operation is proposed in 5 hierarchical levels. The zero level consists on the industrial process per se, the machinery, sensors and the needed human resources. The subsequent level consists on the automation components, it is the interaction between the physical components and the more basic control elements such as PLCs and its peripherals, sensors and actuators, in general. This level is mentioned to be the industry's hardware where the interaction of the top-level systems and the process takes place. In the monitoring and supervision level the equipment can be supervised through human-machine interface (HMI) or supervisory control and data acquisition systems (SCADAs). Level three controls the manufacturing operations through manufacturing execution systems (MES), this managing system controls what processes should be executed and the order of these. At the top level resides the economic, countable and marketing programs. The Enterprise Resources Planning systems (ERP) usually manages the inventory, the billing, the accounting and the logistics. This tool allows to take all the emitted billings in the company as well as the expenses and inventory.

The ISA-95 standard is based on models through which the interfaces, enterprises's business systems and its manufacturing control systems are defined. The standard address benefits such as [32]:

- Reduce the user's time to reach full production levels for new products,
- Enable vendors to supply appropriate tools for implementing integration of control systems to enterprise systems,
- Enable users to better identify their needs,
- Reduce the cost of automating manufacturing processes,
- Optimize supply chains, and
- Reduce life-cycle engineering efforts.

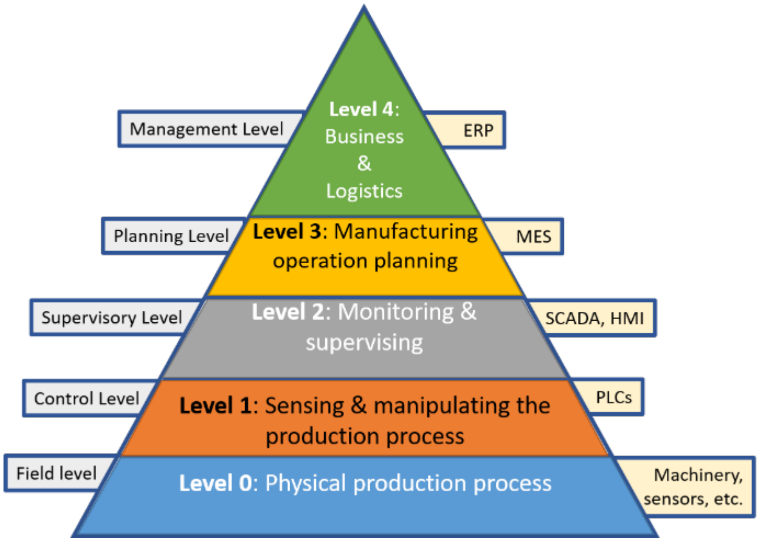


Figure 2.1: Automation Pyramid based on ISA-95 standard

Regarding the assets belonging to the 0-2 levels, the ISA-95 standard organize these in a hierarchical fashion as illustrated in Fig. 2.2.

The ISA-95 standard structures the elements according to the types of industrial processes: batch, continuous and discrete process. In addition, it defines the equipment through which these processes are deployed. According to Part 1, production units are the lowest level of equipment typically scheduled by the level 4 or level 3 functions for continuous manufacturing processes. The production units are composed of elements such as sensors and actuators.

The production line and work cells are the lowest levels of equipment scheduled by the level 3 and 4 functions for discrete manufacturing processes. The process cells and units are also the lowest levels of equipment scheduled by the level 3 and 4 functions for batch manufacturing processes.

The capabilities of production units, production lines, work cells, process cells, and units are used for level 3 functions and are also often used as input to level 4 schedule, even if they are not scheduled by the level 4 functions.

On the other hand, the operational models clarify the application functionality about how the information must be used within the different hierarchical levels. The standard clearly

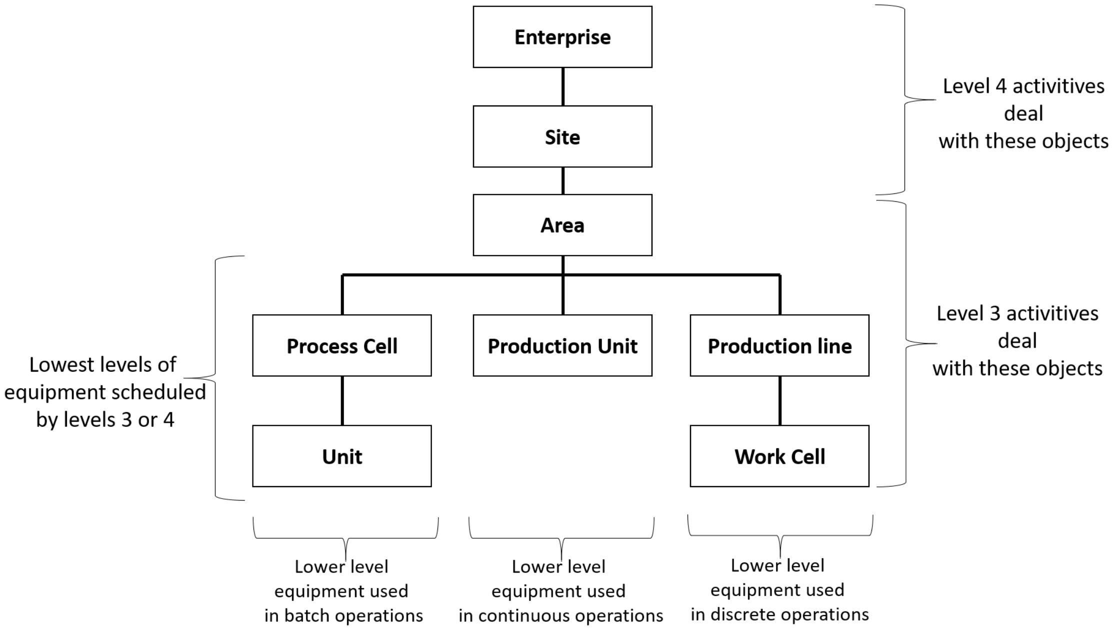


Figure 2.2: Equipment Hierarchy modified from [4]

determines which information has to be exchanged within systems for sales, finance, logistics and also, maintenance systems, production and quality areas. The UML models are the basis for the development of interfaces between ERP systems and MES.

In the literature, the efforts are focused on developing proposals for optimizing and apply conceptually and practically the DT concept to the elements located in the first 2 levels and a few for level 3. For the purposes of this work, it is relevant to discuss the functions executed by the planning and management levels, MES and ERP systems, respectively.

2.1.1 Enterprise Resource Planning (ERP) systems

Enterprise resource planning (ERP) is a generic name given to information systems designed to integrate and efficiently use all the resources of an enterprise. This program assists an enterprise in coordinating processes and data that are executed from sales to accounting, from production to human resources, from stock management to purchasing. Data are entered into ERP systems at the beginning of the foreseeable period to then be transformed into information processed in different areas within the enterprise [33].

In [33], the authors address some benefits the ERP systems contribute to Industry 4.0 (I4.0) implementations:

- Real-time data can be analyzed and early indication of exceptional cases would be possible,
- ERP systems can provide sales and purchasing transparency via automated business rules,
- Mobil applications may use ERP data to convey the messages not only to the manager but also to the machines running in manufacturing suits to perform expected operations,

- Through effective ERP system strategic operation could be easy and the access of information to suppliers, customers, and other partners could be possible for assuring the efficiency of on-line operations, and
- Customers may be able to track the status of their orders on-line receive the information required without delay.

Some interesting proposals about the research of ERP systems are presented in the recent literature. Some of these, are related directly to the implementation of ERP systems and the inclusion of new technologies, such as cloud systems, into the traditional ERP systems [34]. While some authors conceptually sets the incorporation of new emerging technologies, there are proposals aiming to implement the combination of cloud computing and ERP systems [35]. Compared to single ERP implementation, the authors found that a hybrid solution is more suitable for the interaction with the user. Their proposal methodology undoubtedly opens the way to I4.0 technological integration.

An ERP system usually is implemented to manage transactions through company-wide business processes, by using a common database, standard procedures and data sharing between and within functional areas [36]. Currently, in a broad range of production companies, the ERP systems support the production and distribution tasks and these are implemented to integrate and partially automate financial, resource management, manufacturing, commercial, and other business functions into one single system based on a database [37].

The customization of systems is a trend especially in the market for medium-sized companies, so the ERP plans will be offered as a service through providers. Thus, new ways of providing the software are being investigated, mainly related to the development of cloud system hosting [38]. Nowadays, accessibility to remote devices is a fundamental characteristic of personal devices and of course in industry. Remote access to information verification for decision-making is crucial towards optimizing manufacturing processes. That is why ERP system providers are facing these challenges offering mobile-capable ERP solutions [39].

In the content of ISA-95 standard are defined specific functions assigned to the levels of business enterprise management (ERP) systems. Some of these activities are summarized in the Fig 2.3.

As it is shown, the information flows between the functions that cross the enterprise/ control interface. According with the standard, a “Function” is a group of tasks that can be classified as having a common objective. These, are organized in a hierarchical manner and are identified with a name and number. The number represents an identification of the data model hierarchy level. The dotted line illustrates the boundary of the enterprise/control interface. The line is equivalent to the Level 3 - Level 4 interface [32].

The model structure reflects an organizational structure of functions. This work is based on proposing a model which emulate the functions through the concept of Digital Twin (DT). The following functions correspond to those accomplished in the ERP and MES systems, and these will be on which the DT model will be based, as is indicated in Fig. 2.3.

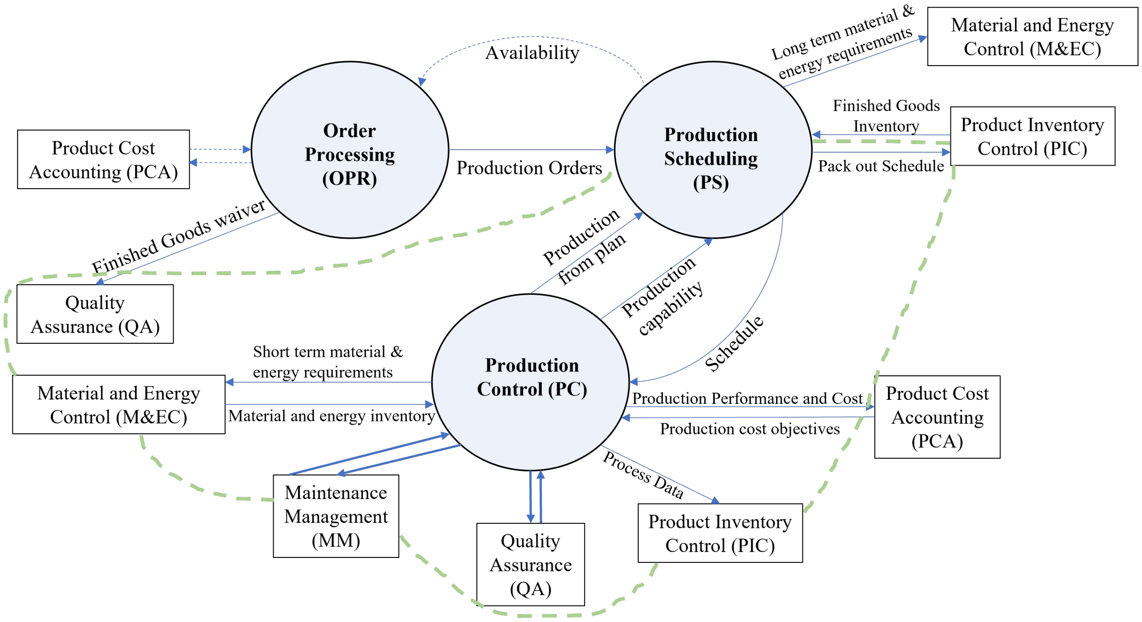


Figure 2.3: Overview of functional enterprise/control model based on [32]

Order processing (OPR)

The tasks assigned to this function are:

- Customer order handling, acceptance and confirmation.
- Sales forecasting.
- Waiver and reservation handling.
- Gross margin reporting.
- Determining production orders.

Production Scheduling (PS)

Here, the function's interface to the manufacturing control system works through a production schedule, actual production information, and production capability information. The functions and the information generated or modified by the production scheduling functions are listed in the Table 2.1.

Production Control (PC)

The main functions in production control include process support engineering (PSE), operations control (OC), and operations planning (OP). These can be summarized as:

- Control of transformation of raw materials into end product in accordance with production schedule and production standards.

Production Scheduling (PS)

Functions	Information generated or modified by PS
Determine the production schedule	The production schedules
Identify long term raw materials requirements	The actual production versus the planned production
Determine pack-out schedule for end product	The production capacity and resource availability
Determine available product for sales	Current order status

Table 2.1: PS Details

- Plant engineering and updating of process plans, etc.
- Issue requirements for raw materials.
- Produce reports of performance and costs.
- Evaluate constraints to capacity and quality.
- Self-test and diagnostics of production and control equipment.
- Creation of production standards and instructions for Standard Operating Procedures (SOPs), recipes, and equipment handling for specific processing equipment.

2.1.2 Manufacturing Execution Systems (MES)

The Manufacturing execution systems (MES) were developed in the early 1990s as a specific application at the shop-level. These systems mainly consist on functions of production management and control such as scheduling, product quality management and control, production cost control, and so on. This program aims to realize integrated production management and control in the shop-floor [20].

According to the ISA-95 standard, MES assume the role of connecting the office ERP systems to the shop-floor equipment by implementing manufacturing operational management (MOM) functions in the factories [40]. Some authors include online characteristic to the MES definition, also, adding the MES capability of accumulation of methods and tools to accomplish production, where online characteristic is used as connecting feature [41].

MES seems to be one of the cornerstones for the fourth industrial revolution (I4.0). MES ensure the cooperation between the complex activities that combine various types of tools and methods and the resulting synergy. Owing to the cooperation with different IT systems inside and outside the enterprise, the MES must have open and flexible features. These are: (i) the real-time continuous communication with the production level, (ii) the online conversion of information models, (iii) the transformation of data presented in accordance with the business model into a form that is easily interpreted and executed by the industrial control systems, and (iv) the conversion and processing of the data that is acquired from the control systems into a form that can be used by other enterprise systems [25].

Nowadays, despite the advanced implementation of MES, there are still issues to be improved regarding its application and expansion within the manufacturing area. Commercial MES, which is typically accompanied by an additional enterprise resource planning (ERP) system, can present a large expense to a manufacturer; this is particularly problematic for small manufacturing enterprises (SMEs),whose ability to afford such systems may be limited. Deployment of MES and ERP systems may also require installation of dedicated hardware. Additionally, some current MES and ERP systems do not address the information needs of individual employees and may not integrate data analytics [42]. Most of the current MES are designed for large enterprises that produce large quantities of a small number of parts, instead of customizable short-run products that are produced by many SMEs [40], something that the tendency of I4.0 to customize the products seems not to be compatible with the ideology. Thus, problems identified in current MES include: manual data entry by operators, lack of near-real time capability, and problems with interoperability and data sharing between different elements of the MES [43]. Therefore, some proposals have addressed certain characteristics which a MES must have in order to ensure its compatibility with the I4.0, which includes decentralization, mobility, connectivity and cloud integration [44].

Despite the evolution of business and resource management systems, the connection between the process control devices and MES seems lacking whenever an MES is implemented. This gap is not surprising, it reflects the fact that the two areas evolved separately and had to address totally different requirements in regard to application context or data characteristics. There is evidence in the industry that these two worlds are also separated by different networking concepts. In the office context, LANs are predominant whereas the control level is the domain of field buses. Hence, the gap to bridge not only concerns the linking of two different network types but also the interconnection of two different mind-sets [45].

In the beginning, the purposes of MES were focused on finite operational scheduling, resource production management, and the dispatching of production units. Also, MES would supply automated data collection and the delivery of detailed documents to work station. The MES would also record production details and analyze performance. What “Planning” handles superficially in batch, the MES handles continuously, up-to-the-minute, and on the spot [46].

2.1.3 The Digital Twin and its applications in industry

This concept was presented in 2003 at the University of Michigan by Grieves [21]. Over the time, several authors have added their perspective to define the digital twin (DT) concept [47, 48]. In [49], the authors define the DT as a kind of ultra-high-fidelity simulation which includes a health management system, historical vehicle and swift data. One of the most used definitions of DT was presented in 2012 by [50] where the DT is defined as an integrated multi-physics, multi-scale, probabilistic simulation of a complex product using the most suitable physical models to emulate the life of its related twin. In [51], it is mentioned the DT is composed of physical product, virtual product, and the connected data which links the both products. Also, the authors define some relevant characteristics of DT:

1. Real-time reflection: DT comprises the physical and the virtual space. The virtual space is the real reflection of the physical space and maintains ultra-high synchronization and

fidelity with its related real space.

2. Interaction and convergence: a) in physical space, b) between historical and real time data, and c) between physical and virtual space. Related to a), DT integrates full-flow, full-element and full-service characteristics, then, the data generated in the physical space phases can connect with each other. Regarding b), the DT data not only depends on expert knowledge but also collects data from all implemented real-timely systems. Finally, the physical and virtual space are smoothly connected and they interact easily.
3. Self-evolution: DT can update data in real time, so that virtual models can endure continuous improvement through comparing virtual space with physical space in parallel.

In Fig. 2.4, the Digital Twin (DT) concept is illustrated. Some authors consider that this representation is clear to highlight the essential characteristics that a DT must possess [52]. However, some others have considered that a complete DT model should have essentially five elements in its structure: physical part, virtual part, connection, data and service [23]. Some authors are proposed theoretical frameworks which considers the mentioned elements incorporating information processing layers [48].

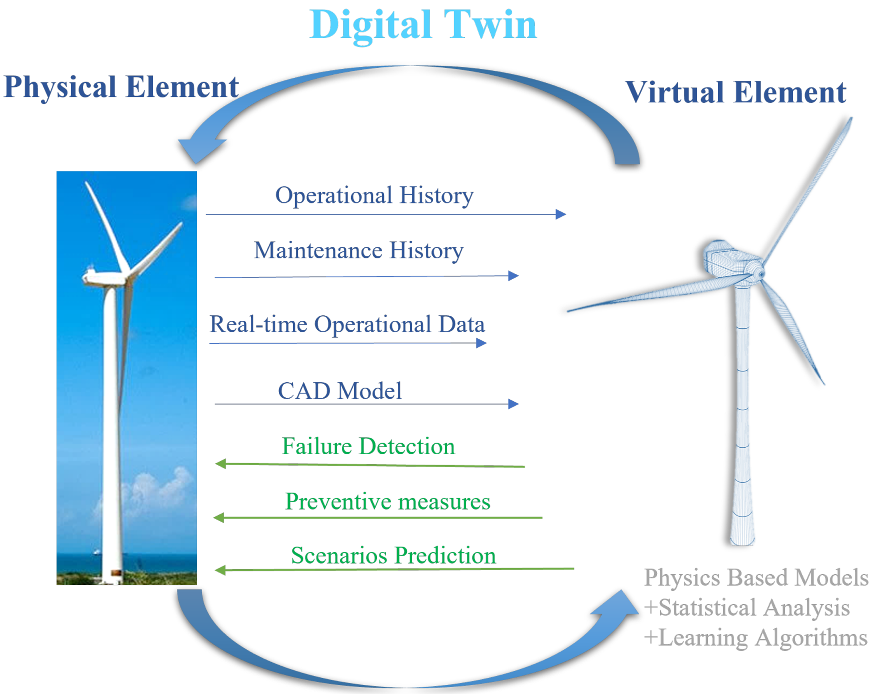


Figure 2.4: Digital Twin Scheme

By its definition, a DT is considered a quintessential Cyber-physical system. In [20], the authors proposed a systematic framework for Ciber-physical production systems (CPPS), its processing relies on two conditions: the cohesion of three physical portions (i.e. smart part, smart shop floor and smart manufacturing operations), (2) the mapping and interaction of physical portions with virtual portions (i.e. virtual smart part, virtual smart shop floor and virtual smart manufacturing operations). The application in manufacturing of DTs is in constant evolution, therefore, the proposal of DT application has different perspectives. In [53], the authors presents a variety of applications in manufacturing environments for the DT. The information, representing the authors perspective, is presented in four sections: DT-based production design, smart manufacturing in DT workshop/factory, product DT for usage monitoring and DT as enabler for smart MRO (Maintenance, Repair & Overhaul).

Some proposals focused their efforts to lay the theoretical foundation for the development of DTs. In [22], the research for developing DTs comprised mainly by four parts: DT modeling, simulation and VV&A (Verification, Validation and Accreditation), Data Fusion, Interaction and collaboration and Service. As relevant information, the work presents an interesting review of DT industrial applications, specifically, DT-related patents and DT applications by industrial leaders.

On the other hand, most of the DTs applied in industry are closely related with the levels below the Automation Pyramid (AP) [23]. In [47], the authors proposed a framework of DT-based smart production management and control approach, then, the authors address the main contribution of this work are: the prediction services for a satellite assembly shop-floor by integrating digital twin and big data technologies, which promotes the realization of predictive manufacturing in the product assembly stage, the framework of digital twin-based smart production management and control for a satellite assembly shop-floor and, the case study to illustrate how to apply the proposed framework practically in a satellite assembly shop-floor. Similarly, in [51] they proposed a framework for product design, manufacturing and service driven by a DT. The authors concluded they attend problem solutions about data in product life cycle, a new method for digital twin-driven product design, manufacturing and service; finally, the detailed application methods and framework of digital twin-driven product design, manufacturing, and service are investigated.

Undoubtedly,the data plays a crucial role in the application of DTs. Theoretical proposals as well as applied knowledge of data management within DT are quite valuable. In [52], the authors address representative applications with focus on the alignment with their proposed reference model, they present a general data processing framework for constructing a DT. It comprises data acquisition and cleansing, data storage and time-sensitive data processing. The intrinsic relationship of data with the ERP and MES systems must be considered as one of the main factors to be represented through the DT concept and its application. The research in [25], focuses on the transformation from the statistic architecture of MES to flexible and dynamic information models. The main contribution is the case-based presentation of a new approach for information modelling that is dedicated for the new generation of manufacturing systems. Since the new models that are presented were applied in an existing manufacturing system of smart electronic devices production, its implementation will focus on a number of constraints that are typical in the case of the previous generation of industrial computer systems.

Certainly, the presence of DT will be more constant and with greater weight in applications within the industry. A well-structured theoretical base, standards for the regulation of its application, as well as its correct implementation are part of the work that employees of the industry and the academic community must seek and continue working on. The correct evolution and application of technological elements in industry is and will be essential for the transformation of industrial life.

Chapter 3

Virtual Model of the Automation Pyramid based on the concept of Digital Twin

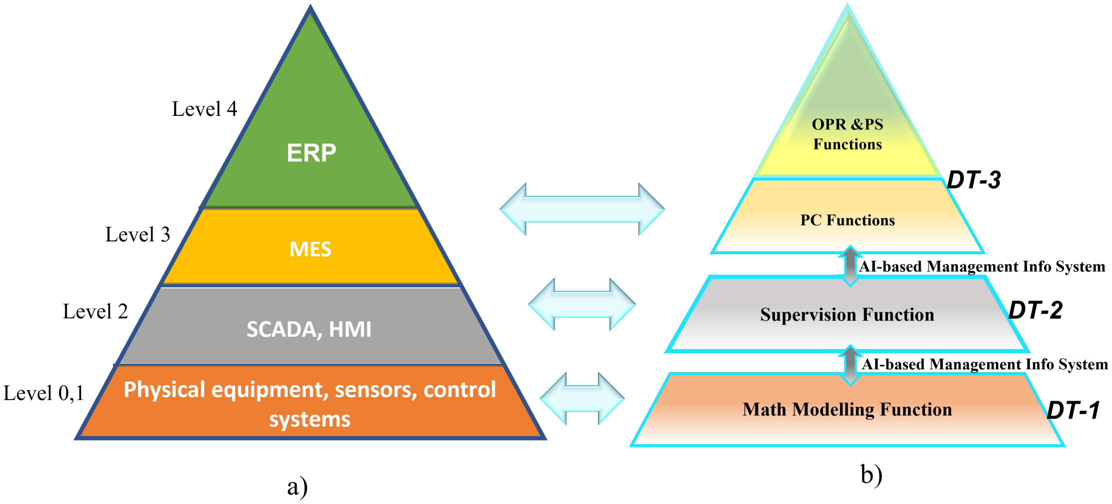
This chapter defines in detail the elements of the proposed model. As mentioned above, several efforts have been made to introduce DT schemes at different levels of the Automation Pyramid (AP), however, there are no proposals that establish the application of DT to the entire structure based on ISA-95 as proposed in this work. The main reason is that MES and ERP systems are essentially digital systems, however, the lack of autonomy and response to unexpected changes in the manufacturing processes are enough to search for new alternatives in these management systems in the industrial environment. Thus, with the aim of addressing the gaps found in the literature, this work aims to set a proposal that covers the weaknesses exposed through an innovative tool such as the DT.

As discussed in 2.1.3, a Digital Twin (DT) is a virtual representation of a system, product, or service, which emulates the characteristics of its physical counterpart but in a virtual environment. Unlike the concept of Digital Shadow (DS) discussed in Chapter 1, the DT interacts with its physical twin, there is bidirectional communication between both entities. A fundamental part in the creation of the DT is the information collected from the operations and the history of the behavior of the physical entity. The fidelity with the virtual entity can represent the physical entity has to do with the analysis of the data on which it is based for its creation. In addition to the features already presented in chapter two, we could add the following as essential to be executed by a DT:

- Making more efficient and accurate decisions.
- Predictive analysis: Through this you can anticipate future problems or have alternatives to unforeseen scenarios.
- Digital simulations before physical simulations: The asset can be tested in a virtual environment and improvements can be identified, avoiding the investment of resources that any physical test represents.

One of the problems described in Chapter 1 is the availability of the large amount of information flowing through all the levels of the pyramid when a single element or level of the original pyramid is virtualized. Thus, from the perspective of this work, by making the entire

AP model virtual, when a simulation is performed, it is expected that the flow of information through the stages will be automatically managed using intelligent algorithms. As shown, this flow would be bidirectional between the levels represented by three DT models. Furthermore, with the entire virtual pyramid, the efficiency of the simulated process can be improved by running a large number of simulations in a shorter time, which would be difficult to achieve with one-stage AP virtualization. Then, the AP model based on DT is discussed below, and its general configuration is shown in Fig. 3.1.



a)

b)

Figure 3.1: a) Traditional AP; b) Proposed AP model based on DTs

The virtualized AP model is made up of 3 DT models. Each DT is interconnected using the AP structure having an AI-based management information system. Initially, it is proposed that the ERP and MES functions presented at the introduction of this work: Order Processing (OPR), Production Scheduling (PS), an Production Control (PC) can be executed by the DT-3. Meanwhile, the role currently assigned to DT-2 will be supervisory. This function is one of the main characteristics of the traditional level-2 systems such as SCADA and HMI. For DT-1, it is assigned the mathematical modeling function, which is essentially the representation of any element at level 0-1 that different simulation software such as Matlab and LabVIEW performs. Thus, the 3 DTs in conjunction with the AI-based information management system form a DT model based on the Automation Pyramid.

3.1 AI-based Management Information System (AI-MIS)

In recent years, Artificial Intelligence (AI) has proven to be a highly useful problem-solving tool for decision-making process. The application of this type of algorithms to large amounts of data allows finding behavior patterns that in turn favor decision making, prediction of future failures, process improvement, and so on.

On the other hand, with the development of industrial processes better adapted to a new reality with more connectivity, the volume of data begins to increase considerably, which poses great challenges for information capture, management and data storage. One of this challenges is the good interpretation of the information that is contained within the large amount of data that we can obtain in a system.

Therefore, breaking down and understanding information effectively becomes a fundamental step in the industry as smart devices integrated through the Internet of Things (IoT) can send different types of structured and unstructured data, such as sensor data, pictures, videos, audios and so on [54].

The performance of manufacturing systems could be increased as decision-making system performance improves and a cooperative operation is promoted. With this, an agile manufacturing process can be implemented. When agile manufacturing based on information management systems is implemented, cooperation between partner subsystems of a process increases. Hence, the entire manufacturing system then becomes a dynamic virtual enterprise that can respond quickly to market demands [55].

Thus, the interaction between the different DTs would generate a large amount of data of different types, with different structures and sizes. Therefore, the exchange of information, the selection of the type of data that must be exchanged, the weighting of the transition times, the selection of the DT to which the information must be sent, must be managed efficiently and intelligently. Therefore, it is proposed that the proposed DTs model have an information management system based on machine learning, given the nature of identification, classification and prediction of these AI algorithms. Fig. 3.2 shows the model proposed for the AI-MIS.

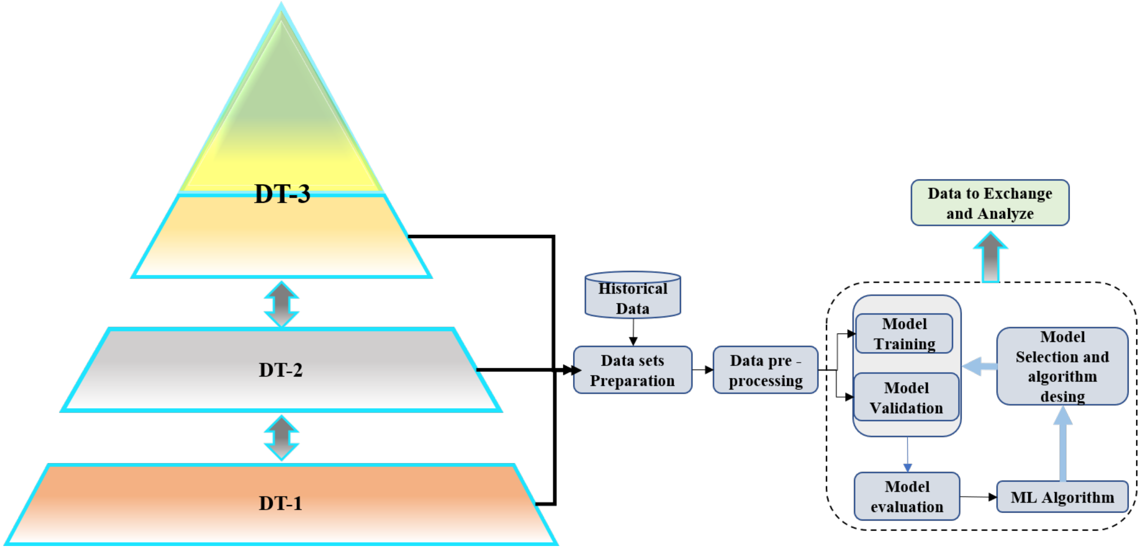


Figure 3.2: Proposed AI-MIS

The proposed AI-MIS model for information management between DTs is based on a model presented in [54]. The data set preparation would extract the data set from historical data base, examine its structure and select through sample and variable directions. The data pre-processing usually helps to improve the data quality by making data transformations. These shifts are related to fitting the time axis data together to avoid inconsistencies in the essential variables. Also, the outliers should be removed from the modeling data set. In addition, some missing relevant data need to be addressed and finally, the scale difference among process variables needs to be considered. Once the training data set is prepared, the machine learning (ML) algorithm is selected according to the data characteristics (different within DTs), the complexity of the data model, and so on. The ML algorithm between DTs would be different, the selection would be based on different criteria such as Akaike Information Criterion, Bayesian Information Criterion, Hannan-Quinn Criterion, etc. [56].

The proposed model is intended to be used either offline or online, according to the functions assigned to each DT, understanding as an online state the processing of information at the time it occurs, and the offline state as the processing of historical information, not performing data processing at present time.

3.2 Field and Control Level Model

The physical elements contained in the field and control levels are commonly described by mathematical models. Usually, these elements are simulated in dedicated software such as MATLAB and LabVIEW. The DT-1 model proposes the mathematical simulation of actuators, sensors, and control systems to be developed in any of these platforms. To be properly synchronized with the rest of levels, these simulations must be developed with specialized hardware that supports real-time simulations. Usually, this kind of hardware is based on field programmable gate arrays (FPGAs). This characteristic enables the proper communication of all the systems integrating the virtual pyramid. Thus, the lowest two levels are proposed to be virtually modeled in the dedicated software mentioned and executed in a real-time environment. The Fig. 3.3 shows the DT-1.

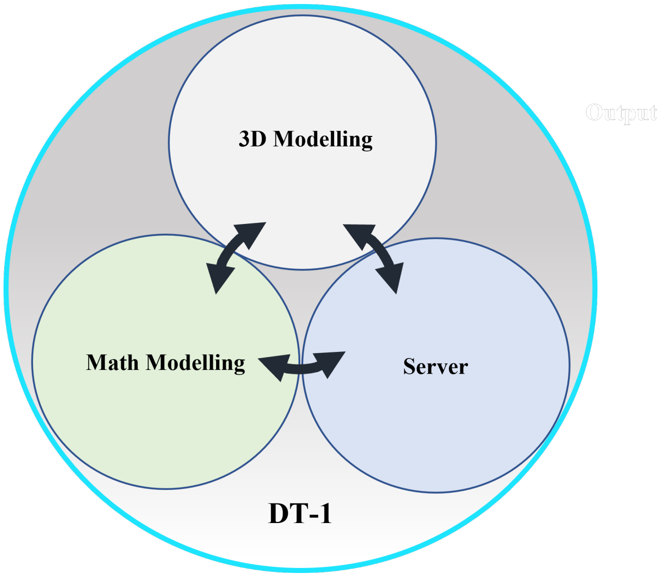


Figure 3.3: DT-1 Virtual Model

In addition to having a mathematical representation of the elements of the first two levels of the original pyramid, it is necessary to have a 3D model that represents these devices. The representation of physical devices in 3D models is essential for user interaction. Through

CAD tools, it is possible to have a virtual representation of the physical models of any machine, reason enough to include a CAD model within the DT-1.

Currently, CAD modeling software allows the interaction of its platforms with mathematical modeling software such as LabVIEW or MATLAB. The mathematical model of an element or system supports the 3D model since it contains the mathematical expressions with the variables, constants, coefficients, etc., that best define the element in reality. This, of course, offers an advantage in the simulation by being able to have results that more accurately reflect the results of a real model. In addition to the above, to remotely access and interact with the DT-1, a virtual server is required. This server will intertwine the mathematical, control and 3D representation models of the desired virtual elements. Like the communication links, the server is a key piece for the interaction between the physical and virtual twins, since the information that comes from the physical elements and with which the digital model will work will be housed in it.

The data obtained from the DT-1 can be extracted for the analysis and application of algorithms that contribute to the maintenance prediction, raw material monitoring, production analysis, etc. In fact, the information generated in this model can be available for any of the rest DTs.

3.3 Supervisory Level

The traditional AP considers SCADA and HIM systems to monitor the shop-floor production. To simulate this characteristic, this work proposes to execute one of the supervision functions carried out by the SCADA system, incorporating the function of detecting defective products through virtual monitoring systems based on vision. Hence, the proposed function of supervision will be simulated in a virtual environment by the DT-2.

Currently, the supervision of production through image analysis is a widely studied field. Techniques for the classification and detection of failures based on AI are usually employed to detect anomalies in the production quality. Hence, the virtual supervisory level is proposed to use a AI algorithm to classify previous-captured images. Images with different characteristics would be stored in an image bank according with the production process. Later, these can be employed as reference to classify those processed in real-time and captured by a high precision camera. In Fig. 3.4 the DT-2 is shown.

The images will be captured by a camera whose handling software must be operating in real-time. The images, as indicated in the 3.4, are extracted from the physical production process. In the image processing stage, the images have a preparation process where their quality is improved by then successfully being interpreted in the interpretation stage. Frequently, the real environments contain backgrounds that are open to being extremely noisy for computer vision algorithms owing to changing lighting conditions, mechanical vibrations on the camera support, and so on [57]. Therefore, to obtain an accurate result from the selected AI algorithm, the real images must be pre-processed to eliminate all that possible graphic noise. For instance, ensuring having proper mechanical circumstances such as non-exist mobility of the camera mount and adequate distance to the capture point, there are techniques such as the frame-difference approach to remove image background [58].

Regarding the interpretation of images, the preprocessed images will be compared with

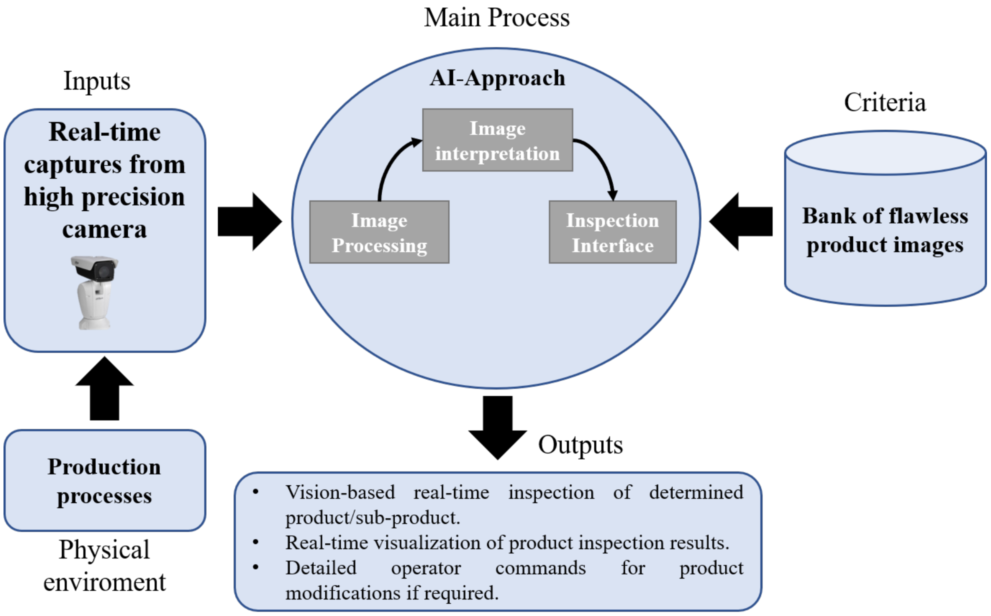


Figure 3.4: DT-2 Virtual Model

those images preselected and stored in the image bank. The images stored will be uniquely images with non-defective patterns. These images can be of a specific subsystem, a subarea of the product, or a full view of the product to detect incorrect positions or defects, for example. The inspection interface must be a type of HMI where the AI results can be displayed. The outputs of this AI approach will generally be vision-based inspection of determined product or product components. Furthermore, if a defective product/component is detected, the DT model must be able to display a brief pre-report with immediate actions to be executed by the operators.

3.4 Planning and Management Level

As an initial proposal, the planning and management levels are intended to be performed by AI-based learning systems as well. Due to the large number of functions that are executed at these levels, for now, it is only considered to work with the functions deployed by the ERP: Order Processing (OPR) and Production Scheduling (PS), and MES: functions related to Control of Production (PC), as indicated in Fig. 2.3. Decision-making systems, such as MES and ERP, can be considered non-linear systems since they involve a considerable variety of scenarios and combinations due to the number of inputs, outputs, relationships and conditions that are carried out in the functions that are performed at these levels.

Usually, AI-based learning algorithms such as Multilayer Neural Networks (MNNs) are used as alternative to learn linear and non-linear relationships between input and output vectors. This is one of the main reasons for the use of MNNs. As is known, these algorithms can carry out operations with complex non-linear relationships between dependent and independent variables, such as the functions that are executed in the ERP and MES. In addition, MNNs offer advantages such as the ability to detect all possible interactions between predictor variables, the availability of multiple training algorithms, the ability to work with incomplete knowledge, fault tolerance (in one or more cells) , parallel processing capacity, etc [59], [60]. MNNs learn events and make decisions from the examples (database) with which they are trained. All the characteristics mentioned are adjusted to the capabilities that this proposal seeks to provide to virtual decision-making systems based on the DT. Further information about Artificial Neural Networks and particularly Back-Propagation Networks used in this work, will be discussed in Chapter 5.

MNN algorithm consists of a system of interconnected neurons, or nodes. The neuron receives signals from other neurons; the neurons' inputs are affected by associated weights so that the output signal can be calculated as the output of an activation function. The input is the sum of the neuron's inputs multiplied by the associated weights. The interconnection of neurons that are grouped into layers allows MNN to approximate nonlinear relationships [61]. Thus, the initial proposal is to use MNN to execute the functions and tasks already mentioned by the ERP and MES systems. Fig. 3.5 shows the approach considering the MNN and the functions mentioned as part of the DT-3 virtual model.

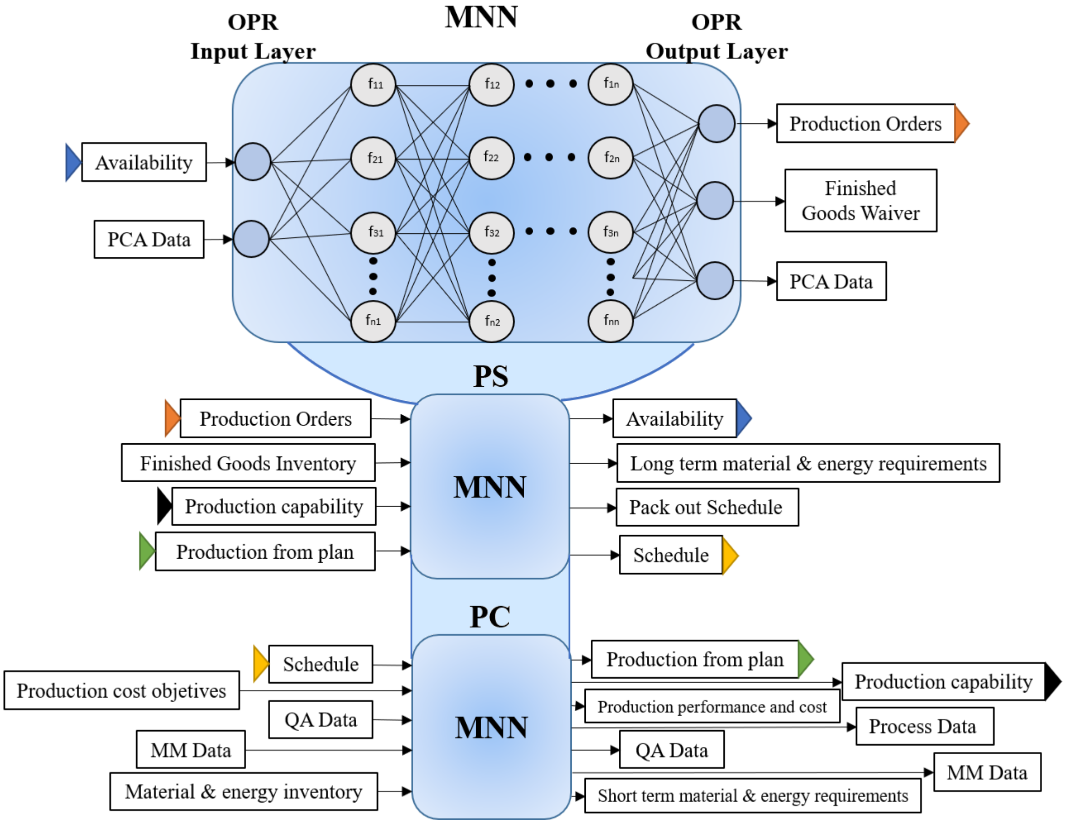


Figure 3.5: DT-3 Virtual Model

Figure 3.5 shows a Multilayer Neural Network (MNN) in which the inputs are *Availability* and *PCA Data*; those inputs are represented by only one input neuron, but they are expanded to a cluster of neurons according to the required inputs. On the other hand, the outputs are *Production Orders*, *Finished Goods Waiver*, and *PCA Data*; those outputs also have to be expended to accomplish the required outputs. In general terms, the MNN only represents the input-output relationship, but it does not represent the total number of neurons required in the input and output layer.

The proposal consists of 3 MNNs that represent the three functions considered for this initial proposal. For practical graphical representation purposes, only the first MNN illustrates a general configuration of the MNN body. In the first MNN, it is observed that the input and output layers contemplate the tasks performed by the order processing (OPR) function. In this case, the OPR function has two input tasks and three output tasks. It is important to mention that the task name reference shown in Fig. 3.5 actually involves all possible values (numeric, characters, etc.) that can be obtained from that specific task. The hidden layers of the network will have a certain number of neurons each associated with an activation function. Remember that an artificial neuronal system tries to model the behavior of a biological network, in MNN the body of each neuron represents a linear adder of external stimuli followed by an activation function (non-linear) whose task is to use the sum of the stimuli to determine the output of the activity of the neuron [62].

Some of the inputs and outputs of each network are labeled ”data”. Taking the first PC network as an example: the inputs and outputs with this label are shown as a single value for illustrative simplicity, but note that these tasks consist of two inputs and two outputs, i.e. the value of ”QA Data” as input is actually made up of two sets of values: ”Standards and Clients” and “QA Results”, depending on the functional control model on which this DT is based. This relationship is applied to the rest of the outputs associated with the PC network labeled as ”Data”. For the OPR network: PCA Data is the information that is shared between the PC and the OPR functions defined in the first part of the standard, in the functional enterprise/control model (see Fig. 2.3). In this network, the value of PCA data as input does not necessarily correspond to PCA data information values as output of the network. For more detail on the information that each label represents within this DT-3 model, one can consult the first part of the standard, where the functions carried out in each entity and the information exchanged between them are defined.

On the other hand, some of the tasks in each of the OPR, PS and PC networks have an arrow after or before the label with a certain color. Those with the same color indicate that the set of values derived from this task as the output will be the same set of input values that some of the two other networks will receive. For instance, the PS network output data set for ”Availability” will be the same data set that the OPR network will receive as input. The graphic union between each network indicates that they are part of the same DT and that the networks will have to be executed as a single system whose internal subsystems interact simultaneously and from which partial and final results are obtained in real time.

The main objective of the application of the MNNs is to have a virtual intelligent system that has the ability to learn and apply that knowledge automatically. Considering this and the nature of the environment where the activities of the input layer are executed and the objective results at the output of the proposed networks, a Back Propagation (BP) algorithm is proposed for the training of the MNN. BP algorithms work under supervised learning, therefore you need a set of training instructions that describe each output and its expected output value. To “train” the neural network, it is necessary to set a data set containing input signals connected with corresponding targets. In each iteration of the training process, the values of the weights are adjusted using new data from the dataset defined for training. Weight modifications are calculated using the backward error algorithm for supervised training. Each step of the training begins by forcing the inputs out of the training set. Then it is possible to determine the output values of the signals of each neuron in each layer of the network [62].

The DT-3 model has as its initial objective to emulate the decision making that is carried out in typical ERP and MES systems, focusing for now on covering those functions discussed in the development of this work. Through the DT-3 model, anticipated answers can be obtained for those tasks that are simulated within any of the proposed networks. This can be a valuable alternative in the simulation of scenarios with conditions attached to reality and responses in a short period of time, or responses scheduled to be displayed at a certain time. Therefore, through the DT-3 model it will be possible to simulate and have answers for a set of activities such as: production monitoring, providing information to control batches of products and labeling them for identification, obtaining information on material waste , machine downtime and process status data, etc. In summary, the activities related to production control that are specifically contemplated for the PC functions, and all those contemplated in the ISA-95 standard for the OPR and PS functions.

With the results coming out of the DT-3 models, decision-makers can prevent, predict and improve specific points for each of the simulated tasks.

Chapter 4

Assessment of a Didactic Manufacturing System through the Virtual AP Model

In the same way that the traditional pyramid can be applied to any manufacturing entity, the DT model proposed in this work can be applied to a company as a whole, to a manufacturing plant, to a designated plant area or to a particular process.

Therefore, this chapter presents the evaluation of a manufacturing system through the model proposed in the previous chapter. The objective of the evaluation is the application of the model as part of the development of DTs for workstations applied in the teaching of undergraduate students. At the end of this case study, opportunity areas of the evaluated system will be obtained and will be addressed in the next chapter. Thus, in the first instance, the didactic system developed in the Remote Laboratory at the Tec de Monterrey CCM will be described and then its components will be located and discussed within the framework of the proposed model. The didactic manufacturing system was developed by undergraduate students and researchers from Tec de Monterrey CCM, the information presented in this section was provided as a collaboration for this work, and the analysis carried out here is based exclusively on the information provided and presented in that work.

4.1 The Modular Production System: A Didactic Manufacturing System

In situations of social isolation such as the one experienced by COVID-19, having access to remote workspaces becomes crucial for day-to-day activities. Besides this advantage, the DT can offer the opportunity to run systems remotely without personal presence in the workplace or classroom to manipulate the any equipment. This case study applies the DT concept to the remote manipulation of industrial equipment used as a learning tool for undergraduate students at the Tec de Monterrey in Mexico City.

Some projects have been developed for the teleoperated manufacturing system, providing technological elements. Within the framework of the proposed AP-based DT model, the Modular Production System (MPS) has, broadly speaking, elements that can be classified in the DT-1 and DT-2 models. A general description of the MPS is presented below, followed by the detailed evaluation of each element in the framework of the proposed DT model.

The Modular Production System (MPS) aims to develop technological platforms for distance education that facilitate the transmission of information and knowledge and develop abilities, skills and competencies obtained through experimentation and practice in real environments. The system has four workstations (see Fig. 4.1) that together represent a line of products that can be remotely configured, monitored, programmed, and manipulated through a platform that manages access and system integrity.

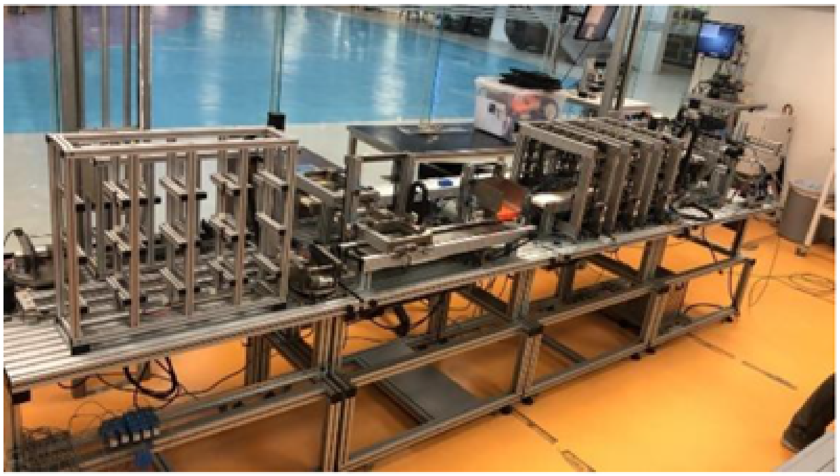


Figure 4.1: Physical Workstations

The access system is a web application stored on a TEC System server, allowing users' access through a section system; only the user who has reserved a time slot can use the MPS. This way, the students can access the virtual laboratory for uploading and configuring the physical workstations (see Fig.4.2).

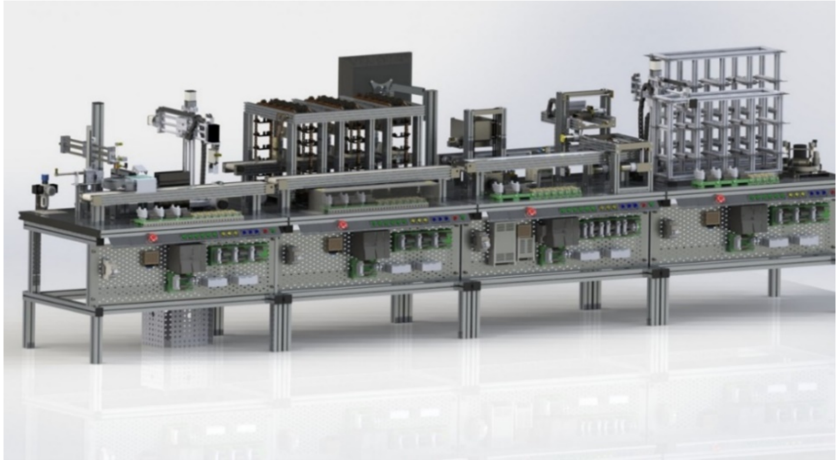


Figure 4.2: Virtual Workstations

The MPS has a three-dimensional computational model in which students can run experiments avoiding damages to the physical equipment. User students they should optimize their user time because the three-dimensional model can be accessed simultaneously by a limited number of users. Once the instructor validates that the students' settings and programs do not have errors, the instructor generates an access key on a website so that students reserve a time slot in the remote lab to test their programs and settings (Fig. 4.3).

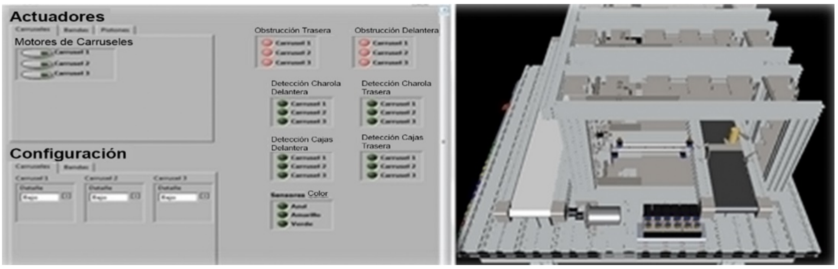


Figure 4.3: View of one module in the Virtual Laboratory Platform

To access the remote lab, the students developed an application designed specifically for the MPS that allows them to view and work with the equipment remotely. Through the application they have visual information in real time through video cameras (Fig. 4.4).

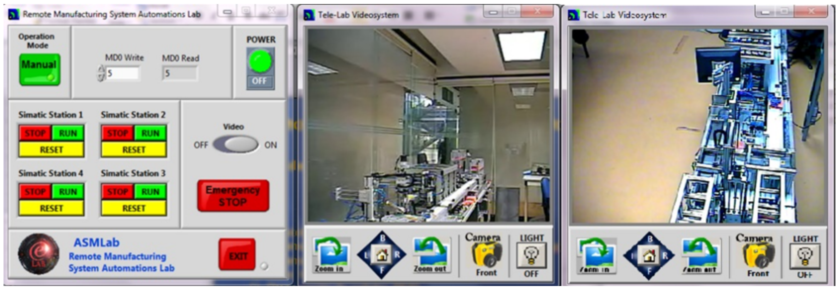


Figure 4.4: View of the application to access the Remote Laboratory

4.1.1 Workstations

Workstation 1
The MPS initiates this workstation for the production and circulation of materials. To start it receives raw material (plastic boxes with two circular spaces and empty metal tokens inside the boxes) to deliver boxes already assembled with two tokens as product final("assembled with" refers to the tokens in the boxes). Then, it moves the assembled product to the end of a conveyor. Finally, a manipulator arm removes the assembled product from the inlet of the next workstation (Fig. 4.5).

Workstation 2
This station process begins when a loaded box is transported to the conveyor belt by the robot manipulator of Workstation 1. Workstation 2 is an automatic unit for sorting and temporary storage. Along the conveyor path three sensors are arranged that identifies the color of the box. The sensors classify the cargo box to store it in one of the three vertical storages arranged along the conveyor belt (Fig. 4.6). The SCADA system counts the parts and sends signals to the workstation controller (PLC) to dispatch a certain number of boxes from the three storehouses to a second output conveyor belt that moves boxes to the table.

Figure 4.5: Virtual Model of Workstation 1

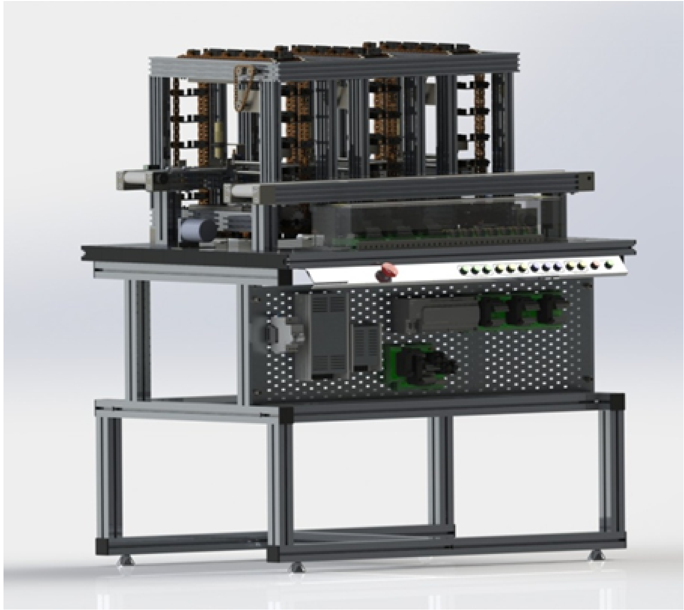


Figure 4.6: Virtual Model of Workstation 2

Workstation 3
This workstation organizes and packages the product that comes from the previous station. It receives the classified product from Workstation 2, then organizes it on pallets to facilitate its transport to the last station on the platform. Once the boxes are organized and assembled on the pallets, they are placed on a conveyor that transports them to Workstation 4 (Fig. 4.7).

Figure 4.7: Virtual Model of Workstation 3

Workstation 4
This storage and delivery station is responsible for storing the pallets delivered by Work Station 3 that contain the finished product in two vertical warehouses for subsequent dispatch. The station consists of two vertical loaders, two turntables, and a manipulator arm with three degrees of freedom (DOF) (Fig.4.8).

The Server
The system has a SQL server, which allows different operations and improves the coding and object orientation. A single operation is equivalent to one or more programs in a low-level language. The server has an ASMLab platform designed to give students easy use of a remote lab. The platform allows monitoring the MPS through cameras and microphones to supervise the process.

4.1.2 Real-time Interface, Monitoring system, Augmented and Virtual Reality

Real-time manipulation interface

The real-time manipulation interface allows interaction between the SCADA system and the MPS. The interface was developed through LabVIEW, so once develop the control logic into this environment, the next step was to achieve communication between LabVIEW and the

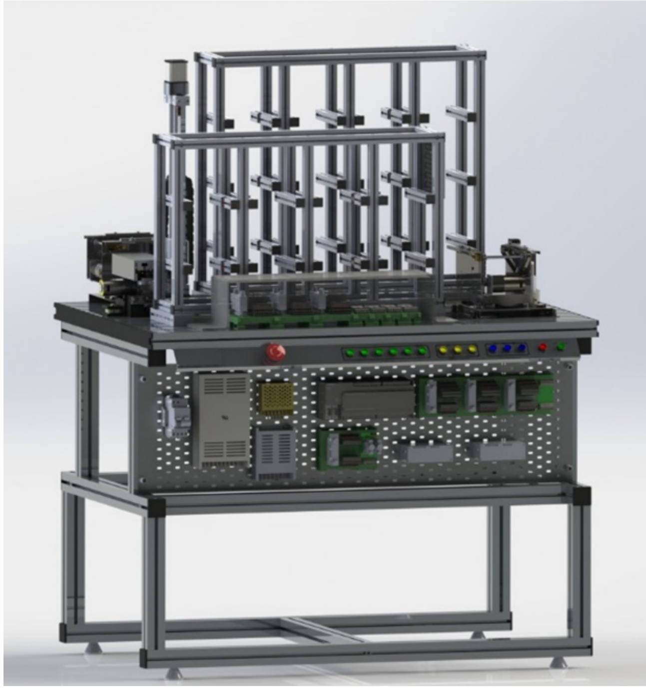


Figure 4.8: Virtual Model of Workstation 4

PLC through an OPC server. The Fig. 4.9 shows the interface developed through LabVIEW and is discussed below.

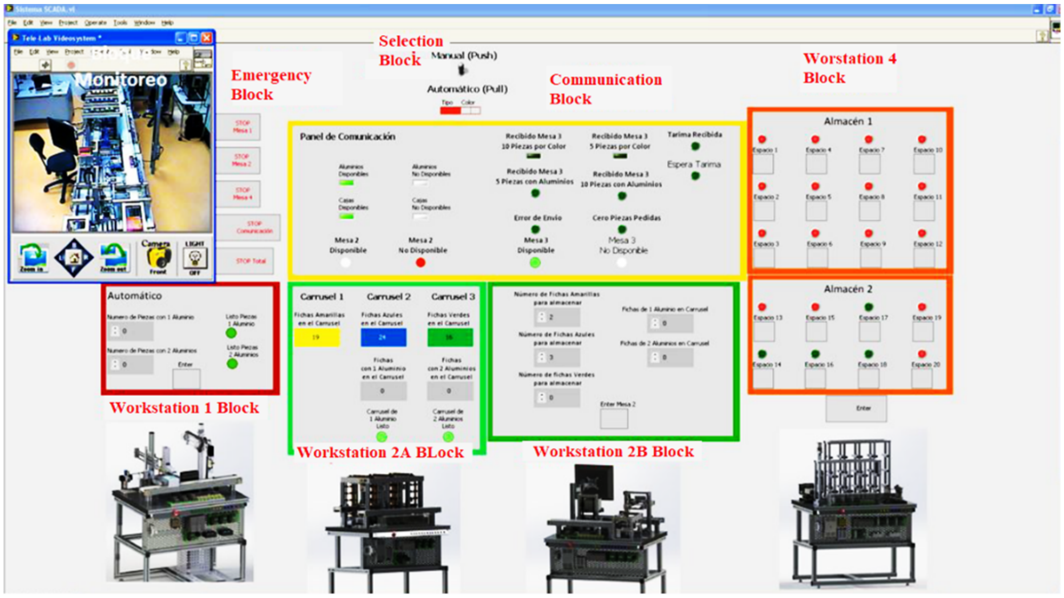


Figure 4.9: MPS Interface in LabVIEW

Emergency Block: The user can stop the SCADA system process with this block if an emergency or error occurs, stop a specific block, or completely stop the program from running.

Selection Block: Through this block the user selects how the system works manually (push) or automatically (pull). The production of the temporary and assembled storage depends only on the stock in the warehouse. Also, it is possible to select if the user needs a production based on the type of card or color.

Communication Block: A communication alert panel is implemented between the four modules, plus the status of critical sensors in the production process. The sensor's status for aluminum cylinders and the sensor for plastic boxes are shown on the right side of the box. The user will be able to identify the availability of material to produce. If there is no availability of material, the user must feed module 1 with the material.

At the bottom of the interface, two indicators show the status of Workstation 2. The user can detect in real time if the module is busy performing some task, such as sorting a new card and identifying the availability status of the carousel. Additionally, to identify and correct physical anomalies, module 4 communication alerts are located at the top right. For example, the user can see when a pallet has been received for storage or in another condition.

In addition, the communication indicators of module 3 are displayed. For example, you can see if 5 or 10 pieces with aluminum or 5 or 10 pieces sorted by color have been received. Likewise, the user detects errors in the connection between modules 2 and 3 and order errors. The system only allows combinations of pieces whose sum is five or ten; any other combination is not processed. In addition, the user can view the availability of module 3 and observe its current status: available, saving tokens or transporting the tokens to the receiving position of module 4.

Workstation Block 1: Here, users can select the number of tokens they want to make with one or two aluminum inserts. This option is only available if manufacturing is done by type. Also, the program hides the keyboard when the production process runs to avoid overwriting values.

Workstation Block 2A: Station Block 2A allows the user to view the status of the three module carousels. This block indicates the number of parts in each carousel to check the availability of parts and carousels, full or empty.

In addition, two indicators inform if carousels 2 and 3 are in the process of storing parts by type. Indicators easily identify errors in communication between field devices and the SCADA system.

Workstation Block 2B: Allows the user to select the number of tokens to request module 2, with the restriction that the sum of the combination is 5 or 10. Both types and colors show the two controllers. The selection process will begin when the user selects the number of boxes they wish to accommodate on a palette, followed by pressing the Enter button.

Workstation Block 4 : Here, the user can view the availability of all 20 warehouse slots. If the indicator is red, that place is not available; otherwise the place is accessible.

MPS Animation: Workstations were simulated in SolidWorks to integrate into the human-machine interface designed in LabVIEW. This animation allows the operator to virtually observe the functions of the stations. The advantage of having this simulation is to simulate the process to detect improvements or failures.

The animation is controlled by LabVIEW and CAD files from the workstations integrated into the LabVIEW project. Workstation variables (inputs, outputs, sensors, etc.) found in the LabVIEW animation project are linked to shared project variables that control the interface, causing the MPS and animation to run synchronously .

Taking Workstation 3 as an example, the movement of the conveyor belt was simulated through a subproject made in LabVIEW. This action was repeated for all moving components such as boxes, platforms and chains. Fig. 4.10 shows the indicators and controls used to simulate station movements. Similarly, Fig. 4.11 shows the indicators and controllers for the variables of Workstation 4.

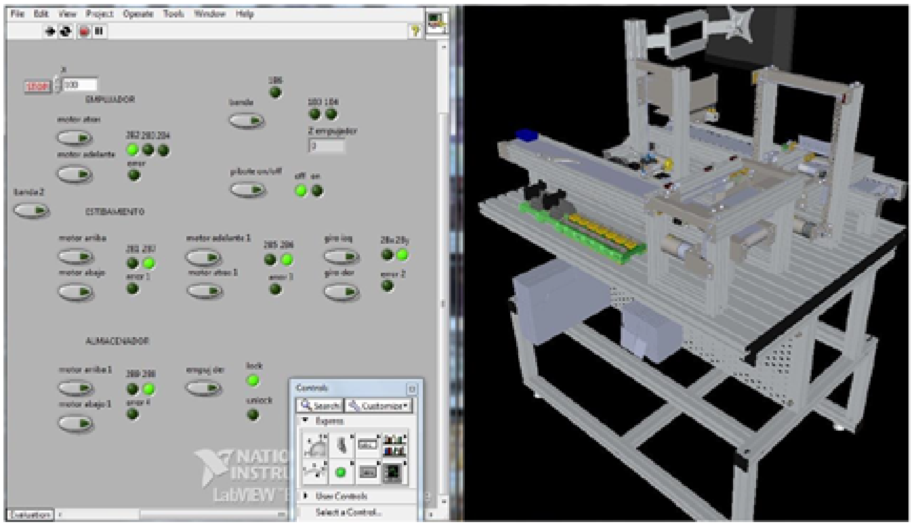


Figure 4.10: Workstation 3 Animation

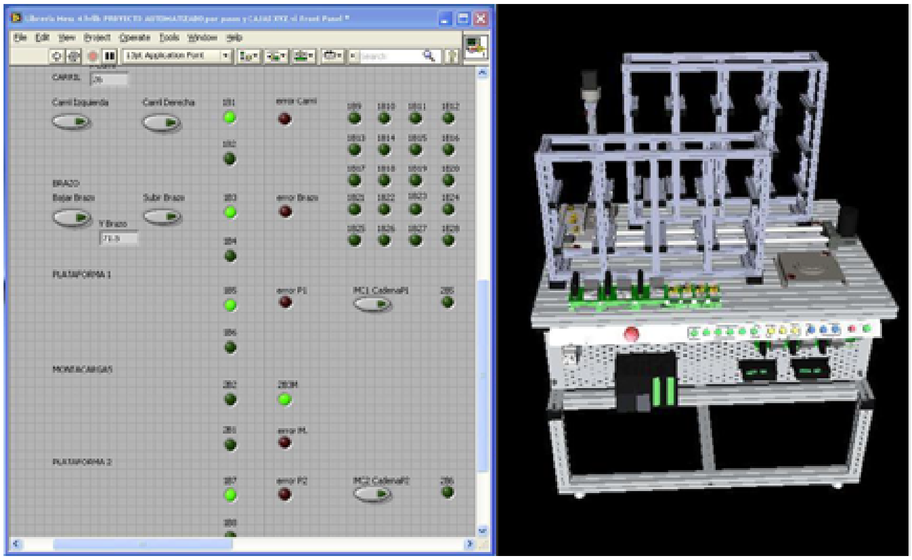


Figure 4.11: Workstation 4 Animation

On the other hand, to have communication between LabVIEW and the PLCs it was needed to use an OPC server. The OPC server allows the declaration and interleaving of shared variables used in PLC programs and the SCADA interface. Shared variables consist of boolean memories, byte memories, counters, inputs, and outputs. The four workstations were created in the OPC panel to function as clients that will communicate with the OPC server.

Table 4.1 illustrates some of the variables shared between the LabVIEW interface and the OPC server for workstation 1. Other variables were declared into the four workstations using LabVIEW similarly. Thus, it was possible to integrate any program, libraries, controls, and modified indicators into one single location.

Name in OPC	**Name in LabVIEW**	**PLC Direction**	**Description**
$Q1_1$	Extended Piston	Q1.1	Allows to monitor the piston position.
$M23_0$	Enter Button	M23.0	Allows production is started.
$I1_1$	Box sensor	I1.1	Allows monitor the sensor state for box detection.

Table 4.1: Variables in LabVIEW and OPC server

Monitoring System

In the monitoring system, security cameras allow the physical system to be monitored in real time, mainly to avoid collisions between components. The cameras are embedded in the ceiling of the laboratory. The cameras have an IP address that allows remote monitoring via the web. Fig. 4.12 shows the web-based platform to access and control the camera.

Pan Speed 0
Tilt Speed -5
Zoom Speed 0
Focus Speed 0

Figure 4.12: MPS view of monitoring system

Communication of all workstations could be done via ethernet through SCADA system to ensure continuous production, control and supervision. Now, the monitoring system is based on the LabVIEW environment. An OPC system is being used that allows the incorporation of new variables that are controlled.

In the MPS currently the user has total control from the SCADA system to each station, and the total manipulation of the production must be from the human-machine interface.

Augmented Reality (AR)

The Augmented Reality (AR) application was carried out for Workstations 3 and 4. The objective was to generate an operation manual for these stations through AR. The AR application was made with the *Vuforia* software, part of the PTC package, where it can be designed from two views, 2D and 3D. The AR app was observed through a Thingmark that works like a QR code. The Vuforia View application made it possible to scan and view the jobs hosted in that environment. Fig. 4.13 shows the Thingmark codes through which the AR model is accessed.

ThingMark 40114:1 ThingMark 40114:2 ThingMark 40114:3

Figure 4.13: Thingmark codes to access the AR model

In addition, the application allows you to interact with the 3D model as a single piece or with each element that makes up the workstation. Each button has an event assigned in the application when it is pressed (see Fig. 4.14).

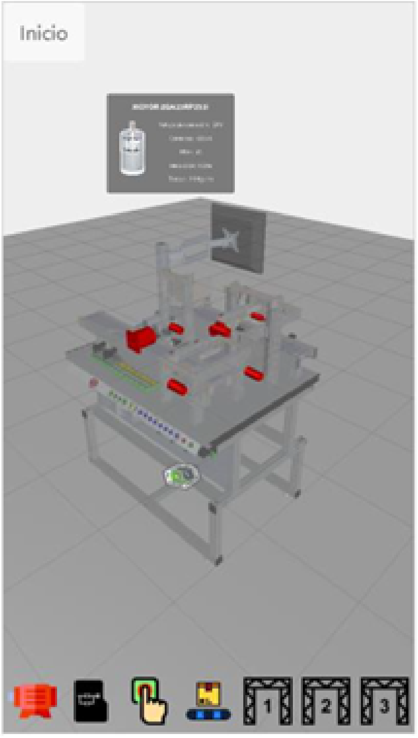


Figure 4.14: AR model at Vuforia platform

The workstations can be visualized using AR glasses and the designed application. See in Fig. 4.15 the AR model for Workstations 3).

Figure 4.15: AR model for Workstation 3

The buttons on the panel allows to select an element from the table that is indicated in the virtual model. A pop-up window will be displayed with relevant information about the selected item. The PLC selection is shown in Fig. 4.15. The Thingmark in Fig. 4.16 can be scanned with the Vuforia View app to access the AR model.

Design - Vuforia Studio

3

ThingMark 40112:1

Figure 4.16: Thingmark to access the Workstation 3 AR model

Another application allows access to the AR model of workstation 2. This is shown in Fig. 4.17. A similar thingmark access code was scanned to view the AR model for Workstation 2.

Virtual Reality

Through the virtual reality application, workstations 3 and 4 can interact and monitor each other. To carry out this application, three Siemens products were used: Process Simulate, OPC Scout and TIA Portal. With the help of the latter, the PLC of workstation 3 was programmed.

The animation of the 3D model of workstation 3 replicates its corresponding physical model (DT). The interaction between both models is done through a client and an OPC server,

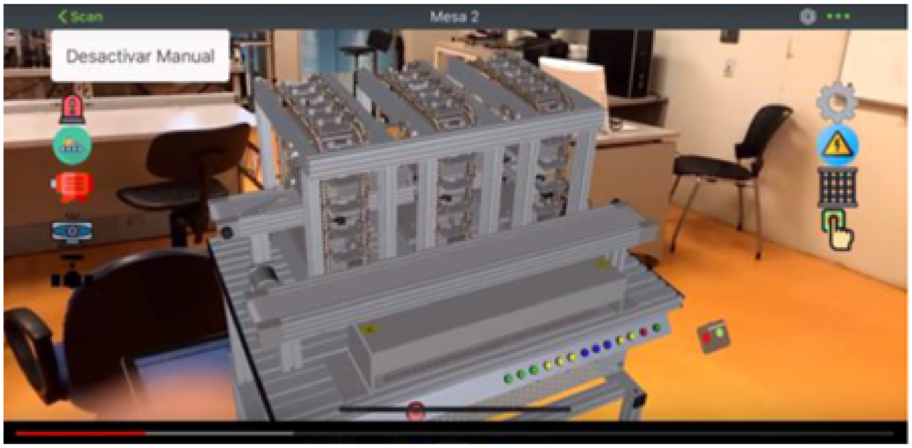


Figure 4.17: AR model for Workstation 2

which obtains valuable information and data from the PLC. The information of the available devices is given by the OPC, and the OPC client links with the server and accesses the offered data.

Process Simulate validates and virtually simulates the movements of every subsystem on the workstation. The interaction between this software and the variables declared for the PLC has a behavior similar to that of virtual and physical systems in real time. OPC communication collaborates in a continuous flow of information without interruptions. Virtual identification of output data under certain stimuli at the system input by actuators, switches, and sensors enables real-time system monitoring.

In addition to the model of workstation 2, through the same Process Simulate platform, you can see the virtual model of Workstation 3 (DT). With this DT you can manipulate and monitor Workstation 3 remotely (Fig. 4.18).

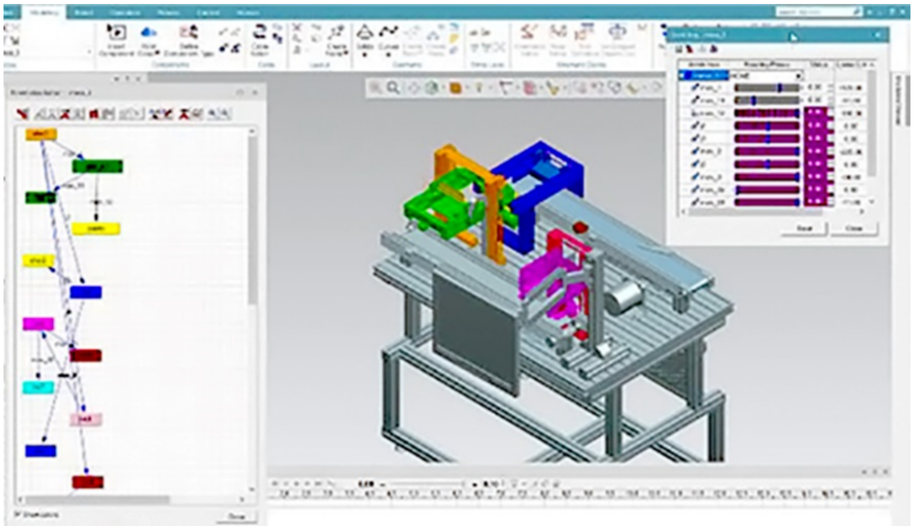


Figure 4.18: Virtual Model (DT) of Workstation 3 in the Process Simulate Platform

4.2 Modular Production System Assessment in the Framework of the DT Model

The present proposal was developed in conjunction with the work published in the open access journal *Sensors* published by MDPI [63]. The evaluation of the MPS through the proposed model of DT is a co-evaluation exercise. On the one hand, with the support of scientific approval by experts in the area, the DT model is used as an evaluation tool in search of improvements for the virtual MPS model. On the other hand, said evaluation serves as feedback to the virtual pyramid proposal by being applied to a set of virtual entities already deployed and in operation whose objective was the development of DTs. The evaluation is based exclusively on the information presented in the previous section.

4.2.1 DT-1: 3D representation, mathematical control model and server.

For the virtual representation of levels 0 and 1 of the AP, this proposal considers that there must be:

- The 3D model
- The mathematical representation of the model and control of the main actuators of the system,
- The server.

The MPS 3D Model

The MPS has a 3D model that represents the complete real model. The 3D model is based on the representation of the 4 workstations and all the components such as sensors and actuators that are part of them. Through these models, students can simulate the process without interaction with the real model. This is presented as an advantage since simulating the process virtually means a saving in resources for the real model. In an educational environment, where there are students in training, the advantages of virtual simulation are increased, since students can run simulations avoiding damage to the system or waste of material.

According to the information presented, the HMI developed through LabVIEW and the communication through the OPC server allow the interaction between the virtual and physical model, that is, the virtual model can work only from the information in the real workstations available at the instant of simulation. Besides, the interaction only takes place for two of workstations 3 and 4.

Limitations

Even when the 3D model of the four stations is available, the interaction of the physical MPS is carried out only for a couple of workstations, preventing the complete process in the physical MPS from being carried out in the digital MPS.

There is no detailed information on the interaction between the virtual and physical models of stations 3 and 4, however, according to the information presented, the interaction between twins is carried out with the present values in the variables declared in the OPC server and found within the LabVIEW interface project shared with the physical controllers in the physical MPS. Although this allows the synchronization of both models, the virtual model, in addition to working with the instantaneous values of its physical twin, should have access to the historical values of the variables that they share through the server.

In this phase of the project, the partial interaction of the virtual and physical models of the workstations would classify the MPS within an incomplete DT scheme. That is, what is executed in the physical model is partially simulated in time and form within the virtual model. Additionally, one of the characteristics of the DT is to be able to use the historical information of the main variables of its physical twin to use it in favor of the forecasting and improvement of scenarios in the real environment.

For the interaction between the physical twin and the digital twin, it is essential to have the complete 3D model, in addition to having a solid infrastructure of hardware, software and communication standard so that information about what is happening in the workshop can be received and work virtually with this.

Mathematical control models

For the interaction with the 3D model, a platform was developed through LabVIEW. It shows control commands for actuators and alarms for the detection of some components within the workstations, however, this interface works only with the 3D model of the MPS.

On the other hand, the web application for remotely interacting with the physical MPS contains functions that control the stopping, starting and restarting of the MPS. In addition, it has controls that control the ignition of the MPS, emergency stop and manual operation. To achieve interaction between this application and the physical MPS there must be some feedback between them, probably through the SCADA system. The information received does not detail this link between platforms, therefore, it is only established that the physical MPS system can execute basic functions through this application.

Another valuable tool used by the students was cosimulation. This allowed the virtual interaction of the mathematical control model in LabVIEW and the 3D model, which is one of the initial steps on the way to having a complete DT scheme.

According to the above, there is a certain control scheme that allows enabling basic functions within the virtual model manipulation platform and the web application. These activation controls are limited to activating and deactivating virtual actuators, in the case of the virtual interface of LabVIEW and Solidworks (co-simulation); and physical actuators, in the case of the web application. The control that is executed on both platforms is basic, without controlling parameters such as the speed of the pistons responsible for driving the MPS components, or the direction of rotation or speed of the motors coupled to elements such as conveyor belts.

For any control process, the data received from the sensor system is essential. Regarding the sensor system within the MPS, it is known that the physical MPS has a vast number of sensors at strategic points that allow its safe operation. Most of these sensors were represented within the virtual interface. The shared declaration of the outputs and inputs of these sensors in LabVIEW and the OPC server allowed the availability of information obtained by them. This was a crucial point to get closer to having a complete DT.

For a virtual representation of any manufacturing system, there must be an initial survey of the number of actuators in the system and the type of control that is desired. In addition, the strategic points where you want to locate the sensors to control the process must be evaluated. With these initial data, it is possible to determine more efficiently what type of representation the actuators deserve and what type of control to exercise over them. In the MPS it seems sufficient to control only the activation and deactivation of the actuators with the help of position and/or presence sensors.

Limitations

The main limitation to complete the DT scheme of the didactic manufacturing system is the interaction between the digital twin and the physical twin in its entirety. Even though certain control schemes exist for the four virtual stations of the MPS, there is only interaction between physical and virtual control for two of the workstations. In order to evolve towards a complete DT model, in addition to adding the interaction between the virtual control interface of workstations 1 and 2 with the physical controllers, the simulations in the digital model would have to return information from the simulation to be executed by the MPS through the SCADA system.

In the framework of industry 4.0, smart sensors perform a critical and essential job because it is through them that monitoring, measurement and data collection processes can be carried out. Having the right amount and the right type of sensors at strategic points within the physical system, coupled with their communication with the virtual system, is an essential task to develop a high-fidelity DT to its real twin. In addition, the connectivity of the sensory system is relevant to have flexible and agile availability of the data set that they collect from the process that they are measuring. It is essential to have the appropriate hardware for the safe and efficient reception of the information delivered by a set of sensors or, with the software (server) that provides the best availability of the data to the digital model.

Server

The system has a Tec system server. This server performs elementary functions such as allowing users access to the web application through which they can interact with the MPS.

In addition to the above and according to the information received about the MPS system, the SQL server improves the encoding and orientation of the objects. SQL servers, depending on the version, are servers focused on database management and work under a client-server scheme, here the information is hosted on the server and network clients only access it. Based on what is presented, the version of SQL server is likely to be an express version, ideal for students and beginning developers looking to develop desktop or web applications, such as the MPS interaction application. Many variables come into play when choosing a server, generally part of the task to be performed and access to it. For the purposes of the MPS, choosing a web-based SQL server appears to be the most feasible and easiest decision to implement.

Limitations

Although the server meets the needs for the MPS, it has limitations that may not allow the system to be exploited in a better way. One of these limitations is the limited access of simultaneous users to the web application for interaction with the MPS model. It does not seem to be essential that a large group of students have simultaneous access to the system, however, having limited participant access also limits the time that students can work and explore the MPS.

4.2.2 DT-2: Supervisory Functions Model

The functions executed at this level are carried out through the SCADA system and a human-machine interface (HMI). As presented in Chapter 3, this proposal takes production monitoring as one of the functions that are carried out through the SCADA system and proposes to perform this function through a vision-based virtual monitoring model. The main components of this model are:

- A high-precision camera,
- A database with images of the product accompanied by the algorithm for its classification based on AI,
- A user intarface.

Monitoring Camera

The MPS has a pair of cameras and microphones for remote monitoring of the physical MPS. The objective of this set of cameras is the prevention of collisions or risk situations during the operation of the MPS. Among the characteristics of the cameras that favor MPS is their remote access through their IP address on the network. Through its web interface, the MPS can be viewed in real time during its operation. The interface allows the switching on and off of cameras, screen capture, movement in 4 directions of the shot, zoom in and out, capture speed, etc.

The set of cameras completely cover the objective for which they were installed.

Limitations

The main criteria for selecting the camera for the monitoring and detection of possible defective products in a production process is the definition of the images it captures. In general, the more definition and precision in the images captured by the camera, the better detail the product's characteristics will have. The selection of the definition level of the camera will depend on the type of product and detail that you want to capture in it. There will be products where it is sufficient to guarantee their geometry within the designed tolerances, or some others where it is required to review some of their sections in greater detail, for example, the dimensions and alignment of the integrated circuits prior to being installed inside an electronic card.

The pair of cameras that the MPS has may not capture the level of detail that would be required to detect defects in the products being manufactured. According to the images received, the definition of the images, as well as the position of the camera, would prevent locating defects in the manufactured products.

The location of the camera plays an important role in capturing details on the product. The closer to the product, the better the image of the product, without its definition being crucial. However, the size of the camera and the available spaces within the manufacturing process could make it difficult in many cases to get close to the camera, which is why the high definition of the lens does become important in these circumstances.

Image Processing Algorithm based on AI

The use of image classification algorithms for the detection of quality problems in a product in the industry is increasing. These algorithms are based on artificial intelligence, whose popularity for solving classification problems is increasing in different areas of industry. Currently there are tools that facilitate the creation, training and even the implementation of own image identification models.

As presented in the previous chapter, the proposal is to detect problems in the quality of the product through an AI algorithm that works with the images captured by one or a system of high-definition cameras. The MPS system lacks a similar algorithm that ensures the quality of the products that are manufactured in it. The supervision work is left to the user and the SCADA system and the pair of cameras installed in the laboratory. This supervision focuses on ensuring that the process runs safely, without collisions, with sufficient material, and without procedural blockages at workstations. The monitoring of the process can be carried out in person or remotely through the cameras installed in the laboratory.

Limitations

Not having a procedure for detecting defective products can result in losses in the sequence of the process, delays in production, waste of material, all translated into economic losses for the industry. The MPS is in an educational environment, so the impact of having defective products on the process is minor. The most noticeable disadvantage of having a mishap with any product in the MPS is time. In order for the students to be able to use the MPS, a time must be scheduled to access the virtual interface or to work on the physical MPS, for which, any failure with the product that is assembled, delays the time of use of the students looking forward to work in this lab.

User Interface

The interface that is proposed in the DT-2 is the one where the results of the detection of some anomaly with the manufactured product can be visualized. This virtual interface would have to be freely accessible to all personnel involved in production, supervision or decision-making tasks. In addition to the information on production, it is possible to add to its content the indicators, events section, alarms and communication controls with strategic points within the manufacturing process, as included in the MPS interaction interface with the SCADA system. That is, the display of information on monitoring through production cameras should only be a module within the HMI, additionally, this interface should contain the rest of the information characteristic of the process to be monitored.

As mentioned, the MPS has a user interface developed in LabVIEW. Through this interface, the status of various critical points within the workstations can be monitored. In addition to communicating the status of the stations, the interface has a set of alarms that indicate to the user the availability of use of the stations, the availability of parts or their type, and the availability in stock to house a new product.

Added to the MPS interface is the DT subproject that simulates the MPS operation and runs in sync with the physical twin (Virtual Reality discussed later). This feature, together with the interface, is essential in a system that intends to function under a complete DT scheme. Even when it was pointed out that the virtual model of the MPS is incomplete, this feature is essential to consider that the MPS has a DT. To interact with the DT, the only means is the creation of a digital interface where the user can access and interact with it (Process Simulate dicussed later). This feature is incorporated in the MPS, adding value and completing part of the cycle to have a DT-PT model.

To make communication between physical and digital twins possible, the OPC server is essential and of vital importance. Without the connection enabled by the server, the DT scheme would be impossible to carry out. OPC is an interoperability standard for secure and flexible data exchange in the automation industry [64]. OPC has variants, the most cutting-edge being OPC Unified Architecture, which is defined as a stand-alone service-oriented architecture that integrates all the functionality of the individual classic OPC specifications within a more extensible framework [65]. The OPC UA communication standard plays a very important role in the development of industry 4.0, we could consider OPC UA as the heart that gives life to the interaction between cyber-physical systems. For MPS, communication via OPC is sufficient, however, if we add digital features to MPS such as AI-based inter-tier information management algorithm, communication via OPC UA would be a must to connect with all virtual systems.

Limitations

The interface developed to interact with the SCADA system completely covers the needs of interaction with the MPS. However, to get closer to the proposed DT-2 model, vision-based virtual supervision should be added with the elements that comprise it, such as the image classification algorithm and the incorporation of cameras that allow the capture of details in the product that is manufactured in the MPS, in addition to the database with images of products with good and poor quality.

In addition to the above, to have the complete DT scheme, the remaining workstation simulations should be created and all integrated for the simulation of the complete manufacturing process in sync with the physical MPS.

With the virtual simulation of the MPS complete and in sync with its physical twin (PT), the ability to feed back to the physical twin should be added to the DT in case the DT detects any anomaly while the manufacturing process is running. Remember that we can ”train” the DT with information from its physical twin to detect possible failures in the process when the twins are executed simultaneously, for example.

Virtual and Augmented Reality

Virtual reality (VR) is a recurring tool today that offers the possibility of digitizing, simulating and interacting with a physical entity. Virtual reality makes use of immersive technologies to simulate interactive virtual environments with which users are involved and in which they feel physically present [66]. In other words, virtual reality is the essence that fosters the creation of a DT.

Through the OPC server, Procces Simulate and the Siemens TIA portal, the virtual environment that allowed the creation of the MPS DT was developed. This set of applications meets the essential requirements of access, interaction and simulation of the model. Actually, what is identified as VR in the development of the MPS is the cover of the DT.

On the other hand, the augmented reality (AR) models of stations 3 and 4 were created to operate them manually and virtually, in addition to offering elemental information to the user of the station’s components. Like VR, the use of AR has been popularized mainly in the areas of education and entertainment. Despite this, this proposal does not consider RA within the digital pyramid model, mainly because there are still challenges to be solved in its incorporation into industrial processes. Unlike an AR game where the user can leave whenever they want, in an AR work environment the user can spend a considerable amount of time using the system, so ergonomics and user cognitive strain are factors that must be considered and addressed before exploiting AR in a work environment [67].

4.2.3 DT-3: Planning and Management Functions Model

The proposal of this work is to add a virtual model that initially performs some of the functions deployed in the AP decision levels and that are usually executed by ERP and MES systems. As mentioned in the introduction, one of the main reasons for including a DT for management functions is the lack of flexibility when creating a DT for a single level and wanting to integrate it with the rest of the levels in the AP and also, the still low level of intelligence and autonomy of the ERP and MES systems facing scenarios with sudden or unexpected issues.

As can be seen in the presented content of the MPS, there is no entity that collaborates with the rest to carry out functions of an ERP or MES. Due to the educational use of the MPS, the objectives of the project were not to include any management software in the system. Despite this, the relevance of developing management skills for students is important for their incorporation into the industrial world and would add value to their training as future engineers.

4.2.4 Assessment Summary

Throughout this section, the work of the MPS was discussed in the framework of the virtual model of the AP that is proposed in this work. The elaborate characteristics that the current MPS possesses and that lead it to have a DT were highlighted. Additionally, the most relevant limitations that the MPS has to adhere to the digital model of the AP presented in this thesis were commented. Among the most visible limitations is the lack of a virtual model that performs the planning and management functions in the MPS, the model that corresponds to the DT-3. For this reason, the following chapter deals with one of the functions that are carried out at the decision-making levels according to ISA-95, particularly within the area of production control: production scheduling.

As shown in Chapter 2, there are a large number of functions that are performed at levels 3 and 4 according to the hierarchical model presented in the first part of ISA-95 (Fig.2.3). In the next chapter, only one of these functions is considered and it is solved through artificial neural networks (ANNs), as suggested by the digital model of the AP.

Chapter 5

DT-3 Model Approach: Artificial Neural Networks (ANNs) to solve a Production Control Task

The validation of any proposal is a necessary task to identify the points of improvement or discard the hypotheses generated. Thus, in this Chapter 5, one of the multiple functions developed through the MES systems is addressed through ANNs. This activity takes place within the production scheduling (PS) and production control (PC), and it is a problem that already has a solution algorithm. What is intended with this approach is to solve this problem through the intelligent algorithm proposed in the DT-3 model and verify its behavior of solving.

5.1 Addressing the two-machine flowshop scheduling problem through ANNs

The assembly that is carried out in the MPS can have variants. Depending on the information in the system, boxes can be assembled with 1 or 2 aluminum tokens, in addition, the pallets where the boxes are stored can have 5 or 10 pieces. That is, we can have 4 different types of batches or final jobs.

In a scenario where the MPS is required to carry out the 4 types of work in the shortest possible time, it would be important to know the order in which the 4 types of work should be carried out in order to have them ready in the shortest possible time. For now, within the work carried out in the MPS, there is no algorithm to help solve this scenario. This, together with the absence of an algorithm like the one proposed for DT-3, motivates the approach presented below.

5.1.1 Production Scheduling

One of the areas that have been studied widely in recent decades is production scheduling. In the literature, there are several academic proposals that have been directly applied in real industrial processes improving the productivity of enterprises. However, the proposals shown by some authors continue to have limitations, which may become obsolete as manufacturing schemes evolve. For this reason, operations research experts remain interested in developing new and more powerful programming methods. The resurgence of neural networks in the 1980s came to provide an alternative to the academic community whose vision recovers the advantages of these algorithms and has incorporated them to explore solutions to scheduling problems.

The scheduling problem can be defined as: *n* jobs should be assigned on *m* machines at specific times. The task is to find a sequence for the jobs which must satisfy the objectives without violating the constraints of the problem [68].

In the literature, the main problems of scheduling jobs are reported. Usually, the solution for small scheduling problems is easily found. Nevertheless, as the problem increases in size, the number of possible solutions tends to increase exponentially. These kinds of problems take place especially in the job shop environment and are called NP-complete problems.

In real applications, the manufacturing systems usually are not static. Therefore, setup and processing times should be estimated based on previous experience. Factors such as cancellation of purchase orders, availability of resources and machines failures cause the pre-schedule is not viable and rescheduling becomes necessary.

In the same sense, the scheduling problem relates to a wide range of manufacturing activities, which is why it is difficult to define criteria to measure and evaluate the overall performance of a schedule and then optimize it. Frequently, practical programming objectives are inconsistent with one another. Hence, the discussed features show that the scheduling problem become dynamic and stochastic, especially in a real environment.

In order to attack the aforementioned problems, several scheduling methods are presented in the literature. These are divided mainly into the following categories: heuristic methods, mathematical methods and artificial intelligence methods.

In recent decades, heuristic methods have shown significant advances in their effectiveness and efficiency. These methods are usually efficient and relatively easy to implement. They are usually applied in practical systems to obtain achievable schedules to reach a single objective even though the solution is non-optimal and may be very general. Nevertheless, their continuous improvement has made them one of the most widely used tools for optimizing scheduling problems.

Regarding mathematical methods, such as linear programming, they can find optimal solutions for problems limited in size. It seems complicated to use these types of methods in a real job shop environment due to the complexity of their models and the extensive time they show for the calculation.

Artificial intelligence approaches, particularly Neural Networks, are presented as a different solution to solve these scheduling problems. These types of algorithms estimate relationships and generalize the knowledge of the problem through learning scenarios, instead of basing their development on a defined mathematical model or a programming algorithm.

This last method is the tool chosen to attack the main problems of decision-making systems due to the great development and tendency shown in recent decades for solving supervised learning problems.

5.1.2 Artificial Neural Networks

Similar to the learning process of humans, an artificial neural network (ANN) takes as a learning base solved problems to build a neural system that can predict or classify (decision-making processes). During the experience of solving problems through ANN, it has been observed that those that require extensive algorithms or, without precise computational solutions, are the ones that are best adjusted to be resolved using ANN. Particularly, ANNs have been employed to solve scheduling problems since the 80s.

In general, the interest of solving problems via ANN comes from the capability to accomplish tasks that traditional methods do not succeed in. According to [68], these are:

- Parallelism: which will greatly increase their speed of calculation.
- Learning and generalization ability: means that neural networks have an ability to learn from external samples, then generalise them and abstract knowledge. This property is particular important for problems which are difficult to define mathematically.
- Distributed memory: allows knowledge to be mapped onto all the neurons of the network, thus the destruction of one neural unit only marginally changes the activation map of the network. This property permits the network to start to work with noisy data and end with correct results.
- At present, ANN are also relatively easy to understand and simulate on current computers.

In contrast, some disadvantages are identified and directly related to the presented benevolent features. Regarding parallelism simulation on sequential machines may result in evident increase in processing time as the problem size become larger. In relation to the second point, to date, there are not methods to design an optimal ANN that allows generalize it. Building a successful ANN depends on the researcher expertise. Respecting the third point, usually, explaining the results from ANN is a complex task, and the performance of a network can only be evaluated by statistical methods. If the researcher does not have experience interpreting statistical indexes, this may give rise to a certain distrust.

Problems solved by ANN usually share characteristics such as:

1. Complexity of setting rules: in fact, the rules used to solve the problem may be unknown or very difficult to formalize. Thus, a set of inputs and outputs can be obtained by carrying out a set of cases under known conditions.
2. The problem may require very high processing speed and short overall resolution time.
3. Noisy data.
4. Initial conditions change.

Punctually, Table 5.1 shows some of the advantages and disadvantages of using ANNs [62]:

Artificial Neural Networks (ANNs)	
Advantages	**Disadvantages**
ANNs are robust, some processing elements may fail but the network continues working which is opposite to what happens in traditional programming	ANNs represent a complex aspect for an external observer who wishes to make changes. To add new knowledge it is necessary to change the iterations between many units so that their unified effect synthesizes this knowledge. For a problem of considerable size it is impossible to do this manually, therefore a network with distributed representation must employ some learning scheme
To use neural technology it is not necessary to know the mathematical details, it only requires familiarity with job data	ANNs must be trained for each problem. Additionally, multiple tests are required to determine the appropriate architecture. The training is long and can consume several hours of the computational work (CPU).
Solving non-linear problems is one of the strengths of ANNs	Because networks are trained rather than programmed, they need a lot of data

Table 5.1: Advantages and Disadvantages of ANNs taken from [62]

Multilayer Neural Networks with Back-propagation learning algorithm

The back-propagation algorithm for multilayer neural networks (MNN) is a generalization of the least squares algorithm. Both algorithms update weights and gains based on the root mean square error (MSE). The back-propagation (BP) works under supervised learning and therefore needs a set of training instructions that describes each output and its expected output value [62].

Networks with BP are commonly multilayer feed-forward networks that have a sigmoid activation function in each neuron. Usually, these types of networks are a good choice for solving recognition and classification problems, but they can also be useful for solving programming problems. Once a well-structured network is trained, it can generate solutions with good results and with relative high speed. To set out and solve a scheduling problem it is necessary to carry out a series of steps. The sequence presented below was the one performed to attack the job scheduling problem shown in this thesis [68]:

- Define the representation scheme of inputs and outputs which can encode the solution to the original problem.
- Determine the structure of the BP network: the numbers of layers and the neurons in each layer.
- Construct a training set, consisting of a number of pairs of input and target output data sets. Some pairs from the training set should be reserved for testing.
- Set up initial values randomly for the weights of the network. and then train it using a suitable BPN algorithm.

- Test the reliability of the trained network using the test data set.

The cited sequence will be shown and explained in detail in following sections, in addition, the implementation for the approach and resolution of a 4/2/F/F$_{max}$ problem is discussed. Previously, the problem to be solved through the NN is defined, in addition, the algorithm that has traditionally been used to solve it is presented.

5.1.3 The two-machine flowshop scheduling problem and the Jhonson's Rule

The problem of optimizing execution times for *n* number of jobs on *m* number of machines is a typical problem of job shop scheduling. It is represented in Fig.5.1. This kind of problem is typically studied in the operations research area. It consists of optimizing the makespan in a set of *n* jobs to be executed in two work centers.

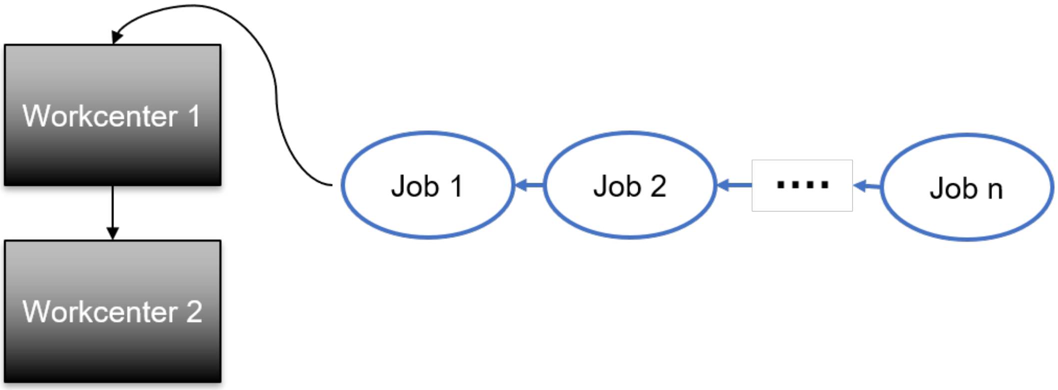
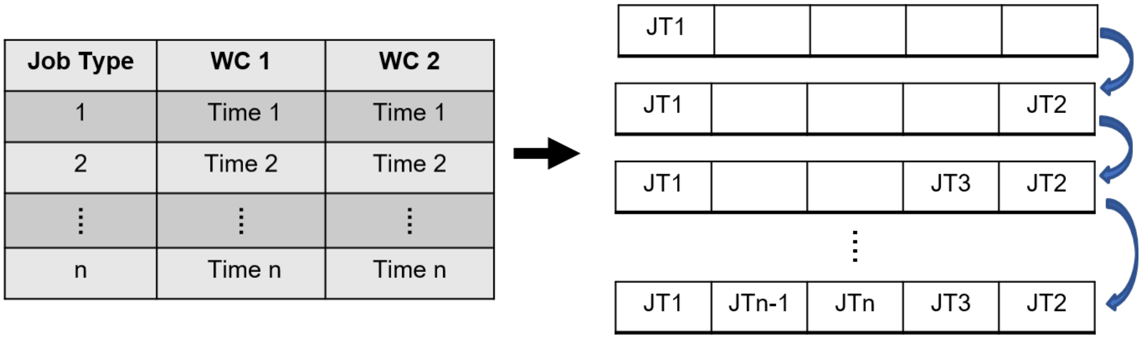


Figure 5.1: Flowshop scheduling problem representation

As mentioned, there are different ways to solve it, among the most common is the Johnson's rule. It is worth mentioning that in the field of operations research, makespan is understood as the period of time that elapses from the start of work to the end. Formally, the problem of minimizing the makespan considering two machines can be defined as follows [69].

Let N = { J$_1$, J$_2$, . . . , J$_n$ } be a set of *n* jobs to be processed in a two-machine flowshop. Each job consists of two operations, which must be processed on the first and second machine in that order, respectively. The processing times of job J$_i$ on the two machines are denoted by p$_i$ and q$_i$, respectively. The problem lies in finding a schedule that completes all the jobs in the shortest possible time (minimizing the makespan). It is clear that any schedule can become a schedule which the processing sequences on the machines are equal, preserving the minimum makespan. Therefore, the found schedules are permutation sequences, it is, two machines can get the same job sequence. Hence, for simplicity it is common to use sequences instead of schedules, as will be seen in this work.

Adopting the three-field notation [70], to solve the F2||Fmax problem, in [71] was proposed gave a decision rule, now popularly called Johnson's rule (author's name): For any two jobs J$_i$,J$_j$ $\in \mathbb{N}$, if min{ p$_i$, q$_j$} $\leq$ min{q$_i$,p$_i$}, then schedule job J$_i$ earlier than job J$_j$. Based on this rule, a solution algorithm, known as Johnson's algorithm, can be designed. Different forms of Johnson's algorithm have been presented in the literature. The following form is probably the most commonly used: —*Select the shortest processing time amongst all the unscheduled operations. If the operation belongs to machine one, then schedule the job of that operation in the earliest open position; else schedule the job of that operation in the last open position. Remove the job from the job set. Repeat the process until all the jobs are scheduled*—. In Fig. 5.2 there is a representation of this form of solution.



Job Type	WC 1	WC 2
1	Time 1	Time 1
2	Time 2	Time 2
⋮	⋮	⋮
n	Time n	Time n

Figure 5.2: Johnson's Rule representation

If we can use a sequence of steps to get the desired sequence through the Johnson's rule, it would be stated as follows:

1. Select the job with the shortest execution time: If the execution time takes place in the first machine, then order the job first. If the execution time takes place in the second machine, then order the job last.
2. Eliminate the shortest job from further consideration
3. Repeat the previous steps moving forward the center of the job schedule until finished all the jobs.

To make clearer the Jhonson's Rule steps, next, an example is presented. Consider the job types and job times presented in the Table 5.2.

Job Types and Job Times

Job Type	Machine 1	Machine 2
A	4.2	3.2
B	4.7	3.5
C	2.2	5.0
D	4.9	4.5

Table 5.2: Job scheduling example

1. The smallest time is located in Job C (1.5 hours). This time corresponds to Machine 1, then, schedule this job first and remove Job C from further consideration.

C			

2. Now, the next smallest time is located in Job A. This time corresponds to Machine 2, then, schedule this job last and remove Job A from further consideration.

C			A

3.- The next smallest time is located in Job B. This time corresponds to Machine 2, then, schedule this job before Job A and remove Job B from further consideration.

C		B	A

4.- Finally, the only job left over is Job D, locates this job in the last place of the sequence.

C	D	B	A

5.1.4 Solving the 4/2/F/Fmax problem with MNN

The problem solved in this case study is based on simulating the Johnson's rule through Artificial Neural Networks (ANNs) with a backpropagation learning algorithm . The type of problem is n/m/F/Fmax, which means flow-shop scheduling with n Jobs and m work centers so as to minimize the maximum Flow time or makespan. In particular, 4 types of jobs (n=4) and two work centers (m=2) are proposed.

In general, the methodology followed to solve problems through a BPN is [68]:

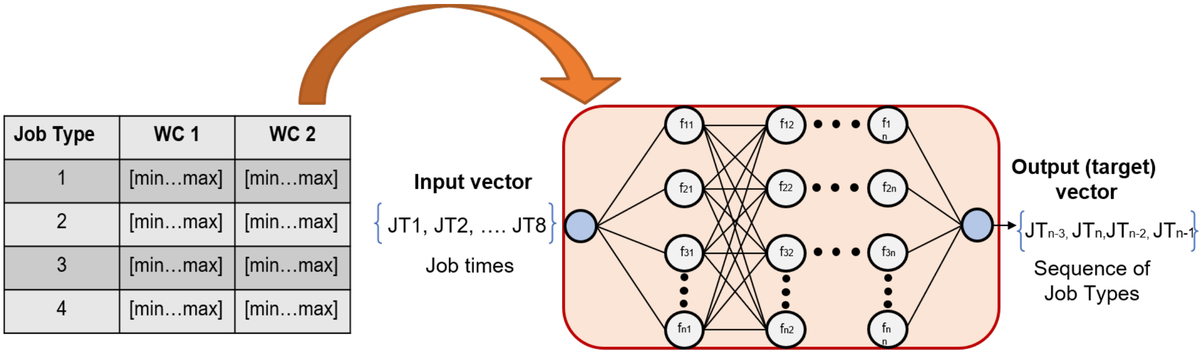
1. Study the problem and define the objectives to be achieved. This makes it possible to evaluate the quality of the obtained solution.
2. Choose the most suitable type of neural network and map the problem on it.
3. Implement the selected neural network, through some computer package or through its own program.

Objective definition

Considering this methodology, the initial objective is to analyze the behaviour of a proposed BPNs to solve flowshop problems of type n/m/f/F_{max}. Knowing the problem, we know the possible outputs, in this case, the sequence of job types that must be followed to minimize the makespan. Therefore, a set of pairs input-output can be determined.

Network type selection and Problem Mapping

BP networks were selected for their performance in recognition and classification task resolution. The structure of the proposed BPN is shown in the next section. To make use of the selected network, we need to map the problem. The network inputs will be two sets that will group the execution times of each job on machine 1 and 2. That is, the number of neurons in the network input layer will depend on the number of jobs performed for both machines (8 inputs). The number of hidden layers depends on the number of inputs and outputs and



Job Type	WC 1	WC 2
1	[min…max]	[min…max]
2	[min…max]	[min…max]
3	[min…max]	[min…max]
4	[min…max]	[min…max]

Figure 5.3: Flowshop schedulin problem mapped on BPN

the number of training patterns (training set size). The network output layer has a number of neurons equal to the number of job types, n. Thus, the network architecture required is *(nx2)/ Hidden Layers /n = 8 / H / 4*. In Fig. 5.3, there is a representation of this problem mapping.

The training set of a BPN must be according to the problem characteristics, in this case, it is a set of two elements, a vector of inputs with 8 elements and a target vector of output with 4 elements. The size of the training set is usually left to the investigator's experience. In general terms, training sets of different sizes were chosen during the training process, finding better performance with larger sets.

Network Development

Everything involved with the implementation of the BPN was done through programming in the Matlab environment and particularly, for the generation of the BPN and its structure, the Matlab toolbox was used. Thus, for clarity, the tasks related to the implementation of the BPN are depicted as a sequence of steps in Fig. 5.4. The Analysis of results shown as final step, will be discussed in the end of this Chapter, thus in this section the left four steps are presenting in next subsections.

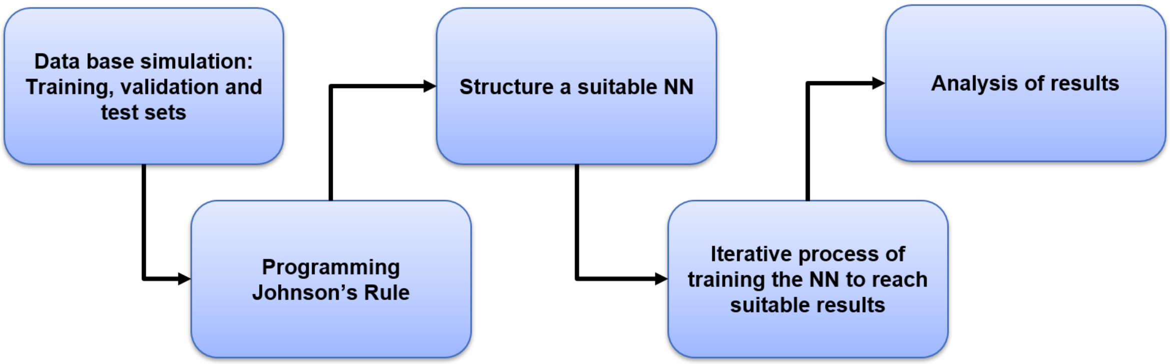


Figure 5.4: Implementation sequence of BPN

Data base simulation: Similar to the example shown for Johnson's Rule, the table shows the job types and execution times for each job type. Note: the value for each Job type in each workcenter is in time units: minutes, hours, etc.

Job Types and Job Times

Job Type	Workcenter 1	Workcenter 2
A	[2-6]	[2-6]
B	[1-5]	[1-5]
C	[3-7]	[3-7]
D	[4-9]	[4-9]

Table 5.3: Job times for each Work center

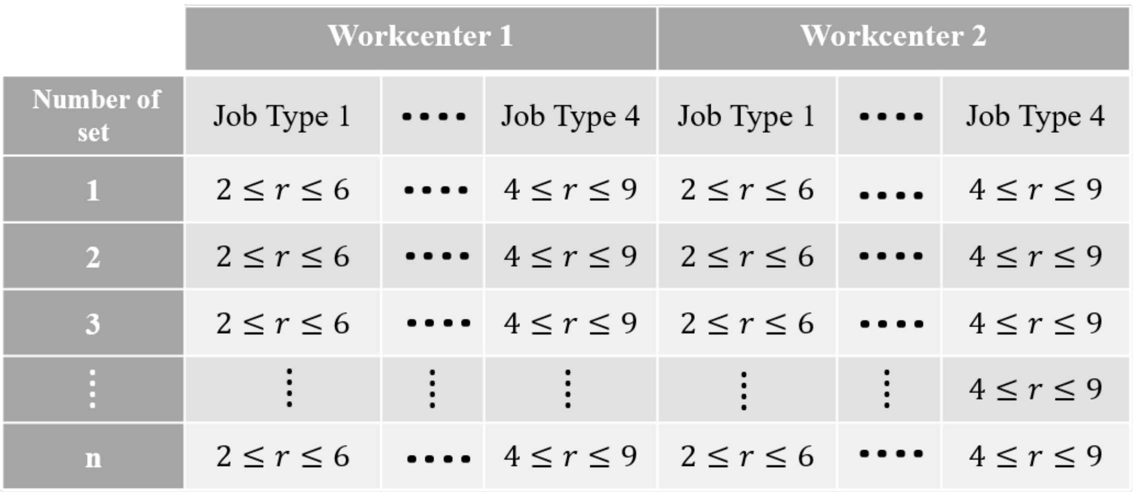
As observed, the time for each job in each work center can take a random value within a certain defined period of time. In a real environment, the execution time of a task by a machine can vary between a certain period of time since the operation of the machines is subject to factors such as the life time of the equipment, failures, poor programming, human errors in pre-programming. , etc. Thus, the range established for each job is observed in the Table 5.3, considering that random values will be generated between these ranges as many times as the size of the database is desired, that is, if the database is wanted to contain 10 thousand elements, 10,000 time data will be randomly generated between the ranges established for each job and for each workcenter.

The pseudocode 1 for the data base generation is deployed below. The original codes used in this work are added in the Appendix A.

```
Algorithm 1 Generation of Time Data Set with n elements
Input: [x_min : lower time limit for each type of job];
       [x_max : higher time limit for each type of job];
       [J: number of Jobs];
       [n: desired number of elements in the data base];
  for $i \leftarrow 1$ to $n$ do
    $Wc_1 = [r_i| \ r \in \mathbb{N}, x_{min} \leq r \leq x_{max}, \ \forall \ n]_{n \times J}$
    $Wc_2 = [r_i| \ r \in \mathbb{N}, x_{min} \leq r \leq x_{max}, \ \forall \ n]_{n \times J}$
  end for
  $M_T = [M_1 M_2]$
Output: Data base with n sets, with time values for each type of job
```

According to the pseudocode, the inputs to the algorithm are vectors with the minimum and maximum time values for each type of job. These values are defined in the Table 5.3. Also, the amount of job types *J* is entered, in our particular case, we work with 4 different types of jobs. As noted, *n* is the desired number of set of time values for each job type.

In the *for* cycle, the desired number of sets are generated for each workcenter. Matrix 1 and 2 are matrices of n×4, with a set of *r* random numbers within the minimum and maximum values defined at the input of the algorithm. At the end, the M_T matrix is generated that groups the Wc_1 and Wc_2 matrices, thus M_T is sized as n × 8. This matrix conforms to the input settings of the Matlab toolbox. For clarity, a graphic representation of the generated database is seen in the Fig 5.5.



	Workcenter 1			Workcenter 2		
Number of set	Job Type 1	••••	Job Type 4	Job Type 1	••••	Job Type 4
1	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$
2	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$
3	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$
⋮	⋮	⋮	⋮	⋮	⋮	$4 \leq r \leq 9$
n	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$	$2 \leq r \leq 6$	••••	$4 \leq r \leq 9$

Figure 5.5: Data base of times with *n* elements

As will be seen later, for the BPN training process the size of the database changes. This is part of the BPN's iterative training process.

Programming the Johnson's Rule: With the database generated, the next step in the BPN implementation is programming the Johnson's rule. This procedure is necessary to obtain the desired outputs (targets) for each set of inputs to the BPN. Thus, the pseudocode for programming the Johnson's rule considering the generated database is shown below.

```
Algorithm 2 Jhonson's Rule for n number of cases
Input: $[Wc_1]_{n\times 4}$ : matrix with n number of sets;
       $[Wc_2]_{n\times 4}$ : matrix with n number of sets;
  for $i \leftarrow 1$ to $n$ do
    $[min_{values}, indices] = min(Wc_1, Wc_2(i, \forall J));$
    $[Wc_{1minvalues}] = find([indices_{Wc1}]);$
    $[Wc_{2minvalues}] = find([indices_{Wc2}]);$
    $[left_{ascend}] = sort([Wc_{1minvalues}]);$
    $[right_{descend}] = sort([Wc_{2minvalues}]);$
    $[indices\ sequence] = [[left_{ascend}], [right_{descend}]];$
  end for
  $target = [indices\ sequence(i,\ \forall\ J)];$
Output: Sequence of indices for n number of cases
```

The defined matrices are taken as inputs for the algorithm. As depicted, the matrices have as many rows as desired number *n* of sets with time data for each type of job. As indicated in the algorithm, the desired output will be a vector with a sequence of indices for each iteration (size of time data set). Therefore, the first step is to find the minimum values and their corresponding indices (time data) for each type of job. The first defined vector $[min_{values}, indices]$ stored these elements. After, it is identified to which workcenter the found values and indices correspond. These are defined in the vectors $[Wc_{1minvalues}]$ and $[Wc_{2minvalues}]$, for workcenter 1 and workcenter 2, respectively. Then, the elements of the previous vectors are organized in ascending and descending form according to their numeric values. These data are collocated in the vectors $[left_{ascend}]$ and $[right_{descend}]$, respectively. Finally, the desired output vector is defined as the concatenation of the previous vectors as indicates the vector $[indices\ sequence]$.

Designing a suitable BPN: The generated database contains *n* number of input vectors for the BPN. Johnson's programmed algorithm contains the set of *n* outputs (targets) corresponding to each of the input vectors in the database.

With the definition of the *n* input-target pairs use of the Matlab toolbox is enabled to structure a BPN. In the Fig. 5.6 the firs Matlab toolbox interface is shown.

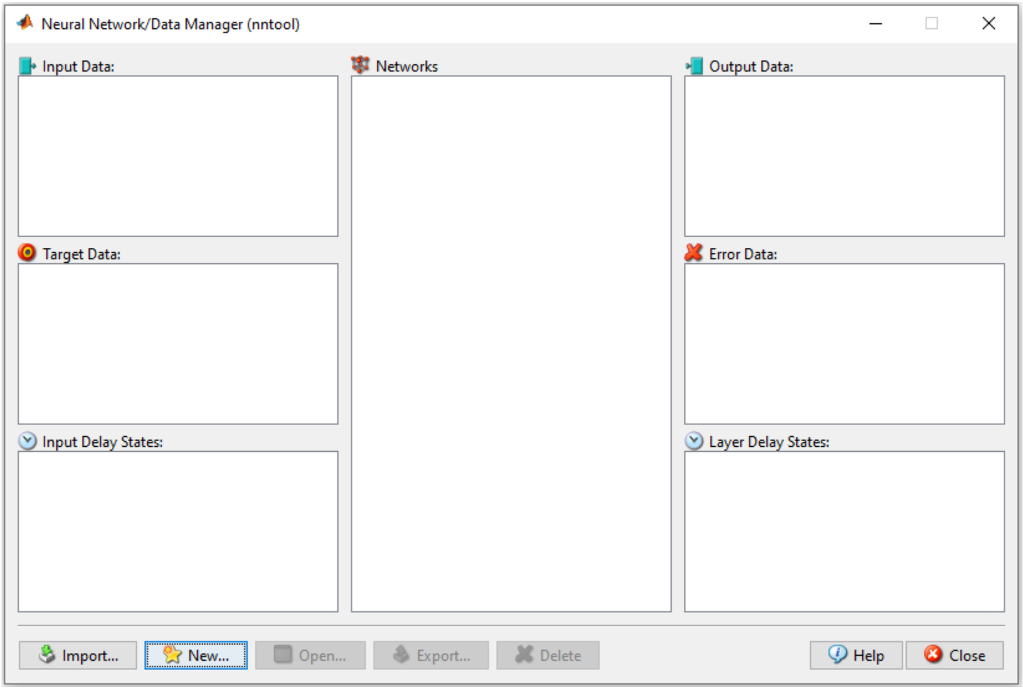
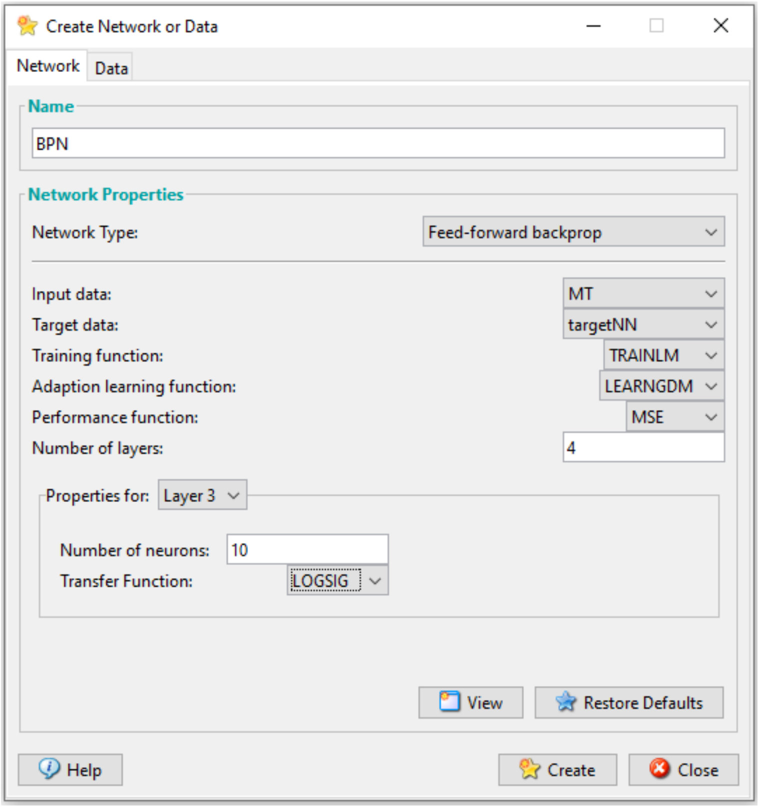


Figure 5.6: Neural Network toolbox interface by Matlab

To start the configuration of a neural network through the interface, it is required to import the input data (Input data) and the desired outputs (Target Data). The generated data can be imported from the Matlab work space, therefore, the *n* input and output vectors are imported from this space. To continue, click on the ”New” tab.

When starting the configuration, the interface shown in the Fig. 5.7 is observed. In this second interface there are different alternatives of network types. This proposal considers the use of a BPN (feed-forward backprop).



Name: BPN
Network Type: Feed-forward backprop
Input data: MT
Target data: targetNN
Training function: TRAINLM
Adaption learning function: LEARNGDM
Performance function: MSE
Number of layers: 4
Properties for: Layer 3
Number of neurons: 10
Transfer Function: LOGSIG

Figure 5.7: Neural Network configuration

The input data and target data must be selected again with the name that was imported from the work space in the previous step. As it is observed, there are some options to be configured, such as the training function, the network performance evaluation function and the number of layers.

The BPN parameters that are manipulated to find the best BPN version that will learn and have the ability to solve the presented problem are: the number of layers in the network, the number of neurons per layer and the size of the data base.

Initially, the observed configuration in 5.7 was used as first attempt in the process to seek the most suitable BPN.

The number of layers to enter includes the final layer. In this first attempt, three hidden layers are entered with a sigmoidal activation function and a linear activation function in the last layer. Also, the number of neurons per layer was set to 10.

Once the BPN configuration has been selected, the network is created by clicking on the ”Create” tab. The toolbox creates a network with the assigned name appearing in the ”Networks” box. It is accessed by clicking on the ”Open” tab (see Fig. 5.8).

The created interface network is shown in Fig. 5.9. When started, the toolbox displays an image with the network settings that were created.

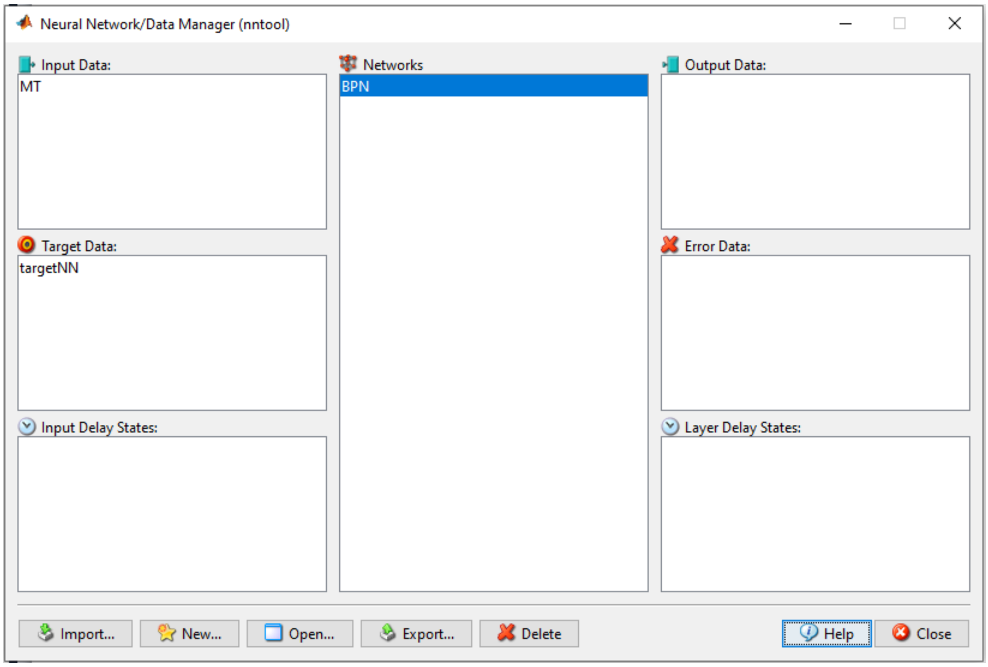


Figure 5.8: Configured BPN 1

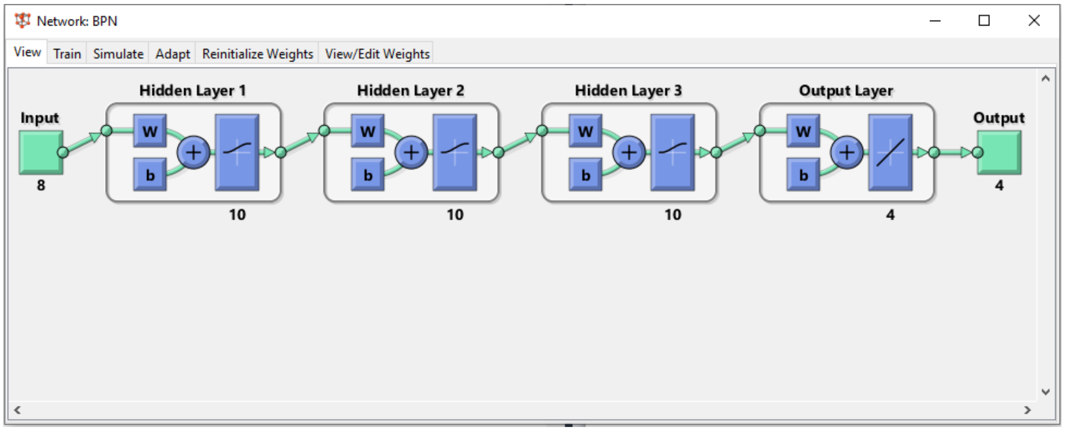
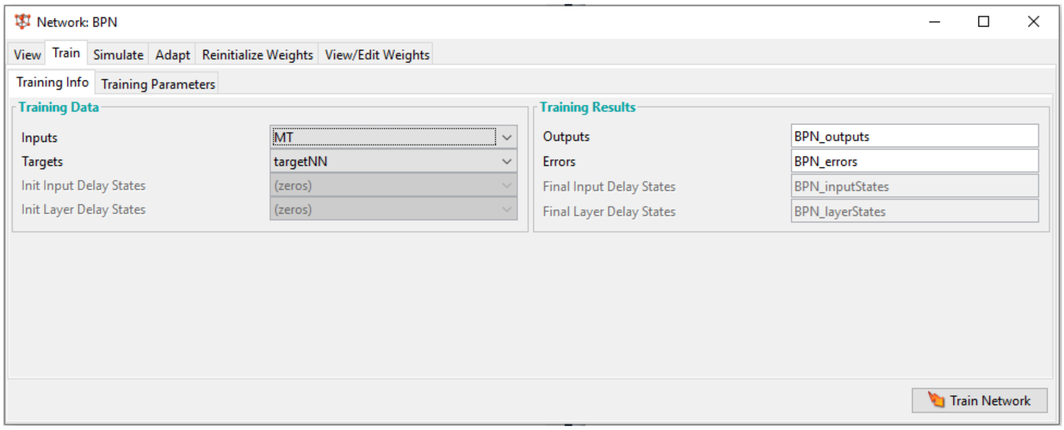


Figure 5.9: General view of the configured BPN

Training Process of the created BPN: Up to this point, a BPN has been structured with the desired characteristics and ready for the training process. Using the Matlab toolbox makes this process easier than if the network were programmed from the beginning. By clicking on the ”Train” tab (Fig. 5.9), the processes of network training can be started. As shown, the input and target vectors need to be selected again.

To initiate the training process, click on the ”Train Network” tab (Fig 5.10). This process regularly lasts a few minutes, this depends on the capabilities of the PC where the process is carried out, the network configuration, the database size, etc.

When the training process has started, a window as that depicted in Fig. 5.11 will be



Training Data

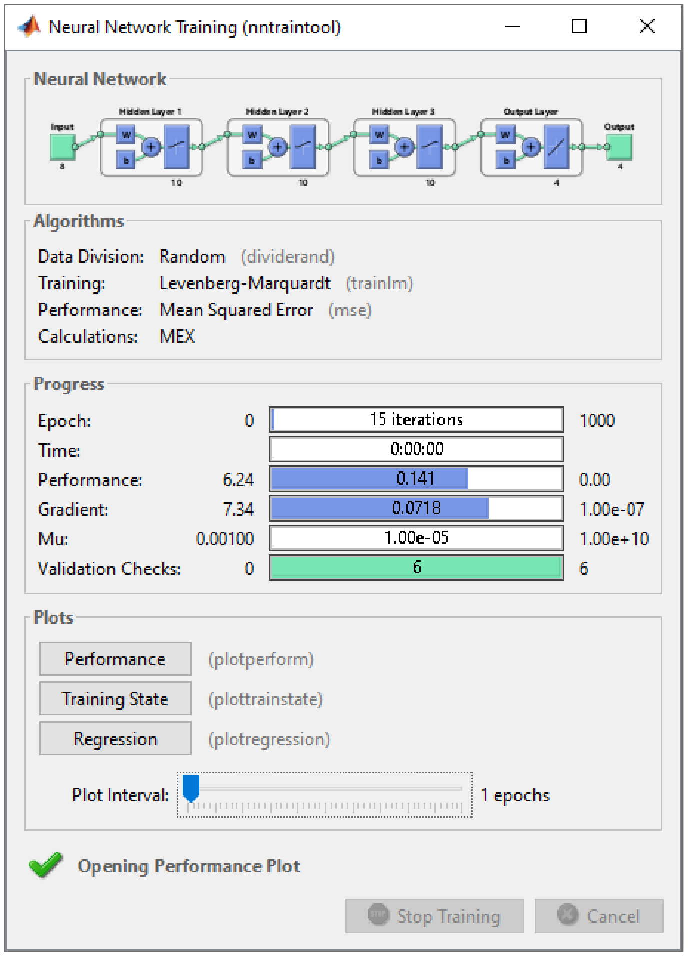
Inputs	MT
Targets	targetNN
Init Input Delay States	(zeros)
Init Layer Delay States	(zeros)

Training Results

Outputs	BPN_outputs
Errors	BPN_errors
Final Input Delay States	BPN_inputStates
Final Layer Delay States	BPN_layerStates

Figure 5.10: Train tab from the Matlab toolbox

opened. The training window displays network configuration information and also, information that changes as network training progresses. In the end, you can access the plots of the training performance, training state, and regression.



Algorithms

Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX

Progress

Epoch:	0	15 iterations	1000
Time:		0:00:00	
Performance:	6.24	0.141	0.00
Gradient:	7.34	0.0718	1.00e-07
Mu:	0.00100	1.00e-05	1.00e+10
Validation Checks:	0	6	6

Performance (plotperform)
Training State (plottrainstate)
Regression (plotregression)

Plot Interval: 1 epochs

✓ Opening Performance Plot

Figure 5.11: Training window from the Matlab toolbox

For training, the Matlab toolbox takes a percentage of the data entered for the training set: 70%; for the validation set: 15%; and for the test set: 15%.

By clicking on the ”Performance” tab, an example of the evolution of the root mean square error (mse) of these three sets with respect to the number of epochs can be observed (Fig. 5.12). The network performance plot is a useful tool in deciding when the network training process (parameter setting and training run) is considered to have acceptable behavior for the intended purpose.

What is sought in the training of any network, is that the validation error is minimum (tends to zero), as the training progresses in the number of epochs and the correlation of the mse between the training, validation and test sets is maintained [62]. Therefore, it is important to keep in mind the value of mse during the training process of the training, validation and test sets.

Therefore, the training process becomes an iterative process until the network configuration that provides the best performance is found. As mentioned, the parameters that were varied throughout this process were the number of hidden layers, the number of neurons per layer and the size of the training set, which as mentioned, a percentage for validation and testing are taken from the original set.

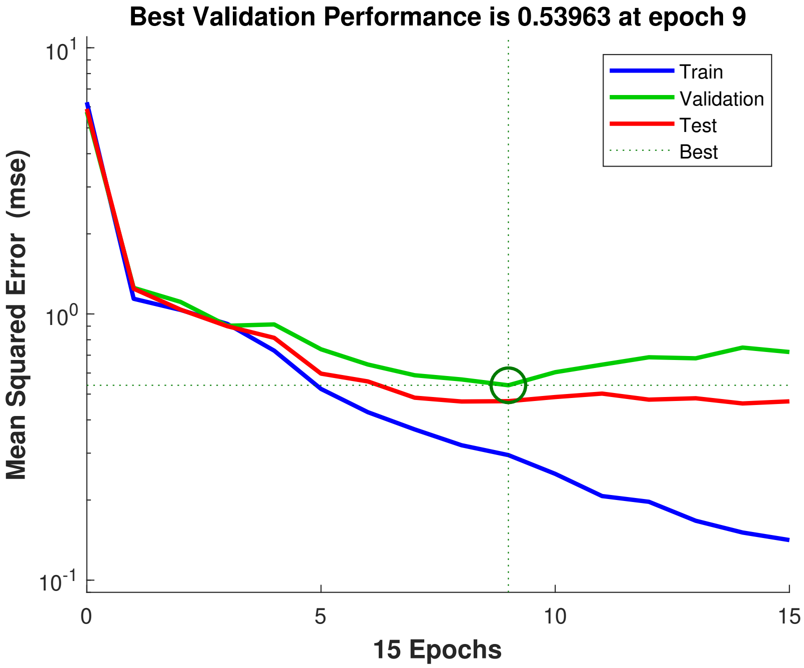


Figure 5.12: Example of a BPN performance after being trained

The section 5.1.5 shows some of the tests that were carried out until reaching what was considered to be the network with the best performance. Besides, the configurations as well as the assertiveness results for each of the designed networks are discussed.

The results of the tests presented are considered useful to obtain conclusions on the resolution of the flow time scheduling problem through BPNs, providing an overview of the feasibility of BPNs for solving this type of problem.

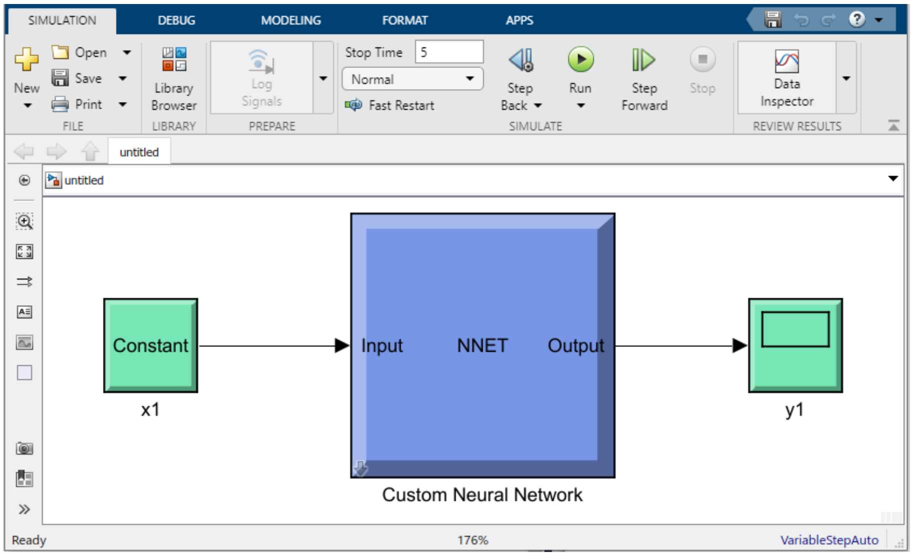
To get part of the results presented for each of the tests, a Simulink representation of the network created through the Matlab toolbox was obtained. The procedure is detailed in the next section.

Exporting and testing the trained network to Simulink

In order to obtain the assertiveness of the BPN designed for each test, the BPN was exported to the workspace of Matlab in order to obtain a model of it in Simulink. To achieve this, the command ”*gensim (network name)*” is executed in Matlab. After executing, a window will open with the generated model as shown in Fig. 5.13.

The Simulink network model will be one for each of the tests presented. For each of them, the following modifications must be accomplished:

- To change the simulation time to 5 seconds.
- In the model parameter settings, remove the ”single simulation output” selection from the ”Dada Import / Export” tab.
- In the scope of the output ”y1”, within the configuration properties in the ”logging” tab, select the option ”log data to workspace” and assign the variable name as ”yi” and save it in an array format.



Stop Time 5

Normal

Figure 5.13: Representation of the network in Simulink

These modifications will be useful when the simulink model for each network is tested with a data set of the same size which it was trained with. That is, the Simulink model will have to be executed for each test n number of times, remembering n as the size of the training set.

To perform this procedure automatically, an algorithm was programmed whose pseudocode (Algorithm 3) is shown below.

Algorithm 3 Execution of Simulink model *n* times

```
Input: [m$_t$ : Matrix of testing of size n×8 ];
       [simOut: repeat (Simulation Outs from 1 to n)];
  for $j \leftarrow 1$ to $n$ do
    $set\ parameters(Network, value, [mt(j, \forall J)]);$
    $simOut(j) = execute(Network);$
    $Results = [simOut\ (yi\ (last\, row, from\ 2\ to\ 5)\forall j];$
  end for
  $Results = [Dataset\ for\ testing]_{n\times 4}$
Output: A matrix of results with n sequences of indices (experimental outputs).
```

As input a matrix containing the test data is declared. This matrix has the same dimensions as the original training set: $n \times 8$. Next, a variable is declared that repeats copies of an array as many times as indicated in its nomenclature. This variable will repeat the Simulink simulation output set *n* times.

Usually, in a Simulink model, the initial parameters are established at the beginning of its execution, changing these each time it is executed. Thus, within the for loop, the first instruction sets the parameters each time the network model is executed, that is, *n* times.

After setting the parameters which the model will be executed with, the instruction for its simulation is called.

Finally, the results matrix is declared, which will be composed of the elements found in the last row, from columns 2 to 5 of the variable ”yi” that is contained in the *simOut* structure that was initially declared. The results matrix has $n \times 4$ dimensions.

The execution of this algorithm is carried out when a trained network is ready to be tested with a new set.

The procedure for each test presented in the following sections can be summarized as follows:

1. Generation of the database with *n* number of elements.
2. Simulation of Johnson’s rule to obtain the desired outputs (target outputs).
3. Configuration and training of the network through the Matlab toolbox.
4. Testing the network with its representative model in Simulink with a data set with n elements (n inputs).
5. Comparing the target outputs with the experimental outputs to measure the effectiveness of the network with the test set from the previous step.

5.1.5 Results to the solution of 4/2/F/Fmax problem through MNN

Test 1

As discussed previously, what is desired in the training process is that the validation mse is minimum, the closest to zero. It is also desired that the percentage of effectiveness be maximum, the closest to 100%. Thus, tests 1-4 will show a couple of plots per test. The first plot corresponds to the mse curves with respect to the number of training epochs in the network, that is, the performance of the network (Fig. 5.14). The second corresponds to the percentage of effectiveness that the network showed when tested with a new set of the same dimension as the set which it was trained with (Fig. 5.15). For convenience, only the most significant tests will be displayed.

The characteristics of the network used for this test are shown in the Table 5.4.

Data in Training set	Hidden Layers	Neurons per Layer
500	3	10

Table 5.4: Network Features in Test 1

It is observed that the mse of the validation error has a minimum value at epoch 9, and it is above 0.5. Despite reaching a minimum value in only 9 epochs, this value is far from indicating good performance by the network.

The minimum validation value shown in the network performance curves coincide with the percentage of effectiveness shown in Fig 5.15. The assertiveness percentage is far from being considered acceptable, showing only 31% effectiveness.

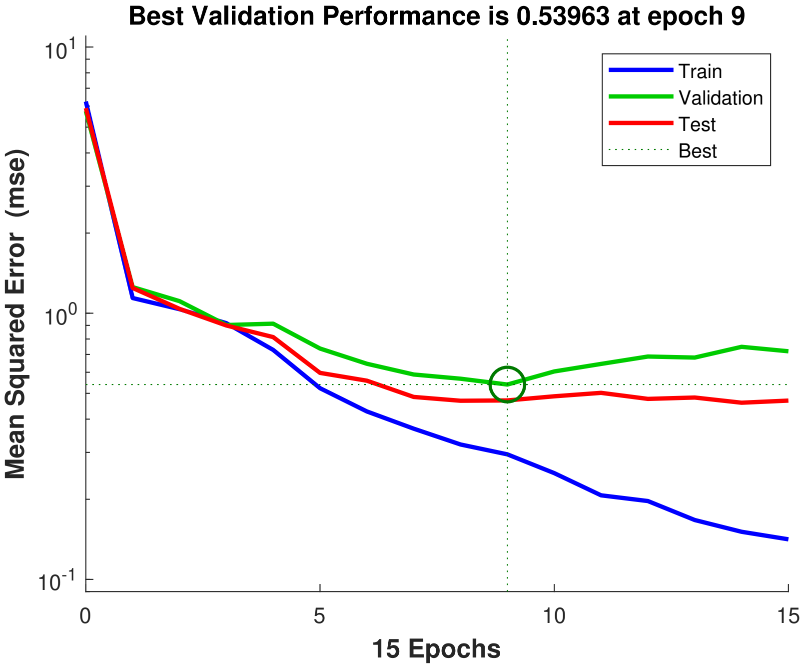


Figure 5.14: Network performance in Test 1

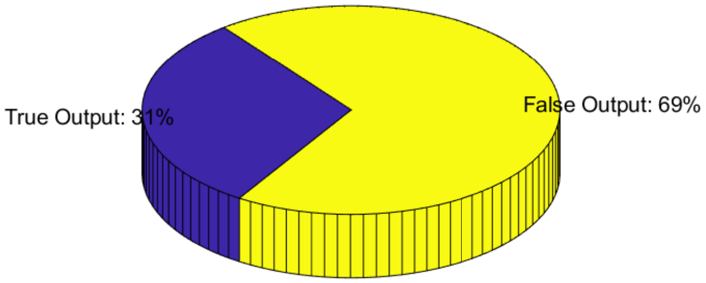


Figure 5.15: Network effectiveness in Test 1

Test 2

The characteristics of the network used for this test are shown in the Table 5.5.

Data in Training set	Hidden Layers	Neurons per Layer
5,000	3	L_1=L_3=20, L_2=10

Table 5.5: Network Features in Test 2

The increase in data resulted in a substantial increase in the percentage of effectiveness. Besides, for this test it was decided to double the number of neurons in the input and output layer. There is a decrease in the validation error (Fig.5.16), Which is reflected in an increment in the percentage of assertiveness of the trained network (5.17).

Unlike the change observed with the increase in data, the increase in neurons per layer provides an increase in a smaller percentage.Thus, despite the fact that the indexes for selecting a final network have increased positively, it is still expected to achieve better values by increasing the number of training and test data for the network.

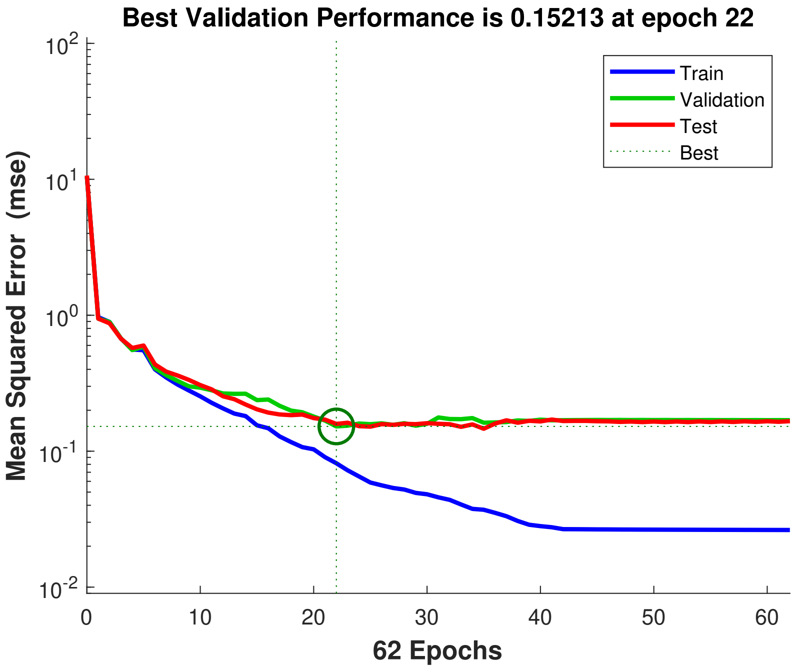


Figure 5.16: Network performance in Test 3

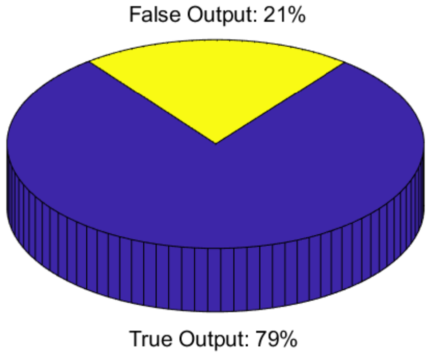


Figure 5.17: Network effectiveness in Test 2

Test 3

The characteristics of the network used for this test are shown in the Table 5.6.

Data in Training set	Hidden Layers	Neurons per Layer
20,000	3	10

Table 5.6: Network Features in Test 3

For this test, the size of the training and test set is again increased. As can be seen in the Table 5.6, the amount of data was incremented considerably and the expected results with this action are shown in Fig. 5.18 and 5.19.

The network validation error has a minimum value below the value found for other tests with similar features. The increment in the data set makes the percentage of assertiveness to be higher.

The increase in the training data base means a better learning of the network, there is a substantial improvement observed in performance or effectiveness compared to a previous test.

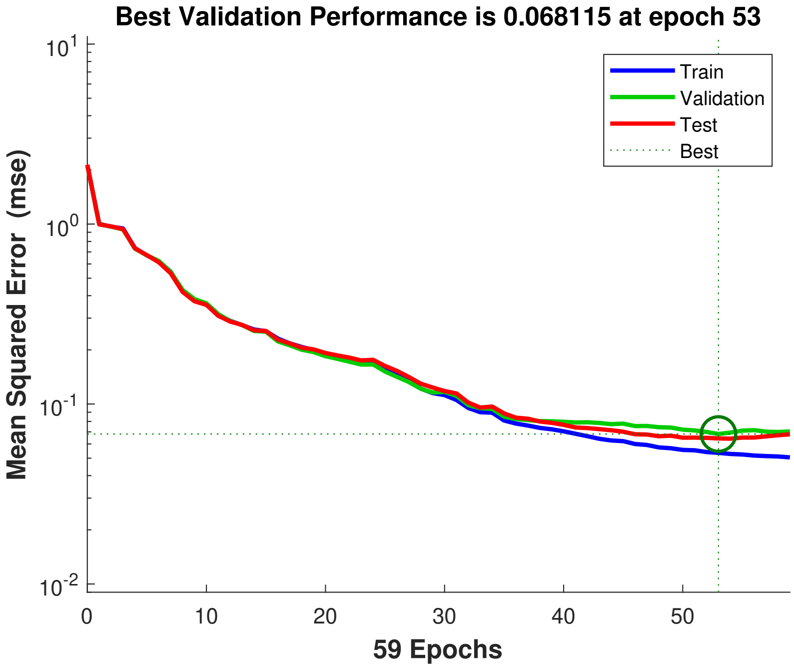


Figure 5.18: Network performance in Test 3

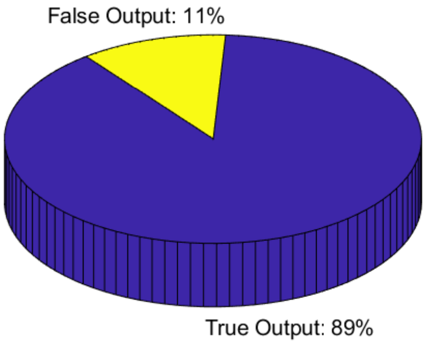


Figure 5.19: Network effectiveness in Test 3

As seen in this test set for a neural network with feed-forwarding backpropagation learning algorithm, the training process, understood as training and testing with a new set, is an iterative evaluation process.

The training process achieves an acceptable solution for being applied in the decision of the shortest makespan. Since the training of the neural network is based on data, it could be necessary to add more data of different cases to cover all the possibilities that are integrated into the universe of decisions. Test 4 shows results with an increase of the data size.

The characteristics of the network used for Test 4 are shown in the Table 5.7.

Data in Training set	Hidden Layers	Neurons per Layer
100,000	5	20

Table 5.7: Network Features in Test 4

For this test, the amount of data was incremented as well as the number of hidden layers. The results with this action are shown in Fig. 5.20 and 5.21.

The network validation error decreased compared to the previous test with less data and hidden layers. So, the increment in these parameters make the percentage of assertiveness to be significantly higher.

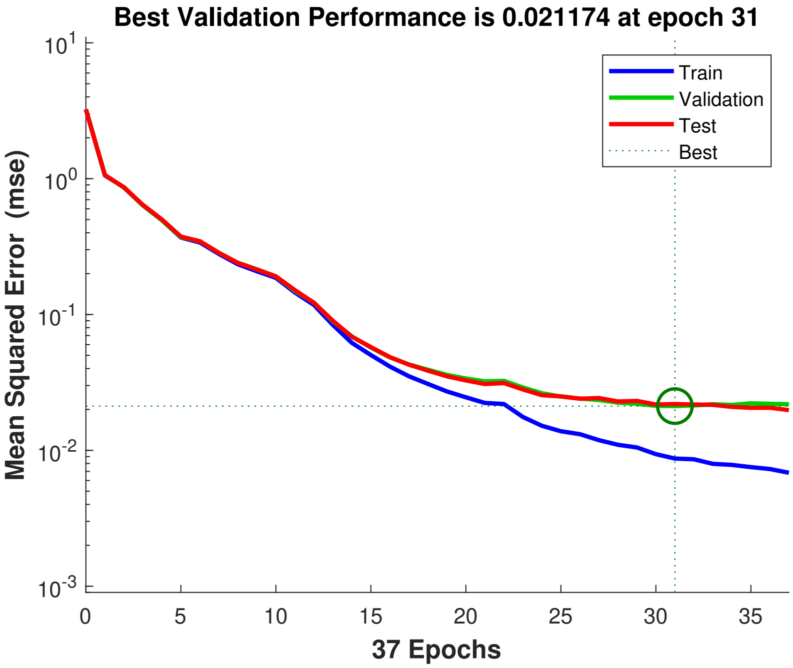


Figure 5.20: Network performance in Test 4

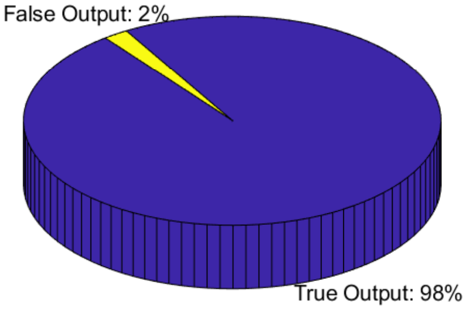


Figure 5.21: Network effectiveness in Test 4

Chapter 6

Conclusions

This work proposed a reference manufacturing AP architecture based on the DT concept. The main objective was proposing a new model obeys to the continuous evolution of manufacturing systems that incorporates new structures and smart technologies to have more flexibility in the way an enterprise operates.

With the help of emerging technological structures such as DT, manufacturing systems are evolving towards systems that offer useful decision-making tools at strategic points in the product production chain. With the incorporation of artificial intelligence algorithms, new manufacturing systems can improve their performance autonomously and in a supervised manner.

The incorporation of the ISA-95 standard within the model gives support to the proposal so that the models can be incorporated into a system with order and structure according to the standard.

In addition to finding areas of improvement for the didactic manufacturing system, the evaluation through the DT models proposed for each level helped to obtain feedback for the proposed architecture. For the DT-1, the relevance of the figure of the server as a link element between the field elements and the virtual model of the system stands out in order to have the information that occurs at the moment of the process available in a timely manner. In addition to this, the OPC UA communication standard was identified as the one that will make it possible for automation systems to communicate with more intelligent components, turning them into cyber-physical systems. Regarding the DT-2, it is concluded that the interface discussed in chapter 3 for the DT-2 must also consider the typical characteristics of a typical HMI. The supervision function proposed for this model through vision stands out as crucial for quality control in production and seems a viable path for this task, based on the good availability that could be had of the elements that make up this model in an industrial and development environment that has vision-based supervision systems.

For the DT-3 model, the resolution of one of the tasks that are usually solved in the MES and that belongs to production control, through multilayer artificial neural networks, was presented. Through the ANNs presented, it is possible to find the optimal makespan for the execution of tasks in two work centers. As is known, the percentage of effectiveness of the networks presented depends largely on the dimension of the database with which it is trained, it is observed that the larger the database, the better assertiveness of the network. The trend of the feedforward backpropagation networks that were presented indicates that the more data available for network training, the better the results. Thus, the most determining variant in the tests was the size of the training set. Through the increase in data, a notable improvement in the performance and effectiveness of the network was observed. For this reason, it is concluded that for the resolution of problems through ANN it is crucial to have a database such that it represents the greatest possible number of scenarios that may arise in a process. Also, as discussed in the advantages and disadvantages of ANNs, the larger the data set for the training process, the longer the time to perform it, as observed during the training process for the networks presented.This situation can increase or decrease depending on the equipment where the procedure is performed. For the execution of a single algorithm, the time it takes for a network in training does not seem to be critical, however, if we extrapolate this scenario to the execution of a set of tasks solved by one or several networks simultaneously, with large test sets , this must be executed with a high performance computer equipment to reduce the time of training execution.

When databases with fewer elements are used, poor performance is observed, which leads to a considerable error rate, which in the execution would mean a poor organization of the sequence of jobs, leading to a reduction in the efficiency of their execution.

The 4/2/F/Fmax problem was only solved through a single network topology, limiting it to a single training algorithm. Even with this, acceptable percentages of effectiveness were obtained, which may motivate to explore new alternatives for those parameters that remained fixed in this case study, including looking for topologies of artificial networks with different characteristics.

Through the proposed neural networks, only one of the many problems that may arise for each of the functions that integrate the higher levels of the AP was solved, therefore, so that the model can be functional, each of the processes, their parameters and variables will have to be clearly identified for each of the tasks that are executed, in each of the defined functions. Therefore, to aspire to the above, it is essential to itemize each of the tasks that are carried out in each function, at each level, identify the typical problems, and map these to be solved through a neural network or well, some other intelligent algorithm.

Appendix A

Appendix A

```
%%Data base Generation
%This routine generates the dataset with n number of elements and stores
%them in an array with dimensions Jxn

clear
rng(’default’);
xmin=[2 1 3 4]; %lower boundary time in time units
xmax=[6 5 7 9]; %higher boundary time in time units
J=4; %number of Job types
n=20000; %number of desired elements in data base
M1=[]; %matrix M1
M2=[]; %matrix M2

for i=1:n
    M1= [M1; i*(round(xmin+rand(1,J).*(xmax-xmin),2))/i]; % M1 row vector with (1xn) random numbers
    M2= [M2; i*(round(xmin+rand(1,J).*(xmax-xmin),2))/i]; % M2 row vector with (1xn) random numbers
    end
MT=[M1(1:n,:) M2(1:n,:)]’; %matrix that joins the data for WC 1 and WC 2
                           %input vector for network training
```

Listing A.1: Data base Generation Code

```
%% Jhonson's rule
%This subrutine execute the Johnson's Rule.
%The output of this code is a vector with the target outputs in the
%process of training

Sequence_in_index =[];
for i=1:n
    [d,rows]= min([M1(i,:);M2(i,:)], [], 1);%get lowest value in each column
    lcols = find(rows==1);          % columns where M1 is smaller
    rcols = find(rows==2);          % columns where M2 is smaller
    [left,lorder] = sort(d(lcols), 'ascend');     %left elements
    [right,rorder] = sort(d(rcols),'descend');    %right elements
    %Sequence_in_numbers = [left right];           %sequence of numbers
    Sequence_in_index = [Sequence_in_index; i*[lcols(lorder), rcols(rorder)]/i];  %index of the sequence
end
targetNN=[Sequence_in_index(1:n,:)]'; %output vector with the sequence of
                                      %indices;
                                      %output vector for training the net
```

Listing A.2: Johnson's Rule Code

```
%% Iterations with the Simulink model of the Network

find_system('Name','Sim_test1'); %Fin the model in the "Current Folder"
open_system('red_6_4'); %open the system with name 'model name'
mt=MT'; %collocating the matrix of times
simOut = repmat(Simulink.SimulationOutput, length(MT), 1); %repeat the # of iterations from the simulation of the results matrix
results=[];
for j=1:length(MT)
set_param('red5/x1','Value','[mt(j,1);mt(j,2);mt(j,3);mt(j,4);mt(j,5);mt(j,6);mt(j,7);mt(j,8)]'); %initial values of network input
simOut(j)= sim('red5','timeout',10); %execute the simulink model j times
results=[results;round(simOut(j,1).yi(6,2:5),0)]; %vector to storage the ouput yi

end
```

Listing A.3: Code of n tests with Simulink Model

```
%% Comparison of Results
%This routine compares the matrices "targetNN" (results from the Johnsons
%rule) and  "results" (simulation results from the simulink model)

A=targetNN';
B=results;
uni=ones(1,4);
final=[]; %results matrix: zero the network does not achieve a successful
          %output, it is, the "targetNN" is different from "results"
for k=1:length(MT)
    final=[final;A(k,:)==B(k,:)];
end

final2=[]; %results matrix No. 2, 1=the net succeed, 0=the net fail
for l=1:n
    final2=[final2;final(l,1)*final(l,2)*final(l,3)*final(l,4)];
end
```

Listing A.4: Code for comparing the target to results vector

```
%% Plot of results

%This routine plots the final graph, the plot of asertiveness percentage

unos=final2(final2==1,:);
unosl=length(unos);
ceros=final2(final2<1,:);
cerosl=length(ceros);
grafi=[unosl cerosl];

%pie3(grafi,{'True Output','False Output'})%graph in cake
p=pie3(grafi)
pText = findobj(p,'Type','text');
percentValues = get(pText,'String');
txt = {'True Output: ';'False Output: '};
combinedtxt = strcat(txt,percentValues);

pText(1).String = combinedtxt(1);
pText(2).String = combinedtxt(2);
```

Listing A.5: Code of results plot

References

[1] M. E. S. A. MESA, “Smart Manufacturing Landscape,” p. 15, 2016.

[2] J. Davis, “Smart manufacturing, manufacturing intelligence and demand-dynamic performance,” *Computers and Chemical Engineering*, p. 12, 2012.

[3] Federal Ministry for Economic Affairs and Energy, “INDUSTRIE 4.0,” Jul. 2020. [Online]. Available: https://www.plattform-i40.de/PI40/Navigation/EN/Industrie40/WhatIsIndustrie40/what-is-industrie40.html

[4] International Society of Automation, *ISA-95.00.01-2000, Enterprise-control system integration. models and terminology.*, 2000th ed. Research Triangle Park, N.C.: ISA, 2000, oCLC: 48633110.

[5] ISA, “ISA95, Enterprise-Control System Integration,” Jul. 2020. [Online]. Available: https://www.isa.org/isa95/

[6] S. M. Kannan, K. Suri, J. Cadavid, I. Barosan, M. Van Den Brand, M. Alferez, and S. Gerard, “Towards industry 4.0: Gap analysis between current automotive mes and industry standards using model-based requirement engineering,” in *2017 IEEE International Conference on Software Architecture Workshops (ICSAW)*. IEEE, 2017, pp. 29–35.

[7] J. Zhou, Y. Zhou, B. Wang, and J. Zang, “Human–cyber–physical systems (hcpss) in the context of new-generation intelligent manufacturing,” *Engineering*, vol. 5, no. 4, pp. 624–636, 2019.

[8] F. Almada-Lobo, “The industry 4.0 revolution and the future of manufacturing execution systems (mes),” *Journal of innovation management*, vol. 3, no. 4, pp. 16–21, 2015.

[9] L. Cassettari, “Digitalization of manufacturing execution systems: the core technology for realizing future smart factories.”

[10] F. Pan, H. Shi, and B. Duan, “Manufacturing execution system present situation and development trend analysis,” in *2015 IEEE International Conference on Information and Automation*. IEEE, 2015, pp. 535–540.

[11] Q. Gao, F. Li, and C. Chen, “Research of internet of things applied to manufacturing execution system,” in *2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER)*. IEEE, 2015, pp. 661–665.

[12] R. Y. Zhong, Q. Dai, T. Qu, G. Hu, and G. Q. Huang, “Rfid-enabled real-time manufacturing execution system for mass-customization production,” *Robotics and Computer-Integrated Manufacturing*, vol. 29, no. 2, pp. 283–292, 2013.

[13] P. Helo, M. Suorsa, Y. Hao, and P. Anussornnitisarn, “Toward a cloud-based manufacturing execution system for distributed manufacturing,” *Computers in Industry*, vol. 65, no. 4, pp. 646–656, 2014.

[14] J. S. Hurwitz, R. Bloor, M. Kaufman, and F. Halper, *Service Oriented Architecture (SOA) for Dummies*. John Wiley & Sons, 2009.

[15] E. Bonabeau, “Agent-based modeling: Methods and techniques for simulating human systems,” *Proceedings of the national academy of sciences*, vol. 99, no. suppl 3, pp. 7280–7287, 2002.

[16] R. Cupek, A. Ziebinski, L. Huczala, and H. Erdogan, “Agent-based manufacturing execution systems for short-series production scheduling,” *Computers in Industry*, vol. 82, pp. 245–258, 2016.

[17] M. Rolon and E. Martinez, “Agent learning in autonomic manufacturing execution systems for enterprise networking,” *Computers & Industrial Engineering*, vol. 63, no. 4, pp. 901–925, 2012.

[18] B. Saenz de Ugarte, A. Artiba, and R. Pellerin, “Manufacturing execution system–a literature review,” *Production planning and control*, vol. 20, no. 6, pp. 525–539, 2009.

[19] Y. Qu, X. Ming, Z. Liu, X. Zhang, and Z. Hou, “Smart manufacturing systems: state of the art and future trends,” *The International Journal of Advanced Manufacturing Technology*, vol. 103, no. 9-12, pp. 3751–3768, 2019.

[20] K. Ding, F. T. Chan, X. Zhang, G. Zhou, and F. Zhang, “Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors,” vol. 57, no. 20, pp. 6315–6334. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/00207543.2019.1566661

[21] Michael Grieves, “Digital twin: Manufacturing excellence through virtual factory replication.”

[22] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, “Digital twin in industry: State-of-the-art,” vol. 15, no. 4, pp. 2405–2415. [Online]. Available: https://ieeexplore.ieee.org/document/8477101/

[23] F. Tao and M. Zhang, “Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing,” vol. 5, pp. 20 418–20 427. [Online]. Available: http://ieeexplore.ieee.org/document/8049520/

[24] C. Cimino, E. Negri, and L. Fumagalli, “Review of digital twin applications in manufacturing,” vol. 113, p. 103130. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0166361519304385

[25] R. Cupek, M. Drewniak, A. Ziebinski, and M. Fojcik, "“digital twins” for highly customized electronic devices – case study on a rework operation," vol. 7, pp. 164 127–164 143. [Online]. Available: https://ieeexplore.ieee.org/document/8890646/

[26] M. Hankel and B. Rexroth, "The reference architectural model industrie 4.0 (rami 4.0)," *ZVEI*, vol. 2, no. 2, pp. 4–9, 2015.

[27] T. Coito, J. L. Viegas, M. S. Martins, M. M. Cunha, J. Figueiredo, S. M. Vieira, and J. M. Sousa, "A novel framework for intelligent automation," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 1825–1830, 2019.

[28] E. Negri, S. Berardi, L. Fumagalli, and M. Macchi, "Mes-integrated digital twin frameworks," *Journal of Manufacturing Systems*, vol. 56, pp. 58–71, 2020.

[29] D. Cortés, J. Ramírez, L. Villagómez, R. Batres, V. Vasquez-Lopez, and A. Molina, "Digital pyramid: an approach to relate industrial automation and digital twin concepts," in *2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*. IEEE, 2020, pp. 1–7.

[30] L. Monostori, B. Kádár, T. Bauernhansl, S. Kondoh, S. Kumara, G. Reinhart, O. Sauer, G. Schuh, W. Sihn, and K. Ueda, "Cyber-physical systems in manufacturing," vol. 65, no. 2, pp. 621–641. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0007850616301974

[31] SIEMENS, "ISA 95 Framework and Layers," 2019. [Online]. Available: https://www.plm.automation.siemens.com/global/es/our-story/glossary/isa-95-framework-and-layers/53244

[32] ISA (Society), *Enterprise-control system integration. models and terminology.* ISA, OCLC: 48633110.

[33] E. Oztemel and S. Gursev, "Literature review of Industry 4.0 and related technologies," *Journal of Intelligent Manufacturing*, vol. 31, no. 1, pp. 127–182, Jan. 2020. [Online]. Available: http://link.springer.com/10.1007/s10845-018-1433-8

[34] M. A. Abd Elmonem, E. S. Nasr, and M. H. Geith, "Benefits and challenges of cloud ERP systems – a systematic literature review," vol. 1, no. 1, pp. 1–9. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2314728816300599

[35] B. Johansson, A. Alajbegovic, V. Alexopoulo, and A. Desalermos, "Cloud ERP adoption opportunities and concerns: The role of organizational size," in *2015 48th Hawaii International Conference on System Sciences*. IEEE, pp. 4211–4219. [Online]. Available: http://ieeexplore.ieee.org/document/7070323/

[36] D. Aloini, R. Dulmin, and V. Mininno, "Risk assessment in ERP projects," vol. 37, no. 3, pp. 183–199. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306437911001268

[37] D. Mourtzis, N. Papakostas, D. Mavrikios, S. Makris, and K. Alexopoulos, "The role of simulation in digital manufacturing: applications and outlook," vol. 28, no. 1, pp. 3–24. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/0951192X.2013.800234

[38] D. Mourtzis, M. Doukas, and D. Bernidaki, "Simulation in manufacturing: Review and challenges," vol. 25, pp. 213–229. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2212827114010634

[39] C. J. Su, "Effective mobile assets management system using RFID and ERP technology," in *2009 WRI International Conference on Communications and Mobile Computing*. IEEE, pp. 147–151. [Online]. Available: http://ieeexplore.ieee.org/document/4797237/

[40] S. Iarovyi, W. M. Mohammed, A. Lobov, B. R. Ferrer, and J. L. M. Lastra, "Cyber–physical systems for open-knowledge-driven manufacturing execution systems," vol. 104, no. 5, pp. 1142–1154. [Online]. Available: http://ieeexplore.ieee.org/document/7430247/

[41] M. McClellan, *Applying manufacturing execution systems.* CRC Press, 1997.

[42] P. D. Urbina Coronado, R. Lynn, W. Louhichi, M. Parto, E. Wescoat, and T. Kurfess, "Part data integration in the shop floor digital twin: Mobile and cloud technologies to enable a manufacturing execution system," vol. 48, pp. 25–33. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S027861251830013X

[43] B. W. Jeon, J. Um, S. C. Yoon, and S. Suk-Hwan, "An architecture design for smart manufacturing execution system," vol. 14, no. 4, pp. 472–485. [Online]. Available: http://www.cad-journal.net/files/vol_14/Vol14No4.html

[44] F. Almada-Lobo, "The industry 4.0 revolution and the future of manufacturing execution systems (MES)," vol. 3, no. 4, pp. 16–21. [Online]. Available: https://journalsojs3.fe.up.pt/index.php/jim/article/view/2183-0606_003.004_0003

[45] Thilo Sauter, "The contuining evolution of integration in manufacturing automation."

[46] MESA International, "MES functionalities & MRP to MES data FLow possibilities."

[47] C. Zhuang, J. Liu, and H. Xiong, "Digital twin-based smart production management and control framework for the complex product assembly shop-floor," vol. 96, no. 1, pp. 1149–1163. [Online]. Available: http://link.springer.com/10.1007/s00170-018-1617-6

[48] Y. Zheng, S. Yang, and H. Cheng, "An application framework of digital twin and its case study," vol. 10, no. 3, pp. 1141–1153. [Online]. Available: http://link.springer.com/10.1007/s12652-018-0911-3

[49] K. Reifsnider and P. Majumdar, "Multiphysics stimulated simulation digital twin methods for fleet management," in *54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*. American Institute of Aeronautics and Astronautics. [Online]. Available: http://arc.aiaa.org/doi/10.2514/6.2013-1578

[50] E. Glaessgen and D. Stargel, “The digital twin paradigm for future NASA and u.s. air force vehicles,” in *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference
20th AIAA/ASME/AHS Adaptive Structures Conference
14th AIAA*. American Institute of Aeronautics and Astronautics. [Online]. Available: http://arc.aiaa.org/doi/abs/10.2514/6.2012-1818

[51] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, “Digital twin-driven product design, manufacturing and service with big data,” vol. 94, no. 9, pp. 3563–3576. [Online]. Available: http://link.springer.com/10.1007/s00170-017-0233-1

[52] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, “Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues,” vol. 61, p. 101837. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0736584519302480

[53] Q. Qi and F. Tao, “Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison,” vol. 6, pp. 3585–3593. [Online]. Available: http://ieeexplore.ieee.org/document/8258937/

[54] Z. Ge, Z. Song, S. X. Ding, and B. Huang, “Data mining and analytics in the process industry: The role of machine learning,” vol. 5, pp. 20 590–20 616. [Online]. Available: http://ieeexplore.ieee.org/document/8051033/

[55] L. Song and R. Nagi, “Design and implementation of a virtual information system for agile manufacturing,” *Iie Transactions*, vol. 29, pp. 839–857, 1997.

[56] T. M. Mitchell, *Machine Learning*, ser. McGraw-Hill series in computer science. McGraw-Hill.

[57] P. Martinez, R. Ahmad, and M. Al-Hussein, “A vision-based system for pre-inspection of steel frame manufacturing,” vol. 97, pp. 151–163. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0926580518306332

[58] J. Guo, J. Wang, R. Bai, Y. Zhang, and Y. Li, “A new moving object detection method based on frame-difference and background subtraction,” vol. 242, p. 012115. [Online]. Available: https://iopscience.iop.org/article/10.1088/1757-899X/242/1/012115

[59] J. V. Tu, “Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes,” *Journal of clinical epidemiology*, vol. 49, no. 11, pp. 1225–1231, 1996.

[60] M. M. Mijwel, “Artificial neural networks advantages and disadvantages,” *Retrieved from LinkedIn https//www. linkedin. com/pulse/artificial-neuralnet Work*, 2018.

[61] M. Gardner and S. Dorling, “Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences,” vol. 32, no. 14, pp. 2627–2636. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1352231097004470

[62] P. P. Cruz, “Inteligencia artificial. con aplicaciones a la ingeniería,” p. 378.

[63] E. M. Martinez, P. Ponce, I. Macias, and A. Molina, “Automation pyramid as constructor for a complete digital twin, case study: A didactic manufacturing system,” *Sensors*, vol. 21, no. 14, p. 4656, 2021.

[64] OPC Foundation, “What is OPC,” 2022. [Online]. Available: https://opcfoundation.org/about/what-is-opc/

[65] W. Mahnke, S.-H. Leitner, and M. Damm, *OPC unified architecture*. Springer Science & Business Media, 2009.

[66] D. Martin, N. Kühl, and G. Satzger, “Virtual sensors,” *Business & Information Systems Engineering*, vol. 63, no. 3, pp. 315–323, 2021.

[67] A. Y. Nee, S. Ong, G. Chryssolouris, and D. Mourtzis, “Augmented reality applications in design and manufacturing,” *CIRP annals*, vol. 61, no. 2, pp. 657–679, 2012.

[68] W.-j. Wang and P. Brunn, “Production scheduling and neural networks,” in *Operations Research Proceedings 1994*. Springer, 1995, pp. 173–178.

[69] T. Cheng and B. Lin, “Johnson’s rule, composite jobs and the relocation problem,” vol. 192, no. 3, pp. 1008–1013. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0377221707011265

[70] R. L. Graham, E. L. Lawler, J. K. Lenstra, and A. R. Kan, “Optimization and approximation in deterministic sequencing and scheduling: a survey,” in *Annals of discrete mathematics*. Elsevier, 1979, vol. 5, pp. 287–326.

[71] S. M. Johnson, “Optimal two-and three-stage production schedules with setup times included,” *Naval research logistics quarterly*, vol. 1, no. 1, pp. 61–68, 1954.